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The Effectiveness of Child Restraint and Bicycle Helmet Policies to Improve Road Safety

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THE EFFECTIVENESS OF CHILD RESTRAINT AND BICYCLE HELMET POLICIES TO IMPROVE ROAD SAFETY

by

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ABSTRACT

Analyzing the effect of legislation in children's safety when they travel as motor-vehicle passengers and bicycle riders can allow us to evaluate the effectiveness in transportation policies. The Child Restraint Laws (CRL) and Bicycle Helmet Laws (BHL) were studied by analyzing the nationwide Fatality Analysis Reporting System (FARS) to estimate the fatality reduction as well as drivers' decisions to use Child Restraint Systems (CRS) and bicycle helmets respectively. Differences in legislation could have different effects on traffic fatalities. Therefore, this study presents multiple methodologies to study these effects. In the evaluation of traffic safety issues, several proven statistical models have shown to be effective at estimating risky factors that might influence crash prevention. These proven models and predictive data analysis guided the process to attempt different models, leading to the development of three specific models used in this study to best estimate the effectiveness of these laws. Then, it was found that legislation in Child Safety Policy has consequences in traffic fatalities. A negative binomial model was created to analyze the CRL influence at the state-level in fatal crashes involving children, and showed that legislating on CRS can reduce the number of fatalities by 29% for children aged 5 to 9. Additionally, at the drivers-level a logistic regression model with random effects was used to determine the significant variables that influence the driver's decision to restrain his/her child. Such variables include: driver's restraint use, road classification, weather condition, number of occupants in the vehicle, traffic violations and driver's and child's age. It was also shown that drivers from communities with deprived socio-economic status are less likely to use CRS. In the same way, a binary logistic regression model was developed to evaluate the effect of BHL in bicycle helmet-use. Findings from this model show that bicyclists from states with the BHL are 236 times more likely to wear a helmet compared to those from states without the BHL. Moreover, the bicyclist's age, gender,

education, and income level also influences bicycle helmet use. Both studies suggest that enacting CRL and BHL at the state-level for the studied age groups can be combined with education, safety promotion, enforcement, and program evaluation as proven countermeasures to increase children's traffic safety. This study evidenced that there is a lack of research in this field, especially when policy making requires having enough evidence to support the laws in order to not become an arbitrary legislation procedure affecting child's protection in the transportation system.

“Entrust your work to the LORD, and your plans will succeed.” Proverbs 16:3.

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LIST OF ABBREVIATIONS

ACS	American Community Survey
AIC	Akaike's Information Criterion
BHL	Bicycle Helmet Law
BIC	Bayesian Information Criteria
CAPS	Car Assessment Programs
CMF	Crash Modification Factor
CRL	Child Restraint Law
CRS	Child Restraint Systems
CRS-use	Use of Child Restraint Systems
FARS	Fatality Analysis Reporting System
ITS	Intelligent Transportation Systems
NB	Negative Binomial
NHTSA	National Highway Traffic Safety Administration
SPF	Safety Performance Function
UCF	University of Central Florida

CHAPTER 1. INTRODUCTION

1.1 Overview

Exploring traffic safety effects in transportation systems is essential for decision making in transportation policy. In 2015, the National Highway Traffic Safety Administration (NHTSA) estimated 35,092 people died in the United States and 2,443,000 people suffered injuries in motor vehicle traffic crashes (National Highway Traffic Safety, 2015). Although the nation's fatality rate is comparatively low to other countries in the world, it is an important matter since there are so many deaths associated with traffic related fatalities due to the interaction between individuals, the road and vehicles. These factors include the major concerns that road safety is based on. Therefore, road safety aims to reduce the occurrence of traffic crashes, minimize their effects and establish prevention countermeasures. Then, policy decisions could use road safety analyses to support the laws in order to not become an arbitrary legislation process.

An accelerated population growth and vehicle usage in the 20th century revealed enumerable transportation risks, particularly in traffic crashes. At a global point of view, we are reaching now to nearly 1.3 million deaths, more than 3000 deaths each day and between 20 to 50 million non-fatal injuries per year in the world, according to the World Health Organization, the United Nations, and the World Bank (United Nations, 2010). To address this, the United Nations created The Road Safety Decade of 2011-2020 plan, which seeks to reduce global traffic fatalities by 2020 through the creation of new policies, control and regulation of the traffic, the construction of roads and safer vehicles, education on driver safety, and providing immediate attention to victims when collisions happen.

As the nation's transportation systems has become more matured and competitive, the use of public infrastructure has required the involvement of government agencies to regulate the use

and transit conditions through laws seeking a safe, equitable, sustainable, and organized mobility of all users. Understanding how transportation policy works, can be considered as a way to analyze people's needs to move from one place to another and their interaction with highway planning, transit, traffic safety, road user's behavior, sustainability and technical standards.

There is no doubt that the advancement of new technology has been taking an important role in Transportation. Intelligent Transportation Systems (ITS), safer roads and vehicles, among lessons learned worldwide have tackled road safety into a broader level to be included into legislation. The use of different transportation modes has achieved a higher level to find regulations which seek for road user's safety. The way to assure mobility for everyone has brought policy concerns to look on the effect of transportation risks for all road users.

1.2 Transportation Policy in the U.S

Transportation laws include a wide set of regulations for different modes, such as air, water, and land transport including rail, roads, bridges, trails, ports and any other ways. Similarly, the laws that regulate transportation pertain not only to these modes of travel, but also to the users, such as older drivers, vulnerable users, children, and teenagers among others. More than half of all fatalities caused by traffic accidents have been shown to involve pedestrians, cyclists and motorcyclists; whereas road safety legislation contributes to reduce traffic crashes. However, this study focuses on the transportation analysis of road-vehicle's interaction between cars, trucks, motorcycles, and bicyclists. Moreover, it focuses on children's traffic safety.

Transportation laws can also differ from state, federal, county, city, or local government and can be applied very broadly at a transport system level such as transit, driving, walking, bicycling, or at the interaction between them. Even if all of them are trying to regulate the same

purpose, differences in their rulemaking processes can create variability in the laws. Consequently, they can cause different effects including higher or lower degrees of credibility and compliance.

Why is transportation policy essential? Because every transportation agency has the responsibility to improve safety conditions and facility opportunities for driving, walking, and bicycling in the U.S. Transportation policy is created to incorporate safe and convenient mobility into transportation projects; complying with design standards, safety, sustainability, and accessibility.

1.3 Road Safety Policies

Road safety policies aim to decrease the number of road traffic fatalities. To include transportation policies as mandatory laws requires technical support to integrate the concepts obtained by research and experience. Nationwide, highway safety plans are being developed to help state agencies, counties, and communities address traffic safety related problems and promote road safety. Additionally, the enforcement system plays an important role in transportation policy. A credible enforcement system relies on the effort that various agencies use to reach towards reducing traffic fatalities.

A relevant topic in road safety is to protect vulnerable users. This study targeted two vulnerable groups, children travelling as motor vehicle passengers and bicycle riders. In the first case, parents should always provide restraint systems for their children, and because of their light weight they could suffer severe injuries when they are unrestrained. In the second case, when a collision occurs between a bicycle and a vehicle, truck, other bicycle or a run off, it happens to be that the bicyclist is highly vulnerable to be injured.

Traffic Safety provides different methodologies to analyze data and determine related factors that can contribute to evaluate traffic crashes. It became an important concept when transportation systems started to increase fatalities and injuries in the society. As a national goal, all states need to develop safety plans to reduce roadway fatalities and serious injuries. In order to achieve this goal, traffic safety involves crash data analysis to reveal a diagnosis of the status of the crashes, encounter solutions to reduce crashes, and create traffic safety plans to evaluate the previous, present and future data in order to find safety countermeasures that can be applied in each situation.

1.4 Child Protection in Traffic Policies

Traffic crashes are a leading cause of fatality and injury among children in the United States. There are nearly 1500 fatalities per year from traffic crashes for children ages 1 to 18 years old (NHTSA, 2014). Moreover, travelling is an essential activity of their daily living, which has to be a right guaranteed with protection. Therefore, children need special consideration because they are vulnerable and inexperienced road users. Providing safe environment and optimum transportation systems for children could reduce their risk on the road. Today's situation is based on several policies created to ensure children's safety. Each state has applicable laws protecting children from different ages. Depending on their transportation modes and population characteristics, the state develops strategies towards protecting children's lives. At a national level the NHTSA has developed different programs to reduce traffic crashes by targeting certain age groups. Laws along with educational and awareness campaigns, and safety equipment were introduced as part of their safety plans to ensure protection.

Regarding children’s protection, there are five categories of traffic safety laws at a national level: bicyclists and pedestrians, child passenger safety, school bus passenger, seat belts, teen and novice drivers. This research study will focus on two main types of laws: The Child Restraint Laws (CRL) and the Bicycle Helmet Laws (BHL).

1.5 Research Objectives

The main objective of this study is to analyze whether selected transportation laws and road users’ characteristics have an influence on traffic fatalities in order to gain a better understanding of traffic related policies. Additionally, it aims to provide suggestions which can potentially improve safety on children’s transportation policy. To achieve these objectives, the following tasks must be completed:

a) Analyze the national Fatality Analysis Reporting System (FARS) database to understand police crash reports, their variables and how to include data preparation procedures for further evaluation.

b) Conduct a literature review to build a conceptual framework in CRL and BHL policy, and how the nation is facing child’s protection with these laws.

c) Study the Child Restraint Law and the Bicycle Helmet Law. These tasks have been achieved in Chapters 3 and 4 through the following sub-tasks:

- Apply Bayesian models, achieving the appropriate one by evaluating the performance of goodness of fit measures

- Develop a negative binomial model which evaluates the CRL effectiveness. Applying a macro-level analysis, the law was evaluated by state.

- Develop logistic regression models to estimate contributing factors for CRS and bicycle helmet use. The contributing factors include crash, person, vehicle and socio-demographic characteristics.

1.6 Thesis Organization

To guide the organizational process of the thesis, a short description here will describe the content of each chapter and in addition, a schematic chart is presented in Figure 1. The first chapter introduces the reader to an overlook of transportation policies and to a deeper side of traffic laws in the United States. Further on, the chapter narrows onto how the legislation process coexists in traffic safety and how legislation provides children protection in transportation. Chapter 2 presents an overview of the multiple statistical analyses that previous research had identified econometric models used in traffic safety. Chapter 3 goes directly into the evaluation of the Child Restraint Laws (CRL). Starting from the literature review, data preparation, methodology, results and discussion, this chapter is divided into 2 sections, focusing on macro and micro levels of analysis. From a macro-level analysis, the CRL is evaluated at state-level and from a micro-level analysis, the CRL is evaluated at the driver's level. In the same way, Chapter 4 describes the Bicycle Helmet Law (BHL), also including the literature review, data preparation, methodology, results, and discussion. Chapter 5 summarizes the findings from the evaluation of both laws in the conclusions and recommendations, raises potential contributions from the findings, describe the limitations and proposes suggestions for future research in transportation policy and decision making to increase traffic safety. Finally, Appendix A, presents the tables and figures from CRL analysis; Appendix B, shows the tables and figures from BHL analysis; and Appendix C defines the variable descriptions. The list of references cites all the literature studied in this research.

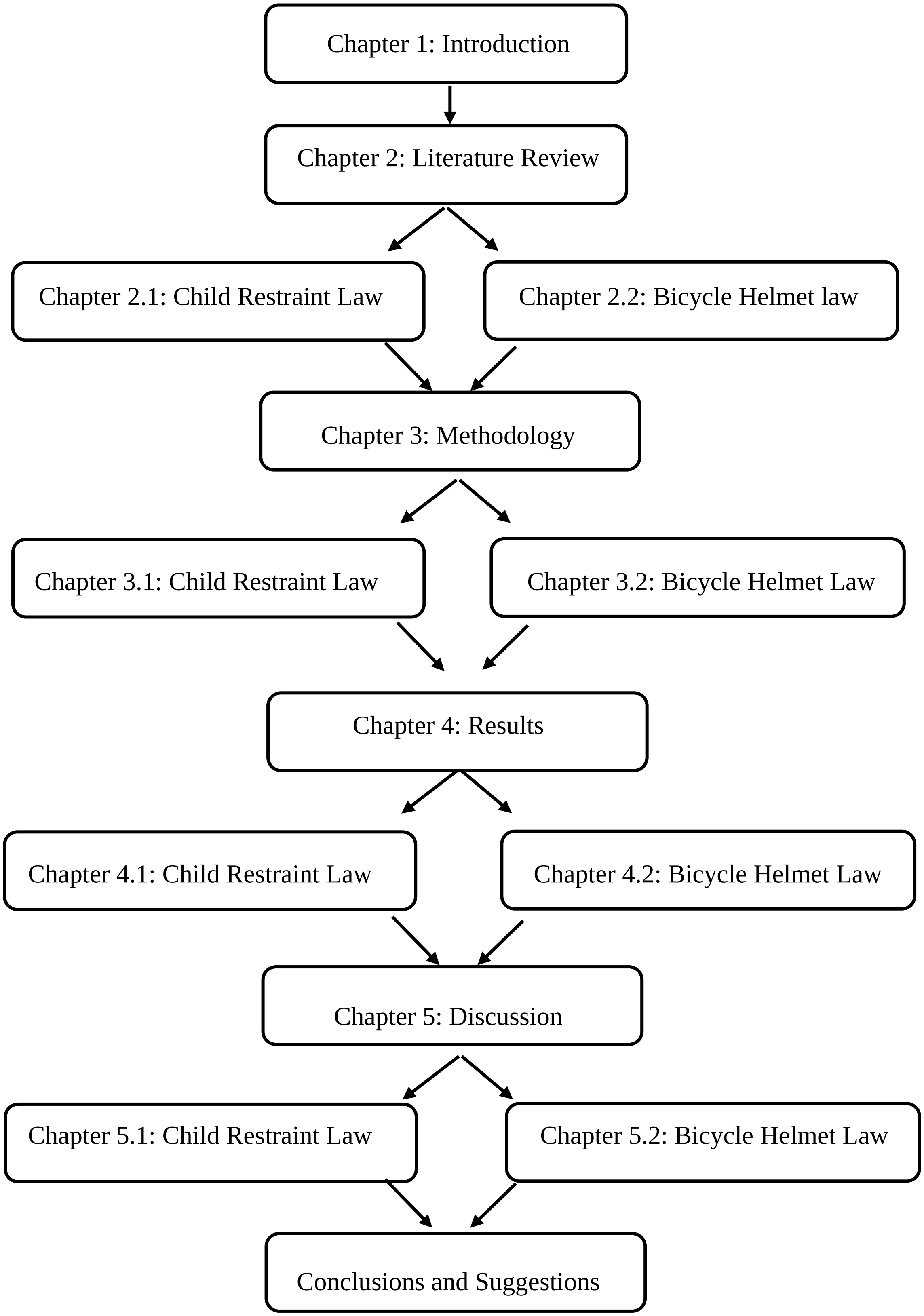


Figure 1: Thesis Organization

CHAPTER 2. LITERATURE REVIEW

2.1 Existing Research on Child Restraint Law

Children fatality and severe injury prevention in motor-vehicle collisions are important components in road safety; it requires a better understanding of its governing factors to promote transportation policy. To ensure its appeal there are several ways in which traffic crashes could be safer for all vehicle occupants, including children. For example, in the past decades, significant studies have been carried out to develop specific preventive measures in children's safety. These includes: *a)* Child Restraint Law (CRL), requires children to be restrained while driving in all states and territories, *b)* technical standards and regulations for Child Restraint Systems (CRS) (e.g., Federal Motor Vehicle Safety Standards (FMVSS)), *c)* educational programs, (e.g., federal's, state's, NGO's and insurance's programs), *d)* Car Assessment Programs (CAPS), created in 1979 to encourage manufacturers to build safer vehicles and consumers to be informed before choosing their option, *e)* CRS equipment-tests (e.g., Five-Star Rating, a program developed to provide CRS information to parents), *f)* highway safety programs (e.g. counties and highway patrol's programs), *g)* awareness campaigns (e.g., "Is your child in the right car seat?", "Think safe, Ride safe, Be safe", "Where is baby?", "Never give up until they buckle up", and "playing it safe"), *h)* law enforcement programs and *i)* capacity building for implementing policy-oriented solutions that reduce traffic childhood injuries.

With the aforementioned efforts, children fatalities have been decreasing in the past years according to the Fatality Analysis Reporting System (FARS) statistics(NHTSA, 2014), Figure 2. However, traffic injuries remain a leading cause of death among children in the United States. In 2014 alone, 602 children aged 12 years and younger died as occupants in motor vehicle crashes,

and more than 121,350 were injured (Center for Disease and Control, 2016). Figure 3, shows children traffic fatality rates by state and the percentage of children traffic fatalities without using CRS. Fortunately, the injury prevention approach has brought an effective measure for reducing the risk of fatal or serious traffic injuries establishing child passenger protection policy. Multiple fact findings and policy settings in CRL has resulted in a better understanding of child safety. Klinich et al. (2016) developed a best practice scoring system of CRL by state. Comparing different countries, it was found that partial or complete legislation among technical standards, education programs and enforcement systems influence CRS-use (Agre, 2016; Chibisenkova, 2016; Eichelberger et al., 2012; Hidalgo-Solórzano et al., 2016; White & Washington, 2001). Recent studies indicate that CRS is becoming more common in societies that are concerned about child fatalities and its prevention (Bowman et al., 1987). A study conducted in Romania in 2016 stated that 67.4% of the observed population were using CRS (Rus et al., 2016). Furthermore, Chen et al. in (2014), presents a study where less than 10% of the population studied in China used CRS. In Australia the CRS-use is around (90%), in the U.S. (86%), and in Beijing (68%) (Chen et al., 2014). According to the Global Status Report on Road Safety in 2013, 61% of the countries did not have CRL, while the remaining 39% has a law at some level (World Health Organization, 2013).

Figure 4, shows that Europe is leading the policy protection in child restraint safety; other countries law attainment are also shown by regions. Accordingly, CRS reports are playing a key-role in becoming a jostle to motivate and enhance governments' involvement in child passenger safety. The rulemaking process for child passenger protection requires technical support to understand the consequences of age coverage in order to not become an arbitrary legislation.

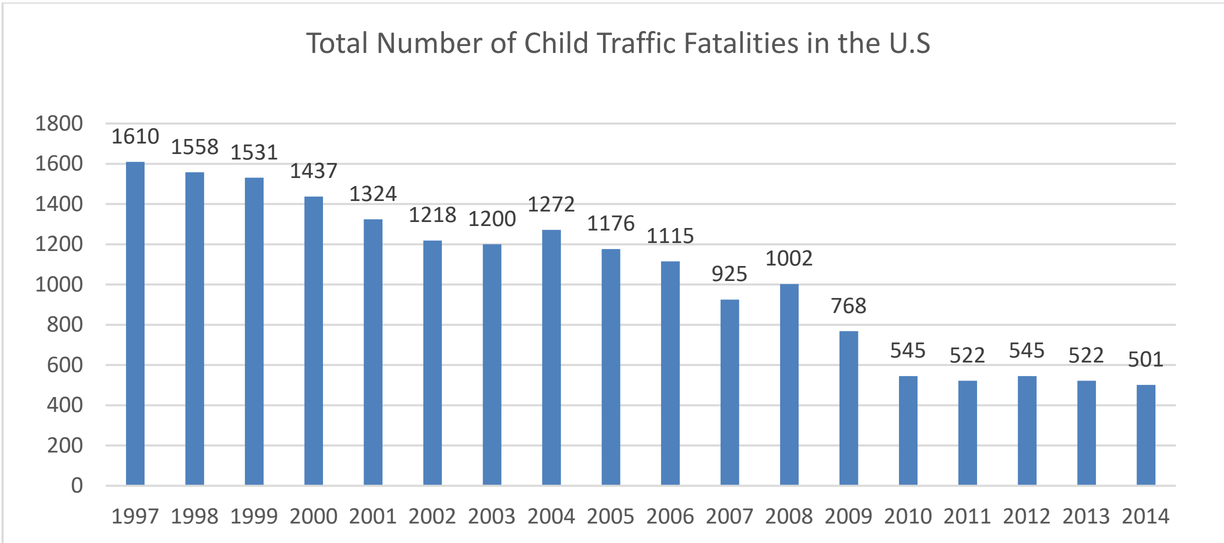


Figure 2: Total Number of Traffic Fatalities where Children were Involved. (FARS Data 1997-2014).

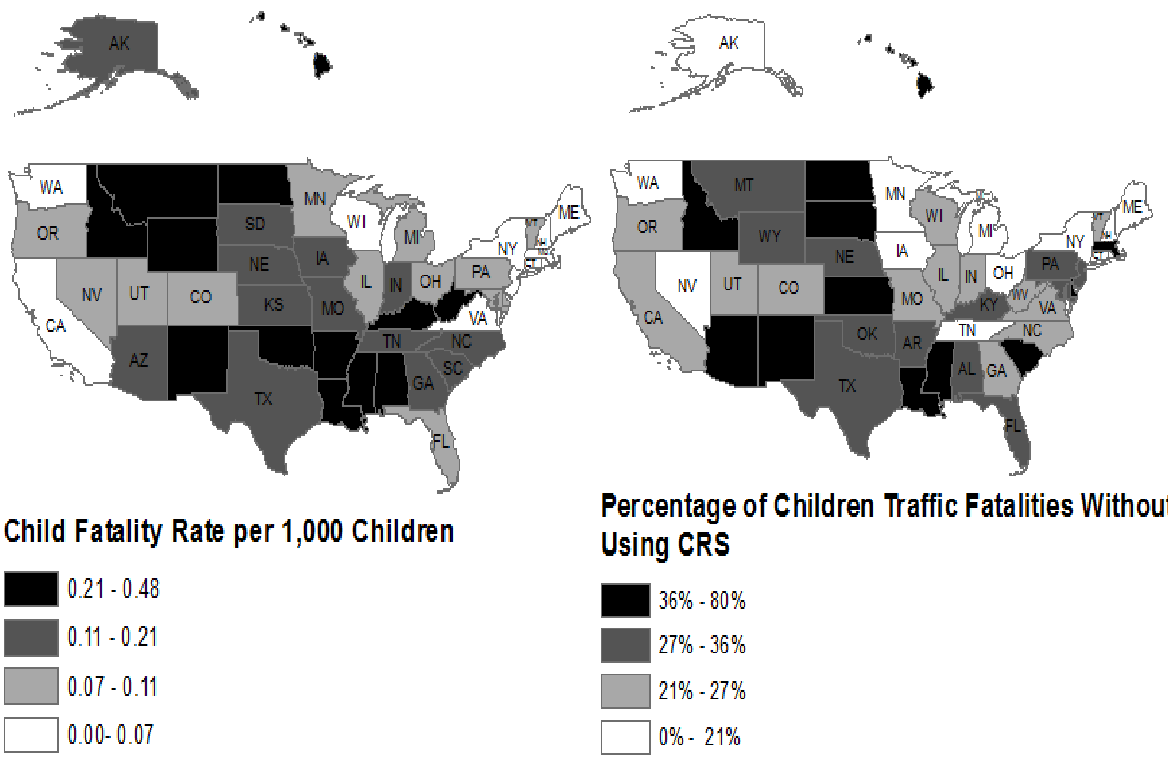


Figure 3: Comparison of Child Traffic Fatality Rates and Proportion of Children Not Using CRS in Fatal Crashes. (FARS Data 2011-2014 and ACS Population).

Table of Child Restraint Law by Region				
	CRL = 0 No law		CRL = 1 Law at some level	
Continent	**Freq.**	**%**	**Freq.**	**%**
Easter Europe	3	15	17	85
Western Europe	3	13	20	87
Anglo American	5	41.7	7	58.3
Latin America	9	45	11	55
Central Asia	1	25	3	75
East Asia	2	50	2	50
Southeastern Asia	8	80	2	20
Southern Asia	11	100	0	0
Western Asia	3	68.8	20	31.3
African	40	83.3	8	16.7
Oceania	10	71.4	4	28.6

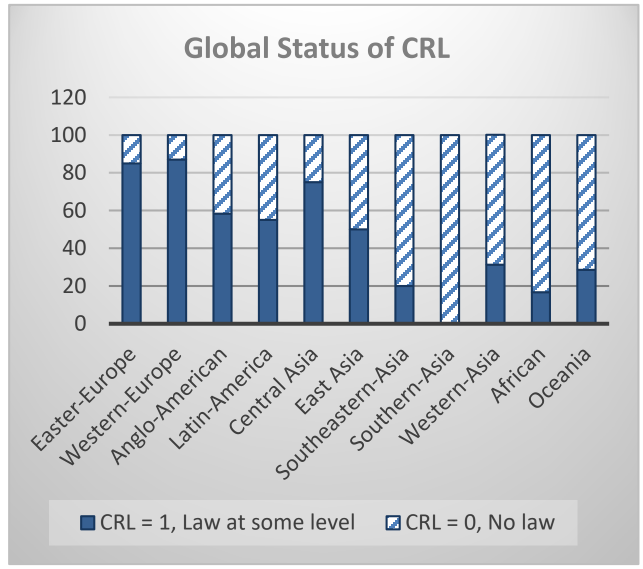


Figure 4**:** Child Restraint Law by Continent. Global Status Report on Road Safety 2013 (World Health Organization, 2013)

Several studies have demonstrated that the proper use of Child Restraint Systems (CRS) can substantially reduce the severity of injuries and the number of fatalities (Elliott et al., 2006; Fleming, 1981; Gallego et al., 2015; Kahane, 1986; Starnes, 2005). In 1971, the National Highway Traffic Safety Administration (NHTSA) adopted the first federal standard for CRS; (Federal Motor Vehicle Safety Standard (FMVSS 213)). After that, Tennessee became the first state enacting the Child Restraint Law in 1979 (Stewart, 2009). Since then, several improvements were made in the states' law, initiating different liability in multiple versions of standards and legislations (Bae et al., 2014). Therefore, NHTSA periodically carries out monitoring tasks of CRS-use in the nation (Russell et al., 1994). Currently, all 50 states and the District of Columbia have CRL. They regulate children to travel in child restraints, booster seats or safety belts depending on their legislation. Most CRL are primary, meaning police may stop vehicles solely for child safety seat violations.

However, other states for example, Nebraska and Ohio, consider child safety to be under a secondary enforcement law, meaning that police must have an additional reason to make a stop (Governors Highway Safety Association, 2016). White and Washington, (2001) evidenced that safety restraint use, is positively related with enforcement intensity. Following numerous studies identifying the major factors that may influence the CRS-use (Bachman et al., 2016; Bowman et al., 1987; Gomez et al., 2016; Williams, 1998), this paper discusses the influence of CRL on child fatalities, as well as evaluates the CRL effect on CRS-use derived from drivers' characteristics.

James et al. (1996) analyzed the effect of CRS-use in Hawaii and found some contributing factors of unrestrained children including local roads, older children, unrestrained drivers and older and younger drivers. The authors stated that toddlers are more likely to be unrestrained in automobiles and trucks, and infants are more likely to be unrestrained in vans, on the freeway, during nighttime hours, and in urban areas (James & Kim, 1996). As mentioned above, there have been several studies exploring the effect of CRS that associate different variables . Nevertheless, the prior studies have not analyzed the impact at a nationwide state-level with child fatalities from 2011-2014 FARS database. Also, no studies have investigated the effects of the CRL on driver's decision to use CRS. Therefore, the main objectives of this study are to: (1) estimate a crash prediction model to measure the effectiveness of the CRL nationwide at the state-level, (2) study the impact of the CRL on CRS-use at a driver's level, and (3) identify contributing factors including those derived from the socio-economic factors and drivers' residence characteristics that could have an influence in CRS-use.

2.2 Existing Research on Bicycle Helmet Law

Children and teenagers frequently use bicycling as a transportation mode. For commuting or recreational purposes, a high predisposition to risk has been associated with bicycle-related fatal injuries. In 2014, bicyclists were estimated to be the 2% of all traffic deaths and 2% of all crash-related injuries in the United States (Schroeder & Wilbur, 2013). Figure 5, shows how bicycle fatalities are distributed by state. Additionally, the National Safety Council estimated in 2012 the total cost for bicyclist's injuries and fatalities as over $4 billion per year (Pedestrian and Bicycle Information Center, 2012). As a proven countermeasure, the Bicycle Helmet Law (BHL) became prominent as a mandatory but non-federal legislation. Being an optional way to protect bikers, BHL creates space for a nationwide law-variability. Thus, this study aims to determine BHL's influence on bicycle helmet use by studying fatal traffic incidents and related socio-demographic factors. Combining all this information together creates a wide overview to help us understand the effectiveness of BHL as a legislative safety strategy for some states.

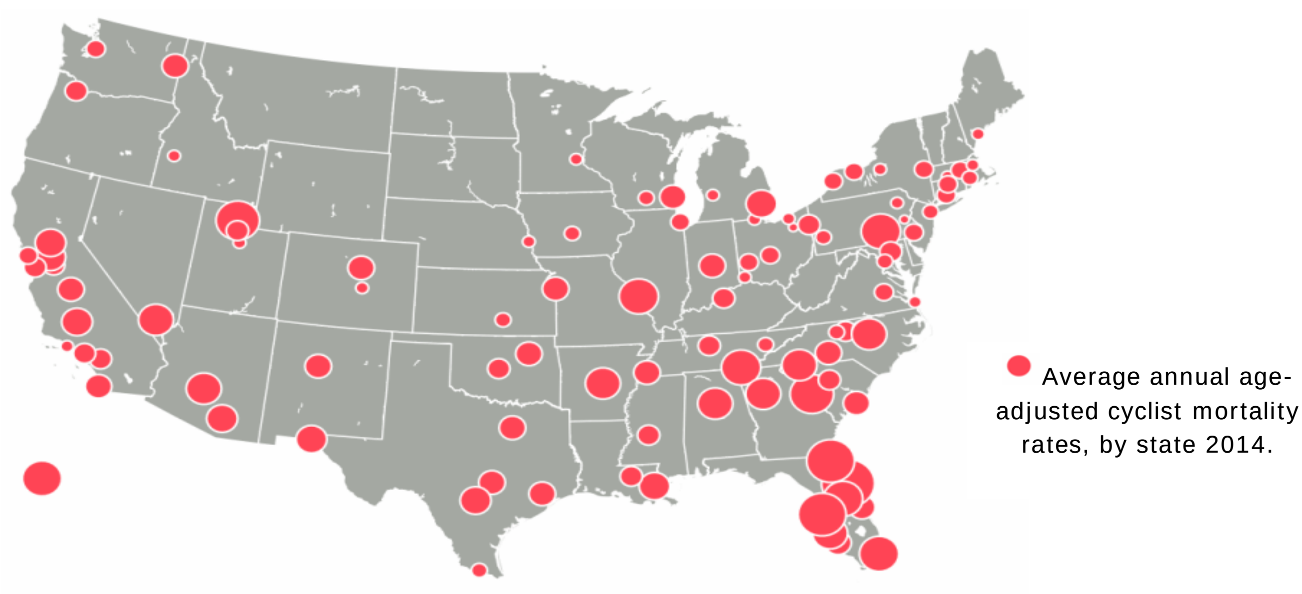


Figure 5. State Distribution of bicycle fatality rates (CDC, 2014).

In 1987, California was the first state to enact a BHL to protect bicyclists. During the 1990's, eighteen states passed the BHL; nowadays, twenty-one states and Washington D.C have implemented mandatory helmet laws targeting bicyclists under 18 years of age, depending on the state (Governors Highway Safety Association, 2016). This study evaluates children aged from 1 under 18 years old and aims to find safety countermeasures to improve their safety, however the national statistics reveals that the highest age group that presents bicyclists' fatalities is in the age group from 20 to 24 years old (Schroeder & Wilbur, 2013). Even though there are victims from all ages in traffic crashes, aiming legislation towards young people seems a starting point to encourage bicyclists to wear helmets. Rosenberg et al. (1995), affirms that persons who begin using helmets as children are more likely to continue to use them as adults.

The BHL varies by jurisdiction, by the year the law becomes effective, by the required safety equipment, by the enforcement system, and by the age-coverage to which the law pertains. Besides the jurisdiction at state-level, many cities and counties across the country also have local helmet laws, meaning that if the state does not provide a helmet law, the city, park, or county jurisdiction can make better efforts to increase bicyclist's safety. Karkhaneh et al. (2006) suggested that the use of legislation in a country as a mandatory rule for bicyclist's helmet use has been shown to be an effective measure to attain compliance. Other researchers expressed that the law increased helmet use (Gilchrist et al., 2000; Ni et al., 1997; Rodgers, 2002; Wesson et al., 2008). Looking at how the U.S. is legislating bicyclists' protection shows a variety in the policy making process where coverage-age groups and state laws show differences that can result in fatalities (Grant & Rutner, 2004; Markowitz & Chatterji, 2015). Moreover, Thompson et al. (1990) found the age group of individuals between 5 to14 years to present higher risks involved with

bicycle-related injuries in Seattle. Similarly to (Rosenberg & Sleet, 1995) who found the highest fatality rates among males aged from 5 to 15.

In 2014, the national statistics found that bicyclists fatalities happened more often between 6 p.m and 9 p.m. From the location, it was estimated that (71%) of the fatalities occurred in urban areas, mostly males (88%) and about one in five bicyclists reported alcohol in their rides (Schroeder & Wilbur, 2013).

Other researchers proved that helmet use is effective in reducing traffic fatalities and severe injuries (Attewell et al., 2001; Grant & Rutner, 2004), but they also show that when the laws are mandatory, they significantly reduce youth bicycling (Carpenter & Stehr, 2011; Robinson, 1996). Additionally, Rivara et al. (1998) and Thompson et al. (1989) provided medical evidence that helmets reduce the likelihood of serious head trauma, brain and facial injuries in bicycle accidents by as much as 85 percent, particularly among children. Carpenter and Stehr (2011), expressed a 19% reduction in youth bicycling fatalities, 20–34% increase in helmet use by and unintentionally reduced bicycling by 4–5 %. National statistics account that approximately 3 out of 10 bicyclists wear a helmet for all rides (Schroeder & Wilbur, 2013).

Socioeconomic characteristics influence helmet use and ownership. For example, it is more common for children from high-income families to follow the law than children in low-income families (Khambalia et al., 2005; Parkin et al., 1993; Rosenberg & Sleet, 1995; Towner & Marvel, 1992). Education was also an associated factor in helmet use confirmed by Hu et al. (1993).

Nowadays, technology influences driving and bicycling behaviors. With technology development, manufacturers have begun to find other ways to prevent traffic crashes. As an example, motor vehicles as well as bicycles are being equipped with collision-prediction systems

that warns the driver of possible risks to avoid a crash (Jeon & Rajamani, 2016). Another way to provide safety is also being studied by data communication systems. Moreover, technology mobile apps, establishes communication between road users including cars, motorcycles and bicyclists, in this case acoustic signals deliver awareness messages for bicyclists under risky situations. (Yoon, 2015). All these systems are providing safety in different ways, however we still do not know their influence in wearing a bicycle helmet and therefore if bicyclists will comply the laws under these circumstances.

So far, numerous studies have established statistical links between bicycle-related fatalities and helmet use. However, there is a lack of understanding of the relationship between bicycle helmet laws and their influence on helmet use. Thus this study aims to determine the association between context-specific, socio-demographic and personal-level factors and bicycle helmet laws and their influence on helmet-use, using a representative sample of 467 bicycle-related fatalities in the United States from 2011 to 2015 for children in the age group from 1 under 18 years.

2.3 Complementary Studies

The present study confirmed with other studies some common contributing factors in CRS and helmet use. Moreover, this study contributes to the evaluation between these factors and the laws, which were analyzed by children's age. Furthermore, this study makes a contribution over existing literature in child's safety protection. While doing the literature review, it was found that CRL and BHL policies are not a common topic. In a few cases, short post-law time periods with before and after comparisons have been evaluating laws for a particular state. Compiling the findings together provided a clear and deep overview of how children's safety is being analyzed by others and exposed the need to address this topic in a more efficient and safer way. At present,

the current concepts and studies concerning this topic can complement this study with other interesting findings such as:

Child Restraint Law (CRL)

- The vehicle type and time of the day influences the restraint use. (e.g. Cars and vans showed a 59.6% restraint use compared to a 43.8% in trucks and SUVs) (e.g. 56.3% demonstrated to wear restraint systems during the day than 39.3% in overnight conditions) (Lee et al., 2015)
- In 2010, CRL was found to have 14 exemptions to the law, when the child is traveling in special cases. (e.g., non-residents, commercial vehicles, large vehicles, non-parents, vehicles without seat belts, age and height/weight considerations) (Bae et al., 2014).
- Educating children in safety protection rather than their parents seems to increase the restraint use. They become ardent advocates for their own safety. (Bowman et al., 1987)

Bicycle Helmet Law (BHL)

- There is a positive influence from parental role on helmet use among children. (Hu et al., 1993)
- A time series analysis demonstrated approximately a 50% reduction in bicyclists' deaths after the effect of introducing BHL in Ontario, Canada (Wesson et al., 2008)
- If all the states would have enacted BHL with a universal age-coverage, then 1620 children's lives would have been saved in a studied period from 1975 to 2000. Another

interesting finding is how Grant and Rutner (2004) calculated the long-term effect of the law differs from the short-term.

- Introducing a bicycle helmet program in Georgia increased 45% of helmet-use. (Gilchrist et al., 2000)

CHAPTER 3. METHODOLOGY

3.1 Econometric Model Analysis

Analysts in the past have applied statistical techniques to develop models where traffic crash predictions are the target. These models were developed by studying the FARS database. Even if this study just focuses on two final models, Negative Binomial and Logistic Regression, other models were also tested in the process of finding the best fitted model. Figure 6, is an overview of different models that are known to be applied in traffic safety.

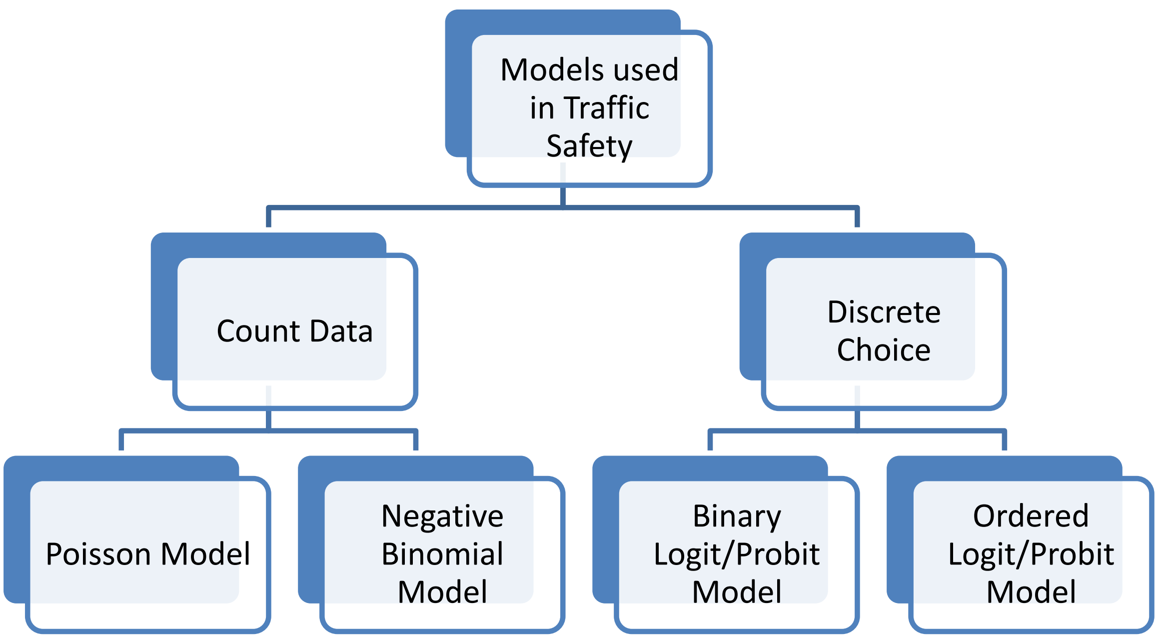


Figure 6: Econometric Models in Highway Safety. Source: Traffic Safety course Abdel-Aty 2017.

Starting with count data models, they can be applied when the observations are nonnegative integer values. This study, evaluates the number of traffic fatalities in children, where traffic fatalities are considered as positive observations. Two count models were estimated for CRL and BHL analyses at a state-level approach using Poisson and Negative Binomial models. Applying

the Poisson Regression Model stablishes that the dependent variable are counts which follow the Poisson Distribution and the observations are independent values. Moreover, the distribution uses the mean of the count process to be equal to its variance. Condition that brings the over-dispersion term. Comparing the variance and the mean, when the variance is greater than the mean is said to be over-dispersed, likewise if the variance is smaller than the mean, it is called to have under-dispersed data. Having evidence that over-dispersion appears, a second approach can be included analyzing the data with a Negative Binomial model. One of the characteristics from the second model is that follows a gamma distribution, therefore the negative binomial (or also called the Poisson-gamma) model is an extension of the Poisson model. Some references that used these models in highway safety are: (Abdel-Aty & Radwan, 2000; Jovanis & Chang, 1986; Lord & Mannering, 2010; Miaou, 1994; Milton & Mannering, 1998; Shankar et al., 1995). In Chapter 3, the methodology will explain how the CRL was tested with Poisson and Negative Binomial models, and why this last one was concluded to be applicable. In the BHL case, even if the Poisson and Negative Binomial models were tested, there was not enough data to show significance for the explanatory variable.

The second part is to apply discrete choice models, introducing logistic and probit models. Depending on the study's objectives they can explain or identify possible relationships between the dependent and the independent or the explanatory variables. The logistic model follows a logistic distribution and the probit model a normal distribution. In this study both models were tested, where the logistic models showed better results for CRS use and bicycle helmet use. Chapter 3 and 4 will explain the final logistic regression models for CRL and BHL respectively. Previous studies that used logistic regression models in highway safety are: (Abdel-Aty, 2003; Abdel-Aty et al., 2004; Lee et al., 2015;Comelli, 2014; White & Washington, 2001). To study the

contributing factors related for child restraint and helmet use, logistic models were applied evaluating crash, vehicle and socio-economic data. (Lee et al., 2014).

Analytical approaches were tried to find the optimal model by using the Statistical Analysis System (SAS), a commercial software for data process, advanced analytics, predictive analytics, etc. The NEGBIN and PROC LOGISTIC procedures were used to obtain the CMF for Child restraints with the NEGBIN and contributing factors for CRS and bicycle helmet use with PORCLOGISTIC.

3.2 Data Preparation for Child Restraint Law

The data for the current study is sourced from: The Fatality Analysis Reporting System (FARS) of the NHTSA and the American Community Survey (ACS) database from the United States Census Bureau. At state-level FARS provided the accumulated (2011-2014) traffic crashes for each state; while at driver's level 2159 crash reports were attained in particular from 2014 database. Crash reports at driver's level were analyzed for all drivers that had a child as a passenger vehicle occupant. All studied reports were selected by person type with occupants' age from 0 to 9 years old. In the same way, the ACS data was used at the state level to collect an average for the socio-demographic characteristics in the 50 states and D.C, while at drivers-level the data represents the average of the communities attained from the registered driver's ZIP-code. Table 1, presents the state's CRS coverage regulated by age groups, where almost half of the states cover 0-7 years, leaving the other states to regulate child's safety in different age groups. Maine is the only state that regulates 0-11 years old, but in this study it was only considered fatalities involving children aged between 0 and 9 years, as Maine is the only state showing an extensive coverage for children greater than 9 years old.

Table 1**:** Mandatory CRS Age Regulation by State and D.C.(Governors Highway Safety Association, 2016)

Coverage age with CRL	**States and D.C.**	**Total**
0-4 years	Oregon	**1**
0-5 years	Alabama, Arkansas, Florida, Iowa, Louisiana, Nebraska, South Carolina, South Dakota	**8**
0-6 years	Connecticut, Mississippi, Montana, Nevada, New Mexico, North Dakota	**6**
0-7 years	Alaska, Arizona, Colorado, Delaware, D.C., Hawaii, Idaho, Indiana, Kansas, Kentucky, Massachusetts, Michigan, Minnesota, Missouri, New Hampshire, New York, North Carolina, Ohio, Oklahoma, Pennsylvania, Rhode Island, Texas, Utah, Vermont, Virginia, West Virginia, Wisconsin	**27**
0-8 years	California, Georgia, Illinois, Maryland, New Jersey, Tennessee, Washington, Wyoming	**8**
0-11 years	Maine	**1**

3.3 Two Approaches to Analyze the Effect of Child Restraint Laws

The methodology description has two levels because different objectives and models were used in the study. Negative Binomial and Logistic Regression models are applicable for state- and driver- level analyses, respectively (Chin & Quddus, 2003; Lord & Mannering, 2010). The first step of the model evaluation is to examine the significance of the 41 potential variables. Table 2 and Table 3 presents the variables that were evaluated in this study, after modeling them just relevant variables will remain within a statistical significance level of 0.05 or lower. Appendix C, classifies the variables and presents the data preparation process for each variable. After several trials evaluating which variables from the state's and driver's characteristics have more inference in child traffic fatalities, the preferred model is obtained by comparing the goodness-of-fit measures. Evaluating the results for each model, the smallest performance measurements will define the best model among the log-likelihood, the Akaike's Information Criterion (AIC) factor that helps to balance the log-likelihood function, the Bayesian Information Criteria (BIC), and the log-likelihood ratio index (ρ^2) (Ben-Akiva & Lerman, 1985).

Table 2: Descriptive Statistics of Socio-Demographic Variables at State-Level. ACS data.

Selected Socio-demographic Variables				
Employment Status	**Mean**	**Std Dev**	**Minimum**	**Maximum**
Population	80752.57	94707.78	6224.6	509941
Employed	0.8684	0.1558	0.2366	0.9558
Unemployed	0.1111	0.1127	0.0315	0.7515
Not in labor	0.5342	0.1081	0.2145	0.7193
Own children under 6 years	0.1423	0.0216	0.1014	0.2169
All parents in family in labor force	0.1367	0.1674	0.0731	0.8081
Others				
Median household income (dollars)/ 1'000.000	55.1830	55.1830	55.1830	55.1830
Education below High school level	14.8541	2.9578	8.7000	20.7800
Education with Bachelor or higher degree	9.3251	3.3191	5.1000	24.7400
Rate below poverty level	15.0533	3.1877	9.0000	22.9400
Population Density	1578.82	3796.87	0.0000	76237
Commuting to Work				
Car, truck, or van- drove alone	0.7397	0.1449	0.2486	0.8537
Car, truck, or van - carpooled	0.0924	0.0200	0.0269	0.1406
Public transportation (excluding taxicab)	0.0394	0.0647	0.0041	0.3821
Walked	0.0310	0.0187	0.0116	0.1244
Bicycles and Motorcycles	0.0201	0.0105	0.0104	0.0540
Worked at home	0.0424	0.0135	0.0051	0.0697
Mean travel time to work (minutes)	0.0041	0.0196	0.0000	0.1296
Occupation				
Primary	0.0326	0.0368	0.0006	0.1810
Secondary	0.2264	0.0669	0.0696	0.4637
Tertiary	0.7631	0.0739	0.4869	0.9303

Table 3: Descriptive Statistics of the Potential Variables from the Crash, Vehicle and Person Reports (FARS data) and socio-demographic characteristics (ACS data) at drivers' level.

Description	Mean	Std Dev	Minimum	Maximum
Number of fatalities	1.2651	0.6831	1	6
Child's age	4.6628	2.8424	0	9
Urban Roads	0.6120	0.4874	0	1
Speeding Related	0.2416	0.4281	0	1
Speed Limit	52.0577	12.5899	10	80
Child's restraint system use	0.5529	0.4973	0	1
Diver's restraint system use	0.8356	0.3708	0	1
Driver's age	35.2300	12.6116	9	89
Gender	1.5672	0.4956	1	2
Fatalities Count	0.6725	0.8665	0	5
Number of occupants	3.8984	1.5708	2	15
Registered Crash State	0.8887	0.3146	0	1
Vehicle age	9.3326	5.2147	0	26
Roadway Alignment	0.1774	0.3821	0	1
Previous crash experience	0.0157	0.1244	0	1
Driver violations	4.4873	18.0716	0	99
Roadway Profile	0.2508	0.4336	0	1
Number of Traffic Lanes	2.5778	1.0890	1	7
Education below High school level	16.7048	9.9676	1	64
Education with Bachelor or higher degree	21.8882	12.7048	1	85
Median household income (dollars)/ 1'000.000	50.5872	50.5872	50.5	50.5
Car, truck, or van- drove alone	79.0374	8.5888	12	93
Car, truck, or van – carpooled	11.0836	4.4386	1	53
Public transportation (excluding taxicab)	2.0753	5.4795	0	75
Transportation by Walking	2.2370	2.7453	0	28
Transportation by Bicycles and Motorcycles	1.7621	2.0054	0	33
Worked at home	4.0545	3.1295	0	41
Mean travel time to work (minutes)	25.3252	6.1127	8	60
Poverty	17.7935	9.4411	0	69
Population Density	1578.82	3796.87	0	76237
Employed	55.3871	8.5161	14	82
Unemployed	6.1727	2.6273	0	22
Not in labor	38.1737	7.9034	13	72
Own children under 6 years	10.0411	3.5056	0	36
All parents in family in labor force with children < 6 yrs.	64.5261	13.4136	0	100
Own children under > 6 years	20.3797	5.3792	3	48
All parents in family in labor force with Children > 6 yrs.	69.8194	10.6601	0	100
Primary Industry	3.8527	6.1351	0	57
Secondary Industry	24.1663	7.5435	0	55
Tertiary Industry	40.1409	7.4594	6	69
Whether the state has the child restraint law that covers the child in the crash	0.7940	0.4045	0	1

3.4 Methodology for Child Restraint Law Analysis at State-Level

As mentioned in Chapter 3.1, to evaluate the child fatalities counts as non-negative integer values, it was employed different models that are routinely applied in these situations including: Poisson and Negative Binomial (NB) distributions (Lord & Mannering, 2010). Therefore, at the state-level, a Negative Binomial model was implemented after dispersion results were obtained. Research has found that if over dispersed data exists, using the Poisson model may not be appropriate for making probabilistic statements about vehicle crashes because the model may underestimate or overestimate the likelihood of occurrence (Abdel-Aty & Radwan, 2000; Geedipally & Lord, 2008; Hauer, 2001). The results from the model estimate the number of child fatalities not using CRS denoted as the dependent variable evaluated with the explanatory variables (i.e., child population) and policy coverage (i.e., CRL) (Jovanis & Chang, 1986). The form is shown in Eq. (1):

$$\lambda_{ij} = exp\left(\beta_0 + \beta_1 \log(population)_{ij} + \beta_2 CRL_{ij}\right) ex\,p\left(\varepsilon_{ij}\right) \tag{1}$$

Where, λ_{ij} is the expected number of child fatalities that showed non-use of CRS; β_1 and β_2 represent the parameters; β_0 is the intercept; the explanatory variables are population and CRL; *i* is the 50 states and D.C.; *j* is the age which ranges from 5-9 years old; and $exp(\varepsilon_i)$ is the gamma-distributed error term with mean = 1 and variance (α) (i.e., over dispersion parameter). CRL_{ij} is a dummy variable indicating if the state *i* has the CRL that covers the specific age *j* (Lord, 2008).

Log-likelihood ratio index, ρ^2 was used as a goodness-of-fit index and it was estimated to measure how much the full model has been improved from the intercept-only model (Ben-Akiva and Swait, 1986). ρ^2 is calculated using the Eq. (2):

$$\rho^2 = 1 - \frac{LL(Full\ model)}{LL(Intercept)} \tag{2}$$

Where *LL* (*full model*) is the log-likelihood value of the fitted model, including the explanatory variables population and CRL, and *LL (*Intercept) is the log-likelihood value of the Intercept-only model. CRL was entered in the model as a dummy variable (1= the state's CRL covers the specific age group, 0 = does not cover) they were explored for aggregated data (5-9 years). Once they were evaluated altogether, a cause of duplicity might be a relevant issue. Researchers found that a suitable alternative under this situation is calculating Negative Binomial with random effects (Anastasopoulos & Mannering, 2009; Lee et al., 2015). Introducing this new feature to the procedure, showed that the dependent variable was not significant. Without treating the data as such, the estimated dependent variable was significant, therefore the model revealed no significance with random effects (Chin & Quddus, 2003). Twenty-one socio-demographic variables were attempted in the negative binomial models; however, it was shown that most of the variables were very highly correlated to each other. Thus, only the child population (by age) as an exposure and the CRL dummy were included in the final model. It was determined by the model results that it would be sufficient to include those two variables to explore the impact of the CRL.

3.5 Crash Modification Factor (CMF) for CRL

The Highway Safety Manual (HSM) provides information for quantifying safety effects used in engineering treatments. A useful tool to evaluate safety effects of a countermeasure is to calculate Crash Modification Factors (CMF). It can estimate potential changes in crash frequency as a result of applying a specific treatment (or countermeasure). In this analysis, the cross-sectional method was applied to estimate the CMF, considering that CRLs have different statutes that vary

by time and no time-dimension analysis was part of the evaluation. The CRL was reviewed for each state since the law became enacted in the early seventies, then the selected period of 2011-2014 was chosen after no law change was observed. For this time period the crash data evaluated was not sufficient to make a before and after study. Therefore, the cross-sectional method was selected because no time-dimension was part of the evaluation and the method aimed to compare the crash frequencies with and without the treatment. The method is based on the coefficient associated with the target variable to estimate the CMF. Here, if a state has the CRL that covers the specific age was used as a treated group. (Abdel-Aty & Radwan, 2000; Park et al., 2015). The functional form is shown in Equation (1) to estimate the $N_{predicted} = \lambda_{ij}$. Finally, to obtain the CMF, it can be calculated as:

$$CMF = exp(estimated\ coefficient\ of\ CRL)$$

3.6 Methodology for Child Restraint Law Analysis at Drivers-Level

A logistic regression model was used to explore the contributing factors for CRS-use at the drivers' level (Al-Ghamdi, 2002). This part of the analysis aims to evaluate the relationship of CRL over CRS-use from drivers' information. Twenty-five variables were collected from crash reports and 22 drivers' residence related variables were obtained from the ACS database. These last ones, provided the socio-demographic characteristics of the communities attained from the drivers' ZIP-code. The dependent variable represents the CRS-use in the crash event (1= restraint used, 0 = non-used).

The equation of the logistic regression is specified as follows, Eq. (3):

$$ln\left(\frac{P_{ij}}{1-P_{ij}}\right) = \beta_0 + \beta * X_{ij} + \mu_{ij} \quad (3)$$

Assuming that the random-effect $\mu_{ij} \sim N(0, \sigma^2)$, then X_{ij} would denote the tested variables. The coefficients (βo, $\beta 1$, $\beta 2$, …, $\beta 13$) represent the intercept and coefficient estimates; P_{ij} refers to the probability from an i= occupant and j= driver (Peng et al., 2002). The main reason for using random effects was to account for repeated observations from the same drivers and vehicles. In this case, one driver could have had several crash reports with more than one child occupant in the vehicle when the crash occurred. Approximately, 57% of the studied crashes reported more than 1 child in the event as it is illustrated in Table 4. Therefore, four different cases were evaluated in order to test the relationships between the drivers' socio-demographic and crash report characteristics including: (1) crash report variables only with random effects; (2) crash report variables without random effects; (3) crash report variables and driver residence variables with random effects; (4) crash report variables and driver residence variables without random effects. The goodness-of-fit results showed that the preferred model is the whole model with crash, residence data and random effects. Pearson and Spearman tests were applied to check for possible correlations between the variables. As some of them showed high associations, one of the correlated pairs were excluded from the final model.

Table 4: Number of Children Involved in the Crash Event. Source: FARS data 2014

Number of children in a vehicle	**Counts**	**Percentage**
1	1,033	42.9%
2	840	34.9%
3	336	13.9%
4	132	5.5%
5	55	2.3%
6	12	0.5%
Total	2,408	100%

3.7 State Level Legislation for Bicycle Helmet Law

This study analyzes the BHL at a state-level, however not all 50 states and Washington D.C. legislate the bicycle helmet as a state law. BHL was also found to be legislating at park, city, and county level, options that were not considered in this study. Studying the law's jurisdiction, it was classified as a state law or not. Consequently, just 35 states were evaluated, the other states were excluded. Figure 5, lists the states with BHL as well as the states without BHL. In Hawaii's case, even if it was found to have a state law, it did not report any fatalities for children 1 under 18 years in the time period 2011- 2015.

Table 5. State-level legislation

States without BHL	**States with BHL**
Arkansas	Alabama
Colorado	California
Idaho	Connecticut
Indiana	Washington D.C.
Iowa	Delaware
Minnesota	Florida
Nebraska	Georgia
North Dakota	Hawaii
South Carolina	Louisiana
South Dakota	Maine
Utah	Maryland
Vermont	Massachusetts
Wyoming	New Hampshire
	New Jersey
	New Mexico
	New York
	North Carolina
	Oregon
	Pennsylvania
	Tennessee
	Rhode Island
	West Virginia
13 states	21 States and D.C

3.8 Data Preparation for Bicycle Helmet Law Analysis

The data was collected from the Fatality Analysis Reporting System (FARS) of the National Highway Traffic Safety Administration (NHTSA) providing the vehicle, person and crash information. Alternatively, the American Community Survey (ACS) database from the United States Census Bureau provided the socio-demographic data on the population, average education, income and poverty levels attained from the bicyclist's ZIP-code. The studied period is from 2011 to 2015. As the objective aims to discover bicycle-related variables, option No.2 from Query Fars data (Bicyclist tables), was filtered by person type in category 6 to provide only bicyclist's information as well as limiting the injury severity in category 4 for only fatal injuries. The total number of bicyclists' fatalities for all ages is 3836 for the 5-year period. Filtering by age group 1 under 18 years old, the total number of bicyclists' fatalities are 542. Lastly, the final data set remains with 467 observations for fatalities aged 1 under 18 years, in the studied 35 states for the 5-year period 2011 to 2015. Figure 8, presents the number of bicyclists fatalities for the mentioned age groups: all ages, group 1 to 18 years and the studied case.

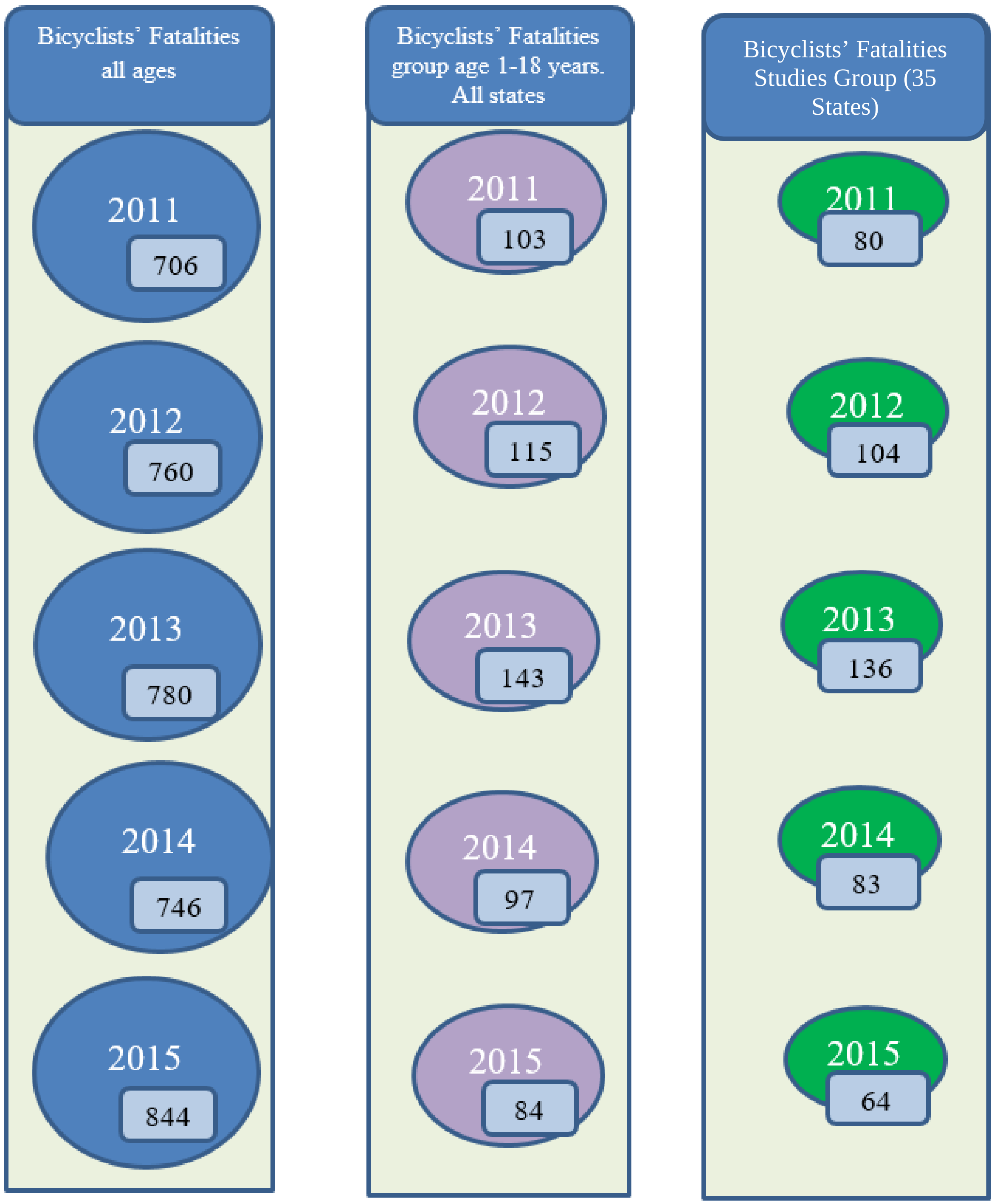


Figure 7. Number of observations for Bicyclists' Fatalities by Year. FARS data

3.9 Statistical Description of Bicycle Helmet Law

During the 5-year period of 2011 to 2015, there were 467 bicycle related fatalities on children 1 under 18 years old in The United States. Table 6, lists the descriptive statistics of bicycle fatalities by year. Nationwide, displays an overview of the bicycle fatality rate by the selected states under study (e.g. 35 states). The rate is estimated from the number of fatalities divided by the population density of the state among children 1 under 18 years, data from ACS, (2014). The states that appeared as N/A, are the states that were not considered in the study, because they do not have a BHL at state level. Frequency and percent distributions of bicyclists' fatalities are shown in Figure 10 and Figure 11, respectively. It is observed that 2013 was the year in which occurred the highest number of bicycle fatalities (29%) from the studied period. Figure 12, displays the age distribution. Nearly the age group from 12 to 17 years old (274 fatalities) doubles the fatalities in the age group from 1 to 11 (133 fatalities), having the age of 17 years old with the highest frequency. The critical pattern was observed among males; it almost triples the other gender's fatalities. (Figure 13).

Table 6. Descriptive statistics of the age in Bicyclists' Fatalities by Year in the 35 Studied States

	Year	N	Mean	Standard Deviation	Minimum	Maximum
Bicyclists' Fatalities by Age	2011	80	12.75	4.25	3	17
	2012	104	12.14	4.86	1	17
	2013	136	15.06	3.57	1	17
	2014	83	11.44	4.87	1	17
	2015	64	12.98	4.45	3	17

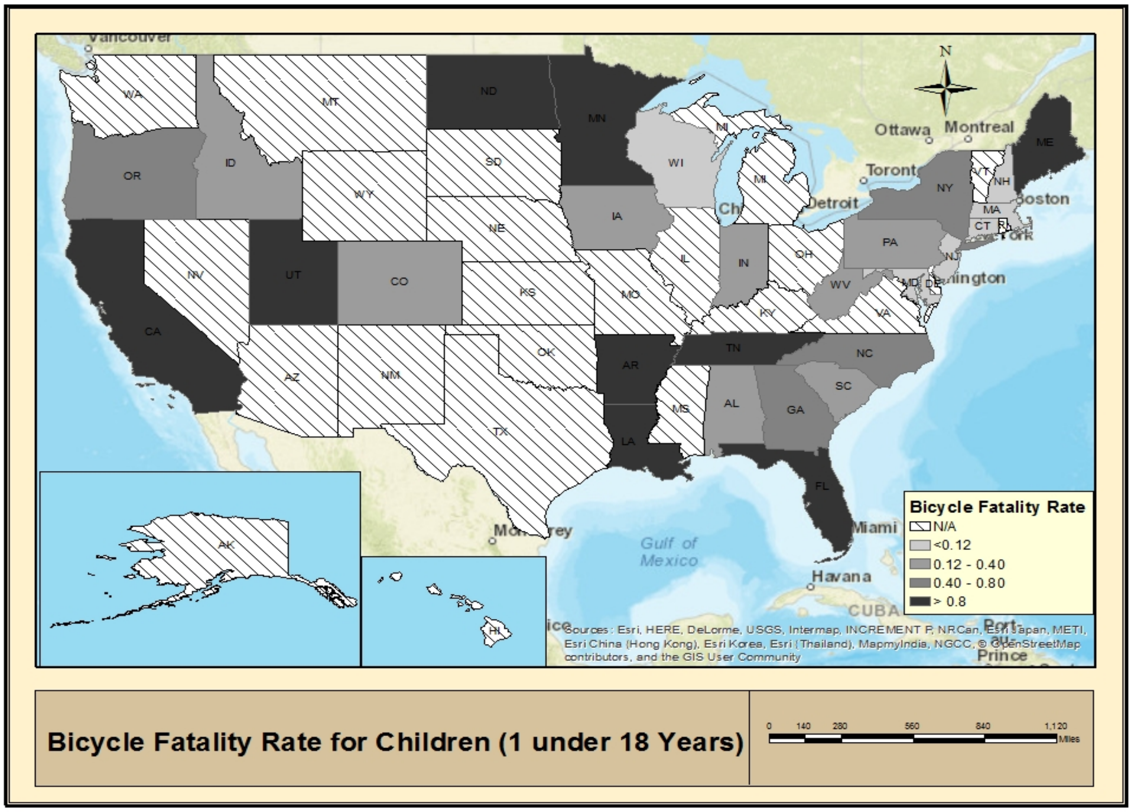


Figure 8. State Distribution of bicyclist's fatality rate in Children 1 to under 18 years

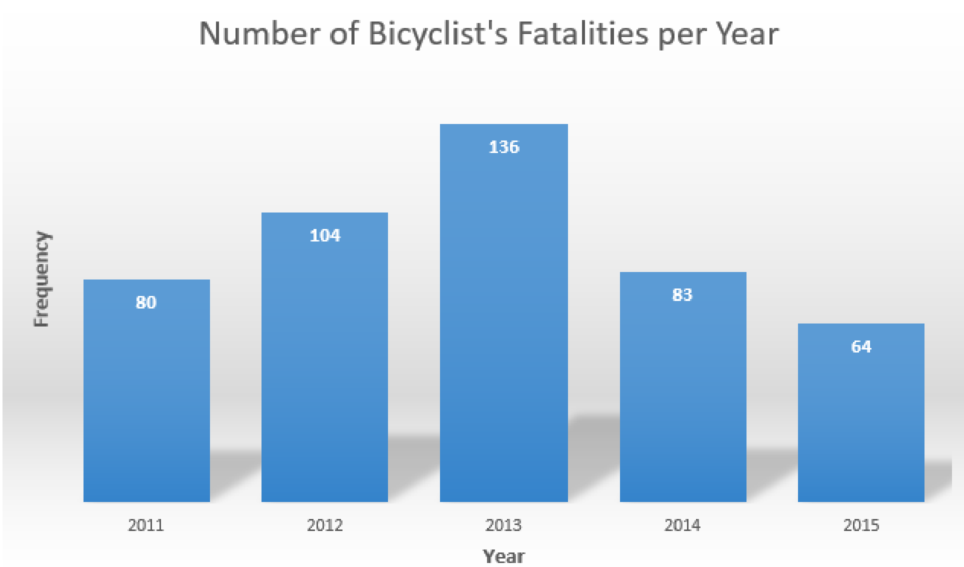


Figure 9. Year Distribution of bicyclist's fatalities

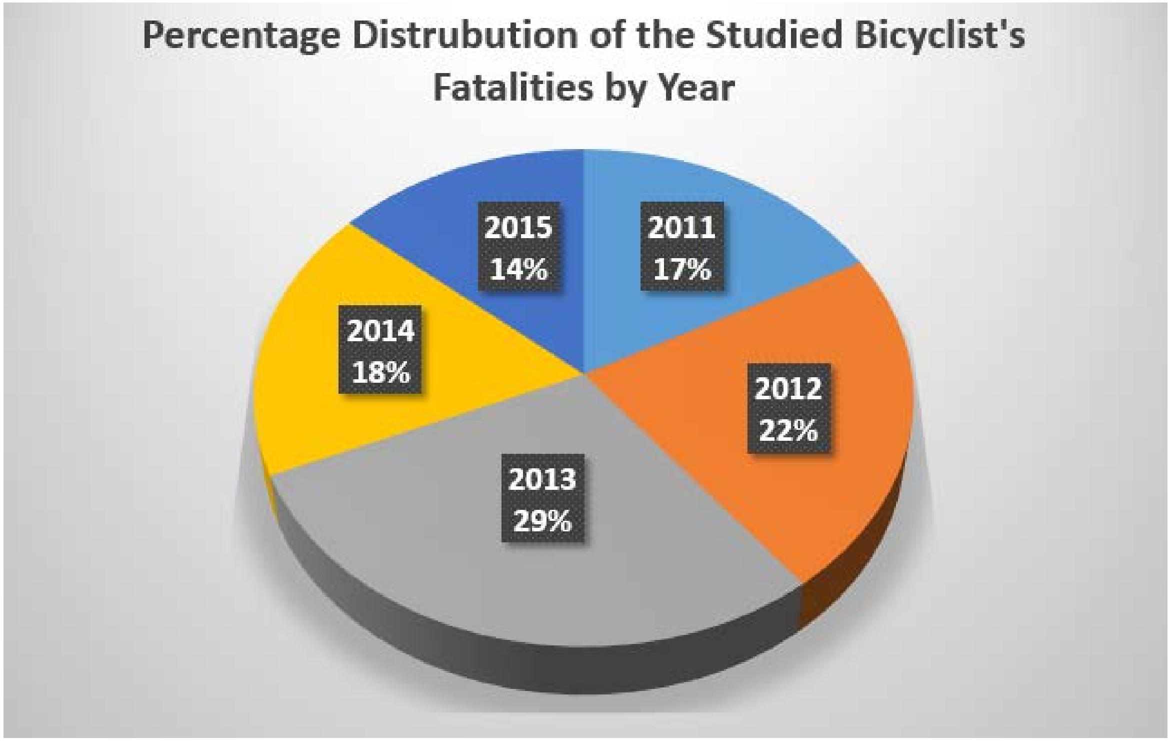


Figure 10. Percentage Distribution by year of bicyclists' fatalities

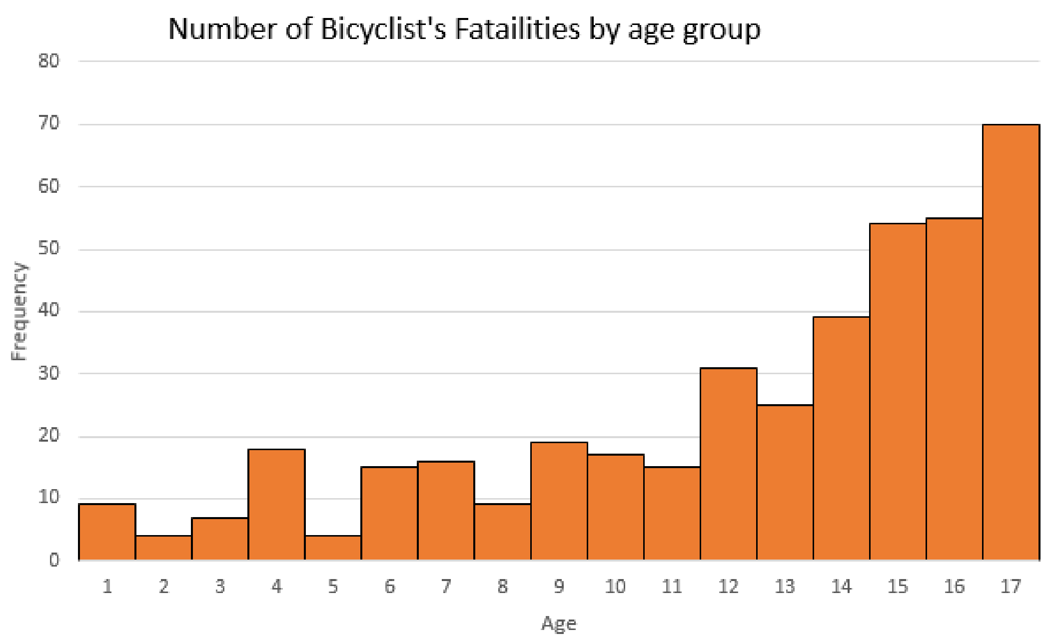


Figure 11. Age Distribution of bicyclists' fatalities in 2011 - 2015

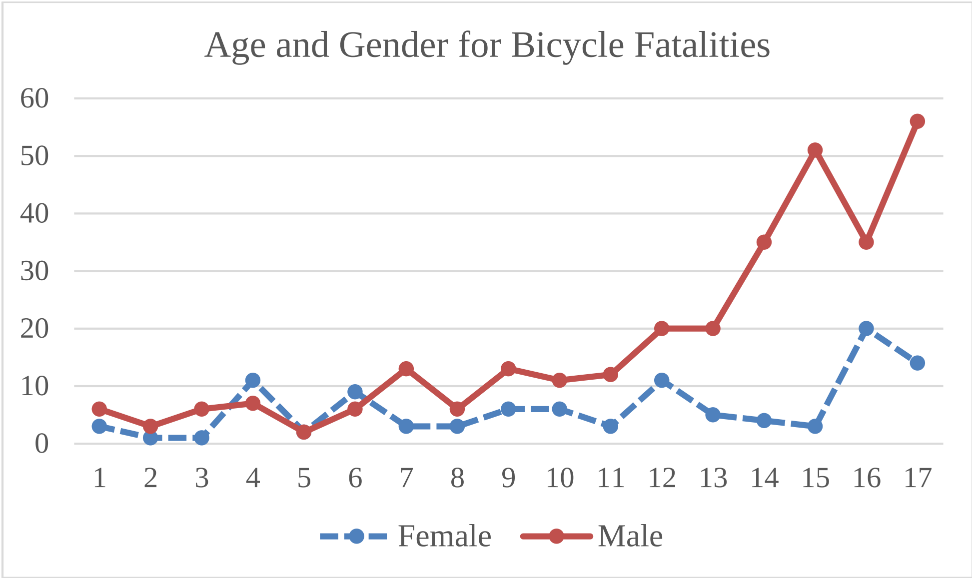


Figure 12. Age and Gender Distribution of bicyclists' fatalities

3.10 Methodology for Bicycle Helmet Law Analysis

To determine the contributing factors for helmet-use, a binary logistic regression model was developed. When the intent is to model binary outcomes as a function of predictor variables, a logistic regression model is often an appropriate solution (Hosmer et al., 2013). The use of this statistical approach was to explore the effects of BHL on helmet-use in bicycle related fatalities while comparing the effect in states with BHL versus states without BHL. Due to these differences between states, the dependent variable represents if the bicyclist was wearing a helmet when the collision happened evaluated once the state had a BHL where the victim was required to wear a helmet or not. By analyzing such conditions, the logistic regression model has a binary evaluation. If the i^{th} observation, when the bicycle fatality is (y_i=1) or (y_i=0). The possibilities for these two outcomes are p_i (y_i=1) when the bicyclist was wearing a helmet or 1- p_i when (y_i=0) when the bicyclist was not wearing the helmet. The model follows the equations (4) and (5):

$$y_i \sim \text{Bernoulli}\ (p_i) \tag{4}$$

$$Logit\ (p_i) = \beta_0 + \sum_{k=1}^{n} \beta_k * X_i \tag{5}$$

Where y_i follows a Bernoulli distribution whose probability of success is p_i , β_0 is the intercept, β_k the regression coefficient of the predictor X_i, and the X_i represent the explanatory variables for the i^{th} observation.

A simple transformation of equation (5) yields to equations (6) and (7), presenting the significant variables.

$$ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 * X_1 + \beta_2 * X_2 + \beta_3 * X_3 + \beta_4 * X_4 + \beta_5 * X_5 \tag{6}$$

$$ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 * BHL + \beta_2 * Age + \beta_3 * Education + \beta_4 * Income + \beta_5 * Gender \tag{7}$$

Initially, 15 possible variables were evaluated in the model. (e.g. time of the day, age, road function, weather conditions, day, race, hour, drinking, drugs-use, education level (below high school and after bachelor's degree), log of population, CRL, income and poverty level. Pearson and Spearman tests were applied to check for possible correlations between the variables; correlated pairs excluded the least significant variable from the final model. Insignificant variables were eliminated to look for a better fitted model. Using the PROC LOGISTIC procedure in SAS was used to obtain the final model with the significant and non-correlated variables. Appendix B, provides the correlation results. The significance of the variables was defined with a statistical significance level of 0.05.

In order to decide which of the independent variables perform better in the model, a scoring process evaluating the goodness of fit measures was implemented to determine the final model. In the model evaluation, three indexes were used: The Area Under the Curve (AUC), the Akaike's Information Criterion (AIC) and the Bayesian Information Criteria (BIC). The AUC is a frequently used method in traffic safety research, to calculate the sensitivity and specificity of the dependent variable; in this case it is targeting bicyclists with helmets and those without helmets. The larger the AUC value, the better goodness-of-fit estimate (Choi, 1998; Ying et al., 2011). Hosmer et al. (2013), quantifies AUC values by different levels. He mentions, that an AUC greater than 0.9 is considered an outstanding value, 0.8-0.9 is excellent, 0.7-0.8 is acceptable, 0.5-0.7 poor. The AIC and BIC are ways to measure deviance information. The model with the smallest deviance information criteria stands for the model that would better predict the data set with the best approximation among different number of explanatory variables. A smaller value of AIC and BIC means the model performs better. Finally, a statistical approach is given in terms of the odds ratio concept. The Odds Ratio (OR) is used as a measure of association between the binary options of the model-development, or in other words, how much more likely it is for a bicyclist to use a helmet (Hosmer & Lemeshow, 2005).

3.11 Bicyclists' Characteristics

The final model defined the significant bicyclists' characteristics. Somehow these variables were tested individually and evaluated from possible interactions between them. To do so, several categorizations were applied, in the following categories. The age variable was seggregated into two categories. The first group is from 1 to 10 years. The second age group is from 11 to under 18 years. Also, the income was tested into different ranges, the critical amounts were: less than \$40,000 annually, less than \$50,000 annually, less than \$60,000 annually and less than \$70,000

annually. Consequently, education was divided into two categories, participants with a bachelor degree or lower (ED1), and the other category is the participants with a higher degree than a bachelor (ED2). This category was tested if the community from the bicyclist's ZIP-code had ED1 and/or ED2 less than 10%, 20% and 30%. Furthermore, the poverty level was analyzed as the percentage of population when the family's total income is less than the family's threshold values estimated from the Census Bureau. Poverty level was tested as if the bicyclist's community has less than 5%, 10%, 20%, and 30% of people under poverty circumstances.

3.12 Variables Description

The two data sources used in this study (ACS, Census Bureau for the socio-demographic information) and (FARS, for the crash data) provide the definition for the evaluated variables. From FARS data, the variables' description is described in Appendix C. The significant variables accounted in the models collected from ACS dataset are defined as:

- Mean Travel Time to Work (minutes): It refers to the travel time to go to work. It sums the total number of minutes that a person greater than 16 years old usually takes to get from home to work each day during the reference week. This time contains complementary times, including the waiting time a person spends for public transportation, picking up passengers in carpools, and the time spent in other activities related to getting to work.
- Education Attainment, was evaluated in two levels. First, High school diploma or less includes people whose highest degree was a high school diploma or its equivalent, people who attended school but did not receive a degree, or people who did not complete 12th grade. Second, People with a Bachelor's Degree or Higher, are those who have received a

bachelor's degree from a college or university, or a master's, professional, or doctorate degree.

- Poverty. For this purpose, the Census Bureau uses a set of money income thresholds that vary by family size and composition to determine who is in a poverty level. If a family's total income is less than the family's threshold, then that family and every individual in it is considered in poverty. The official poverty thresholds do not vary geographically, but they are updated for inflation using the Consumer Price Index (CPI-U). The official poverty definition uses money income before taxes and does not include capital gains or noncash benefits (such as public housing, Medicaid, and food stamps).
- Industry. Industry information describes the kind of business conducted by a person’s employing organization. After selecting the business type, the industries are segregated into three classifications: primary, secondary and tertiary industry. It includes workers from ages greater than 15 years old.

CHAPTER 4. RESULTS

4.1 Child Restraint Law Results at State-Level

A crash prediction model was developed to quantify the impact of CRL. In traffic safety analysis the negative binomial approach is well-known for estimating the effectiveness of safety treatments (Lord et al., 2005; Park et al., 2015). An examination at state level shows that ‘Log of Population’ and ‘Child Restraint Law’ have a significant impact on child fatalities not using CRS, Table 7. The population variable was used as an exposure and it has a positive effect as expected, while CRL has a negative effect, which infers that the CRL is effective to reduce child fatalities when a traffic crash happens and the law covers the child’s safety by law. Finally, the results showed that the model found a significant reduction in child traffic fatalities not using CRS when the state at “*j*” age group has CRL coverage. The estimated value of 0.712 = (exp (-0.34)), implies that if a state has a law covering a specific age, the state experiences 29% less child traffic fatalities compared to those without CRL.

Table 7**:** Safety performance function for child fatalities not using CRS.

State Level Results			
Parameter	**Estimate**	**Standard**	**Pr > ChiSq**
Intercept	-7.8723	0.9189	<.0001
Log (population of age *j* in state *i*)	1.7777	0.1894	<.0001
CRL dummy (whether the CRL of the state *i*	-0.34	0.1642	0.0384
α (overdispersion)	0.4818	0.1334	-
Likelihood ratio index (ρ^2)	0.6553		

CMF	Confidence Interval			
	95% Lower Limit	**90% Lower Limit**	**90% Upper Limit**	**95% Upper Limit**
0.712 = exp(-0.34)	0.516	0.543	0.932	0.982

4.2 Child Restraint Law Results at Drivers-Level

In safety research, driver's demographics have always been considered to have a substantial association in traffic fatalities.

Table 8, shows the results from the logistic regression model, revealing 13 independent variables which would influence drivers' decisions to restraint children. The dependent variable reveals if the selected traffic crashes reported the occupant's usage of restraint equipment at the time of the crash. The criteria considered for this factor evaluated the number of fatalities in the age group of children from 0–9 years old in the 50 states and D.C. The factors that increase CRS-use include: restraint drivers, 25-49 years old drivers, if the state covered the child's age group and if the child was between 0-4 years old. On the other hand, exogenous factors that reduce CRS-use include: older (>49 years) and younger (<25 years) drivers, impaired drivers and with vehicle equipment violations, child's age (>4 years old), driving in local roads, rainy weather, greater number of occupants in the vehicle and driver's zip-code characteristics (e.g., education, commuting travel time, industry type and poverty level).

Table 8: Logistic regression modeling results from crash, residence data, and random effects.

Driver level Results				
Category	Variable	Estimate	Standard Error	Pr > |t|
-	Intercept	-2.7647	0.6266	<.0001
Policy	Whether state's CRL was covering the child's age (1=yes, 0 = no)	3.7681	0.2916	<.0001
Driver	Whether driver's age is between 25 and 49 years old (1=yes, 0=no)	0.3754	0.1855	0.0432
	Whether the driver used seat-belt (yes=1, no=0)	1.406	0.2379	<.0001
	Whether the driver was impaired (yes=1, no=0)	-1.8235	0.8954	0.0419
	Whether the driver violated equipment regulations (yes=1, old=0)	-2.3484	1.0918	0.0316
Child	Whether the child is between 0 and 4 years old (yes=1, no=0)	1.7981	0.2036	<.0001
Environment	Whether the crash occurred on local roads (yes=1, no=0)	-1.0841	0.3937	0.006
	Rainy (Yes=1, no = 0)	-0.7929	0.3295	0.0162
Vehicle	No of occupants in the vehicle	-0.2529	0.0582	<.0001
Driver Related Variables (ZIP-based)	% of people whose educational attainment is less than high school diploma	-0.0311	0.0122	0.0108
	Mean travel time to work (min)	-0.0371	0.0146	0.0109
	% of secondary industry employees	0.0308	0.0119	0.0093
	% of households below poverty line	-0.0246	0.0130	0.06
Variance of random effects (*u*)		3.0946	0.5687	<.0001
Log-likelihood ratio index (ρ^2)		0.293		

Goodness-of-Fit Results Applying Logistic Regression Models				
Model	-2 Log Likelihood	AIC	BIC	ρ2
The model with crash, residence data, and random effects	2105.3	2135.3	2214.6	0.29
The model with crash and residence data without random effect	2202.3	2230.3	2309.8	0.26
The model with crash data only with random effect	2146.6	2168.6	2226.7	0.28
The model with crash data only without random effect	2254.5	2274.5	2331.3	0.24

4.3 Bicycle Helmet Law Results

A Binary Logistic Regression model was developed to estimate helmet-use behavior on children 1 to under 18 years and the influence of having a BHL at state-level. The analysis was constructed from bicyclist's traffic fatalities information conveyed from traffic crash reports and the socio-demographic variables.

Preliminary empirical results indicated that the parameters of time, day, race, hour, drinking, log of population, drugs-use and poverty level were not significant. The higher education level more than a bachelor's degree parameter was removed to improve the model structure. The empirical results of the final model are shown in Table 9 along with the AIC, BIC, AUC and OR outcomes. The AUC obtained from the model was 0.80, which shows a good ability to disseminate between the use and non-use of bicyclists' helmets, also the lowest values of AIC= 227.982 and BIC= 252.860 between models were reached. Using a significant level of 0.05 or less, findings show that five independent variables may influence helmet-use including: if the state has BHL, child's age, education level, income and gender.

Table 9: Logistic regression modeling results for bicycle helmet use with crash and residence data.

Parameter	Estimate	Standard Error	Wald Chi-Square	P-value	Odds Ratio
Intercept	-1.7267	0.4409	15.3362	<.0001	
Whether the state's BHL was covering the child's age (1=yes, 0 = no)	1.1904	0.3931	9.1688	0.0025	3.288
Whether the bicyclist's age is between 11 and 18 years old (1=yes, 0=no)	-1.1968	0.4245	7.9476	0.0048	0.302
Less than 10% of population has at least a high school diploma	0.8705	0.4199	4.2984	0.0381	2.388
Percent of households' income level below $50,000/year	-1.7102	0.4556	14.0876	0.0002	0.181
Whether the bicyclist is a male (1=male, 0=other)	-0.7658	0.3911	3.8344	0.0502	0.465
Goodness-of-Fit Results Applying Logistic Regression					
Model	**AUC**		**AIC**		**BIC**
Binary Logistic Model	0.80		227.982		252.860

CHAPTER 5. DISCUSSION

5.1 Contributing Factors for Child Restraint Use

Whether the state has a CRL that covers the child during the crash reveals a significant relation that can influence driver's behavior. It was estimated that as long as the law requires CRS, it is more likely that the drivers will provide safety to the children by using the equipment.

According to the results, there are some relationships inferred from the driver's characteristics. Numerous research studies have attempted to examine the relationship between driver's age and traffic risk. In this case, driver's age was a variable that revealed that younger drivers less than 25 years and older drivers more than 50 years were less likely to provide CRS when a fatal traffic crash happened. This observance might be explained in a way that younger drivers (i.e., under 25 years old), might not represent a high proportion of the child's parents in all cases, therefore they are assuming less responsibility over the child. On the other hand, older drivers do not have the same behavior as adults (i.e., >49 years old), maybe because by the time they were raised in their childhood, the child restraint policy was not a mandatory law (Russell et al., 1994). Alternatively, Decina et al. (2005) compares the relation between the restraint driver's use or misuse, and how CRS is provided to the children in two different studies, one conducted in 2002 and the other one in 1996. The 2002 study showed a small difference between adults' restraint and CRS misuse, compared to the one in 1996. At the end he states: "*The general public appears to have reached the same restraint use levels as drivers with young child passengers*" (Decina & Lococo, 2005).

The liability of the driver wearing a seat belt during the time of the crash is also denoted as an influential factor. If the driver did not wear a restraint him/herself, it is more likely that it

will not provide safety to the child either, also denoted by Decina et al. (2005). Another finding suggests that impair offenses and equipment violations indicate that the driver is less likely to care about CRS. Alcohol or drugs may also influence this behavior and he/she will care less about the vehicle safety compliance.

Another characteristic that showed CRL influence in the CRS-use was the child’s age. The child’s age variable was found significant and has a negative coefficient, meaning that as the child’s age increases, their use of safety equipment decreases. Furthermore, a child occupant has a higher likelihood to use a restraint system at a younger age (0-4). Parents might think that once they are sufficiently grown up, the children do not need CRS anymore, confirmed also by James et al. (1996).

Referring to the number of occupants reported at the time of the crash, shows that it is less likely to have restraint systems for children when there are more occupants in the vehicle. Confirmed also by Agran et al. (1998). Considering that a restraint equipment utilizes the space for an occupant, it is more likely that the driver might fill the vehicle with more people instead of providing safety to the child. Optimizing passenger space in a vehicle leaves CRS as a second option. Referring now to the functional road classification, it was tested as a categorical variable with the reference group of local streets. The results indicate that it is less likely for people to provide CRS on local roads. Despite James et al. (1996) claim that it is less likely to have restraint systems on freeways and urban roads, findings from this current study do not reach the same conclusion in regards to freeways. Expected results could be interpreted from Hawaii’s freeway characteristics because it is the state with the lowest speed limit (60 mph) in the U.S.(Skszek, 2004). On urban roads, common findings can be mentioned comparing urban with local roads by

similar characteristics such as shorter travel distance, geometric design characteristics and low speed**.** Finally, results show that it is more likely that under rainy conditions, drivers use less CRS.

Analyzing driver’s residence characteristics revealed the following results; the most significant industry sector that showed a low CRS-use is the secondary industry. Those employed in transportation, construction, extraction, maintenance, production, manufacturing and material moving occupations (truck drivers, carrier industry, other vehicle fleets) might use their personal vehicles for work purposes, leaving no space for CRS. Another significant variable was the mean travel time, analyzed as a commuting factor for transportation purposes. People that spend more time getting to work will increase their probability of not providing CRS. The level of education was also a significant factor in the model. Low education level was analyzed as the percentage of the population with a high school diploma or less, which revealed that is more likely the non-use of CRS. Finally, poverty level was analyzed as the percentage of population when the family's total income is less than the family's threshold. Less wealthy people are more likely to avoid CRS, indicating the need for more education, awareness and information in how to afford a restraint system. Race did not show significance in this model, however Winston et al. (2007) mentioned the non-Hispanic black ethnic group has the highest sub-optimal child restraints and Zonfrillo et al. (2015) provides a survey with parent’s excuses to unrestraint children done by ethnicity.

5.2 Contributing Factors for Bicycle Helmet Use

Analyzing the Odd ratio results, it was found that if the state has a BHL that covers the child/teenager during the crash, bikers were 229% more likely to wear helmets (Chi-square=9.17, P=0.0025). Results in accordance with Karkhaneh et al. (2006). From the bicyclists’ characteristics, age and gender were shown as significant factors. Children younger than 11 years

old are more likely to wear a helmet compared to the age group 11 to under 18 years old (Chi-square=7.95, P=0.0048). This observation might be explained in a way that bikers under 11 years old might follow directly their parents' orders or do not feel that wearing a helmet goes against their style. Thompson et al. (1990) found that helmet use was very low among riders under 15 years of age. The present findings in contrast with Thompson age group, shows a change over time that could be possible due to awareness campaigns and safety educational programs in the past years. This could have had positive awareness towards children under 11 years old. From the gender's side, findings show that males are 53% less likely to wear helmets than females (Chi-square=3.83, P=0.0502). Ethnicity did not show significant relationships with helmet-use.

Secondly, education and income level also indicated a possible influence factor in helmet-use; both variables were attained from the bicyclist's ZIP-code. Low education level was analyzed as the percentage of the population with a high school diploma or less degree. In this case, the bicyclists' communities were analyzed, showing that those with a 10% or less population in this low education-level are 138% more likely to use a helmet (Chi-square=4.29, P=0.0381). This means that a higher proportion (>10%) of less educated people in an area might influence the non-use of bicycle helmets. Finally, income level was analyzed and found that households earning less than $50,000 per year are 82% more likely to not use helmets while biking (Chi-square=14.09, P=0.0002). The present study confirmed that education and income are influent factors in helmet-use (Hu et al., 1993; Parkin et al., 1993).

These findings suggest that the helmet law is associated with helmet use behavior among youth. One of the ways to increase helmet use includes legislation (Carpenter & Stehr, 2011; Rosenberg & Sleet, 1995) , therefore it is recommended to consistently adopt BHL at a federal level based on the results of this study and the successful legislation among states, accompanied

with education, promotion, enforcement, and program evaluations to stimulate helmet use as a proven way to reduce cyclists' fatalities.

CHAPTER 6. CONCLUSIONS

6.1 Child Restraint Law Conclusions

The effectiveness of the Child Restraint Laws (CRL) on the number of fatalities as well as drivers' decisions to use Child Restraint Systems (CRS) was evaluated in the first part of this thesis. In the late 1970s, policy-makers tried to regulate the use of CRS at state-level. Afterwards, CRL has become a federal law that covers children from 0-4 years old, and some states have extended the age coverage. In the evaluation process it was determined whether the extended CRL can be effective for the additional age groups. In order to answer the question, a negative binomial model was developed to evaluate the effectiveness of the law. Findings suggests that the CRL contributes to a reduction of 29% of traffic fatalities for unrestrained children from 5-9 years old. Another significant finding revealed some contributing factors for the likelihood of the CRS-use, using a logistic model is useful to explain that the enforcement of CRL has positive effect on CRS-use for the corresponding age groups. Such findings include: child's and driver's age, driver's restraint-use, whether the driver was impaired or violated equipment regulations, weather conditions, number of occupants in the vehicle, whether the CRL covered the age of the child, and driver's zip-code characteristics (e.g., education, commuting travel time, industry type and poverty level). Therefore, legislation in Child Safety Policy was shown to have consequences in traffic fatalities. The findings suggest that CRL is an effective countermeasure for injury prevention, as well as influencing the CRS-use.

6.2 Bicycle Helmet Law Conclusions

The evaluation of contributing factors for the helmet-use behavior was analyzed when there is a state-level Bicycle Helmet Law (BHL) in the process. For this purpose, a logistic regression model was developed to analyze the Fatality Analysis Reporting System (FARS) data of 2011 to 2015. The findings show that bicyclists from the states with the BHL are 229 times more likely to wear a helmet compared to those from the states without the BHL. Moreover, the bicyclist's age and gender were found to be significant. It was revealed that the age group from 11 to under 18 years old, are less likely to wear a helmet compared to other ages from 1 to 10 years old. It was also observed that male bikers are less likely to wear helmets than females. The other two significant variables were the education and income level; both variables were attained from the bicyclist's ZIP-code. The bicyclists from communities with low educational level and lower family income are less likely to wear a helmet. It is concluded, that the helmet law has a significant effect to increase helmet-use among children and adolescents. Furthermore, the results suggest that it needs more emphasis on the socially and economically deprived areas to promote bicycle helmet use. In conclusion, it is strongly encouraged to enact state-level BHL, as well as education, safety promotion, enforcement, and program evaluations to stimulate helmet-use as a proven way to increase bicyclist's traffic safety.

CHAPTER 7. RECOMMENDATIONS AND CONTRIBUTIONS

7.1 Accomplishments and Recommendations

The results obtained from this study disclose some contributing factors in CRS and helmet use and reveal a considerable reduction in children's traffic fatalities because of the CRL improving traffic safety. First, the results revealed that enacting CRL can reduce the number of fatalities by 29% for children aged 5 to 9. Due to this, it is recommended to have a statewide CRL for a wider range of age groups, such as 0 to 9 years rather than the current law from 0 to 4 years, which will consequently reduce the age-coverage variability and improve children's safety. Second, in the drivers' analysis, it was shown that crash and residence characteristics have a possible effect on safety; for example, drivers residing in communities with deprived socio-economic statuses were less likely to use CRS. Similarly, in the bicyclist's analysis, it was shown that crash and residence characteristics have a possible effect on safety also; in this case, bicyclists residing in communities with deprived socio-economic statuses were less likely to use helmets. Based on this, it is recommended that appropriate research should be conducted to study drivers' and bicyclists' behaviors to discover influential variables for drivers to restrain his/her child and for the use of bicycle helmets. In addition, it is recommended to dedicate more effort and resources towards creating community-based transportation programs aimed towards these communities by providing better and safer opportunities to commute to work and school, subsidies for children to obtain protection equipment, insurance discounts for using CRS and helmets, and safety education and awareness campaigns. Detailed results for CRS and bicycle helmet use are presented at the end of Chapters 3 and 4, respectively.

The analysis of traffic safety in crash reports and the identification of possible contributing factors to their occurrence are possible due to proven statistical methods. Findings show that the negative binomial and the logistic regression models, as used in this research, are reliable tools in providing meaningful interpretations. Applying statistical models in traffic safety policy provides a way to estimate solutions as well as to determine policy making consequences. To do so, historical crash data are relevant to estimate traffic safety. Having a nationwide crash-data source, as how it was analyzed in this study, could help define relevant policy decisions, in this case, children's protection. Studying the crash and sociodemographic characteristics of traffic fatalities presents a framework on how children's protection is being faced for occupant passengers and bicyclists in the past years.

Five factors are important to support transportation policy with a traffic safety study: a) previous research studies, b) data necessary to determine the crash risks, driver's behavior, or possible cause interpretations, c) a diagnosis of the situation d) appropriate methodology to evaluate the safety effects, and e) a complete analysis of the results.

Through multiple policy interventions, road traffic crashes in the United States have been reduced in the studied time period, along with their associated injuries and fatalities. Interventions, including enforcement of penalties for not providing protection to children, financial rewards for citizens who abide by traffic legislations, the introduction of road safety programs in school areas, and road safety awarness campaigns and education programs are some examples of how transportation policy is providing safety for children. However, road traffic crashes still pose a major public health problem for children.

Although further progress has been achieved in child passenger safety policy through laws, enforcement, programs, and education since these laws were enacted, the analysis revealed a substantial number of children who are still traveling as motor vehicle passengers or in non-motorized vehicles without complying to safety laws. At a state level, the variability and exemptions in the child passenger safety laws result in a weak way to provide traffic safety policy in the United States. Moreover, it can result in difficulties in reaching compliance with the laws.

7.2 Contributions

Most of the studies were developed in the late 80's and 90's, maybe because the law at this time was a new concept. However, this is an ongoing problem that requires more up-to-date research, which can reveal how the nation is facing the CRL and BHL nowadays. Therefore, a contribution that this study provides is a recent overview of child restraint use in 2011 to 2014 and bicycle related fatalities from 2011 to 2015. Overall, limited research has been conducted on child's protection policy in transportation system policy decisions require to have enough evidence to support the laws in order to not become an arbitrary legislation process affecting children's protection.

Finally, this study confirms the importance of establishing safety laws in transportation systems. Protecting road users with legislation evidenced interesting findings that can support plans that aim to reduce traffic injuries and fatalities, especially ones that target vulnerable users, such as children and bicyclists. Previous research in transportation policies regarding CRL and BHL had tried to justify protection systems as road safety countermeasures. This study has shown that regulating with these laws as a mandatory rather than a voluntary solution influences our society protecting children when they are traveling.

7.3 Limitations

Findings are based on the data consistency from FARS crash reports. Somehow, there are some limitations, including:

- A general limitation for both cases is that this study just focuses on traffic fatalities. The reason why it does not reflect the general child protection for all population (e.g. injuries). It represents the higher risk that a child can be exposed to, once the event is a fatality. FARS data relies on police crash-reports where wrong categorization and missing data could affect the results. Furthermore, FARS reports an incident under two circumstances, first it must involve a motor vehicle traveling on a public roadway and second it must have resulted with a fatality of a motorist or a non-motorist within 30 days of the crash. Leaving out of the sample collisions where a motor vehicle was involved (e.g. bicycle-bicyclists or run off crash types) and if they occurred on private roads.
- Even if CRL was studied at a state level, it was just analyzed as a general law, which regulates children traveling as motor vehicle passengers to wearing a child restraint system for children 0 to 4 years old. However, states changed their law several times and had different statutes with stronger or weaker regulations, leaving space for exemptions that are not considered in this study, including public service, transit, non-residents, large vehicles, vehicles without seat-belts, emergency vehicles, etc.
- For BHL, there are several limitations. Without information about the number of bicyclists per state and per age group, fatalities per unit time bicycling, distance traveled, or number of trips, the statistical inferences cannot be compared between groups. This means that there are limitations in the exposure data creating uncertainty about how many miles does bicyclists travel each year, how long it takes them to cover those miles (and thus how long

they are exposed to motor vehicle traffic). Therefore, risks vary on the bicyclist's exposure including time of day (with night time being riskier), experience level of rider, location of riding, alcohol use, and many other factors. Another concern is that the bicyclist's fatalities were analyzed once the collision happened and the child was wearing a helmet or not. In this case, this study is not reflecting the effectiveness or misuse of the helmet to prevent the fatality. It is just revealing the contributing factors for helmet-use. Moreover, comparing the age in bicyclist's behaviors, in the teenagers' side they use to cycle for longer distances and durations than younger children due to several factors as parents' protection and allowance, physical ability and behavior characteristics of each age group. Meaning that the older the bicyclist are they would be more exposed to the traffic than younger bicyclists.

- This report underscores the influence of improving bicycle safety in the roads, where bicyclist's might think in safer paths they don't need to use helmets. In fact, other countries that want to promote cycling, introduced safety solutions in bicycle infrastructure (e.g., physically separated bike lanes, cycle tracks or sidepaths, painting markings), traffic calming measures (e.g., speed humps), legal interventions (e.g., lowered speed limits, traffic bicycle signals), travel programs (e.g., safe routes to school, cycle routes networks, reflective vests), and education programs to encourage safety in bicyclist and driver's behavior.

7.4 Further Research

After analyzing the described safety laws in this study, the findings present several recommendations for transportation policy improvement. Further research can be made evaluating other transportation laws.

- This research study is part of an evaluation of different laws related to transportation systems. From a list of 10 different laws that the NHTSA regulate in road safety they are specific programs targeting different objectives; Child safety, teen driving, pedestrian safety, alcohol and drugs, drivers with disabilities, bicyclists, motorcycles, passenger vans, school buses and old drivers. So far, UCF has previously researched some of these regulations, the motorcycle helmet law (Lee et al., 2017), alcohol and drugs, among with this study focusing on two other regulations, the child safety and bicyclists.
- The analyzed data in this study, was chosen from the FARS database, which just focuses on fatalities. Somehow it is well known that when a collision occurs there can be different injury types. Following a KABCO classification there could be more research space to study other injury severities.
- Applying more advanced statistical models and data mining techniques for studying different protection equipment created to attain child's safety can expand the objectives of this study. Perhaps in CRL, boosters and seat belts for older ages and for BHL other body armors.
- BHL was only analyzed as a state level law, however if was found that other jurisdictions also have BHL at a county, city, or park level. This could be a broader scope for the analysis. Introducing zonal-level safety analysis can also be applied at Traffic Analysis Zones (TAS) and Traffic Analysis Districts (TAD) level.
- Expanding the possibilities of this research, not limiting to children's protection, more transportaion laws could be analyzed. Being aware of other research studies that the faculty is conducting in transportation, including a study observing transportation in fog conditions, where there is no legislation yet, seems like a need to start thinking in regulating

transportation under weather conditions. Currently, states are facing fog situations with suggestions and operational recommendations as Variable Message Signs (VMS), Dynamic Messege Signs (DMS), traffic management and ramp metering control. As it is demonstrated that weather conditions affect traffic safety, a further study can demonstrate the need of leveling this into legislation to protect drivers. A before and after study can be created because data will be analyzed before the rulemaking process begins.

- So far, CRS and bicycle helmets are known passive countermeasures in traffic safety. However, Intelligent Transportation Systems (ITS) are moving towards finding solutions for active safety. New on-board information and communication technologies are looking toward solutions to provide safer transportation systems, among other benefits. From the children's safety point of view, we are facing new technology penetration with Autonomous Vehicles (AV) and Connected Vehicles (CV) that will reduce traffic fatalities for all occupants and all road users, where implicitly children will benefit. Furthermore, these technologies are looking to comply with a long goal of reducing fatalities and severe injuries. When society's priorities, cost-benefit analysis and willingness to pay choices decide the effect of children's safety in transportation systems, then planning decisions related to safety strategies will have to look for better options; they could become a jostle to integrate ITS solutions. Nowadays, AV and CV technologies are under study, nevertheless there is no research about safety strategies that can be incorporated to look for children's safety. What is known is that transportation policy could make substantial changes towards it. Including legislation, ITS use, increasing social awareness, safer vehicles and infrastructure are influential factors that are changing today's established countermeasures to move towards active ones including new technologies.

APPENDIX A: FIGURES AND TABLES CHILD RESTRAINT LAW

Table 10: Pearson Correlation Check

Pearson Correlation Coefficients, N = 2165
Prob > |r| under H0: Rho=0

	CRL	Driver's age	Local	rain	b_restraint	b_numoccs	Child's age	impair	equip	ED1	TRANS7	POV	OCC2
CRL	1	-0.05434	-0.00948	-0.00474	-0.0072	-0.07732	0.38873	0.03238	0.02685	0.03179	0.00898	0.00749	0.02622
		0.0114	0.6594	0.8257	0.7377	0.0003	<.0001	0.1321	0.2118	0.1393	0.6764	0.7276	0.2226
Driver's	-0.05434	1	-0.03438	0.01036	-0.00756	-0.00893	-0.10542	0.0151	-0.0199	-0.07137	-0.01643	-0.04495	-0.04327
age	0.0114		0.1098	0.63	0.7252	0.6778	<.0001	0.4825	0.3547	0.0009	0.4449	0.0365	0.0441
Local	-0.00948	-0.03438	1	0.02992	-0.15887	0.07342	-0.02097	-0.01508	-0.06585	0.00895	-0.10653	0.01843	0.1494
roads	0.6594	0.1098		0.164	<.0001	0.0006	0.3294	0.4831	0.0022	0.6773	<.0001	0.3913	<.0001
rain	-0.00474	0.01036	0.02992	1	0.05552	0.04877	-0.01598	-0.00441	-0.00005	-0.01748	-0.02123	0.02069	0.00433
	0.8257	0.63	0.164		0.0098	0.0233	0.4572	0.8376	0.9981	0.4161	0.3236	0.3359	0.8404
b_restraint	-0.0072	-0.00756	-0.15887	0.05552	1	0.05699	-0.0067	-0.03112	-0.04194	-0.05653	0.03054	-0.11439	-0.00674
	0.7377	0.7252	<.0001	0.0098		0.008	0.7555	0.1477	0.051	0.0085	0.1555	<.0001	0.7539
b_numoccs	-0.07732	-0.00893	0.07342	0.04877	0.05699	1	-0.12233	-0.00757	0.04191	0.10413	0.00826	0.09833	0.00244
	0.0003	0.6778	0.0006	0.0233	0.008		<.0001	0.7247	0.0512	<.0001	0.701	<.0001	0.9096
Child's	0.38873	-0.10542	-0.02097	-0.01598	-0.0067	-0.12233	1	0.03899	0.00212	0.01475	-0.02446	0.01788	-0.02564
age	<.0001	<.0001	0.3294	0.4572	0.7555	<.0001		0.0697	0.9213	0.4927	0.2553	0.4057	0.233
impair	0.03238	0.0151	-0.01508	-0.00441	-0.03112	-0.00757	0.03899	1	-0.00718	0.03414	0.04065	0.02357	0.00845
	0.1321	0.4825	0.4831	0.8376	0.1477	0.7247	0.0697		0.7386	0.1122	0.0586	0.273	0.6945
equip	0.02685	-0.0199	-0.06585	-0.00005	-0.04194	0.04191	0.00212	-0.00718	1	0.04634	0.04946	0.0622	0.01809
	0.2118	0.3547	0.0022	0.9981	0.051	0.0512	0.9213	0.7386		0.0311	0.0214	0.0038	0.4002
ED1	0.03179	-0.07137	0.00895	-0.01748	-0.05653	0.10413	0.01475	0.03414	0.04634	1	0.02519	0.069527	0.20066
	0.1393	0.0009	0.6773	0.4161	0.0085	<.0001	0.4927	0.1122	0.0311		0.2413	<.0001	<.0001
TRANS7	0.00898	-0.01643	-0.10653	-0.02123	0.03054	0.00826	-0.02446	0.04065	0.04946	0.02519	1	-0.17279	0.11852
	0.6764	0.4449	<.0001	0.3236	0.1555	0.701	0.2553	0.0586	0.0214	0.2413		<.0001	<.0001
POV	0.00749	-0.04495	0.01843	0.02069	-0.11439	0.09833	0.01788	0.02357	0.0622	0.069527	-0.17279	1	0.01707
	0.7276	0.0365	0.3913	0.3359	<.0001	<.0001	0.4057	0.273	0.0038	<.0001	<.0001		0.4272
OCC2	0.02622	-0.04327	0.1494	0.00433	-0.00674	0.00244	-0.02564	0.00845	0.01809	0.20066	0.11852	0.01707	1
	0.2226	0.0441	<.0001	0.8404	0.7539	0.9096	0.233	0.6945	0.4002	<.0001	<.0001	0.4272	

Table 11: Spearman Correlation Check

Spearman Correlation Coefficients, N = 2165
Prob > |r| under H0: Rho=0

	CRL	Driver's age	Local roads	rain	b_restraint	b_numoccs	Child's age	impair	equip	ED1	TRANS7	POV	OCC2
CRL	1	-0.05434	-0.00948	-0.00474	-0.0072	-0.08085	0.38873	0.03238	0.02685	0.03314	0.01446	0.01148	0.03169
		0.0114	0.6594	0.8257	0.7377	0.0002	<.0001	0.1321	0.2118	0.1232	0.5013	0.5934	0.1405
Driver's	-0.05434	1	-0.03438	0.01036	-0.00756	0.01537	-0.10542	0.0151	-0.0199	-0.06638	-0.01429	-0.02506	-0.03602
age	0.0114		0.1098	0.63	0.7252	0.4748	<.0001	0.4825	0.3547	0.002	0.5064	0.2437	0.0938
Local	-0.00948	-0.03438	1	0.02992	-0.15887	0.06031	-0.02097	-0.01508	-0.06585	0.03659	-0.12056	0.03125	0.14847
roads	0.6594	0.1098		0.164	<.0001	0.005	0.3294	0.4831	0.0022	0.0887	<.0001	0.146	<.0001
rain	-0.00474	0.01036	0.02992	1	0.05552	0.02879	-0.01598	-0.00441	-0.00005	0.00293	-0.02973	0.03807	0.00778
	0.8257	0.63	0.164		0.0098	0.1806	0.4572	0.8376	0.9981	0.8915	0.1667	0.0766	0.7176
b_restraint	-0.0072	-0.00756	-0.15887	0.05552	1	0.06154	-0.0067	-0.03112	-0.04194	-0.07287	0.0437	-0.10382	-0.00908
	0.7377	0.7252	<.0001	0.0098		0.0042	0.7555	0.1477	0.051	0.0007	0.042	<.0001	0.6729
b_numoccs	-0.08085	0.01537	0.06031	0.02879	0.06154	1	-0.11963	0.00496	0.04651	0.1274	-0.00324	0.12853	0.01064
	0.0002	0.4748	0.005	0.1806	0.0042		<.0001	0.8176	0.0305	<.0001	0.8804	<.0001	0.6207
Child's	0.38873	-0.10542	-0.02097	-0.01598	-0.0067	-0.11963	1	0.03899	0.00212	0.01633	-0.02067	0.03217	-0.02604
age	<.0001	<.0001	0.3294	0.4572	0.7555	<.0001		0.0697	0.9213	0.4477	0.3363	0.1345	0.2258
impair	0.03238	0.0151	-0.01508	-0.00441	-0.03112	0.00496	0.03899	1	-0.00718	0.0333	0.03173	0.02161	0.00833
	0.1321	0.4825	0.4831	0.8376	0.1477	0.8176	0.0697		0.7386	0.1214	0.14	0.3149	0.6985
equip	0.02685	-0.0199	-0.06585	-0.00005	-0.04194	0.04651	0.00212	-0.00718	1	0.05564	0.05367	0.0593	0.02636
	0.2118	0.3547	0.0022	0.9981	0.051	0.0305	0.9213	0.7386		0.0096	0.0125	0.0058	0.2202
ED1	0.03314	-0.06638	0.03659	0.00293	-0.07287	0.1274	0.01633	0.0333	0.05564	1	0.03502	0.07435	0.25934
	0.1232	0.002	0.0887	0.8915	0.0007	<.0001	0.4477	0.1214	0.0096		0.1033	<.0001	<.0001
TRANS7	0.01446	-0.01429	-0.12056	-0.02973	0.0437	-0.00324	-0.02067	0.03173	0.05367	0.03502	1	-0.18278	0.15801
	0.5013	0.5064	<.0001	0.1667	0.042	0.8804	0.3363	0.14	0.0125	0.1033		<.0001	<.0001
POV	0.01148	-0.02506	0.03125	0.03807	-0.10382	0.12853	0.03217	0.02161	0.0593	0.07435	-0.18278	1	0.05466
	0.5934	0.2437	0.146	0.0766	<.0001	<.0001	0.1345	0.3149	0.0058	<.0001	<.0001		0.011
OCC2	0.03169	-0.03602	0.14847	0.00778	-0.00908	0.01064	-0.02604	0.00833	0.02636	0.25934	0.15801	0.05466	1
	0.1405	0.0938	<.0001	0.7176	0.6729	0.6207	0.2258	0.6985	0.2202	<.0001	<.0001	0.011	

Table 12: Descriptive Statistics for Child Restraint Systems

The MEANS Procedure					
Variable	**N**	**Mean**	**Std Dev**	**Minimum**	**Maximum**
CRL	2165	0.793995	0.404527	0	1
a_age	2165	4.662818	2.842431	0	9
local	2165	0.612009	0.487405	0	1
rain	2165	0.071594	0.257873	0	1
b_restraint	2165	0.835566	0.370755	0	1
b_numoccs	2165	3.898383	1.570824	2	15
b_age	2165	35.23002	12.61156	9	89
impair	2165	0.007852	0.088284	0	1
equip	2165	0.006467	0.080173	0	1
ED1	2165	16.70485	9.967609	1	64
TRANS7	2165	25.32517	6.112662	8	60
POV	2165	17.79353	9.441147	0	69
OCC2	2165	24.16628	7.543532	0	55

Table 13: Cross tabulation of Children having a Restraint System and was covered by the CRL

Table of CRL by Children using a Restraint System				
CRL		**Child using a Restraint System**		
		No	**Yes**	**Total**
Not having CRL	Frequency	401	45	446
	Percentage	18.52	2.08	20.60
Having CRL	Frequency	567	1152	1719
	Percentage	26.19	53.21	79.40
Total	Frequency	968	1197	2165
	Percentage	44.71	55.29	100.00

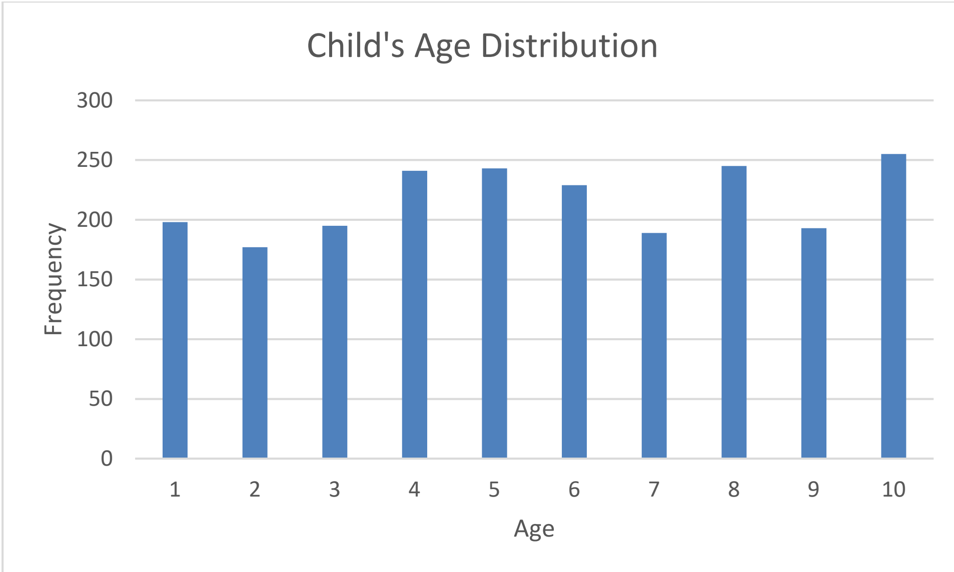


Figure 13: Child’s Age Distribution

Table 14: Child’s Age Distribution (Frequency and Percentage)

Child's Age	Frequency	Percent	Cumulative Frequency	Cumulative Percent
0	198	9.15	198	9.15
1	177	8.18	375	17.32
2	195	9.01	570	26.33
3	241	11.13	811	37.46
4	243	11.22	1054	48.68
5	229	10.58	1283	59.26
6	189	8.73	1472	67.99
7	245	11.32	1717	79.31
8	193	8.91	1910	88.22
9	255	11.78	2165	100

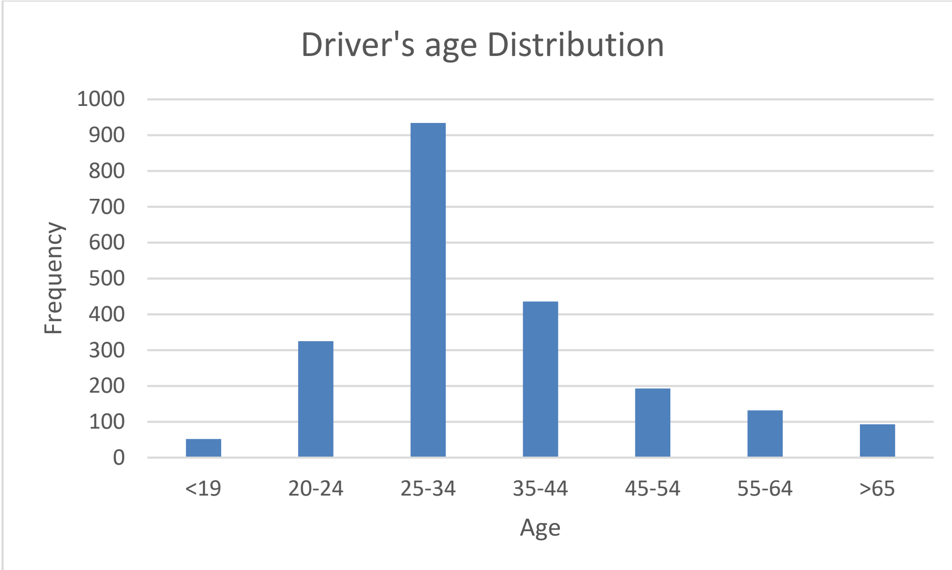


Figure 14: Driver’s Age Distribution

Table 15: Driver’s Age Distribution (Frequency and Percentage)

age	Frequency	Percent	Cumulative Frequency	Cumulative Percent
<19	52	2.4	52	2.4
20-24	325	15.01	377	17.41
25-34	934	43.14	1311	60.55
35-44	436	20.14	1747	80.69
45-54	193	8.91	1940	89.61
55-64	132	6.1	2072	95.7
>65	93	4.3	2165	100

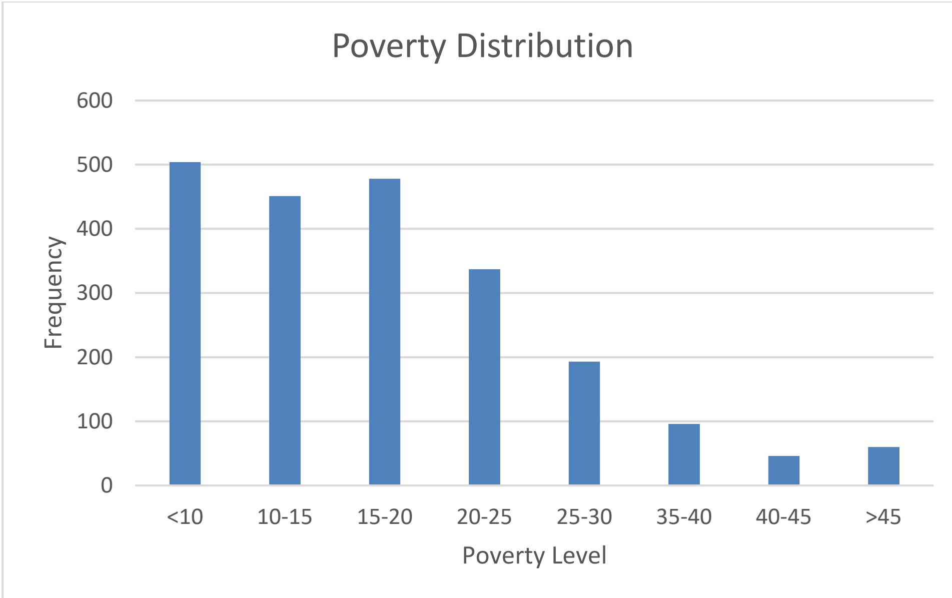


Figure 15: Poverty Level Distribution

Table 16: Poverty Level Distribution (Frequency and Percentage)

Poverty Level	Frequency	Percent	Cumulative Frequency	Cumulative Percent
<10	504	23.28	504	23.28
10-15	451	20.83	955	44.11
15-20	478	22.08	1433	66.19
20-25	337	15.57	1770	81.76
25-30	193	8.91	1963	90.67
35-40	96	4.43	2059	95.1
40-45	46	2.12	2105	97.23
>45	60	2.77	2165	100

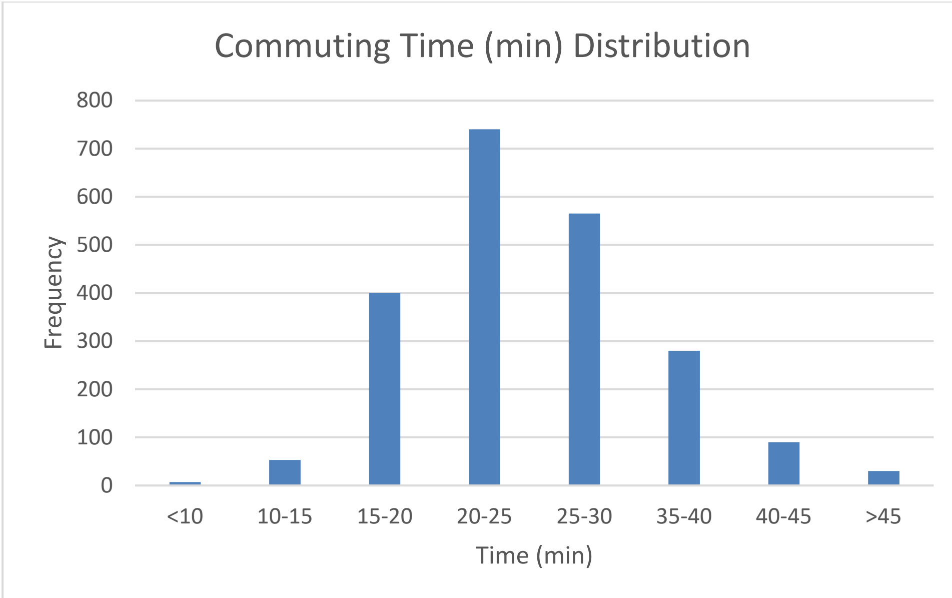


Figure 16: Commuting time Distribution

Table 17: Commuting time Distribution (Frequency and Percentage)

Commuting time (min)	**Frequency**	**Percent**	**Cumulative Frequency**	**Cumulative Percent**
<10	7	0.32	7	0.32
10-15	53	2.45	60	2.77
15-20	400	18.48	460	21.25
20-25	740	34.18	1200	55.43
25-30	565	26.1	1765	81.52
35-40	280	12.93	2045	94.46
40-45	90	4.16	2135	98.61
>45	30	1.39	2165	100

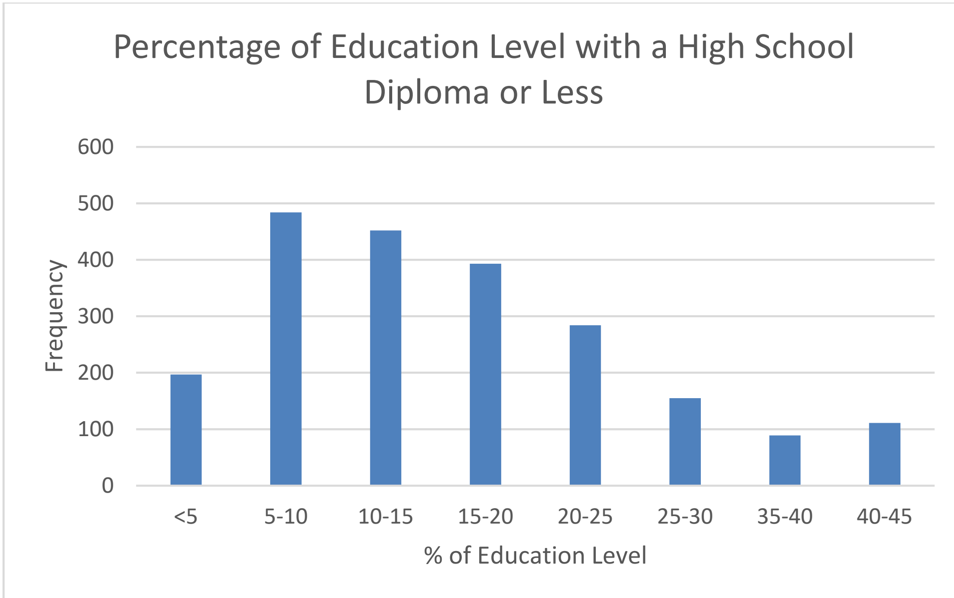


Figure 17: Percentage of Education Level Distribution

Table 18: Percentage of Education Level Distribution (Frequency and Percentage)

Education Level	Frequency	Percent	Cumulative Frequency	Cumulative Percent
<5	197	9.1	197	9.1
5-10	484	22.36	681	31.45
10-15	452	20.88	1133	52.33
15-20	393	18.15	1526	70.48
20-25	284	13.12	1810	83.6
25-30	155	7.16	1965	90.76
35-40	89	4.11	2054	94.87
>45	111	5.13	2165	100

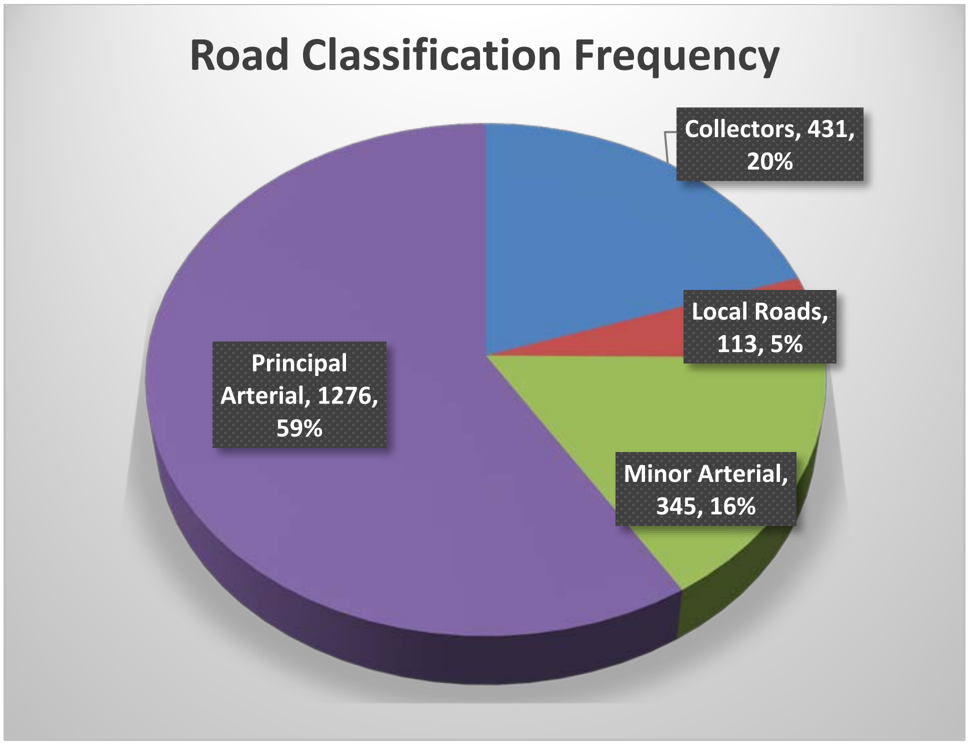


Figure 18: Road Classification Distribution

Table 19: Road Classification Distribution (Frequency and Percentage)

Road Classification	**Frequency**	**Percent**	**Cumulative Frequency**	**Cumulative Percent**
Collectors	431	19.91	431	19.91
Local Roads	113	5.22	544	25.13
Minor Arterial	345	15.94	889	41.06
Principal Arterial	1276	58.94	2165	100.00

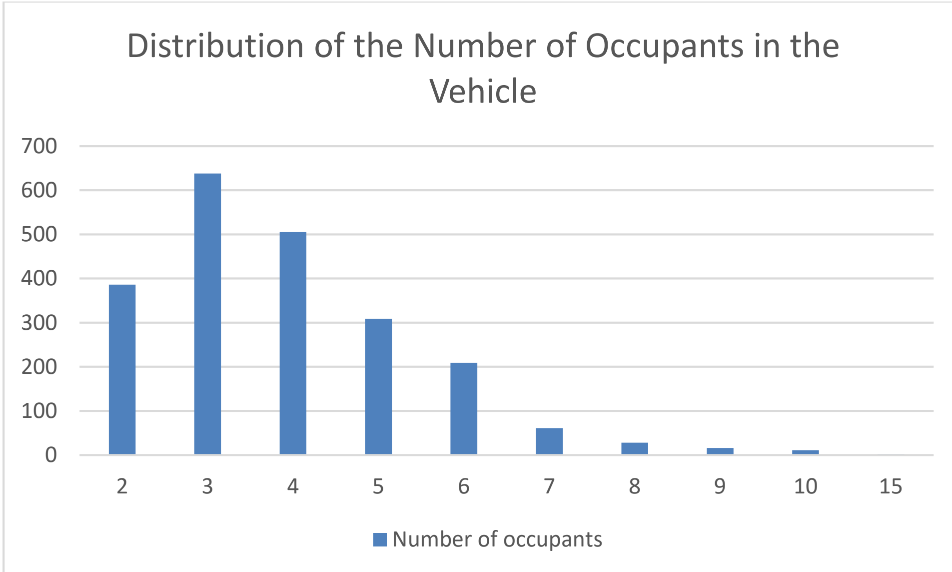


Figure 19: Number of Occupants in the Vehicle Distribution

Table 20: Distribution of the Number of Occupants in the Vehicle (Frequency and Percentage)

Number of occupants	**Frequency**	**Percent**	**Cumulative Frequency**	**Cumulative Percent**
2	386	17.83	386	17.83
3	638	29.47	1024	47.30
4	505	23.33	1529	70.62
5	309	14.27	1838	84.90
6	209	9.65	2047	94.55
7	61	2.82	2108	97.37
8	28	1.29	2136	98.66
9	16	0.74	2152	99.40
10	11	0.51	2163	99.91
15	2	0.09	2165	100.00

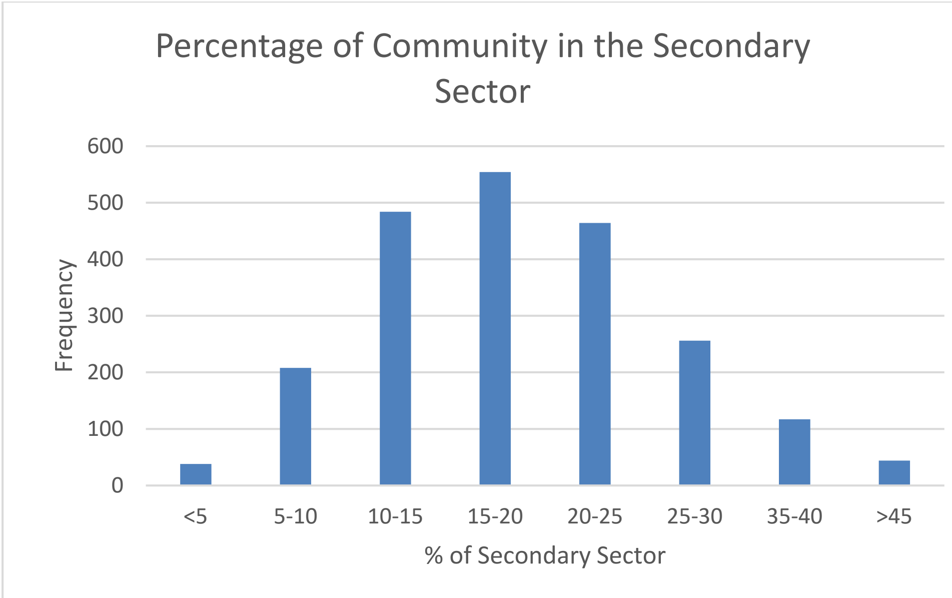


Figure 20: Percentage of Community in the Secondary Sector Distribution

Table 21: Percentage of Community in the Secondary Sector (Frequency and Percentage)

% Of Community in the Secondary Sector	Frequency	Percent	Cumulative Frequency	Cumulative Percent
<5	38	1.76	38	1.76
5-10	208	9.61	246	11.36
10-15	484	22.36	730	33.72
15-20	554	25.59	1284	59.31
20-25	464	21.43	1748	80.74
25-30	256	11.82	2004	92.56
35-40	117	5.4	2121	97.97
>45	44	2.03	2165	100

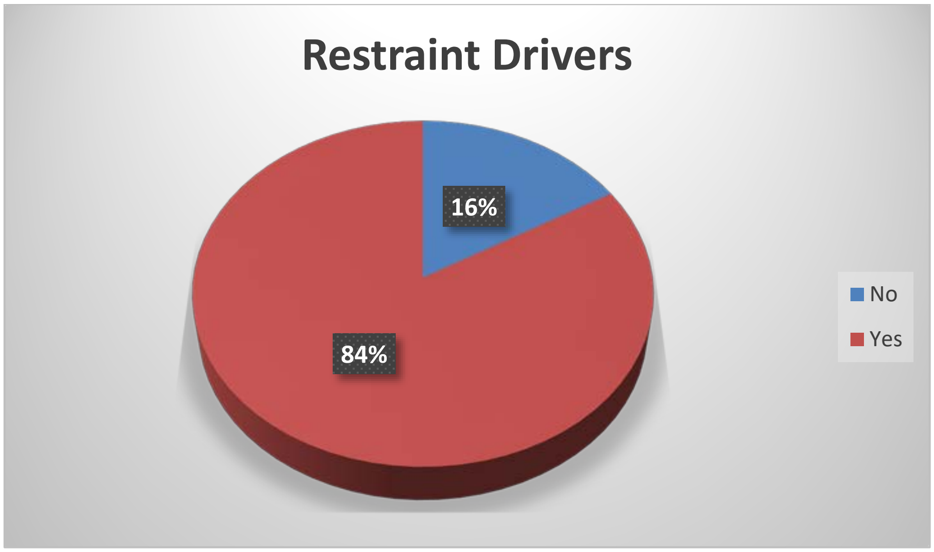


Figure 21: Percentage of Drivers who were using their Seat Belt

Table 22: Drivers who were using their Seat Belt (Frequency and Percentage)

	Frequency	Percent	Cumulative Frequency	Cumulative Percent
No	356	16.44	356	16.44
Yes	1809	83.56	2165	100

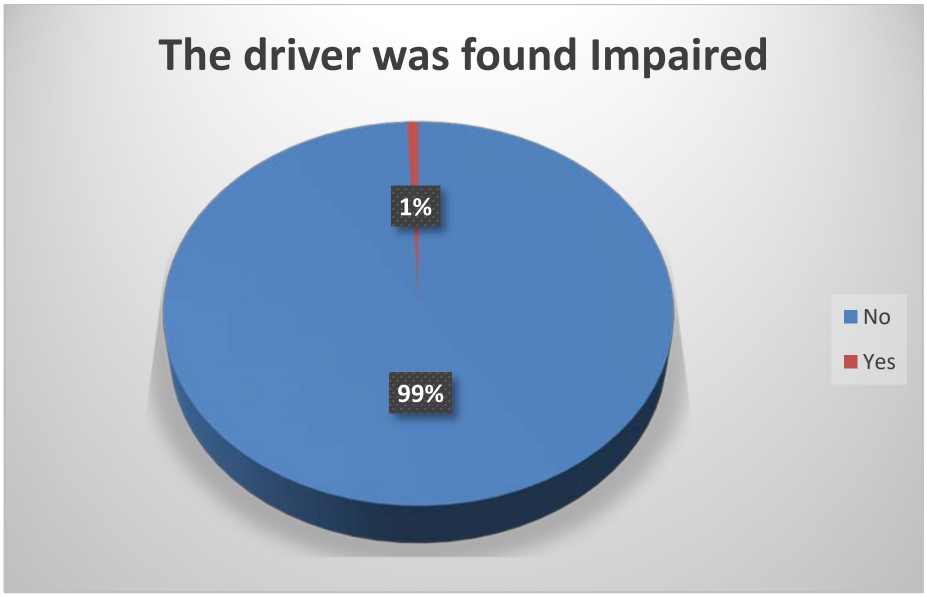


Figure 22: Percentage of Drivers who were found Impaired

Table 23: Drivers who were found Impaired (Frequency and Percentage)

Driver impaired	Frequency	Percent	Cumulative Frequency	Cumulative Percent
0	2148	99.21	2148	99.21
1	17	0.79	2165	100

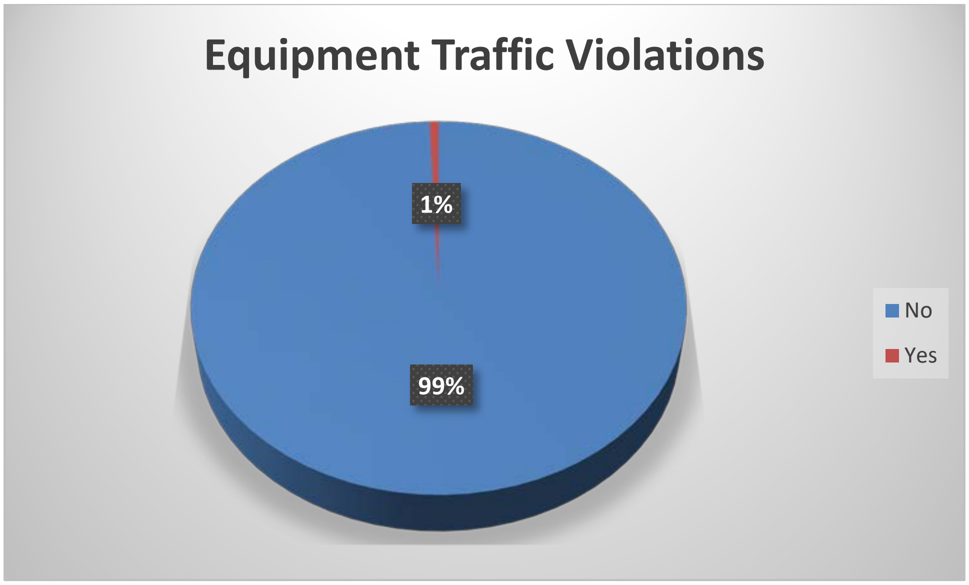


Figure 23: Percentage of Community in the Secondary Sector Distribution

Table 24: Percentage of Community in the Secondary Sector (Frequency and Percentage)

Equipment Violations	Frequency	Percent	Cumulative Frequency	Cumulative Percent
0	2151	99.35	2151	99.35
1	14	0.65	2165	100

APPENDIX B: FIGURES AND TABLES BICYCLIST HELMET LAW

Table 25: Descriptive Statistics of the Selected Variables

Simple Statistics						
Variable	**N**	**Mean**	**Std Dev**	**Median**	**Minimum**	**Maximum**
BHL	467	0.44968	0.49799	0	0	1
age11to17	467	0.50535	0.50051	1	0	1
ED10P	467	0.14133	0.34873	0	0	1
INC5K	467	0.55246	0.49777	1	0	1
male	467	0.74732	0.43501	1	0	1

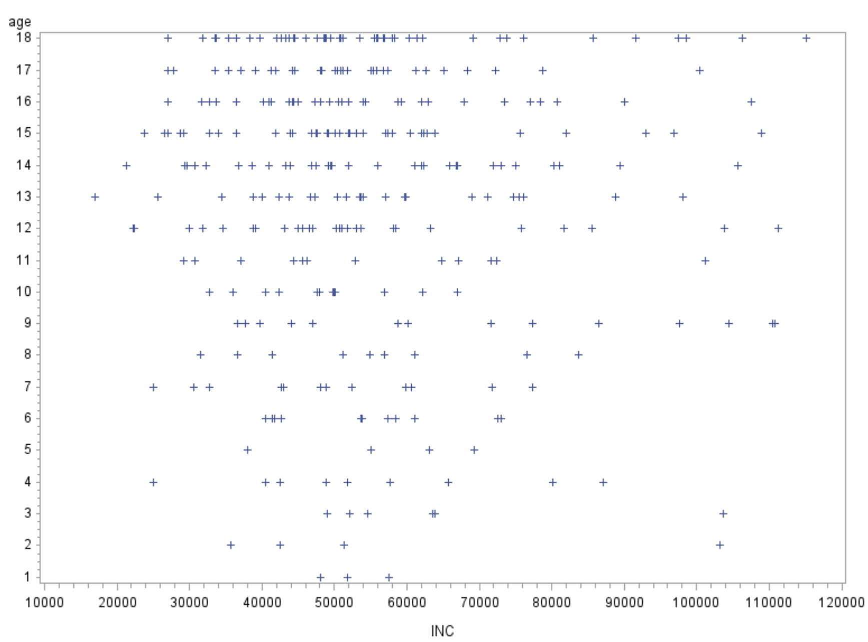
Table 26: Pearson Correlation Check

Pearson Correlation Coefficients, N = 467 Prob > |r| under H0: Rho=0					
	BHL	**age11to17**	**ED10P**	**INC5K**	**male**
BHL	1	0.17112	0.01633	-0.12134	0.02043
		0.0002	0.7249	0.0087	0.6597
age11to17	0.17112	1	0.00795	0.00533	0.07522
	0.0002		0.8639	0.9085	0.1045
ED10P	0.01633	0.00795	1	-0.32713	0.05201
	0.7249	0.8639		<.0001	0.262
INC5K	-0.12134	0.00533	-0.32713	1	-0.0873
	0.0087	0.9085	<.0001		0.0594
male	0.02043	0.07522	0.05201	-0.0873	1
	0.6597	0.1045	0.262	0.0594	

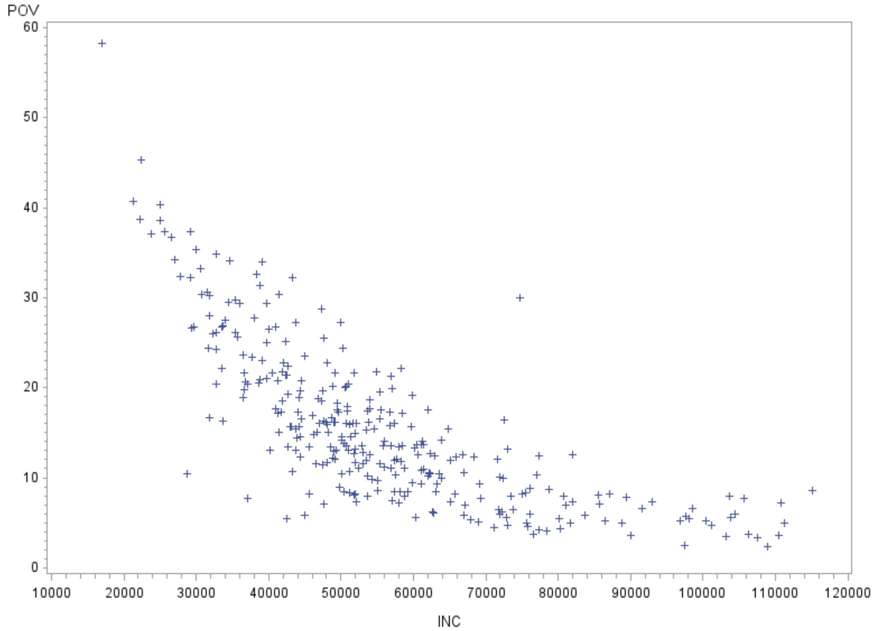
Table 27: Spearman Correlation Check

Spearman Correlation Coefficients, N = 467					
Prob > |r| under H0: Rho=0					
	BHL	**age11to17**	**ED10P**	**INC5K**	**male**
BHL	1	0.17112	0.01633	-0.12134	0.02043
		0.0002	0.7249	0.0087	0.6597
age11to17	0.17112	1	0.00795	0.00533	0.07522
	0.0002		0.8639	0.9085	0.1045
ED10P	0.01633	0.00795	1	-0.32713	0.05201
	0.7249	0.8639		<.0001	0.262
INC5K	-0.12134	0.00533	-0.32713	1	-0.0873
	0.0087	0.9085	<.0001		0.0594
male	0.02043	0.07522	0.05201	-0.0873	1
	0.6597	0.1045	0.262	0.0594	

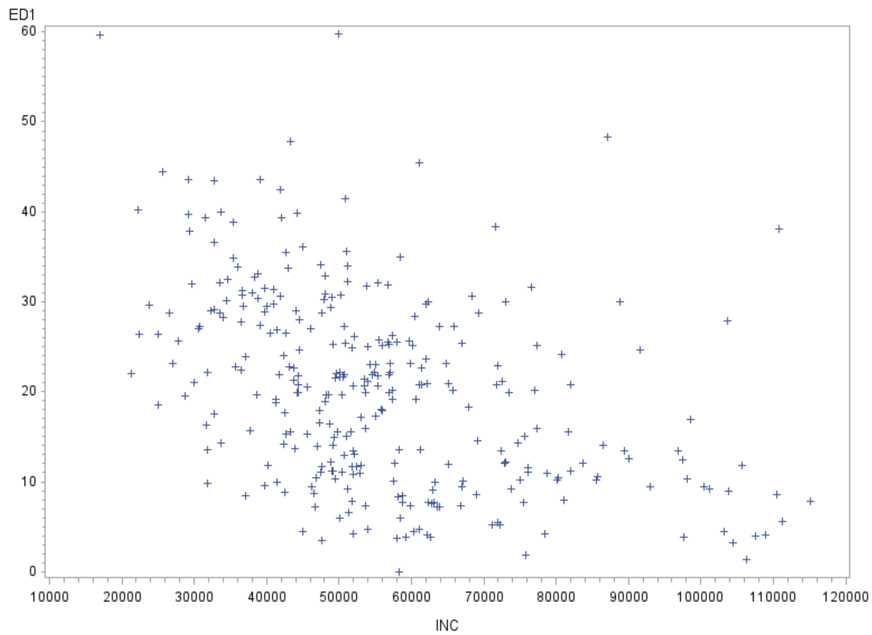
Scatterplot Check out for Variable Correlations (Income - Age)



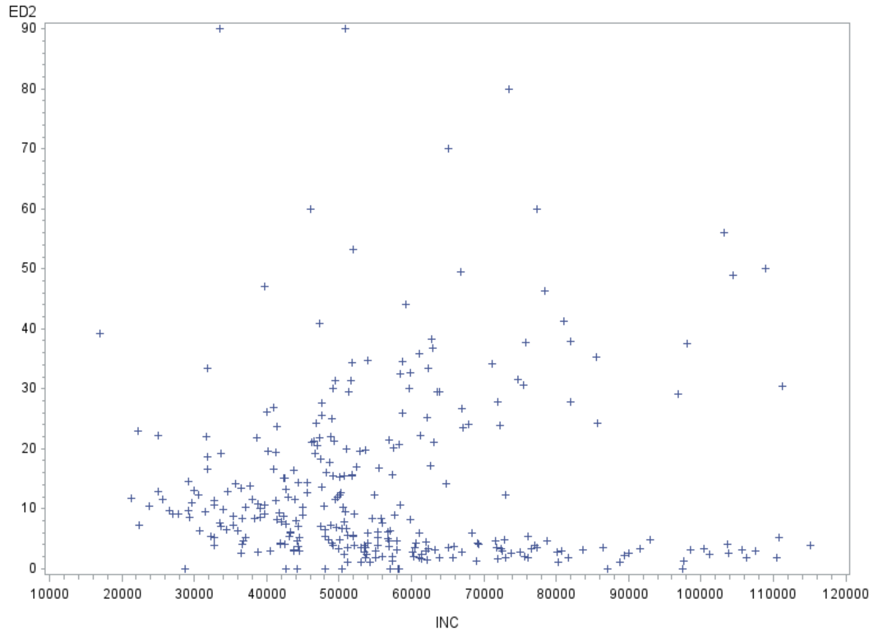
Scatterplot Check out for Variable Correlations (Income - Poverty)



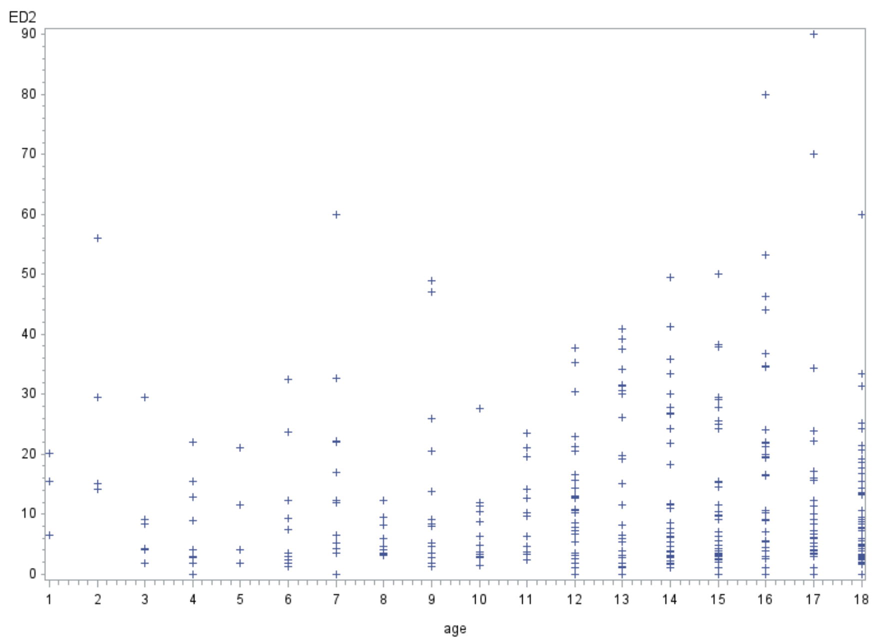
Scatterplot Check out for Variable Correlations (Income – Education Level: Less than High School Diploma)



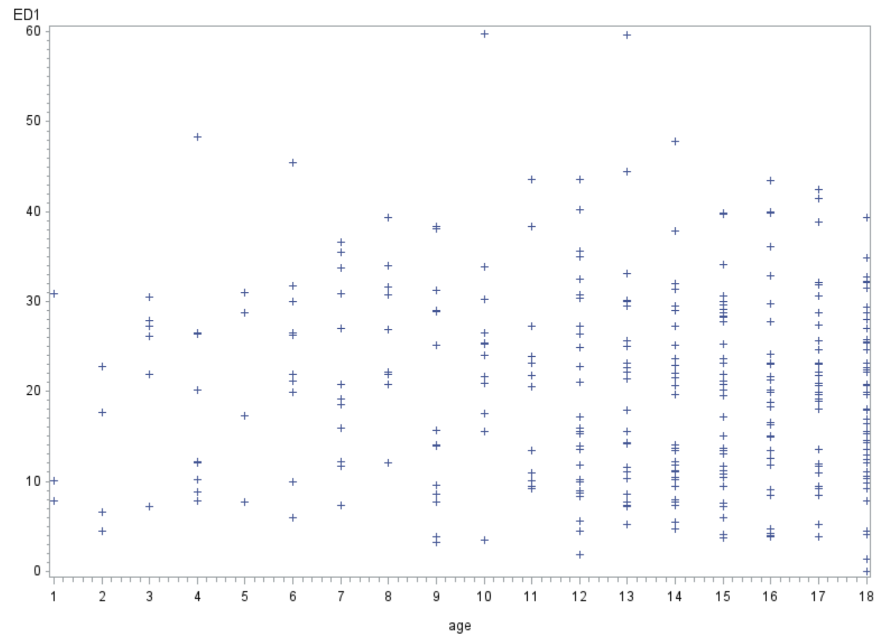
Scatterplot Check out for Variable Correlations (Income – Education Level: Greater than Bachelor's Degree)



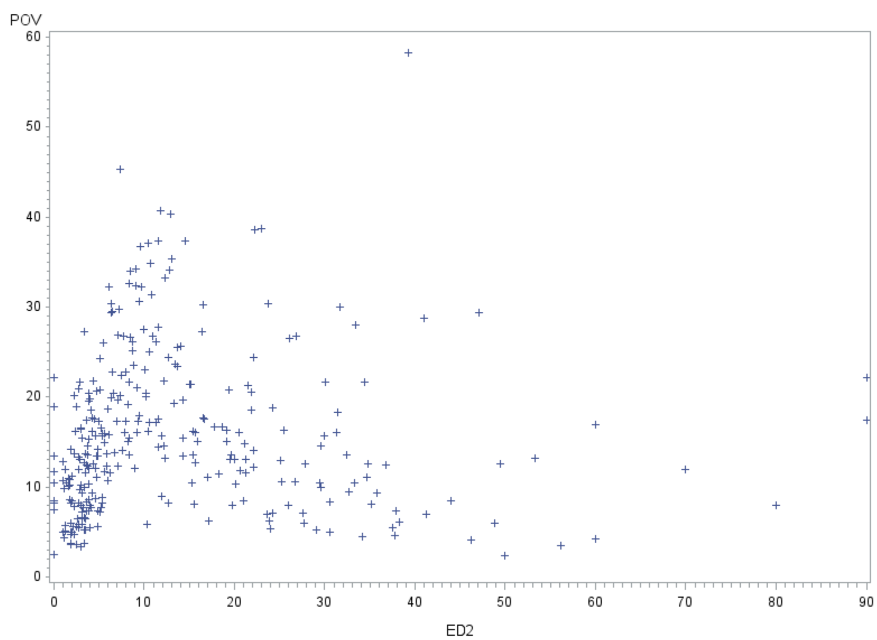
Scatterplot Check out for Variable Correlations (Age – Education Level: Greater than Bachelor's Degree)



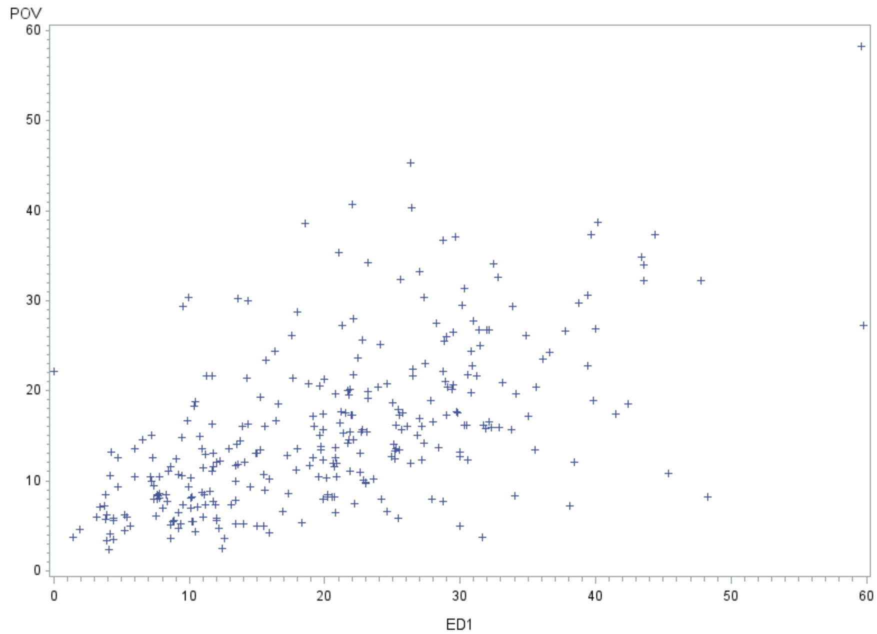
Scatterplot Check out for Variable Correlations (Age– Education Level: Less than High School Diploma)



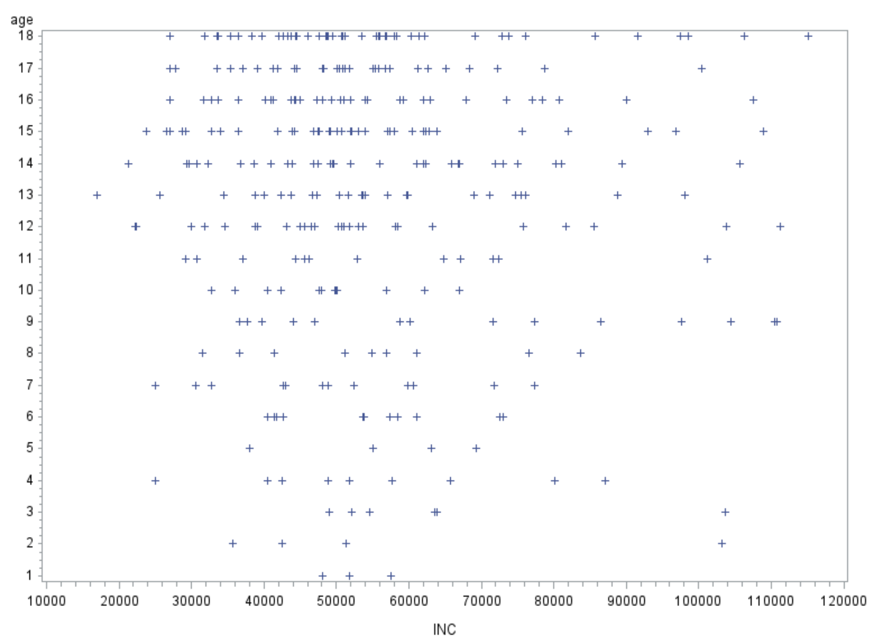
Scatterplot Check out for Variable Correlations (Poverty – Education Level: Greater than Bachelor's Degree)



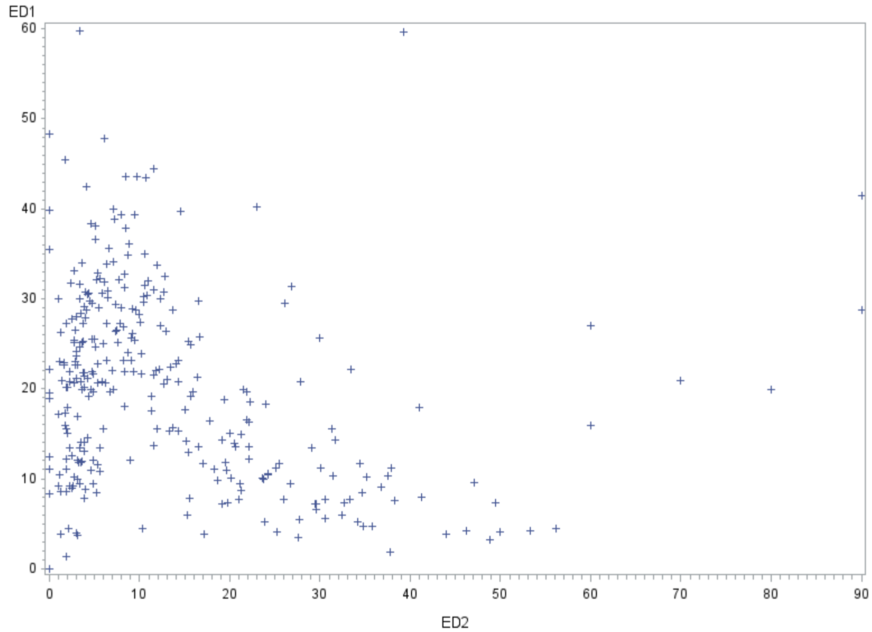
Scatterplot Check out for Variable Correlations (Poverty– Education Level: Less than High School Diploma)



Scatterplot Check out for Variable Correlations (Age - Income)



Scatterplot Check out for Variable Correlations (Education Level: Less than High School Diploma – Education Level: Greater than Bachelor’s Degree)


ED1
60
50
40
30
20
10
0
0
10
20
30
40
50
60
70
80
90
ED2

APPENDIX C: VARIABLES DESCRIPTION AND PREPARATION

Type	Parameter	Form	Description
Crash Information	Day of week	Meaning	This data element records the day of the week.
		Preparation	Categorical variable. This variable was coded from 1-7 for each day of the week starting on Sunday. 1= Sunday, 2 = Monday, 3 = Tuesday, 4 = Wednesday, 5 = Thursday, 6 = Friday, 7 =Saturday. From the 7 categories, its classification was changed to weekends = 1 or weekdays = 0. Day of the week was not perceived as a significant variable in the model.
	Number of fatalities	Meaning	This data element records the number of fatalities that occurred in the vehicle.
		Preparation	Number of fatalities. Counted as a continuous variable, the original information was observed from 1 to 6. Variable resulted as statistically not significant in the model.
	Whether the state has the child restraint law that covers the child in the crash	Meaning	Each state covers defines CRS law with a mandatory age specifications
		Preparation	Defined as a dummy variable, it was treated as (1=law protects child, 0 = otherwise)

Type	Parameter	Form	Description
Person Type	Driver's age	Meaning	This data element records 4 age groups of the driver of the vehicle: adolescent (15-24), young (25-34), adult (35-64) and older (+65) years.
		Preparation	Original data had continuous values that showed driver's age ranging from (15 – 100). A second classification was made into four groups as (Adolescent 15-24, Young 25-34, Adult 35-49, Old >=50. Young and Adult categories did not demonstrate noteworthy difference, but it resulted as significant. A third classification was made as (Adolescent <=24, Adult (24-50), Old >=50). As young group was the only level that showed significant results, a forth classification came on-board transforming it into dummy variable, where adults from 25-50 years old are evaluated 1= yes, 0 = no.
	Child's age	Meaning	This data element records 9 age groups of the children as an occupant of the vehicle: 0,1,2,3,4,5,6,7,8 and 9 years.
		Preparation	As a categorical variable referenced by age groups 0-3, 4, 5, 6, 7, 8 and 9 years. The reference number = Age of 3
	Gender	Meaning	This data element identifies the sex of this person involved in the crash.
		Preparation	Categorical variable (1=female, 2=male)
	Number of occupants	Meaning	This data element is a count of the number of occupants in the vehicle.
		Preparation	Treated as a continuous variable.

Type	Parameter	Form	Description
Roadway	Relation to Junction- Within Interchange Area	Meaning	Relation to junction - within Interchange Area
		Preparation	As many crashes occur near-by intersections areas, this variable demonstrates by two categories any relationship. Dummy variable (Relation 0 = No, 1= Yes). Variable resulted as statistically not significant in the model
	Roadway Function Class	Meaning	Categorizing it as principal, collector or local road. This category was changed as a dummy variable just for local roads.
		Preparation	The data provided by FARS specifies different codification values for rural or urban roads. Rural (1-6), Urban (11-16). A second categorization to the data was made as COLL = Collector, LOCAL = Local, MA = Minor Arterial, PA= Principal Arterial, X= Otherwise. Results showed that the only level that showed significance was LOCAL, reason why a third category was created converting it as a dummy variable Local = 1, Otherwise=0.
	Route Signing	Meaning	This data element identifies the route signing of the traffic way on which the crash occurred.
		Preparation	Nine categories were provided to show the signage of the road. Route Signage was statistically not significant in the model.
	Speeding Related	Meaning	This data element records whether the driver's speed was related to the crash as indicated by law enforcement.
		Preparation	As a categorical variable referenced by (0 = No, 1= Yes) a speeding behavior is shown. Speeding variable resulted statistically not significant in the model.
	Roadway Alignment	Meaning	This data element identifies the attribute that best represents the roadway alignment prior to this vehicle's critical pre-crash event.
		Preparation	As a categorical variable referenced by (0 = Straight, 1= Curve) Horizontal alignment variable resulted statistically not significant in the model.
	Roadway Profile	Meaning	This data element identifies the attribute that best represents the roadway grade prior to this vehicle's critical pre-crash event.
		Preparation	As a categorical variable referenced by (0 = Otherwise, 1= Grade) Vertical alignment variable resulted statistically not significant in the model.
	Total Lanes in Roadway	Meaning	This data element identifies the attribute that best describes the number of travel lanes just prior to this vehicle's critical pre-crash event.
		Preparation	As a continuous variable defines the number of lanes from 1-6, and seven if it has more than 7 lanes. Number of lanes variable resulted statistically not significant in the model.
	National Highway System	Meaning	This data element identifies whether this crash occurred on a traffic way that is part of the National Highway System.
		Preparation	Represented as a dummy variable (0= Not in NHS system, 1= is in NHS). NHS variable resulted statistically not significant.
	Speed Limit	Meaning	This data element identifies the attribute that best represents the speed limit just prior to this vehicle's critical pre-crash event.
		Preparation	Created as a continuous variable from 5-80 Speed Limit (5 mph Increments). Speed limit variable resulted statistically not significant in the model.

Type	Parameter	Form	Description
Traffic Rules	Restraint System/Helmet Use	Meaning	This data element was converted into a dummy variable that evidences if the driver was wearing restraint equipment at the time of the crash.
		Preparation	Treated as a dummy variable (1= driver used seat belt, 0 = otherwise). This variable showed no significance level.
	Previous accidents	Meaning	Defined as a dummy variable, represents if the driver has violations history.
		Preparation	Treated as a dummy variable (1= driver with a traffic violation history, 0 = otherwise).
	Driver violations	Meaning	This data element identifies violations charged to this driver in this crash. Equipment, Impairment Offenses, Lane Usage, License & Registration Violations, Reckless/Careless/Hit-And-Run Offenses, Turning, Yielding, Signaling, Traffic Sign & Signals, Speed-Related Offenses, Wrong Side, Passing & Following, Other Violations, No Violation
		Preparation	10 categories defined this variable as a first approach. After reviewing the results, a second categorization came aboard with the significant categories. Converted as a dummy variable Whether the driver was impaired (impaired=1, otherwise=0), Whether the driver violated equipment regulations (violated=1, otherwise=0)

Type	Parameter	Form	Description
Vehicle	Registration owner	Meaning	This data element identifies the type of registered owner of the vehicle.
		Preparation	Four categories represent this variable: Business, no owner, rent, own. Owner variable resulted statistically not significant in the model.
	Vehicle age	Meaning	This data element identifies the difference in years between the model year of the vehicle and the crash year. Speed limit variable resulted statistically not significant in the model.
		Preparation	Treated as a continuous variable.
	Vehicle type	Meaning	Trucks and semi-trucks, Autos
		Preparation	Under 2 categories: Light Trucks (pickup truck, SUV and Van), Passenger car this variable showed no significance level.
	Airbag	Meaning	This data element records air bag availability and deployment for this person as reported in the case materials.
		Preparation	Treated as a dummy variable (1= it was deployed, 0 = otherwise).This variable showed no significance level.

Type	Parameter	Form	Description
Environment	Atmospheric Conditions	Meaning	This data element records the prevailing atmospheric conditions that existed at the time of the crash as indicated in the case material. Blowing sand, Blowing Snow, Cloudy, Frizzing Rain Or Drizzle, Fog, Other, Rain, Severe Crosswind, Sleet, Snow, Clear
		Preparation	Under these 12 categories the only one that showed significance was rain. This variable was converted in dummy for rain. Atmospheric conditions (rain=1, otherwise=0)
	Light Condition	Meaning	This data element records the type/level of light that existed at the time of the crash as indicated in the case material. Dark – Lighted, Dark – Not Lighted, Unknown Lighting, Dawn, Dusk, Other, Daylight
		Preparation	Treated as a categorical variable. This variable showed no significance level.

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