AN ABSTRACT OF THE DISSERTATION OF

Hong Zhu for the degree of Doctor of Philosophy in Civil Engineering presented on November 17, 2009.

Title: Cross-Section Fatal Crash Type Prediction Models

Abstract approved:

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Karen K. Dixon

The rural two-lane highway in the southeastern United States is frequently associated with a disproportionate number of serious and fatal crashes. The major research objectives are to investigate the relations between probabilities of fatal crash type occurrence and potential contributing factors from road geometric design characteristics and roadside, environmental features. This dissertation analyzes the regional fatal crash database and successfully develops statistical models to examine the relations and provided meaningful research findings.

This dissertation contributes to current traffic safety analysis by directly examining the connection between major fatal crash type occurrence and roadway geometrics, roadside characteristics, and environmental conditions through a regional case study. This study effort addresses the less understood relationship between fatal crash types and road features compared to other crash measures, such as crash frequency, crash rate, and injury severity. The developed fatal crash type prediction models not only demonstrate strong connections between crash types and road characteristics, but also provide a quantitative assessment tool for countermeasures in terms of reduction of fatal crash type occurrence. Since most countermeasures are more effective at mitigating certain type of crashes, the information revealed from the crash type

prediction models help clarify the relationship between candidate countermeasures and expected crash reductions.

Cross-Section Fatal Crash Type Prediction Models

by
Hong Zhu

A DISSERTATION

submitted to

Oregon State University

in partial fulfillment of
the requirements for the
degree of

Doctor of Philosophy

Presented November 17, 2009
Commencement June 2010

Doctor of Philosophy dissertation of Hong Zhu presented on November 17, 2009.

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I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

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Hong Zhu, Author

ACKNOWLEDGEMENTS

I would like to express my deepest thanks to my Ph.D committee chair, Dr. Karen Dixon, committee members: Dr. Kate Hunter-Zarworski, Dr. Robert Layton, Dr. Daniel Schafer, and Dr. Jon Kimerling. I would not have been able to finish my dissertation without your consistent guidance and support. I would also like to thank for the support from my family and friends. Thanks for your patient, your love, your care, and kindness.

For all research assistants from each state who carried out the site visits, my work is building upon all of your works, you made this happen, we made this happen, all together—across 9 years! Thank you all! I have not met most of you, though I knew you through your work already.

Thank you all! Things will never be the same because all of you.

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CHAPTER 1 INTRODUCTION

Traffic related crashes are a major source of fatalities in the Unites States. Statistics released by the National Highway Traffic Safety Administration (NHTSA) show that motor vehicle crashes were the leading cause of death for persons from age 3 through 6 and from age 8 through 34 in 2005 (National Highway Traffic Safety Administration, 2008). Compared to urban areas, rural road safety has been a more prominent safety concern nationwide. Rural non-Interstate roadways, among which 94% are rural two-lane roads, have the highest fatality rates compared to all other types of roads (Highway Statistics 2005, Federal Highway Administration).

The southeastern states in the United States have been struggling with rural fatalities the most. Responding to this substantial safety concern and the deadliest crash records on two-lane rural roadways in the southeastern region, this dissertation focuses on fatal crashes at a disaggregated level on two-lane rural highways of southeastern states. This study also aims to identify and quantify potential contributing factors from roadway environments, geometric characteristics, and traffic conditions on the probability of fatal crash type occurrences. The major study objective is to develop safety prediction models that can be used to help safety engineers assess effective countermeasures and treatments in order to reduce the deadly traffic conditions in the southeastern region.

1.1 Background

This section presents and discusses the historical trends of fatal crashes and fatalities of the southeastern states and the United States. The 12-year fatal crash data consistently demonstrates the disproportionately distributed higher fatal crashes and fatality rates on two-lane rural roadways from southeastern states compared to the country as a whole. These alarming statistics raise the need of an in-depth regional

traffic safety investigation focusing on the fatal crashes of southeastern two-lane rural highways.

1.1.1 Fatal Crashes and Fatality Rates

Washington et al. (1999, 2002) reported a disproportionately higher total number of fatal crashes in eight southeastern states (Alabama, Georgia, Mississippi, South Carolina, Florida, Kentucky, North Carolina, and Tennessee), the former Federal Highway Administration (FHWA) region 4, while comparing to those of other regions and the entire country. As presented in Table 1, from 1995 to 2006, more than a quarter of traffic related fatal crashes in the United States occurred in the eight southeastern states. Collectively, using a 12-year average (from 1995 to 2006), southeastern states account for 26.8% of the nation's fatal crashes. This outcome becomes even more striking while considering the fact that this region only accounts for 19% of the nation's population as reported by the U.S. Census 2000 (Perry and Mackun, 2001). In addition, Figure 1 depicts a gradually increasing trend of the fatal crash proportion from the southeastern region compared to the entire country across 12 years. The trend seems to be even more aggressive from 2003 to 2006 with the southeastern fatal crashes percentage continuously increasing from 26.3% to 28.3%. These crash statistics demonstrate the continuous regional over-representation of fatal crashes contributed by eight southeastern states. Additionally, this pattern is becoming more prominent over time.

Table 1: Southeastern and United States Fatal Crash Summary (1995 – 2006)

States	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	12 Year Total
AL	991	1024	1050	958	992	910	900	931	902	1032	1021	1074	11785
GA	1333	1402	1405	1414	1314	1380	1471	1362	1463	1463	1582	1557	17146
MS	738	695	741	842	832	846	704	769	786	786	840	812	9391
SC	782	821	798	912	944	948	962	949	905	946	981	966	10914
FL	2546	2496	2528	2548	2629	2733	2714	2810	2874	2927	3176	3097	33078
KY	732	734	774	766	724	721	762	810	854	854	885	837	9453
NC	1305	1329	1290	1433	1350	1408	1360	1427	1396	1417	1418	1429	16562
TN	1130	1120	1104	1110	1169	1177	1126	1058	1091	1191	1161	1164	13601
SE Sub Total	9557	9621	9690	9983	9954	10123	9999	10116	10271	10616	11064	10936	121930
U.S. Total*	37241	37494	37324	37107	37140	37526	37862	38491	38477	38444	39252	38588	454946
Percent of U.S. Total [%]**	25.7	25.7	26.0	26.9	26.8	27.0	26.4	26.3	26.7	27.6	28.2	28.3	26.8

** The U.S. values include the 50 states and the District of Columbia.*
*** Percent of U.S total = SE Sub Total / U.S. Total.*
Source: Fatality Analysis Reporting System (FARS), NHTSA.

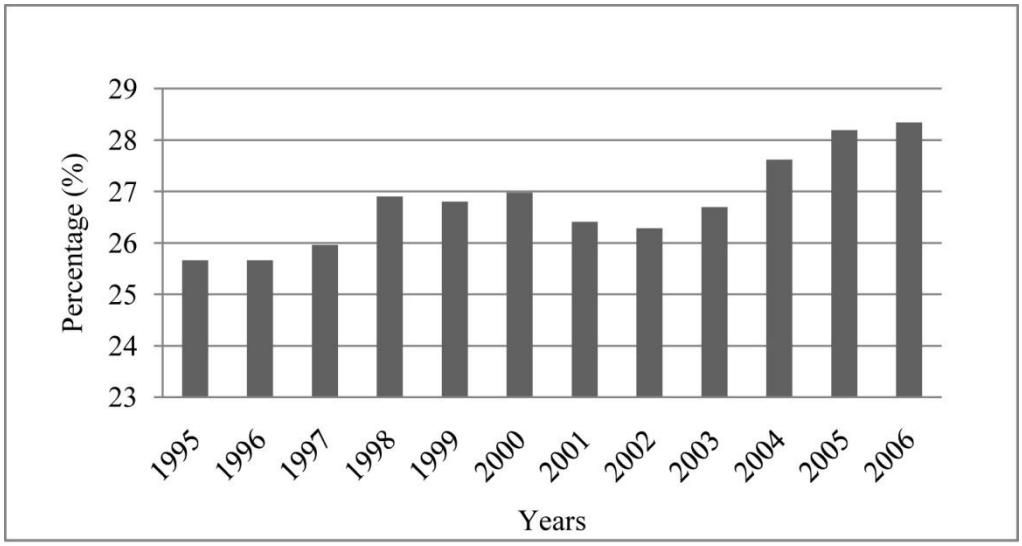


Figure 1: Percent of U.S. Total Fatal Crashes of Southeastern States

Comparing the number of fatal crashes alone can sometimes leave a skewed perspective. However, comparing fatality rates may help compensate for potential drawbacks of the crash frequency and helps to identify a true problem that needs to be solved for roads with similar traffic conditions. The fatality rate is presented as the number of fatalities per 100 million vehicle miles traveled (VMT) annually. As shown in Table 2 and Figure 2, the fatality rates in the southeastern region have been consistently higher than those in the United States for 12 consecutive years, although both fatality rates for the southeastern region as well as the national rates have generally declined over the years. The last row of Table 2 shows that the increment of the southeastern region's fatality rate over the United States ranged from 0.26 to 0.40 during the 12 year study period. The 12-year average increment of fatality rate is 0.34, which corresponds to an additional 34 fatalities per million VMT each year above the average United States fatality level.

Table 2: Southeastern and United States Fatality Rate (1995 – 2006)
Fatalities are Shown as per 100 Million VMT

States	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	12 Year Average
AL	2.20	2.20	2.20	1.90	2.00	1.90	1.75	1.80	1.71	1.95	1.90	2.00	1.96
GA	1.70	1.80	1.70	1.60	1.50	1.50	1.50	1.41	1.47	1.45	1.52	1.49	1.55
MS	2.90	2.70	2.70	2.80	2.70	2.70	2.18	2.43	2.32	2.28	2.21	2.20	2.51
SC	2.30	2.30	2.20	2.30	2.40	2.30	2.27	2.23	2.01	2.11	2.21	2.07	2.23
FL	2.20	2.10	2.10	2.10	2.10	2.00	1.93	1.76	1.71	1.65	1.76	1.66	1.92
KY	2.10	2.00	1.90	1.80	1.70	1.80	1.83	1.95	1.99	2.04	2.08	1.91	1.93
NC	1.90	1.90	1.80	1.96	1.70	1.60	1.67	1.70	1.63	1.62	1.51	1.54	1.71
TN	2.20	2.10	2.00	1.90	2.00	2.00	1.85	1.72	1.73	1.82	1.79	1.82	1.91
Southeastern (SE) *	2.11	2.07	2.01	1.98	1.94	1.89	1.82	1.78	1.74	1.75	1.78	1.74	1.88
U.S.	1.73	1.69	1.64	1.58	1.55	1.53	1.51	1.51	1.48	1.44	1.46	1.41	1.54
SE - U.S.	0.38	0.38	0.37	0.40	0.39	0.36	0.31	0.27	0.26	0.31	0.32	0.33	0.34

** Southeastern fatality rate is calculated based on eight state fatalities per 100 million miles VMT for each year.*
Source: Fatality Analysis Reporting System (FARS), NHTSA.

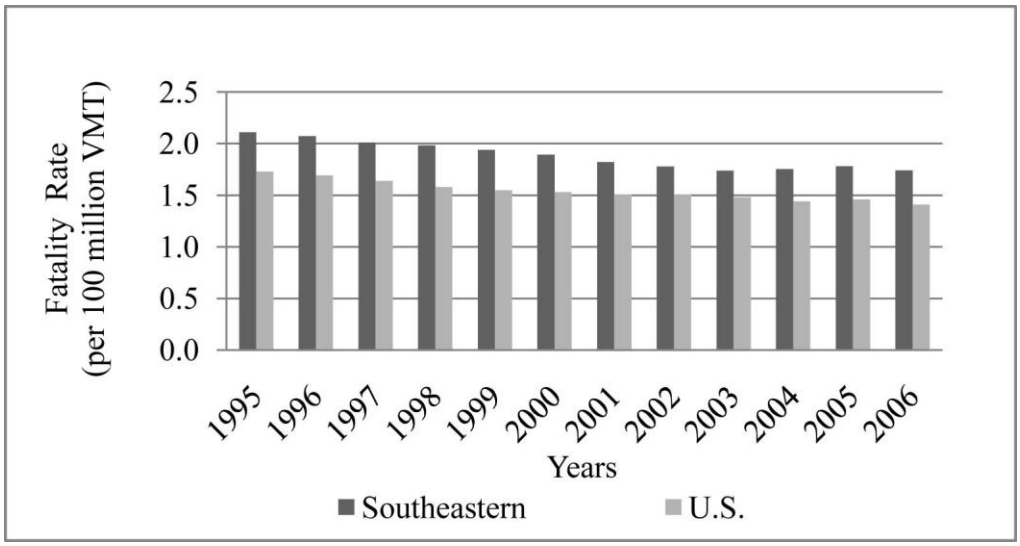


Figure 2: Fatality Rate: Southeastern States vs. Entire United States

1.1.2 Rural and Two-lane Rural Fatal Crashes

There are 8.4 million lane-miles of public roads in the United States (U.S.), among which more than 6 million are rural roads. In 2006, while about 23% of the U.S. population lived in rural areas, rural fatalities accounted for 56% of the total fatalities for the entire country as a whole (NHTSA, 2006). Table 3 and Figure 3 demonstrate a national 10-year trend demonstrating more than 50% of the traffic fatalities occurred on rural roads. This statistic is alarming when paired with the fact that rural roads have lower traffic volumes than urban roads (U.S. DOT, 2008). It is reported that from 1999 to 2001 rural roads had 11.6 trillion VMT compared to the 17.9 trillion VMT for urban roadways nationwide (Burgess, 2005). As a result of higher fatalities and lower traffic on rural roads, crash fatality rates of rural roads are more than twice as high as urban fatality rates. Figure 4 shows that this pattern has existed for 10 years. Evidently, rural roadways are continuously more dangerous than their urban counterparts. This condition certainly highlights the need for effective strategies to help reduce rural fatalities and severe injuries.

Table 3: U.S. Fatalities and Fatality Rate By Rural/Urban by Year (1997 – 2006)

Year	Rural Roadway Fatalities			Urban Roadway Fatalities		
	Number	Percentage [%]	Rate	Number	Percentage [%]	Rate
1997	25,135	60	2.52	16,829	40	1.08
1998	25,185	61	2.44	16,219	39	1.02
1999	25,548	61	2.40	16,058	38	0.99
2000	24,838	59	2.29	16,113	38	0.97
2001	25,150	60	2.27	16,988	40	1.01
2002	25,896	60	2.30	17,013	40	0.98
2003	24,957	58	2.30	17,783	41	0.98
2004	25,179	59	2.36	17,581	41	0.93
2005	24,587	57	2.38	18,627	43	0.95
2006	23,339	55	2.25	18,359	43	0.93

Source: "The U.S Department of Transportation Rural Safety Initiative", February 2008.

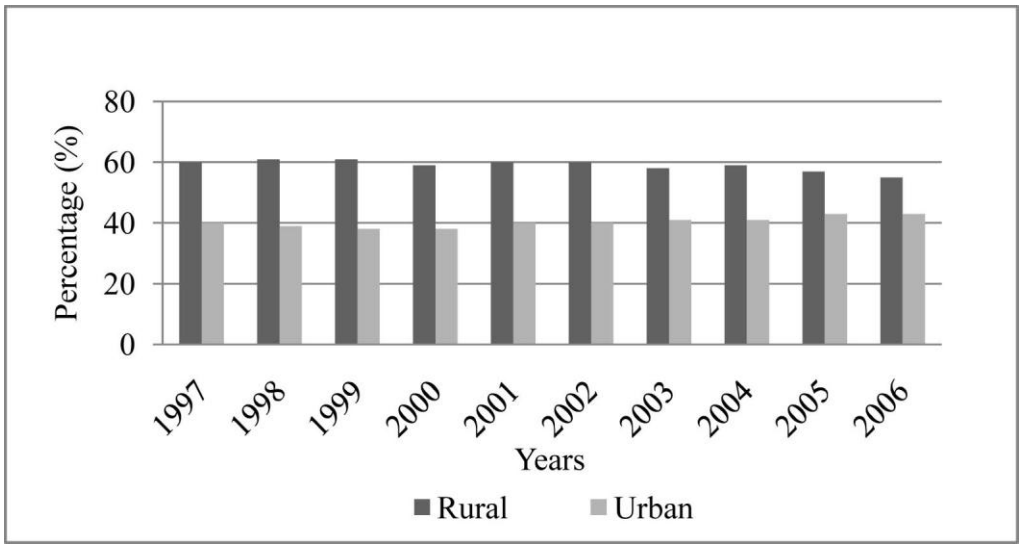


Figure 3: U.S. Rural and Urban Fatality Percentage (1997-2006)

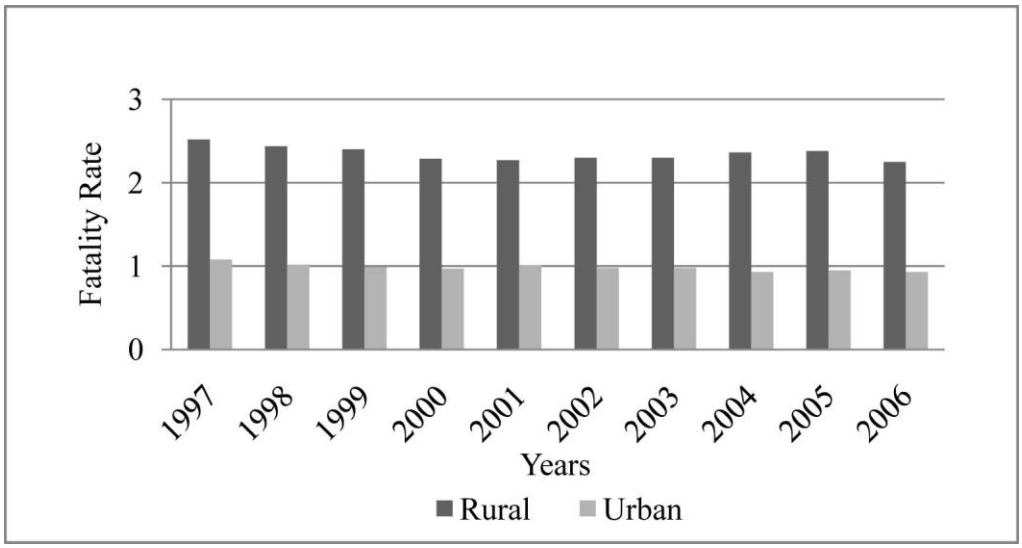


Figure 4: U.S. Rural and Urban Fatality Rate (1997-2006)

As shown by a decade of observations at the national level, rural roadways appear to be more dangerous to road users than urban roadways. Upon specific examination of fatality locations, it can be noted rural interstate highways maintained similar records to their urban counterpart. Rural interstates largely benefit from higher and consistent design standards. On the other hand, two-lane rural highways, a major rural road category, were the location for more than half of the fatal crashes in the United States during the 12 year period, as presented in Table 4 and Figure 5. The average percentages of fatal crashes on two-lane rural roadways in the eight southeastern states have been higher than the average U.S. level for many years. Florida has considerably lower percentages of two-lane rural fatal crashes (about 36%) than the other seven southeastern states which range from 50% in Georgia to 80% in South Carolina, as shown in Table 4. The large discrepancy between Florida and the other seven states can mask the regional status. By excluding the State of Florida, the 12-year average of the rural fatal crash percentage for the remaining states is 63%, which is about 12% higher than the U.S. average. Figure 5 presents two-lane rural road fatal statistics for the southeastern states (with and without the State of Florida) as compared to the U.S. average.

Table 4: Percent Two-Lane Rural Fatal Crashes (1995 – 2006)

States	1995 [%]	1996 [%]	1997 [%]	1998 [%]	1999 [%]	2000 [%]	2001 [%]	2002 [%]	2003 [%]	2004 [%]	2005 [%]	2006 [%]	12 Year Average [%]
AL	63.7	65.5	60.0	61.0	66.9	66.4	65.9	67.2	63.6	53.6	53.1	54.9	62
GA	53.0	53.5	53.5	55.0	53.7	51.2	51.3	54.8	51.9	47.5	37.4	39.0	50
MS	67.8	70.9	75.8	78.4	79.4	77.7	75.0	69.7	62.7	66.9	57.0	56.3	70
SC	87.6	91.2	89.2	84.4	85.2	74.4	64.7	66.0	68.3	81.6	85.9	82.2	80
FL	30.5	29.7	32.3	36.3	37.2	38.2	37.5	37.4	39.4	41.8	35.2	33.7	36
KY	77.7	71.8	76.5	75.2	78.7	74.5	74.5	72.7	73.2	71.9	70.5	71.7	74
NC	63.4	57.9	57.4	52.9	49.9	55.3	56.7	63.2	62.5	63.6	58.5	60.2	58
TN	60.7	58.3	55.1	60.1	60.2	62.3	61.9	59.6	55.5	55.0	53.4	42.0	57
Southeastern *	56.3	55.6	55.8	57.3	57.9	56.9	55.5	56.4	55.3	55.9	51.0	49.8	55
Southeastern (excluding FL)	65.7	64.7	64.2	64.5	65.3	63.9	62.2	63.7	61.5	61.3	57.4	56.1	63
U.S. **	51.6	51.4	52.3	53.2	53.8	51.3	51.8	52.6	50.7	51.4	48.9	47.5	51

** Percent two-lane rural fatal crashes of southeastern states =Total number of two-lane rural fatal crashes of southeastern states / Total number fatal crashes of southeastern states.*
*** The U.S. values include the 50 states and the District of Columbia.*
Source: FARS, NHTSA.

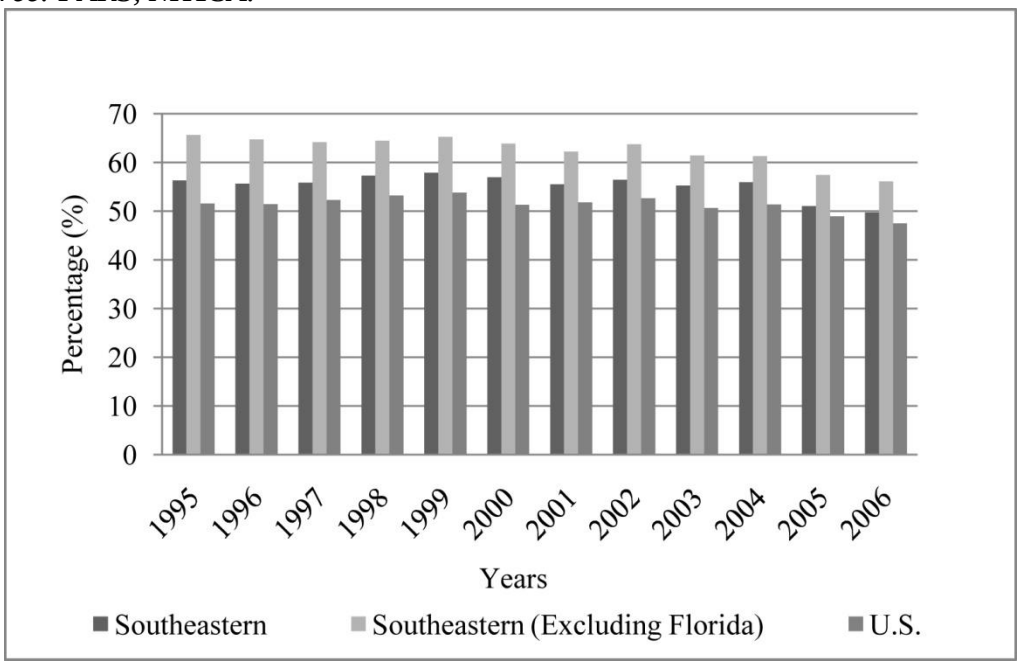


Figure 5: Percent Two-Lane Rural Road Fatal Crashes

The definition of “rural” and “urban” may vary from state to state. The Fatality Analysis Reporting System (FARS) uses the definitions of urban and rural provided by the FHWA. This definition, from the Bureau of the Census 2000 Decennial Census, indicates urban areas as including all urbanized regions (over 50,000 population) and Urban Clusters (2,500 to 49,999 population). In addition to the definition of urban, the “Federal transportation legislation allows responsible states and local officials in cooperation with each other, and subject to approval by the Secretary of Transportation, to adjust the Census boundaries outward, as long as they encompass, at a minimum, the entire Census designated area” (Federal Highway Administration, 2003). Rural is then defined as areas that are not urban.

The State of Florida is a more urbanized state than the others in the southeastern region. The remaining southeastern states still clearly demonstrate the over-represented two-lane rural fatal crashes. Some states, such as South Carolina, Mississippi, and Kentucky, have exceptionally high proportions with 12-year average higher than the U.S. average by 20% to 30%.

The previously presented 12-year observations outline the severity and scale of the problem and the importance of devoting research efforts to reduce two-lane rural fatal crashes in the southeastern states. Rural roadways are more likely to adhere to lower design standards compared to rural interstate highways and urban roads. More often, rural roads contain sharp curves, rolling hills, and winding roads. In addition, since rural roads are often located in remote areas, emergency rescuers may experience longer response times resulting in delayed medical service to injured individuals. Emergency reaction time may also be compromised by the potentially delayed crash identification. These facts make the individuals involved in rural crashes much more vulnerable than those who are involved in crashes in urbanized environments.

The previously presented summary statistics are based on various data sources, including the latest U.S. census data, updated traffic safety facts summaries, and over 10 years of fatal crash data at both regional and national levels. These various analyses support the findings of over-represented total fatal crashes and fatality rates on rural two-lane highways for the southeastern region as compared to the country as a whole. The 12-year crash trend analysis demonstrates a necessity for research efforts focused on reducing fatal crashes on two-lane rural roads in the southeastern region. By identifying the potential influential factors and reaching a better understanding of fatal crash occurrences in the rural environment, safety researchers and engineers will be able to implement more effective countermeasures and treatments to mitigate this unacceptable situation and promote a safer driving environment in this region.

1.2 Previous Southeastern States Crash Studies

Previously, researchers found that high fatal crash frequencies and fatal crash rates, mostly on two-lane rural highways, are the major traffic safety concerns of the southeastern region of the United States (Washington et al., 1999; Washington et al, 2002; Dixon, 2005).

Washington et al. (1999) analyzed fatal crash records extracted from FARS for the year 1995 and focused on inter-regional comparisons between the southeastern and non-southeastern United States. The study supported the speculation of the existence of regional differences. Researchers also explored possible common traits shared by southeastern states that might contribute to the regional differences. The identified differences in fatal crashes between southeastern and non-southeastern regions include seat-belt use, VMT by functional classification, and speed limit differences. The researchers recommended a future study approach of in-depth investigation of using disaggregate data at the infrastructure level aiming to quantify the potential contributing factors.

Originated from the preliminary findings from Washington et al.'s inter-regional fatal crash study, a pooled fund study initiated by the FHWA and eight southeastern states provided a joint research effort to examine the over-represented fatal crashes in the southeastern region. Researchers suggested methods to reduce fatalities which included widening shoulders, enhancing delineation, and protecting the clear zone. All of the southeastern states except Florida concluded that rural two-lane road conditions were the source of the elevated fatal crashes in the region with high representation of fatality. In a further effort to narrow the study scope, the FHWA and state representatives decided to focus on evaluating fatal crashes on two-lane rural roads.

This dissertation acts as a continuation of the previous pooled fund study. The study includes randomly sampled fatal crashes available from the southeastern states of Alabama (AL), Georgia (GA), Mississippi (MS), and South Carolina (SC), with sample sizes of 150, 150, 100, and 157, respectively. Figure 6 shows the eight southeastern states discussed previously. Among which, the four states that are marked with check marks are MS, AL, GA, and SC. All of the samples were selected from the 1997 FARS database except for the SC data which used data from 1998 (Dixon, 2005). Each participating state was responsible for performing random sampling and conducting crash site visits or inspection of the video log for the crash sites. Therefore, the uniqueness of this dataset is that the final data includes detailed and more accurate information on road geometric features and roadside characteristics not available in police crash reports. In this dissertation, the author uses the rich data information to explore and quantify effects from various sources on fatal crash occurrences for each state as well as for the four states as a whole. In addition, this research is an opportunity to capitalize on all of the previous related study efforts by offering meaningful findings and practical recommendations at the infrastructure level.

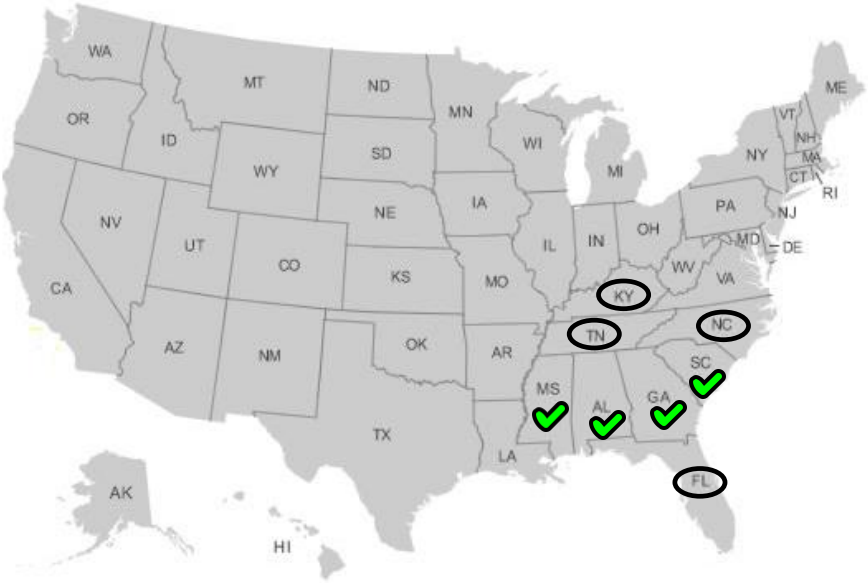


Figure 6: Southeastern States of the United States

1.3 Current Research Objectives and Contribution

A crash prediction model is one of the most popular and effective approaches to quantify safety performance. While most safety performance is measured by crash frequency, crash rate, injury severity, etc, the author decided to focus on crash type outcome probability. Since the available crash database only includes fatal crashes, crash prediction models developed for this study simply estimate the probability of fatal crash type outcomes based on road geometrics as well as roadside and environmental features for fatal crashes.

The uniqueness and benefits from using crash types as a measure of crashes can be seen through three aspects:

- **To researchers**: Crash types imply information about crash mechanisms which help to achieve a better understanding of crash formation and causation.

- **To traffic safety engineers**: Through targeting crash types, the crash type-road geometrics relations provide a clear guidance to choose, develop, and implement effective countermeasures.
- **To the public**: Crash type conveys a straightforward, intuitive, and effective description and information of crash occurrences.

Researchers and safety engineers can gain insight into how to reduce the frequency of crash types by considering potential contributing factors and their association with various crash types. Figure 7 illustrates the relationship between countermeasures, crash types, and road geometric characteristics. Countermeasures are often observed to be more effective at reducing certain types of crashes. This observation suggests that countermeasures can be specific to a crash type. For example, medians are a known effective type of treatment to reduce head-on collisions by providing physical separation for opposing traffic. Countermeasures also have close ties with existing road geometrics, roadside features, and environmental conditions. Evaluations of countermeasure effectiveness are often conducted through before–after studies. Bayesian statistics-based analysis provides reliable results and is the recommended method by many researchers.

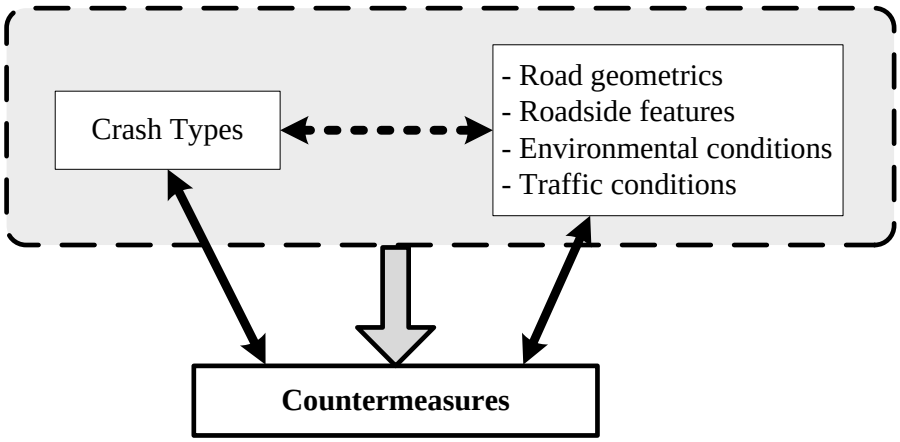


Figure 7: Relations among Crash Types, Road geometrics, and Countermeasures

One missing link in current research is the direct relation between crash types and roadway-related characteristics. It is reasonable to assume that road geometrics, roadside features, as well as environmental and traffic conditions may be associated with various crash types differently. The fatal crash type prediction model has the advantage of providing new insights of how road geometrics and roadside environment conditions impact the chance of a major fatal crash type occurrence. The crash prediction model can be more sensitive and effective in terms of identifying potential contributing factors from this perspective.

In addition, the analysis is based on individual crash site information which is different from studies that are conducted with general road features. Site-based information is more suitable for safety engineers to assess individual projects which focus on fatality and severe injury mitigation.

Four major study objectives that are performed in this dissertation include:

1. Present descriptive statistics and crash trend analysis of the four states fatal crash databases and examine data representation.
2. Apply a statistical model to investigate the relationship between the probability of fatal crash type occurrences and potential contributing factors. This effort offers a unique perspective to inspect crash occurrences by crash type and to investigate interaction effects among some predictors that are poorly understood.
3. Investigate intra-region (among four states) differences on effects of influential factors in terms of definition, effectiveness, and applicability of countermeasures. Model transferability is investigated to see whether a model developed from one state's crash data is valid for the other state.
4. Provide recommendations regarding improved rural highway safety for the Georgia Department of Transportation (DOT) based on these findings.

The original contribution of this dissertation is to provide an initial effort to examine the direct connection between probabilities of fatal crash type outcomes and road geometrics as well as roadside and environmental features of fatal crashes on two-lane rural highways for four southeastern states as a regional study. The resulting statistical models directly relate targeted fatal crash types and safety improvement strategies. The study findings confirmed the initial assumption of the potential connections between crash type outcomes and road geometrics. Meanwhile, the modeling results also are consistent with expert panel evaluations from two previous fatal crash investigations based on Georgia fatal crash data. The common recommendations resulted from very different study techniques suggesting that the fatal crash type prediction models are a reliable and reproducible quantitative assessment tools. Meanwhile, this research also reveals new insights into potential practical applications. From the empirical perspective, the model can serve as an evaluation tool for traffic safety engineers to assess candidate safety benefits as they relate to expected fatal crash types.

This crash type centered study effort complements current crash analysis on crash frequency, crash rate, and crash severity predictions. The application of crash type models is to serve as an analytical assessment tool for projects in the Highway Safety Improvement Program (HSIP), the federal funded safety program targeting fatalities and severe injury reduction. Therefore, this dissertation approaches safety concerns of two-lane rural highways in the southeastern U.S. through a new study perspective-crash type analysis-a research area that is still evolving. The study results include empirical values that can be used by traffic safety engineers as one tool in their countermeasure decision making processes.

In this dissertation, the author conducted a thorough review of published pivotal literature related to the study objective, introduced and examined the fatal crash databases, discussed the study methodologies, presented and discussed analysis

results, and summarized major findings and future study tasks. A brief description of each chapter included in this dissertation is listed below:

Chapter 2: Review the documented pivotal studies and major findings as well as the differences and similarities.

Chapter 3: Discuss the available study methodologies, and the approach that is applied in this study.

Chapter 4: Provide a comprehensive fatal crash summary statistics and trend analysis based on the crash database.

Chapter 5: Develop probabilistic models to identify the potential contributing factors, such as traffic, environmental, and roadway geometric characteristics, related to the probabilities of crash type occurrence.

Chapter 6: Demonstrate the practical applications of how to apply the model in real world projects.

Chapter 7: Summarize major findings, conclusions and offer future study recommendations.

CHAPTER 2 LITERATURE REVIEW SUMMARY

This chapter provides a review of previous studies and findings of the impact on crash injury severity as well as association with crash types for various factors that are related to driving behavior, vehicle occupancy, vehicle related attributes, roadway design features, roadside characteristics, and environmental conditions. The literature review includes national and international research from the past two decades.

Sections 2.1 through 2.5 introduce recent research for potential contributing crash factors. Some of the factors, such as driver and vehicle related attributes, have been well researched, while others have not yet been explored in depth. For most well studied variables, the reported findings are relatively consistent. Studies with limited data or analysis, however, often provided conflicting results. In addition to the study efforts across potential contributing factors, a majority of the studies focused on the impact on crash injury severities, with relatively less research investigating the corresponding associations with crash types.

2.1 Driver and Passenger Related Characteristics

One of the crash impact factor categories that has been under extensive study in the published literature is vehicle occupant related attributes. Numerous previous studies identified vehicle occupant related characteristics as influential factors on crash injury severity and crash type. Common human-related factors include gender, age group, alcohol and drug use, the presence and use of a safety restraint system, passenger seating position, and driver speed choice. Table 5 provides an overview of the published driver and passenger characteristics further summarized in Sections 2.1.1 through 2.1.5 of this summary.

Table 5: Summary of Driver and Passenger Related Characteristics Literature

Attributes	*Severity*	*Crash Type*
Gender and Age	• Increase injury severity for female and older drivers • Dependent on other associated factors • Younger drivers associated with higher severity • Inconsistent findings in studies	• Older drivers are prone to more serious injury in side-impact crashes • Insignificant gender association with injury severity of older drivers in fixed-object crashes
Alcohol and Drug Use	• Increase injury severity consistently • Interactions with gender and age groups	• Less severe injury for older drivers in fixed-object crashes suggesting abusive use more common for younger drivers
Safety Restraints	• Reduce injury severity effectively	• Reduce injury severity in single-vehicle crashes, two-vehicle crashes, and fixed object crashes
Seating Positions	• Greater risk for occupants seated on side of impact • Greater risk of head and neck injuries for elder drivers on far side of vehicle	• Most frequently an issue for two-vehicle side-impact crashes
Speeding	• Increase injury severity consistently with speed increase • High speed differentials increase severity risk	• Speed related fixed-object crashes frequently associated with severe injuries

2.1.1 Gender and Age

Researchers have performed extensive investigations on the relationship between injury severity level and vehicle occupants' gender and age. Most studies demonstrated significant evidence of the gender and age effects on crash injury severity after accounting for other influential analysis variables (Ulfarsson and Mannering, 2004; O'Donnell and Connor, 1996; Kweon and Kockelman, 2003; Farmer et al., 1997; Bedard et al., 2002; Khattak et al., 2002; Savolainen and Mannering, 2007; Jones and Jorgensen, 2003; Abdel-Aty et al., 1998). The well known physical and psychological differences among gender and age provide logical

support for the reported significant impacts on crash injury severity; however, a few studies provided unexpected results (Dissanayake and Lu, 2002; Kim et al., 1995).

Most studies reported a higher risk of serious injury associated with female drivers, as well as older and younger drivers, if a crash occurred. Ulfarsson and Mannering (2004) distinguished the injury severity differences for male and female drivers involved in crashes categorized by vehicle types, including the sport-utility vehicle, minivan, pickup, and passenger car. They found that there is a significant gender difference of how other factors influence injury severities. Abdelwahab and Abdel-Aty (2001) found that female drivers are more likely to suffer from severe injuries than male drivers based on a study of two-vehicle crashes that occurred at signalized intersections. Abdel-Aty et al. (1998) studied the relationship between driver age and injury severity and reported an increasing risk of involvement in crashes for older and younger driver groups. Srinivansan (2002) found that older drivers as well as female drivers face greater risk of mild injury while involved in crashes. The study did not find significant differences of gender and age for severe injuries.

Considering that rollover crashes tend to lead to more severe injuries than non-rollover crashes, Kweon and Kockelman (2003) classified crash data for rollover and non-rollover crashes and incorporated traffic exposure in the analysis. Their study presented a statistically significant association between injury severity and driver's age and gender. The researchers emphasized the importance of incorporating traffic exposure across driver groups stratified by age and gender. The major findings included:

- Younger drivers (younger than age 20) tend to be associated with higher injury severity risk than middle-aged (20 to 60 years of age) or older drivers (above 60 years old).
- Female drivers tend to sustain more severe injuries in crashes than male drivers.

Based on their findings, Kweon and Kockelman recommended providing more restricted driving policies for younger persons through various approaches, such as raising the legal driving age and prohibiting freeway driving.

As for crash type classification, Farmer et al. (1997) analyzed the relationships of occupant, vehicle, and crash characteristics to injury severities for side-impact crashes. The researchers found that older vehicle occupants were three times as likely as younger occupants to be seriously injured in similar crashes.

Several other international studies also reported consistent findings. Based on a 10-year crash database from Norway, Jones and Jorgensen (2003) reported an increasing risk of fatality for older and female drivers. In Australia, O'Donnell and Connor (1996) determined that female drivers are more likely to have higher serious injury probabilities than male drivers involved in crashes. Ryan et al. (1998) investigated the potential of driver's age related patterns with crash type. They found that the younger driver group is more likely to be involved in single-vehicle crashes, the middle age driver group has a greater proportion of same direction crashes, and the older age driver group is over-represented in the angle crash category.

While most of the studies focused on crash severity, Bedard et al. (2002) investigated the effects of driver, crash, and vehicle characteristics on fatalities. The model that was estimated was based on data from the FARS and predicted the likelihood of involvement in fatal crashes will increase as the driver's age increases. For example, drivers older than age 80 are about five times as likely to have fatal injuries in a crash as drivers aged 40-49 years old. Female drivers are about 1.5 times more likely to sustain fatal injuries compared to male drivers.

Aiming to address safety issues of the increasingly older driver population in the U.S., Khattak et al. (2002) investigated influential factors that are associated with severe crash injuries to older drivers (age above 65 years). The study found that an increase in the age of older drivers tends to increase the likelihood of having more severe injuries. The male older drivers are more likely to be injured compared to female older drivers. This finding appears to conflict with the previous findings based on drivers from all age groups (O'Donnell and Connor, 1996; Ulfarsson and Mannering, 2004; Kweon and Kockelman, 2003, and Wang and Kockelman, 2005). A study from Hong Kong had a similar finding: male drivers faced a greater risk of involvement in serious or fatal crashes (Yau et al., 2006).

In general, researchers suggested that several physical deteriorations associated with the aging process increase the vulnerability of older drivers on the road and contribute to the increased injury level witnessed in the older driver population. Some commonly mentioned factors include declining visual functions, cognitive impairment, and increasing difficulty of focus.

While most of the studies focused on the injury level of motor vehicle occupants involved in a traffic crash, researchers also found consistent evidence of the strong relationship between age and injury severity for motorcyclists. The older the motorcyclists, the more likely they are to sustain more severe injuries in crashes (Savolainen and Mannering, 2007).

Even though most of these human-related studies showed evidence of statistically significant gender and age differences on injury severity for vehicle occupants and motorcyclists, a few additional studies reported inconsistent findings. Some researchers investigated potential influential factors on injury severity for older drivers by focusing on fixed-object passenger car crashes. In this case, Dissanayake and Lu (2002) did not identify the gender of older drivers as a statistically significant factor

associated with injury severity. Kim et al. (1995) studied the relationships of driver characteristics and behavior with crash and injury severity and did not find statistically significant effects of driver's age and gender.

Overall, the majority of previous research reached consistent findings on the significant effects of age and gender on injury severity and crash types. These studies showed strong evidence of the importance and necessity of a gender based injury severity study while taking into account the vehicle occupants' age groups. Many authors recommended taking into consideration the interactions of age and gender with other factors in future research on various safety issues.

Even though researchers focused on the effects of driver related attributes, select studies incorporated either passenger characteristics in the study or treated vehicle occupants as a whole to present a full picture of crash injury severity outcomes for all individuals involved in crashes. It is a common understanding that drivers and passengers have different influences on crash occurrence. Thus, it may be meaningful to explore and compare the similarities and differences of effects from driver and passenger related characteristics on injury severity level and crash type.

2.1.2 Alcohol and Drug Use

Previous studies of vehicle crash injury severity predominantly provided consistent evidence that alcohol use is one of the contributing factors leading to crashes and severe injuries (Kim et al., 1995; Bedard et al., 2002; Khattak et al., 2002; Traynor, 2005; Krull et al., 2000; Keall et al., 2004; Dissanayake and Lu, 2002; Duncan et al., 1998; Jones and Jorgensen, 2003; Shibata and Fukuda, 1994; Srinivasan, 2002).

Kim et al. (1995) investigated the relationship of driver characteristics and behavior with crash injury severity. The study showed that the driver's alcohol and drug use dramatically increases the odds of having a more severe crash injury. Bedard et al.

(2002) presented evidence indicating that drivers with blood alcohol concentration (BAC) greater than 0.3 gram per deciliter (g/dl) will triple their likelihood of fatal injuries. Aiming to address safety issues regarding the increasingly older driver population in the United States, Khattak et al. (2002) investigated influential factors associated with severe crash injuries for drivers over the age of 65. The study found that alcohol consumption will increase the probability of being seriously injured in a crash. Traynor (2005) studied the impact of driver alcohol use on crash severity and found that alcohol consumption by the driver at-fault not only increases the likelihood of injury severity, but also increases the number of injuries and fatalities per crash. Krull et al. (2000) also reported an increasing trend of driver injury severity with alcohol use.

International studies also reported similar results. A fatal injury study from New Zealand reported that the increasing BAC exponentially increases the risk for drivers of experiencing fatal injuries while driving at night (Keall et al., 2004). Based on crash data from Norway, Jones and Jorgensen (2003) reported an increasing trend of fatalities associated with alcohol use. Shibata and Fukuda (1994) also had similar findings based on a crash severity study in Japan.

While focusing on fixed-object passenger car crashes, Dissanayake and Lu (2002) reported an inconsistent result. Finding that older drivers under the influence of drugs or alcohol have less likelihood of severe injuries, they offered the explanation that older drivers may pay extra attention to driving while under the influence of alcohol or drugs than drivers in other age groups.

2.1.3 Safety Restraints

Previous researchers have recognized the important role of safety restraints in reducing crash severity. These studies primarily focused on safety restraint usage for motor vehicle occupants as well as helmet use for motorcyclists. Kim et al. (1995)

investigated the relationship between driver characteristics and behavior with crash and injury severity. They found that drivers who did not use safety restraints significantly increased their chance of experiencing more severe crashes and injuries. Wang and Kockelman (2005) also reported dramatic reductions in the probability of being injured (36.5%) or killed (47.3%) for vehicle occupants who wear safety restraints compared to those who do not use safety restraints and are involved in a crash with two vehicles. In single-vehicle crashes, those who wear safety restraints face a probability reduction of 90.2% for injury and 71.9% for fatality compared with those who do not. In a study concentrating on older drivers involved in fixed-object passenger car crashes, Dissanayake and Lu (2002) presented similar findings for the effectiveness of safety restraint usage on injury severity reduction. Abdelwahab and Abdel-Aty (2001) studied two-vehicle crashes that occurred at signalized intersections and reported that drivers wearing safety restraints reduced the likelihood of any occupant having severe injuries. After taking into account other factors, Krull et al. (2000) and Srinivasan (2002) also found an increasing trend of driver injury severity associated with those who failed to use safety restraints. As for motorcyclists' safety concerns, more severe injuries are associated with motorcyclists who do not wear helmets than those who do (Savolainen and Mannering, 2007).

While many studies confirm the effectiveness of safety restraint usage on crash and injury severity reduction, some point out the role of selective recruitment, also called sampling bias, in the evaluation process (Evans, 1996; Derrig el al., 2002; Nakahara et al., 2006). Drivers who have more safety awareness will be more likely to wear safety restraints; drivers who are more aggressive and less safety conscious will be less likely to wear safety restraints, even in locations with primary and secondary seat belt laws. This second group, taken as a whole, includes the drivers who are more likely to be involved in more severe crashes and injuries. Therefore, selective recruitment may discount the alleged effectiveness of safety restraint usage for assessment studies.

Evans (1996) challenged the study method by measuring the safety restraint effectiveness with overall crash reduction. He recognized that the better measure of the effectiveness of safety restraint usage is the reduction of injury severity. The study showed that using safety restraints can more efficiently prevent fatalities than for less severe injuries in crashes. Evans also indicated that the drivers who do not wear safety restraints are riskier drivers, and that the safety restraint wearing rate dropped as the injury severity increased. The drivers who should benefit the most from safety restraints are more likely not to wear them. The study advocated reinforcing drivers' education program, especially targeting the aggressive driver population.

Using the FARS database from 1983 to 1996, Derrig et al. (2002) studied the impact on fatalities from the overall increasing safety restraint usage rate. The study showed that the increasing rate of safety restraint usage had little impact on reducing the fatality rate (fatalities per million populations and per 10 billion vehicle miles traveled). Primary enforcement laws effectively increased the overall safety restraint usage rate; however, non-aggressive drivers tend to adhere to the law better than riskier drivers. The riskier drivers, however, are the population who are most likely to be involved in fatal crashes. The study by Derrig et al. (2002) provided analysis results consistent with those found by Evans (1996).

A recent study echoed Derrig and Evans's findings. Research by Eluru and Bhat (2007) supported the selective recruitment (sample selection) hypothesis. They applied a mixed joint binary logit model—an ordered logit model with random coefficients—focusing on the analysis of non-commercial driver safety restraint usage and crash severity. The study showed those drivers who have more awareness of safety will be more likely to wear safety restraints. Drivers who are more aggressive and less safety conscious, on the other hand, will be more likely not to wear safety restraints, even in jurisdictions with a primary safety restraint law. According to the authors, defensive driving habits and driver consciousness will result in less severe

injuries, given a crash occurrence. Eluru and Bhat further suggested that safety restraint usage and a self-conscious driving attitude both contribute to fatality reduction and recommended that policy makers advocate giving non-safety restraint users' fines as a punishment as well as providing a mandatory defensive driving course.

The majority of the analyses for safety restraint usage are based on police report crash records. Therefore the accuracy of the police report influences the analysis results. While police reports are the source for major crash databases, researchers should be aware of the level of precision of this crash data and make corresponding adjustments to their findings whenever necessary. Some reporting patterns regarding safety restraint usage in police report crash databases include:

- Police were least likely to make errors in instances of safety restraint usage regarding fatally injured occupants (Schiff and Cummings, 2004). However, Robertson (2002) found that police tend to report an unbelted status for occupants who do not survive. This reporting trend may lead to an overestimation of the effectiveness of safety restraint usage in reducing crash severity.
- Police tend to categorize unbelted survivors as belted when they were not.

2.1.4 Seating Position

A study by Farmer et al. (1997) for two-vehicle side-impact crashes showed an increasing risk of sustaining serious injuries for vehicle occupants seated on the side of the vehicle struck during the crash. Meanwhile, Farmer also noted the tendency of serious injury for elder occupants seated on the far side of the crash. Most of the far side occupants were suffering from head and neck injuries of a greater magnitude than those on the side where the vehicle was hit. The study provided evidence to advocate vehicle structural design improvements in order to provide better protection to occupants in side-impact crashes. Huelke and Compton (1995) examined the effect of

safety restraint usage on injury severity for front and rear seat vehicle occupants and indicated that rear seat occupants are safer than front seat occupants.

2.1.5 Speeding

As with alcohol consumption, speeding is another well known contributing factor that increases crash injury severity. Based on physical law, Shinar (1998) indicated that the vehicle that has a greater momentum with a faster speed will introduce a larger amount of exchange energy in a crash. This greater energy could cause more damage to vehicles and significant harm to occupants. In addition, the higher speed will also increase the required stopping sight distance and make it difficult for driver's to make adjustments and corrections during a crash event.

Driving at speeds over 69 mph (111 km/h) will double the odds of a fatality (Bedard et al, 2002). Joksch (1993) found that injury severity increases at a higher rate than the increasing rate of speed. Higher travel speed also increases the likelihood of causing more severe injuries for older driver groups involved in fixed-object passenger car crashes (Dissanayake and Lu, 2002).

Not only does the speed level contribute to increased injury severity, the speed difference of two vehicles also increases the likelihood of experiencing severe injuries (Abdelwahab and Abdel-Aty, 2001). In an earlier study examining collisions between heavy trucks and passenger cars, Duncan et al. (1998) also indicated that a high speed differential increases the risk of more serious injuries.

High speeds are also a safety risk for motorcyclists. In the event of a crash, driving at an unsafe speed is one of the factors that increases the likelihood that motorcyclists will suffer from severe injuries (Savolainen and Mannering, 2007). Shibata and Fukuda (1994) reported the significant impact on injury severity from speeding. Their

study also found that injury severity is due to the interaction between speed and motorcycle helmet protection use. Helmets will perform more effectively under a speed range less than 31 mph (50 km/h) and will be less effective at speeds greater than 31 mph (50 km/h).

2.2 Vehicle Related Characteristics

Vehicle related factors that have been discussed in the literature that focus on injury severity include vehicle type, weight, size, and vehicle occupancy. The number of vehicles involved along with the effects from interactions with other factors such as crash types also influence these vehicle related characteristics (Farmer et al., 1997; Chang and Mannering, 1999; Abdel-Aty and Abdelwahab, 2004a; Abdel-Aty and Abdelwahab, 2004b; Wang and Kockelman, 2005; Ulfarsson and Mannering, 2004; Zhang et al., 2000; Chang and Mannering, 1998). Table 6 provides an overview of the literature for vehicle related characteristics as further summarized in Sections 2.2.1 and 2.2.2.

Table 6: Summary of Vehicle Related Characteristics Literature

Attributes	*Severity*	*Crash Type*
Vehicle Weight, Size, and Type	• Less severe injuries associated with occupants of heavy vehicles, pickups, SUVs, and vans when compared to those in passenger cars or on motorcycles • Dependent also on rollover likelihood due to other factors	• Significant impact on two-vehicle side impact, rear-end and rollover collisions
Vehicle Occupancy	• Acting as interactions with other factors • Greater severity risk for multi-occupant vehicles	• Increase injury severity while involving turning movement and rear-end collisions • Increase in rear-end and angle crashes due to vehicle mix with larger vehicles • Light trucks, SUVs, and pickups are more likely to be involved in roll-over crashes than other vehicle types

2.2.1 Vehicle Weight, Size, and Type

According to a two-vehicle side-impact study conducted by Farmer et al. (1997), the likelihood of serious injuries tends to increase for the occupants in lightweight passenger vehicles. This finding is consistent with the fundamental principles of physics. Vehicles with a lighter weight and smaller size tend to be more vulnerable in a crash. Krull et al. (2000) also reported that passenger car drivers have a higher probability of sustaining more severe injuries in crashes compared to pickup truck drivers. Abdelwahab and Abdel-Aty (2001) studied two-vehicle crashes occurring at signalized intersections and also reported similar findings about injuries and vehicle type. By examining fatal crash records, Evans and Frick (1993) suggested that lighter weight vehicles pose less risk to others, while heavier vehicles offer less risk to their own occupants. Sirinivasan's (2002) study reinforced previous findings in terms of how strong impacts on injury severity result from the physical protection of vehicles. The researchers reported that sports utility vehicles (SUVs) and light-duty trucks only reduce risk for moderate injuries while heavy-duty trucks are much safer for all their occupants at all injury severity levels.

For motorcycle crashes in Hong Kong, the motorcyclists exhibited higher risks of sustaining severe injuries than drivers of passenger cars and taxis (Yau et al., 2006). Motorcyclists are more vulnerable on the road than drivers of motor vehicles. Other driver related characteristics and driving behaviors such as age, speed, gap acceptance, and blind spot positioning also contribute to the higher risk of experiencing more serious injuries.

Abdel-Aty and Abdelwahab (2004b) investigated rear-end collisions and the drivers' visibility across various types of light truck vehicles (e.g., light trucks, vans, and SUVs). The study found that drivers' inattention and sight obstruction due to a leading light truck vehicle contributed to vehicle involvement in rear-end crashes. This finding included the age, gender, traffic control devices, and actions initiated by

leading vehicles. Abdel-Aty and Abdelwahab (2004a) also investigated the fatality trend of angle crashes with an increasing percentage of light truck vehicles. The study predicted an increase in fatalities due to angle crashes as the number of light truck vehicles increases.

With respect to crash types, Farmer and Lund (2002) observed that light trucks are twice as likely to experience rollover crashes compared to passenger vehicles. Kweon and Kockelman's (2003) study also revealed that drivers of SUVs and pickups are more likely to be involved in rollover crashes than are drivers of passenger cars. According to a study of SUV safety issues, Khattak and Rocha (2003) reported that SUVs have a higher likelihood of rollover and these crash types lead to more severe injuries. Alternatively, SUVs provide more protection to the occupants in a crash. This finding agreed with recent study results indicating that SUVs, vans, and pickups tend to be more crashworthy than passenger cars (Toy and Hammitt, 2003).

2.2.2 Vehicle Occupancy

Chang and Mannering (1999) studied crash and injury severities for a variety of crash vehicle occupancy and specifically evaluated whether trucks were involved in the crash. After accounting for vehicle occupancy, Chang and Mannering identified influential factors that significantly increase injury severity for truck-involved crashes. These factors included high speed limits, turning maneuver associated crashes, or rear-end collisions. The study also indicated that truck-involved crashes tend to more significantly increase crash and injury severities for multi-occupant vehicles than for single-occupant vehicles. Vehicles with a higher numbers of occupants will tend to display a greater likelihood of having someone seriously injured should a crash occur. In another earlier study, Chang and Mannering (1998) also reported a significant association between injury severity and multi-occupant vehicles.

2.3 Roadway and Roadside Related Characteristics

The role of roadway geometric features and roadside characteristics on crash and injury severity provides valuable information for roadway designers, safety engineers, and policy decision makers. Physical roadway data is rarely included comprehensively in a crash database so adequate evaluation of these features is limited when assessing their influence on injury severity and crash types. Table 7 depicts a summary of the literature regarding roadway and roadside characteristics. This information is further summarized in Sections 2.3.1 through 2.3.6.

Table 7: Summary of Roadway and Roadside Related Characteristic Literature

Attributes	*Severity*	*Crash Type*
Alignment and Vertical Grade	• Increased injury severity with horizontal curves present and steep grades • Various additional dependencies due to urban versus rural location characteristics and associated geometric design	• Various associations with crash types: single-vehicle and two-vehicle crashes
Lane and Shoulder	• Paved or wider shoulder and lane width reduce crash severity and crash rate	• Various associations with crash types: side-swipe, single-vehicle and two-vehicle crashes • Wider paved shoulders reduce single vehicle crashes
Roadside Characteristics	• Guardrail use has a mixed effect on crash severity	• Centerline rumble strips on two-lane rural roads reduce front- and opposing-direction crashes
Speed Limit	• Increasing speed limits increases injury severities	• Increasing speed limit increases injury severities for single-vehicle, two-vehicle, and multiple-vehicle crashes
Wet vs. Dry Pavement Condition	• Conflicting findings regarding the association of severity to wet road conditions	• Wet pavement conditions interact with crash types: hit-object crashes, multiple-vehicle crashes (specifically sideswipe and opposite direction crashes) • Dry pavement and daylight associated with rear-end conditions
Traffic Volume	• Significant impact factor	• Not significant to crash type

2.3.1 Roadway Alignment and Grades

Previous studies reviewed the effects due to horizontal or vertical alignments and grades at various road junction types and traffic control devices, such as road segments, intersections, or signalized and unsignalized traffic controls. Most of these studies reported that horizontal and vertical curvature presence and steeper grades were associated with a higher risk of severe injuries.

Horizontal curves located downstream of long straight roadway segments on level terrain tend to increase the likelihood of injuries in crashes for older drivers (Khattak et al., 2002). Researchers recommended the installation of curve warning signs or rumble strips on long sections of highways in order to alert older and younger drivers of the oncoming geometric changes. Wang and Kockelman (2005) found that negotiating at curve sections which have high speed limits tends to increase the chance of experiencing injury and fatality for older and female vehicle occupants. For two-vehicle crashes, they estimated a 56.7% increasing in fatalities for curves to the left (in the direction of travel) and a 39.2% increase in fatalities for curves to the right when compared to straight road segments. Single-vehicle crashes exhibited similar crash characteristics at curve locations. These findings are also consistent with study reports from Dissanayake and Lu (2002) and Abdel-Aty (2003).

The presence of horizontal and vertical curvature is also associated with more severe injuries for motorcyclists involved in single- and multi-vehicle crashes (Savolainen and Mannering, 2007). Kim et al. (2007) determined that for crash types, for example, the presence of horizontal curvature is among the contributing factors that increase the likelihood of angle crashes.

While the majority of previous studies presented convincing evidence that curvilinear roads increase the chance of crash occurrences, one New Zealand fatal crash study found that there was no significant evidence of the association between curves and

fatal crashes on rural state highways (Haynes et al., 2008). The study did show, however, that curvilinear roads reduce the likelihood of fatal crashes on urban roads.

Wang and Kockelman (2005) also examined the effect of vertical grade on injury severity for one-vehicle and two-vehicle crashes. The study distinguished between the effects on injury severity for uphill as well as downhill conditions. Wang and Kockelman did not find grade to be significant for single-vehicle crashes. Meanwhile, vertical grade played a significant role for two-vehicle crashes for both uphill and downhill conditions. They found a downhill grade was associated with a 37.3% increase in fatalities and a 13.3% increase in all forms of injury. The 2002 study by Dissanayake and Lu also provided evidence to support the association of vertical grades and more severe injuries.

2.3.2 Lane and Shoulder

Numerous studies have identified significant reductions in overall crash rate as a result of wider travel lanes or shoulders (Foody and Long,1974; Shannon and Stanley,1976; Jorgensen and Associates, 1978; Zegeer et al., 1979; Zegeer et al., 1988; Griffin and Mak, 1989). Few of these studies focused on the effects on crash injury severity and crash type though. Heimbach et al. (1974) performed a study in North Carolina and found a significant decrease in crash severity by paving 3 to 4 ft. (0.9 to 1.2 m) of unpaved shoulders. Kim et al. (2007) predicted that same direction sideswipe crashes have less chance to occur at intersections with shoulders compared to intersections without shoulders.

According to a study by Ivan et al. (1999), increasing shoulder width, sight distance and traffic intensity are more likely to reduce crash rate for single-vehicle crashes than for multi-vehicle crashes. Meanwhile, factors that may increase the multi-vehicle crash rate include the increasing number of traffic signals, daily single-unit truck percentage, and shoulder width.

A research effect conducted by Gross et al. (2009) evaluated the safety performance for various lane-shoulder configurations for given pavement widths ranging from 26 to 36 ft (7.9 to 12 m) on two-lane rural roadways. The targeted crash types included head-on, run-off road, and sideswipe crashes. The researchers applied a matched case-control analysis based on at least five-year aggregated crash data from the states of Pennsylvania and Washington. The study provided findings which are consistent with previous research efforts that wider lane, shoulder, and paved width are more likely to help reduce crashes. Gross et al., however, were not able to reach a conclusion about the safety effects of different lane and shoulder combinations for a given total (combined) paved width. The essential finding from this research is that safety performance of paved lane and paved shoulder width should be evaluated together rather than separately. In other words, the effects of shoulder width are more likely to vary for a given lane width, suggesting the existence of interaction effects between lane and paved shoulder widths. Harwood et al. (2000) also recognized and discussed the lack of understanding about the potential interactions between contributing factors.

2.3.3 Roadside Characteristics

Based on a three-year vehicle crash database of northbound State Route 3 in Washington State, Lee and Mannering (2002) investigated the relationship between crash severity, roadside features, and driver behavior. The various roadside features examined in the study included guardrail, fixed objects, sign supports, tree groups, and utility poles. The study revealed that the impact on crash injury severity is a complex interaction for combined roadside features. A tree group along the roadside will increase the likelihood of having evident injuries by 43.7%. In spite of the fact that the primary purpose of a guardrail is to reduce crash injury severity by preventing crashes as cars run off the road at curvature locations, the study showed that guardrail implementation increased the likelihood of a disabling injury or fatality by 90%. The somewhat counter-intuitive findings imply that there may be potential interactions

with other observed and unobserved factors. The study findings were also based on data for only one direction of travel for one study corridor in the State of Washington.

By taking into account the number of vehicles involved in crashes, Wang and Kockelman (2005) reported that manufactured barriers slightly reduce injury severity while dividers and one-way roads have the opposite effects for single-vehicle crashes. With two-vehicle crashes, dividers, medians and manufactured barriers reduced injury severity. Among them, manufactured barriers have the strongest effect and can reduce fatalities by 53.7%. Another promising result is that the installation of centerline rumble strips on two-lane rural roads significantly decreased front and opposing-direction sideswipe crashes by 25% (Persaud et al., 2004)

2.3.4 Speed Limit

Wang and Kockelman (2005) reported that roads with higher speed limits increase the percentage of fatalities for two-vehicle crashes, with a similar trend of lesser significance exhibited for single-vehicle crashes. This result implies different critical variables for single-vehicle versus two-vehicle crashes. A separate modeling effort is, therefore, worthwhile in order to separate the confounding factors and to show the significant effects for variables that tend to be crash-type specific. Yau et al. (2006) also identified an association of higher speed limits and crash severity for multiple-vehicle crashes. Ossiander and Cummings (2002) concluded that speed limit increases from 55 mph (89 km/h) to 65 mph (105 km/h) contributed to the increase in the fatal crash rate on freeways in Washington State. Duncan et al. (1998) also reported a trend of increasing crash severity with high speed limits.

By treating the regulatory speed limit as a categorical variable with two conditions—legal speed limit greater than 53 mph (85 km/h) or below 53 mph (85 km/h), Lee and Mannering (2002) found that a crash will be more likely to have evident injury for speed limits above 53 mph (85 km/h).

A study by Khattak et al. (2002) found that older drivers have a lower probability of severe injury in crashes preceding 1997. Iowa increased speed limits on many of its highways in 1996 after the United States Congress repealed the national maximum speed limit in 1995. It is possible, therefore, that increasing speed limits may be one of the contributing factors to increased injury levels for older drivers after 1997. The Iowa Safety Management System Task Force on Speed Limits (1998) also recorded a trend of increasing fatalities, injuries, and total crashes after the speed limit change. The researchers indicated, however, the need for an in-depth analysis and assessment for the impact of the policy that permitted the increase in legal speed limit.

While many previous studies seemingly correlated increasing fatalities to higher speed limits and presumably higher associated operating speeds, some researchers reported study results with different perspectives. Renski et al. (1999) reported an inconclusive result of the effects of speed limit changes on fatalities due to having a small sample size of fatal crashes. They also argued that limitation and bias may have been present from factors such as study site selection (only sites with good safety records were chosen), crash type (single-vehicle crashes only), road functional classification (Interstate only), and time period (two-years only).

Balkin and Ord (2001), after accounting for seasonal patterns, assessed the influence of speed limit increases on fatal interstate crashes for a variety of United States rural and urban interstates. The influence of higher speed limits had different impacts on fatalities for rural and urban interstates and also varied from state to state. After many speed limits increased nationwide in 1995, higher speed limits were believed to slightly increase fatalities on rural interstates and to exhibit either a slight increase or no change for fatalities on urban interstates. Balkin and Ord (2001) emphasized the various effects of speed limit increases on injury severity for each individual state.

2.3.5 Wet versus Dry Pavement Conditions

The research focusing on pavement conditions has primarily addressed wet or dry pavement rather than pavement type. According to research by Kim et al. (2007), wet road conditions increase the likelihood of sideswipe, opposite direction crashes. Golob and Recker (2003) studied the relationships of crash types and traffic volume for prevailing weather and lighting conditions for an urban freeway in southern California. They found that wet road conditions increase the chance of crash occurrences that involve lane changing maneuvers, such as hit-object collisions and multiple-vehicle collisions. Meanwhile, dry road and day light conditions increase the occurrence of rear-end collisions.

Duncan et al. (1998) reported an increase in injury severity under wet pavement conditions while Krull et al. (2000) reported the opposite findings. Savolainen and Mannering (2007) found that wet pavement conditions were associated with less severe driver injuries.

2.3.6 Traffic Volume

A study by Golob and Recker (2003) revealed that traffic volume has a greater impact on crash severity than does speed. This result highlights the importance of incorporating traffic exposure in crash severity studies. Furthermore, Washington et al. (1999) reported the interactions of the traffic exposure as VMT for various road functional classifications. Duncan et al. (1998) also reported that congested conditions reduce injury severity.

While some studies confirmed the significant impact traffic exposure has on injury severity, Kim et al. (2007) found the influence of average annual daily traffic (AADT) on the probability of a specific crash type to be insignificant. They estimated models to predict the probability of crash occurrence categorized by crash types (including

angle, rear-end, and same and opposite direction sideswipe crashes) using crash data from rural signalized and unsignalized intersections in Georgia. They also indicated that AADT is highly associated with crash frequency with no direct relationship to crash types.

2.4 Crash Related Characteristics

Though many agencies historically have studied total crashes, it is clear that crash types and number of involved vehicles are directly associated with crash causation. Table 8 briefly summarizes the published literature for these crash related characteristics. This information is further summarized in Sections 2.4.1 and 2.4.2.

Table 8: Summary of Crash Related Characteristic Literature

Attributes	*Severity*
Crash Type	• Associated directly with specific road features such as horizontal curves or paved shoulders • Rollover, head-on crashes most fatal • Side-impact also more severe
Number of Involved Vehicles	• Increased number of occupants increases likelihood of severe injury

2.4.1 Crash Type

A variety of crash types such as rear-end, angle, single-vehicle, etc. are addressed in the published literature. Previous researchers identified the important role of crash type for safety analysis (Kim et al., 2007; Retting et al., 1994). Various studies have associated crash type with other potential contributing factors for crash injury severity and crash rate reduction.

Side-impact crashes tend to double the chance of a fatality compared to front impact crashes according to a study by Bedard et al. (2002). Evans and Frick (1993) also reported a higher driver fatality risk for side-impact crashes. For two-vehicle crashes

at signalized intersections, Abdelwahab and Abdel-Aty (2001) found that side-impact crashes increase injury severities compared to other impact points while an angle crash is one of the major crash types that will occur at intersections. Jones and Jorgensen (2003) analyzed a database for crashes in Norway and reported that fatality risk increased with head-on collisions compared to rear-end and side-impact collisions, a finding that is inconsistent with those of Bedar et al. (2002). Srinivasan (2002) found that crash severity increases for front impact, head-on collisions when compared to side-impact crashes. Krull et al. (2000) studied the effect of severity for rollover single-vehicle crashes and reported an increasing trend of driver injury severity with rollover crashes.

A few studies have targeted the older driver population and how this relates to crash type for fixed-object passenger car crashes involving older drivers. The probability of having more serious injuries tends to increase with front impact crashes, while side-impact crashes appear to increase minor injuries for the older driver population (Dissanayake and Lu, 2002).

In order to determine the influence on the probabilities of various crash types, Kim et al. (2007) estimated five separate multilevel models to predict the probability of crash occurrence categorized by crash types, including angle, head-on, rear-end, and same and opposite direction sideswipe crashes. This study used crash data from rural signalized and unsignalized intersections in Georgia. The study identified geometric features and signal control types as influential factors that impact the occurrence of corresponding types of crashes. Factors that contributed to increasing the odds of an angle crash included horizontal curve alignments compared to straight segments, and unsignalized intersections compared to signalized intersections. Rear-end crashes also were more likely to occur at unsignalized rural intersections compared to signalized rural intersections. Sideswipe same direction crashes occurred less at horizontal curves near intersections and at skewed intersections. Sideswipe opposite direction

crashes are also less likely to occur at horizontal or vertical curves near intersections. The study produced inconclusive results for head-on crashes due to a small sample size (n=16).

In addition to the studies devoted to the influence of crash types on severity, road geometric features, and traffic control devices, Golob and Recker (2003) studied the relationships between crash types and traffic volume after accounting for weather and lighting conditions for urban freeways in southern California. Their study found a strong association between collision types and typical traffic speed as well as temporal speed variations in the left and interior lanes.

According to a motorcycle fatal crash study (Preusser et al., 1995), crash types where vehicles leave their travel lanes and the crash led to either hitting a roadside fixed object or colliding with opposing traffic, were more likely to occur in rural areas, at high speed roadways, and at curve locations. Preusser et al. also noted that alcohol was often associated with these types of crashes. Meanwhile, urban intersections, where more traffic interaction occurs, were more often associated with angle crashes. Motorcycle crash patterns were generally consistent with motor vehicle crash patterns.

Jonsson et al. (2009) proposed to develop safety performance functions (SPFs) for crash counts by crash type rather than for total crash counts. This study challenged one common assumption of applying intersection SPFs, that crash type outcomes follow fixed proportions. The pre-assumed crash type distribution is often computed based on the crash data that are used to develop the SPFs. By only including AADT as an independent variable, this study clearly demonstrated that the fixed crash type proportion assumption is not always valid. Crash type proportion appeared to vary as a function of AADT for major and minor streets.

2.4.2 Number of Involved Vehicles

As stated previously, single-vehicle crashes have different crash dynamics compared to multiple-vehicle crashes. Studies have shown different influences on crash severity. For one Hong Kong study, Yau et al. (2006) found that the number of vehicles involved in traffic crashes had a significant impact on injury severities. The study determined that more vehicle involvement increases the likelihood of more serious or fatal injuries.

2.5 Environment Related Characteristics

The location and conditions under which a crash occurs can directly influence the likelihood of a crash as well as associated crash severity. Table 9 briefly summarizes the literature for environmental issues that is reviewed in detail in Section 2.5.1 through 2.5.3.

Table 9: Summary of Environment Related Characteristic Literature

Attributes	*Severity*	*Crash Type*
Weather Conditions	• Conflicting results regarding adverse weather injury severity depending on weather type • Dependent on other factors such as clearance policies and vehicle weather devices (tire traction, chains, etc.)	• Influence crash types: one-vehicle and two-vehicle crashes
Lighting Conditions	• Inconsistent results • Dependent on other factors such as reflective pavement marking, signage, etc.	• Influence crash types: single-vehicle and multiple-vehicle crashes
Urban and Rural	• Rural crashes increase injury severities	N/A

2.5.1 Weather Conditions

An interesting question in safety analysis is whether adverse weather conditions increase crash severity. Several studies reported a trend that adverse weather conditions tend to decrease injury severities (Wang and Kockelman, 2005; Edwards,1998). Khattak et al. (1998) found that adverse weather crashes occur more frequently but tend to be less severe.

Wang and Kockelman (2005) had a general finding that injury probability for vehicle occupants is lower during adverse weather conditions. They estimated a reduction by 16.4% and 32.5% for injury probability and fatality, respectively, for two-vehicle crashes during adverse weather conditions. The effect is even more significant for single-vehicle crashes. Wang and Kockelman interpreted the effect as possibly more cautious driving behavior during inclement weather conditions. Researchers have applied potential adjustments and compensations made by drivers corresponding to driving condition changes as a commonly used interpretation for some of these counterintuitive results (Khattak et al., 1998). Edwards (1998) also reported that rain significantly decreases crash severity compared to crashes occurring during dry weather conditions. Meanwhile, the study showed the effect from fog varies across geographical locations.

Some studies provide different findings based on weather and driver age groups. A study by Zhang et al. (2000) found that crashes during snow substantially increase the likelihood of fatal crashes by 60% for older drivers while the snowy/icy road surface (often after the snow has ceased to fall) has opposite effects. One hypothesis is that older drivers may tend to be more cautious, alert, or avoid driving entirely during icy road conditions. For younger drivers, Mao et al. (1997) did not find a significant impact from snow weather on crash severity. Kim et al. (2007) found clear weather conditions among the contributing factors that increase the odds of an angle crash.

2.5.2 Lighting Conditions

Research results regarding road lighting conditions and their role on crash occurrence present inconsistent findings for crash severity and crash types. These conflicting and sometimes counterintuitive results demonstrate the complexity of the role of lighting on safety and further suggest that there may be potential interactions with other unknown confounding factors.

Several studies suggest that reduced lighting conditions may significantly increase injury severity (Abdel-Aty, 2003; Khattak et al., 2002; Duncan et al., 1998). Other studies reported inconsistent findings regarding lighting conditions while taking into account the number of vehicles involved in crashes and crash types.

Wang and Kockelman (2005) determined that insufficient lighting conditions decrease injury severity for single-vehicle crashes while increasing injury severity for two-vehicle crashes. Yau et al. (2006) demonstrated a different observation for multiple-vehicle crashes in Hong Kong. At night, the poor street lighting appeared to decrease the risk of severe and fatal injuries while good light conditions at night presented the greater risk involving severe or fatal traffic crashes. Regional differences, such as driving behavior, roadway design standards, and geographical features might contribute to these inconsistent results. Kim et al. (2007) reported an increasing trend for all types of crashes when lighting is sufficient.

Pasetto and Manganaro (2009) investigated driving speed variation for nighttime versus daytime while negotiating S-shaped curves on rural roads. They found that the drivers' perceptions of horizontal curves were delayed for night driving no matter what the average driving speed. There was only a 45% deceleration observed on the tangent segment while approaching the horizontal curve leaving 55% deceleration in the curve. On the contrary, for daytime driving, most decelerations were completed on the approach tangent. Pasetto and Manganaro concluded that drivers are more

likely to be vulnerable at some geometric configurations where there is an underestimated night time driving risk.

2.5.3 Urban versus Rural

Various studies revealed a consistent pattern across roadway segments and intersections that rural locations tend to have an increased risk for more severe injuries than in urban environments (Krull et al., 2000; Jones and Jorgensen, 2003; Dissanayake and Lu, 2002; Abdelwahab and Abdel-Aty, 2001; Lee and Mannering, 2002). By their nature alone, urban and rural roadways differ in many ways including design standards, physical features, and traffic exposure. It is also likely that driving behavior differences also contribute to the safety performance for rural versus urban areas.

Krull et al. (2000) presented evidence that rural roads are more likely to increase the chances of drivers sustaining severe injury. In Norway, Jones and Jorgensen (2003) reported fatality risks increased in rural areas. After accounting for horizontal and vertical curvature conditions, crashes that occurred at rural locations still tended to be associated with more severe crashes compared to their in urban counterparts (Dissanayake and Lu, 2002). According to the study by Abdelwahab and Abdel-Aty (2001), drivers were more likely to sustain severe injuries at rural signalized intersections than at urban signalized intersections when the crash involved two vehicles.

2.6 Literature Summary

Table 5 through Table 9 provided an overview of the primary research findings in each of the five categories: driver and passenger related characteristics, vehicle related characteristics, roadway and roadside related characteristics, crash related characteristics, and environment related characteristics.

Many of the previous studies were based on crash databases from one state or select study corridors, while other studies focused on national fatality data. The various studies demonstrate many contradictions about crash type and severity and associated factors justifying the need to further explore both crash conditions and the rural road environment. In addition, most of the previous safety research focused on predicting crash frequency, crash rate, or injury severity. Crash types have not been well-studied or well-understood. This study will shed light on this issue based on the crash database from select southeastern states (specifically Alabama, Georgia, Mississippi, and South Carolina). The research will investigate the cross state differences and similarities in terms of the impact on crash conditions and potential contributing factors. The study's findings will ultimately help to explain the various safety performances on two-lane rural highways among the four states and offer guidance for generating countermeasures to mitigate potential safety concerns.

CHAPTER 3 SUMMARY STATISTICS OF STUDY CRASH DATA

3.1 Data Description

Previously, researchers from several states in the southeastern part of the United States participated in a rural fatal crash study. Of these states, final data is available for five states including Alabama, Georgia, North Carolina, South Carolina, and Mississippi. The database provided by North Carolina, however, does not include all of the study variables included in databases by the other four states. As a result, this summary focuses on fatal crash data statistics for the remaining states. Alabama and Georgia randomly selected 150 fatal crashes from FARS that occurred during 1997 for two-lane rural highways (Dixon, 2005). Mississippi has a smaller crash population and so researchers from that state developed a random sample of 100 fatal crashes for the year 1997. South Carolina evaluated 157 fatal crashes in their final analysis. These South Carolina fatal crashes occurred during 1998 (Dixon, 2005). Each participating state identified the candidate crashes and performed physical or video site visits. These site visits helped identify physical road features that are not commonly available in police crash reports.

Generally, each database included five types of data: crash data elements, site data elements, environmental data elements, person data elements, and vehicle data elements. All five data elements are presented in Appendix A (Dixon, 2005). Though certain overlaps can be expected between these data categories, the variables common to each are generally summarized as follows:

- *Crash Data Element*

  Crash data elements contain general crash characteristics such as crash date, time, location, numbers of involved vehicles, drivers, occupancy, severity, drug or alcohol usage, and similar information unique to each crash.

- *Site Data Element*

  Included in the crash databases is information unique to each specific crash location. Common variables included as site data elements are horizontal and vertical alignment information, cross-slope, functional classification, lane width, shoulder type, lane configuration, road surface type and condition, average daily traffic, intersection or driveway information, speed limit, roadside hazard ratings, and similar information unique to a specific location.

- *Environmental Data Element*

  The prevailing weather and lighting may influence crash causation. As a result, the environmental data elements included in the database include weather conditions, ambient light conditions, and road surface conditions.

- *Person Data Element*

  Data about the individuals involved in a crash can help illuminate how the crash occurred or why certain occupants survived the crash. This driver and passenger characteristic information includes gender, age, occupant protection equipment use, injury status, seating position, ejection status, and similar information unique to the vehicle occupants.

- *Vehicle Data Element*

The type of vehicle as well as vehicle status can directly influence crash conditions and survivability. As a result, the vehicle data elements included in the crash database incorporate vehicle characteristics include vehicle make, model, year, configuration, vehicle maneuvers, and vehicle towing status.

3.2 Data Representation

3.2.1 Driver Population

The FARS database contains all fatal traffic crashes in the United States including those that occur in the 50 states, the District of Columbia, and Puerto Rico. For a crash to be included in the FARS database, all resulting fatalities of vehicle occupants and non-motorists must have occurred within 30 days of the crash.

Figure 8 through Figure 11 depict a distribution of the four-state driver population distributions for nine age groups based on the driver gender. The male drivers in the age group of 16 to 20 years old represent a relatively high frequency across all four. For all states except Mississippi, both male and female drivers have the highest fatal crash frequency in the age group of 25 to 34 years old, while in Mississippi both the 25 to 34 years old age group and the 35 to 44 years old groups have similar high level frequencies for both male and female drivers.

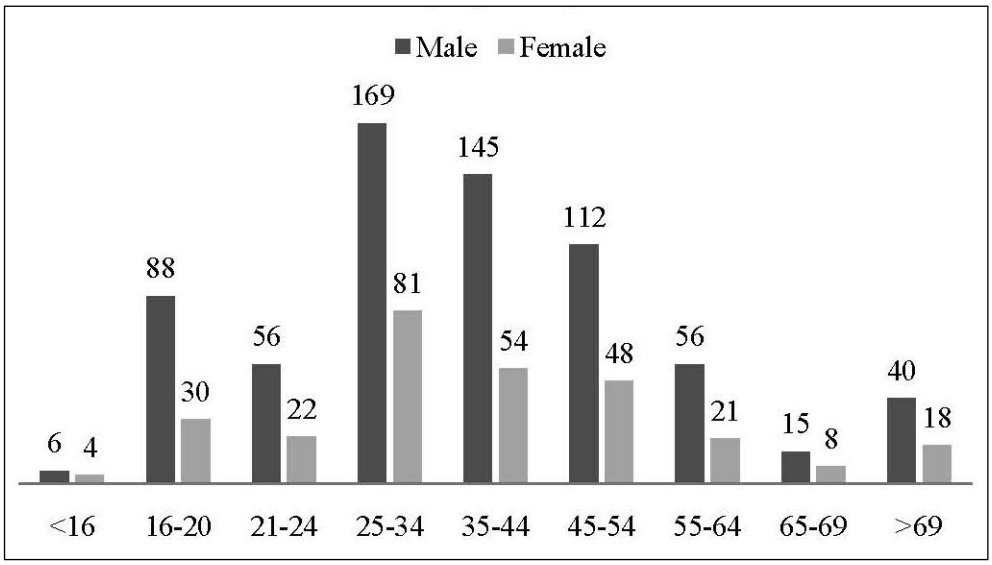


Figure 8: Alabama Driver Population Distribution by Age Group

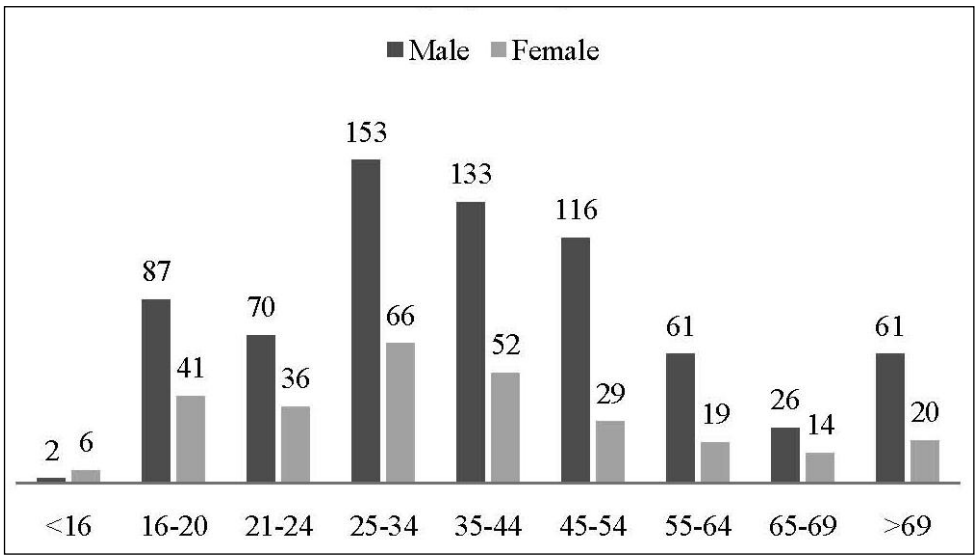


Figure 9: Georgia Driver Population Distribution by Age Group

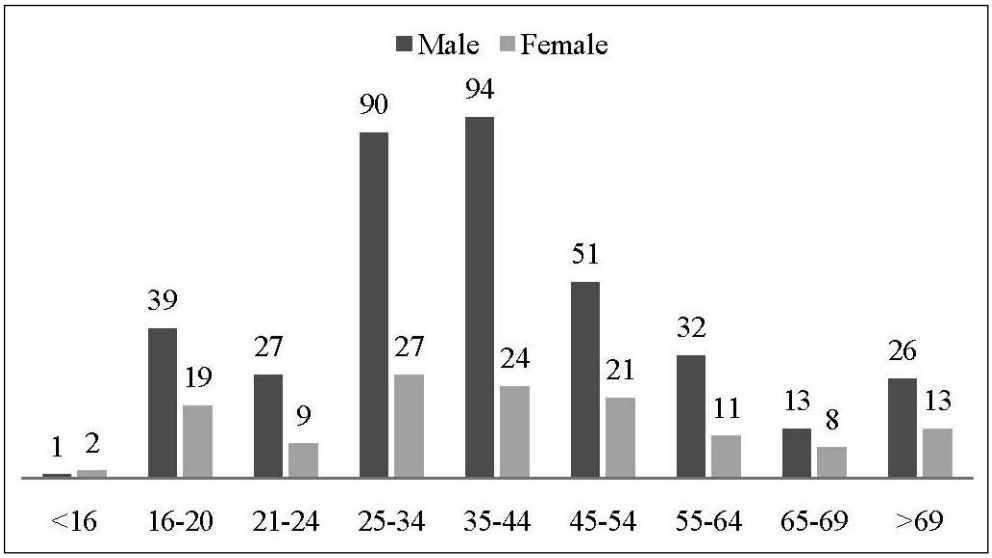


Figure 10: Mississippi Driver Population Distribution by Age Group

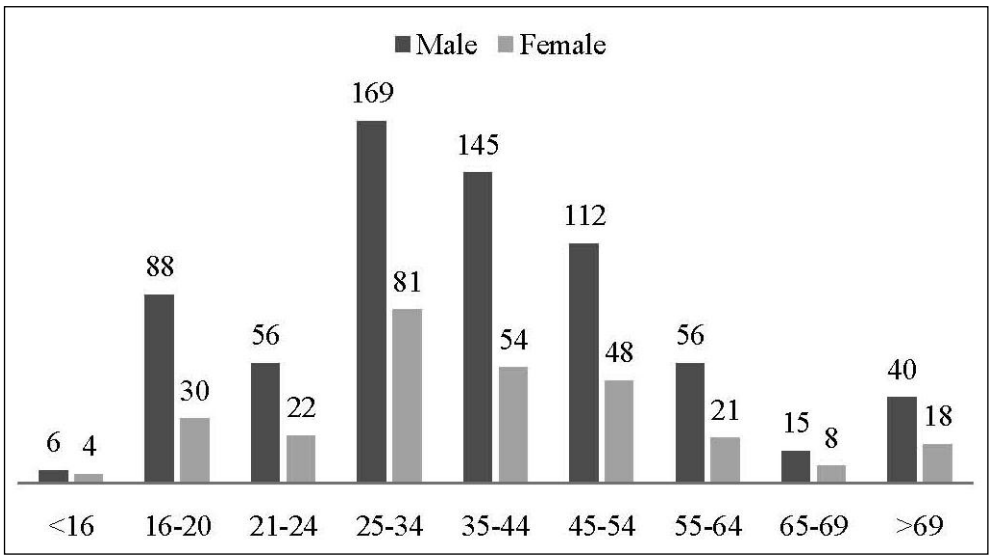


Figure 11: South Carolina Driver Population Distribution by Age Group

To determine whether the fatal crash sample data used for this study represents the general crash data population in FARS, the author applied a Pearson's chi-square test to the observed crash data. In this study, the Pearson's chi-square test is used to evaluate a null hypothesis that the frequency distribution of male and female drivers by age groups in the sample is consistent with the population distribution of drivers who were involved in fatal crashes for each individual state. Equation (3-1) demonstrates the equation for calculating this chi-square statistic. The degree of freedom of the chi-square statistic is the number of outcome categories (age groups of drivers = 9) minus one (df = 9-1 = 8).

$$\chi^2 = \sum_{i=1}^{n} \frac{(Observed_i - Expected_i)^2}{Expected_i} \tag{3-1}$$

Given:

$Observed_i$ = an observed frequency;

$Expected_i$ = an expected (theoretical) frequency under null hypothesis;

n = the number of outcome categories, n = 9 age groups.

Figure 12 through Figure 19 demonstrate the observed and expected male and female driver sample frequency distribution by age group for the four individual states. The graphs present the pattern of a consistent frequency distribution of drivers by age group for the study sample and the total FARS population. Table 10 presents chi-square test results for male and female drivers for the four focus states. The majority of the p-values from the tests are greater than the 0.05 statistically significant level (assuming 95% acceptance). This means that the statistical chi-square test does not reject the null hypothesis and the sample data is representative of the larger FARS data for the individual states. Overall, the test demonstrates convincing evidence that the sample data has a good representation of the data from FARS in this study. Noticeably, the p-value from male drivers of Georgia slightly exceeds but is very close to 0.05 (p-value=0.051). This suggests that the frequency of Georgia male drivers do not conform as closely to the FARS data as shown for other states and genders; however, the statistical test still gives compelling evidence that the data from all four states is a good representative sample of the overall FARS data in these states.

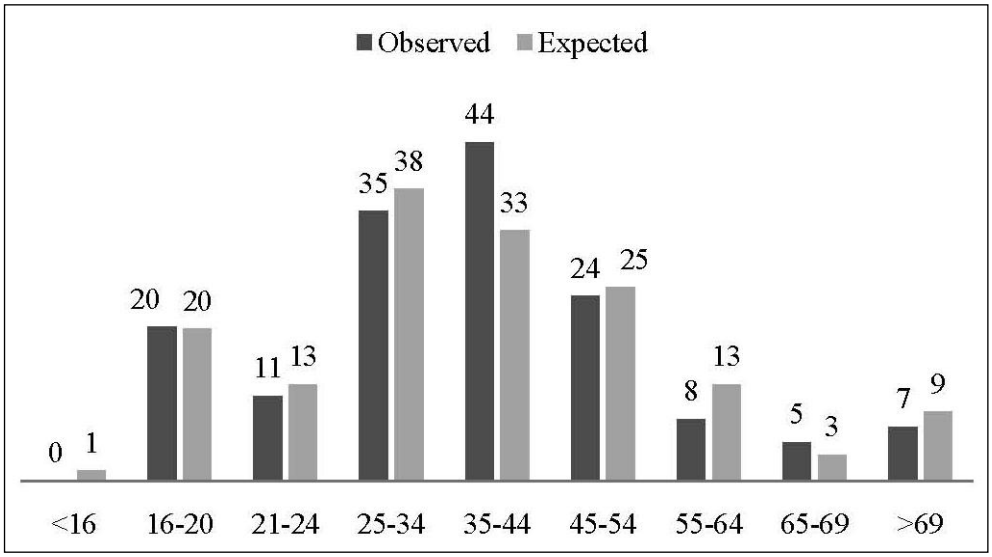


Figure 12: Alabama Male Driver Sample Distribution by Age Group

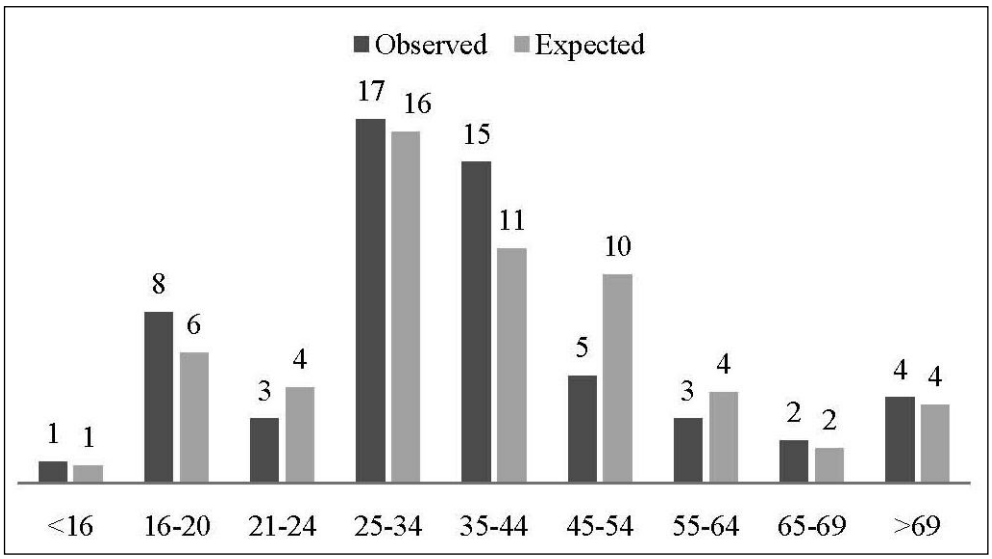


Figure 13: Alabama Female Driver Sample Distribution by Age Group

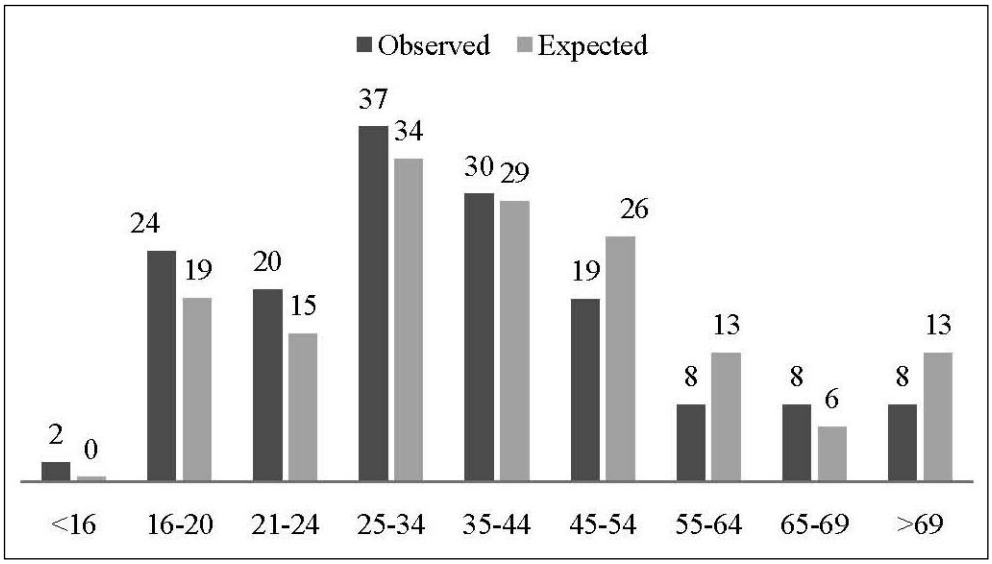


Figure 14: Georgia Male Driver Sample Distribution by Age Group

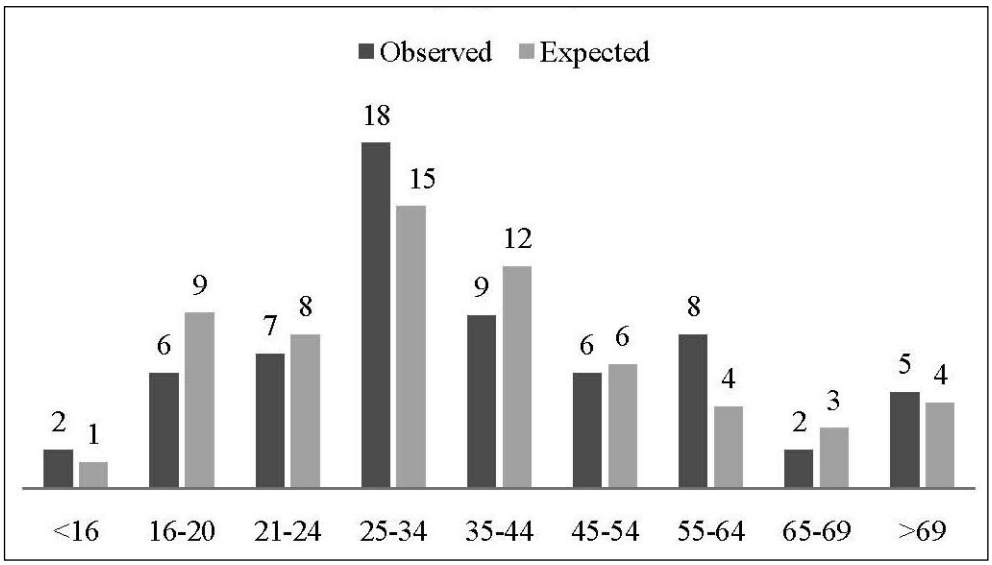


Figure 15: Georgia Female Driver Sample Distribution by Age Group

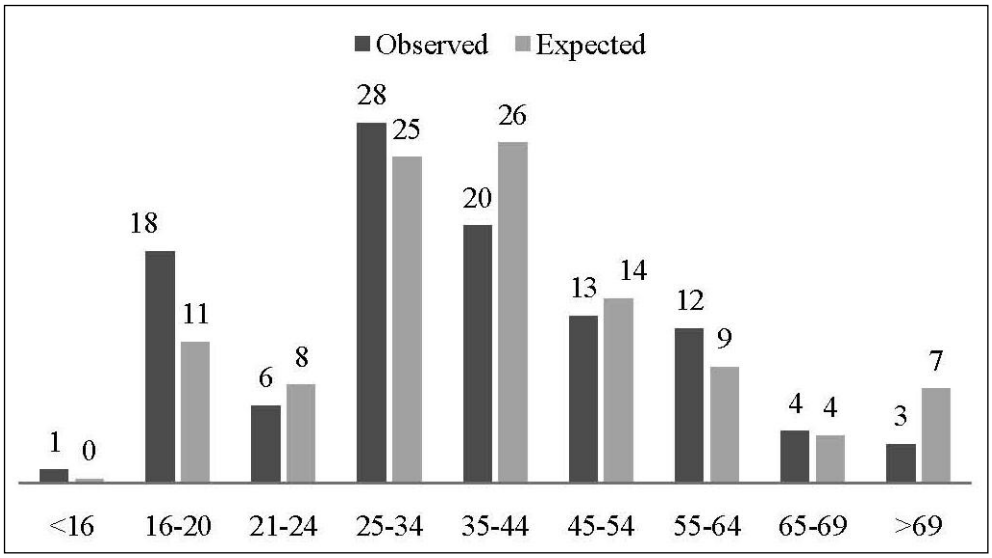


Figure 16: Mississippi Male Driver Sample Distribution by Age Group

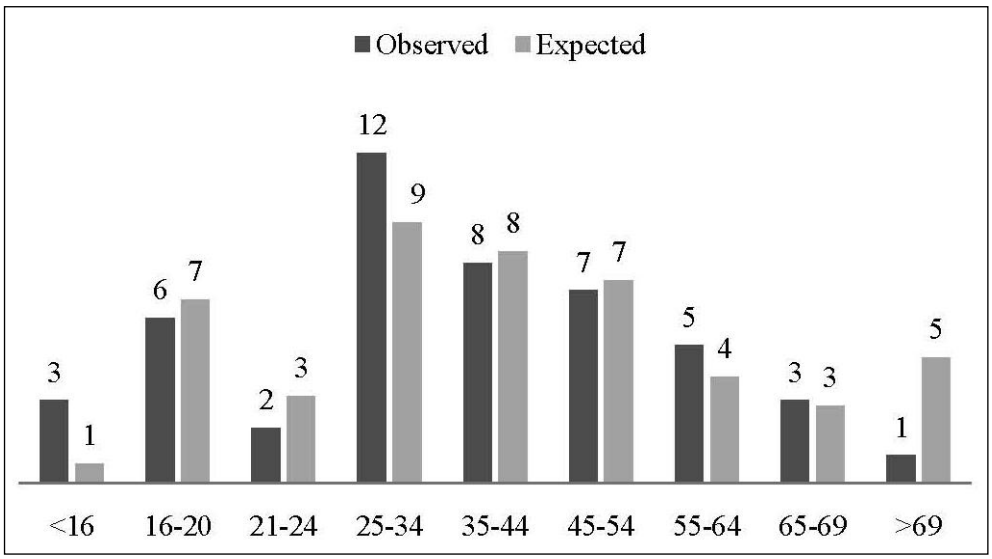


Figure 17: Mississippi Female Driver Sample Distribution by Age Group

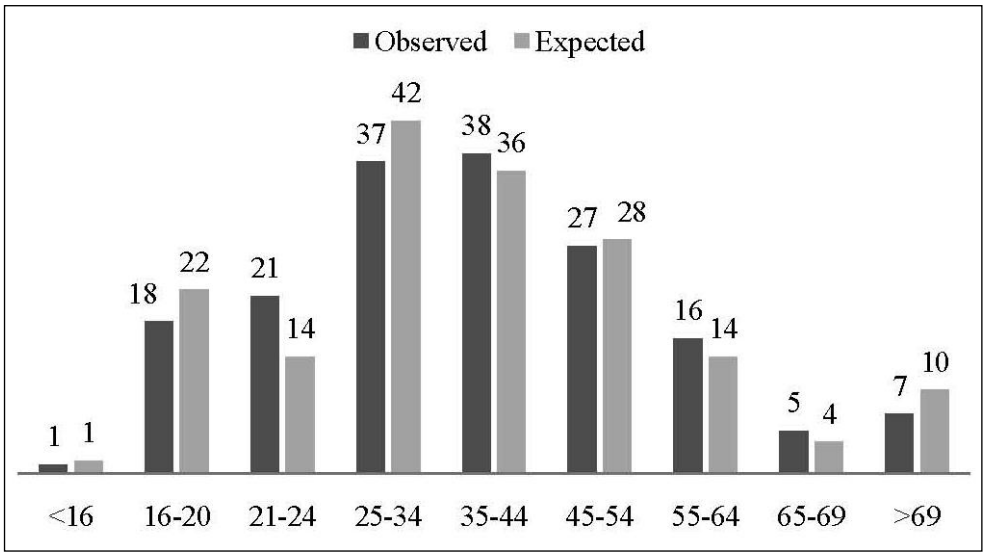


Figure 18: South Carolina Male Driver Sample Distribution by Age Group

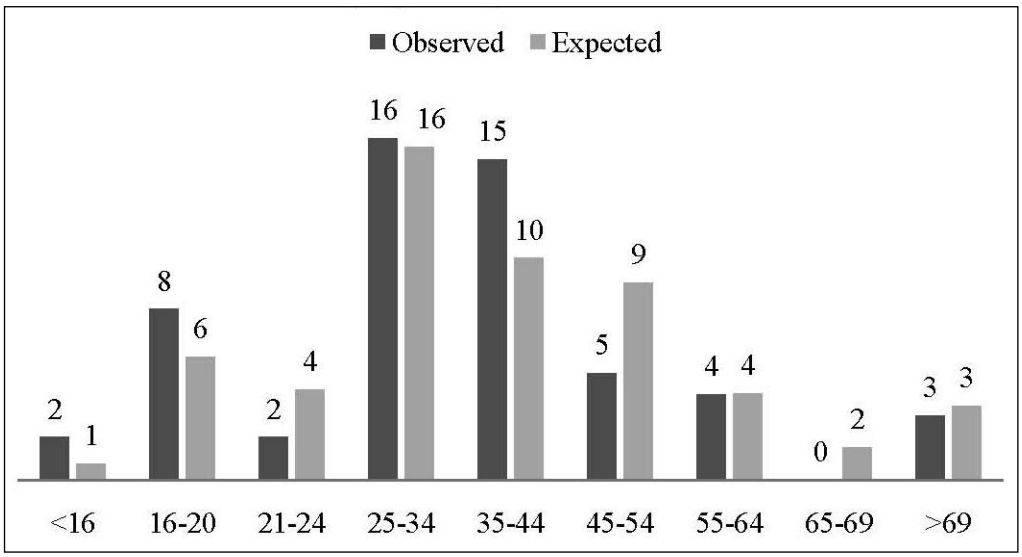


Figure 19: South Carolina Female Driver Sample Distribution by Age Group

Table 10: Pearson's Chi-Square Test Results of Driver Distribution

State	Male Driver		Female Driver	
	Chi-square Statistic	p-value	Chi-square Statistic	p-value
Alabama	8.76	0.36	5.44	0.71
Georgia	15.44	0.051	6.71	0.57
Mississippi	12.22	0.14	11.87	0.16
South Carolina	6.82	0.56	9.61	0.29

3.2.2 Regional Fatal Crash Trend

Since the fatal crash database was based on data that are now over ten years old, the research team examined a twelve-year fatal crash trend (1997 to 2008) based on the information extracted from the FARS for each individual state. The goal of this trend analysis was to determine if crash types and characteristics are the same today as over ten years ago. This analysis explored the fatal crash proportion changes of major fatal

crash characteristics across 12 years. The author chose to focus on the available variables in the FARS that are also used in the prediction models, including single-vehicle fatal crash proportion, head-on fatal crash proportion, lighting condition (Crash occurred under dark without supplemental lighting conditions), and crash location (Crash occurred on Non-Junctions or On Traffic Ways). Table 11 summarized the means and standard deviations for the corresponding variables. Most of the standard deviations have small thresholds, which indicate low variation of fatal crash distribution over time. Only Mississippi fatal crash proportions presented relatively larger variations for variables including single-vehicle, Non-Junction, and On-Traffic Ways. Meanwhile, Figure 20 to Figure 23 illustrate the 12-year profiles of the variables discussed in Table 11. The generally flat profiles of each state's fatal crash proportions while categorized by each variable under analysis depict a relatively stable pattern of fatal crash distributions in the past 12 years.

Table 11: Summary Statistics of 12-year (1997-2008) Fatal Crash Trend (AL, GA, MS, and SC)

Categories	Summary Statistics	Percentage of Fatal Crashes (1997-2008)			
		AL	**GA**	**MS**	**SC**
Single-Vehicle Fatal Crash	Mean	64.1	58.6	64.8	64.5
	Standard Deviation	2.7	2.8	4.9	3.2
Head-On Fatal Crash	Mean	15.1	14.7	18.0	9.8
	Standard Deviation	4.2	2.8	2.7	2.1
Dark without Supplemental Lighting Condition	Mean	40.9	36.2	39.1	45.9
	Standard Deviation	2.4	1.6	2.4	3.1
Non-Junction Locations	Mean	83.7	80.0	79.7	80.4
	Standard Deviation	3.2	2.0	5.9	3.0
On Traffic ways	Mean	45.6	51.9	44.0	48.2
	Standard Deviation	2.9	2.8	6.8	3.2

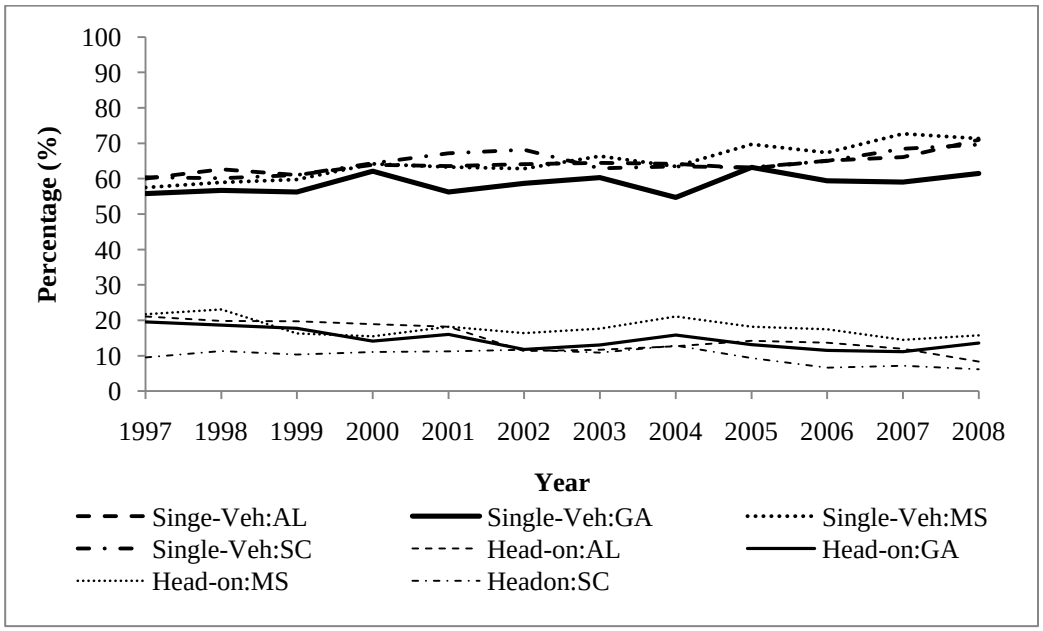


Figure 20: Percentage of Fatal Crash Types (1997-2008)

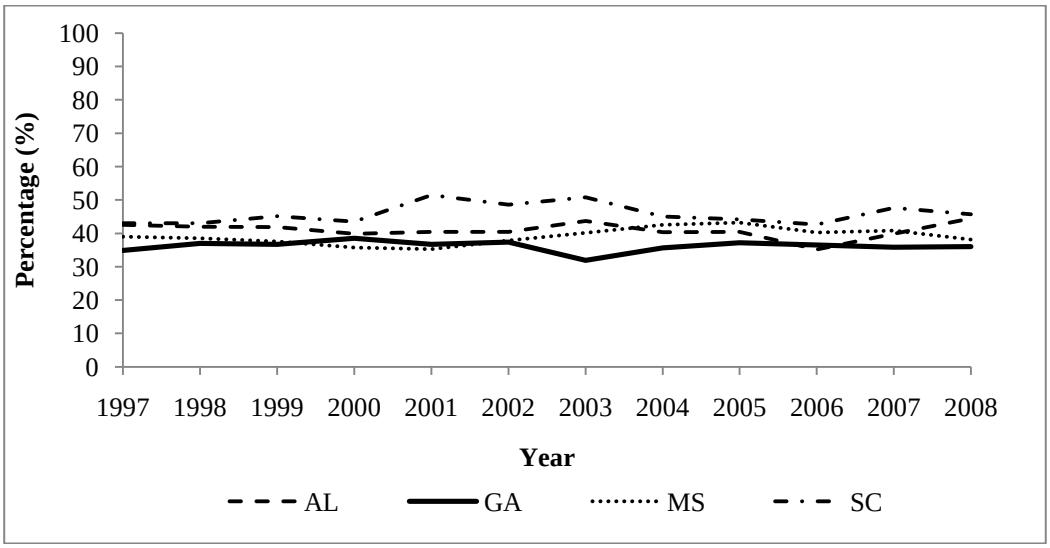


Figure 21: Percentage of Fatal Crashes Occurring Under Dark without Supplemental Lighting Conditions (1997-2008)

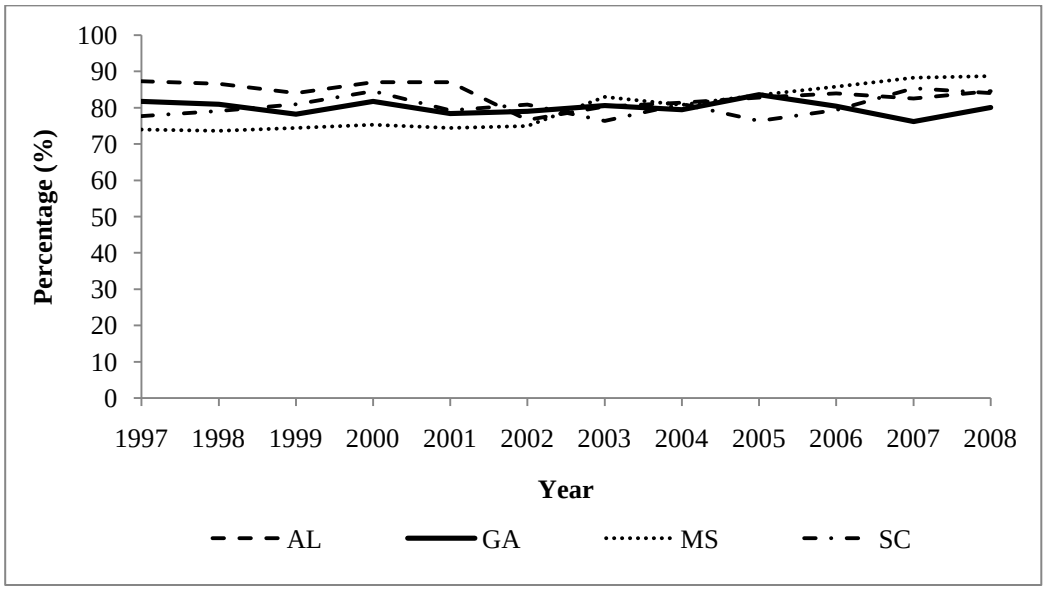


Figure 22: Percentage of Fatal Crashes Occurring on Non-Junction Locations (1997-2008)

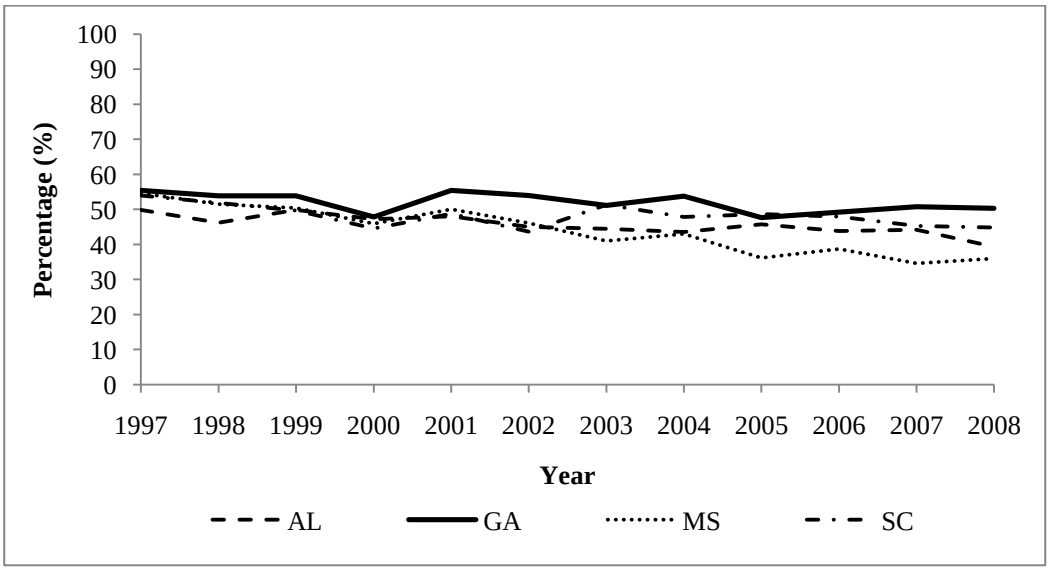


Figure 23: Percentage of Fatal Crashes Occurring On Trafficway (1997-2008)

Overall, the analysis suggests that fatal crash proportions did not appear to vary significantly over the past 12 years for the study states. The stable pattern of fatal crash proportion suggests that major fatal crash characteristics may only have mild

fluctuations rather than significant shifts in the past decade. The stability of fatal crash data within a 12-year period offers confidence and reliability for applying the fatal crash type prediction models that the author developed based on the fatal crash data from 1997 to 1998 for current practice.

3.3 Descriptive Statistics

3.3.1 Crash Data Characteristics

For fatal crashes in the four states, an average of 58% were single-vehicle crashes and 42% were multiple-vehicle crashes (see Table 12 and Figure 24). As shown in Figure 25, head-on crashes and angle crashes were two common multiple-vehicle crash types accounting for 36% of total fatal crashes. The study data clearly demonstrates that single-vehicle crashes, head-on crashes, and angle crashes are three major fatal crash types that tend to have a greater risk for fatalities compared to rear end and sideswipe crashes.

Table 12: Crash Type Distribution for Study Crashes

Crash Type	Alabama (%)	Georgia (%)	Mississippi (%)	South Carolina (%)	Average (%)
Single-Vehicle Crash	64	59	50	61	58
Multiple-Vehicle Crash	36	41	50	39	42
Head-on	18	17	19	15	17
Angle	12	18	21	24	19
Rear End	5	2	4	0	3
Sideswipe Same Direction	1	2	1	0	1
Sideswipe Opposite Direction	0	2	5	0	2
Others	0	0	0	1	0

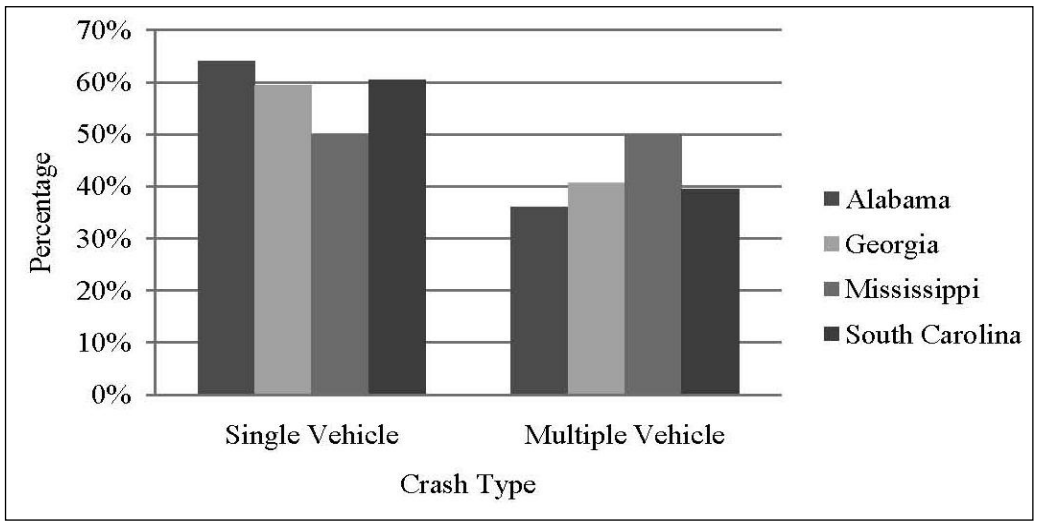


Figure 24: Single vs. Multiple-Vehicle Fatal Crashes

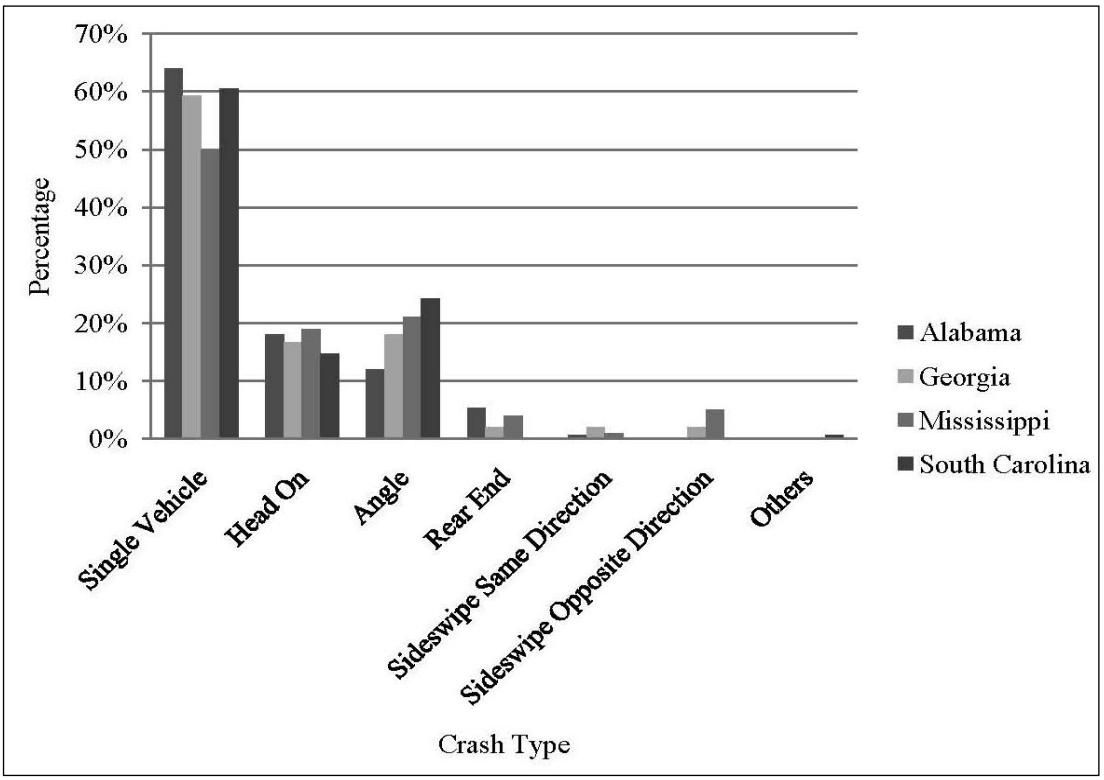


Figure 25: Fatal Crash Type Distribution

3.3.1.1 Crash Distribution by Month

The distribution patterns for single-vehicle fatal crashes and multiple-vehicle fatal crashes differed. For single-vehicle fatal crashes, most states exhibited a relatively higher crash frequency around April and May, while the crash frequency of multiple-vehicle fatal crashes peaked around May and October (see Table 13, Figure 26 and Figure 27). More notably, single-vehicle fatal crash frequency for Georgia and Mississippi peaked in April with 11% and 9% of total fatal crashes, respectively. Meanwhile, multiple-vehicle fatal crash frequency for Georgia peaked in November with 7% of total fatal crashes. Mississippi experienced a peak of 8% of total fatal crashes in October.

Table 13: Crash Distribution by Month

State	Crash Type	Month											
		Jan (%)	Feb (%)	Mar (%)	Apr (%)	May (%)	Jun (%)	Jul (%)	Aug (%)	Sep (%)	Oct (%)	Nov (%)	Dec (%)
AL	Single-Vehicle	3	7	5	5	7	3	5	6	7	5	5	4
	Multiple-Vehicle	2	1	5	1	5	3	3	3	3	4	3	5
	AL Total	5	8	10	6	12	6	8	9	10	9	8	9
GA	Single-Vehicle	5	5	7	11	5	3	4	4	3	4	4	5
	Multiple-Vehicle	4	3	1	3	5	5	1	4	5	2	**7**	2
	GA Total	9	8	8	14	10	8	5	8	8	6	11	7
MS	Single-Vehicle	2	2	5	9	5	3	3	3	5	5	4	4
	Multiple-Vehicle	3	3	4	3	5	4	3	5	3	8	3	4
	MS Total	5	5	9	12	10	7	6	8	8	13	7	8
SC	Single-Vehicle	5	5	4	6	9	8	4	4	6	5	2	3
	Multiple-Vehicle	1	1	2	4	6	3	5	4	1	6	2	3
	SC Total	6	6	6	10	15	11	9	8	7	11	4	6

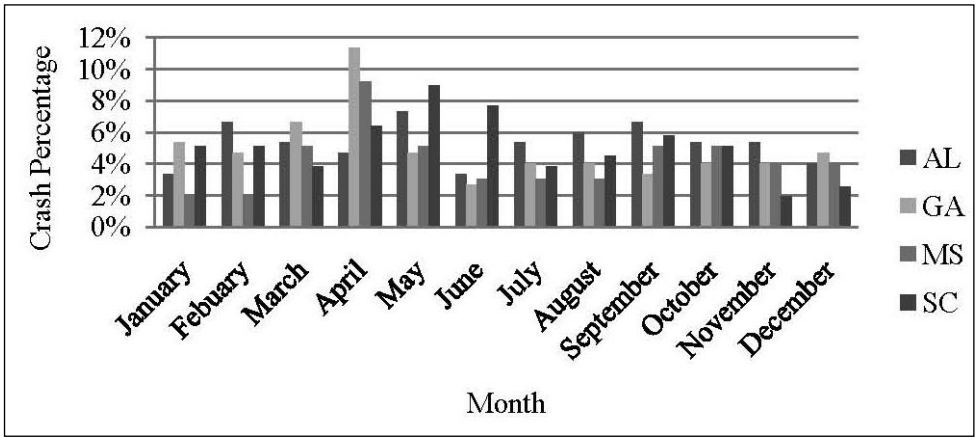


Figure 26: Single-Vehicle Fatal Crashes by Month

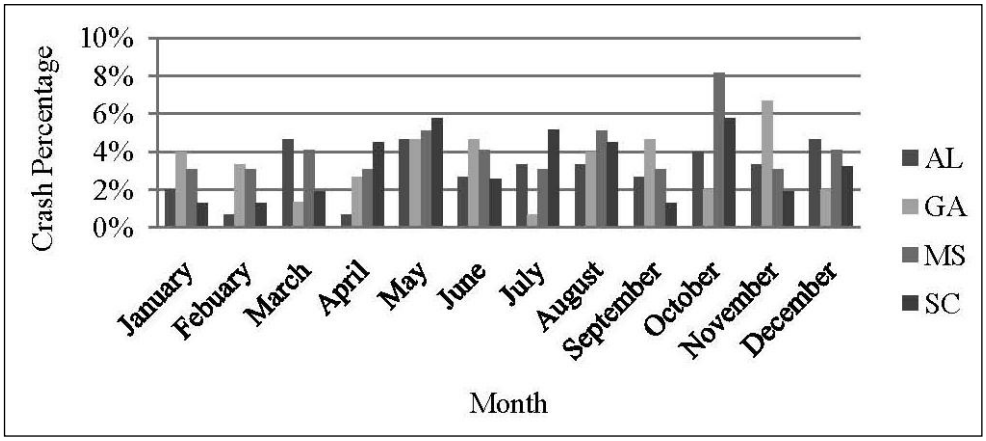


Figure 27: Multiple-Vehicle Fatal Crashes by Month

3.3.1.2 Crash Distribution by Day of Week

Table 14 and Figure 28 present a day-of-week pattern for single-vehicle fatal crash distribution across the four states when about 10% to 15% of the total fatal crashes occurred during the weekend compared to 3% to 9% during weekdays. Figure 29, however, demonstrates that multiple-vehicle fatal crashes occurred regularly on Friday

and Saturday. The crash percentage was as high as 14% on these days compared to a high of 9% for weekdays. South Carolina data did not provide adequate information for a day of week evaluation.

Table 14: Crash Distribution by Day of Week

State	Crash Type	Day of Week (percent per state)							Total Percent
		Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	
		(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)
AL	Single-Vehicle	7	8	7	9	7	14	12	64
	Multiple-Vehicle	3	3	6	3	9	7	5	36
	AL Total	10	11	13	12	16	21	18	--
GA	Single-Vehicle	5	7	4	6	8	13	15	58
	Multiple-Vehicle	4	5	6	8	5	9	4	41
	GA Total	9	12	10	14	13	22	19	--
MS	Single-Vehicle	6	6	6	4	4	14	10	50
	Multiple-Vehicle	4	6	4	6	9	11	10	50
	MS Total	10	12	10	10	13	25	20	--

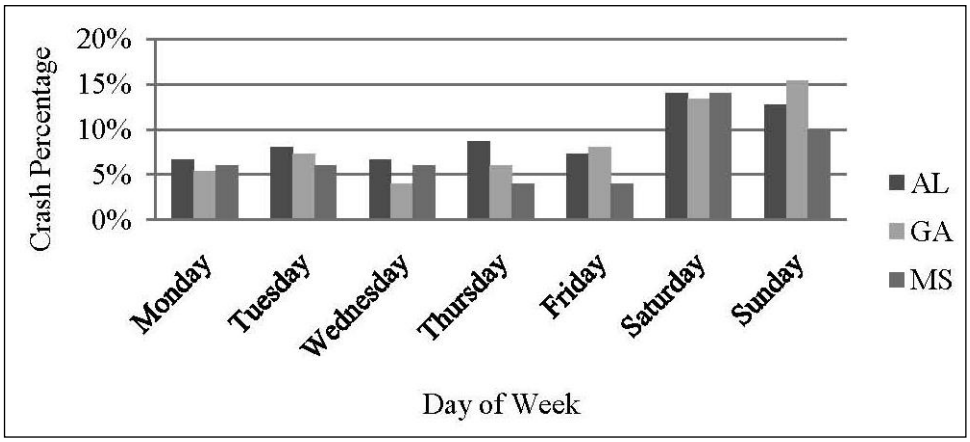


Figure 28: Single-Vehicle Fatal Crashes by Day of Week

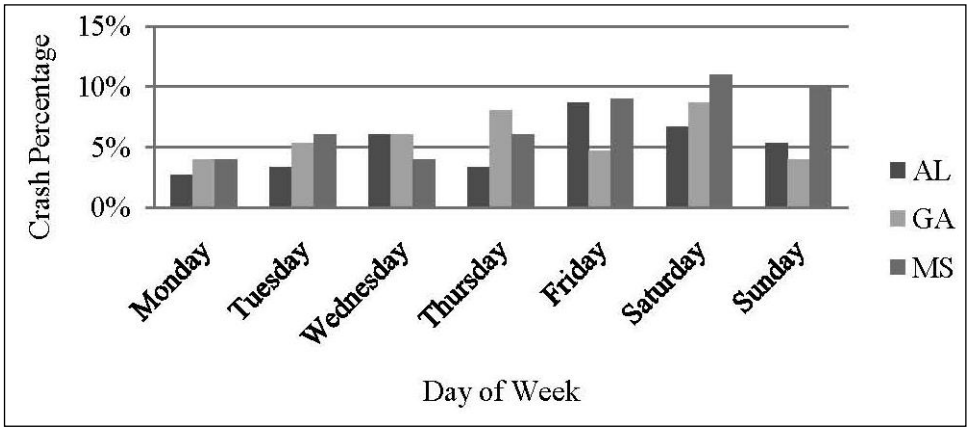


Figure 29: Multiple-Vehicle Fatal Crashes by Day of Week

3.3.2 Roadway and Roadside Related Characteristics

3.3.2.1 Horizontal Alignment Direction and Curve Radius

The horizontal alignment variable includes three conditions: straight alignment, horizontal curve to the left, and horizontal curve to the right. A second variable referred to as horizontal curvature further separates curves into two groups: sharp and mild curve. Sharp curves are those that require drivers to make speed adjustments, while mild curves do not require drivers to reduce their speeds.

For the four states with comprehensive data, more than 50% of the rural two-lane road fatal crashes occurred on road segments with straight horizontal alignments (see Table 15). At horizontal curve locations, curves to the left tended to have a stronger association with the single-vehicle fatal crashes than did similar crashes at curves to the right (see Figure 30). Meanwhile, as shown in Figure 31, curves to the right were more frequently associated with multiple-vehicle fatal crashes.

In Alabama and South Carolina, mild horizontal curves (curves with large radii) were often associated with single-vehicle fatal crashes (see Figure 32). In Georgia and Mississippi, sharp horizontal curve locations were strongly associated with single-vehicle fatal crashes. Many of the multiple-vehicle fatal crashes occurred at straight alignment locations, but Mississippi and South Carolina had stronger associations between mild curve locations and multiple-vehicle fatal crash occurrences than those that occurred in from Alabama and Georgia.

Table 15: Crash Type by Horizontal Alignment Direction and Horizontal Curvature

State	Crash Type	Straight Alignment (%)	Curve to the Left (%)	Curve to the Right (%)	Unknown Curve Direction (%)	Sharp Curve (%)	Mild Curve (%)	Unknown Curve Radius (%)
AL	Single-Vehicle	31	23	10	-	10	23	-
	Multiple-Vehicle	28	5	3	-	3	5	-
	AL Total	59	28	13	-	13	28	-
GA	Single-Vehicle	31	17	12	-	17	11	-
	Multiple-Vehicle	20	6	15	-	10	11	-
	GA Total	51	23	27	-	27	22	-
MS	Single-Vehicle	22	14	14	-	18	10	-
	Multiple-Vehicle	29	9	12	-	6	15	-
	MS Total	51	13	26	-	24	25	-
SC	Single-Vehicle	27	17	16	1	3	31	1
	Multiple-Vehicle	22	8	9	1	2	15	-
	SC Total	49	25	25	2	5	46	1

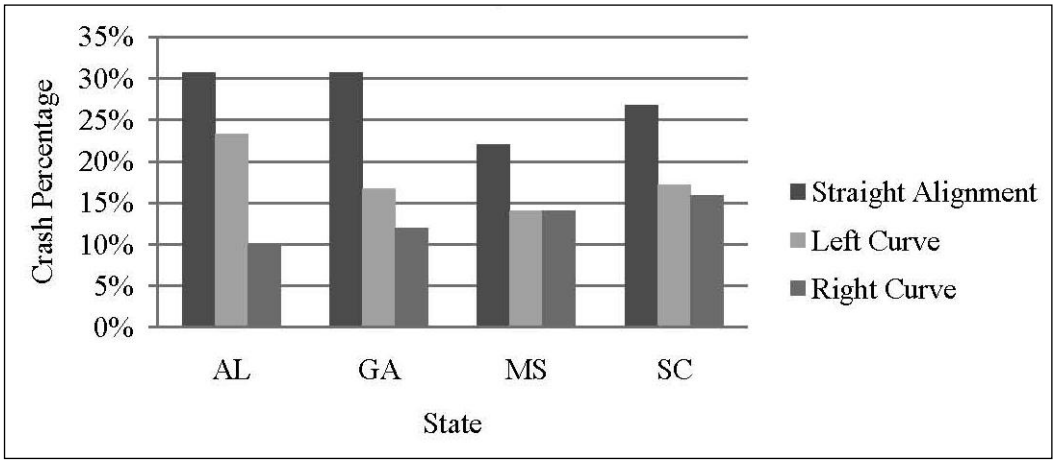


Figure 30: Single-Vehicle Fatal Crashes and Associated Horizontal Alignment

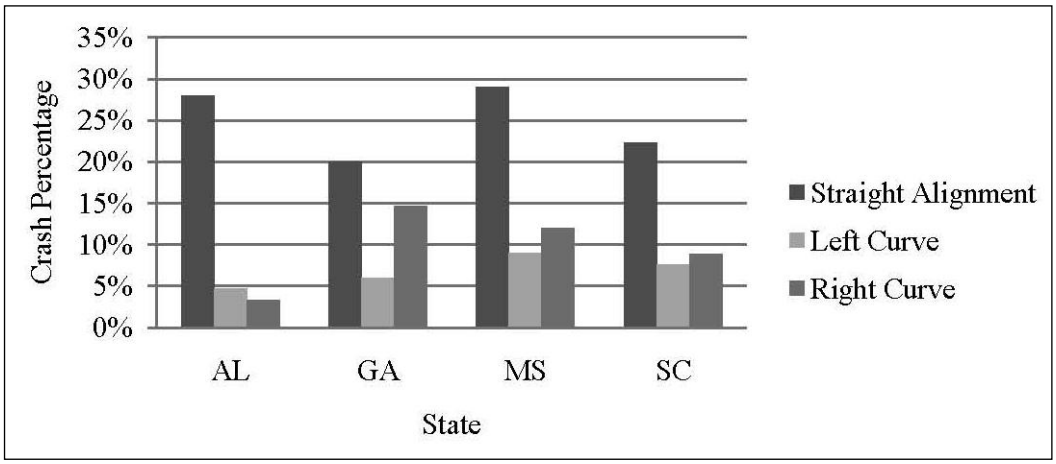


Figure 31: Multiple-Vehicle Fatal Crashes and Associated Horizontal Alignment

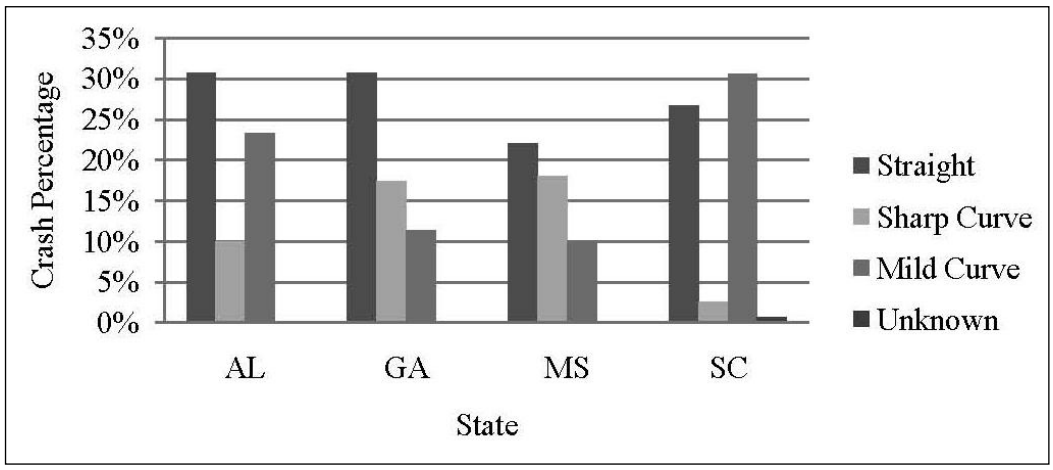


Figure 32: Single-Vehicle Fatal Crashes and Associated Horizontal Curvature

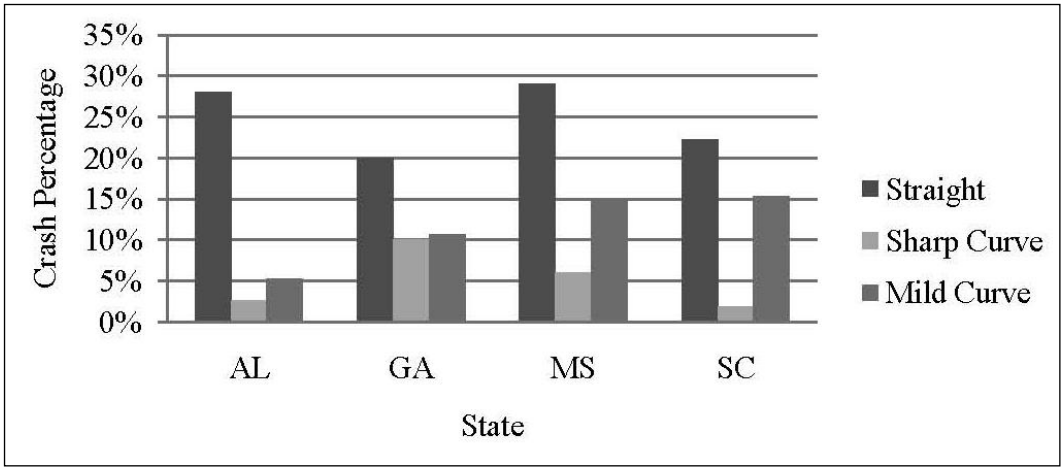


Figure 33: Multiple-Vehicle Fatal Crashes and Associated Horizontal Curvature

3.3.2.2 Vertical Grade

A steep vertical grade could have a potential influence on the likelihood of crashes, so the database included a vertical grade variable that incorporated the direction of vertical slope (uphill, downhill, and flat) and percentage of grade (level: 1%; mild slope: 2-6%; steep slope: >6%).

Table 16 demonstrates the distribution of single-vehicle and multiple-vehicle fatal crashes located at uphill, downhill, and flat locations (see also Figure 34 and Figure 35). In Alabama, Georgia, and Mississippi, single-vehicle fatal crashes were more often associated with downhill slopes than uphill slopes. Figure 35 demonstrates that in Alabama and Georgia, multiple-vehicle fatal crashes were also more often associated with downhill slopes than their uphill counterparts. As depicted in Table 16, most of the study crashes occurred at mild or level vertical grade locations.

Table 16: Crash Type by Vertical Grade

State	Crash Type	Direction of Slope				Vertical Grade			
		Uphill (%)	Downhill (%)	Flat (%)	NA (%)	Level (%)	Mild (%)	Steep (%)	NA (%)
AL	Single-Vehicle	7	33	25	-	13	26	1	23
	Multiple-Vehicle	6	11	19	-	11	11	0	13
	AL Total	13	44	44	-	24	37	1	36
GA	Single-Vehicle	19	20	21	-	12	25	1	21
	Multiple-Vehicle	13	19	9	-	13	17	1	9
	GA Total	32	39	30	-	25	42	2	30
MS	Single-Vehicle	9	17	24	-	18	20	1	11
	Multiple-Vehicle	12	12	26	-	18	20	1	11
	MS Total	21	29	30	-	36	40	2	22
SC	Single-Vehicle	15	14	31	-	15	15	1	30
	Multiple-Vehicle	11	10	18	1	10	12	1	17
	SC Total	26	24	49	1	25	27	2	47

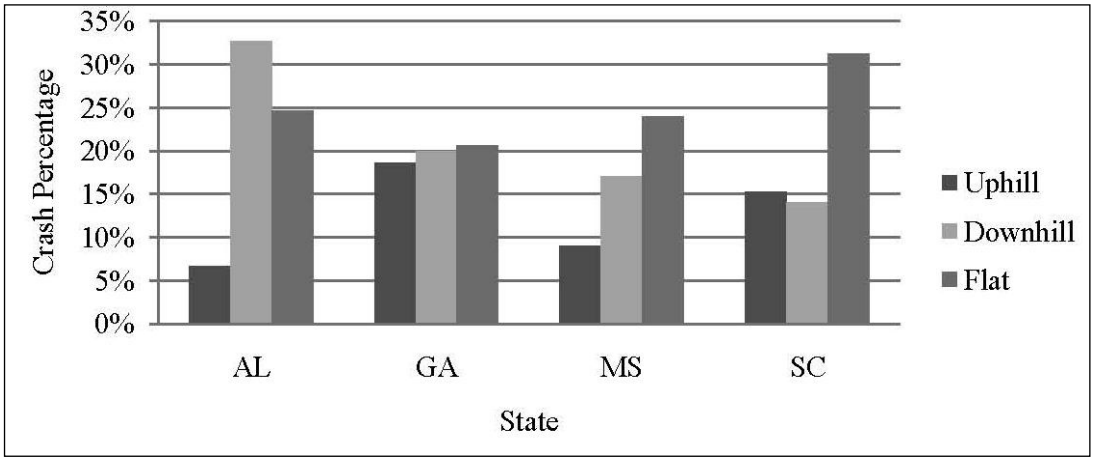


Figure 34: Single-Vehicle Crashes by Vertical Grade

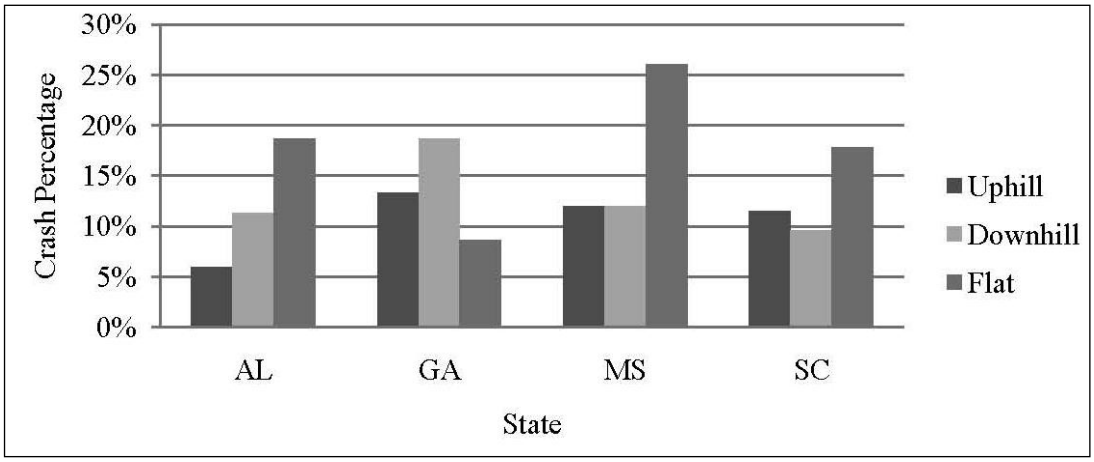


Figure 35: Multiple-Vehicle Crashes by Vertical Grade

3.3.2.3 Cross Section Configuration

The cross section configuration variable describes the cross-slope of the road segment at the crash location. Single-vehicle fatal crashes occurred more often at locations with typical rooftop configurations than at superelevated locations (see Table 17 and Figure 36). Highway design principles typically require the use of rooftop cross sections at

straight (tangent) alignment locations, while curved locations are generally superelevated. Multiple-vehicle crashes in Alabama, Mississippi, and South Carolina occurred more often at locations with rooftop cross sections. In Georgia, multiple-vehicle fatal crashes occurred similarly at rooftop and superelevated locations (see Figure 37).

Table 17: Cross Section Configuration by Crash Type

State	Crash Type	Cross Section		
		Rooftop (%)	Superelevated (%)	Others (%)
AL	Single-Vehicle	35	29	1
	Multiple-Vehicle	27	8	1
	AL Total	62	37	1
GA	Single-Vehicle	32	26	1
	Multiple-Vehicle	21	19	1
	GA Total	53	45	2
MS	Single-Vehicle	26	23	1
	Multiple-Vehicle	34	16	0
	MS Total	60	39	1
SC	Single-Vehicle	34	26	1
	Multiple-Vehicle	24	16	0
	SC Total	58	42	1

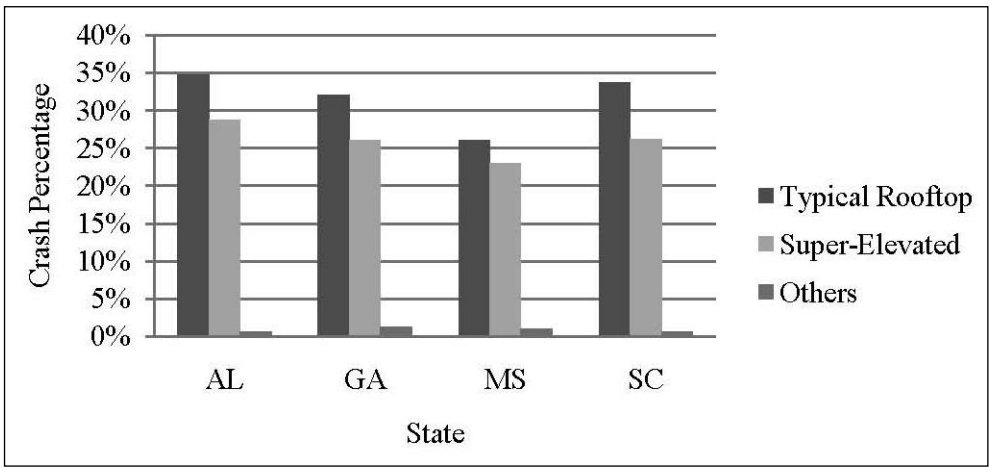


Figure 36: Single-Vehicle Crashes by Cross Section Configuration

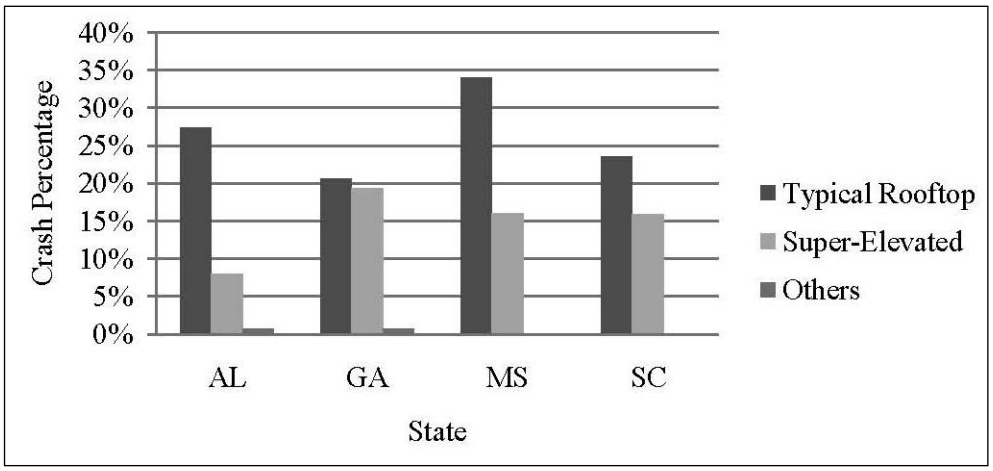


Figure 37: Multiple-Vehicle Crashes by Cross Section Configuration

3.3.2.4 National Highway System

As shown in Table 18, all four states had 79% or more of the fatal crashes that occurred on two-lane rural highways that were not a part of the national highway system. A higher percentage of the multiple-vehicle fatal crashes occurred on the national highway system than for the single-vehicle fatal crashes.

Table 18: Crash Occurrence on National Highway System

State	Crash Type	National Highway System	
		Yes (%)	No (%)
AL	Single-Vehicle	2	62
	Multiple-Vehicle	9	27
	AL Total	11	89
GA	Single-Vehicle	9	50
	Multiple-Vehicle	12	29
	GA Total	21	79
MS	Single-Vehicle	0	50
	Multiple-Vehicle	3	47
	MS Total	3	97
SC	Single-Vehicle	4	57
	Multiple-Vehicle	7	32
	SC Total	11	89

3.3.2.5 Road Functional Classification

The functional classification for the two-lane rural highways included major arterial, minor arterial, major collector, minor collector, local roads, and unknown. As shown in Table 19, Figure 38, and Figure 39, the road functional classifications were distributed differently between single-vehicle and multiple-vehicle fatal crashes. In addition, the study observed a unique functional classification distribution for Mississippi by the complete absence of arterials for the study sites. It is reported recently in the “2008 Mississippi Five Percent Report to the FHWA” that some data

errors were identified in previous years' crash database. Even though it is not clear how much data were affected and to what level, there is a chance that the Mississippi fatal crash data might contain some potential issues. The process of correcting the existing errors is ongoing. The notable fatal crash distribution difference for the functional classification between Mississippi and the other three southeastern states may be caused by differing standards applied to classify rural two-lane highways in each state.

Table 19: Crash Occurrence per Road Functional Classification

State	Crash Type	Road Functional Classification					
		Major Arterial (%)	Minor Arterial (%)	Major Collector (%)	Minor Collector (%)	Local (%)	Unknown (%)
AL	Single-Vehicle	5	11	28	11	9	1
	Multiple-Vehicle	10	8	13	1	4	0
	AL Total	15	19	41	12	13	1
GA	Single-Vehicle	4	11	21	9	14	0
	Multiple-Vehicle	9	13	15	3	2	0
	GA Total	13	24	36	12	16	0
MS	Single-Vehicle	0	0	0	27	23	0
	Multiple-Vehicle	0	0	1	41	8	0
	MS Total	0	0	1	68	31	0
SC	Single-Vehicle	4	11	30	4	1	10
	Multiple-Vehicle	9	15	13	1	1	1
	SC Total	13	26	43	5	2	11

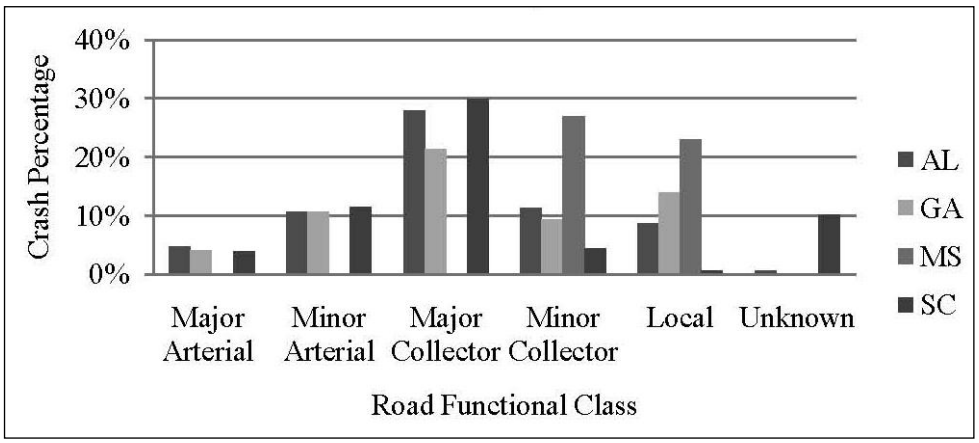


Figure 38: Single-Vehicle Fatal Crashes by Road Functional Classification

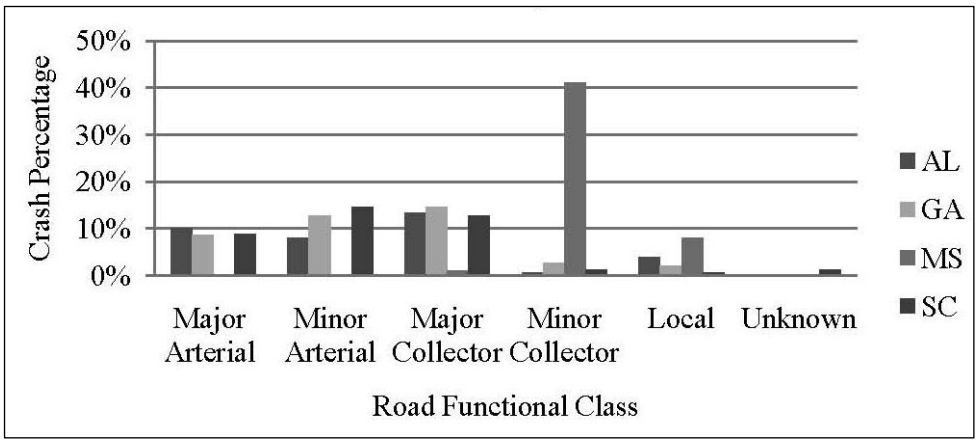


Figure 39: Multiple-Vehicle Fatal Crashes by Road Functional Classification

3.3.2.6 Lane Width

Table 20, Figure 40, and Figure 41 clearly demonstrate a pattern that the association of lane width is different for the single-vehicle fatal crashes than for the multiple-vehicle fatal crashes. As the lane widths narrow from 12 ft (3.6 m) to 10 ft (3.0 m), the associated percentages of fatal crashes that were single-vehicle crashes increased from

12% to 21% on average, while multiple-vehicle crashes decreased from 21% to 7% on average.

Many researchers have suggested that wider lanes are more likely to enable speeding behavior. This increase in speed is thought to lead to many potential crash causation factors. Even though the data can be interpreted that 12 ft (3.6 m) wide lanes appear to be safer compared to the 10 ft (3.0 m) lanes for single-vehicle fatal crashes, lane widening may not always assure crash reduction due to the possible increased speed environment.

Table 20: Crash Type by Lane Width Distribution

Lane Width (ft)	AL		GA		MS		SC	
	Single-Vehicle (%)	Multiple-Vehicle (%)	Single-Vehicle (%)	Multiple-Vehicle (%)	Single-Vehicle (%)	Multiple-Vehicle (%)	Single-Vehicle (%)	Multiple Vehicle (%)
7	0	0	0	0	2	0	0	0
8	1	1	1	0	0	0	2	1
8.5	0	0	1	1	0	0	0	0
9	8	1	5	2	4	2	6	0
9.5	0	0	6	1	0	0	0	0
10	21	9	15	3	18	7	29	7
10.5	0	0	3	3	0	0	0	0
11	19	5	12	9	12	15	16	14
11.5	0	0	1	1	0	0	0	0
12	15	21	11	20	14	25	7	17
12.5	0	0	1	0	0	0	0	0
13	0	0	1	0	0	0	1	0
14	0	0	0	0	0	1	0	0
17	0	0	0	0	0	0	1	0
NA	0	0	1	0	0	0	0	1

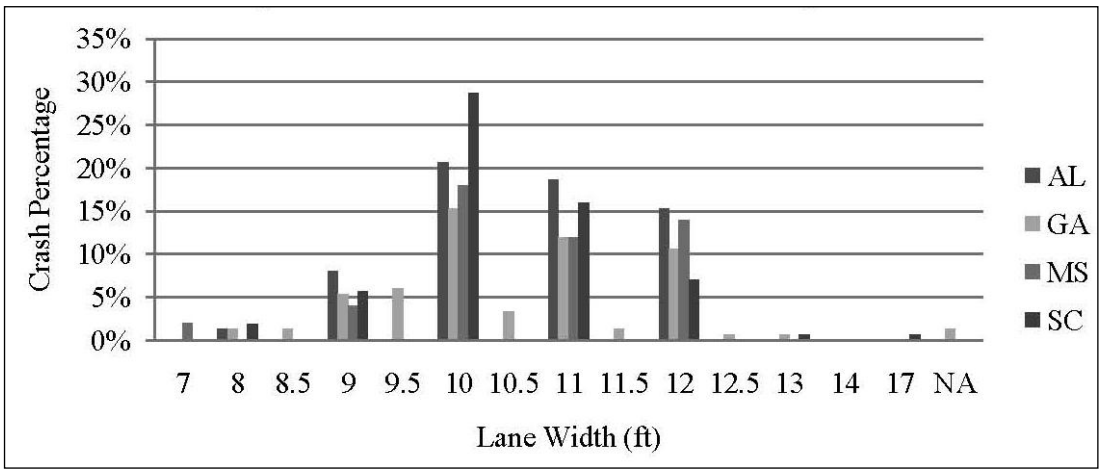


Figure 40: Single-Vehicle Fatal Crashes by Lane Width

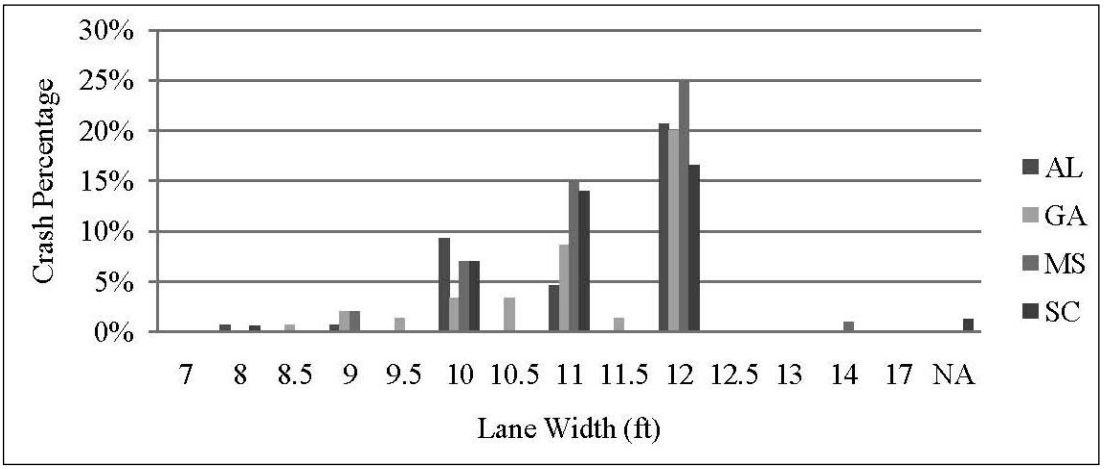


Figure 41: Multiple-Vehicle Fatal Crashes by Lane Width

3.3.2.7 Shoulder Type

Overall, approximately 50% of the single-vehicle crash study locations were characterized by the presence of graded shoulders, while multiple-vehicle crash study locations had graded shoulders at around 30% of the sites (see Table 21, Figure 42,

and Figure 43). Paved shoulders were minimal at the crash sites, but a few locations did have a combination of narrowly paved shoulders combined with graded shoulders.

Table 21: Crashes by Shoulder Type

State	Crash Type	Shoulder Type			
		Paved (%)	Graded (%)	Combination Paved and Graded (%)	Others (%)
AL	Single-Vehicle	5	45	5	9
	Multiple-Vehicle	7	21	5	3
	AL Total	12	66	10	12
GA	Single-Vehicle	3	44	9	4
	Multiple-Vehicle	1	21	16	3
	GA Total	4	65	25	7
MS	Single-Vehicle	0	44	3	3
	Multiple-Vehicle	6	34	7	3
	MS Total	6	78	10	6
SC	Single-Vehicle	1	57	1	1
	Multiple-Vehicle	3	34	2	1
	SC Total	4	91	3	1

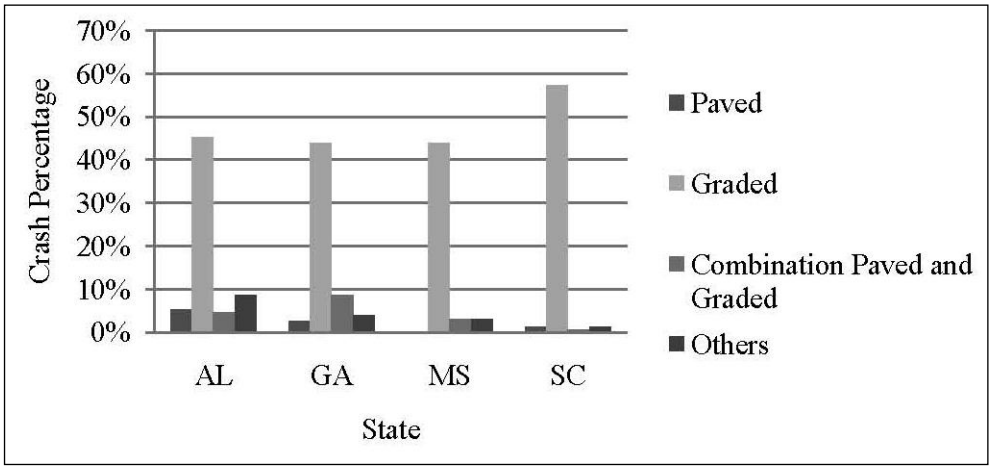


Figure 42: Single-Vehicle Fatal Crashes by Shoulder Type

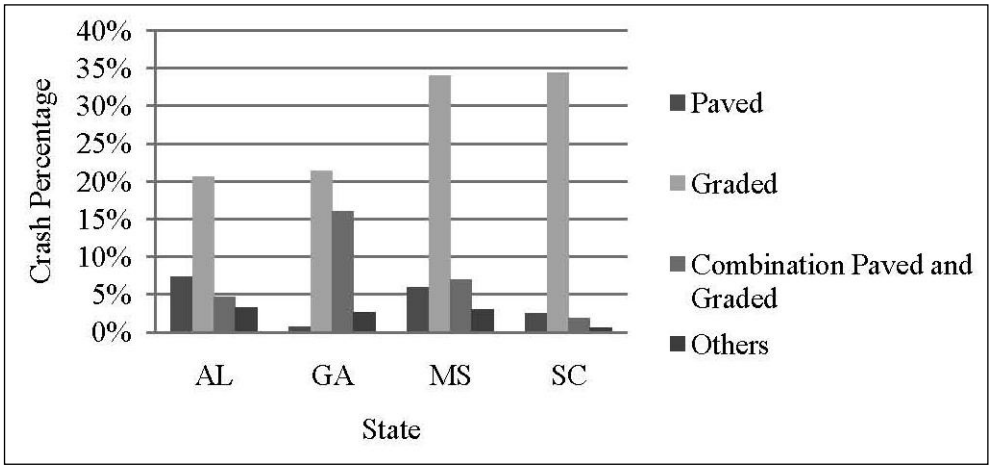


Figure 43: Multiple-Vehicle Fatal Crashes by Shoulder Type

3.3.2.8 Auxiliary Lane Configuration

As indicated in Table 22, over 90% of fatal crashes occurred at locations without either turning lanes, passing lanes, or emergency lanes. The research team used a two-lane rural road as a key requirement for study crash selection, so the minimal presence of auxiliary lanes at these location is to be expected as a result of the experimental design.

Table 22: Crashes by Auxiliary Lane Configuration

State	Number of Turning Lanes (%)				Number of Passing Lanes (%)			Number of Emergency Lanes (%)	
	0	1	2	4	0	1	2	0	1
AL	95	5	0	1	97	1	3	99	1
GA	96	4	0	0	97	3	0	100	0
MS	93	3	4	0	100	0	0	100	0
SC	100	0	0	0	100	0	0	100	0

3.3.2.9 Road Surface Type

The road surface type variable depicts the driving surface material at each crash site, including concrete, blacktop (asphalt), slag gravel or stone, and dirt. As shown in Table 23, Figure 44, and Figure 45, more than 95% of total fatal crashes in Alabama and Georgia occurred on road segments with blacktop surfaces. Fatal crashes in Mississippi and South Carolina had a slightly smaller percentage of blacktop surfaces at 68% and 65%, respectively.

Table 23: Crash Type by Road Surface Material

State	Crash Type	Road Surface Type			
		Concrete (%)	Blacktop (%)	Slag, Gravel or Stone (%)	Dirt (%)
AL	Single-Vehicle	0	61	1	1
	Multiple-Vehicle	1	35	1	0
	AL Total	1	96	2	1
GA	Single-Vehicle	1	57	1	1
	Multiple-Vehicle	1	39	0	1
	GA Total	2	96	1	2
MS	Single-Vehicle	1	28	21	0
	Multiple-Vehicle	0	40	10	0
	MS Total	1	68	31	0
SC	Single-Vehicle	23	38	0	0
	Multiple-Vehicle	12	27	0	0
	SC Total	35	65	0	0

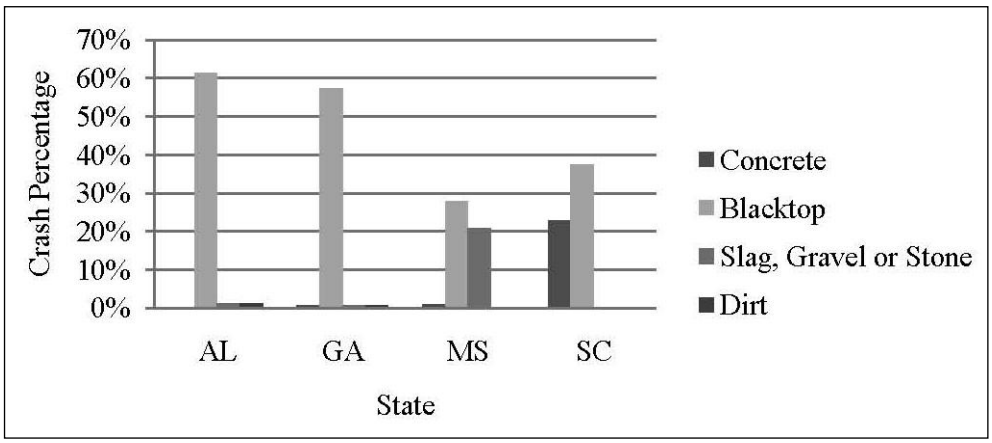


Figure 44: Single-Vehicle Fatal Crashes by Road Surface Material

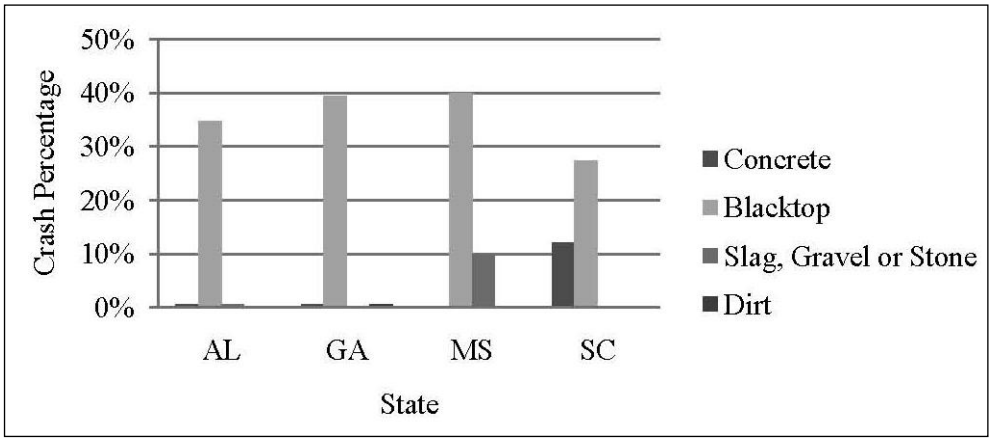


Figure 45: Multiple-Vehicle Fatal Crashes by Road Surface Material

3.3.2.10 Average Daily Traffic

The average daily traffic (ADT) was provided to the researchers for the study sites. Though an ADT value is often an approximated traffic volume (particularly for low-volume roads), the ADT value can still provide a context for the approximate traffic exposure per day. As shown in Figure 46, a large portion of the single-vehicle fatal crashes (about 40% of total fatal crashes) occurred at locations with an ADT below 2000 vehicles per day (vpd). An additional 15% of fatal crashes occurred at sites with ADT values ranging from 2000 vpd to 6000 vpd. Figure 47 demonstrates that the

majority of the multiple-vehicle fatal crashes (approximately 30% of the total fatal crashes) occurred at locations with ADT values below 6000 vpd.

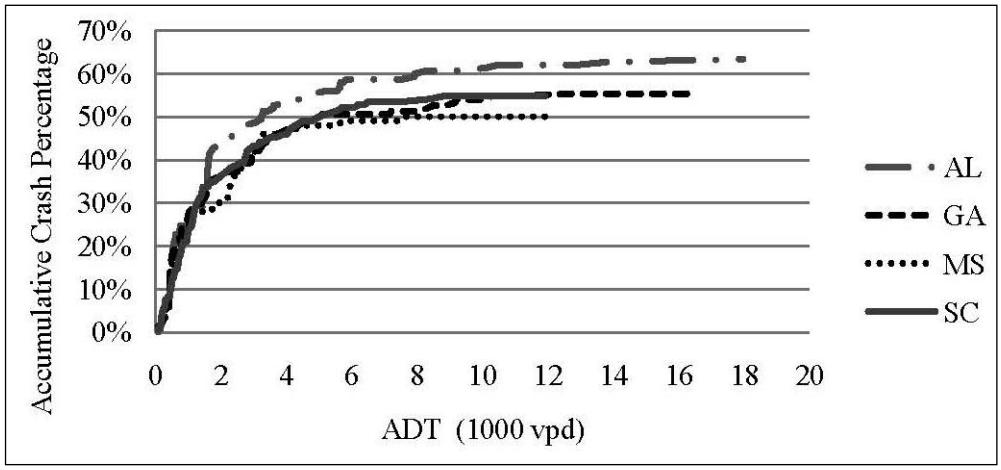


Figure 46: Single-Vehicle Fatal Crashes by Average Daily Traffic

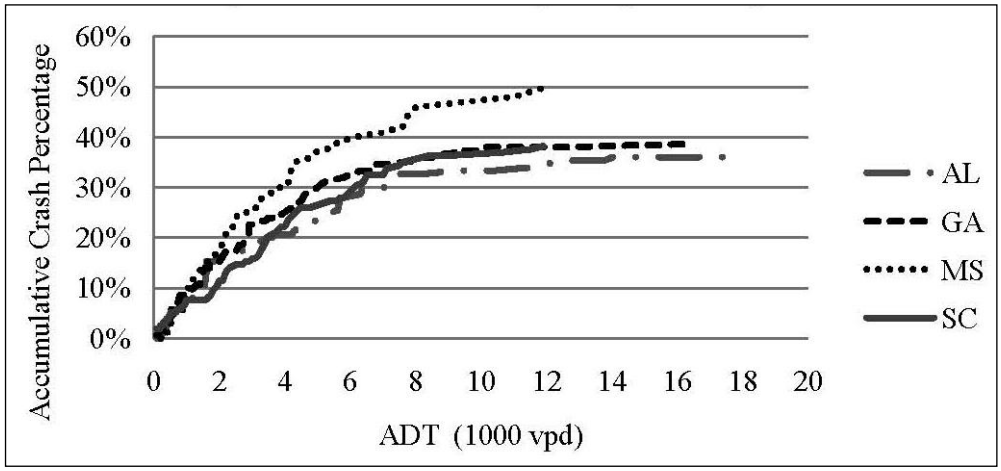


Figure 47: Multiple-Vehicle Fatal Crashes by Average Daily Traffic

3.3.2.11 Roadway Junction Proximity

For the fatal crashes in this study, single-vehicle fatal crashes predominately occurred at non-junction locations (see Table 24 and Figure 48) with percentages ranging from

31% to 59% of total fatal crashes. Similar to the single-vehicle fatal crashes, most of multiple-vehicle fatal crashes also occurred at non-junction locations at about one fourth of total fatal crashes on average (see Figure 49). More than 10% of the total fatal crashes, however, were multiple-vehicle crashes located in the proximity of intersections, such as four-way, T- and Y-intersections.

Table 24: Crash Type based on Roadway Junction Proximity

State	Crash Type	Roadway Junction Type				
		Non-Junction (%)	Four-way Intersection (%)	T-Intersection (%)	Y-Intersection (%)	Others (%)
AL	Single-Vehicle	59	1	3	1	0
	Multiple-Vehicle	23	7	3	1	2
	AL Total	82	8	6	2	2
GA	Single-Vehicle	52	1	7	0	0
	Multiple-Vehicle	23	11	5	1	0
	GA Total	75	12	12	1	0
MS	Single-Vehicle	47	0	2	0	1
	Multiple-Vehicle	32	11	2	2	3
	MS Total	79	11	4	2	4
SC	Single-Vehicle	31	7	10	3	11
	Multiple-Vehicle	19	8	5	0	8
	SC Total	50	15	15	3	19

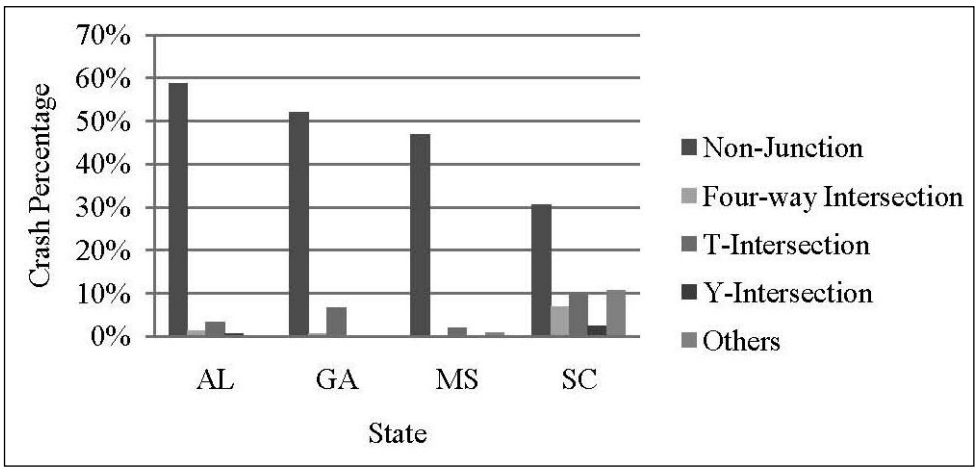


Figure 48: Single-Vehicle Crashes by Roadway Junction Proximity

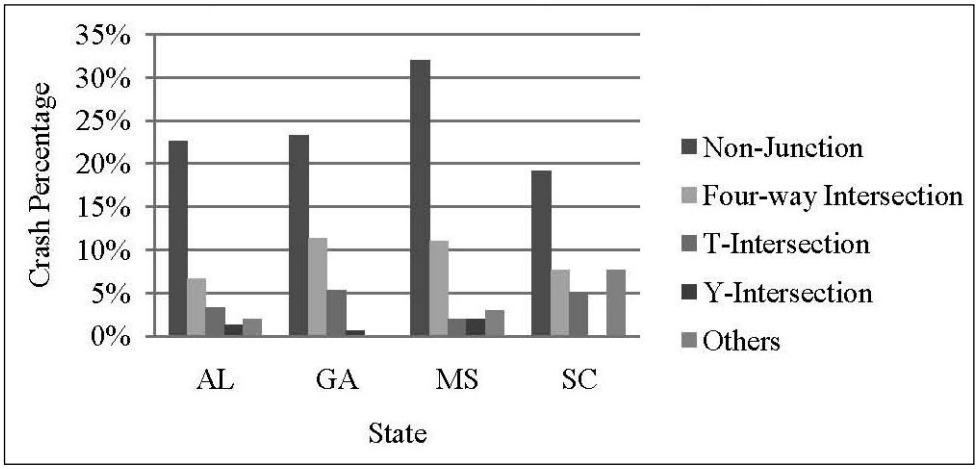


Figure 49: Multiple-Vehicle Crashes by Roadway Junction Proximity

3.3.2.12 Number of Driveways per Mile

Due to the rural nature of the dataset, fatal crash sites were generally characterized by infrequent driveways. Though an increase in driveway density can be correlated with increased interactions between vehicles, a common single-vehicle driveway consideration is the disruption of traversable longitudinal roadside grading resulting in the potential launching of errant vehicles. As shown in Table 25 as well as Figure 50

and Figure 51, there is no substantial difference between crashes and driveway density for the single-vehicle or multiple-vehicle fatal crashes.

Table 25: Crash Type by Number of Driveways per Mile

State	Crash Type	Number of Driveways per Mile					
		0 (%)	1 (%)	2 (%)	3 (%)	4 (%)	5+ (%)
AL	Single-Vehicle	17	15	11	10	8	3
	Multiple-Vehicle	13	6	7	5	1	5
	AL Total	30	21	18	15	9	8
GA	Single-Vehicle	18	17	7	6	4	7
	Multiple-Vehicle	14	11	9	2	3	3
	GA Total	32	28	16	8	7	10
MS	Single-Vehicle	17	16	5	6	2	4
	Multiple-Vehicle	16	9	10	9	0	6
	MS Total	33	25	15	15	2	10
SC	Single-Vehicle	24	15	11	4	3	2
	Multiple-Vehicle	8	11	11	3	4	2
	SC Total	32	26	22	7	7	4

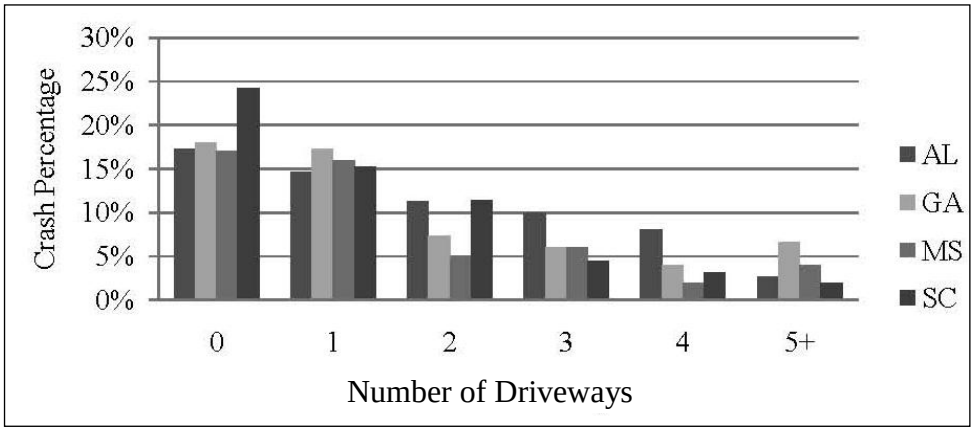


Figure 50: Single-Vehicle Fatal Crashes for Number of Driveways per Mile

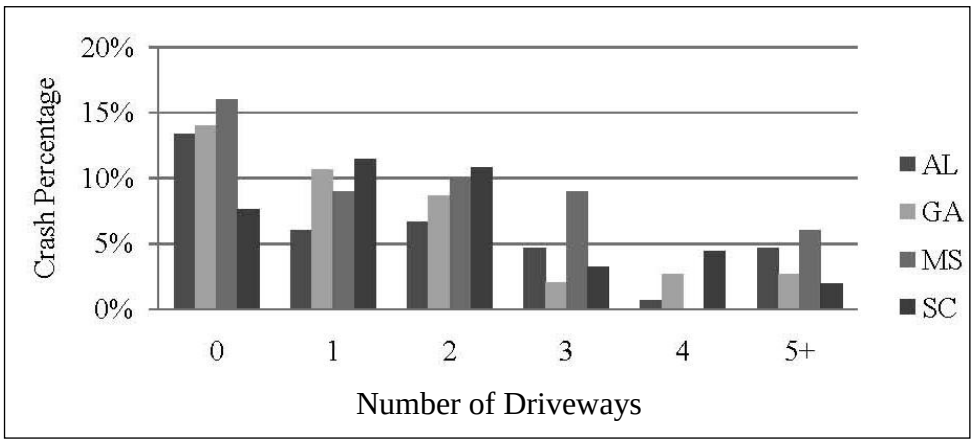


Figure 51: Multiple-Vehicle Fatal Crashes for Number of Driveways per Mile

3.3.2.13 Regulatory Speed Limit

The regulatory speed limit assigned to a road at the time of a crash may not directly reflect the operating speeds during the crash, but can help identify the nature of the crash site (high speed road versus low speed road). As shown in Table 26, the majority of the study crashes for Georgia, Mississippi, and South Carolina occurred on roads with a 55 mph speed limit. Alabama single-vehicle crashes tended to occur at roads with 45 mph speed limits and multiple-vehicle crashes occurred on roads with 55 mph speed limits. Figure 52 and Figure 53 graphically demonstrate this observed trend.

Table 26: Crash Type per Regulatory Speed Limit

State	Crash Type	Posted Speed Limit (mph)						
		<=30 (%)	35 (%)	40 (%)	45 (%)	50 (%)	55 (%)	Unknown (%)
AL	Single-Vehicle	1	5	3	23	1	13	0
	Multiple-Vehicle	0	2	3	18	0	31	0
	AL Total	1	7	6	41	1	44	0
GA	Single-Vehicle	2	5	0	4	0	28	4
	Multiple-Vehicle	1	3	1	6	0	45	0
	GA Total	3	8	1	10	0	73	4
MS	Single-Vehicle	3	3	0	1	1	22	3
	Multiple-Vehicle	3	0	2	5	0	56	1
	MS Total	6	3	2	6	1	78	4
SC	Single-Vehicle	0	3	1	9	0	29	0
	Multiple-Vehicle	0	3	3	10	1	40	0
	SC Total	0	6	4	19	1	69	0

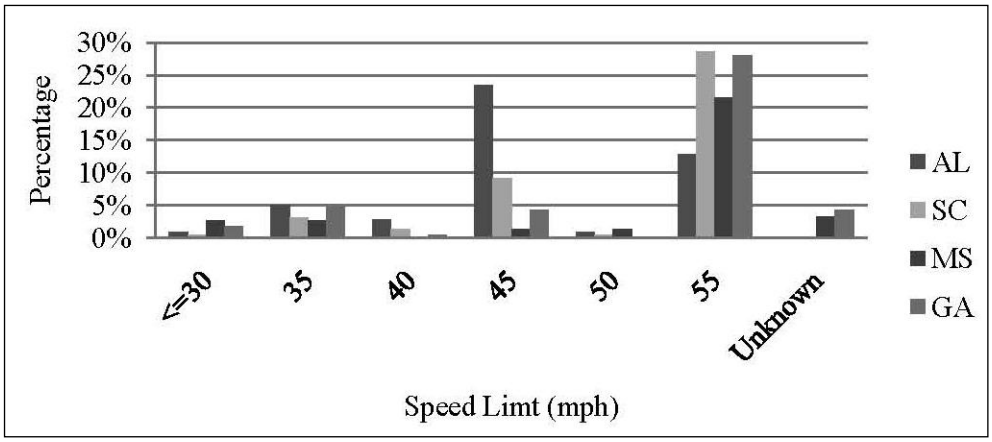


Figure 52: Single-Vehicle Fatal Crashes per Regulatory Speed Limit

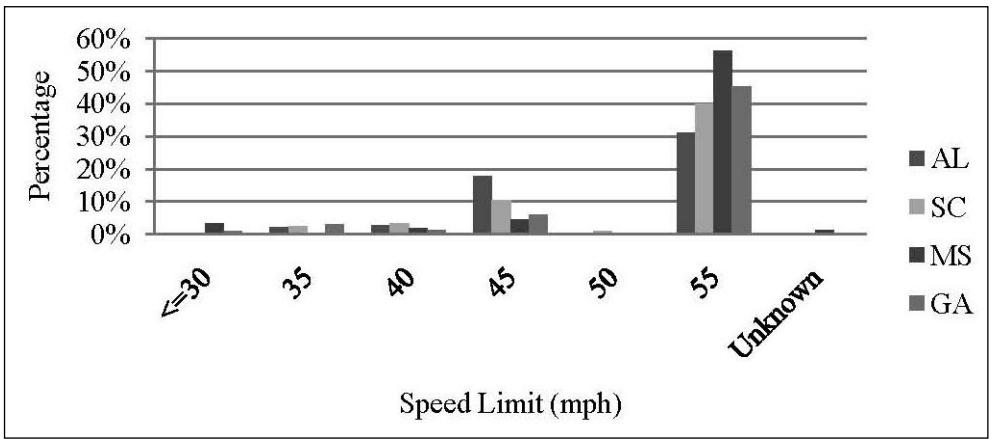


Figure 53: Multiple-Vehicle Fatal Crashes per Regulatory Speed Limit

3.3.2.14 Traffic Control Device

The traffic control device variable was only available in the database for the Alabama, Georgia, and Mississippi fatal crashes. As shown in Table 27, Figure 54 and Figure 55, from 44% up to 88% of total fatal crashes occurred on roadways without traffic control devices in the immediate vicinity of the crash sites. Georgia sites did have warning signs present (as reported in the database) more than in the other two states. The researchers acquired this information from site inspections.

Table 27: Crash Type and Associated Traffic Control Devices

State	Crash Type	Traffic Control Device Type						
		No Control (%)	Traffic Control Signal (%)	Flashing Traffic Control Sign (%)	Stop Sign (%)	Warning Sign (%)	Railway Crossing Device (%)	Unknown (%)
AL	Single-Vehicle	55	0	0	4	1	0	0
	Multiple-Vehicle	33	0	1	7	0	0	0
	AL Total	88	0	1	11	1	0	0
GA	Single-Vehicle	31	0	0	2	18	1	4
	Multiple-Vehicle	13	0	0	9	22	0	0
	GA Total	44	0	0	11	40	1	4
MS	Single-Vehicle	42	0	0	2	0	0	0
	Multiple-Vehicle	43	1	0	12	0	0	0
	MS Total	85	1	0	14	0	0	0

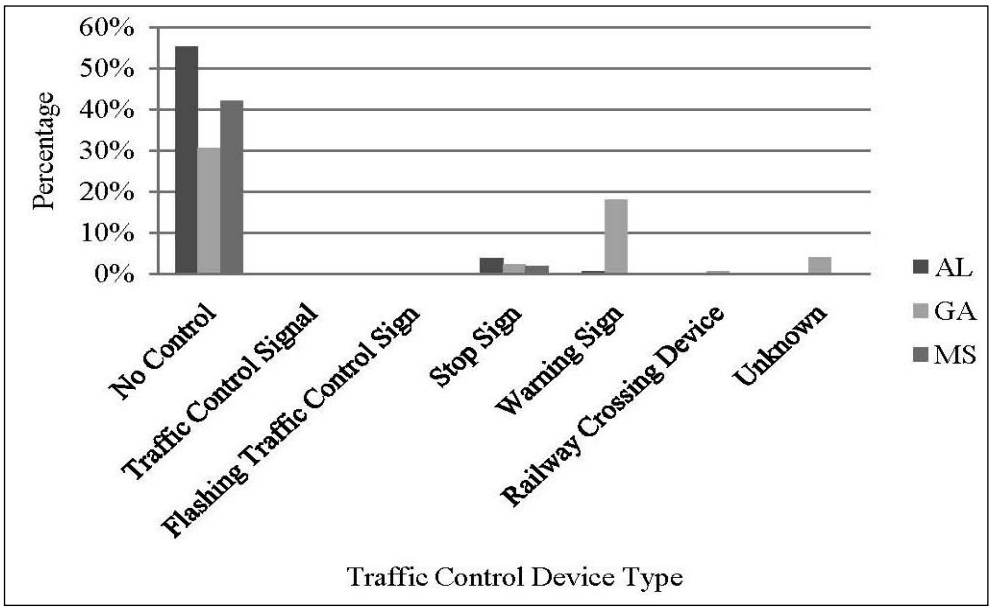


Figure 54: Single-Vehicle Fatal Crashes and Associated Traffic Control Devices

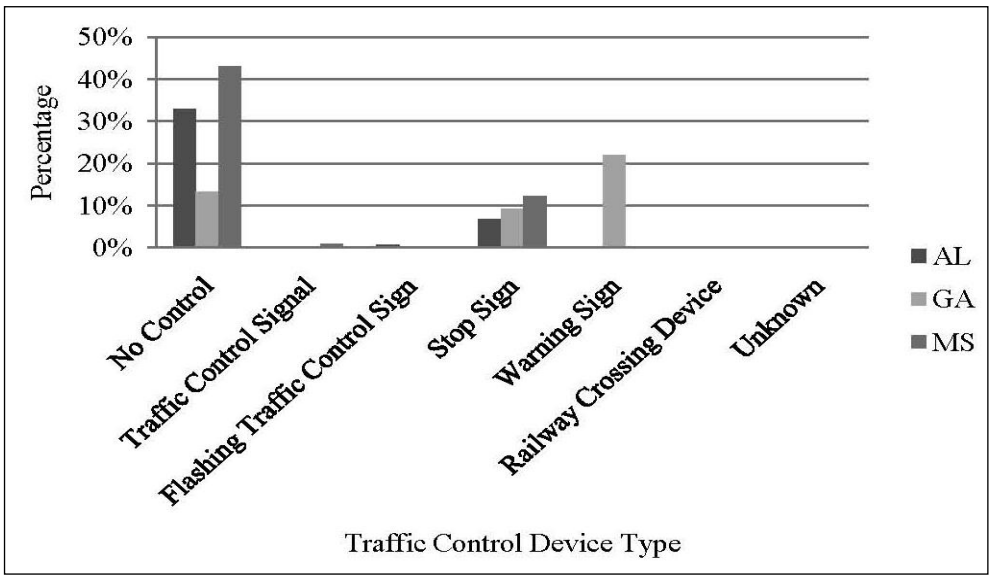


Figure 55: Multiple-Vehicle Fatal Crashes and Associated Traffic Control Devices

3.3.2.15 Roadside Hazard Rating

The original study included a roadside hazard rating (RHR) consistent with values ranging from one (for easily traversable roadside conditions) up to seven (roadsides that are extremely hazardous). Each research team assigned a RHR based on sample photographs of each respective rating value. Appendix B presents the pictorial scale of RHR. Across the states as the RHR increased from one to five, the fatal crash occurrence steadily increased for single-vehicle and multiple-vehicle crashes (see Table 28, Figure 56, and Figure 57). RHR values for six and seven varied for the individual states.

Table 28: Crash Type and Associated Roadside Hazard Rating

State	Crash Type	Roadside Hazard Rating						
		1 (%)	2 (%)	3 (%)	4 (%)	5 (%)	6 (%)	7 (%)
AL	Single-Vehicle	0	1	8	20	23	11	1
	Multiple-Vehicle	1	3	7	14	11	1	0
	AL Total	1	4	15	34	34	12	1
GA	Single-Vehicle	1	7	16	17	16	3	1
	Multiple-Vehicle	0	5	16	12	7	1	0
	GA Total	1	12	36	29	23	4	1
MS	Single-Vehicle	0	1	4	7	14	24	0
	Multiple-Vehicle	0	2	3	16	21	8	0
	MS Total	0	3	7	23	35	32	0
SC	Single-Vehicle	0	0	0	12	43	6	0
	Multiple-Vehicle	0	0	1	10	28	1	0
	SC Total	0	0	1	22	71	7	0

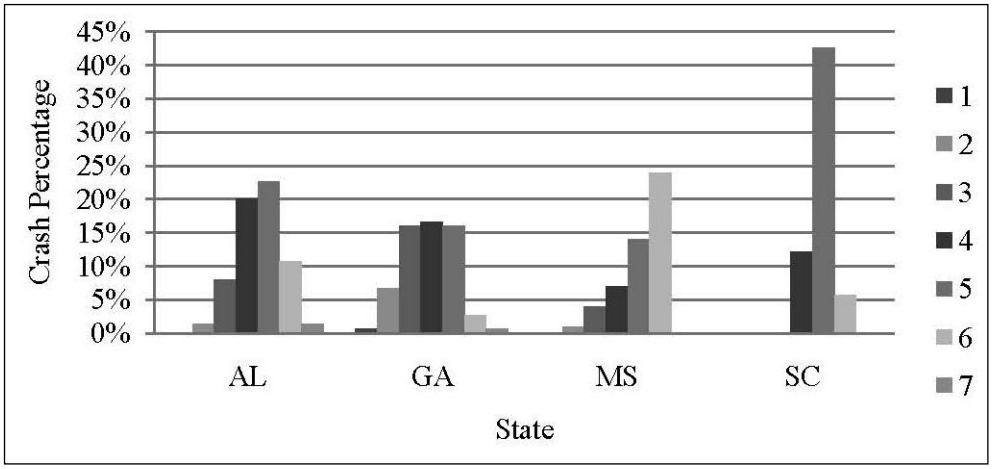


Figure 56: Single-Vehicle Fatal Crashes and Associated Roadside Hazard Ratings

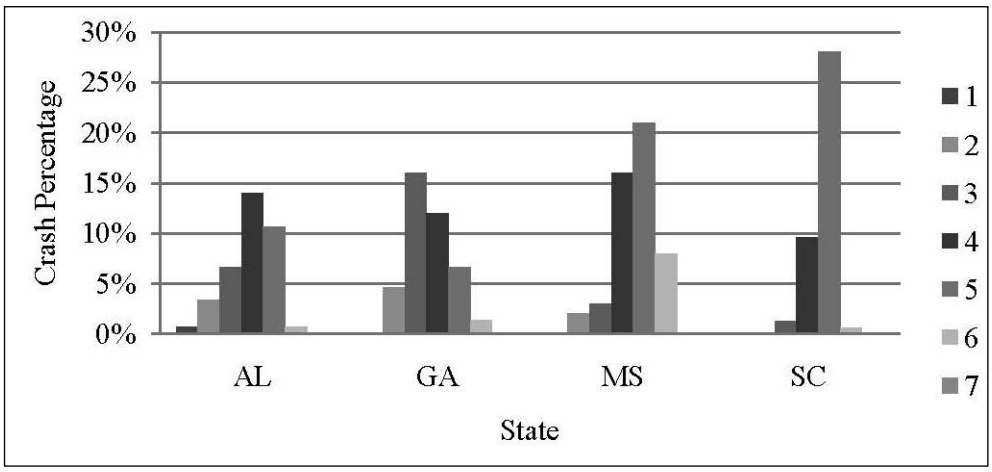


Figure 57: Multiple-Vehicle Fatal Crashes and Associated Roadside Hazard Ratings

3.3.2.16 Guardrail and Bridge Rail Type

A guardrail or bridge rail type variable was only available for the three states of Alabama, Georgia, and Mississippi. The individual state researchers acquired this variable from site inspection. As presented in Table 29, more than 90% of the fatal crashes for each state occurred at locations without guardrails and bridge rails.

Table 29: Fatal Crashes and Associated Guardrail/Bridge Rails

State	Guardrail/Bridge Rail Type				
	None (%)	Steel Breakaway (%)	Concrete Barrier (%)	Concrete Bridge Rail (%)	Others (%)
AL	91	3	1	1	3
GA	98	1	0	1	0
MS	96	3	0	1	0

3.3.2.17 Terrain

The road terrain variable describes the general regional terrain at crash locations. Terrain is defined loosely as flat terrain, rolling terrain, and mountainous terrain. As shown in Table 30 and further reflected in Figure 58 and Figure 59, most of the crashes occurred in flat or rolling terrain regions.

Table 30: Crash Type and Associated Terrain

State	Crash Type	Terrain		
		Flat (%)	Rolling (%)	Mountainous (%)
AL	Single-Vehicle	39	24	1
	Multiple-Vehicle	22	14	0
	AL Total	61	38	1
GA	Single-Vehicle	35	22	2
	Multiple-Vehicle	16	24	1
	GA Total	41	46	3
MS	Single-Vehicle	8	42	0
	Multiple-Vehicle	6	44	0
	MS Total	14	86	0
SC	Single-Vehicle	28	32	0
	Multiple-Vehicle	19	20	1
	SC Total	47	52	1

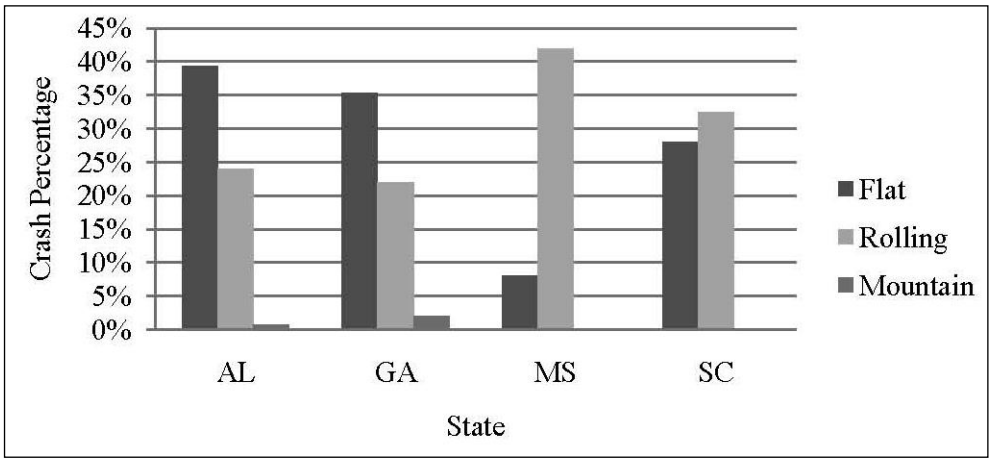


Figure 58: Single-Vehicle Fatal Crashes and Associated Terrain

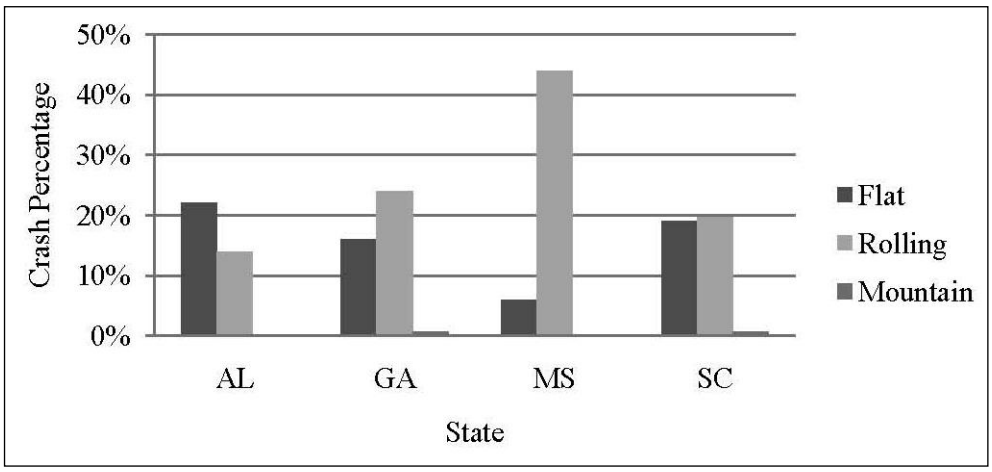


Figure 59: Multiple-Vehicle Fatal Crashes and Associated Terrain

3.3.2.18 Relation to Roadway

The relation to roadway variable identifies the vehicle location where the first harmful event occurred as it related to the traffic-way. This variable includes the roadway, shoulder, roadside, or other unknown off-road locations. According to this "relation to roadway" variable, a majority of single-vehicle fatal crashes occurred either at off-road or roadside locations, while multiple-vehicle fatal crashes occurred primarily on the roadway (see Table 31, Figure 60, and Figure 61).

Table 31: Crash Type and Relation to Roadway

State	Crash Type	Relation to Roadway			
		Roadway (%)	Shoulder (%)	Roadside (%)	Off-road or Unknown Location (%)
AL	Single-Vehicle	5	0	0	59
	Multiple-Vehicle	36	0	0	0
	AL Total	41	0	0	59
GA	Single-Vehicle	7	8	2	43
	Multiple-Vehicle	41	0	0	0
	GA Total	48	8	2	43
MS	Single-Vehicle	0	1	49	0
	Multiple-Vehicle	47	0	3	0
	MS Total	47	1	52	0
SC	Single-Vehicle	4	4	11	42
	Multiple-Vehicle	38	0	2	0
	SC Total	42	4	13	42

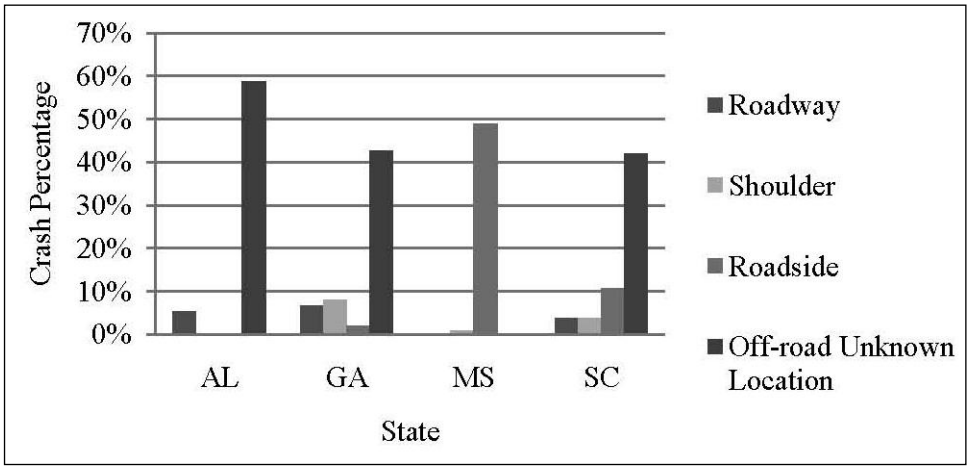


Figure 60: Single-Vehicle Fatal Crashes and Relation to Roadway

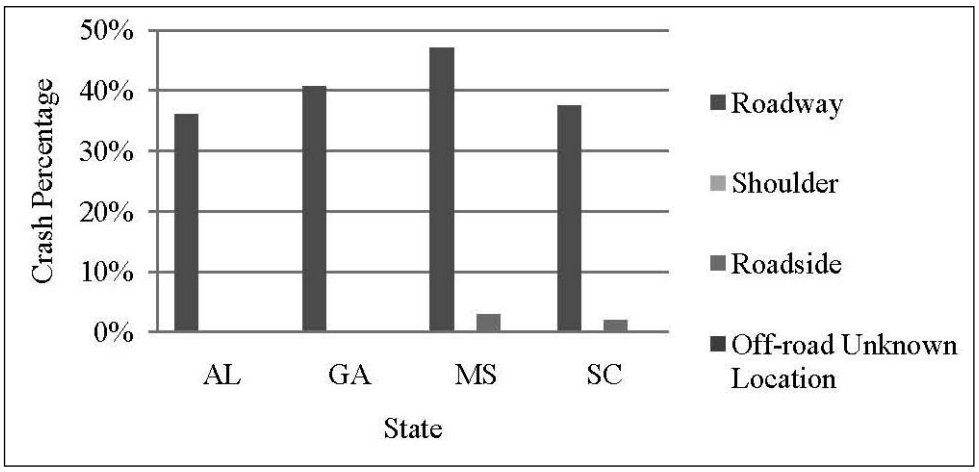


Figure 61: Multiple-Vehicle Fatal Crashes and Relation to Roadway

3.3.3 Environment Related Characteristics

3.3.3.1 Ambient Light Condition

The ambient light condition variable describes the lighting conditions at the time of the crashes. This variable includes daylight, dark unlit, and others (dawn, dusk, dark lighted, and unknown). As shown in Table 32, approximately one-third of the total fatal crashes were single-vehicle crashes that occurred when conditions were dark with no lighting (see also Figure 62), while only about one-tenth (ranging from 8% to 13%) of the total multiple-vehicle fatal crashes observed under dark unlit conditions (see Figure 63).

Table 32: Crash Type and Ambient Light Conditions

State	Crash Type	Ambient Light Condition		
		Daylight (%)	Dark Unlit (%)	Others (%)
AL	Single-Vehicle	24	37	3
	Multiple-Vehicle	27	8	1
	AL Total	51	45	4
GA	Single-Vehicle	27	31	1
	Multiple-Vehicle	27	12	1
	GA Total	54	43	2
MS	Single-Vehicle	13	33	4
	Multiple-Vehicle	34	13	3
	MS Total	47	46	7
SC	Single-Vehicle	22	36	3
	Multiple-Vehicle	24	11	4
	SC Total	46	47	7

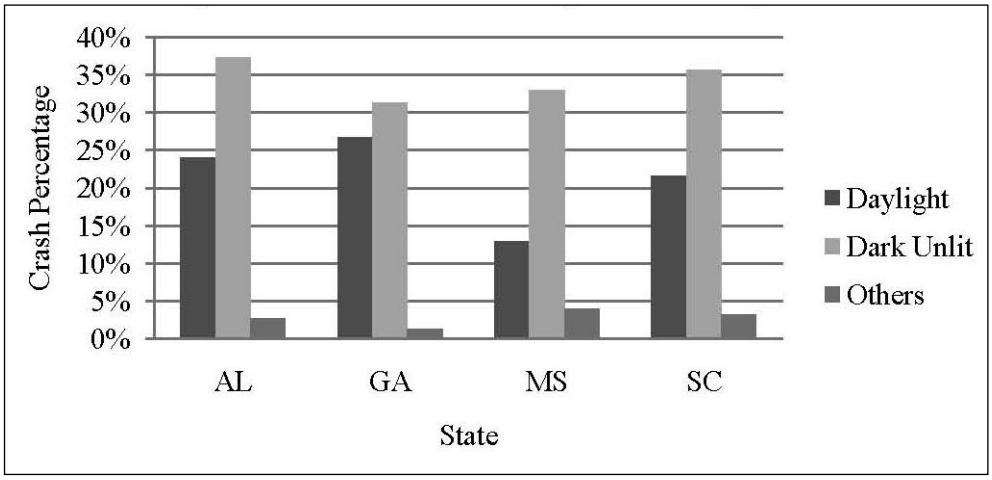


Figure 62: Single-Vehicle Fatal Crashes and Ambient Lighting Conditions

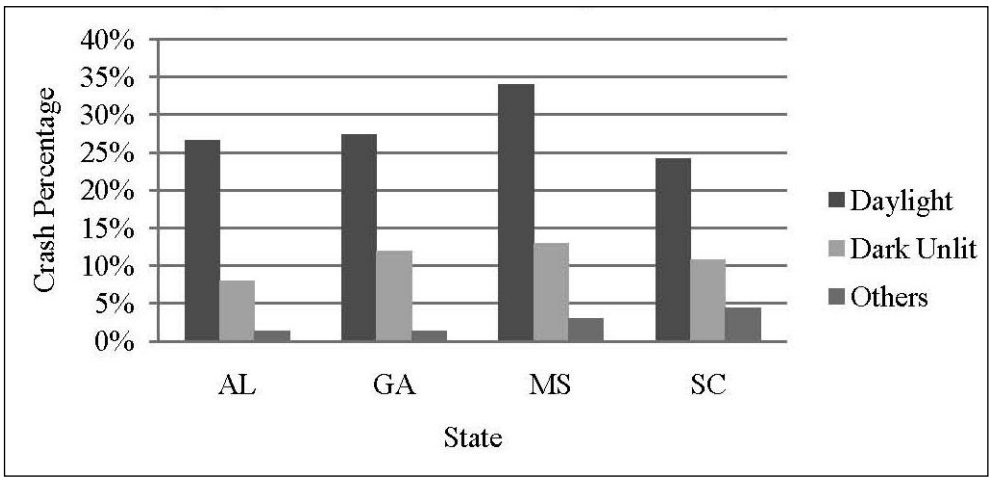


Figure 63: Multiple-Vehicle Fatal Crashes and Ambient Light Conditions

3.3.3.2 Weather Condition

The weather condition variable described the prevailing atmospheric conditions at the time of the crashes. This variable includes weather conditions ranging from clear, cloudy, and rain, to other less common conditions (fog, smoke, smog, sleet, hail, snow, etc). Single-vehicle and multiple-vehicle fatal crashes were similarly distributed for the various weather conditions (see Table 33, Figure 64 and Figure 65). More than two-thirds (ranging from 64% to 83%) of the fatal crashes occurred during the clear weather condition.

Table 33: Crash Type by Weather Conditions

State	Crash Type	Weather Condition			
		Clear (%)	Cloudy (%)	Rain (%)	Others* (%)
AL	Single-Vehicle	40	15	5	3
	Multiple-Vehicle	24	6	5	1
	AL Total	64	21	10	4
GA	Single-Vehicle	47	1	11	1
	Multiple-Vehicle	36	1	3	0
	GA Total	83	2	14	1
MS	Single-Vehicle	33	11	4	2
	Multiple-Vehicle	34	7	7	2
	MS Total	67	18	11	4
SC	Single-Vehicle	46	7	6	1
	Multiple-Vehicle	31	4	3	1
	SC Total	77	11	9	2

* Others: fog, smog, smoke, snow, etc.

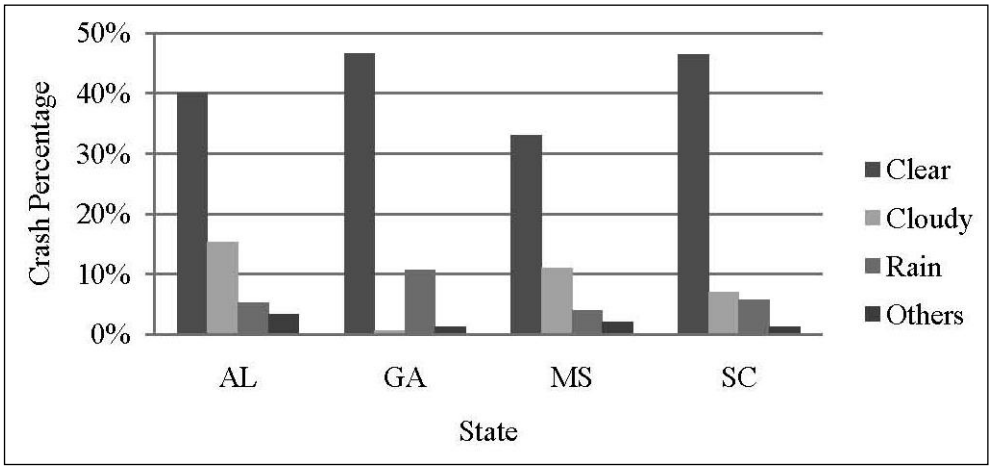


Figure 64: Single-Vehicle Crashes by Weather Conditions

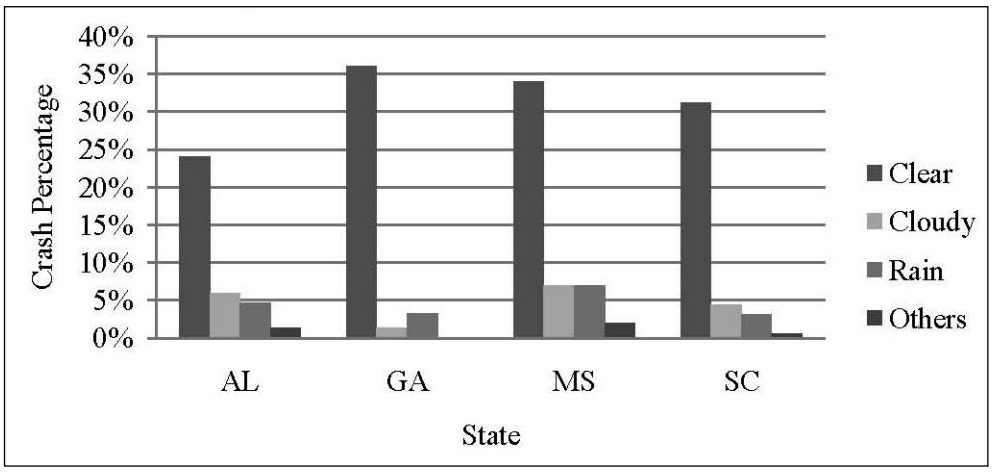


Figure 65: Multiple-Vehicle Crashes by Weather Conditions

3.3.3.3 Road Surface Condition

The road surface condition variable describes the surface of the road condition, at the time of the crash, due to current or previous weather (for example, the crash may have occurred during a cloudy weather condition but the road surface could still have been wet due to a previous rain). This variable includes three major conditions - dry surfaces, wet surfaces, and all other conditions (snow, ice, etc). As presented in Table 34, Figure 66, and Figure 67, 78% up to 89% of the fatal crashes occurred during dry road surface conditions.

Table 34: Crash Type and Associated Road Surface Conditions

State	Crash Type	Road Surface Condition		
		Dry (%)	Wet (%)	Others (%)
AL	Single-Vehicle	49	13	2
	Multiple-Vehicle	29	7	0
	AL Total	78	20	2
GA	Single-Vehicle	45	14	0
	Multiple-Vehicle	35	5	0
	GA Total	80	19	0
MS	Single-Vehicle	42	7	1
	Multiple-Vehicle	42	8	0
	MS Total	84	15	1
SC	Single-Vehicle	54	7	0
	Multiple-Vehicle	35	4	0
	SC Total	89	11	0

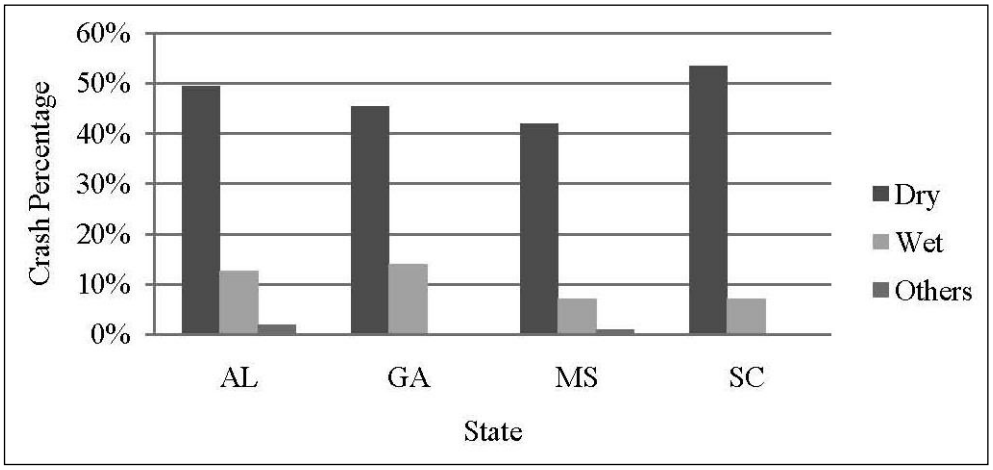


Figure 66: Single-Vehicle Crashes and Associated Road Surface Conditions

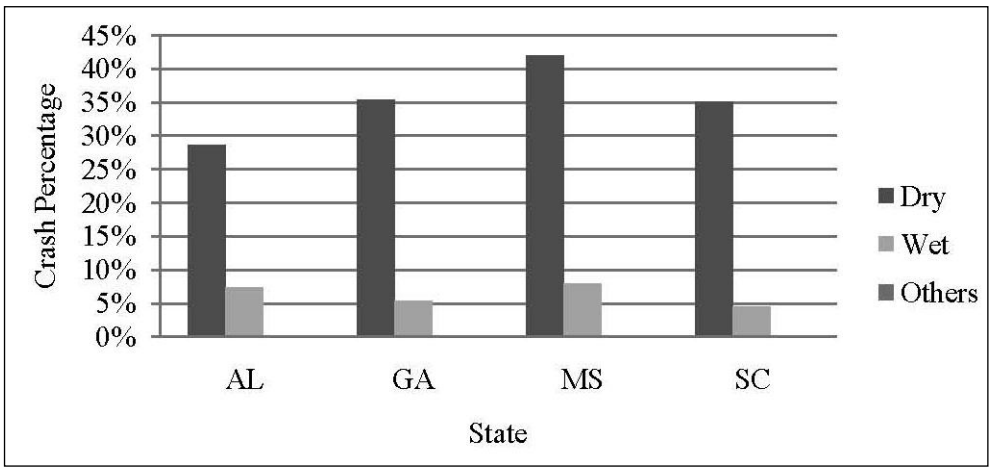


Figure 67: Multiple-Vehicle Crashes and Associated Road Surface Conditions

3.3.4 Driver and Passenger Related Characteristics

3.3.4.1 Gender

Table 35, Figure 68 and Figure 69 present the gender distribution when drivers and passengers are shown collectively for single-vehicle and multiple-vehicle fatal crashes. More than twice as many male drivers were involved in the fatal crashes than female drivers. Male passengers still show more involvements in single-vehicle fatal crashes compared to their counterparts, while the pattern is no longer prominent for multiple-vehicle fatal crashes.

Table 35: Crash Type by Driver and Passenger Gender

State	Crash Type	Person Involved						
		Driver		Passenger			Non-Motorist	
		Male (%)	Female (%)	Male (%)	Female (%)	Not Reported (%)	Male (%)	Female (%)
AL	Single-Vehicle	20	7	9	6	1	0	0
	Multiple-Vehicle	22	9	8	12	5	0	0
	AL Total	42	16	17	18	6	0	0
GA	Single-Vehicle	19	7	9	6	0	2	1
	Multiple-Vehicle	27	11	10	9	0	0	0
	GA Total	46	18	19	15	0	2	1
MS	Single-Vehicle	12	6	10	5	0	0	0
	Multiple-Vehicle	26	11	16	15	0	0	0
	MS Total	38	17	26	20	0	0	0
SC	Single-Vehicle	22	5	10	5	0	1	0
	Multiple-Vehicle	26	10	9	10	0	0	0
	SC Total	48	15	19	15	0	1	0

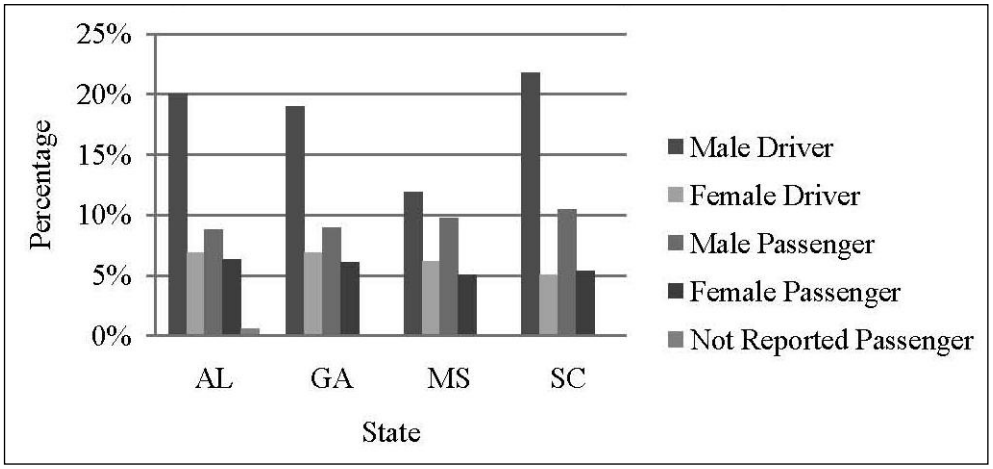


Figure 68: Single-Vehicle Fatal Crashes by Driver and Passenger Genders

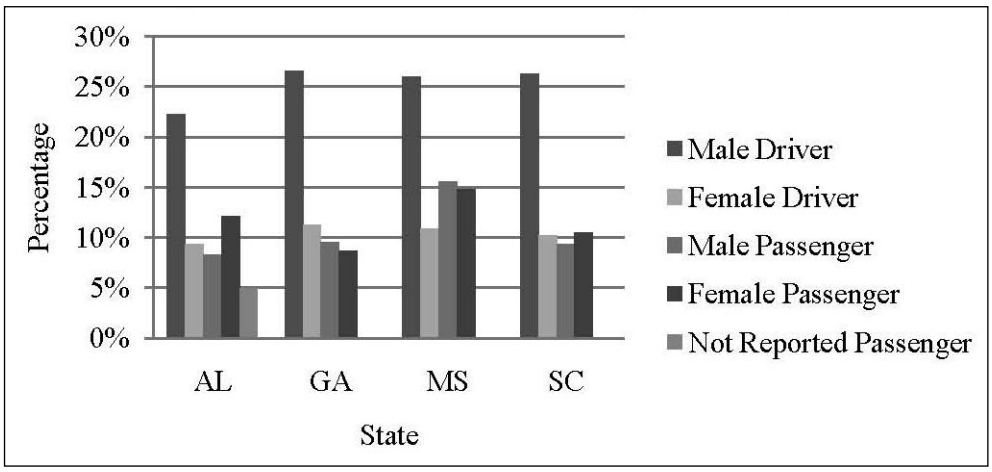


Figure 69: Multiple-Vehicle Fatal Crashes by Driver and Passenger Genders

3.3.4.2 Driver Age Group

As shown in Table 36, Figure 70, and Figure 71, drivers ages 25 to 34 and ages 35 to 44 were involved more often in the single-vehicle and multiple-vehicle fatal crashes selected for this study. In addition, Alabama drivers in the 35 to 44 year old age group were involved in single-vehicle fatal crashes more often than those in a similar age group in the other three study states.

Table 36: Crash Type by Driver Age Group

State	Crash Type	Driver Age Group (years old)								
		<16 (%)	16-20 (%)	21-24 (%)	25-34 (%)	35-44 (%)	45-54 (%)	55-64 (%)	65-69 (%)	>69 (%)
AL	Single-Vehicle	0	5	4	12	15	5	1	1	2
	Multiple-Vehicle	0	8	3	13	13	9	4	2	3
	AL Total	0	13	7	25	28	14	5	3	5
GA	Single-Vehicle	1	6	7	11	6	4	3	1	1
	Multiple-Vehicle	1	7	5	14	11	7	5	3	5
	GA Total	2	13	12	25	17	11	8	4	6
MS	Single-Vehicle	1	6	2	8	7	3	3	2	1
	Multiple-Vehicle	1	10	3	18	11	10	9	3	2
	MS Total	2	16	5	26	18	13	12	5	3
SC	Single-Vehicle	1	5	8	12	11	4	1	0	0
	Multiple-Vehicle	0	7	3	12	13	10	8	2	3
	SC Total	1	12	11	24	24	14	9	2	3

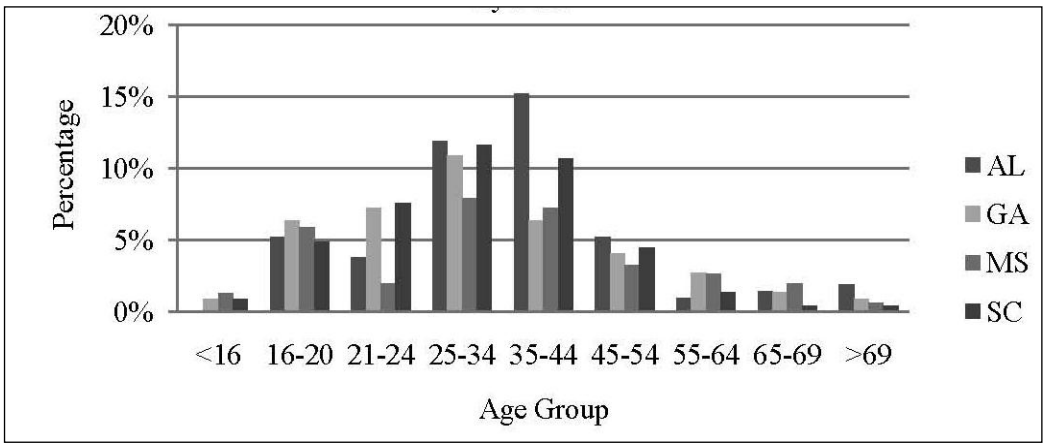


Figure 70: Single-Vehicle Fatal Crashes by Driver Age Group

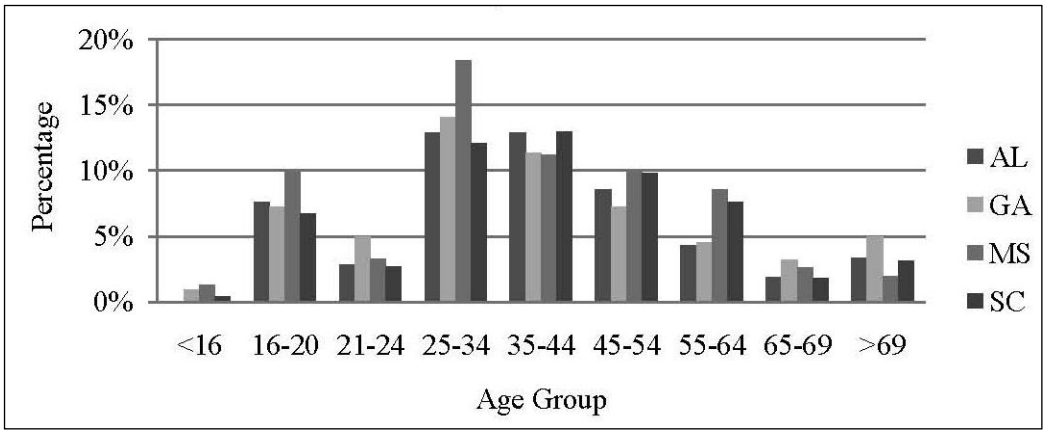


Figure 71: Multiple-Vehicle Fatal Crashes by Driver Age Group

3.3.4.3 Ejection Status of Vehicle Occupants

For a small percentage of crashes, a vehicle occupant was partially or completely ejected from the vehicle (see Table 37, Figure 72, and Figure 73). With the exception of the South Carolina crashes, the percentage of ejected occupants involved in single-vehicle fatal crashes was almost twice that of multiple-vehicle fatal crashes.

Table 37: Crash Type and Associated Occupant Ejection Status

State	Crash Type	Ejection Status		
		Not Ejected (%)	Ejected (%)	Others (%)
AL	Single-Vehicle	29	13	2
	Multiple-Vehicle	49	6	1
	AL Total	78	19	3
GA	Single-Vehicle	30	14	1
	Multiple-Vehicle	49	7	0
	GA Total	79	21	1
MS	Single-Vehicle	20	13	0
	Multiple-Vehicle	59	8	0
	MS Total	79	21	0
SC	Single-Vehicle	35	8	0
	Multiple-Vehicle	45	12	0
	SC Total	80	20	0

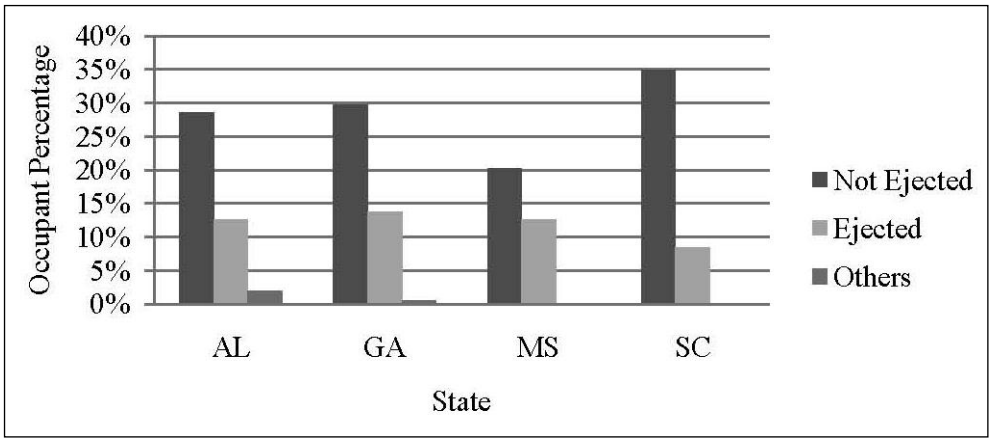


Figure 72: Single-Vehicle Fatal Crashes and Associated Occupant Ejection Status

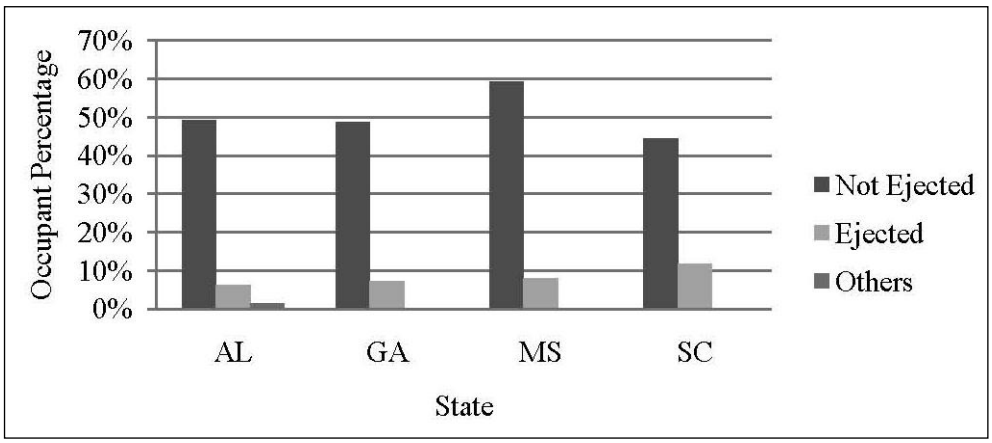


Figure 73: Multiple-Vehicle Fatal Crashes and Associated Occupant Ejection Status

3.3.4.4 Occupant Protection System Use

The occupant protection system variable primarily represents safety restraint (not used, shoulder and lap belt use, shoulder belt use only, lap belt use only, and others such as well as helmet use for motorcyclists). Most of vehicle occupants in single-vehicle fatal crashes did not use safety restraints (this percentage ranged from 23% to 32%) as shown in Table 38 and Figure 74. Figure 75 further demonstrates that for multiple-vehicle fatal crashes the proportion of vehicle occupants who wore safety restraints compared to those without restraints were similar at approximately 25%.

Table 38: Crash Type Compared to Occupant Protection System Use

State	Crash Type	Occupant Protection System Use				
		Not Used (%)	Shoulder and Lap Belt (%)	Shoulder Belt Only (%)	Lap Belt Only (%)	Other Situations (%)
AL	Single-Vehicle	32	6	0	1	4
	Multiple-Vehicle	28	22	0	2	5
	AL Total	60	28	0	3	9
GA	Single-Vehicle	27	6	1	0	10
	Multiple-Vehicle	22	23	0	3	8
	GA Total	49	29	1	3	18
MS	Single-Vehicle	23	6	0	0	3
	Multiple-Vehicle	24	26	9	2	6
	MS Total	47	32	9	2	9
SC	Single-Vehicle	32	9	0	0	3
	Multiple-Vehicle	23	29	0	1	4
	SC Total	55	38	0	1	7

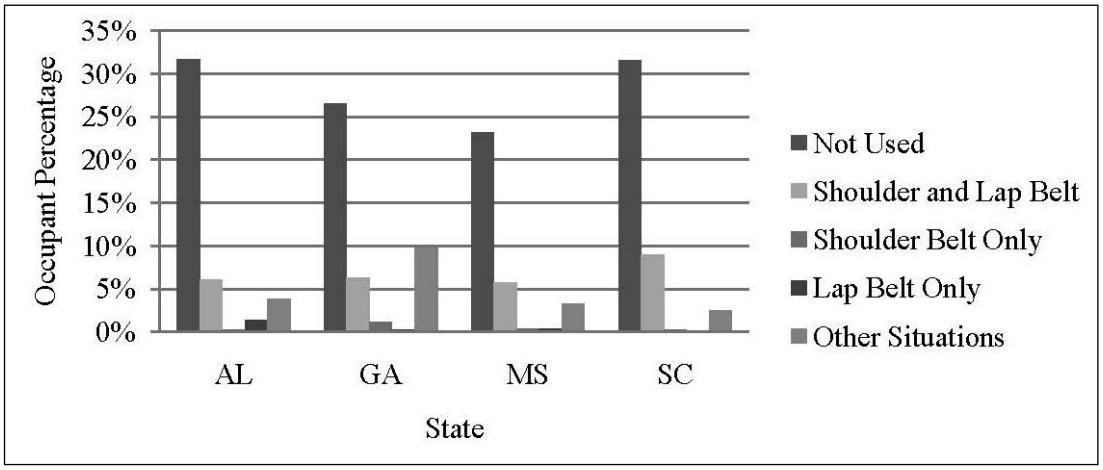


Figure 74: Single-Vehicle Fatal Crashes and Occupant Protection System Use

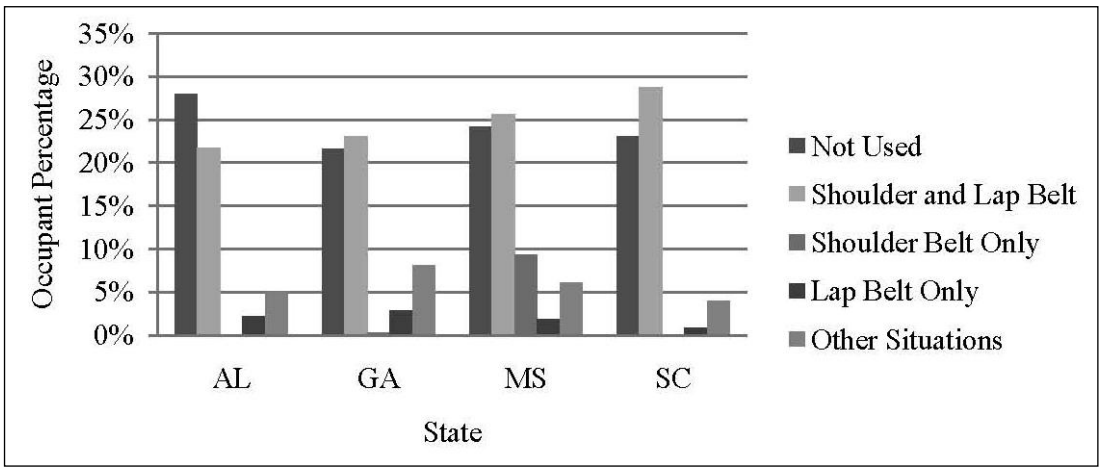


Figure 75: Multiple-Vehicle Fatal Crashes and Occupant Protection System Use

3.3.5 Vehicle Related Characteristics

3.3.5.1 Vehicle Configuration

The vehicle configuration variable describes the type of motor vehicles involved in the fatal crashes. This variable included passenger car, light truck, truck/trailer/ tractor, motorcycle, bus, other types, or unknown vehicle types. This variable is not available in the database for Georgia.

In general, the vehicle configuration distributions for the three states exhibit similar distributions (see Table 39, Figure 76, and Figure 77) with passenger cars and light trucks as the most common vehicle types for both single-vehicle and multiple-vehicle fatal crashes.

Table 39: Crash Type and Associated Vehicles

State	Crash Type	Vehicle Configuration						
		Passenger Car (%)	Light Truck (%)	Truck/ Tractor Trailer (%)	Motorcycle (%)	Bus (%)	Others (%)	Unknown (%)
AL	Single-Vehicle	28	17	0	0	1	0	0
	Multiple-Vehicle	30	16	7	0	0	0	0
	AL Total	58	33	7	0	1	0	0
MS	Single-Vehicle	18	13	1	0	0	0	1
	Multiple-Vehicle	37	18	9	1	1	1	1
	AL Total	55	31	10	1	1	1	2
SC	Single-Vehicle	26	13	2	1	0	0	0
	Multiple-Vehicle	30	17	7	3	0	0	0
	AL Total	56	30	9	4	0	0	0

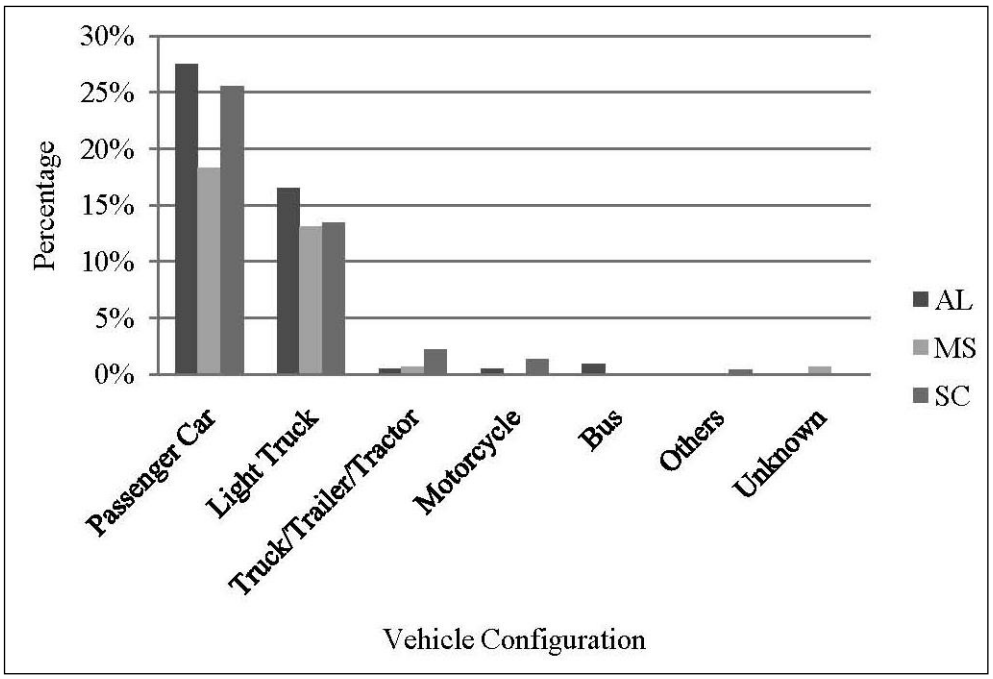


Figure 76: Single-Vehicle Fatal Crashes and Associated Vehicles

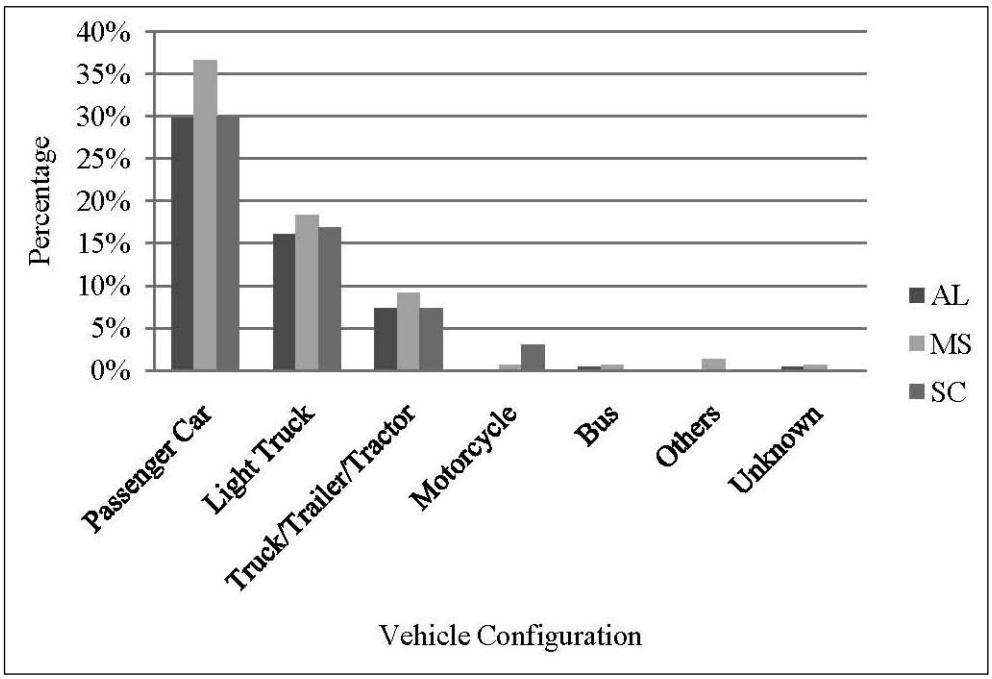


Figure 77: Multiple-Vehicle Fatal Crashes and Associated Vehicles

3.3.5.2 Vehicle Travel Speed

Travel speed is the estimated speed of the vehicle before a crash. This variable is prone to be based on the judgment of the reporting law enforcement officer instead of an actual known driving speed of a vehicle. As shown in the Table 40, Figure 78, Figure 79, while only about 42% of the travel speed information was available for Mississippi crashes, Georgia does not include vehicle speed on crash reports so the Georgia database does not include this vehicle speed variable. For Alabama and South Carolina, the travel speed distribution of single-vehicle fatal crashes skews towards high speeds with observed speeds often greater than 55 mph. Alternatively, the travel speed distribution skews towards lower speeds with the 46 to 55 mph range accounting for a large portion of the multiple-vehicle fatal crashes.

Table 40: Crash Type by Vehicle Travel Speed

State	Crash Type	Travel Speed (mph)					
		<= 30 (%)	35-45 (%)	46-55 (%)	56-65 (%)	> 65 (%)	Unknown (%)
AL	Single-Vehicle	0	9	9	12	12	3
	Multiple-Vehicle	10	13	21	6	3	2
	AL Total	10	22	30	18	15	5
GA	Single-Vehicle	0	0	0	0	0	44
	Multiple-Vehicle	0	0	0	0	0	56
	GA Total	0	0	0	0	0	100
MS	Single-Vehicle	1	1	5	2	1	23
	Multiple-Vehicle	4	7	20	2	0	35
	MS Total	5	8	25	4	1	58
SC	Single-Vehicle	2	2	10	9	19	1
	Multiple-Vehicle	13	16	22	3	2	1
	SC Total	15	18	32	12	21	2

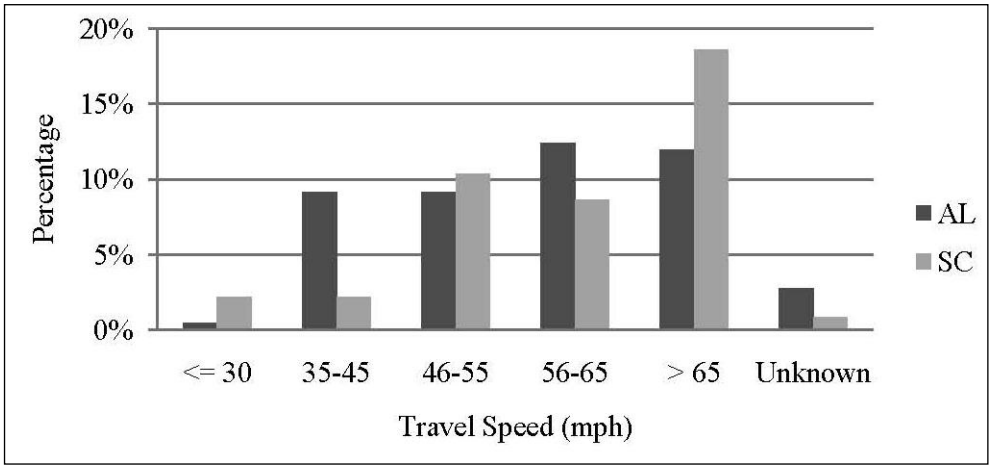


Figure 78: Single-Vehicle Fatal Crashes by Vehicle Travel Speed

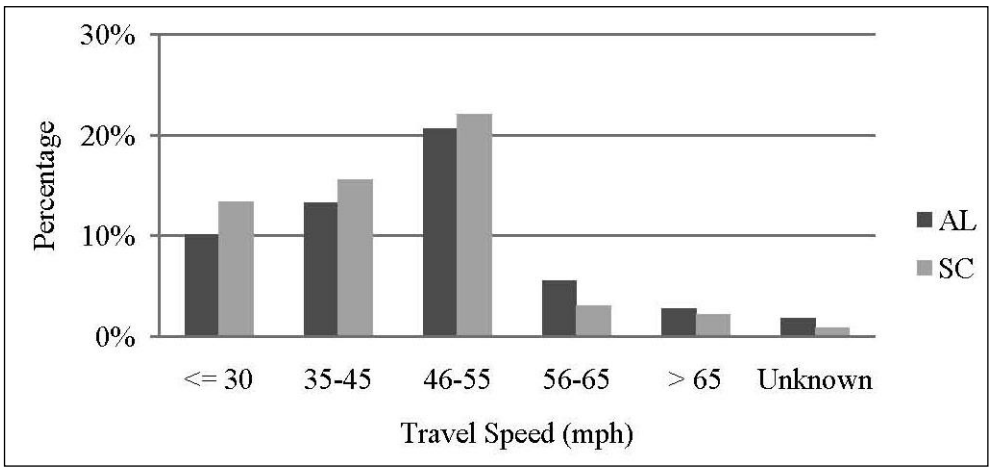


Figure 79: Multiple-Vehicle Fatal Crashes by Vehicle Travel Speed

3.3.5.3 Vehicle Maneuver

The vehicle maneuver variable describes the action taken by the driver of a vehicle prior to the crash. As presented in Table 41, Figure 80, and Figure 81, more than 70% of all involved vehicles were traveling in a straight direction prior to the fatal crashes.

Table 41: Crash Type and Associated Vehicle Maneuver

State	Crash Type	Vehicle Maneuver					
		Straight (%)	Lane Changing/ Passing/ Overtaking (%)	Turning Movement (%)	Entering Traffic (%)	Slowing/ Stopped (%)	Others/ Unknown (%)
AL	Single-Vehicle	31	2	1	0	0	11
	Multiple-Vehicle	39	2	3	2	4	3
	AL Total	70	4	4	2	4	14
GA	Single-Vehicle	35	3	0	2	1	3
	Multiple-Vehicle	47	3	5	2	0	0
	GA Total	82	6	5	4	1	3
MS	Single-Vehicle	28	1	0	0	0	4
	Multiple-Vehicle	57	3	4	1	1	2
	MS Total	85	4	4	1	1	6
SC	Single-Vehicle	42	0	0	0	0	1
	Multiple-Vehicle	48	2	4	3	0	0
	SC Total	90	2	4	3	0	1

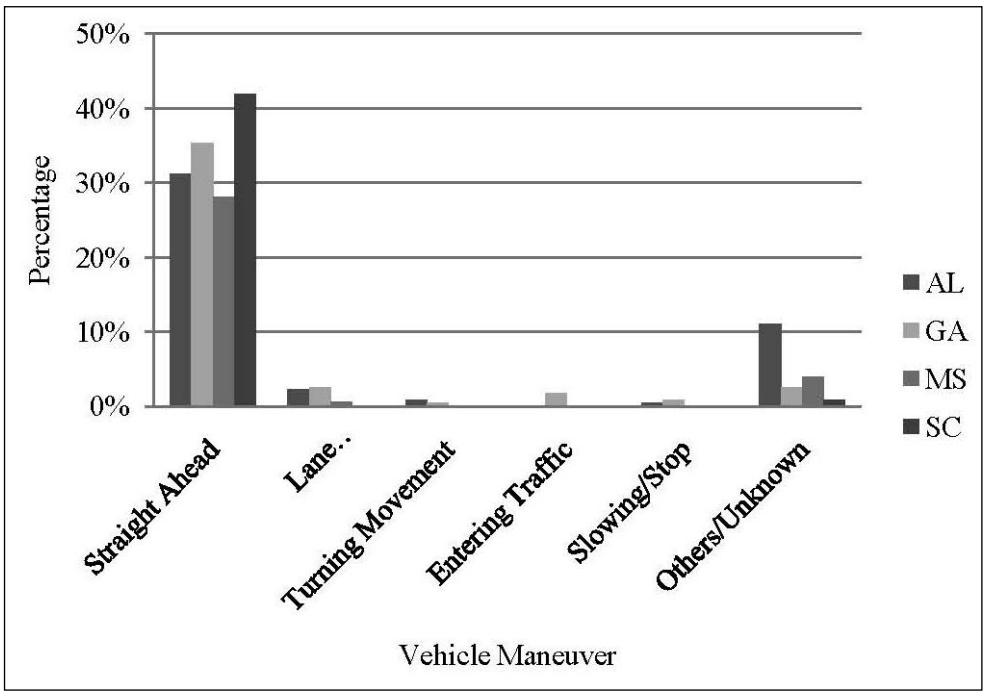


Figure 80: Single-Vehicle Fatal Crashes and Associated Vehicle Maneuver

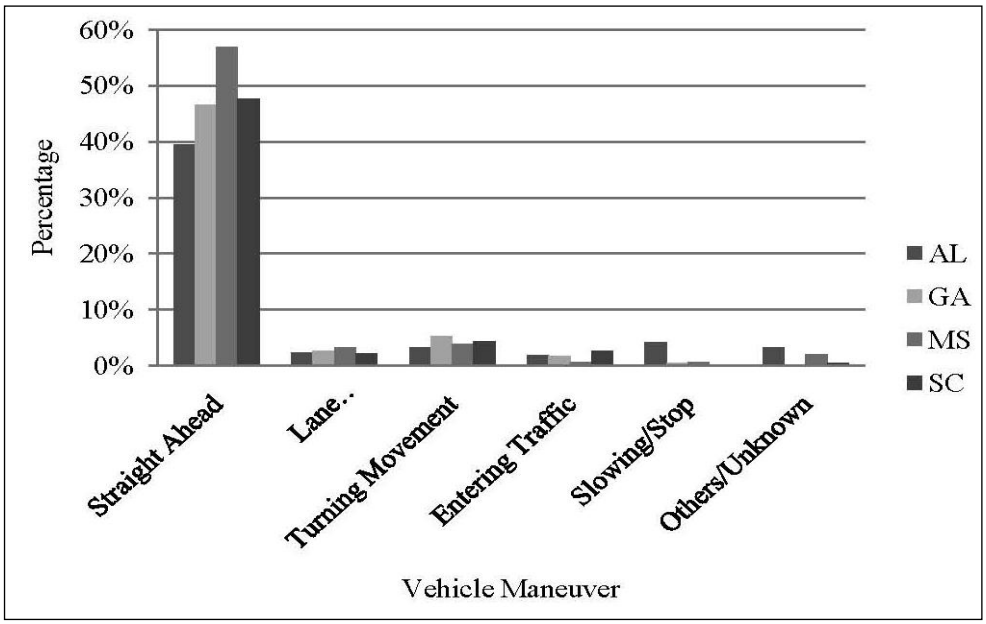


Figure 81: Multiple-Vehicle Fatal Crashes and Associated Vehicle Maneuver

3.3.5.4 Extent of Damage – Towing Status

It is not surprising to observe that more than 90% of the vehicles involved in the fatal crashes were seriously damaged and towed from the crash scene (see Table 42). This depicts the severe vehicle destruction common to fatal crashes.

Table 42: Crash Type and Associated Vehicle Condition (Towing Status)

State	Crash Type	Vehicle Towing Status		
		Driven (%)	Towed (%)	Abandoned/Unknown (%)
AL	Single-Vehicle	0	45	0
	Multiple-Vehicle	0	54	0
	AL Total	0	99	0
GA	Single-Vehicle	1	37	5
	Multiple-Vehicle	2	53	1
	GA Total	3	90	6
MS	Single-Vehicle	0	33	0
	Multiple-Vehicle	2	64	1
	MS Total	2	97	1
SC	Single-Vehicle	1	41	1
	Multiple-Vehicle	2	55	0
	SC Total	3	96	1

3.3.5.5 Vehicle Model Year

The age of a vehicle can be directly associated with crash severity, as newer vehicles should be equipped with advanced occupant protection features not common to earlier vehicle models. Less than 10% of the fatal crashes involved vehicles older than 20 years. Table 43, Figure 82, and Figure 83 demonstrate typical vehicle ages with most vehicles ten years old or newer (recall crashes are from the years 1997 through 1998 for the various states in this study). The vehicle age distribution was similar for the single-vehicle and multiple-vehicle crashes.

Table 43: Crash Type and Associated Vehicle Model Year

State	Crash Type	Vehicle Model Year			
		<= 1977 (%)	1978 – 1987 (%)	1988 – 1992 (%)	>= 1993 (%)
AL	Single-Vehicle	5	19	13	9
	Multiple-Vehicle	3	18	18	15
	AL Total	8	37	31	24
GA	Single-Vehicle	3	11	10	17
	Multiple-Vehicle	2	17	20	20
	GA Total	5	28	30	37
MS	Single-Vehicle	4	8	9	12
	Multiple-Vehicle	4	21	20	22
	MS Total	8	29	29	34
SC	Single-Vehicle	1	14	17	11
	Multiple-Vehicle	2	13	18	24
	SC Total	3	27	35	36

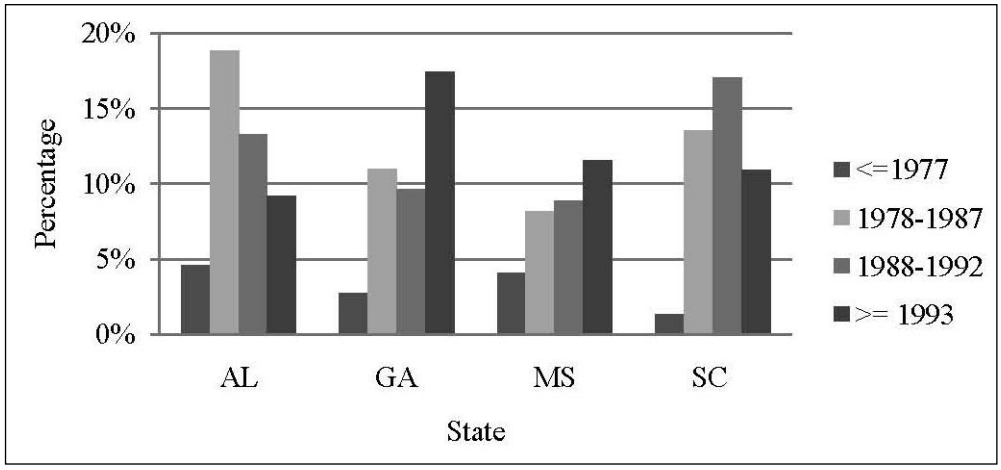


Figure 82: Single-Vehicle Fatal Crashes and Associated Vehicle Model Year

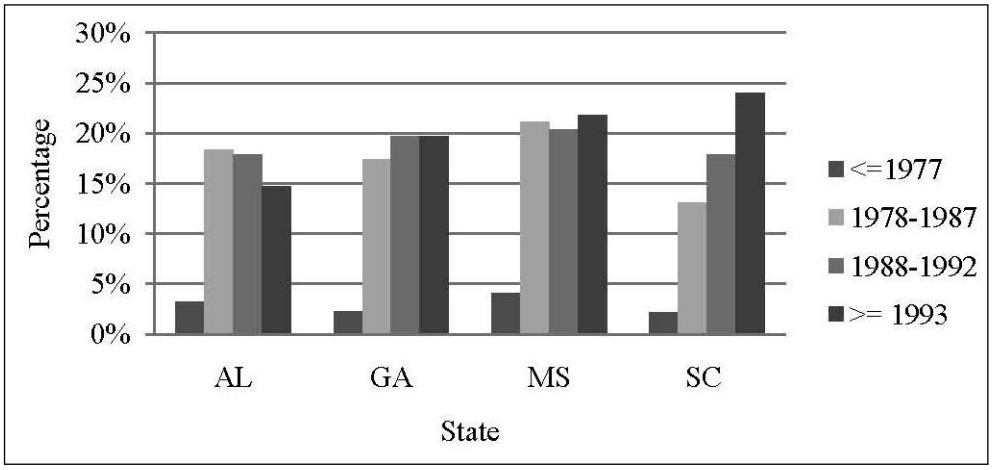


Figure 83: Multiple-Vehicle Fatal Crashes and Associated Vehicle Model Year

3.3.6 Summary

This section presented descriptive statistics of the fatal crash database for five data characteristics, including:

- Crash data characteristics;
- Roadway and roadside related characteristics;
- Environment related characteristics;
- Driver and passenger related characteristics; and
- Vehicle related characteristics.

The author carried out the primary data analysis for single-vehicle fatal crash and multiple-vehicle fatal crash, respectively. Most variables showed different characteristics across crash types, including variables of roadway geometrics, roadside and environmental characteristics, and traffic conditions. This finding provides valuable information for the model and variable selection of statistical modeling.

CHAPTER 4 MODELING METHODOLOGY AND STRATEGY

Regression has been widely used for transportation safety analysis for decades. It still remains one of the commonly applied analysis tools for traffic crash data analysis and modeling. Regression models offer the opportunity to reveal the potential association between safety measures of interest and contributing factors. This chapter introduces how to apply the logit model—a generalized linear regression model—to predict fatal crash types and also reviews the corresponding theoretical background.

4.1 Regression Model for Crash Type Prediction

In transportation safety analysis, it is important to be able to predict the safety impact of various contributing factors of roadways. This predictive capability provides a way to quantify the safety performance of roads and offers information for potential safety treatments. Safety predictive models are a range of models that represent relationships between safety performance measures and major influential variables, such as traffic volume and roadway geometry features through statistical procedures. Even though safety prediction models can be very useful, one needs to be aware of their limitations. Safety prediction models can only identify the associations between safety measures and other variables rather than define associated crash causes. This is because traffic crash analysis is an observational study. It is not practical to have controlled and randomized experiments of traffic crashes in the real world. From this aspect, computer simulation and driving simulators may be able to carry out experiments in a "pseudo-world" under a more controllable environment. Meanwhile, some critical influential variables are missing in most crash databases. For example, driving speed at the time of a crash, which has an association with crash severity, is often substituted with posted speed limit or estimated speed through crash reporting techniques.

4.1.1 Safety Predictive Models

Efficient and effective safety predictive models can vary based on specific objectives such as what to predict, at which level to predict, and which method to use. The vast majority of safety prediction models attempt to predict crash frequency (number of crashes that occurred during a period of time) or crash rate (crash frequency over the traffic exposure). These safety measures are treated as continuous variables. Common models often used for these assessments include Poisson regression models, negative binomial regression models, or variations of these models. Systematic-level safety measures, such as number of crashes that occurred over a time period for specific road segments, require analysts to aggregate crash counts and extract road geometric and roadside information for each individual road segment. In this case, a variable only represents an average condition of the corresponding road segment rather than reflecting a unique feature of a crash site. Studies also have shown that the way of segregating roadways into road segments can influence the prediction results.

Safety performance prediction at an aggregated level is important for roadway network screening and facility evaluation as it can help identify problematic areas. However, these systematic models do not permit evaluation at the individual crash level. In some cases, road or crash characteristics may have unique associations with safety measures at a disaggregated level that can be different than at the category or aggregated level. This phenomenon is known as ecological fallacy, an error that occurs when falsely assuming individuals in a group have the average attributes of the group as a whole. In other cases, some crash level variables are inappropriate for aggregation.

Among a range of safety measures, the most frequently evaluated measures of performance are crash frequency and crash rate. Meanwhile, as discussed in Chapter 2, a considerable number of researchers have also developed models to predict crash injury severity levels and their associated crash cost. Crash type, on the other hand,

has only been minimally investigated. Some researchers recognized the shortcomings of estimating crash total alone. Jonsson et al. (2009) compared the performance of SPFs for total crash count estimation and crash counts by crash types. They concluded that models estimated by crash types fit better than models of crash total estimations. Crash data separated by crash types can increase homogeneity of crash data since it is reasonable to assume that similar crash types will tend to have similar crash mechanisms. On one hand, a homogenous dataset will be more likely to improve how well the resulting model fits. On the other hand, this kind of crash type analysis may exclude potential connections between different types of crashes since crashes are modeled separately. Additionally, most safety prediction models have been developed based on aggregated crash data. This type of data is often developed by summing up the overall number of crashes that occurred on a certain length of road segments during a period of time. Accordingly, this type of study can only use the road geometric characteristics that are averaged over road segments. Not surprisingly, various ways of data aggregation may influence estimation results as well.

After thorough analysis and comparisons of previous research methods, this author used a crash type based safety prediction modeling approach using dis-aggregated crash data from four southeastern states. Researchers and safety engineers can gain insights of how to reduce the frequency of crash types by considering potential contributing factors and their association with various crash types. For this effort, the research team has elected to focus on crash types for fatal crash analysis on two-lane rural highways. It is expected, for example, that the distribution of crash types is different for crashes with all injury severities versus fatal crashes alone. Some types of crashes may be more likely to result in one or more fatality while others would be more directly associated with less severe injuries. Therefore, the evaluation of fatal crash types may help reveal crash type associations that will be different from what can be determined when studying all crashes. Furthermore, certain crash types tend to be over-represented for a specific type of highway facility. For example, a single-

vehicle run-off-road crash type makes up over 50% of overall fatal crashes on two-lane rural highway, while the single-vehicle crash is less common and less severe at urban locations.

4.1.2 Crash Type Prediction Model Application

Fatal crash type prediction models can serve as an analytical assessment tool for projects from the Highway Safety Improvement Program (HSIP) as well as other related rural roadway safety improvements. In the process of identifying locations with the greatest safety needs, most current methods do not directly consider specific crash types. Crash type prediction models provide an approach to quantify safety performance measures by taking into account roadway design characteristics, road environmental features, as well as traffic conditions. A random sample of fatal crash records is available for this analysis. These records include detailed crash-specific roadway geometric characteristics that were collected through site investigation or video log inspection during a previous Georgia Department of Transportation (GDOT) study. This comprehensive data set will allow the research team to better understand the relationships between roadway design features, fatal crash types, and expected associations with prospective crash countermeasures.

Since the models described in this report were developed based on fatal crashes, the author recommends using the models to assess expected reductions for fatality and severe injury crashes. It is generally recognized that fatal crashes and crashes with severe injuries may share common traits and are similar compared to crashes with minor injuries or with Property Damage Only (PDO). Most crash countermeasures are specific to a crash type; therefore, knowing how the road geometric design features and roadside environment conditions relate to fatal crash types will help safety engineers select more effective remedies for these hazardous crash conditions.

For this study, the author's goal was to develop models to predict fatal crash type outcomes and identify potential contributing factors which differentiate one type of fatal crash from others. Since crash type is a categorical variable, the author performed categorical data analysis with a logistic regression model to predict categorical response variables with both continuous and categorical predictors. The next two sections introduce the definition of each crash type and the modeling approach used for this study.

4.1.3 Crash Types

This study defines crash types based on the definition of "Manner of Collision" in the "First Harmful Events" category used by FARS (U.S. DOT and NHTSA, 2007). Figure 84 presents the fatal crash type classification structure. FARS describes the first harmful event as either the first property damage or injury-producing event of a crash occurrence. The single-vehicle run-off-road crash identifier is applied when the first harmful event is a non-collision (for example: driving off a cliff, rollover), a collision with an object that is not fixed (for example: pedestrians or animals), or a collision with a fixed-object (for example: trees, utility poles). Since there are only a few crashes striking objects that are not fixed, a simplified representative description for this study is a single-vehicle crash where the vehicle exited the roadway and either struck a fixed object or overturned.

For crashes that involved more than one vehicle, the two major fatal crash types observed for this data set were head-on collisions and angle crashes. A head-on collision is defined as two vehicles colliding with their front ends while traveling in opposite directions. An angle crash is categorized as the front end of one vehicle making contact with the broad side of another one.

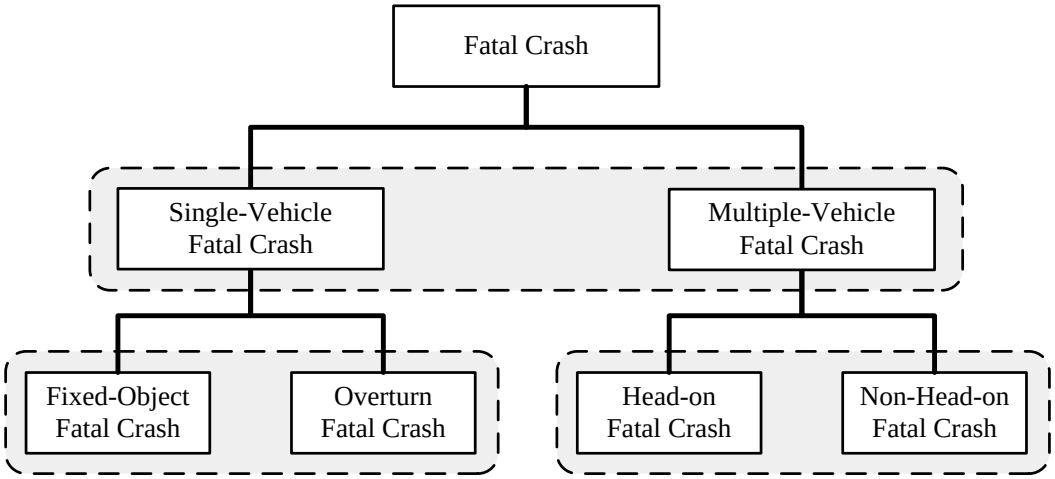


Figure 84: Fatal Crash Type Classification

4.2 Logit Models

Based on previous discussions, this study focuses on predicting the probability of a fatal crash to be a certain type of crash. Figure 84 presents the hierarchical structure of fatal crash type categorization. Crash type is a categorical variable. The type of statistical method that is suitable for this type of study is logistic regression, which is a powerful model to help analyze the association between a categorical dependent variable and other independent variables.

Logistic regression covers a group of models. Among them the options for this study include multinomial logit model, nested logit model, and binary logit model. In the case a categorical variable has more than two categories; one may use a multinomial logit model. A nested logit model is designed to deal with a categorical variable with a hierarchical structure. A binary logit model is appropriate for the categorical response with dichotomous alternatives.

The initial intention of this research effort was to apply a multinomial logit model to predict the probability of a fatal crash as a fixed-object crash, overturn crash, head-on

crash, or a non-head-on multiple-vehicle crash. However, one of the drawbacks of a multinomial logit model is that the number of parameters that need to be estimated will increase quickly as the number of categories of the response variable is increasing. As previously discussed, one of the objectives of this study was to develop crash type models based on the premise that roadway design characteristics, roadside environment features, and traffic conditions each directly influence crash type occurrence. Finally, the author applied a statistical model called a binary logit model to help identify influential factors that can differentiate two crash types at a time. These models reveal the association between crash type outcomes and contributing variables. Initial efforts resulted in the creation of three binary logit models based on the crash type classifications indicated with dashed lines in Figure 84. The research team examined several sets of potential factors that could significantly differentiate two types of crashes. These crash type pairs included:

- Single-vehicle fatal crash vs. Multiple-vehicle fatal crash
- Fixed object fatal crash vs. Overturn fatal crash
- Head-on fatal crash vs. Other fatal crash (not head-on)

The use of the binary logit model to differentiate a fixed-object fatal crash from a rollover fatal crash proved unsuccessful. This outcome may be because these two types of single-vehicle crashes have similar potential causes initially as the vehicle will generally depart the travel lane prior to the crash. The likelihood of a vehicle rollover following lane departure may be due to steep side slope, narrow clear zone, pavement edge drop-offs, or similar conditions. Most of these variables, however, are not available individually in the crash database and are generally represented by a single subjective variable known as the roadside hazard rating. This binary logit model approach, therefore, may be suitable to differentiate single-vehicle fatal crashes from multiple-vehicle fatal crashes. As a result, this research presents two crash type prediction models as shown in the following section:

- Single-vehicle fatal crash vs. Multiple-vehicle fatal crash
    - Based on fatal crash history for rural two-lane highways, predict the probability of a single-vehicle fatal crash
- Head-on fatal crash vs. Other fatal crash (not a head-on)
    - Based on multiple-vehicle fatal crash history for rural two-lane highways, predict the probability of a head-on fatal crash

4.2.1 Binary Logit Model

The response variable in this study is a categorical variable with two values, 1 for single-vehicle fatal crash, 0 for multiple-vehicle fatal crash. While ordinary regression models are only valid to analyze data with normally distributed response variables, logistic regression is the suitable model for categorical response data. This study is trying to model the probability of a fatal crash to be one type instead of another as a function of various roadway design characteristics and roadside, environment, and traffic conditions.

The binary logistic regression model is formulated as (Agresti, 2002):

$$P(Y=1|\mathbf{x}) = \frac{e^{(\beta_0+\boldsymbol{\beta}'\mathbf{x})}}{1+e^{(\beta_0+\boldsymbol{\beta}'\mathbf{x})}} \tag{4-1}$$

Given:

Y: binary response variable, Y=1 when the fatal crash is a crash type of interest (single-vehicle crash for single-vehicle fatal model, and head-on crash for head-on fatal crash model), Y=0, otherwise;

X: a vector of p independent variables $\mathbf{x}=(x_1, x_2, \ldots, x_p)'$,

β_0: parameter reflect the impact of changes in **X** on the probability.

β: a set of parameters reflect the impact of changes in **X** on the probability.

The logistic regression model, Equation (4-1), formulates a nonlinear but monotonic relationship between the probabilities of event occurrence and independent variables. Therefore, positive coefficients suggest that variables tend to increase the single-vehicle fatal crash occurrences, while negative coefficients imply that variables tend to reduce the risk of single-vehicle fatal crashes after accounting for the effects of other independent variables.

4.2.1.1 Single-vehicle vs. Multiple-vehicle Crash

To compare conditions using a binary logit model, the first step is to assign a value of either zero or one for the crash type of interest. For this effort, the research team assigned the following values for variable Y for each fatal crash:

Y= 1, if the crash type is single-vehicle run-off-road fatal crash;

Y= 0, otherwise.

The binary logit model then estimates the probability while Y has the value of 1 with independent variables X_1 ,….., X_k , that represent features associated with the crash conditions. The logistic function form estimates what the probability would be of observing a single-vehicle run-off-road crash in the event of a fatal crash, as shown below:

$$\Pr(Y=1) = \Pr(Single-veh-runoff) = \frac{\exp(\beta_0 + \sum_{i=1}^{i=k} \beta_i X_i)}{1+\exp(\beta_0 + \sum_{i=1}^{i=k} \beta_i X_i)} \qquad (4\text{-}2)$$

Given:

Pr(Single-veh-runoff): the probability of observing a single-vehicle run-off-road fatal crash occurrence in the event a fatal crash occurred, this will be a value between 0 and 1;

β_0: estimated intercept;

β_i: estimated coefficient for the corresponding independent variable X_i;

X_i: the ith independent variable.

This model can be used to predict the likelihood that if a fatal crash should occur that it will be a single-vehicle run-off-road fatal crash. This is defined by a set of independent variables that have significant impacts on the specific crash type. Initially, the research team estimated this type of model based on the four-state (AL, GA, MS, and SC) combined fatal crash database. This database includes approximately 550 randomly selected fatal crashes that contain data for crash site conditions, environmental features, and general crash information. For variables related to drivers and vehicles, the analysis focused on the at-fault drivers and their vehicles. This assessment incorporated the driver's gender, age, safety belt usage, vehicle's type, model, year, etc. This study defines at-fault drivers as those drivers identified as the responsible parties whose actions directly contributed to crashes. As a result, each crash includes driver and vehicle information for only one driver. At-fault driver information could not be obtained for Mississippi and South Carolina fatal crash samples. Therefore, the combined-state model could not examine effects based on these variables.

This analysis also included the development of crash type models for each individual state crash database. Where available, this individual state analysis includes the at-fault driver and vehicle information. The state specific models offer the opportunity to investigate differences as well as similarities for features that may significantly influence fatal crashes in the various states.

4.2.1.2 Head-on vs. Other Multiple-Vehicle Fatal Crashes

As previously indicated, the two most common multiple vehicle fatal crashes were head-on and angle crashes. Other observed crash types such as rear-end and sideswipe crashes account for approximately six-percent of the total number of fatal crashes. This study focuses on reducing fatality collisions at rural road segments rather than the less common rural intersection crashes. Therefore, the second crash type model will focus on predicting the probability that when a multiple vehicle fatal crash occurs, that it is a head-on collision. By evaluating multiple vehicle crashes separate from single-vehicle crashes, the crash data has more homogenous characteristics resulting in better fitting models. The probability that if a multiple vehicle fatal crash occurs, that the crash type is a head-on is represented as:

$$\Pr(Head-on) = \frac{\exp(\beta_0 + \sum_{i=1}^{i=k} \beta_i X_i)}{1 + \exp(\beta_0 + \sum_{i=1}^{i=k} \beta_i X_i)} \tag{4-3}$$

Given:

Pr(Head-on): probability of observing a head-on crash occurrence in the event that a multiple-vehicle fatal crash occurred, this will be a value between 0 and 1;

β_0: estimated intercept;

β_i: estimated coefficient for the corresponding independent variable X_i;

X_i: the ith independent variable.

In a manner similar to the development of the single-vehicle fatal crash model, the author estimated a head-on crash model for the combined-state database as well as for the individual states. Potential contributing factors include roadway geometric characteristics, roadside features, environment conditions, as well as at-fault drivers

and their vehicle information. The final models and example use and interpretation of the models are presented later in this report.

4.2.2 Model Estimation

For a binary logit model, each observation is assumed to be one draw (a random selection) from binomial distribution (n_i=1). These samples are Bernoulli events, which implies that each observation is independent from one another. Therefore, the joint probability—the likelihood function—for sample data with sample size of n is shown as Equation (4-4):

$$L(\beta \mid y, \mathbf{x}) = \prod_{i=1}^{n} \left[P(Y=1 \mid x)\right]^{y_i} \left[1 - P(Y=1 \mid x)\right]^{(1-y_i)}$$

$$L(\beta \mid y, \mathbf{x}) = \prod_{i=1}^{n} \left[\frac{e^{\beta_0+\beta x_i}}{1+e^{\beta_0+\beta x_i}}\right]^{y_i} \left[1 - \frac{e^{\beta_0+\beta x_i}}{1+e^{\beta_0+\beta x_i}})\right]^{(1-y_i)} \tag{4-4}$$

The logarithmic form of Equation (4-4) is:

$$\ln L = \sum_{i=1}^{n} \left\{ y_i \ln\left(\frac{e^{\beta_0+\beta x_i}}{1+e^{\beta_0+\beta x_i}}\right) + (1-y_i)\ln\left(1 - \frac{e^{\beta_0+\beta x_i}}{1+e^{\beta_0+\beta x_i}}\right)\right\}$$

$$= \sum_{i=1}^{n} \left\{ y_i \left(\beta_0 + \beta x_i\right) - \ln\left(1+e^{\beta_0+\beta x_i}\right)\right\} \tag{4-5}$$

Since the maximum likelihood equation, $\frac{\partial \ln L}{\partial \beta} = 0$, is nonlinear, an iterative solution is obtained by the Fisher scoring method. Fisher scoring method is one of the common mathematical methods to solve maximum likelihood equations numerically.

Meanwhile, a Wald test is used for a significant test of parameters. The null hypothesis (H_0: β_i =0), implies that the probability of Y=1 is independent of the corresponding independent variable x_i. For large samples, the Wald test statistic

$z = \frac{\beta}{SE}$ is standard normally distributed when the H_0 assumption is true. Even though the Wald test is based on the asymptotic normality of parameter estimators, it has less computational burden and is easier to construct confidence intervals than a likelihood-ratio based test. With large sample sizes, the Wald test provides adequate results (Agresti, 2002).

4.2.3 Model Interpretation: Marginal Effects

Understanding the marginal effects from individual contributing factors on the estimated dependent variable is critical for model development. First, most safety prediction models are developed based on observational data. Therefore, it is inappropriate to extend the association between a dependent variable and independent variables to causal relationships. In other words, it is misleading to claim that changes in the estimated dependent variable are caused by a unit change in one of the independent variables while holding other predictors constant. The bottom line is that researchers can only make statistical interpretations based on the assumption of association rather than causation.

Secondly, it may be troublesome to analyze marginal effects of individual contributing factors when independent variables are strongly correlated with each other. In other words, the change in one independent variable is more likely to vary the level of other predictors in the model. Therefore, the impact on the prediction of the dependent variable is unlikely to occur by the change of just one independent variable since other variables are also likely to then change. In this case, the theoretical marginal effect will lose its empirical meaning from an application perspective.

Therefore, before proceeding to analyze marginal effects of fatal crash type models, the author examined correlation relationships among independent variables for each

crash type model. The overall result showed that independent variables do not appear to be strongly correlated with one another. Based on that, the author then performed a marginal effect analysis.

Marginal effects of logit models are often interpreted by odds and odds ratio rather than solely by parameter estimates. For example, the logit model for single-vehicle crashes, Equation (4-2), can be written as:

$$\begin{aligned}
&\log\left(\frac{\Pr(Y=1)}{1-\Pr(Y=1)}\right) \\
&= \log\left(\frac{\Pr(Single-veh-runoff)}{1-\Pr(Single-veh-runoff)}\right) \\
&= \log\left[odds(Single-veh-runoff)\right] \\
&= \beta_0 + \sum_{i=1}^{i=k} \beta_i X_i
\end{aligned} \tag{4-6}$$

As shown in Equation (4-6), there is a linear relationship between the independent variables and the log (odds of fatal crashes as single-vehicle crashes). The effect of a continuous variable on the odds of fatal crashes as single-vehicle crashes can be computed as:

$$\begin{aligned}
&oddsratio(Single-veh-runoff) \\
&= \frac{odds(Single-veh-runoff \mid x_j = x_j + 1)}{odds(Single-veh-runoff \mid x_j = x_j)} \\
&= \frac{\exp(\beta_0 + \beta_1 x_1 + \ldots + \beta_j \times \left(x_j + 1\right) + \ldots + \beta_k x_k)}{\exp(\beta_0 + \beta_1 x_1 + \ldots + \beta_j \times x_j + \ldots + \beta_k x_k)} \\
&= \exp(\beta_j)
\end{aligned} \tag{4-7}$$

The effect of a dummy variable on the odds of fatal crashes as single-vehicle crashes can be computed as:

$$
\begin{aligned}
& oddsratio(Single-veh-runoff) \\
&= \frac{odds(Single-veh-runoff \mid x_j = 1)}{odds(Single-veh-runoff \mid x_j = 0)} \\
&= \frac{\exp(\beta_0 + \beta_1 x_1 + \ldots + \beta_j \times 1 + \ldots + \beta_k x_k)}{\exp(\beta_0 + \beta_1 x_1 + \ldots + \beta_j \times 0 + \ldots + \beta_k x_k)} \\
&= \exp(\beta_j)
\end{aligned}
\tag{4-8}
$$

Both cases show that the marginal effect of an independent variable is the exponential of the coefficient of that variable. This value is also the odds ratio of fatal crashes as single-vehicle crashes. The Wald confidence interval of the odds ratio is the exponential of the corresponding confidence interval of the coefficient.

The confidence interval of coefficient β_i is computed as follow:

$$\beta_i \pm z_{(1-\alpha/2)}\left[SE(\beta_i)\right] \tag{4-9}$$

Given,

$z_{(1-\alpha/2)}$: z-multiplier, (1 - α/2) percentile of the standard normal distribution, in this study, α=0.1;

β_i : Estimated coefficient for the parameter β_i ;

$SE(\beta_i)$: Standard error of the estimate β_i .

Therefore, the 90% Wald confidence interval for oddsratio (α=0.1) is:

$$\left(\exp\left\{\beta_i - z_{(1-\alpha/2)}\left[SE(\beta_i)\right]\right\}, \exp\left\{\beta_i + z_{(1-\alpha/2)}\left[SE(\beta_i)\right]\right\}\right) \tag{4-10}$$

4.2.4 Goodness-of-fit Test

Pearson and deviance goodness-of-fit test have both been used widely. However, the Pearson test is only valid while there are a sufficient numbers of replications in subgroups (cell number >5). It is difficult to meet this condition for sparse data. In order to avoid potential violation of Pearson and deviance test, the author applied the Hosmer-Lemeshow goodness-of-fit test instead, which is only available for a binary logit model. The Hosmer-Lemeshow statistic follows a chi-square distribution with degree of freedom as: number of group-2. The Hosmer-Lemeshow test does not require sufficient replications within subpopulations. A small p-value (<0.05) indicates lack-of-fit of the model. The Hosmer-Lemeshow test statistic is written as:

$$\chi^2_{HL} = \sum_{i=1}^{g} \frac{\left(O_i - N_i \overline{\pi}_i\right)^2}{N_i \overline{\pi}_i \left(1 - \overline{\pi}_i\right)} \tag{4-11}$$

Given,

Ni: Total frequency of subjects in the ith group;

Oi: Total frequency of event outcomes in the ith group;

$\overline{\pi}_i$: Average estimated predicted probability of an event outcome for the ith group;

g: Number of groups, The degree of freedom = (g – 2);

χ^2_{HL} : Chi-square test statistic with degree of freedom as g-2.

4.2.5 Predictive Power

The author applied the Receiver Operating Characteristic (ROC) curve to assess the predictive power of fitted binary logit models. A ROC curve plots the relationship between two summaries of predictive power: sensitivity and 1-specificity for cutoffs π_0. Sensitivity is defined as the probability that the prediction from the model complies with the observation for an event occurred (Y=1) according to a cutoff point π_0, see Equation (4-12). The specificity is the probability that the prediction complies

with the observation for an event not occurring (Y=0) according to a cutoff point $\pi_{0,}$ see Equation (4-13).

$$sensitivity = P(\hat{Y} = 1 \mid Y = 1) \tag{4-12}$$

$$specificity = P(\hat{Y} = 0 \mid Y = 0) \tag{4-13}$$

A ROC curve is usually a concave curve connecting (0,0) and (1,1). The higher the area under the curve, the better the prediction resulted from the model. For example, a value of the area of 0.5 implies that the prediction is no better than a random guess. The area under the curve provides a measure of discrimination. For single-vehicle fatal crash model, it measures the likelihood of a fatal crash as a single-vehicle crash will have a higher probability of P(Y=1) than a multiple-vehicle crash. As proposed by Lemonshow, a general rule can be followed to assess the predictive power based on the actual value of the area under the ROC curve, see Table 44 (Hosmer, and Lemeshow, 2000).

Table 44: General Rule of ROC Value

ROC = 0.5	No discrimination
$0.7 \leq$ ROC < 0.8	Acceptable discrimination
$0.8 \leq$ ROC < 0.9	Excellent discrimination
ROC $\geq$ 0.9	Outstanding discrimination

An example is shown in Figure 85, the area under the curve of about 0.83 suggests the model provides a good prediction.

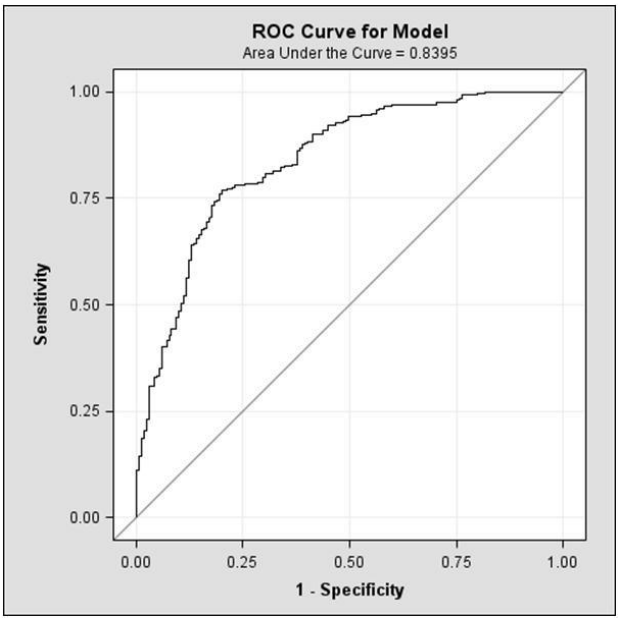


Figure 85: ROC Curve Example

4.2.6 Variable Selection and Model Selection

The goal of variable selection is to include as few predictors as possible. A simple model which fits the data adequately has the advantage of achieving model parsimony. A parsimonious model is the simplest plausible model with the least predictors under a given model quality. Even though some of vehicle and driver related factors are known contributing factors to traffic crashes, this study focused on road, roadside and environment related characteristics.

One of the problems of incorporating too many predictors in the model is the increased possibility for the model to suffer from multicollinearity. Multicollinearity is the situation when predictors are correlated with each other; theoretically, everything is related with everything else. Perfect independence among variables rarely exists. Existence of strong correlation is what one wants to avoid.

It is then necessary to determine a reasonable number of predictors to include in the binary logit model. One of the guidelines suggests having at least 10 outcomes from each category for every predictor (Agresti, 2007). For example, if there are 50 observations with Y=1 out of 100 observations, the model should incorporate no more than approximately five predictors. The author used this guideline as a general consideration.

Common model verification procedures frequently used for ordinary regression models and other types of logistic regression models may not be suitable for evaluating a binary logit model (Agresti, 2002; Ramsey and Schafer, 2002). The model checking and selection for a binary logit model mainly relies on examining the significance of extra terms in the model including squared terms or possible interactions between variables. For this effort, influential variables that may significantly help differentiate crash types for the final model (with a p-value less than 0.20) were retained in the model during the examination of potential contributing factors.

Meanwhile, the ultimate goal for developing safety predictive models was to identify valuable information and quantify relationships between highway design characteristics and associated safety performance. While the statistical significance and model goodness-of-fit are very important considerations in this process, the research team members also made decisions based on their knowledge of how highway design characteristics relate to crash types. This known relationship between design characteristics and safety performance is why the ultimate final models may include higher-than-typical p-values of 0.20 or larger.

The likelihood ratio test can be used to compare models under a hierarchical structure. In addition, the Akaike Information Criterion (AIC) and the Schwarz (Bayesian Information) Criterion also can help to select a better model. These two criteria do not

require models to be constructed under the same hierarchical structure. The smaller the value, the better the model. Both AIC and Schwarz Criterion statistics adjust the -2logL statistic with number of terms used in the model for model comparison. In this study, the Schwarz Criterion is used for model selection.

- *Akaike Information Criterion (AIC):*

$$AIC = -2\log L + 2p \tag{4-14}$$

Given,

L: likelihood function;

p: number of parameters in the model.

- *Schwarz (Bayesian Information) Criterion:*

$$BIC = -2LogL + p\log(\sum_j f_j) \tag{4-15}$$

Given,

f_j: Frequency values of the jth observation,

4.2.7 Correlation Examination

Correlation is a measure of linear association between two variables. The strength of association is measured by the Pearson correlation coefficient as shown in Equation (4-16). The Pearson coefficient can measure the correlation for a pair of continuous variables, or a pair of variables constituted with a continuous and a dichotomous variable.

$$r_{xy} = \frac{\sum_i \left(\left(x_i - \bar{x} \right) \left(y_i - \bar{y} \right) \right)}{\sqrt{\sum_i \left(x_i - \bar{x} \right)^2 \sum_i \left(y_i - \bar{y} \right)^2}} \tag{4-16}$$

Given,

x_i , y_i : sample value of variable X and Y;

$\bar{x}$, $\bar{y}$: sample mean of X and Y.

Meanwhile the correlation between two dichotomous variables is measured by the Phi Coefficient as shown in Equation (4-17) (Edwards, 1976). The Phi Coefficient has a value between -1 and 1 for two dichotomous variables.

$$\phi = \frac{(n_{11}n_{22} - n_{12}n_{21})}{\sqrt{n_{1.}n_{2.}n_{.1}n_{.2}}} \quad (4\text{-}17)$$

Given,

n_{11}, n_{22}, n_{12}, n_{21}: the observed frequency in the 2x2 table cell (1,1), (2, 2), (1, 2), and (2, 1);

$n_{1.}$, $n_{2.}$ $n_{.1}$, $n_{.2}$: the " . " represent the frequency total in the corresponding row or column in the 2x2 table.

For both the Pearson coefficient and the Phi coefficient, values are between -1 and 1. These values represent the presence of negative or positive correlation. The author also investigated the potential correlation among several variables through the linear regression technique, but did not identify any strong associations.

CHAPTER 5 CRASH TYPE MODEL EVALUATION

5.1 Single-vehicle Run-off-road Fatal Crash Models: SV Models

For this study the research team developed fatal crash type prediction models to estimate the probability of a single-vehicle run-off-road fatal crash occurrence in the event of a fatal crash based on the four-state combined fatal crash database (AL, GA, MS, SC), three-state combined database (AL, GA, SC), and state specific database. The combined-state model benefits from a larger sample size, with approximately 530 fatal crashes. This larger sample size enabled the author to investigate more potential contributing factors at various significance levels. Meanwhile, the author also developed state-specific models in order to investigate the opportunity of examining spatial transferability as well as to explore unique variables that may only have impacts on fatal crash outcomes in one or two states.

5.1.1 Combined-State Models

The author developed single-vehicle fatal crash prediction models based on combined-state crash databases as well as state-specific crash databases. This modeling strategy provides opportunities to investigate common contributing factors at a regional level as well as unique variables for individual states. Also, combined-state models benefit from a larger sample size which provides a stronger statistical testing power.

5.1.1.1 Four-State Model (AL, GA, MS, SC)

- *Independent Variables (Four-State, Single-vehicle (SV))*

Table 45 presents independent variables that the author determined to be statistically significant for differentiating SV run-off-road fatal crashes from multiple-vehicle fatal crashes. These variables include: presence of road junction (intersection), lane width, paved shoulder width, graded shoulder width, horizontal curve direction, crest presence, road hazard rating, ADT, presence of commercial driveways, dark without

supplemental lighting, and time of crash. In addition, Table 46 illustrates descriptive statistics for four continuous variables. Table 47 summarizes the distribution of categorical variables, which are represented by values of either zero or one as defined in Table 45.

Table 45: Variable Description (Combined-State, SV)

Types	Variables	Descriptions
Location indicator	AL	1 if in Alabama, 0 otherwise
	MS	1 if in Mississippi, 0 otherwise
	SC	1 if in South Carolina, 0 otherwise
Road junction type	JUNCTION	1 if a road junction, 0 if road segment
Geometric design features	LW	Lane width (ft)
	PSW	Paved shoulder width (ft)
	GSW	Graded shoulder width (ft)
	LCURV	1 if curve to the left, 0 otherwise (curve to the right or straight alignment)
	CREST	1 if vertical crest curve, 0 otherwise
Roadside condition	RHR67	1 if road hazard rating is 6 or 7, 0 otherwise
Traffic volume	ADT	Average daily traffic (10^3 veh/day)
Land use type	LU_C	1 if commercial driveways in the proximity of the crash location, 0 otherwise
Lighting condition	DARKUNLIT	1 if dark with no supplemental street lights, 0 otherwise
Circadian biological clock	HR_DEEPSLEEP	1 if crash time between 1a.m. and 3a.m., 0 otherwise

Table 46: Continuous Variable Descriptive Statistics (Four-State, SV)

Variable	Mean	Std Dev	Minimum	Maximum
LW (ft)	10.8	1.1	7	12
PSW (ft)	0.6	1.7	0	12
GSW (ft)	5.0	3.4	0	16
ADT (vpd)	2,871	2,891	75	17,960

Table 47: Distribution of Categorical Variables (Four-State, SV)

Variable	Status	Percent (%)
JUNCTION	0 (Segment)	77
	1 (Intersection)	23
LCURV	0 (Curve to Right or Straight)	75
	1 (Curve to Left)	25
CREST	0 (Not a Crest Vertical Curve)	88
	1 (Crest Vertical Curve)	12
RHR67	0 (Roadside Hazard Rating < 6)	88
	1 (Roadside Hazard Rating of 6 or 7)	12
LU_C	0 (No Commercial Driveways)	94
	1 (Near Commercial Driveways)	6
DARKUNLIT	0 (Daylight, Dark with Lights, Dusk, or Dawn)	55
	1 (Dark without Supplemental Lights)	45
HR_DEEPSLEEP	0 (Not between 1 a.m. and 3 a.m.)	95
	1 (From 1 a.m. until 3 a.m.)	5

The value for lane width at crash locations ranged from 7 ft to 12 ft with an average of 10.8 ft (approximately 11 ft). Paved shoulder widths ranged from 0 ft to 12 ft, but the average paved shoulder width was near the minimum value at 0.6 ft with a 1.7 ft standard deviation. This low value for the paved shoulder width indicates that most fatal crash locations have narrow paved shoulders. The graded shoulder width was an

average of 5 ft wide with a standard deviation of 3.4 ft, and a range from 0 ft to 16 ft. Graded shoulder widths varied dramatically for the four states. The average ADT value was 2,871 vehicles per day, with a range from 75 up to 17,960 vehicles per day. While the distribution of the ADT was skewed to the right or the higher traffic exposure end, most of crashes occurred at low to moderate traffic locations. The curve to the left (LCURV) variable will have the value of 1 if the horizontal alignment of a crash location is a curve to the left. The author investigated the different categorizations of horizontal alignments. The curve to the left variable tends to have significantly different influences on the likelihood of a single-vehicle fatal crash occurrence compared to the conditions as a curve to the right or a straight alignment. A straight alignment and curve to the right do not appear to have significantly different influences on the occurrence of single-vehicle fatal crash occurrence. The author categorized the horizontal alignment condition with two categories: a curve to the left and a straight alignment or curve to the right.

- *Correlation Evaluation (Four-State, SV)*

The author also examined potential correlation among independent variables. Table 48 presents the correlation matrix. As discussed in Chapter 4, correlation coefficients between continuous variables or between continuous and dichotomous variables are computed as Pearson correlation coefficients, while the Phi Coefficient is used to measure the correlation between dichotomous variables. As shown in Table 48, the largest correlation coefficient is 0.53 for LW and ADT, which implies that lane width, has moderate and positive correlation with the ADT. The remaining coefficients are all between -0.3 and 0.3, which indicate that most independent variables in the four-state single-vehicle model only have weak correlations. Overall, none of the independent variables are highly correlated with others. Therefore, multi-colinearity is less likely to be a potential concern in the four-state single-vehicle fatal crash model.

Table 48: Correlation Matrix (Four-State, SV)

	LW	ADT	PSW	GSW	DARK UNLIT	HR_ DEEP SLEEP	LCURV	CREST	RHR67	JUNC TION	LU_C
LW	1.00	0.53	0.25	0.12	-0.07	0.03	-0.08	0.04	-0.11	0.08	0.05
ADT		1.00	0.23	0.09	-0.14	-0.05	-0.02	0.01	-0.13	0.05	0.15
PSW			1.00	-0.29	-0.10	-0.02	-0.09	0.05	-0.09	0.11	0.17
GSW				1.00	-0.02	0.02	0.00	-0.09	-0.20	0.01	0.05
DARK UNLIT					1.00	0.16	0.03	-0.04	0.07	-0.04	-0.10
HR_DEEP SLEEP						1.00	-0.04	-0.02	0.07	-0.05	-0.02
LCURV							1.00	-0.01	0.06	-0.13	0.02
CREST								1.00	0.05	0.10	0.01
RHR67									1.00	-0.10	-0.10
JUNC TION										1.00	0.13
LU_C											1.00

- *Model Estimations and Interpretations (Four-State, SV)*

Table 49 summarizes the actual model estimation for the four-state combined (AL, GA, MS, SC) model. Among the 527 fatal crashes available for the four-state combined model, 309 crashes were single-vehicle run-off-road fatal crashes. Based on the model estimation results shown in Equation (5-1) and
Table 49, the variables that can significantly differentiate single-vehicle run-off-road fatal crash from multiple-vehicle fatal crash include junction type, lane width, paved shoulder width, graded shoulder width, horizontal curve direction, crest vertical curve, roadside hazard rating, ADT, driveway land use type, lighting condition, and crash time.

Table 49: Model Estimation (Four-State, SV)

Variable	Estimate	P- value
Intercept	5.906	<.0001
AL	-0.1984	0.532
MS	-1.3453	0.0004
SC	-0.0836	0.8091
JUNCTION	-0.9922	0.0003
LW	-0.463	0.0006
PSW	-0.1087	0.2325
GSW	-0.0463	0.304
PSW*GSW [1]	-0.0622	0.0995
LCURV	0.7255	0.0132
CREST	-1.5389	0.0002
LCURV*CREST [1]	2.2686	0.0142
RHR67	1.3314	0.0022
ADT	-0.1078	0.025
LU_C	-1.4298	0.02
DARKUNLIT	1.3135	<.0001
HR_DEEPSLEEP	1.9744	0.0081
Observations (Single-Vehicle/Others)	527 (309/218)	
AIC	530.16	
Schwarz Criterion	602.703	
-2 Log L	496.16	
R-Square	0.3396	

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
9.692	8	0.2873

[1] Note: LCURV*CREST and PSW*GSW indicate these variable pairs interact.

The resulting single-vehicle run-off-road fatal crash prediction model as depicted in Table 49 is presented as follows:

Let :

$$\eta_{4-state} = 5.906 - 0.1984AL - 1.3453MS - 0.0836SC - 0.9922JUNCTION - 0.463LW$$
$$-0.1087PSW - 0.0463GSW - 0.0622(PSW * GSW) + 0.7225LCURV - 1.5389CREST$$
$$+2.2686(LCURV * CREST) + 1.3314RHR67 - 0.1078ADT - 1.4298LU\_C$$
$$+1.3135DARKUNLIT + 1.9744HR\_DEEPSLEEP$$

The probability of a single-vehicle run-off-road fatal crash can then be predicted for a given set of road and environment conditions as:

$$\Pr(Single - veh - runoff)_{4-state} = \frac{\exp(\eta_{4-state})}{1 + \exp(\eta_{4-state})} \quad (5\text{-}1)$$

The three location indicator variables, AL, MS, and SC, will have the value of 1 only if the crash occurred in the corresponding state, otherwise they will have a value of 0. Therefore, a crash location will be Georgia when all three indicator variables are equal to zero. As shown in Table 49, the estimation results are not significant for AL and SC, but the MS p-value is significant. This observation indicates that fatal crash types in Alabama and South Carolina are more likely to follow a similar pattern to those in Georgia as compared to the disparate findings for similar crash types in Mississippi. Since one objective of this study is to identify rural two-lane highway fatal crash models that can help analysts better understand crash trends in Georgia, the author investigated a separate combined-state model based on the fatal crash database from AL, GA, and SC (the three similar states). Model estimation results and discussion are presented in the following section in detail.

5.1.1.2 Three-State Model (AL, GA, SC)

As determined in the previous section, rural two-lane highway fatal crashes for three of the four study states did not appear to be significantly different from one another as

the estimates of state indicator variables (AL and SC) are not statistically significant at 90% confidence level. Mississippi crashes, however, were atypical. Therefore, a three-state model can be developed to further assess the crashes and their influences in the three similar states while still maintaining a reasonable sample size of 428. The three-state combined model includes the same set of independent variables as identified for the four-state model and as indicated in Table 45.

- *Independent Variables (Three-State, SV)*

Table 50 and Table 51 summarize descriptive statistics for continuous and categorical variables, respectively. The value for lane width at crash locations ranges from 8 ft to 12 ft with an average of 10.8 ft (approximately 11 ft). Paved shoulder widths ranged from 0 ft to 12 ft, but the average paved shoulder width was near the minimum value at 0.6 ft with a 1.6 ft standard deviation. This low value for the paved shoulder width indicates that most fatal crash locations did not have paved shoulders. The graded shoulder width was an average of 5.2 ft wide with a standard deviation of 3.5 ft, and a range from 0 ft to 16 ft. Graded shoulder widths varied dramatically for the three states. The average ADT value was 2,896 vehicles per day, with a range from 75 up to 17,960 vehicles per day. While the distribution of the ADT was skewed to the right or the higher traffic exposure end, most of crashes occurred at low to moderate traffic locations.

Table 50: Continuous Variable Descriptive Statistics (Three-State, SV)

Variable	Mean	Std Dev	Minimum	Maximum
LW (ft)	10.8	1.1	8	12
PSW (ft)	0.6	1.6	0	12
GSW (ft)	5.2	3.5	0	16
ADT (veh/day)	2,896	2,941	75	17,960

Table 51: Distribution of Categorical Variables (Three-State, SV)

Variable	Status	Percent (%)
JUNCTION	0 (Segment)	75
	1 (Intersection)	25
LCURV	0 (Curve to Right or Straight)	75
	1 (Curve to Left)	25
CREST	0 (Not a Crest Vertical Curve)	89
	1 (Crest Vertical Curve)	11
RHR67	0 (Roadside Hazard Rating < 6)	92
	1 (Roadside Hazard Rating of 6 or 7)	8
LU_C	0 (No Commercial Driveways)	94
	1 (Near Commercial Driveways)	6
DARKUNLIT	0 (Daylight, Dark with Lights, Dusk, or Dawn)	55
	1 (Dark without Supplemental Lights)	45
HR_DEEPSLEEP	0 (Not between 1 a.m. and 3 a.m.)	96
	1 (From 1 a.m. until 3 a.m.)	4

- *Correlation Evaluation (Three-State, SV)*

As shown in the correlation matrix, Table 52, most independent variables appear to have moderate to weak correlations with other variables. None of the independent variables are strongly correlated. This result is similar to that from the four-state model.

Table 52: Correlation Matrix (Three-State, SV)

	LW	ADT	PSW	GSW	DARK UNLIT	HR_ DEEP SLEEP	LCURV	CREST	RHR67	JUNC TION	LU_C
LW	1.00	0.54	0.25	0.10	-0.06	-0.02	-0.08	0.01	-0.11	0.09	0.03
ADT		1.00	0.24	0.07	-0.12	-0.05	-0.02	-0.01	-0.11	0.04	0.12
PSW			1.00	-0.27	-0.12	-0.07	-0.08	-0.01	-0.08	0.04	0.19
GSW				1.00	-0.01	0.06	-0.01	-0.08	-0.24	0.02	0.06
DARK UNLIT					1.00	0.11	0.05	-0.03	0.08	-0.03	-0.08
HR_DEEP SLEEP						1.00	-0.01	-0.04	0.03	-0.06	0.0004
LCURV							1.00	-0.01	0.12	-0.14	-0.01
CREST								1.00	0.09	0.09	0.03
RHR67									1.00	-0.06	0.01
JUNC TION										1.00	0.11
LU_C											1.00

- *Model Estimation and Interpretation (Three-State, SV)*

As presented in Table 53, among the 428 fatal crashes available for the three-state combined model, 259 crashes were single-vehicle run-off-road fatal crashes. Also shown in Equation (5-2), variables that can significantly differentiate a single-vehicle fatal crash from a multiple-vehicle fatal crash include the presence of a road intersection (junction), lane width, paved shoulder width, graded shoulder width, horizontal curve direction, presence of a crest vertical curve, a roadside hazard rating 6 or 7, ADT, driveway land use type, lighting condition, and time of crash.

Table 53: Model Estimation (Three-State, SV)

Variable	Estimate	P- value
Intercept	6.6717	<.0001
AL	-0.1855	0.5614
SC	-0.1167	0.7404
JUNCTION	-0.8078	0.0051
LW	-0.5407	0.0003
PSW	-0.0542	0.5873
GSW	-0.0475	0.3202
PSW*GSW [1]	-0.0676	0.0929
LCURV	0.788	0.0156
CREST	-1.7264	0.0002
LCURV*CREST [1]	2.5199	0.0223
RHR67	1.1581	0.0716
ADT	-0.0965	0.0558
LU_C	-1.3722	0.0313
DARKUNLIT	1.3101	<.0001
HR_DEEPSLEEP	1.8318	0.0926
Observations	428	
(Single-Vehicle/Others)	(259/169)	
AIC	440.976	
Schwarz Criterion	505.922	
-2 Log L	408.976	
R-Square	0.3204	

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
7.4889	8	0.4849

[1] Note: LCURV*CREST and PSW*GSW indicate these variable pairs interact.

Let:

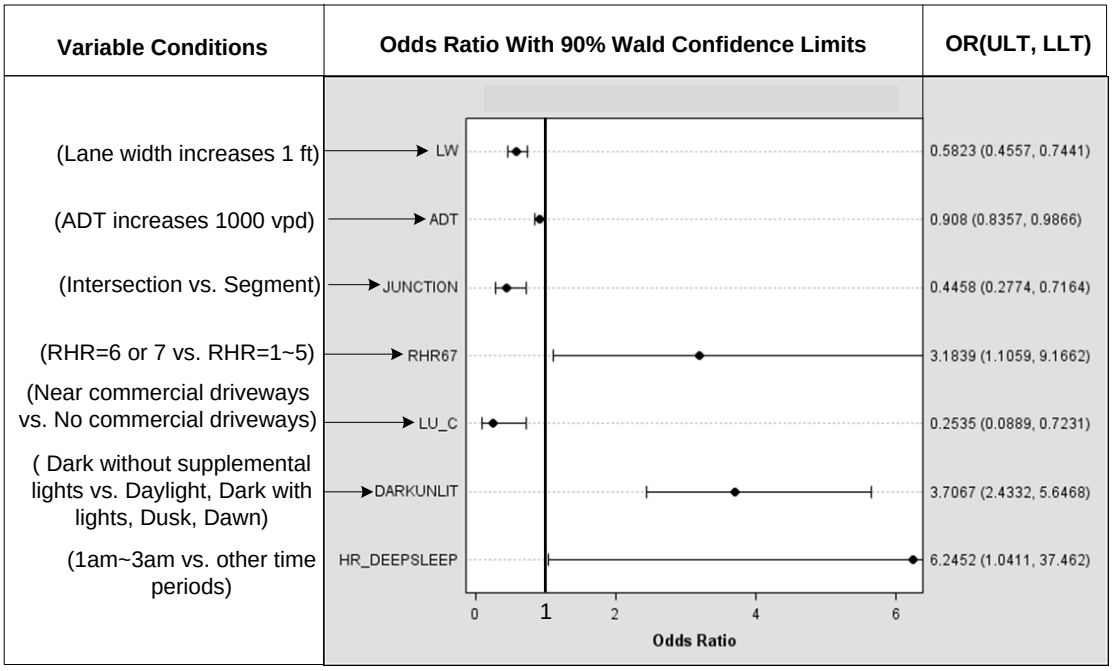
$$\eta_{3-state} = 6.6717 - 0.1855AL - 0.1167SC - 0.8078JUNCTION - 0.5407LW$$
$$-0.0542PSW - 0.0475GSW - 0.0676(PSW * GSW) + 0.788LCURV$$
$$-1.7264CREST + 2.5199(LCURV * CREST) + 1.1581RHR67 - 0.0965ADT$$
$$-1.3722LU\_C + 1.3101DARKUNLIT + 1.8318HR\_DEEPSLEEP$$

Then, the probability of a single-vehicle run-off-road fatal crash can be predicted under a given set of road and environment conditions as:

$$\Pr(Single - veh - runoff)_{3-state} = \frac{\exp(\eta_{3-state})}{1 + \exp(\eta_{3-state})} \quad (5\text{-}2)$$

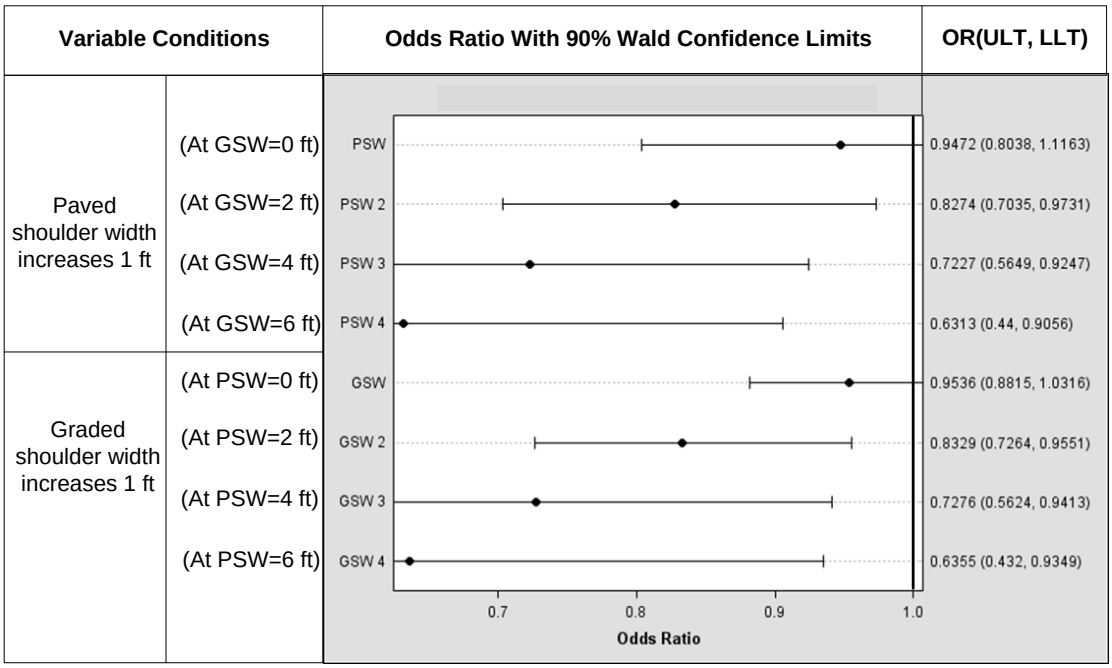
As observed previously in the four-state model, the state indicator variables AL and SC in the three-state model are again shown with insignificant estimation results. This result implies that there is no evidence of any difference between the three states' single-vehicle fatal crash occurrences. One of the major purposes of this research study is to develop analytical models that can be used as evaluation tools for safety investment by the Georgia Department of Transportation. It is a reasonable approach to apply the three-state combined model for these assessments.

As discussed in Chapter 4, since relationships between independent variables and the probability of event occurrence are non-linear, estimated parameters do not have straightforward interpretations of impacts from each corresponding independent variables as they do in ordinary regression models. Studies often adopt odds ratio for model interpretation in the case of logistic regression model. Figure 86, Figure 87 and Figure 88 present plots of odds ratio from the changes of each corresponding independent variables along with 90% Wald confidence limits. Chapter 4 discussed the formulation of how to calculate Wald confidence intervals of odds ratio. The rest of this section presents the odds ratio based on an interpretation of marginal effects.



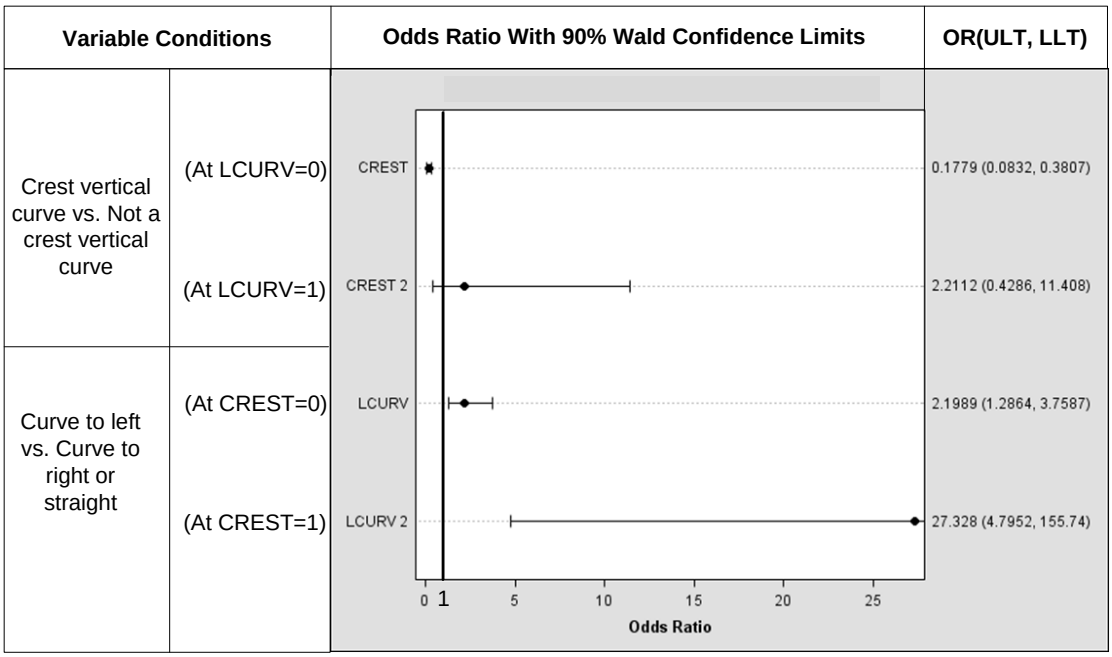
Notes: OR(ULT, LLT): Odds Ratio (Upper Limit, Lower Limit)

Figure 86: Odds Ratio for Main Effects (Three-State, SV)



Notes: OR(ULT, LLT): Odds Ratio (Upper Limit, Lower Limit)

Figure 87: Odds Ratio for Interactions: PSW*GSW (Three-State, SV)



Notes: OR(ULT, LLT): Odds Ratio (Upper Limit, Lower Limit)

Figure 88: Odds Ratio for Interactions: CREST*LCURV (Three-State, SV)

Based on the correlation analysis presented in the previous section, the data does not show evidence of strong correlation among the independent variables used in the three-state model for single-vehicle fatal crashes. Therefore, it is reasonable to provide marginal effect interpretations of individual contributing factors in the crash type model. The odds ratio based interpretations are presented for each individual predictor.

- **Variable:** LW

  Effect: The odds of fatal crashes as single-vehicle crashes are estimated to decrease by a factor of 0.6 with each 1-ft increase in lane width (8ft ≤ LW ≤ 12ft), after accounting for the effects of other contributing factors from road geometrics to environment characteristics. The estimated 90% confidence interval for this odds ratio is 0.4 to 0.7.

- **Variable:** ADT

  Effect: The odds of fatal crashes as single-vehicle crashes are estimated to decrease by a factor of 0.9 with each 1000 vpd increase in ADT after accounting for the effects of other predictors. The estimated 90% confidence interval for this odds ratio is 0.8 to 0.98. ADT has a skewed distribution with a long tail towards the higher ADT end. Also, the data contains a large ADT range, from 75 to 17,960 vehicles per day. One should be cautious of applying this ADT effect on both low and high ADT conditions.

- **Variable:** JUNCTION

  Effect: The odds of fatal crashes as single-vehicle crashes at intersections are estimated to decrease by a factor of 0.4 from the odds of single-vehicle fatal crashes at road segments, after accounting for the effects of other variables. The estimated 90% confidence interval for this odds ratio is 0.3 to 0.7.

- **Variable:** RHR67

  Effect: The odds of fatal crashes as single-vehicle crashes at locations with roadside hazard rating at 6 or 7 are estimated to be 3.2 times the odds of a single-vehicle fatal crash at locations with a roadside hazard rating below 6 after all other independent variables are taken into account. The estimated 90% confidence interval for this odds ratio is 1.1 to 9.2.

- **Variable:** LU_C

  Effect: The odds of fatal crashes as single-vehicle crashes at locations near commercial driveways are estimated to decrease by a factor of 0.3 of the odds of single-vehicle fatal crashes at locations not proximate to commercial driveways, after accounting for the effects of other independent variables. The estimated 90% confidence interval for this odds ratio is 0.1 to 0.7.

- **Variable:** DARKUNLIT

  Effect: The odds of fatal crashes as single-vehicle crashes at locations under dark without supplemental lighting conditions are estimated to be 3.7 times the odds of single-vehicle fatal crashes at locations with lighting conditions as either daylight, dark with lights, dusk or dawn, after accounting for the effects of other independent variables. The estimated 90% confidence interval for this odds ratio is 2.4 to 5.6.

- **Variable:** HR_DEEPSLEEP

  Effect: The odds of fatal crashes as single-vehicle crashes occurring between 1am to 3am are estimated to be 6.2 times the odds of single-vehicle fatal crashes occurring during other time periods of a day, after accounting for all other independent variables. The estimated 90% confidence interval for this odds ratio is 1.1 to 37.5.

- **Variable:** PSW * GSW

  Effect: This is the interaction effect between paved shoulder width and graded shoulder width. It indicates that the effect of paved shoulder width depends on the level of graded shoulder width, and vice versa.

  PSW

  The odds of fatal crashes as single-vehicle crashes decreases by a factor of 0.9, 0.8, 0.7, and 0.6 with 1-ft increasing of paved shoulder width while graded shoulder width at 0, 2, 4, and 6 ft, respectively, after taking into account of other variables. Figure 87 presents the estimated 90% confidence intervals for these odds ratios.

GSW

The odds of fatal crashes as single-vehicle crashes decreases by a factor of 0.9, 0.8, 0.7, and 0.6 with 1-ft increasing of graded shoulder width for paved shoulder widths at 0, 2, 4, and 6 ft, respectively, after taking into account other variables. The estimated 90% confidence intervals for these odds ratios are shown in Figure 87.

Overall, this interaction effects suggest that each 1-ft increase of paved shoulder width tend to reduce the odds that a fatal crash is a single-vehicle crash more effectively while accompanied by wider graded shoulders. The similar effects are presented for a graded shoulder width, too. These results imply that more efficient safety benefit may be gained by the "working partnership" between paved and graded shoulders along two-lane rural highways in the southeastern states.

- **Variable:** CREST * LCURV

  Effect: This is an interaction effect between vertical curve and horizontal curve.

  CREST

  Without the presence of horizontal curves to the left, the odds of fatal crashes as single-vehicle crashes at locations with crest vertical curves are estimated to decrease by a factor of 0.2 (90% confidence limit: 0.1 to 0.4) from the odds at locations where crest vertical curves are not present, after accounting for the effects of other variables. While horizontal curves to the left are present, the odds of fatal crashes as single-vehicle crashes at locations with crest vertical curves are estimated to increase by a factor of 2.2 (90% confidence limit: 0.4 to 11.4) from the odds at locations where crest vertical curves are not present, after accounting for other variables.

LURV

Without the presence of vertical crest curves, the odds of fatal crashes as single-vehicle crashes at locations with horizontal curves to the left are estimated to increase by a factor of 2.2 (90% confidence limit: 1.3 to 3.8) from the odds at locations with straight alignments or curves to the right, after accounting for the effects of other variables. On the other hand, with the presence of vertical crest curves, the odds of fatal crashes as single-vehicle crashes at locations with horizontal curves to the left are estimated to increase by a factor of 27 (90% confidence limit: 5 to 156) from the odds at locations with straight alignments or curves to the right, after accounting for the effects of other variables.

Vertical crest curves alone do not appear to increase the risk of single-vehicle fatal crash occurrences. The presence of horizontal curves to the left appear to alter the influence of vertical crest curves on the risk of single-vehicle fatal crash occurrence. On the other hand, locations with curves to the left are associated with a higher risk of single-vehicle fatal crash occurrence regardless of the vertical alignments. Additionally, with vertical crest curves present, the effect of a curve to the left on single-vehicle fatal crash occurrences appears to be amplified.

Overall, the interaction effects of horizontal and vertical curvature imply a complex relationship between road geometric design features and road safety performance. The current road geometric design procedures carry out horizontal alignment and vertical alignment design separately. However, it has been recognized by researchers that some of the overlapping situations of horizontal and vertical alignments can pose great safety dangers to drivers. For example, the well-known condition of a hidden-dip, where a horizontal curve is followed by a sag vertical curve results in sight distance limited by geometric configurations. Even though the combined effects of horizontal and vertical curves are

documented from the perspective of roadway design, few safety prediction models identify and take into account this condition. The significant interaction effects revealed from this study effort suggest potential relationships of geometric features that may contribute to the crash condition.

- *Model Goodness-of-Fit and Predictive Power (Three-State, SV)*

As presented in Table 53, the Hosmer and Lemeshow Goodness-of-Fit test showed an acceptable indication that the model fits the data well (p-value = 0.4849 >0.05). The author also applied the ROC curve procedure to examine the model predictive power. The mathematical background of the ROC curve is presented in Chapter 4. As shown in Figure 89 , the area under the curve is 0.8395, which provides a measure of discrimination of two types of crash outcomes. Based on the general rule, this result suggests a good predictive power for the three-state model.

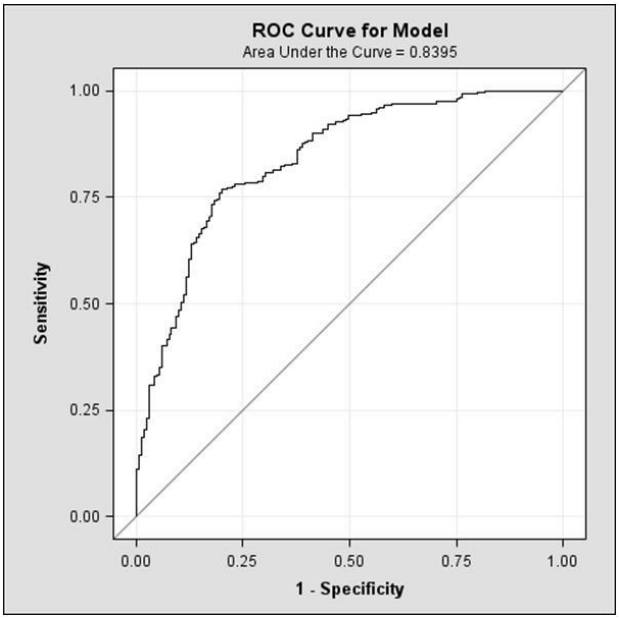


Figure 89: ROC Curve (Three-State, SV)

5.1.2 Models by State

This section presents four model estimates based on the fatal crash sample data for the four individual states of Alabama, Georgia, Mississippi, and South Carolina. In addition to the modeling effort for a regional level as summarized by the four-state combined model (AL, GA, MS, SC) and the three-state combined model (AL, GA, SC), this individual state assessment can be used as an indicator for identifying potential state-specific significant influential factors and their corresponding effects on the probability of single-vehicle run-off-road fatal crash occurrence. This state-level modeling effort can also help determine the suitability of model transferability for other state applications.

5.1.2.1 Alabama

- *Independent Variables (AL, SV)*

The fatal crash database for the state of Alabama included 155 random fatal crashes for rural two-lane highways. Table 54 presents the independent variables determined to have significant influences on the fatal crash type outcomes. These variables include the presence of a road intersection (junction), lane width, horizontal curve direction, grade direction, roadside hazard rating, roadside lighting condition, and time of crash. The descriptive statistics for the continuous variable (lane width) and the categorical variables are presented in Table 55 and Table 56, respectively. For the Alabama fatal crash database, the lane widths ranged from 8 ft to 12 ft with an average lane width of 10.8 ft (approximately 11 ft).

Table 54: Variable Description (AL, SV)

Types	Variables	Descriptions
Road Junction type	JUNCTION	1 if a road junction, 0 if road segment
Geometric design features	LW	Lane width (ft)
	LCURV	1 if curve to the left, 0 otherwise (curve to the right or straight alignment)
	DOWN	1 if direction of slope is down (negative), 0 otherwise
Roadside condition	RHR67	1 if road hazard rating is 6 or 7, 0 otherwise
Lighting condition	DARKUNLIT	1 if dark with no supplemental street lights, 0 otherwise
Circadian biological clock	HR_EM	1 if crash occurred between 12a.m. – 6 a.m., 0 otherwise

Table 55: Continuous Variable Descriptive Statistics (AL, SV)

Variable	Mean	Std Dev	Minimum	Maximum
LW (ft)	10.8	1.1	8	12

Table 56: Distribution of Categorical Variables (AL, SV)

Variable	Status	Percent (%)
JUNCTION	0 (Segment)	83
	1 (Intersection)	17
LCURV	0 (Curve to Right or Straight)	73
	1 (Curve to Left)	27
DOWN	0 (Vertical grade positive or level)	56
	1 (Vertical grade negative)	44
RHR67	0 (Roadside Hazard Rating < 6)	88
	1 (Roadside Hazard Rating of 6 or 7)	12
DARKUNLIT	0 (Daylight, Dark with Lights, Dusk, or Dawn)	54
	1 (Dark without Supplemental Lights)	46
HR_EM	0 (Not between 6 a.m. and 12 midnight)	84
	1 (From 12 midnight until 6 a.m.)	16

- *Correlation Evaluation (AL, SV)*

As shown in the correlation matrix presented in Table 57, there is no evidence of strong correlation among the independent variables of the AL only model. The maximum correlation coefficient is 0.37. This value is associated with the DARKUNLIT and HR_EM variables. As a result, the multi-colinearity is unlikely to be a major concern for the AL only model.

Table 57: Correlation Matrix (AL, SV)

	LW	JUNCTION	LCURV	DOWN	RHR67	DARKUNLIT	HR_EM
LW	1.00	0.07	-0.16	-0.17	-0.25	-0.07	0.09
JUNCTION		1.00	0.20	-0.12	-0.12	-0.03	-0.06
LCURV			1.00	0.10	0.26	-0.07	-0.07
DOWN				1.00	0.07	0.02	-0.07
RHR67					1.00	0.09	-0.004
DARKUNLIT						1.00	0.37
HR_EM							1.00

- *Model Estimation and Interpretation (AL, SV)*

As presented in Table 58, among the 159 fatal crashes available for the AL only model, 99 crashes were single-vehicle run-off-road fatal crashes. Also shown in Equation (5-3), variables that can significantly differentiate single-vehicle fatal crashes from multiple-vehicle fatal crashes include the presence of a road intersection (junction), lane width, horizontal curve direction, slope direction, roadside hazard rating 6 or 7, lighting condition, and time of crash.

Table 58: Model Estimation (AL, SV)

Variable	Estimate	P- value
Intercept	4.7369	0.0446
JUNCTION	-1.2158	0.039
LW	-0.5111	0.0158
LCURV	1.5906	0.0048
DOWN	0.8342	0.0603
RHR67	1.8195	0.1117
DARKUNLIT	1.3682	0.0032
HR_EM	2.8888	0.0089
Observations	155	
(Single-Vehicle/Others)	(99/56)	
AIC	149.483	
Schwarz Criterion	173.83	
-2 Log L	133.483	
R-Square	0.3605	
Hosmer and Lemeshow Goodness-of-Fit		
Chi-Square	DF	Pr > ChiSq
8.9815	8	0.3439

Let:

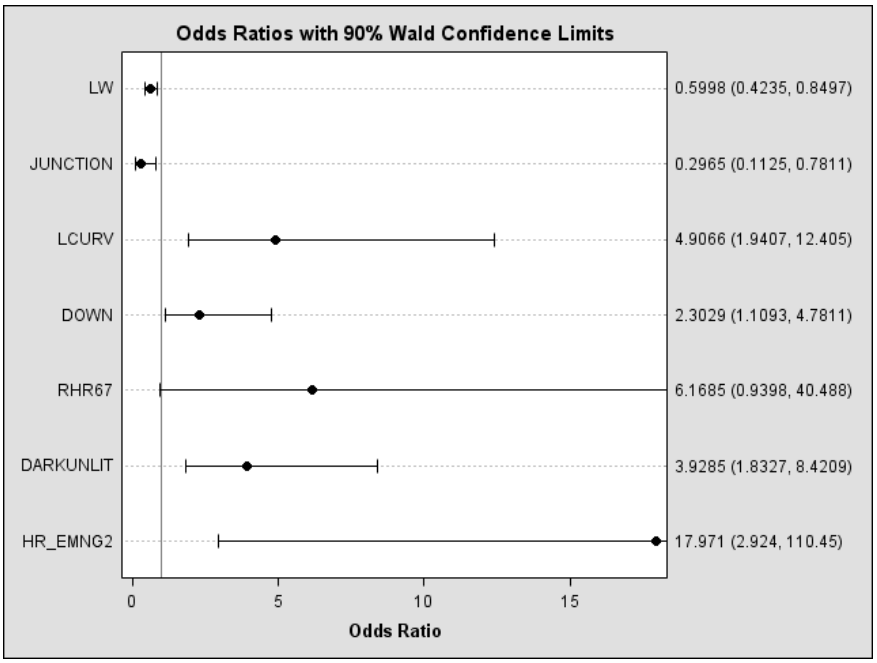
$$\eta_{AL} = 4.7369 - 1.2158JUNCTION - 0.5111LW + 1.5906LCURV$$
$$+0.8342DOWN + 1.8195RHR67 + 1.3682DARKUNLIT + 2.888HR\_EM$$

The probability of single-vehicle run-off-road fatal crash can then be predicted under a given set of conditions as:

$$\Pr(Single - veh - runoff)_{AL} = \frac{\exp(\eta_{AL})}{1 + \exp(\eta_{AL})} \tag{5-3}$$

Based on the correlation analysis presented in previous section, the data does not show evidence of strong correlation among the independent variables used in the AL only model for single-vehicle fatal crashes. Therefore, it is reasonable to provide marginal

effect interpretations of individual contributing factors in the crash type model. The odds ratio of each independent variable is illustrated in Figure 90.



Notes: OR(ULT, LLT): Odds Ratio (Upper Limit, Lower Limit)

Figure 90: Odds Ratio (AL, SV)

- **Variable:** LW

  Effect: The odds of fatal crashes as single-vehicle crashes are estimated to decrease by a factor of 0.6 with each 1-ft increase in lane width after accounting for the effects of other predictors. The approximate 90% confidence interval for this odds ratio is 0.4 to 0.8.

- **Variable:** JUNCTION

  Effects: The odds of fatal crashes as single-vehicle crashes at intersections are estimated to decrease by a factor of 0.3 from the odds of single-vehicle fatal crashes at road segments, after accounting for other variables. The approximate 90% confidence interval for this odds ratio is 0.1 to 0.8.

- **Variable:** LCURV

  Effect: The odds of fatal crashes as single-vehicle crashes at locations with horizontal curves to the left are estimated to be 4.9 times the odds of single-vehicle fatal crashes at locations with straight alignments or curves to the right, after accounting for other variables. The approximate 90% confidence interval for this odds ratio is 2 to 12.4.

- **Variable:** RHR67

  Effect: The odds of fatal crashes as single-vehicle crashes at locations with roadside hazard rating at 6 or 7 are estimated to be 6.2 times of the odds of a single-vehicle fatal crash at locations with RHR rating below 6 while all else are equal. The approximate 90% confidence interval for this odds ratio is 0.9 to 40.5.

- **Variable:** DARKUNLIT

  Effect: The odds of fatal crashes as single-vehicle crashes at locations under dark without supplemental lightings are estimated to be 3.9 times the odds of single-vehicle fatal crashes at locations with lighting conditions as either daylight, dark with lights, dusk or dawn, after accounting for the effects of other independent variables. The approximate 90% confidence interval for this odds ratio is 1.8 to 8.4.

- **Variable:** HR_EM

  Effect: The odds of fatal crashes as single-vehicle crashes occurring between 1am to 6am are estimated to be 18 times the odds of single-vehicle fatal crashes occurring during other time period of a day, after accounting for all other independent variables. The approximate 90% confidence interval for this odds ratio is 3 to 110.5.

- *Model Goodness-of-Fit and Predictive Power (AL, SV)*

The Hosmer and Lemeshow Goodness-of-Fit test showed evidence that the model provides a good fit for the observed data (p-value=0.3439 >0.05). Meanwhile, as shown in Figure 91 , the area under the ROC curve is 0.8663, which suggests a good predictive power of the AL only model in terms of the ability of distinguishing single-vehicle fatal crashes and multiple-vehicle fatal crashes for the state of Alabama.

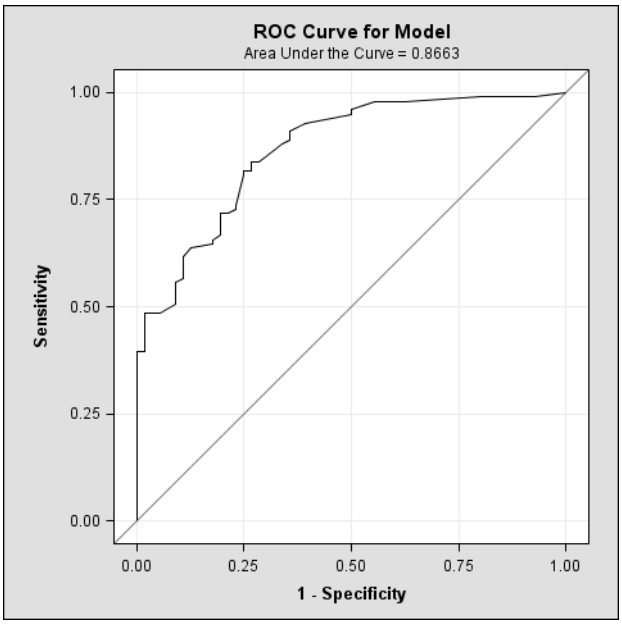


Figure 91: ROC Curve (AL, SV)

5.1.2.2 Georgia

- *Independent Variables (GA, SV)*

As presented in Table 59, independent variables which have significant impacts on the fatal crash type outcomes in the GA only model include intersection (junction) type, lane width, paved shoulder width, horizontal curve direction, horizontal alignment type, roadside lighting condition, and safety restraint system usage for at-fault drivers. Table 60 and Table 61 summarize the descriptive statistics for those contributing factors. In the Georgia fatal crash database, lane widths ranged from 8 ft to 12 ft with

an average lane width at 10.7 ft (approximately 11 ft). Average width of paved shoulders was 0.6 ft but ranged from 0 ft to 6 ft wide.

Table 59: Variable Description (GA, SV)

Types	Variables	Descriptions
Road Junction type	JUNCTION	1 if a road junction, 0 if road segment
Geometric design features	LW	Lane width (ft)
	PSW	Paved shoulder width (ft)
	LCURV	1 if curve to the left, 0 otherwise (curve to the right or straight alignment)
	STRAIGHT	1 if tangent horizontal alignment, 0 otherwise
Lighting condition	DARKUNLIT	1 if dark with no supplemental street lights, 0 otherwise
Safety Protection	RESTRAINT	1 if driver wore safety restraint, 0 otherwise

Table 60: Continuous Variable Descriptive Statistics (GA, SV)

Variable	Mean	Std Dev	Minimum	Maximum
LW (ft)	10.7	1.1	8	12
PSW (ft)	0.6	1.2	0	6

Table 61: Distribution of Categorical Variables (GA, SV)

Variable	Status	Percent (%)
LCURV	0 (Curve to Right or Straight)	77
	1 (Curve to Left)	23
JUNCTION	0 (Segment)	75
	1 (Intersection)	25
STRAIGHT	0 (Curved location)	49
	1 (Tangent)	51
DARKUNLIT	0 (Daylight, Dark with Lights, Dusk, or Dawn)	57
	1 (Dark without Supplemental Lights)	43
RESTRAINT	0 (Safety Restraint not Used)	71
	1 (Safety Restraint Used)	29

- *Correlation Evaluation (GA, SV)*

As shown in the correlation matrix presented in Table 62, variables that represent a horizontal curve to the left and a straight segment are negatively correlated with a correlation coefficient as -0.54, while the remaining correlation coefficients are between -0.2 and 0.35. Therefore, there is no evidence of strong correlation between independent variables for the GA only model. The multi-colinearity is unlikely to be a concern for the GA only model.

Table 62: Correlation Matrix (GA, SV)

	LW	PSW	JUNCTION	LCURV	STRAIGHT	DARKUNLIT	RESTRAINT
LW	1.00	0.35	0.11	-0.02	0.12	-0.02	0.08
PSW		1.00	-0.06	0.05	0.03	-0.15	-0.14
JUNCTION			1.00	-0.08	0.23	-0.09	0.14
LCURV				1.00	-0.54	0.11	-0.20
STRAIGHT					1.00	-0.07	-0.05
DARKUNLIT						1.00	0.02
RESTRAINT							1.00

- *Model Estimation and Interpretation (GA, SV)*

As presented in Table 63, among the 146 fatal crashes available for the GA only model, 85 crashes were single-vehicle run-off-road fatal crashes. Also shown in Equation (5-4), variables that can significantly differentiate single-vehicle fatal crash from multiple-vehicle fatal crash include the presence of a road intersection (junction), lane width, paved shoulder width, horizontal curve direction, lighting condition, and safety restraint system usage for at-fault drivers.

Table 63: Model Estimation (GA, SV)

Variable	Estimate	P- value
Intercept	8.9011	0.0003
JUNCTION	-2.1473	<.0001
LW	-0.835	0.0003
PSW	-0.3506	0.0647
LCURV	1.7437	0.0112
STRAIGHT	1.5662	0.0046
DARKUNLIT	1.1195	0.0124
RESTRAINT	-1.1604	0.0151
Observations	146	
(Single-Vehicle/Others)	(85/61)	
AIC	151.893	
Schwarz Criterion	175.762	
-2 Log L	135.893	
R-Square	0.3484	
Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
4.983	7	0.662

Let:

$$\eta_{GA} = 8.9011 - 2.1473 JUNCTION - 0.835 LW - 0.3506 PSW$$
$$+1.7437 LCURV + 1.5662 STRAIGHT + 1.1195 DARKUNLIT - 1.1604 RESTRAINT$$

The probability of a single-vehicle run-off-road fatal crash for Georgia can then be predicted as follows:

$$\Pr(Single - veh - runoff)_{GA} = \frac{\exp(\eta_{GA})}{1 + \exp(\eta_{GA})} \tag{5-4}$$

Based on the correlation analysis presented in the previous section, the data does not show evidence of strong correlation among independent variables used in the GA only state model for single-vehicle fatal crashes. Therefore, it is reasonable to provide marginal effect interpretations of individual contributing factors in the crash type model. The odds ratio of each independent variable is illustrated in Figure 92.

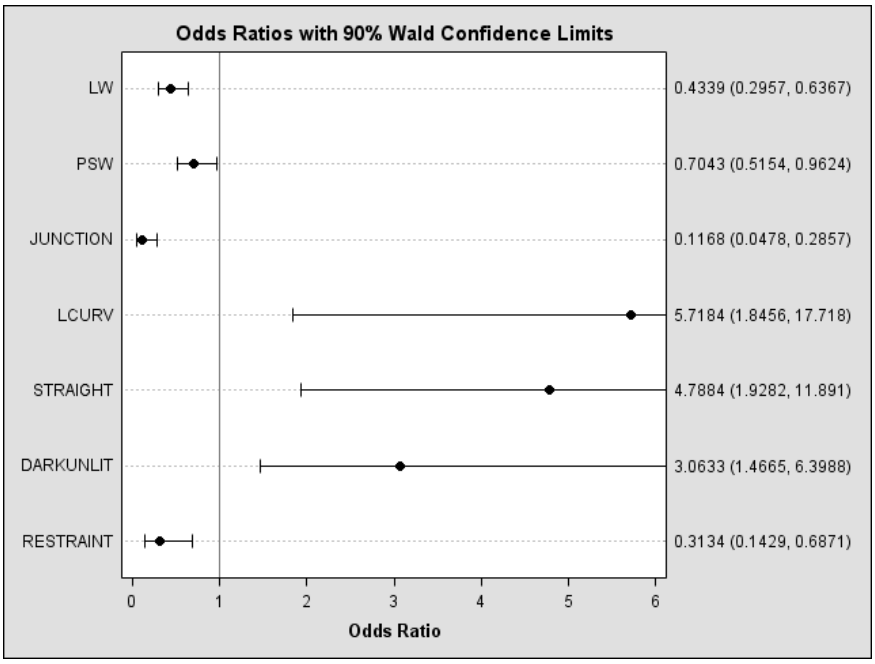


Figure 92: Odds Ratio (GA, SV)

- **Variable:** LW

  Effect: The odds of fatal crashes as single-vehicle crashes are estimated to decrease by a factor of 0.4 with each 1-ft increase in lane width after accounting for the effects of other predictors. The approximate 90% confidence interval for this odds ratio is 0.3 to 0.6. The range of lane width in the sample data is from 8-ft to 12-ft, therefore, it is inappropriate to extrapolate the marginal effect of lane width outside this range.

- **Variable:** PSW

  Effect: The odds of fatal crashes as single-vehicle crashes are estimated to decrease by a factor of 0.70 with each 1-ft increase in paved shoulder width after accounting for the effects of other predictors. The approximate 90% confidence interval for this odds ratio is 0.5 to 0.96. The range of paved shoulder width in the

sample data is from zero ft to 6-ft, therefore, the marginal effect of the paved shoulder width should not be extrapolated outside this range.

- **Variable:** JUNCTION

  Effect: The odds of fatal crashes as single-vehicle crashes at intersections are estimated to decrease by a factor of 0.1 from the odds of single-vehicle fatal crashes at road segments, after accounting for the effects of other variables. The approximate 90% confidence interval for this odds ratio is 0.05 to 0.3.

- **Variable:** LCURV, STAIGHT

  Effect: The odds of fatal crashes as single-vehicle crashes at locations with horizontal curves to the left are estimated to be 5.7 times the odds of single-vehicle fatal crashes at locations with a curve to the right, after accounting for other variables. The approximate 90% confidence interval for this odds ratio is 1.8 to 17.7. Meanwhile, the odds of fatal crashes as single-vehicle crashes at locations with straight alignments are estimated to be 4.79 times the odds of single-vehicle fatal crashes at locations with curves to the right, after accounting for other variables. The approximate 90% confidence interval for this odds ratio is 1.9 to 11.9.

- **Variable:** DARKUNLIT

  Effect: The odds of fatal crashes as single-vehicle crashes at locations under dark without supplemental lightings are estimated to be 3.1 times the odds of single-vehicle fatal crashes at locations with lighting conditions as either daylight, dark with lights, dusk or dawn, after accounting for the effects of other independent variables. The estimated 90% confidence interval for this odds ratio is 1.5 to 6.4.

- **Variable:** RESTRAINT

  Effects: The odds of fatal crashes as single-vehicle crashes while at-fault drivers were wearing safety restraints are estimated to reduce by a factor of 0.3 from the odds of single-vehicle fatal crash occurrences while at-fault drivers not wearing safety restraints while everything else remains equal. The approximate 90% confidence interval for this odds ratio is 0.2 to 0.7.

- *Model Goodness-of-Fit and Predictive Power (GA, SV)*

The recommended goodness-of-fit test reports a p-value as 0.662, which indicates that the estimated model fits the observed data well. Meanwhile, as shown in Figure 93, the area under the ROC curve is 0.8419, which suggests a good predictive power of the GA only model in terms of distinguishing single-vehicle fatal crashes and multiple-vehicle fatal crashes.

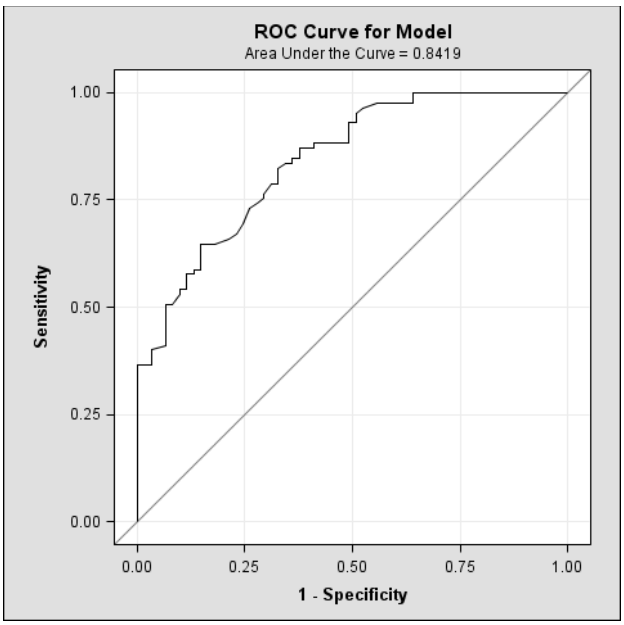


Figure 93: ROC Curve (GA, SV)

5.1.2.3 Mississippi

- *Independent Variables (MS, SV)*

As shown in Table 64, independent variables which have significant impacts on the fatal crash type outcomes in Mississippi include lane width, paved shoulder width, horizontal curve direction, roadside hazard rating 6 or 7, dark without supplemental lighting, and time of crash. Table 65 and Table 66 summarize the descriptive statistics for continuous and categorical variables, respectively. In the Mississippi fatal crash database, lane widths ranged from 7 ft to 12 ft with an average lane width at 10.9 ft (approximately 11 ft). The average width of the paved shoulders was 0.8 ft with an overall range from 0 ft to 10 ft.

Table 64: Variable Description (MS, SV)

Types	Variables	Descriptions
Geometric design features	LW	Lane width (ft)
	PSW	Paved shoulder width (ft)
	LCURV	1 if curve to the left, 0 otherwise (curve to the right or straight alignment)
Roadside condition	RHR67	1 if roadside hazard rating is 6 or 7, 0 otherwise
Lighting condition	DARKUNLIT	1 if dark with no supplemental street lights, 0 otherwise
Circadian biological clock	HR_DEEPSLEEP	1 if crash time is between 1a.m. and 3a.m., 0 otherwise

Table 65: Continuous Variable Descriptive Statistics (MS, SV)

Variable	Mean	Std Dev	Minimum	Maximum
LW (ft)	10.9	1.1	7	12
PSW (ft)	0.8	2.3	0	10

Table 66: Distribution of Categorical Variables (MS, SV)

Variable	Status	Percent (%)
LCURV	0 (Curve to Right or Straight)	77
	1 (Curve to Left)	23
RHR67	0 (Roadside Hazard Rating < 6)	68
	1 (Roadside Hazard Rating of 6 or 7)	32
DARKUNLIT	0 (Daylight, Dark with Lights, Dusk, or Dawn)	54
	1 (Dark without Supplemental Lights)	46
HR_DEEPSLEEP	0 (Not between 1 a.m. and 3 a.m.)	89
	1 (From 1 a.m. until 3 a.m.)	11

- *Correlation Evaluation (MS, SV)*

As shown in the correlation matrix presented in Table 67, there is no evidence of strong correlation between independent variables for the MS only model as the absolute values of correlation coefficients are all below 0.32. Multi-colinearity, therefore, is unlikely to be a concern for the MS only model.

Table 67: Correlation Matrix (MS, SV)

	LW	PSW	LCURV	RHR67	DARKUNLIT	HR_DEEPSLEEP
LW	1.00	0.25	-0.06	-0.20	-0.11	0.11
PSW		1.00	-0.13	-0.16	-0.06	0.05
LCURV			1.00	-0.07	-0.03	-0.12
RHR67				1.00	0.05	0.03
DARKUNLIT					1.00	0.32
HR_DEEPSLEEP						1.00

- *Model Estimation and Interpretation (MS, SV)*

As presented in Table 68, among the 99 fatal crashes available for the MS only model, 50 crashes were single-vehicle run-off-road fatal crashes. Also shown in Equation (5-5), variables that can significantly differentiate a single-vehicle fatal crash from a

multiple-vehicle fatal crash include lane width, paved shoulder width, horizontal curve direction, roadside hazard rating, lighting condition, and crash time.

Table 68: Model Estimation (MS, SV)

Variable	Estimate	P- value
Intercept	3.2578	0.2469
LW	-0.4282	0.092
PSW	-0.7045	0.1156
LCURV	0.8562	0.1516
RHR67	1.6633	0.0043
DARKUNLIT	1.626	0.0027
HR_DEEPSLEEP	2.0741	0.088
Observations (Single-Vehicle/Others)	99 (50/49)	
AIC	105.39	
Schwarz Criterion	123.556	
-2 Log L	91.39	
R-Square	0.3706	
Hosmer and Lemeshow Goodness-of-Fit		
Chi-Square	DF	Pr > ChiSq
7.1436	8	0.5212

Let:

$$\eta_{MS} = 3.2578 - 0.4282LW - 0.7045PSW + 0.8562LCURV + 1.6633RHR67$$
$$+1.626DARKUNLIT + 2.0741HR\_DEEPSLEEP$$

The probability of a single-vehicle run-off-road fatal crash in Mississippi can be predicted as follows:

$$\Pr(Single - veh - runoff)_{MS} = \frac{\exp(\eta_{MS})}{1 + \exp(\eta_{MS})} \quad (5\text{-}5)$$

Based on the correlation analysis presented in the previous section, the data does not show evidence of strong correlation among the independent variables used in the MS

only state model for single-vehicle fatal crash. Therefore, it is reasonable to provide marginal effect interpretations of individual contributing factors in the crash type model. The odds ratio of each independent variable is illustrated in Figure 94.

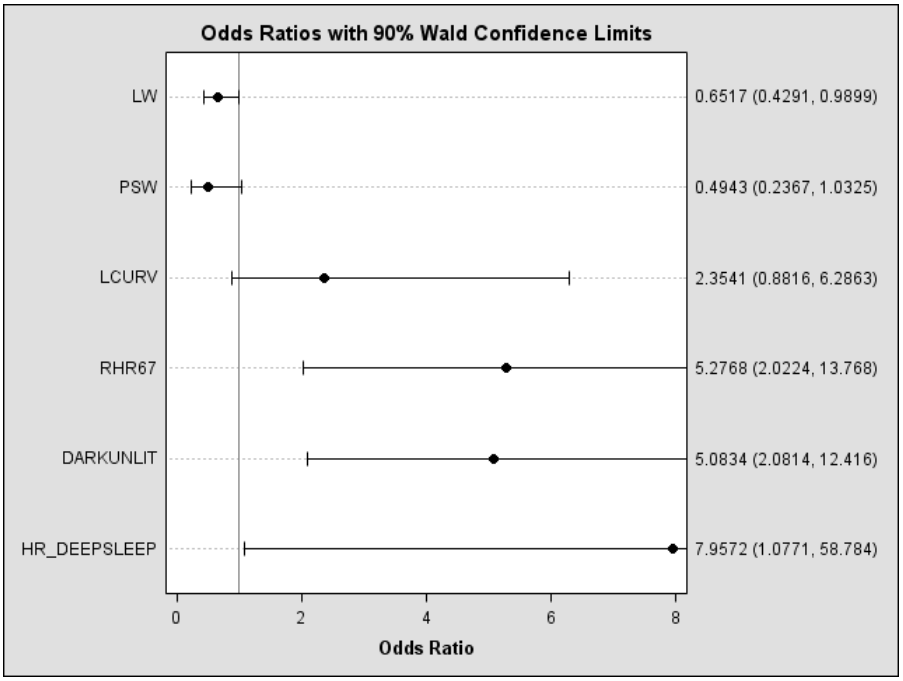


Figure 94 Odds Ratio (MS, SV)

- **Variable:** LW

  Effect: The odds of fatal crashes as single-vehicle crashes are estimated to decrease by a factor of 0.7 with each 1-ft increase in lane width after accounting for the effects of other predictors. The approximate 90% confidence interval for this odds ratio is 0.4 to 0.99. This effect should not be extended beyond the range of lane width (7 to 12 ft) for this sample data.

- **Variable:** PSW

  Effect: The odds of fatal crashes as single-vehicle crashes are estimated to decrease by a factor of 0.5 with each 1-ft increase in paved shoulder width after accounting for the effects of other predictors. The approximate 90% confidence

interval for this odds ratio is 0.2 to 1.0. This effect should not be extended beyond the range of the paved shoulder width (zero to 10 ft) of this sample data.

- **Variable:** LCURV

  Effect: The odds of fatal crashes as single-vehicle crashes at locations with horizontal curves to the left are estimated to be 2.3 times the odds of single-vehicle fatal crashes at locations with straight alignments or curves to the right after accounting for the effects of other variables. The approximate 90% confidence interval for this odds ratio is 0.9 to 6.3.

- **Variable:** RHR67

  Effect: The odds of fatal crashes as single-vehicle crashes at locations with a roadside hazard rating at 6 or 7 are estimated to be 5.3 times of the odds of a single-vehicle fatal crash at locations with RHR rating below 6 after accounting for the effects of other variables. The estimated 90% confidence interval for this odds ratio is 2.0 to 13.8.

- **Variable:** DARKUNLIT

  Effect: The odds of fatal crashes as single-vehicle crashes at locations under dark without supplemental lightings are estimated to be 5.1 times the odds of single-vehicle fatal crashes at locations with lighting conditions as either daylight, dark with lights, dusk or dawn after accounting for the effects of other variables. The approximate 90% confidence interval for this odds ratio is 2.1 to 12.4.

- **Variable:** HR_DEEPSLEEP

  Effect: The odds of fatal crashes as single-vehicle crashes occurring between 1am to 3am are estimated to be 7.9 times the odds of single-vehicle fatal crashes occurring during other time period of a day, after accounting for all other

independent variables. The approximate 90% confidence interval for this odds ratio is 1.1 to 58.8.

- *Model Goodness-of-Fit and Predictive Power (MS, SV)*

As summarized in Table 68, the Hosmer and Lemeshow Goodness-of-Fit test showed evidence that the model provides a good fit for the observed data (p-value=0.5212 >0.05). Meanwhile, as shown in Figure 95, the area under the curve is 0.8565, which suggests a good predictive power of the MS only model in terms of distinguishing single-vehicle fatal crashes and multiple-vehicle fatal crashes.

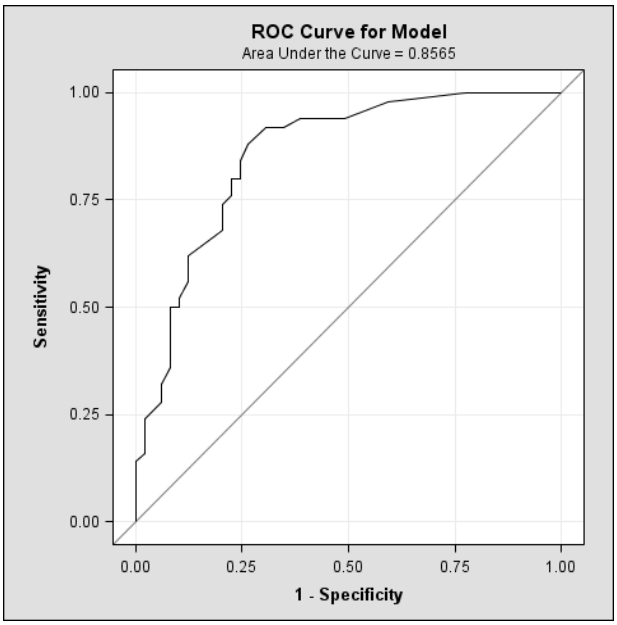


Figure 95 ROC Curve (MS, SV)

5.1.2.4 South Carolina

- *Independent Variables (SC, SV)*

Table 69 depicts the independent variables determined to have significant impacts on the fatal crash type outcomes in the South Carolina model. These critical variables include the lane width, graded shoulder width, horizontal curve direction, crest vertical

curvature, proximity to commercial driveways, road lighting condition, and time of crash. Table 70 and Table 71 summarize the descriptive statistics for continuous and categorical variables, respectively. For the fatal crash database for South Carolina, lane widths ranged from 8 ft to 12 ft with an average lane width of 10.7 ft (approximately 11 ft). The average width of graded shoulders was 7.4 ft with a range from 0 ft to 15 ft. Among the four state-specific models, the South Carolina model is the only one that identified the graded shoulder width as having a significant effect in terms of differentiating between single-vehicle and multiple-vehicle fatal crashes.

Table 69: Variable Description (SC, SV)

Types	Variables	Descriptions
Geometric design features	LW	Lane width (ft)
	GSW	Graded shoulder width (ft)
	LCURV	1 if curve to the left, 0 otherwise (curve to the right or straight alignment)
	CREST	1 if crest, 0 otherwise
Land use type	LU_C	1 if commercial driveways in the proximity of the crash location, 0 otherwise
Lighting condition	DARKUNLIT	1 if dark with no supplemental street lights, 0 otherwise
Circadian biological clock	HR_DEEPSLEEP	1 if crash time is from 1a.m. till 3 a.m., 0 otherwise

Table 70: Continuous Variable Descriptive Statistics (SC, SV)

Variable	Mean	Std Dev	Minimum	Maximum
LW (ft)	10.7	1.0	8	12
GSW (ft)	7.4	3.2	0	15

Table 71: Distribution of Categorical Variables (SC, SV)

Variable	Status	Percent (%)
LCURV	0 (Curve to Right or Straight)	76
	1 (Curve to Left)	24
CREST	0 (Not a Crest Vertical Curve)	91
	1 (Crest Vertical Curve)	9
LU_C	0 (No Commercial Driveways)	91
	1 (Near Commercial Driveways)	9
DARKUNLIT	0 (Daylight, Dark with Lights, Dusk, or Dawn)	53
	1 (Dark without Supplemental Lights)	47
HR_DEEPSLEEP	0 (Not between 1 a.m. and 3 a.m.)	95
	1 (From 1 a.m. until 3 a.m.)	5

- *Correlation Evaluation (SC, SV)*

As shown in the correlation matrix presented in Table 72, there is no evidence of strong correlation presence between independent variables of the SC only model as the absolute values of correlation coefficients are all at or below 0.2. The multi-colinearity is unlikely to be a concern for the AL only model.

Table 72 Correlation Matrix (SC, SV)

	LW	GSW	LCURV	VCREST	LU_C	DARKUNLIT	HR_DEEPSLEEP
LW	1.00	0.20	0.03	0.03	0.08	-0.10	0.02
GSW		1.00	0.03	-0.03	-0.05	-0.02	0.07
LCURV			1.00	0.09	0.03	0.06	0.07
VCREST				1.00	-0.02	0.07	0.03
LU_C					1.00	-0.11	-0.07
DARKUNLIT						1.00	-0.04
HR_DEEPSLEEP							1.00

- *Model Estimation and Interpretation (SC, SV)*

As presented in Table 73, among the 155 fatal crashes available for the SC only model, 94 crashes were single-vehicle run-off-road fatal crashes. Also shown in Equation (5-6), variables that can significantly differentiate a single-vehicle fatal crash from a multiple-vehicle fatal crash include lane width, graded shoulder width, horizontal curve direction, vertical curve status, land use types, lighting condition, and crash time.

Table 73: Model Estimation (SC, SV)

Variable	**Estimate**	**P- value**
Intercept	12.1999	<.0001
LW	-1.0576	<.0001
GSW	-0.1247	0.0813
LCURV	1.1555	0.0293
CREST	-1.5341	0.0254
LU_C	-2.5984	0.006
DARKUNLIT	1.3523	0.0017
HR_DEEPSLEEP	2.0821	0.1114
Observations (Single-Vehicle/Others)	155 (94/61)	
AIC	159.735	
Schwarz Criterion	184.082	
-2 Log L	143.735	
R-Square	0.3385	
Hosmer and Lemeshow Goodness-of-Fit		
Chi-Square	DF	Pr > ChiSq
11.5871	8	0.1706

Let:

$$\eta_{SC} = 12.1999 - 1.0576LW - 0.1247GSW + 1.1555LCURV - 1.5341CREST$$
$$-2.5984LU\_C + 1.3523DARKUNLIT + 2.0821HR\_DEEPSLEEP$$

The probability of a single-vehicle run-off-road fatal crash can then be predicted as follows:

$$\Pr(Single-veh-runoff)_{SC} = \frac{\exp(\eta_{SC})}{1+\exp(\eta_{SC})} \tag{5-6}$$

Based on the correlation analysis presented in the previous section, the data does not show evidence of strong correlation among the independent variables used in the SC only model for single-vehicle fatal crashes. Therefore, it is reasonable to provide marginal effect interpretations of individual contributing factors in the crash type model. The odds ratio of each independent variable is illustrated in Figure 96.

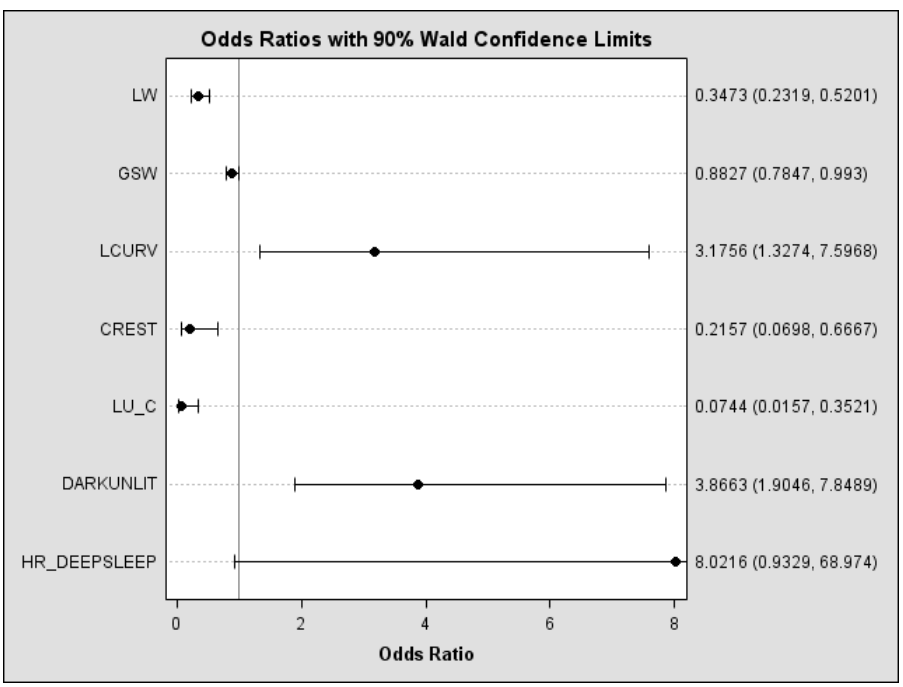


Figure 96: Odds Ratio (SC, SV)

- **Variable:** LW

  Effect: The odds of fatal crashes as single-vehicle crashes are estimated to decrease by a factor of 0.3 with each 1-ft increase in lane width after accounting

for the effects of other predictors. The approximate 90% confidence interval for this odds ratio is 0.2 to 0.5. This effect should not be extrapolated beyond the range of lane width (8 to 12 ft).

- **Variable:** GSW
  Effect: The odds of fatal crashes as single-vehicle crashes are estimated to decrease by a factor of 0.9 with each 1-ft increase in graded shoulder width after accounting for the effects of other variables. The approximate 90% confidence interval for this odds ratio is 0.8 to 0.99.

- **Variable:** LCURV
  Effect: The odds of fatal crashes as single-vehicle crashes at locations with horizontal curves to the left are estimated to be 3.2 times the odds of single-vehicle fatal crashes at locations with straight alignments or curves to the right after accounting for the effects of other variables. The approximate 90% confidence interval for this odds ratio is 1.3 to 7.6.

- **Variable:** CREST
  Effect: The odds of fatal crashes as single-vehicle crashes at locations with crest vertical curves are estimated to reduce by a factor of 0.2 from the odds of a single-vehicle fatal crash at locations without a crest vertical curve present after accounting for the effects of other variables. The approximate 90% confidence interval for this odds ratio is 0.1 to 0.7.

- **Variable:** LU_C
  Effect: The odds of fatal crashes as single-vehicle crashes at locations close to commercial driveways are estimated to reduce by a factor of 0.1 from the odds of a single-vehicle fatal crash at locations not close to commercial driveways after

accounting for the effects of other variables. The approximate 90% confidence interval for this odds ratio is 0.02 to 0.4.

- **Variable:** DARKUNLIT

  Effects: The odds of fatal crashes as single-vehicle crashes at locations under dark without supplemental lightings are estimated to be 3.9 times the odds of single-vehicle fatal crashes at locations with lighting conditions as either daylight, dark with lights, dusk or dawn after accounting for the effects of other variables. The approximate 90% confidence interval for this odds ratio is 1.9 to 7.8.

- **Variable:** HR_SLEEP

  Effects: The odds of fatal crashes as single-vehicle crashes occurring between 1am to 3am are estimated to be 8 times the odds of single-vehicle fatal crashes occurring during other time period of a day after accounting for all other independent variables. The approximate 90% confidence interval for this odds ratio is 0.9 to 68.9.

- *Model Goodness-of-Fit and Predictive Power (SC, SV)*

As summarized in Table 73, the Hosmer and Lemeshow Goodness-of-Fit test showed evidence that the model provides a good fit for the observed data (p-value=0.1706 >0.05). Meanwhile, as shown in Figure 97, the area under the ROC curve is 0.8522, which suggests a good predictive power of the SC only model in terms of distinguishing single-vehicle fatal crashes and multiple-vehicle fatal crashes.

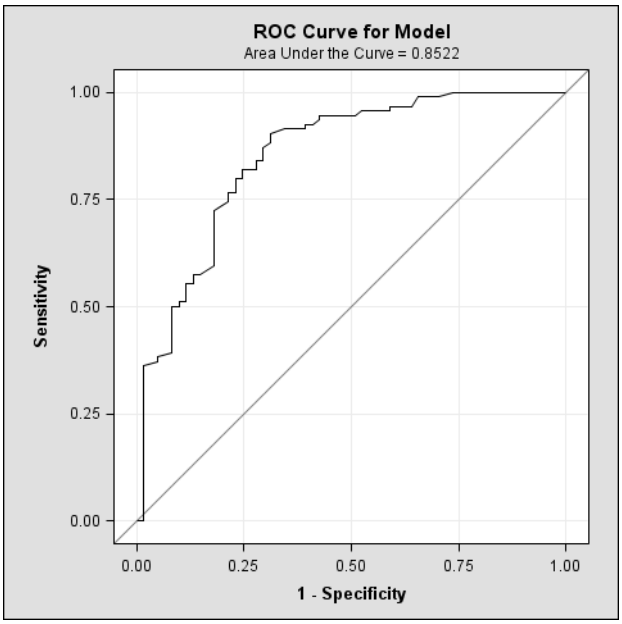


Figure 97: ROC Curve (SC, SV)

5.1.3 Summary of Single-Vehicle Fatal Crash Models

Table 74 and Table 75 summarize the model estimation results and odds ratios for the four individual-state models, the three-state combined model (AL, GA, SC), and the four-state combined model (AL, GA, MS, SC). The four individual-state models do not all contain the same set of independent variables. The two combined-state models include a collection of independent variables included in all four individual-state models. The effort of fitting four individual-state models with the same set of independent variables is not supported by the data. One of the requirements of testing model spatial transferability is to fit models with the same set of predictors. This condition can only be achieved if all four individual-state models include a limited collection of independent variables such as ADT only. These models would then have less accurate predictive power since critical contributing factors may be excluded.

The different model specifications for the individual-state models may indicate that a model developed for one state is unlikely to apply to another state. However, a

smaller sample size might also contribute to this result. Both of the combined state models provided similar estimates for the categorical location indicator variables for Alabama and South Carolina. As previously discussed, this observation indicates that the fatal crash type outcome prediction might be similar across at least three states: Alabama, South Carolina, and the base state, Georgia.

Spatial transferability has been an interesting study topic with empirical applications in the transportation safety analysis field. However, researchers also recognize the challenges in terms of the data scale, data quality, and modeling technique. It is more so in the fatal crash analysis. Crashes are random events, while fatal crashes have even greater uncertainties. A larger sample size is more critical for a fatal crash study in order to identify patterns and embedded characteristics. However, the practical aspects of the field data collection limit the opportunities for increasing fatal data sets while including physical site characteristics.

Table 74: Model Comparison by Estimates (SV)

Variables	AL only Model	GA only Model	MS only Model	SC only Model	Three-State Model (AL, GA, SC)	Four-State Model (AL, GA, MS, SC)
AL					-0.1855	-0.1984
MS						-1.3453**
SC					-0.1167	-0.0836
INTERSECTION	-1.2158**	-2.1473**			-0.8078**	-0.9922**
LW	-0.5111**	-0.8350**	-0.4282*	-1.0576**	-0.5407**	-0.463**
PSW		-0.3506*	-0.7045		-0.0542	-0.1087
GSW				-0.1247*	-0.0475	-0.0463
PSW*GSW					-0.0676*	-0.0622*
LCURV	1.5906**	1.7437**	0.8562	1.1555**	0.788**	0.7255**
STRAIGHT		1.5662**				
VCREST				-1.5341**	-1.7264**	-1.5389**
DOWN	0.8342*					
LCURV*VCREST					2.5199**	2.2686**
RHR67	1.8195		1.6633**		1.1581*	1.3314**
ADTSCALE					-0.0965*	-0.1078**
LU_C				-2.5984**	-1.3722**	-1.4298**
DARKUNLIT	1.3682**	1.1195**	1.6260**	1.3523**	1.3101**	1.3135**
HR_DEEPSLEEP			2.0741*	2.0821	1.8318*	1.9744**
HR_EM	2.8888**					
RESTRAINT		-1.1604**				

** Significant level < 0.05
* Significant level < 0.1

Table 75: Model Comparison by Odds Ratios (SV)

Variables	AL only Model	GA only Model	MS only Model	SC only Model	Three-State Model (AL, GA, SC)	Four-State Model (AL, GA, MS, SC)
AL					0.83	0.82
MS						0.26**
SC					0.89	0.92
INTERSECTION	0.30**	0.12**			0.45**	0.37**
LW	0.60**	0.43**	0.65*	0.35**	0.58**	0.63**
PSW		0.70*	0.49		0.95	0.90
GSW				0.88*	0.95	0.95
PSW*GSW					0.93*	0.94*
LCURV	4.91**	5.72**	2.35	3.18**	2.20**	2.07**
STRAIGHT						
VCREST				0.22**	0.18**	0.21**
DOWN	2.30*					
LCURV*VCREST					12.43**	9.67**
RHR67	6.17		5.28**		3.18*	3.79**
ADTSCALE					0.91*	0.90**
LU_C				0.07**	0.25**	0.24**
DARKUNLIT	3.93**	3.06**	5.08**	3.87**	3.71**	3.72**
HR_DEEPSLEEP			7.96*	8.02	6.25*	7.20**
HR_EM	17.97**					
RESTRAINT		0.31**				

** Significant level < 0.05
* Significant level < 0.1

The two combined-state models present very similar modeling results when the same set of independent variables is retained. As discussed previously, the author proposed to use the three-state (AL, GA, and SC) combined model for safety evaluation of two-lane rural highways in Georgia.

As shown in Table 74 and Table 75, despite the differences among the individual-state models and the combined-state models, there are three independent variables (lane width, horizontal curve direction, and lighting conditions) which are significant

predictors with similar effects for all six models. These three variables are labeled as "level one variables".

- **LW:** The odds ratios in all six models are estimated between 0.35 and 0.65. The odds of fatal crashes as single-vehicle crashes are estimated to decrease at least by a factor of 0.65 with each 1-ft increase in lane width after accounting for the effects of other predictors. This result should be used within the range of lane width that is presented in the data.
- **LCURV:** The odds ratios for the horizontal curve to the left variable are estimated between 2 and 5.7 for all six models. The odds of fatal crashes as single-vehicle crashes at locations with horizontal curves to the left present are estimated to increase at least more than two-fold from the odds of single-vehicle fatal crashes at locations with straight alignments or curve to the right after accounting for other variables.
- **DARKUNLIT:** The odds ratios for dark driving condition are estimated between 3.1 and 5.1 for all six models. The odds of fatal crashes as single-vehicle crashes at locations under dark without supplemental lightings are estimated to increase at least more than three-fold from the odds of single-vehicle fatal crashes at locations with lighting conditions as either daylight, dark with lights, dusk or dawn, after accounting for the effects of other independent variables.

These findings suggest that the lane width, curve direction, and lighting condition are consistently and strongly associated with the probability of single-vehicle fatal crash outcome at both the state and regional level. In addition, four other variables (referred to as "level two variables") also presented stable and similar effects for both combined-state models and at least two state-specific models.

- **INTERSECTION:** The odds ratios are estimated to be smaller than 0.5 at 0.05 significance level for the two combined-state models and AL, GA only models. The odds of fatal crashes as single-vehicle crashes at road junctions are estimated

to decrease at least more than half from the odds of single-vehicle fatal crashes at road segments.

- **PSW, GSW:** Paved shoulder width was identified to interact with graded shoulder width for combined-state models and presented as main effects in the GA and MS only model. The odds of fatal crashes as single-fatal crash are estimated to reduce with paved shoulder width increase. The corresponding detailed influences can be found in the previous section.
- **RHR67:** The odds ratios are estimated to between 3.2 and 6.2 for the two combined-state models as well as AL, MS only models. The odds of fatal crashes as single-vehicle crashes at locations with roadside hazard rating 6 or 7 are estimated to increase at least more than three-fold from the odds of single-vehicle fatal crashes occurring at locations with lower roadside hazard ratings (RHR <6).
- **HR_DEEPSLEEP:** The odds ratios are estimated to between 6.2 and 8.1 in the two combined-state models as well as MS, SC only models. The odds of fatal crashes as single-vehicle crashes occurred between 1am to 3am are estimated to increase at least more than six-fold from the odds of single-vehicle fatal crashes occurred at other time of day.

Apparently, besides lane width, horizontal alignment conditions, and lighting conditions, the road junction type, roadside hazard rating, and crash time are also more likely to be important predictors for single-vehicle fatal crash outcome prediction models in the southeastern region. Based on previous discussions, single-vehicle fatal crash type models evidently support the presumption that the road geometrics as well as roadside and environmental features are associated with the probability of single-vehicle fatal crash occurrence in the southeastern region. This outcome echoes the evident connection between crash type and countermeasures which can be quantified by the models.

Two interaction effects support the speculations discussed by several previous studies. The ability to identify interactions in the crash type model could be contributed from disaggregated crash data. It is also possible that crash types are related to road geometric features with a more fundamental nature. The crash type model appears to be sensitive to identifying significant interactions from road related variables.

5.1.4 Analysis of Variables for Single-Vehicle Run-off-Road Crashes

The previous section interpreted the marginal effects of each independent variable through odds ratios. Even though there is no evidence of strong correlations present among independent variables, some variables are still correlated with one another at a low or moderate level. Considering this fact, the author also examined how one variable influences the probability of fatal crashes as single-vehicle crashes at different levels of other variables of interest. This section presents a sensitivity analysis for the probability of single-vehicle run-off-road fatal crash occurrence for a variety of previously identified contributing variables, including:

- Lane width,
- Paved shoulder width,
- Graded shoulder width,
- Average Daily Traffic,
- Junction (intersection) versus segment,
- Horizontal and vertical alignment,
- Roadside hazard rating,
- Land use type of driveways,
- Lighting condition, and
- Time of day for crash occurrence.

The author performed an analysis based on the recommended three-state combined model (AL, GA, and SC), as shown in Equation (5-2) in Section 5.1.1.2. Meanwhile, the analysis also extended to the GA only model, as shown in Equation (5-4) in

Section 5.1.2.2. In order to assess changes of predicted crash type outcome probabilities at different levels for an independent variable, all other independent variables have to be held constant while the candidate variable's value is modified. Table 76 presents values that can be used to define a nominal condition for a typical study road segment for the crash sites. Most of the variables were assigned a value similar to their average condition in the sample data (e.g. lane width of 11 ft and graded shoulder width of 5 ft). Since approximately 80% of the crash locations did not have paved shoulders, the paved shoulder width is assigned a value of zero feet for the nominal condition. For a state indicator value of zero for AL and SC, a road segment defined by the nominal condition represents Georgia conditions. Since lighting conditions consistently had a significant influence on fatal crash type outcomes, the research team evaluated the influence from each predictor under day light and dark without supplemental lighting conditions separately so as to identify unique patterns.

Table 76: Description of Road Nominal Condition for Evaluating SV Models

Variables	Conditions
AL	0
SC	0
JUNCTION	0 (a road segment)
LW	11 ft (lane width = 11 ft)
PSW	0 ft (paved shoulder width = 0 ft)
GSW	5 ft (graded shoulder width = 5 ft)
LCURV	0 (road horizontal alignment is not a curve to the left)
CREST	0 (road vertical alignment is not a crest vertical curve)
RHR67	0 (roadside hazard rating 1 through 5)
ADT	3000 veh/day (average daily traffic estimated as 3000 veh/day)
LU_C	0 (not in the proximity of a commercial driveway)
DARKUNLIT	1 (dark without supplemental lighting) or 0 (other)
HR_DEEPSLEEP	0 (crash did not occurred between 1 a.m. – 3 a.m.)

5.1.4.1 Lane Width

Table 77, Figure 98, and Figure 99 demonstrate the probability of a single-vehicle fatal crash and how it varies with lane width (from 8 to 12 ft) at four daily traffic volume levels ranging from low to high volumes (400 veh/day, 2000 veh/day, 5000 veh/day, and 10,000 veh/day). All other variables in the model used the nominal condition values (see Table 76).

Table 77: Lane Width and ADT (Three-State, SV)

ADT (veh/day)	Lane Width (ft)									
	8		9		10		11		12	
400	0.97	0.89	0.94	0.82	0.91	0.73	0.85	0.61	0.77	0.48
2000	0.96	0.87	0.94	0.80	0.90	0.70	0.83	0.57	0.74	0.44
5000	0.95	0.84	0.92	0.75	0.86	0.63	0.79	0.50	0.68	0.37
10,000	0.92	0.76	0.87	0.65	0.80	0.52	0.70	0.38	0.57	0.27

Note: The values shown in the shaded cells represent the probability of a crash during dark conditions where supplemental lighting is not present. The values in the cells that are not shaded represent crash probability for daylight conditions, dark conditions with supplemental lighting, dusk, and dawn.

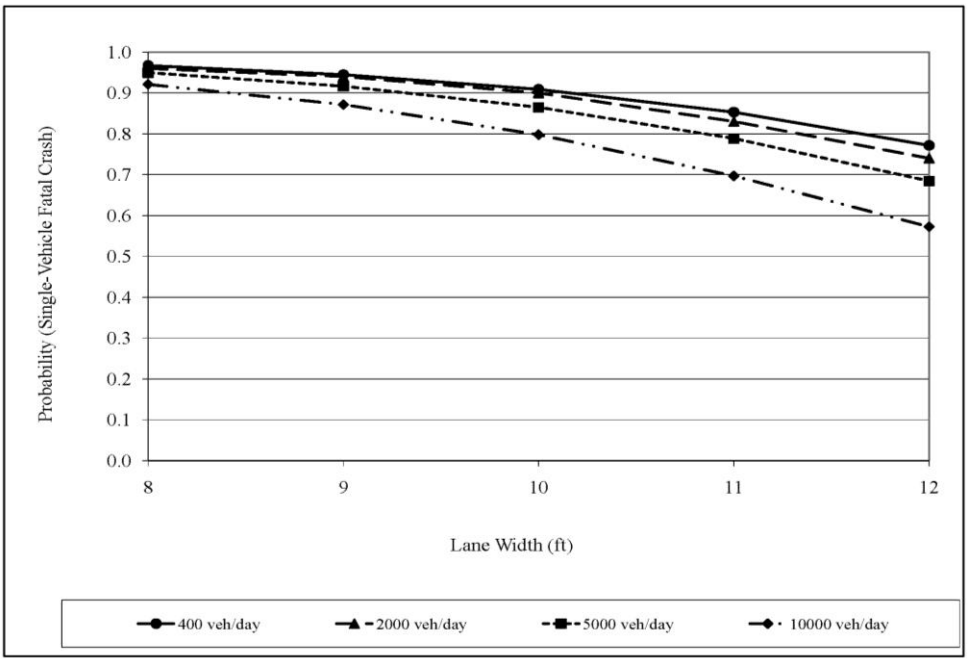


Figure 98: Dark without Street Lights -- Lane width by ADT (Three-State, SV)

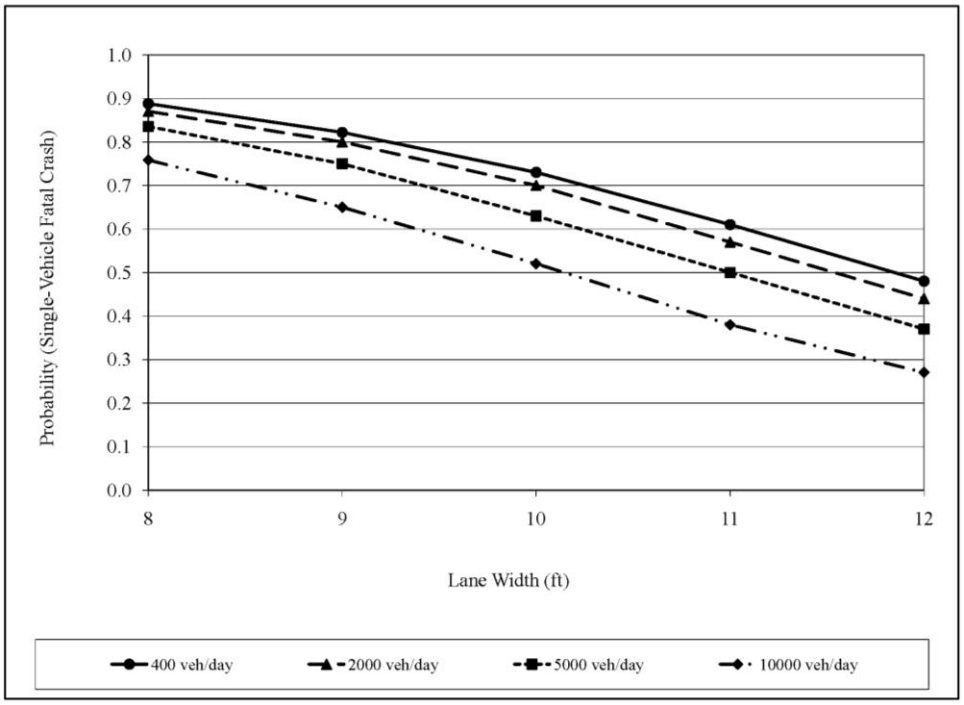


Figure 99: Daylight, Dark with Lighting, Dusk, or Dawn -- Lane width by ADT (Three-State, SV)

The likelihood of a single-vehicle fatal crash occurring reduces with an increase in the lane width despite lighting conditions and traffic volume levels. Alternatively, as the lane width increases, the single-vehicle run-off-road likelihood decreases more rapidly during daylight conditions than when it is dark without supplement lighting. This trend may imply that lane widening is a more effective countermeasure to help prevent daytime single-vehicle fatal crashes. More than half of the single-vehicle fatal crashes in this study, however, occurred during dark conditions without any supplemental lighting.

Single-vehicle fatal crash occurrence is sensitive to the various daily traffic volume levels for all lane width values. Interestingly, a higher traffic exposure can be associated with a lower likelihood of a single-vehicle fatal crash. As found in the project data, the higher traffic volume locations were more likely to occur at roads with the wider lane widths of 11 or 12 ft. For crashes that occur during nighttime conditions and where there was no supplement lighting, the probability of a single-vehicle fatal crash was less sensitive to the various ADT levels. This lack of sensitivity is particularly evident for roads with narrow lane widths (8 to 10 ft).

5.1.4.2 Paved and Graded Shoulder Width

As previously indicated, the three-state model includes a statistically significant interaction effect between the paved and graded shoulder width. As a result, this analysis illustrates how sensitive the probability of a single-vehicle crash is based on varying graded shoulder widths (0 ft, 2ft, 4ft, 6ft, and 8ft) at various levels of paved shoulder width. As shown in Table 78, Figure 100, and Figure 101, the probability of a single-vehicle fatal crash when the graded shoulder width is increased does not vary substantially if there is no companion paved shoulder (paved shoulder width = 0 ft). Alternatively, if there is a paved shoulder present, the probability of a single-vehicle fatal crash drops significantly when the graded shoulder width is increased. This

relationship suggests that the combination of paved and graded shoulders collectively helps to enhance safety and reduce the likelihood of single-vehicle fatal crashes.

Table 78: Paved and Graded Shoulder Width (Three-State, SV)

Paved Shoulder width (ft)	Graded Shoulder Width (ft)									
	0		2		4		6		8	
0	0.85	0.61	0.84	0.58	0.83	0.56	0.81	0.54	0.80	0.51
2	0.84	0.58	0.78	0.49	0.71	0.40	0.63	0.32	0.54	0.24
4	0.82	0.55	0.71	0.40	0.56	0.26	0.41	0.16	0.27	0.09
6	0.81	0.53	0.63	0.31	0.40	0.15	0.21	0.07	0.10	0.03

Note: The values shown in the shaded cells represent the probability of a crash during dark conditions where supplemental lighting is not present. The values in the cells that are not shaded represent crash probability for daylight conditions, dark conditions with supplemental lighting, dusk, and dawn.

For daylight conditions or locations with supplemental lighting, the probability of a single-vehicle fatal crash occurring decreases at a slower rate for wider graded shoulders than when the lighting conditions are dark with no supplemental lighting. This observation is particularly true at locations with a wider paved shoulder.

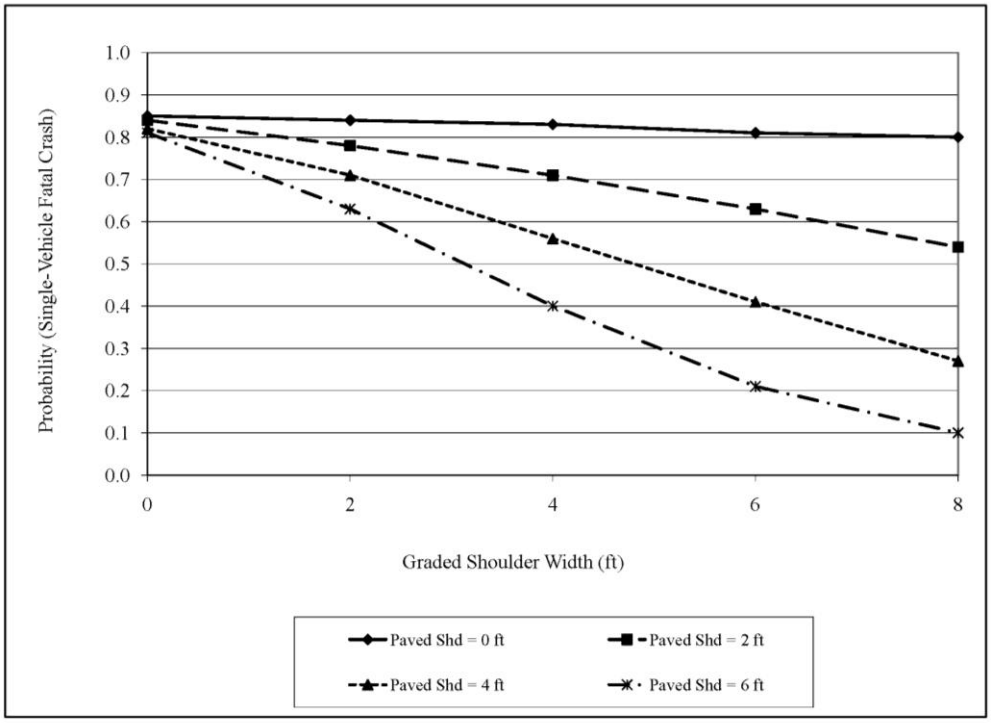


Figure 100: Dark without Street Lights -- Graded and Paved Shoulder Width (Three-State, SV)

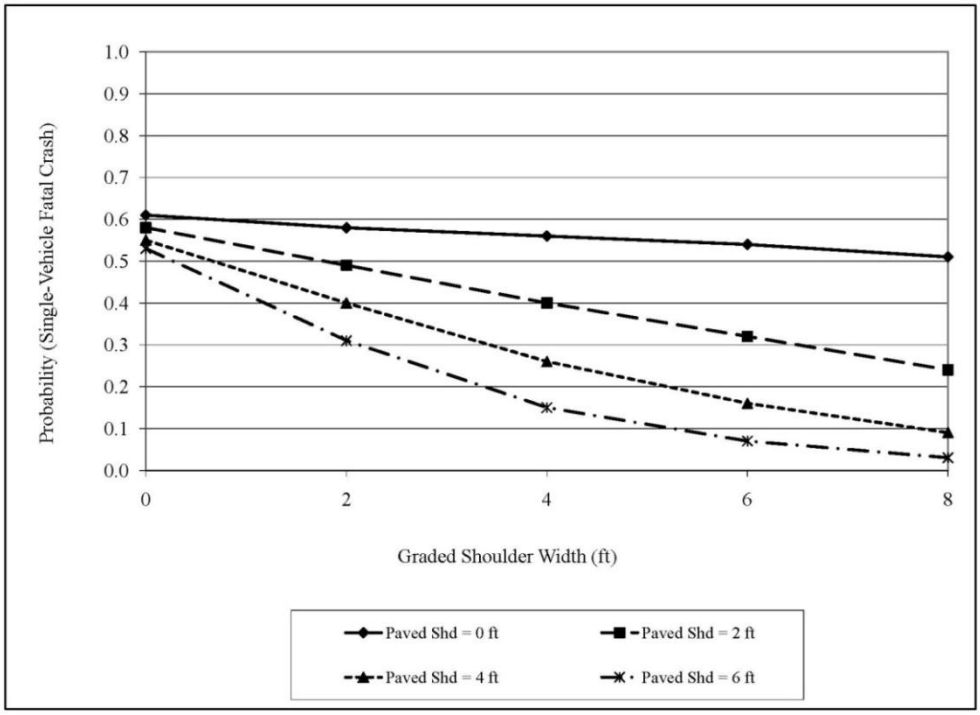


Figure 101: Daylight, Dark with Lights, Dusk, or Dawn -- Graded and Paved Shoulder Width (Three-State, SV)

While the three-state model includes the interaction effect between paved and graded shoulder width, the Georgia model only includes the paved shoulder width as a significant shoulder-type variable. To enable a comparison of modeling results between the Georgia model and the three-state combined model, the variable analysis for the Georgia model is also based on the same road nominal conditions as described in Table 76. The Georgia model also includes fatal crash type probabilities as they are associated with safety restraint usage by at-fault drivers at the time of the crash.

Overall, the Georgia model predicts a reduction in the probability of a single-vehicle fatal crash occurring as the lane width increases for various paved shoulder widths. This observation is consistent with the findings for the three-state model. For at-fault drivers who use safety restraints, the likelihood of being involved in a single-vehicle

fatal crash for various lanes widths and paved shoulder widths is depicted in Table 79. The observed relationship between paved shoulder widths (0 ft, 2 ft, 4 ft, and 6 ft) and lane widths (9 ft to 12ft) appears to vary in a manner similar to that observed for the three-state model for dark conditions without supplemental lighting (see Figure 102 and Figure 106) and for daylight or dark with supplemental lighting conditions (see Figure 103 and Figure 107), respectively.

Table 79: Paved Shoulder and Restraint System Usage (GA, SV)

	Paved Shoulder Width (ft)	Lane Width (ft)							
		9		10		11		12	
Driver Used Safety Restraints (RESTRAINT =1)	0	0.95	0.86	0.89	0.72	0.78	0.53	0.60	0.33
	2	0.90	0.75	0.80	0.56	0.63	0.36	0.43	0.20
	4	0.82	0.60	0.66	0.39	0.46	0.22	0.27	0.11
	6	0.69	0.42	0.49	0.24	0.30	0.12	0.15	0.06
Driver Did Not Use Safety Restraints (RESTRAINT =0)	0	0.98	0.95	0.96	0.89	0.92	0.78	0.83	0.61
	2	0.97	0.90	0.93	0.80	0.85	0.64	0.70	0.44
	4	0.94	0.82	0.86	0.67	0.73	0.47	0.54	0.28
	6	0.88	0.70	0.76	0.50	0.57	0.31	0.37	0.16

Note: The values shown in the shaded cells represent the probability of a crash during dark conditions where supplemental lighting is not present. The values in the cells that are not shaded represent crash probability for daylight conditions, dark conditions with supplemental lighting, dusk, and dawn.

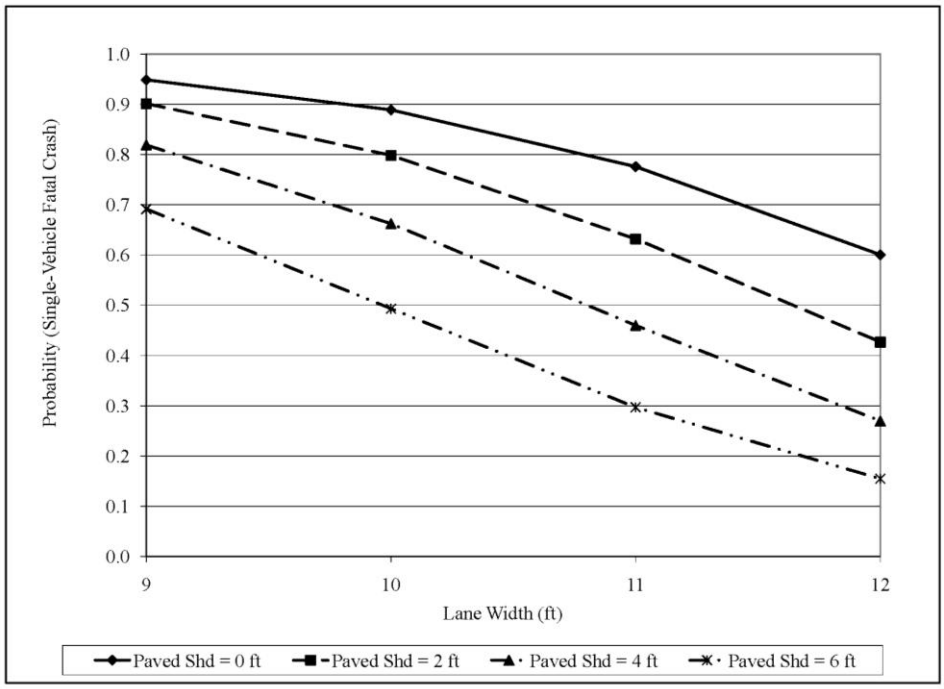


Figure 102: Dark without Street Lights -- Paved Shoulder Width and Safety Restraint Used (GA, SV)

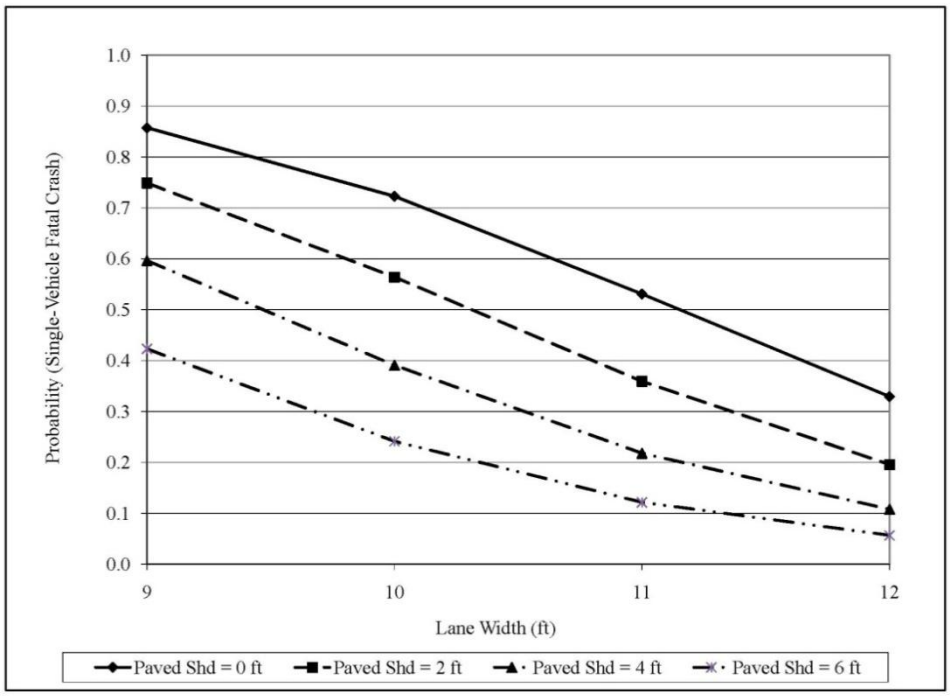


Figure 103: Daylight, Dark with Lights, Dusk, or Dawn -- Paved Shoulder Width and Safety Restraint Used (GA, SV)

For at-fault drivers who do not utilize safety restraints (see Figure 104 and Figure 105) the Georgia model predicts a slightly different pattern for the single-vehicle fatal crash occurrence. In general, the likelihood that an at-fault driver who does not use safety restraints will be involved in a single-vehicle fatal crash is greater for all lighting conditions.

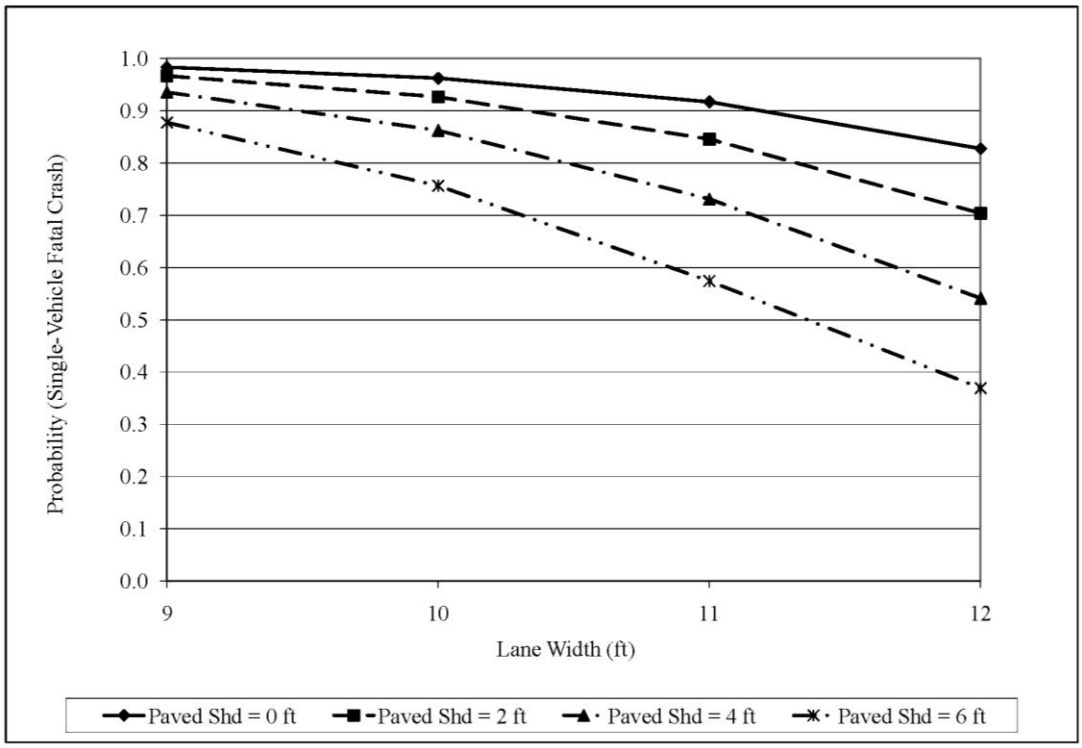


Figure 104: Dark without Street Lights -- Paved Shoulder Width and Safety Restraint Not Used (GA, SV)

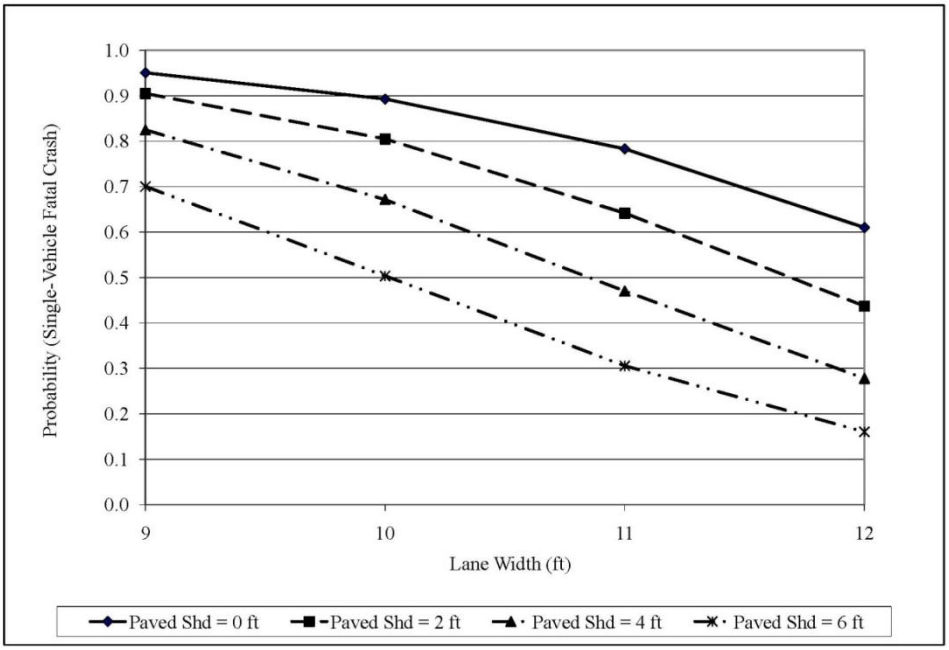


Figure 105: Daylight, Dark with Lights, Dusk, or Dawn -- Paved Shoulder Width and Safety Restraint Not Used (GA, SV)

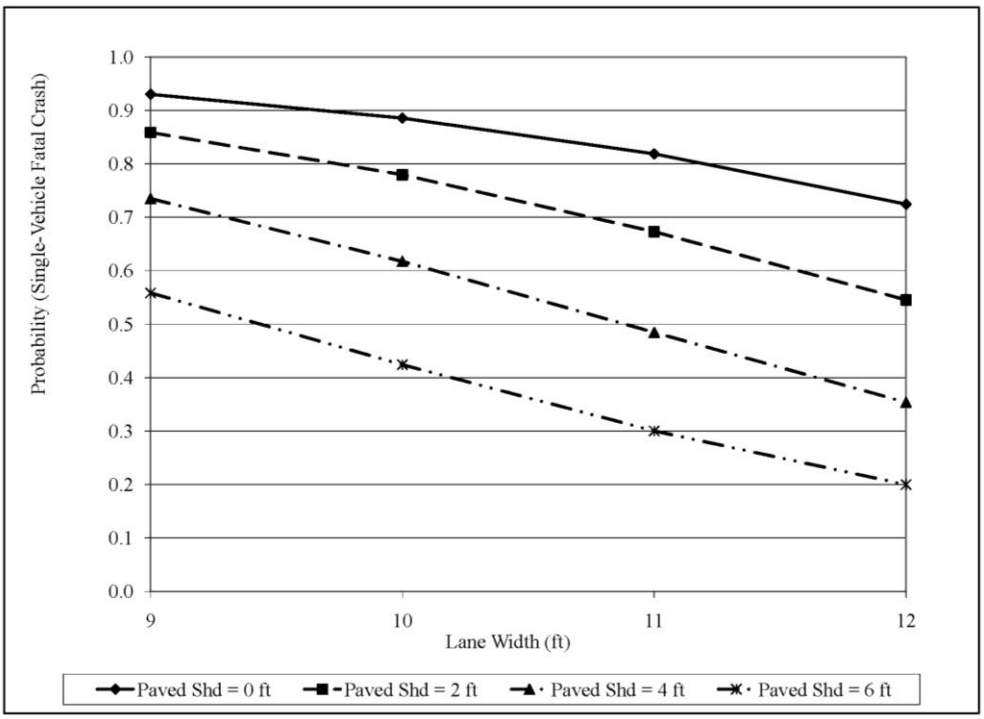


Figure 106: Dark without Street Lights--Paved Shoulder Width (Three-State, SV)

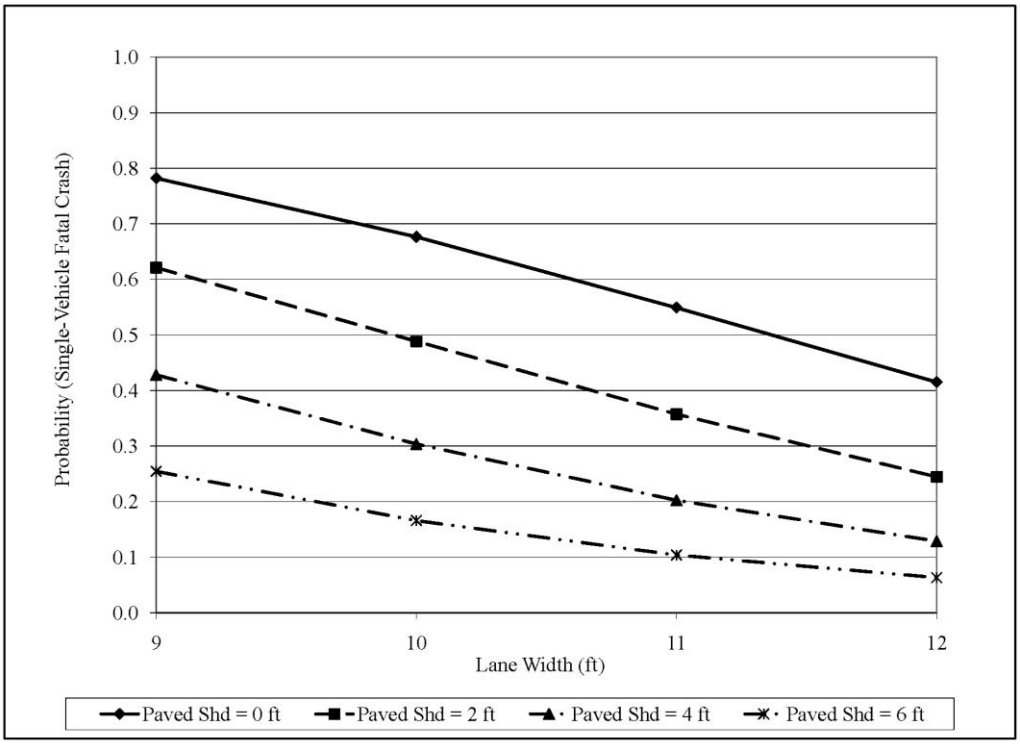


Figure 107: Daylight, Dark with Lights, Dusk, or Dawn--Paved Shoulder Width (Three-State, SV)

5.1.4.3 Roadside Condition

Table 80 and Figure 108 demonstrate the sensitivity of the roadside hazard rating on the likelihood of a single-vehicle fatal crash occurring if all other conditions are nominal (as shown in Table 76). The perceived hazardous roadside environment (RHR67=1) increases the risk of a single-vehicle fatal crash for all lighting conditions. For example, sites with a roadside hazard rating 6 or 7 have an increased likelihood of a single-vehicle fatal crash ranging from 9 to 28% for daylight, dark with supplemental lighting, dusk, and dawn conditions when compared to the more traversable roadside condition (represented by RHR67=0). For dark conditions without supplemental lighting, the steeper, less traversable roadside condition also increases the likelihood of a fatal, single-vehicle crash from 3 to 17% for lane widths

of 8 ft to 12 ft. Values shown in Table 80 also indicate that the probability of a fatal single-vehicle crash for all roadside hazard rating categories is substantially greater at locations with narrower lane widths.

Table 80: Roadside Hazard Rating (Three-State, SV)

RHR67	LANE WIDTH (ft)									
	8		9		10		11		12	
Flatter, More-Traversable Roadside (RHR67=1)	0.99	0.95	0.98	0.92	0.96	0.87	0.93	0.79	0.89	0.69
Steeper, Non-Traversable Roadside (RHR67=0)	0.96	0.86	0.93	0.78	0.89	0.68	0.82	0.55	0.72	0.41

Note: The values shown in the shaded cells represent the probability of a crash during dark conditions where supplemental lighting is not present. The values in the cells that are not shaded represent crash probability for daylight conditions, dark conditions with supplemental lighting, dusk, and dawn.

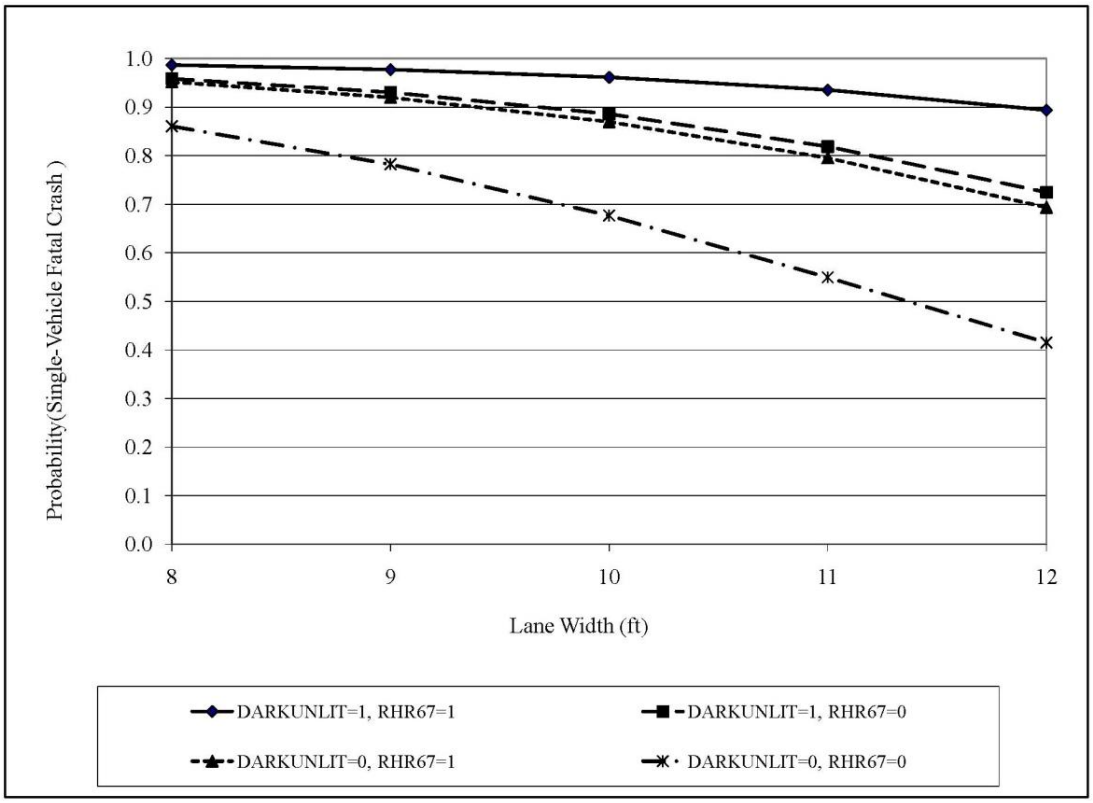


Figure 108: Roadside Hazard Rating (Three-State, SV)

5.1.4.4 Horizontal and Vertical Alignment

Table 81, Figure 109, and Figure 110 depict the influence of horizontal and vertical curvature for the two general lighting conditions and the influence of this geometry on the probability of a single-vehicle fatal crash. The three-state model previously discussed included an interaction effect between horizontal curve direction and crest vertical curvature. It is likely that this interaction is due to deteriorated sight distance conditions resulting from the combined effects of the horizontal and vertical geometry. For dark conditions without supplemental lighting, the presence of a crest vertical curve combined with a horizontal curve to the left will increase the chance of a single-vehicle fatal crash substantially. This crash probability is marginally reduced with improved lighting conditions. For locations that do not have overlapping horizontal and vertical geometry, the locations with curves to the left have a lower probability of the single-vehicle fatal crash than the combined geometry conditions, but also have a higher probability of this crash type when compared to roads that did not have horizontal curves to the left.

Table 81: Sensitivity to Curve Direction and Vertical Alignment (Three-State,SV)

Curve to the Left	CREST	LANE WIDTH (ft)									
		8		9		10		11		12	
Yes (LCURV =1)	Yes (CREST =1)	0.99	0.97	0.98	0.95	0.97	0.91	0.96	0.86	0.93	0.78
Yes (LCURV =1)	No (CREST =0)	0.98	0.93	0.97	0.89	0.94	0.82	0.91	0.73	0.85	0.61
No (LCURV =0)	Yes (CREST =1)	0.80	0.52	0.70	0.39	0.58	0.27	0.45	0.18	0.32	0.11
No (LCURV =0)	No (CREST =0)	0.96	0.86	0.93	0.78	0.89	0.68	0.82	0.55	0.72	0.41

Note: The values shown in the shaded cells represent the probability of a crash during dark conditions where supplemental lighting is not present. The values in the cells that are not shaded represent crash probability for daylight conditions, dark conditions with supplemental lighting, dusk, and dawn.

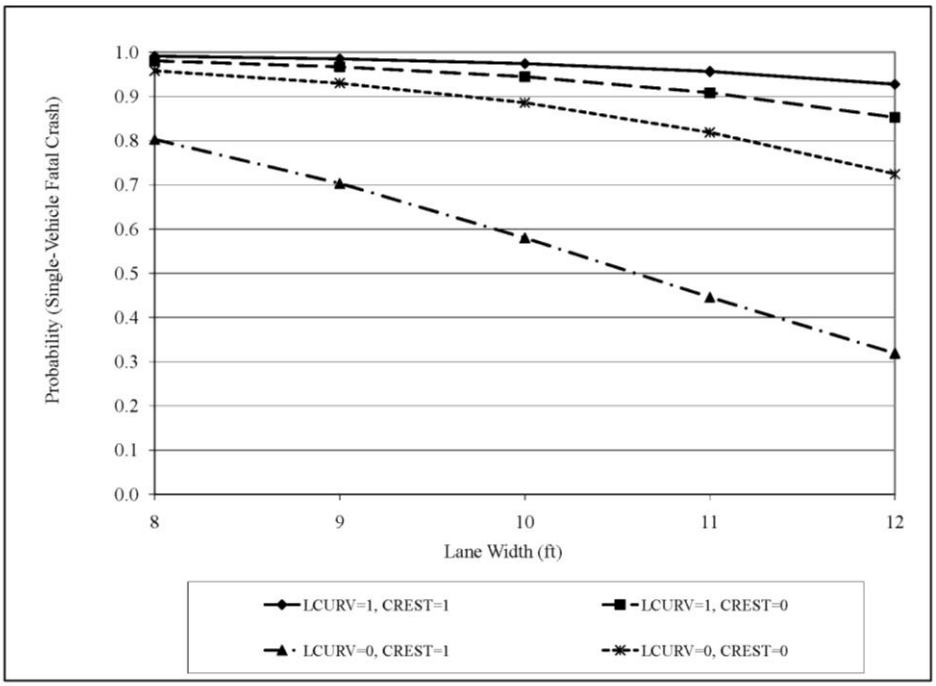


Figure 109: Dark without Street Lights -- Road Alignment (Three-State, SV)

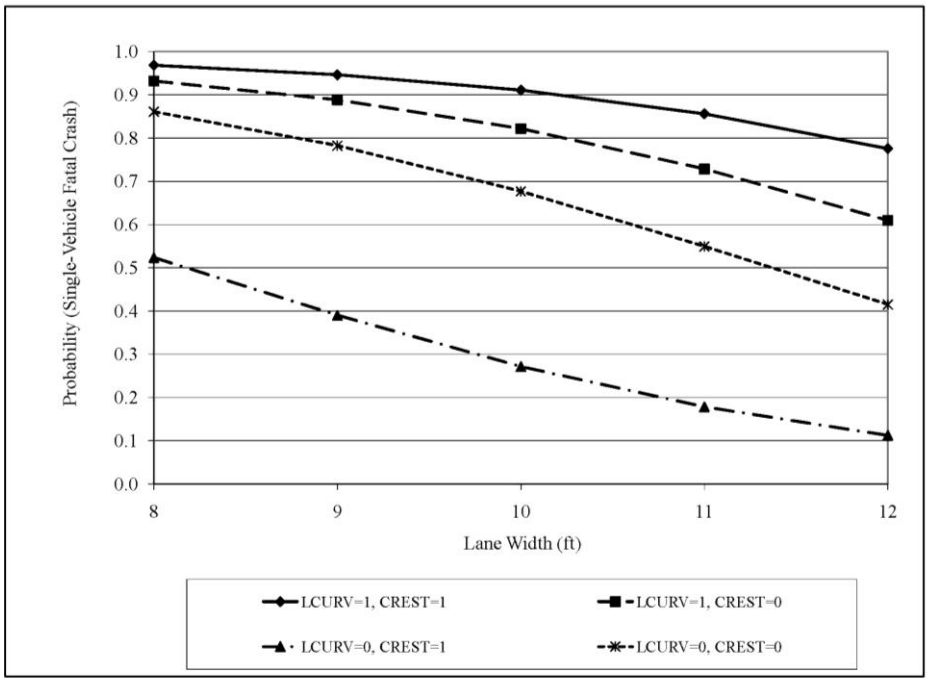


Figure 110: Daylight, Dark with Lights, Dusk, or Dawn -- Road Alignment (Three-State, SV)

5.1.4.5 Road Junction/Intersection

As previously indicated, single-vehicle run-off-road and head-on crashes are primarily associated with road segment locations rather than intersections, while angle crashes are more likely to be associated with road junctions/intersections. Table 82 and Figure 111 present the sensitivity analysis for evaluation of the probability of a single-vehicle fatal crash occurring at an intersection or at a road segment. The three-state model predicts that single-vehicle fatal crashes have approximately a 13 to 20% greater chance of occurring at road segments than at intersection locations. This analysis assumes all other conditions are held constant at the nominal values (see Table 76). As can be expected, angle crashes are more likely to occur at intersection locations since they involve two vehicles that cross paths. Single-vehicle crashes occur more frequently at segment locations. Narrow lane widths at intersection locations will tend to increase the likelihood of a single-vehicle crash at those locations as well.

Table 82: Sensitivity to Road Junction/Intersection (Three-State, SV)

Location	Lane Width (ft)				
	8	9	10	11	12
Intersection (JUNCTION=1)	0.73	0.62	0.48	0.35	0.24
Segment (JUNCTION=0)	0.86	0.78	0.68	0.55	0.41

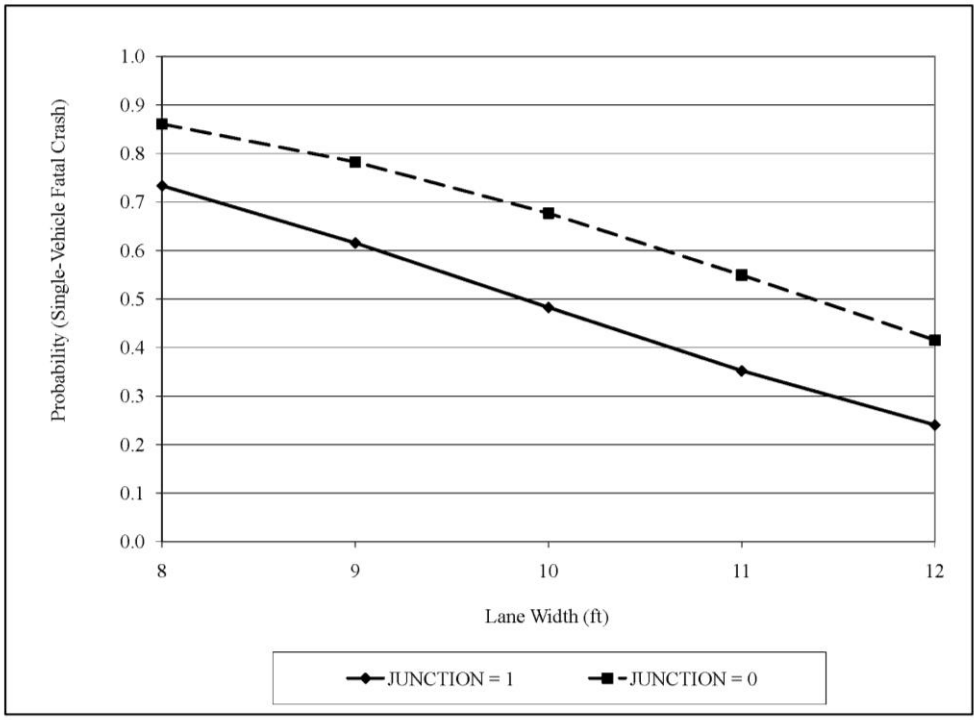


Figure 111: Road Junction (Three-State, SV)

5.1.4.6 Land Use Type

As shown in Table 83 and Figure 112, single-vehicle fatal crashes are approximately 25 to 33% less likely to occur in the vicinity of a commercial driveway than at other locations (including near residential and industrial driveway locations). At commercial driveway locations, heavier traffic can be expected resulting in a greater opportunity for vehicle interactions. The observed reduction in single-vehicle crash probability at these locations may be due to a more alert driver in the vicinity of a commercial driveway, but this trend could also simply be due to the greater opportunity for a multiple-vehicle crash due to the higher traffic volumes.

Table 83: Sensitivity to Land Use Types (Three-State, SV)

Dark Conditions/ No Lighting	Land Width (ft)				
Proximity to Driveways	8	9	10	11	12
Near Commercial Driveway (LU_C=1)	0.61	0.48	0.35	0.24	0.15
Not in proximity of a Commercial Driveway(LU_C=0)	0.86	0.78	0.68	0.55	0.41

Note: The data in this table represents daylight, dark with supplemental lighting, dusk, and dawn conditions.

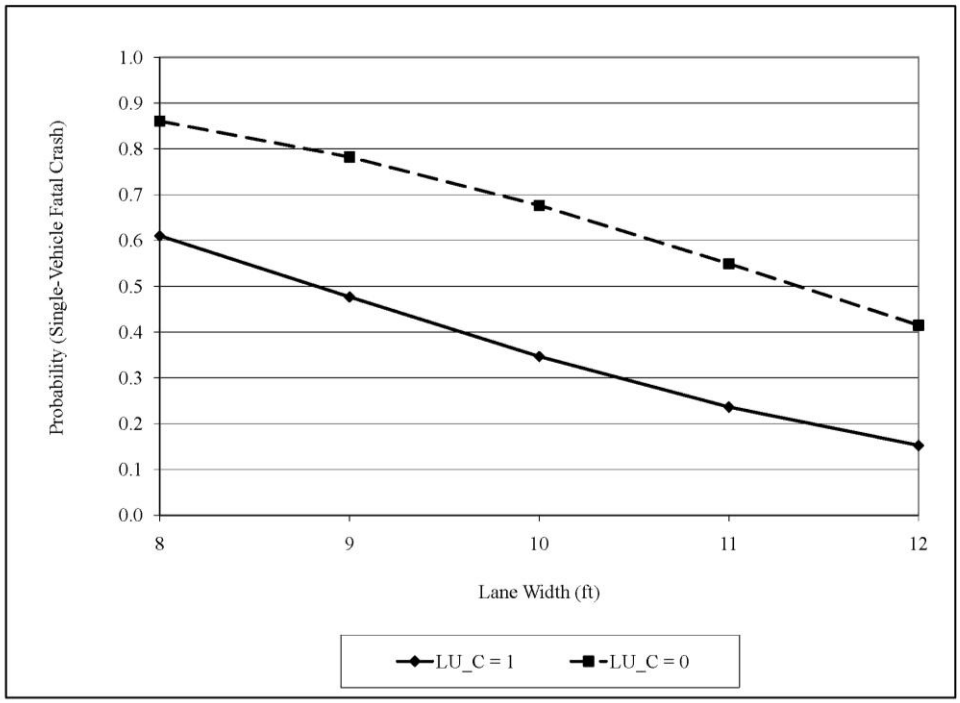


Figure 112: Land Use Type (Three-State, SV)

5.1.4.7 Time of Day

Single-vehicle fatal crashes occurred during all times of the day; however, the model development process identified an increased probability for single-vehicle fatal crashes on rural two-lane roads between the hours of 1 a.m. and 3 a.m. This time period coincides with the conventional deep sleep stage of the circadian biological

clock for the drivers. Table 84 and Figure 113 demonstrate that the probability of a single-vehicle fatal crash (based on various lane widths) does not fluctuate considerably during this "deep sleep" time period. Alternatively, this time period can be contrasted to the remainder of the day and evaluated based on lane width to identify a decreasing probability of a single-vehicle crash with an increasing lane width. In general terms, these finding reinforce the perception that the driver's performance during the "deep sleep" time period can be impaired due to increasing fatigue or similar biological reactions. It is also important to note that the toxicology information in the crash database was incomplete (due to a delay in testing and reporting), but it is also likely that some drivers may be under the influence of drugs or alcohol following an evening of entertainment. This could indirectly be represented by these findings.

Table 84: Sensitivity to Time of Crash (Three-State, SV)

Time of Crash	Lane Width (ft)				
	8	9	10	11	12
1 a.m. to 3 a.m. (HR_DEEPSLEEP=1)	0.99	0.99	0.98	0.97	0.94
All hours excluding 1 a.m. to 3 a.m. (HR_DEEPSLEEP=0)	0.96	0.93	0.89	0.82	0.72

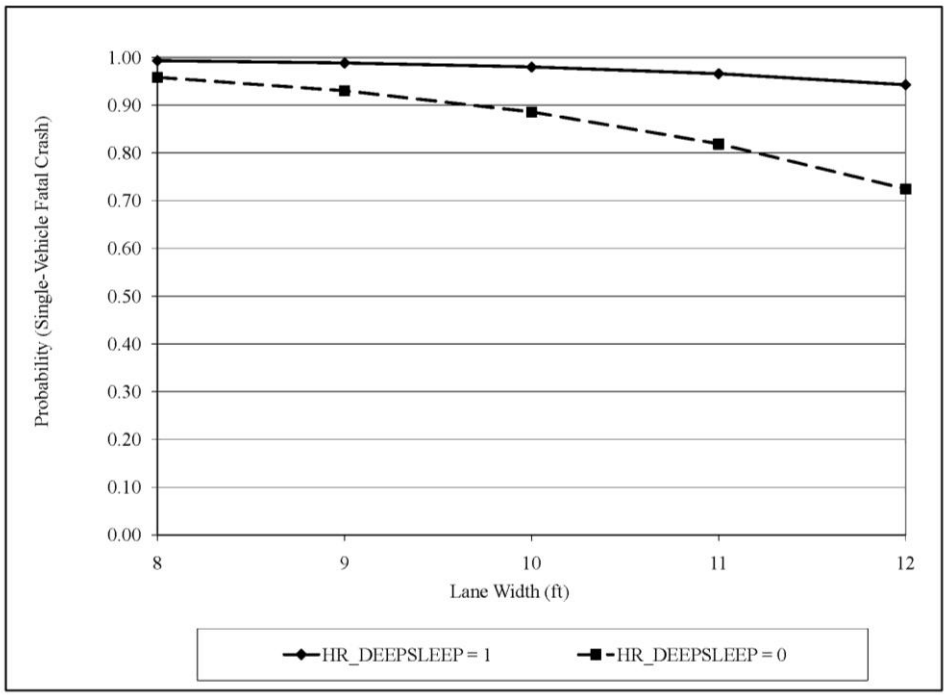


Figure 113: Time of Crash (Three-State, SV)

5.1.4.8 Lighting Condition

As summarized in the previous sensitivity evaluations, the author determined that there is a greater chance of a single-vehicle fatal crash during dark driving conditions where supplemental street lights are not present. As shown in Figure 98 and Figure 99, the narrower width of the travel lane has a greater influence on the increased crash probability during all lighting conditions (with dark conditions resulting in the greatest crash probability). This observation may also suggest that lane widths that are narrower than common standard widths introduce a much greater safety risk for all lighting conditions. Improving visibility with enhanced lane marking or supplemental delineation at night may help to reduce single-vehicle run-off-road fatal crashes at these locations. Since horizontal curves appear to be one of the most common locations for single-vehicle fatal crashes on rural two-lane highways, the use of

supplemental devices such as reflective pavement markers may prove beneficial at these select locations.

5.2 Head-on Fatal Crash: HO Model

Commonly observed multiple-vehicle fatal crashes on rural two-lane highways are head-on crashes. As a result, this section presents binary logit models developed for the combined four-state (AL, GA, MS, and SC) multiple-vehicle fatal crash database. In addition, this study also presents three state-specific models for Alabama, Georgia, and Mississippi. The similar state-only South Carolina model for head-on fatal crashes and other types of multiple-vehicle fatal crashes did not produce meaningful results.

5.2.1 Combined-State Models (AL, GA, MS, and SC, HO)

- *Independent Variables (Four-State, HO)*

Table 85 presents independent variables that the author determined to be significant for differentiating head-on fatal crashes from other multiple-vehicle fatal crashes. These variables include: presence of road segment (not an intersection), lane width, horizontal curve direction, ADT, and number of driveways. In addition, Table 86 illustrates descriptive statistics for these independent variables. As shown, the average lane width was 11.2 ft with a range from 8 ft to 12 ft. The observed daily traffic volume at crash locations ranged from 150 up to 16,550 vehicles/day, with an average value of 3,990. The number of driveways within 250 ft upstream and downstream of the crash locations was, on average, a value of two. In addition to location indicators (for the individual states), there were two categorical variables: road junction type (segment) and horizontal curve direction. The proportional distribution of these two variables is presented in Table 87.

Table 85: Variable Description (Four-State, HO)

Types	Variables	Descriptions
Location Indicator	AL	1 if in Alabama, 0 otherwise
	MS	1 if in Mississippi, 0 otherwise
	SC	1 if in South Carolina, 0 otherwise
Road Junction type	SEGMENT	1 if a road segment, 0 otherwise
Geometric design features	LW	Lane width (ft)
	RCURV	1 if curve to the right, 0 otherwise (curve to the left or straight alignment)
Traffic volume	ADT	Average daily traffic (10^3 veh/day)
Roadside Conditions	NUMDRVWAY	Number of driveways within 250 ft upstream and downstream of the crash location

Table 86: Continuous Variables Descriptive Statistics (Four-State, HO)

Variable	Mean	Std Dev	Minimum	Maximum
LW (ft)	11.2	0.9	8	12
ADT (veh/day)	3,990	3,139	150	16500
NUMDRVWAY	2	2	0	13

Table 87: Distribution of Categorical Variables (Four-State, HO)

Variable	Status	Percent (%)
AL	0 (Not Alabama)	73
	1 (Alabama)	27
MS	0 (Not Mississippi)	82
	1 (Mississippi)	18
SC	0 (Not South Carolina)	72
	1 (South Carolina)	28
SEGMENT	0 (Intersection)	30
	1 (Segment)	70
RCURV	0 (Curve to Left or Straight)	78
	1 (Curve to Right)	21

- *Correlation Evaluation (Four-State, HO)*

The correlation matrix is presented in Table 88. The maximum absolute value of correlation coefficient is 0.46 for lane width and average daily traffic, while the absolute values of the remaining coefficients are all at or below 0.2. Therefore, there is no evidence of strong correlation among independent variables.

Table 88: Correlation Matrix (Four-State, HO)

	LW	ADT	NUMDRVWAY	SEGMENT	RCURV
LW	1.00	0.46	-0.09	0.05	-0.02
ADT		1.00	0.10	0.01	-0.10
NUMDRVWAY			1.00	-0.11	-0.08
SEGMENT				1.00	0.15
RCURV					1.00

- *Model Estimation and Interpretation (Four-State, HO)*

Table 89 illustrates the model estimation results. Among the 219 multiple-vehicle fatal crashes available for the four-state combined model, 95 of the crashes were head-on fatal crashes. The application of this head-on model should be limited to the range of data available in the dataset as presented in Table 86 for the continuous variables in the model. The three location indicator variables, AL, MS, and SC, were statistically insignificant. This result suggests that head-on fatal crashes for all four states (Georgia was the base state for this model) are similar and do not have significant differences. As discussed previously, the single-vehicle fatal crash model identified crashes in Mississippi as unique when compared to the other states. Since this relationship does not extend to the head-on fatal crash model, the final combined-state model for the head-on fatal crashes will retain all four states and a three-state model is not necessary.

Table 89: Model Estimation (Four-State, HO)

Variable	Estimate	P- value
Intercept	4.5746	0.0421
AL	0.6566	0.1591
MS	0.0817	0.8607
SC	0.1125	0.8004
SEGMENT	1.8649	<.0001
RCURV	1.1569	0.0027
LW	-0.6344	0.0024
ADT	0.2293	0.0003
NUMDRVWAY	-0.1715	0.0517
Observations (Head-on/Other)	219 (95/124)	
AIC	253.849	
Schwarz Criterion	284.351	
-2 Log L	235.849	
R-Square	0.2531	
Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
9.5647	8	0.2969

The resulting multiple-vehicle head-on fatal crash prediction model is then presented as follows:

$$\eta_{4-state} = 4.5746 + 0.6566AL + 0.0817MS + 0.1125SC + 1.8649SEGMENT$$
$$+1.1569RCURV - 0.6344LW + 0.2293ADT - 0.1715NUMDRVWAY$$

The probability of multiple-vehicle head-on fatal crash can then be predicted under a given set of conditions as:

$$\Pr(Head-on)_{4-state} = \frac{\exp(\eta_{4-state})}{1+\exp(\eta_{4-state})} \quad (5\text{-}7)$$

Based on the correlation analysis presented in the previous section, the data does not show evidence of strong correlation among the independent variables used in the four-

state model. Therefore, it is reasonable to provide marginal effect interpretations of individual contributing factors in the crash type model. The odds ratio of each independent variable is illustrated in Figure 114.

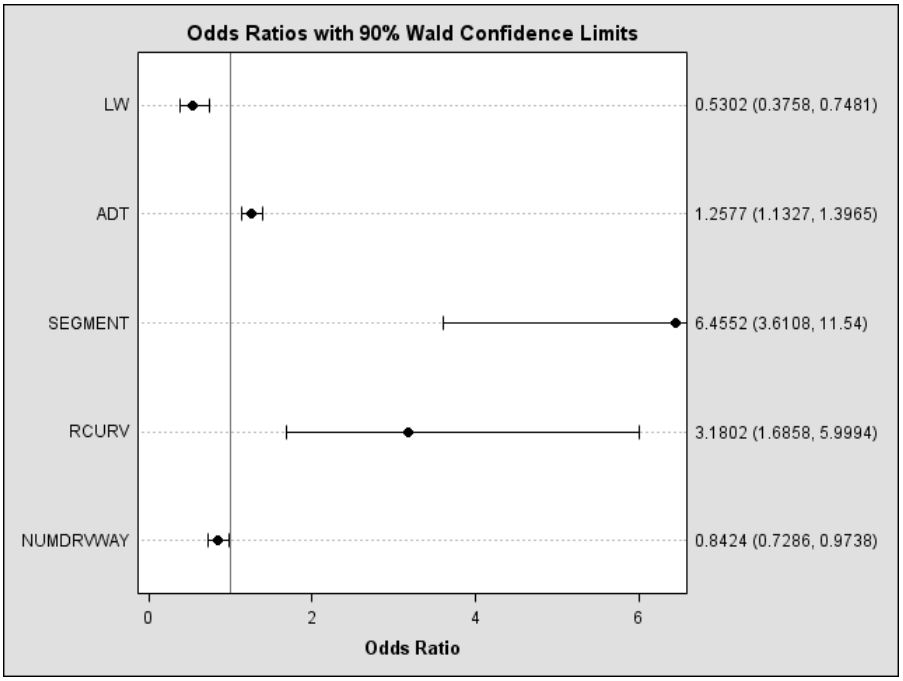


Figure 114: Odds Ratios (Four-State, HO)

- **Variable:** LW

  Effect: The odds of multiple-vehicle fatal crashes as head-on crashes are estimated to decrease by a factor of 0.5 with each 1-ft increase in lane width after accounting for the effects of other variables. The approximate 90% confidence interval for this odds ratio is 0.4 to 0.8. This effect should not be extrapolated beyond the range of lane width (8 to 12 ft) in the data.

- **Variable:** ADT

  Effect: The odds of multiple-vehicle fatal crashes as head-on crashes are estimated to increase by a factor of 1.3 with each 1000 vpd increase in daily traffic

volume after accounting for the effects of other variables. The estimated 90% confidence interval for this odds ratio is 1.1 to 1.4.

- **Variable:** SEGMENT

  Effect: The odds of multiple-vehicle fatal crashes as head-on crashes at road segment locations are estimated to be 6.5 times the odds of head-on fatal crashes at road junction locations, after accounting for other variables. The estimated 90% confidence interval for this odds ratio is 3.6 to 11.5.

- **Variable:** RCURV

  Effect: The odds of multiple-vehicle fatal crashes as head-on crashes at locations with horizontal curves to the right present are estimated to be 3.2 times the odds of head-on fatal crashes at locations with straight alignments or curves to the left, after accounting for the effects of other variables. The estimated 90% confidence interval for this odds ratio is 1.7 to 6.

- **Variable:** NUMDRVWAY

  Effect: The odds of multiple-vehicle fatal crashes as head-on crashes are estimated to decrease by a factor of 0.8 with each additional driveway located within 250ft upstream and downstream from crash locations after accounting for the effects of other variables. The approximate 90% confidence interval for this odds ratio is 0.7 to 0.97.

- *Model Goodness-of-Fit and Predictive Power (Four-State, HO)*

The Hosmer and Lemeshow goodness-of-fit test that measures how well a binary logit model fits the observed data reports an acceptable result (p-value = 0.2969 > 0.05) as shown in Table 89. The author also applied the ROC curve procedure to examine the model predictive power. As shown in Figure 115, the area under the curve is 0.7988,

which provides a measure of discrimination for two groups of crash outcomes. Based on the general rule, this result suggests a good predictive power for the model.

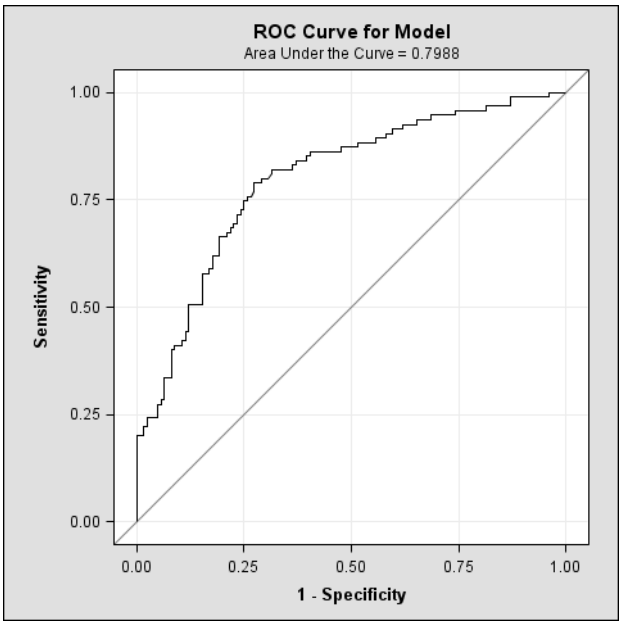


Figure 115: ROC Curve (Four-State, HO)

5.2.2 Models by State

This section presents results for state-specific head-on fatal crash prediction models for Alabama, Georgia, and Mississippi. As previously indicated, the individual state head-on crash modeling effort for South Carolina did not result in a meaningful fatal crash prediction model.

5.2.2.1 Alabama

- *Independent Variables (AL, HO)*

For the state of Alabama, the head-on fatal crash probability model included the following four significant independent variables: road segment locations, lane width, ADT, and number of driveways within 250 ft upstream and downstream of crash locations (see Table 90). Table 91 lists the descriptive statistics for the continuous

variables of lane width, ADT, and the number of driveways. Similarly, Table 92 depicts the distribution of the road junction type, the only significant categorical variable for this model. As shown in Table 91, the estimated daily traffic volume for the crash locations ranged from 150 up to 14,036 vehicles per day, with an average value of 3,924. Lane widths ranged from 8 to 12 ft with an average value of 11.2 ft. Crashes occurred at locations with an average of two driveways in the immediate vicinity of the crash.

Table 90: Variable Description (AL, HO)

Variables	Descriptions
SEGMENT	1 if crash location is road segment, 0 otherwise
LW	Lane width (ft)
ADT	Average Daily Traffic (veh/day)
NUMDRVWAY	Number of driveways within 250ft upstream and downstream of the crash location

Table 91: Continuous Variable Descriptive Statistics (AL, HO)

Variable	Mean	Std Dev	Minimum	Maximum
LW (ft)	11.2	1.0	8	12
ADT (veh/day)	3,924	3,471	150	14,036
NUMDRVWAY	2	2.4	0	13

Table 92: Distribution of Categorical Variables (AL, HO)

Variable	Status	Percent (%)
SEGMENT	0 (Intersection)	37
	1 (Segment)	63

- *Correlation Evaluation (AL, HO)*

As shown in Table 93, all correlation coefficients of independent variables are between -0.17 to 0.44, which suggests that independent variables in the AL only head-on model do not appear to be strongly correlated.

Table 93: Correlation Matrix (AL, HO)

	LW	ADT	NUMDRVWAY	SEGMENT
LW	1.00	0.44	0.04	-0.13
ADT		1.00	0.31	-0.05
NUMDRVWAY			1.00	-0.17
SEGMENT				1.00

- *Model Estimation and Interpretation (AL, HO)*

As shown in Table 94 and Equation (5-8), out of the 56 multiple-vehicle fatal crashes studied for Alabama, 29 crashes were head-on fatal crashes. Based on the correlation analysis presented in the previous section, the data does not show evidence of strong correlation among the independent variables used in the AL only model for single-vehicle fatal crashes. Therefore, it is reasonable to provide marginal effect interpretations of individual contributing factors in the crash type model. The odds ratio of each independent variable is illustrated in Figure 116.

Table 94: Model Estimation (AL, HO)

Variable	Estimate	P- value
Intercept	3.9412	0.4129
SEGMENT	3.8084	0.0003
LW (ft)	-0.6225	0.172
ADT (10^3 veh/day)	0.2973	0.0696
NUMDRVWAY	-0.3525	0.0591
Observations	56	
(Head-on/Other)	(29/27)	
AIC	54.425	
Schwarz Criterion	64.552	
-2 Log L	44.425	
R-Square	0.4466	
Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
9.2624	7	0.2344

Let:

$$\eta_{AL} = 3.9412 + 3.8084 SEGMENT - 0.6225 LW + 0.2973 ADT$$
$$-0.3525 NUMDRVWAY$$

The probability of a multiple-vehicle head-on fatal crash can then be predicted as:

$$\Pr(Head-on)_{AL} = \frac{\exp(\eta_{AL})}{1+\exp(\eta_{AL})} \tag{5-8}$$

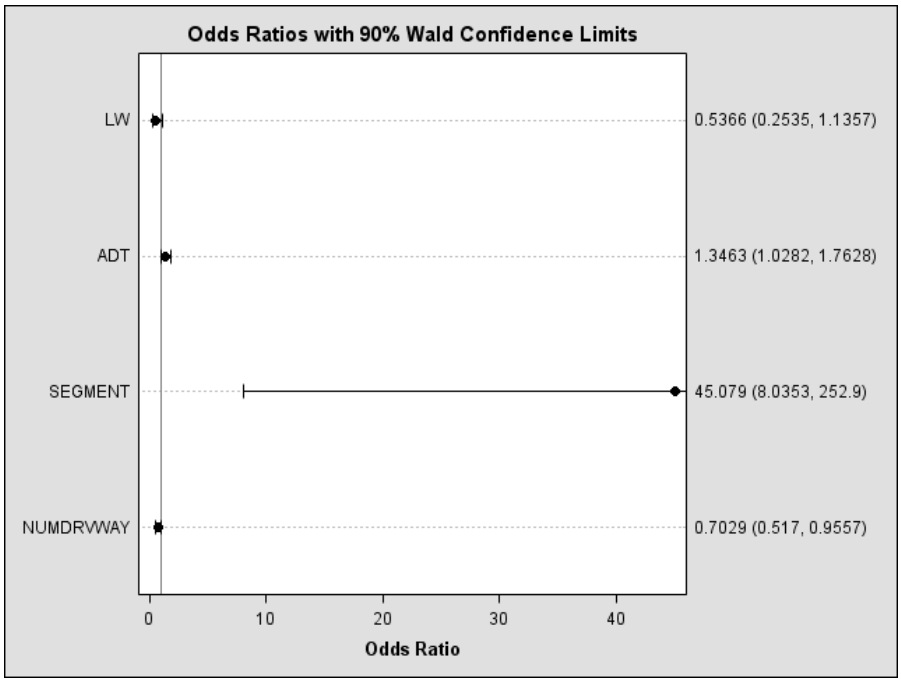


Figure 116: Odds Ratio (AL, HO)

- **Variable:** LW

  Effect: The odds of multiple-vehicle fatal crashes as head-on crashes are estimated to decrease by a factor of 0.5 with each 1-ft increase in lane width after accounting for the effects of other variables. The estimated 90% confidence interval for this odds ratio is 0.3 to 1.1. This effect should not be extrapolated beyond the range of lane width (8 to 12 ft) in the data.

- **Variable:** ADT

  Effect: The odds of multiple-vehicle fatal crashes as head-on crashes are estimated to increase by a factor of 1.3 with each 1000 vpd increase in daily traffic volume after accounting for the effects of other road geometrics. The estimated 90% confidence interval for this odds ratio is 1.0 to 1.7.

- **Variable:** SEGMENT

  Effect: The odds of multiple-vehicle fatal crashes as head-on crashes at road segment locations are estimated to be 45 times the odds of head-on fatal crashes at road junction locations after accounting for other variables. The estimated 90% confidence interval for this odds ratio ranges from 8 to 253.

- **Variable:** NUMDRVWAY

  Effect: The odds of multiple-vehicle fatal crashes as head-on crashes are estimated to decrease by a factor of 0.7 with each additional driveway present within 250 ft upstream and downstream from crash locations after accounting for the effects of other variables. The estimated 90% confidence interval for this odds ratio is 0.5 to 0.96.

- *Model Goodness-of-Fit and Predictive Power (AL, HO)*

As presented in Table 94, the Hosmer and Lemeshow goodness-of-fit test resulted in a p-value as 0.2344. Meanwhile, as shown in Figure 117, the area under the ROC curve is 0.9112, which provides a measure of discrimination for two groups of crash outcomes. Based on the general rule, this result suggests a good predictive power of the model.

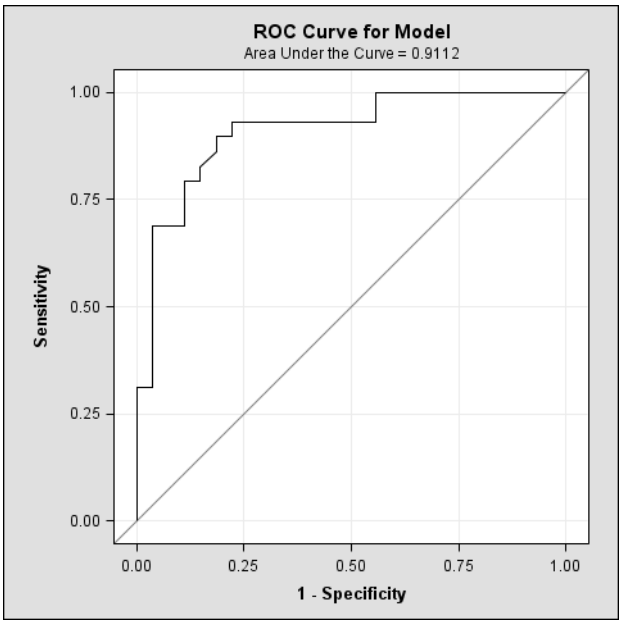


Figure 117: ROC Curve (AL, HO)

5.2.2.2 Georgia

- *Independent Variables (GA, HO)*

Table 95 summarizes a description of the key (independent) variables determined to be significantly associated with the head-on fatal crash probability model for the state of Georgia. These variables include: road junction type (segment), horizontal curve direction, lane width, ADT, and safety-restraint use by the at-fault drivers. Table 96 further defines the ranges for the continuous variables with an average lane width of 11.2 ft (range from 8.5 up to 12.0 ft) and an average observed ADT of 4,000 vehicles per day (ranging from 1,500 up to 16,500 vehicles per day). Table 97 depicts the distribution of the observed categorical variables (RCURV, SEGMENT, and RESTRAINT).

Table 95: Variable Description (GA, HO)

Variables	Descriptions
SEGMENT	1 if crash location is road segment, 0 otherwise
LW	Lane width (ft)
RCURV	1 if curve to the right, 0 otherwise (curve to the left or straight alignment)
ADT	Average Daily Traffic (veh/day)
RESTRAINT	1 if driver used safety restraint, 0 otherwise

Table 96: Continuous Variable Descriptive Statistics (GA, HO)

Variable	Mean	Std Dev	Minimum	Maximum
LW	11.2	1.0	8.5	12.0
ADT (veh/day)	4,000	3,080	1500	16,500

Table 97: Distribution of Categorical Variables (GA, HO)

Variable	Status	Percent (%)
SEGMENT	0 (Intersection)	25
	1 (Segment)	75
RCURV	0 (Curve to Left or Straight)	73
	1 (Curve to Right)	27
RESTRAINT	0 (Safety Restraint not Used)	71
	1 (Safety Restraint Used)	29

- *Correlation Evaluation (GA, HO)*

The correlation matrix of independent variables used in the GA only head-on model does not show evidence of strong correlation presents. The absolute values of most coefficients are below 0.3, while ADT and LW have positive mild correlation with correlation coefficient of 0.54.

Table 98: Correlation Matrix (GA, HO)

	LW	ADT	SEGMENT	RCURV	RESTRAINT
LW	1.00	0.54	0.04	-0.20	-0.15
ADT		1.00	0.13	-0.15	-0.16
SEGMENT			1.00	0.30	-0.06
RCURV				1.00	0.27
RESTRAINT					1.00

- *Model Estimation and Interpretation (GA, HO)*

Table 99 and Equation (5-9) depicts the head-on fatal crash probability model for the state of Georgia. Out of the 58 multiple-vehicle fatal crashes studied for Georgia, 25 were head-on fatal crashes.

Table 99: Model Estimation (GA, HO)

Variable	**Estimate**	**P- value**
Intercept	10.251	0.0776
SEGMENT	2.5699	0.0028
RCURV	1.975	0.0372
LW (ft)	-1.2112	0.0314
ADT (10^3 veh/day)	0.3684	0.0368
RESTRAINT	-1.9335	0.0403
Observations (Head-on/Other)	58 (25/33)	
AIC	59.817	
Schwarz Criterion	72.18	
-2 Log L	47.817	
R-Square	0.4189	
Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
5.0253	8	0.7549

Let:

$$\eta_{GA} = 10.251 + 2.5699SEGMENT + 1.975RCURV - 1.2112LW + 0.3684ADT - 1.9335RESTRAINT$$

The probability of a multiple-vehicle head-on fatal crash can then be represented as:

$$\Pr(Head - on)_{GA} = \frac{\exp(\eta_{GA})}{1 + \exp(\eta_{GA})} \tag{5-9}$$

Based on the correlation analysis presented in the previous section, the data does not show evidence of strong correlation among the independent variables used in the GA only model for head-on fatal crashes. Therefore, it is reasonable to provide marginal effect interpretations of individual contributing factors in the crash type model. The odds ratio of each independent variable is illustrated in Figure 118.

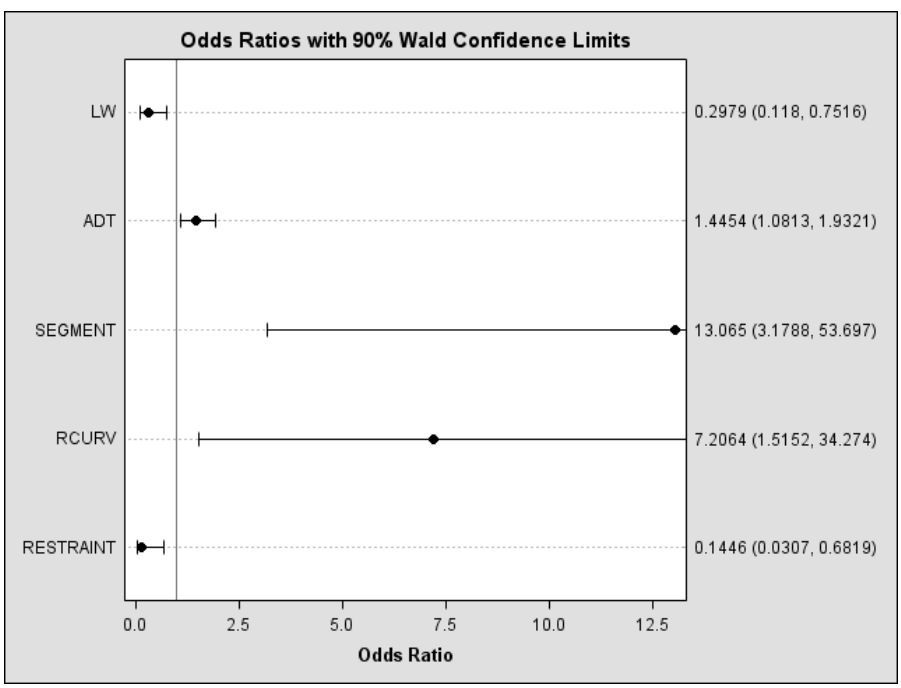


Figure 118: Odds Ratio (GA, HO)

- **Variable:** LW

  Effect: The odds of multiple-vehicle fatal crashes as head-on crashes are estimated to decrease by a factor of 0.3 with each 1-ft increase in lane width after accounting for the effects of other variables. The estimated 90% confidence interval for this odds ratio is 0.1 to 0.8. The lane width effect should not be extrapolated over the range from 9 ft to 12 ft lane width.

- **Variable:** ADT

  Effect: The odds of multiple-vehicle fatal crashes as head-on crashes are estimated to increase by a factor of 1.4 with each 1000 vpd increase in daily traffic volume after accounting for the effects of other variables. The approximate 90% confidence interval for this odds ratio ranges from 1.1 to 1.9.

- **Variable:** SEGMENT

  Effect: The odds of multiple-vehicle fatal crashes as head-on crashes at road segment locations are estimated to be 13 times the odds of head-on fatal crashes at road junction locations, after accounting for other variables. The estimated 90% confidence interval for this odds ratio is 3.2 to 53.7.

- **Variable:** RCURV

  Effect: The odds of multiple-vehicle fatal crashes as head-on crashes at locations with horizontal curves to the right are estimated to be 7.2 times the odds of head-on fatal crashes at locations with straight alignments or curves to the left, after accounting for the effects of other variables. The estimated 90% confidence interval for this odds ratio is 1.5 to 34.3.

- **Variable:** RESTRAINT

  Effect: The odds of multiple-vehicle fatal crashes as head-on crashes with at-fault-drivers wearing safety restraints are estimated to decrease by a factor of 0.15 from the odds of head-on fatal crashes while at-fault drivers without wearing safety restraints after accounting for the effects of other variables. The estimated 90% confidence interval for this odds ratio ranges from 0.03 to 0.68.

- *Model Goodness-of-Fit and Predictive Power (GA, HO)*

The Hosmer and Lemeshow goodness-of-fit test resulted in an acceptable model fit (p-value = 0.7549 > 0.05) as shown in Table 89. As shown in Figure 119, the area under the ROC curve is 0.8909, which provides a measure of discrimination for two groups of crash outcomes. Based on the general rule, this result suggests a good predictive power of the model.

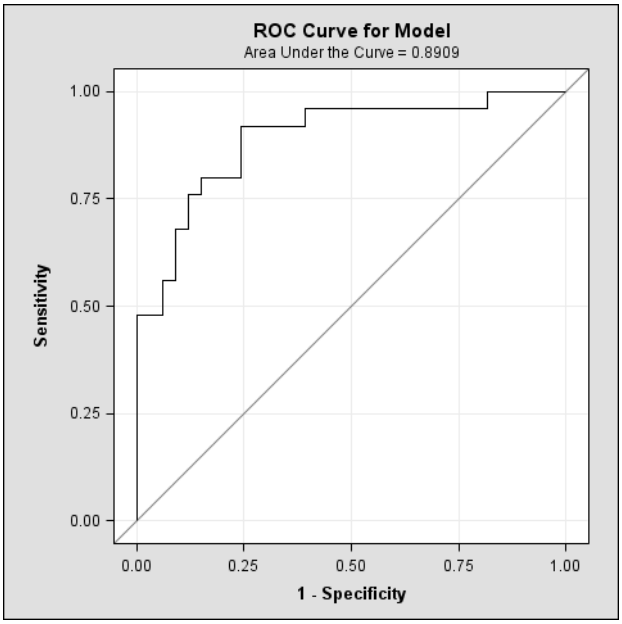


Figure 119: ROC Curve (GA, HO)

5.2.2.3 Mississippi

- *Independent Variables (MS, HO)*

Table 100 depicts that in the event a multiple-vehicle crash should occur in Mississippi, the significant independent variables associated with the probability that the crash would be a head-on include road junction type, horizontal curve direction, and ADT. The observed daily traffic at the crash sites varied from 230 to 12,000 vehicles per day with an ADT volume of 3,823 (see Table 101). Table 102 demonstrates the distribution of the categorical variables (RCURV and SEGMENT) with approximately 25% of the observed multiple-vehicle fatal crashes occurred at locations with a horizontal curve to the right, and about two-thirds occurring at road segment locations.

Table 100: Variable Description (MS, HO)

Variables	Descriptions
SEGMENT	1 if crash location is road segment, 0 otherwise
RCURV	1 if curve to the right, 0 otherwise (curve to the left or straight alignment)
ADT	Average Daily Traffic (veh/day)

Table 101: Continuous Variable Descriptive Statistics (MS, HO)

Variable	Mean	Std Dev	Minimum	Maximum
ADT (veh/day)	3,823	3,118	230	12,000

Table 102: Distribution of Categorical Variables (MS, HO)

Variable	Status	Percent (%)
SEGMENT	0 (Intersection)	36
	1 (Segment)	64
RCURV	0 (Curve to Left or Straight)	76
	1 (Curve to Right)	24

- *Correlation Evaluation (MS, HO)*

As shown in Table 103, the correlation matrix does not show evidence of strong correlation among three independent variables in the MS only head-on crash model while correlation coefficients are all between -0.09 and 0.23.

Table 103: Correlation Matrix (MS, HO)

	ADT	SEGMENT	RCURV
ADT	1	0.11	-0.09
SEGMENT		1	0.23
RCURV			1

- *Model Estimation and Interpretation (MS, HO)*

Table 104 and Equation (5-10) illustrates the head-on fatal crash prediction model for Mississippi. For the 50 multiple-vehicle fatal crashes studied for Mississippi, 21of them were head-on fatal crashes.

Table 104: Model Estimation (MS, HO)

Variable	**Estimate**	**P- value**
Intercept	-3.2673	0.0018
SEGMENT	2.3899	0.0079
RCURV	1.2984	0.1146
ADT (10^3 veh/day)	0.2255	0.0544
Observations	50	
(Head-on/Other)	(21/29)	
AIC	57.921	
Schwarz Criterion	65.57	
-2 Log L	49.921	
R-Square	0.3038	
Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
9.6335	8	0.2917

Let:

$$\eta_{MS} = -3.2673 + 2.3899 SEGMENT + 1.2984 RCURV + 0.2255 ADT$$

Then, the probability of single-vehicle run-off-road fatal crash can be predicted under a given set of conditions as:

$$\Pr(Head - on)_{MS} = \frac{\exp(\eta_{MS})}{1 + \exp(\eta_{MS})} \tag{5-10}$$

Based on the correlation analysis presented in the previous section, the data does not show evidence of strong correlation among the independent variables used in the MS only head-on fatal crash model. Therefore, it is reasonable to provide marginal effect interpretations of individual contributing factors in the crash type model. The odds ratio of each independent variable is illustrated in Figure 120.

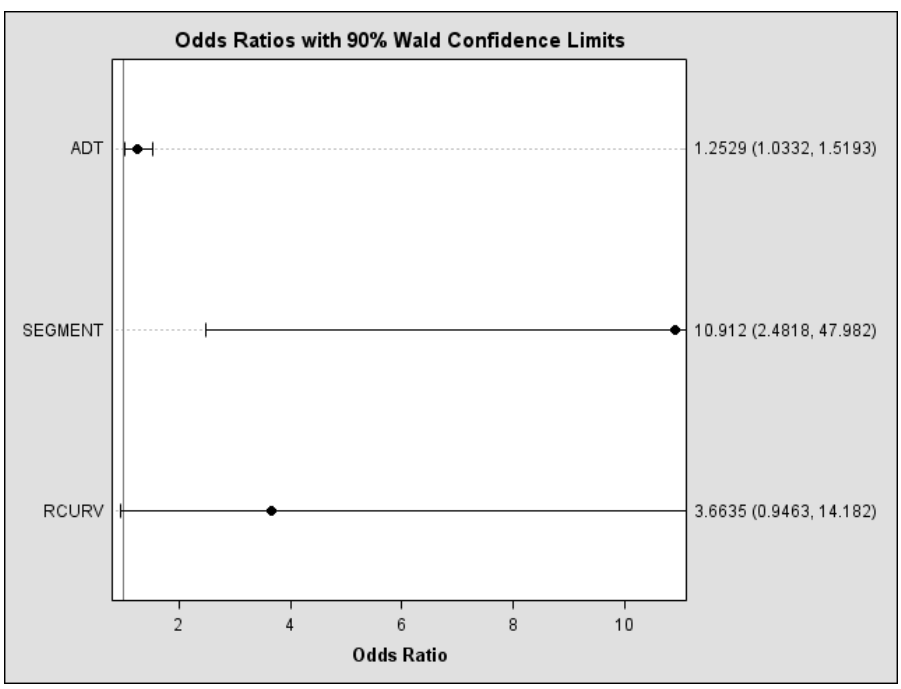


Figure 120: Odds Ratio (MS, HO)

- **Variable:** ADT

  Effects: The odds of multiple-vehicle fatal crashes as head-on crashes are estimated to increase by a factor of 1.3 with each 1000 vpd increase in daily traffic volume after accounting for the effects of other road geometrics. The estimated 90% confidence interval for this odds ratio is 1.0 to 1.5.

- **Variable:** SEGMENT

  Effects: The odds of multiple-vehicle fatal crashes as head-on crashes at road segment locations are estimated to be 10.9 times the odds of head-on fatal crashes at road junction locations, after accounting for other variables. The estimated 90% confidence interval for this odds ratio ranges from 2.5 to 48.

- **Variable:** RCURV

  Effects: The odds of multiple-vehicle fatal crashes as head-on crashes at locations with horizontal curves to the right are estimated to be 3.7 times the odds of head-on fatal crashes at locations with straight alignments or curves to the left, after accounting for other variables. The estimated 90% confidence interval for this odds ratio ranges from 0.9 to 14.1.

- *Model Goodness-of-Fit and Predictive Power (MS, HO)*

As shown in Table 89, the goodness-of-fit test resulted in p-value as 0.2917, indicating a good fit to the observed data. As shown in Figure 121, the area under the ROC curve is 0.8194, which provides a measure of discrimination for two groups of crash outcomes. Based on the general rule, this result suggests a good predictive power of the model.

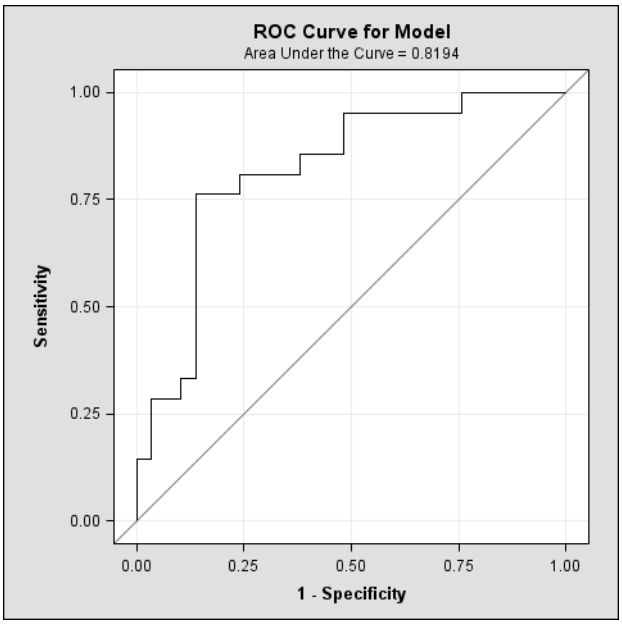


Figure 121: ROC Curve (MS, HO)

5.2.3 Summary of Head-on Fatal Crash Models

Table 105 and Table 106 summarize the model estimation results and the corresponding odds ratios for the state-specific models (AL, GA, and MS) as well as a combined-state model for head-on fatal crashes, respectively. In general, the head-on probability models include fewer influential variables than the models developed for the single-vehicle fatal crashes. Though it may be possible that there are simply fewer influential factors on the head-on crashes, this difference may also be due to the smaller sample size for head-on fatal crashes. The variables associated with the head-on fatal crashes include road segment location, horizontal curvature to the right, lane width, ADT, driveway density, and at-fault drivers' safety restraint use. The individual state models for Alabama, Georgia, and Mississippi generally contain a subset of the variables identified for the combined-state model. The use of safety-restraints, however, was only determined to be critical in the Georgia model. As previously indicated, there was no meaningful model available for head-on fatal

crashes in South Carolina. The use of the state-only models for estimating crash probabilities in other states could not be tested due to the limited data sample size.

Table 105: Model Comparison by Parameter Estimates (HO)

Variables	AL only Model	GA only Model	MS only Model	Four-State Model (AL, GA, MS, SC)
AL				0.6566
MS				0.0817
SC				0.1125
SEGMENT	3.8084**	2.5699**	2.3899**	1.8649**
RCURV		1.975**	1.2984	1.1569**
LW (ft)	-0.6225	-1.2112**		-0.6344**
ADT ($x10^3$ veh/day)	0.2973*	0.3684**	0.2255*	0.2293**
NUMDRVWAY	-0.3525*			-0.1715*
RESTRAINT		-1.9335**		

** Significant level <0.05
* Significant level <0.1

Table 106: Model Comparison by Odds Ratios (HO)

Variables	AL only Model	GA only Model	MS only Model	Four-State Model (AL, GA, MS, SC)
AL				1.9
MS				1.1
SC				1.1
SEGMENT	45.1**	13.1**	10.9**	6.5**
RCURV		7.2**	3.7	3.2**
LW (ft)	0.5	0.3**		0.5**
ADT ($x10^3$ veh/day)	1.3*	1.4**	1.3*	1.3**
NUMDRVWAY	0.7*			0.8*
RESTRAINT		0.1**		

** Significant level <0.05
* Significant level <0.1

As discussed previously, the research team recommends the use of the four-state (AL, GA, MS, and SC) combined model for evaluating the probability of head-on fatal crashes for two-lane rural highways. Despite the observed differences between the state-specific models and combined-state model, the crash location (road segment) and ADT were determined to be significant independent variables with similar effects for all four models. These two variables are labeled as "level one variables."

- **ADT:** The odds that multiple-vehicle fatal crashes are head-on crashes is estimated to increase with each 1000 vpd raise in daily traffic volume.
- **SEGMENT:** The odds that multiple-vehicle fatal crashes are head-on crashes at road segment locations (not intersections) is estimated to increase from the odds of head-on fatal crashes at road junctions.

Furthermore, horizontal alignment directions and lane width also appear associated with head-on fatal crash occurrence for the four-state model and at least two of the state-specific models with consistent impacts on the head-on fatal crash outcomes. These two variables are labeled as "level two variables".

- **RCURV:** The odds of multiple-vehicle fatal crashes as head-on crashes at locations with curves to the right are estimated to increase at least by three-fold from the odds of head-on fatal crashes at locations with curves to the left or straight alignments.
- **LW:** The odds of multiple-vehicle fatal crashes as head-on crashes are estimated to decrease at least by a factor of 0.5 with each 1-ft increase of lane width after accounting for the effects of other variables. Lane widths ranged from 8 ft to 12 ft in the study models.

In addition to ADT and road junction types, horizontal alignment directions and lane width are also more likely to be important predictors for head-on fatal crash outcome prediction models in the southeastern region. Similar to the results from single-vehicle fatal crash models, head-on fatal crash type models evidently support the

assumption that the road geometrics are associated with the probability of head-on fatal crash occurrence in the southeastern region after accounting for traffic conditions. This outcome echoes the evident connection between crash type and countermeasures which can be quantified by the models.

5.2.4 Variable Analysis

The previous section interpreted the marginal effects of each independent variable through odds ratios. Even though there is no evidence of strong correlation present among independent variables, some variables are still correlated with one another at low or moderate level. Considering this fact, the author also examined how one variable influences the probability of multiple-vehicle fatal crashes as head-on crashes at different levels of other variables of interest. This section presents a sensitivity analysis for the probability of head-on fatal crashes for a variety of previously identified contributing variables, including:

- Lane width,
- ADT,
- Junction type (intersection) versus segment,
- Lane width,
- Horizontal alignment,
- Number of driveways, and
- Safety restraint use.

The author performed an analysis based on the recommended four-state model (AL, GA, MS, and SC), as shown in Equation (5-7) in the Section 5.2.1. The analysis also includes the Georgia only model that was presented in Section 5.2.2.2 and represented by Equation (5-9). In order to assess changes of predicted crash type outcome probabilities at different levels of an independent variable, all other independent variables are held constant while the candidate variable's value is modified. Table

107 presents values that can be used to define the nominal condition for a typical study road segment for the crash sites. Most of the variables were assigned a value similar to their average condition in the sample data (e.g. lane width of 11 ft and ADT of 4,000 vehicles per day). For a state indicator value of zero for AL, MS, and SC, a road segment defined by the nominal condition represents Georgia conditions. The research team also investigated the impact on the head-on fatal crash type occurrence for safety restraint usage by at-fault drivers in Georgia.

Table 107: Description of Road Nominal Conditions (HO)

Variables	Conditions
AL	0
MS	0
SC	0
SEGMENT	1 (a road segment)
LW	11 ft (lane width = 11 ft)
RCURV	0 (road horizontal alignment is not a curve to the right)
ADT	4,000 vehicles/day (average daily traffic estimated as 4,000)
NUMDRVWAY	2 (on average 2 driveways located within 250 ft of crash site)
RESTRAINT	1 (at-fault driver used safety restraint) or 0 (safety restraint not used)

5.2.4.1 Lane Width

Table 108 and Figure 122 demonstrate the probability of a multiple-vehicle, head-on fatal crash and how it varies with lane width (from 9 to 12 ft) at four daily traffic volume levels ranging from low to high volumes (400, 2000, 5000, and 10,000 vehicles per day). All other variables in the model used the nominal condition values (see Table 107). The head-on fatal crash occurrence is clearly sensitive to the various traffic volume levels for all lane width values. In particular for ADT values of 400, 2000, and 5000 vehicles per day, the three lines shown in Figure 122 appear to be relatively parallel indicating that the chance of a head-on fatal crash due to lane width

changes at these various ADT levels is similar. In addition, wider lane width is associated with a lower chance of head-on fatal crashes, though as traffic volume increases this difference appears to diminish.

Table 108: Lane Width (Four-State, HO)

ADT (veh/day)	Lane Width (ft)			
	9	10	11	12
400	0.62	0.46	0.31	0.19
2,000	0.70	0.55	0.40	0.26
5,000	0.82	0.71	0.57	0.41
10,000	0.94	0.89	0.80	0.68

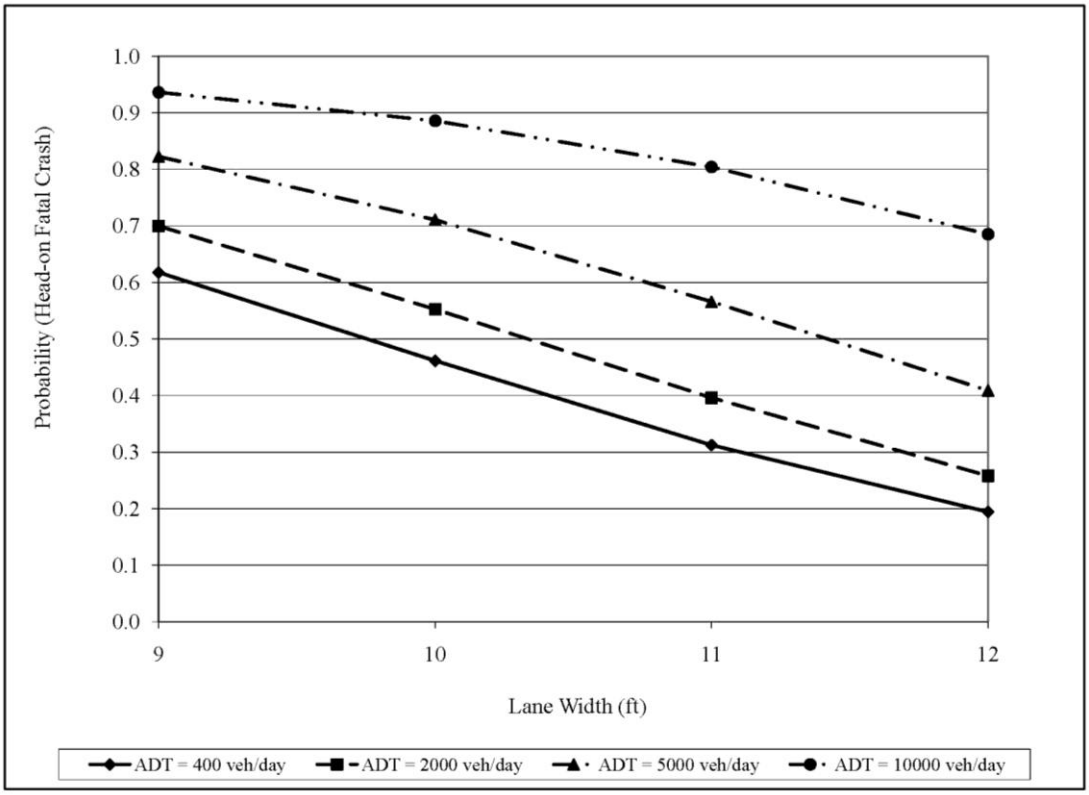


Figure 122: Lane Width by ADT (Four-State, HO)

Table 109, Figure 123, and Figure 124 present the sensitivity of head-on fatal crash occurrence to lane width based on the Georgia-only model. The results are shown based on at-fault driver safety restraint usage. For conditions where at-fault drivers did not use their safety restraints, Figure 124 shows a limited sensitivity for the probability of a head-on fatal crash based on lane width at high traffic volume (10,000 vehicles per day) conditions, while stronger sensitivities are associated with medium to low volumes. The probability of a head-on fatal crash is less sensitive to ADT levels at lane widths of 9 or 10 ft. For example, the probability changes from 0.70 to 0.99 for lanes widths of 10 ft and ADT values of 400 to 10,000 vehicles per day, respectively. The probability varies from 0.17 to 0.88 for 12 ft lanes under similar traffic exposure conditions. For all traffic volume conditions, the head-on crash probabilities are sensitive to lane width and traffic volume when the at-fault driver was using safety restraints (see Figure 123).

Overall, the Georgia model indicates that appropriate use of safety restraints by at-fault drivers is more likely to reduce the likelihood of a head-on fatal crash for all levels of lane width and traffic exposure. When at-fault drivers do not appropriately use safety restraints, there is a higher probability that vehicles will be involved in head-on fatal crashes at all ADT levels across the various lane widths.

Table 109: Lane Width (GA, HO)

Safety Restraints	ADT (veh/day)	Lane Width (ft)			
		9	10	11	12
Driver Used Safety Restraints (RESTRAINT=1)	400	0.53	0.25	0.09	0.03
	2,000	0.67	0.38	0.15	0.05
	5,000	0.86	0.65	0.36	0.14
	10,000	0.98	0.92	0.78	0.51
Driver Did Not Use Safety Restraints (RESTRAINT=0)	400	0.89	0.70	0.41	0.17
	2,000	0.93	0.81	0.56	0.27
	5,000	0.98	0.93	0.79	0.53
	10,000	0.99	0.99	0.96	0.88

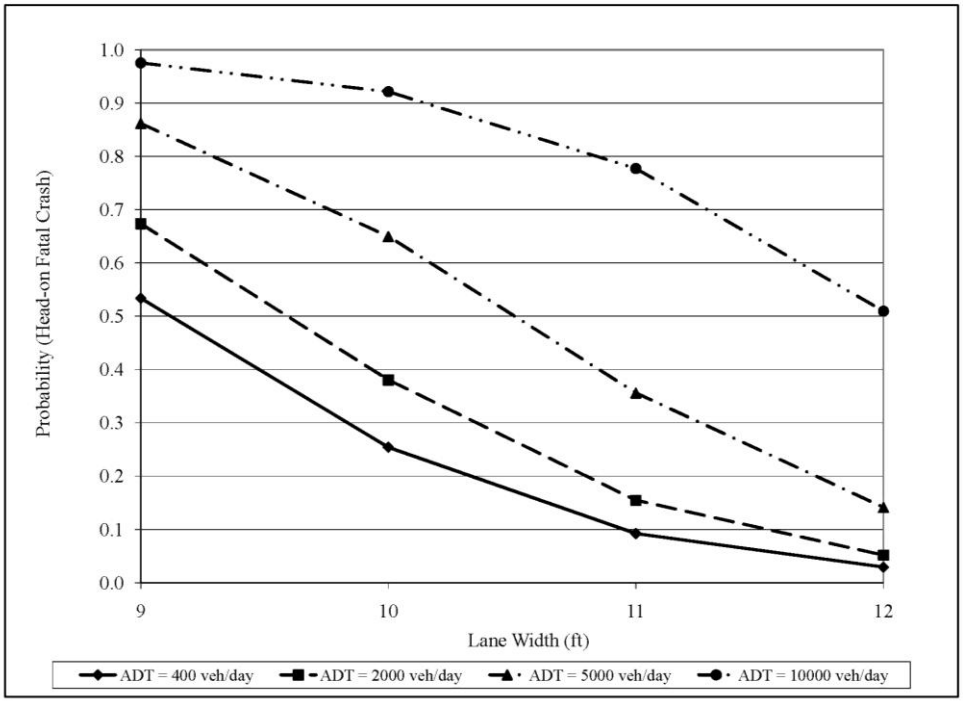


Figure 123: Lane Width by ADT and Used Safety Restraints (GA, HO)

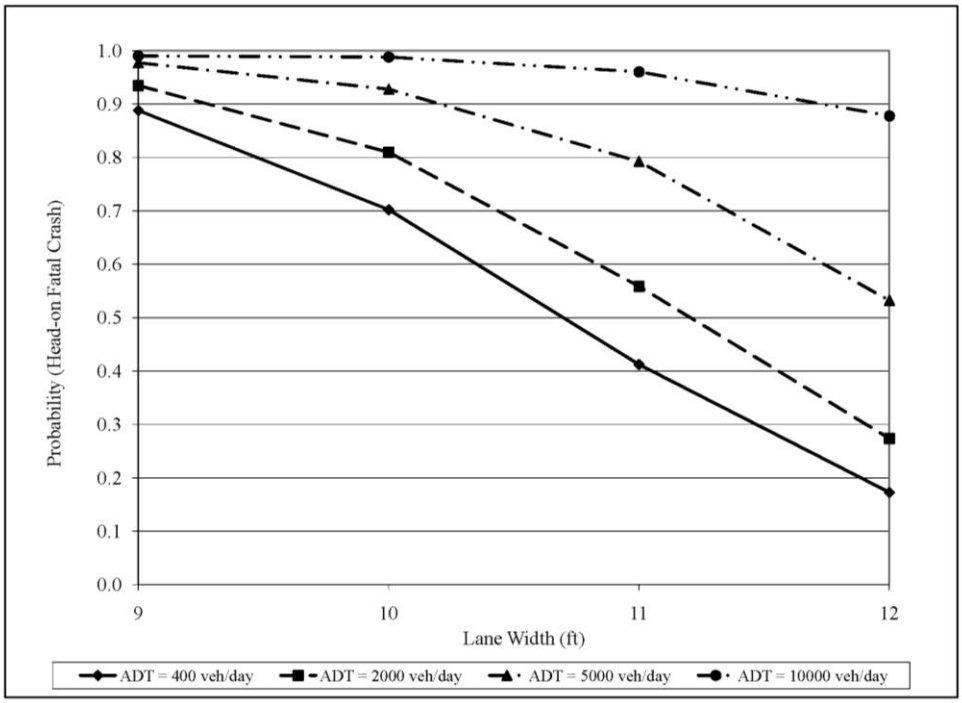


Figure 124: Lane Width by ADT and No Safety Restraints (GA only, HO)

5.2.4.2 Curve Direction

Table 110 and Figure 125 illustrate the influence of a curve to the right on the probability that a head-on fatal crash occurs based on varying lane widths. While the likelihood of a head-on fatal crash is substantial for lane widths of 9 ft and horizontal curves to the right, this probability reduces as lane widths increase. The likelihood that a road with a horizontal curve to the right will have a head-on fatal crash (in the event of a multiple fatal crash) is greater than for other horizontal geometry configurations (straight or curves to the left) by as much as 13 to 29% for 9 and 12 ft lanes, respectively.

Table 110: Curve Direction (Four-State, HO)

Curve to the Right?	Lane Width (ft)			
	9	10	11	12
Yes (RCURVE=1)	0.92	0.86	0.77	0.64
No (RCURVE=0)	0.79	0.66	0.51	0.35

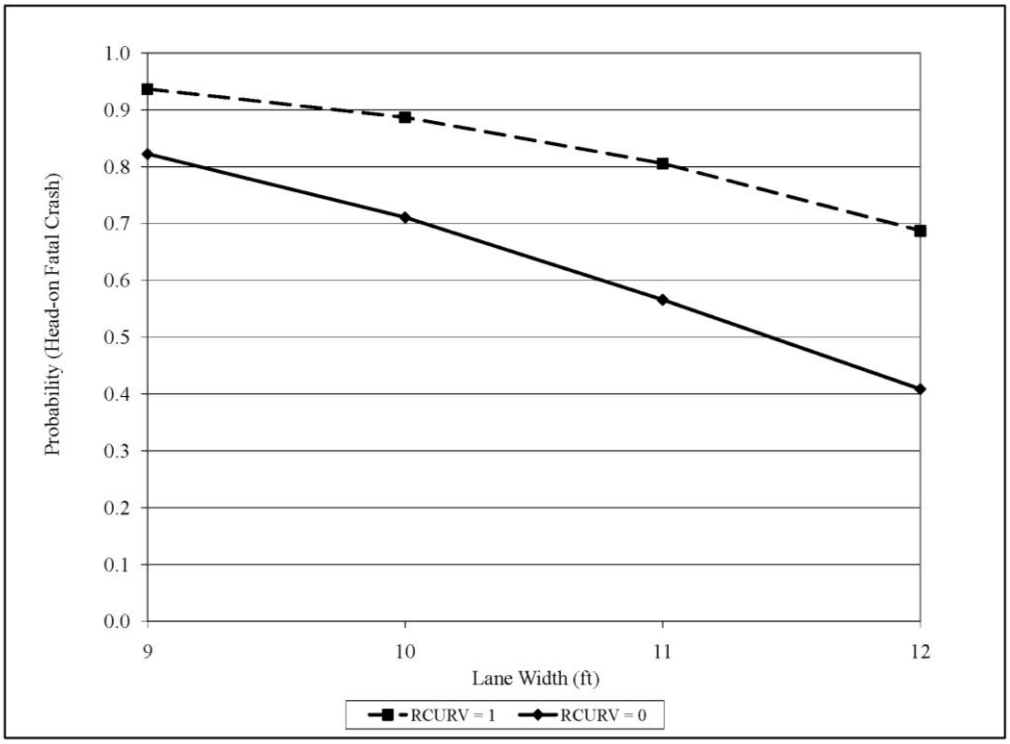


Figure 125: Curve Direction (Four-State, HO)

The previous sensitivity analysis assessing Georgia head-on crashes for lane widths and horizontal curvature can be extended to the use of safety restraints by the at-fault drivers. For crashes where safety restraints were used, the relationship of lane width and horizontal curvature appears similar to that previously reviewed (see Figure 126); however, as shown in Table 111 and Figure 127, the probability of the multiple-vehicle crash being a head-on crash is considerably greater when the at-fault driver does not utilize safety restraints.

Table 111: Curve Direction (GA, HO)

Safety Restraints	Curve to the Right?	Lane Width (ft)			
		9	10	11	12
Driver Used Safety Restraints (RESTRAINT=1)	Yes (RCURV=1)	0.97	0.90	0.73	0.45
	No (RCURV=0)	0.81	0.56	0.28	0.10
Driver Did Not Use Safety Restraints (RESTRAINT=0)	Yes (RCURV=1)	0.99	0.98	0.95	0.85
	No (RCURV=0)	0.97	0.90	0.73	0.44

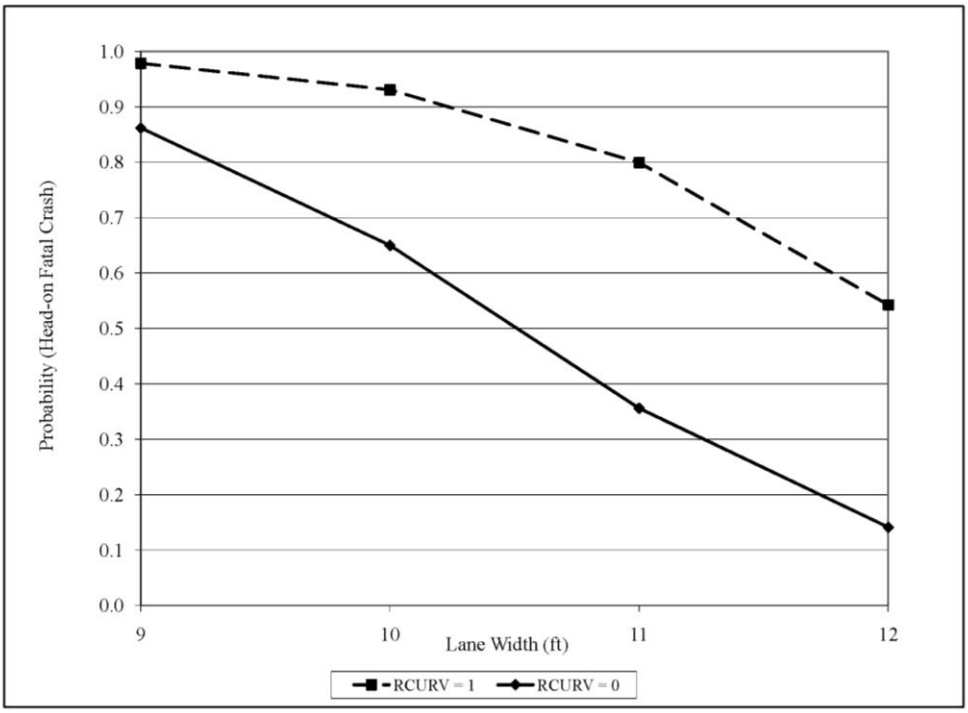


Figure 126: Curve Direction and Used Safety Restraints (GA, HO)

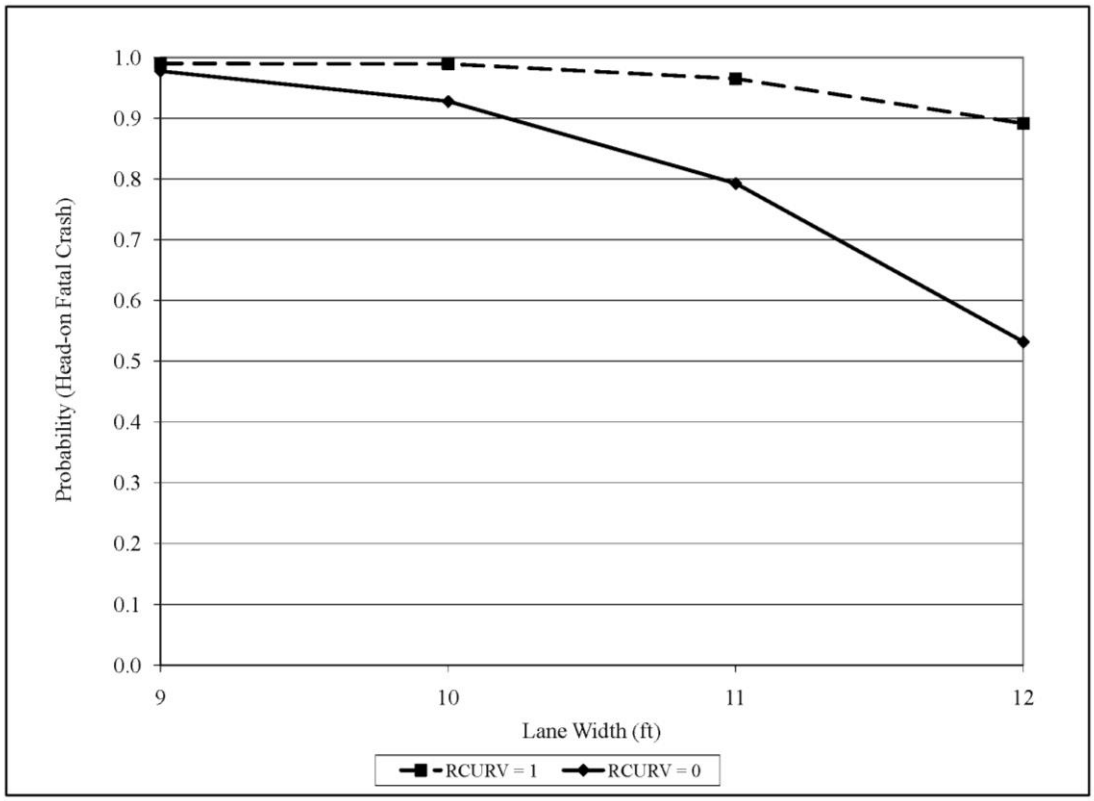


Figure 127: Curve Direction and No Safety Restraints (GA, HO)

5.2.4.3 Road Segment

According to the three-state model, road segments are more likely to be the location where a head-on multiple-vehicle fatal crash will occur (see Table 112 and Figure 128). For the Georgia-only model, the use of safety restraints by at-fault drivers consistently results in a greater chance that a head-on fatal crash will occur at road segment locations with curves to the right more often than when the driver appropriately used the safety restraints (see Table 113, Figure 129, and Figure 130). Interpretation of this observation does not imply that the at-fault driver who does not use safety restraints has a more difficult time navigating the curve to the right, particularly at narrow lane locations. This observation provides possible insight that

should a crash occur at this location, the crash with an at-fault driver who is not using safety restraints is more likely to result in a fatality.

Table 112: Road Junction (Four-State, HO)

Location	Lane Width (ft)			
	9	10	11	12
Segment (SEGMENT=1)	0.79	0.66	0.51	0.35
Intersection (SEGMENT=0)	0.36	0.23	0.14	0.08

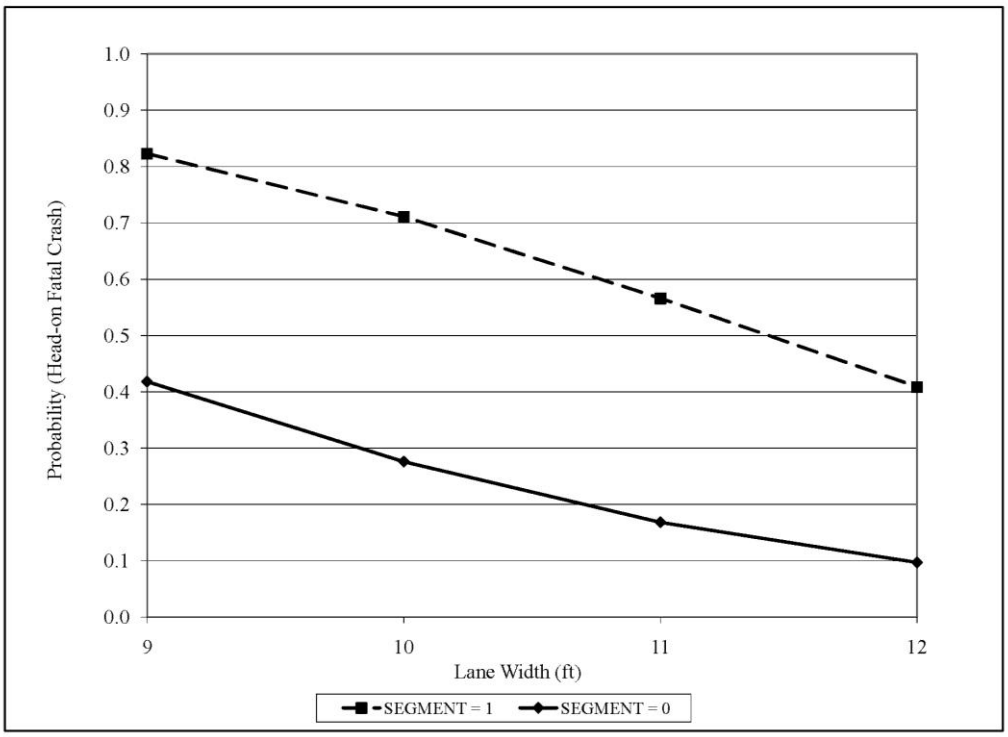


Figure 128: Road Junction (Four-State, HO)

Table 113: Road Junction (GA, HO)

Safety Restraints	Location	Lane Width (ft)			
		9	10	11	12
Driver Used Safety Restraints (RESTRAINT=1)	Segment (SEGMENT=1)	0.81	0.56	0.28	0.10
	Intersection (SEGMENT=0)	0.25	0.09	0.03	0.01
Driver Did Not Use Safety Restraints (RESTRAINT=0)	Segment (SEGMENT=1)	0.97	0.90	0.73	0.44
	Intersection (SEGMENT=0)	0.70	0.40	0.17	0.06

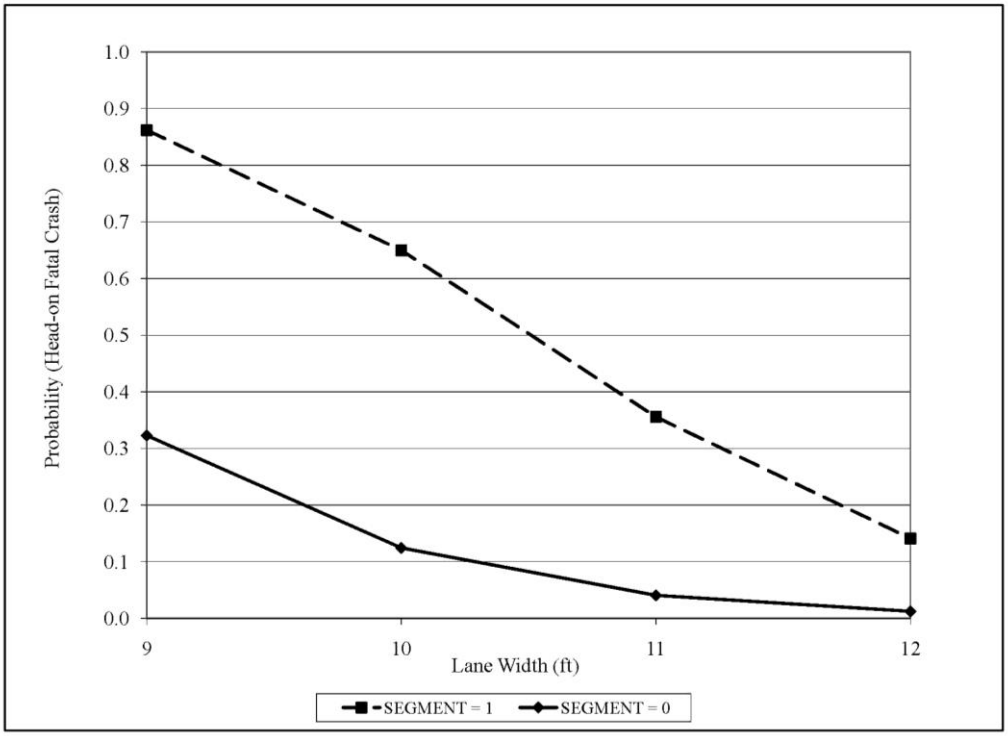


Figure 129: Road Junction and Used Safety Restraints (GA, HO)

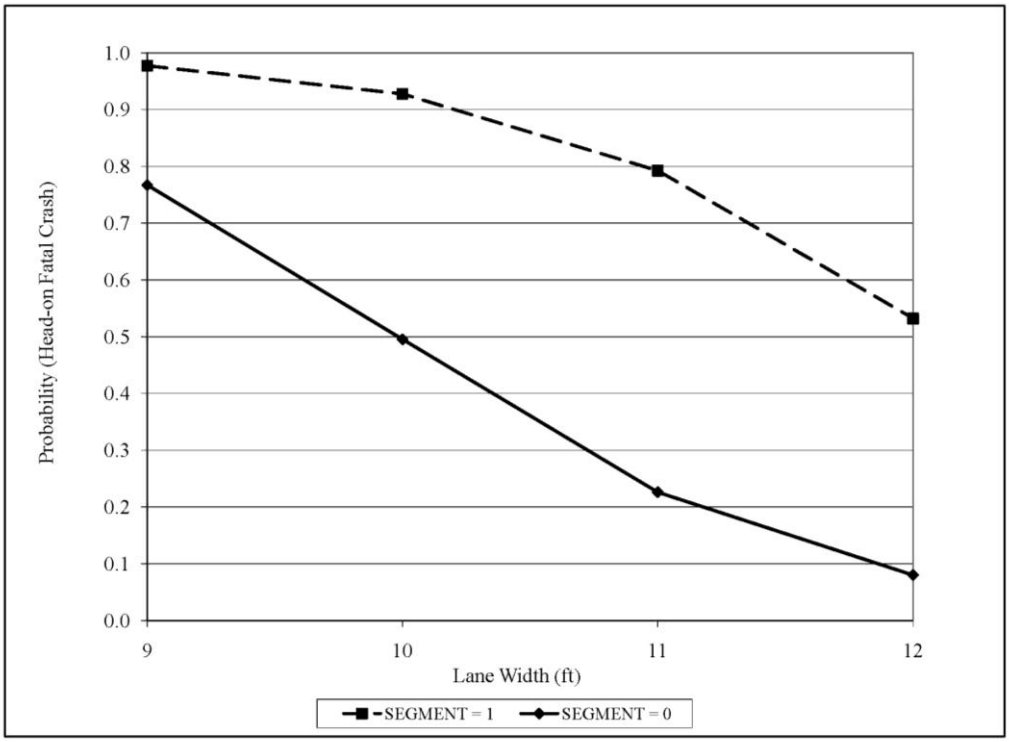


Figure 130: Road Junction and No Safety Restraints (GA, HO)

5.2.4.4 Number of Driveways

Table 114 and Figure 131 demonstrate the influence the number of driveways has on the probability that a multiple-vehicle fatal crash will be a head-on. As the lane width increases and the number of driveways increase the probability decreases. This observed trend likely indicates that with an increased driveway density, the multiple-vehicle fatal crashes are more likely to be crash types other than the target head-on crashes (such as angular crashes).

Table 114: Number of Driveways (Four-State, HO)

Number of Driveways	Lane Width (ft)			
	9	10	11	12
0	0.84	0.73	0.59	0.44
2	0.79	0.66	0.51	0.35
4	0.72	0.58	0.42	0.28

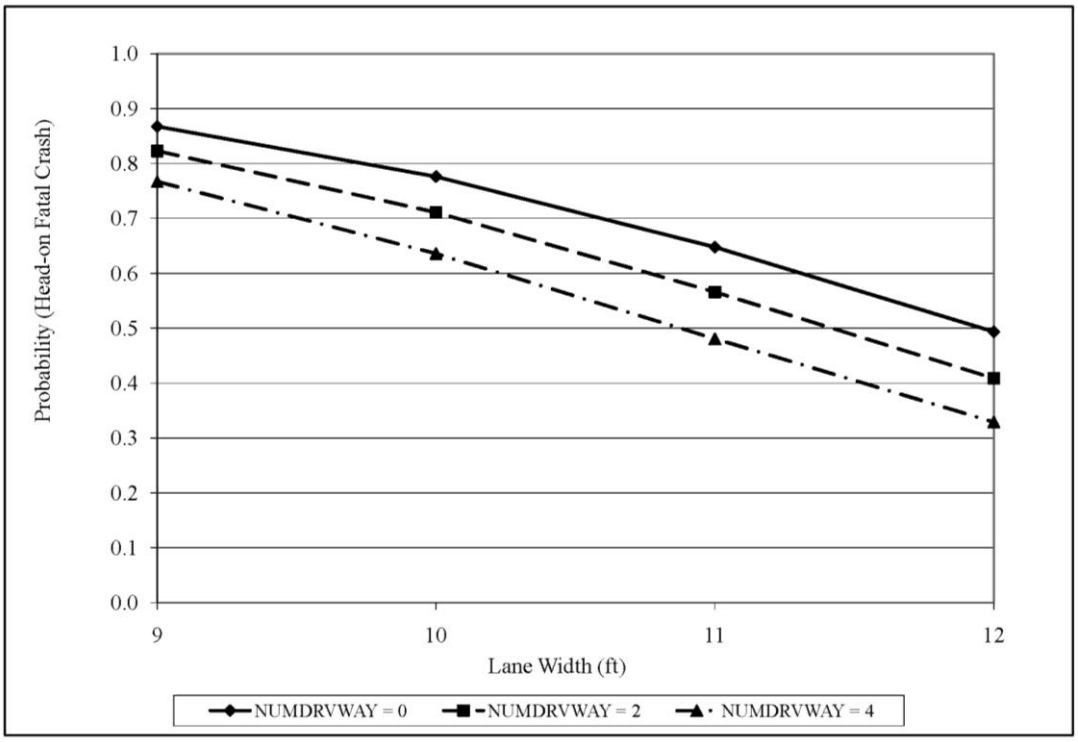


Figure 131: Number of Driveways (Four-State, HO)

5.2.4.5 Restraint System (GA-only, HO)

As shown in Table 115 and Figure 132, if a multiple-vehicle fatal crash occurs, at-fault drivers who use safety restraints are less likely to be involved in a head-on fatal crash than at-fault drivers who do not use their safety restraints. This relation is consistent for a variety of lane widths (9 to 12 ft) but with an increasing probability as the lane width increases. This observation is similar to the relationship observed for the single-vehicle run-off-road fatal crash model.

Table 115: Restraint System Use (GA, HO)

Safety Restraints	Lane Width (ft)			
	9	10	11	12
Driver Used Safety Restraints (RESTRAINT=1)	0.81	0.56	0.28	0.10
Driver Did Not Use Safety Restraints (RESTRAINT=0)	0.97	0.90	0.73	0.44

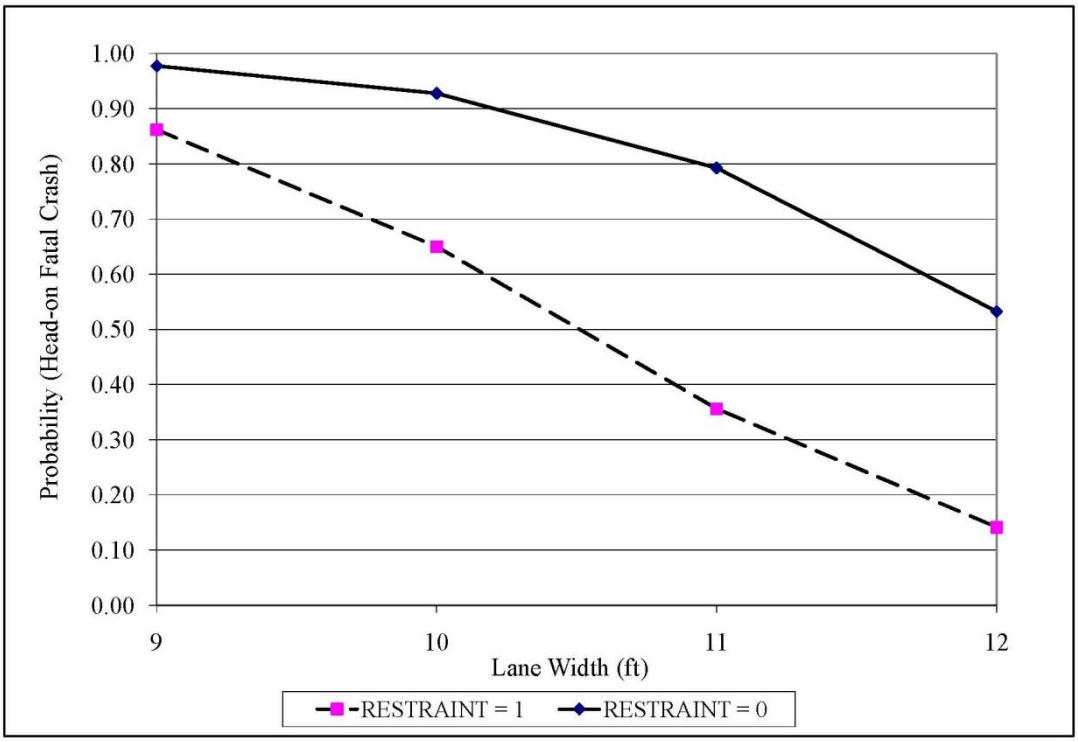


Figure 132: Restraint System (GA, HO)

5.3 Countermeasure Evaluation Comparison

The recent development of the Highway Safety Manual and various other traffic safety research programs have incorporated expert panel evaluations into the safety analysis process (Washington et al., 2009). Expert panel's participation is essentially valuable in extracting collective information from inconsistent research results and complex crash conditions. One of the major roles of expert panel is to develop crash modification factors (CMFs), an effectiveness measure of traffic safety treatments. The CMF provides a quantitative measurement of the potential influence from a specific countermeasure in terms of the number of crashes from before to after countermeasure implementation. For example, as shown in Table 116, the experts estimated that improving the clear zone, in contrast, had an estimated effectiveness expressed with a CMF as 0.78. This value is equivalent to an estimated 22% reduction in fatal crashes for the specific crash conditions.

Two previous southeastern fatal crash studies with a focus on countermeasure evaluation incorporated expert panel's effectiveness assessment for the proposed safety treatments. This dissertation approaches the fatal crash study from a different methodology. Since all three studies used fatal crash data primarily from the southeastern region in 1997, those study results are theoretically expected to be consistent with one another. This section compares the study results between the previous two studies and the results from fatal crash type prediction models. A successful comparison acts as a reasonable validation of this research effort.

In the first study, a group of experts in transportation engineering and transportation safety were asked to evaluate the effectiveness of a set of commonly accepted strategies, as shown in Table 117, for improving safety on rural roads based on 150 randomly selected fatal crashes on rural roads individually from Georgia (Melcher et al., 2001). Experts studied crash documents, police reports, etc., and examined relevant conditions associated with the random sample of crashes. Also, experts made their individual decisions on how effective a countermeasure would have been in preventing the crash if it had been in place at the time of crash. Their assessments were analyzed under statistical procedures in order to draw collective evaluation results. Another portion of the southeastern study occurred in 2002 and the authors evaluated fatal crashes on two-lane rural highways in Georgia. They recommended five countermeasure categories that could be effective in reducing fatal crashes on two-lane rural highways statewide (Washington, et al., 2002).

Table 116: Expert Panel Evaluation vs. Model Effects

Rural Road Fatal Crash Countermeasures	CMF	Georgia Fatal Crash Investigation	Fatal Crash Type Prediction Model	
			Single-Vehicle Fatal Crash	Head-on Fatal Crash
Geometric realignment	0.9	Geometric alignment improvements (Horizontal, vertical, separation)	• Horizontal Curve direction • Vertical alignment • Interaction effect between curve to the left and crest	• Curve direction
--	--	Widen of lanes/pavement widths	• Lane width	• Lane width
Add/widen gravel shoulders; Pave/widen existing shoulders	0.80	Add and/or widen graded/stabilized shoulders	• Paved and graded shoulder width • Interaction effect of paved and graded shoulder width	--
Improve clear zones	0.78	Widen/improve clear zones	• Roadside hazard rating	--
Flatten side slope	0.88	--		--
Remove/relocate roadside rigid objects	0.81/ 0.91	--		--
Improve lighting condition at critical road segments	0.91	--	• Lighting condition (dark without supplemental light condition)	--

Table 117: Countermeasures Examined in Southeastern U.S. Fatal Crash Study

Category	Countermeasures
Pavement Markings	1. Add edge line, or upgrade existing edge line 2. Add centerline, or upgrade existing centerline 3. Add no passing zone lines
Lighting	4. Add segment lighting
Roadside Improvements	5. Install guardrail 6. Improve clear zone 7. Relocate fixed object 8. Remove fixed object 9. Flatten side slope
Reconstruct Roadway	10. Geometric realignment 11. Improve sight distance without geometric realignment 12. Install paved shoulder, or improve existing paved shoulder

The comparison between these two previous studies and the current study are presented in Table 116. The fatal crash type prediction models developed from this dissertation produced consistent findings that aligned with both expert panel countermeasure evaluation studies. Additionally, the safety prediction models also indicated that previously identified effective safety treatments targeted single-vehicle fatal crash reduction. Since more than half of the fatal crashes on two-lane rural highways were single-vehicle crashes in this region, the effort to reduce the occurrences of this type of fatal crash certainly contribute to achieving greater safety benefits. The CMF is a measure of crash total variation due to the implementation of treatments. Therefore it should be noticed that the values of CMF do not comply with the values of either probabilities or odds ratios for the corresponding changes of certain potential contributing factors as presented in single-vehicle and head-on vehicle fatal crash models.

Fatal crash type models demonstrate the ability to provide consistent predictions with expert panel based countermeasure evaluation results. Both expert panel studies used GA fatal crash data applied in this study. Nevertheless, the general results for the probability models agree with those from the earlier study even though the analysis extended to neighboring states. Furthermore, fatal crash type models also provide more flexibility for predicting fatal crash type outcomes given various road geometrics, environmental features and traffic conditions. Additionally, prediction models also identified impacts from interactions between contributing factors. This result suggests that the fatal crash type prediction models developed for this research effort not only agree with previous study findings, but also provide the flexibility to quantify the crash type outcomes across various road conditions. As a result, the fatal crash type models can be used to assist potential countermeasure evaluations for an individual site.

CHAPTER 6 PRACTICAL APPLICATIONS OF CRASH TYPE PREDICTION MODELS

6.1 Application Methodology

The Highway Safety Improvement Program (HSIP), a Federal-aid funding program initiated in 2006, has a goal to achieve a significant reduction in fatalities and severe injuries on all public roads nationwide. The Georgia Department of Transportation is facing the challenge of how to effectively reduce fatal and serious injury crashes for rural two-lane highways since this road type is disproportionately representative of fatal crashes. Ultimately, an effective safety project provides the greatest benefit by reducing these serious crashes and, where possible, improving road conditions that may contribute to conditions conducive to such crashes.

Safety engineers can apply fatal crash type prediction models as a unique tool for safety improvement projects, such as HSIP projects. This analytical tool also responds to the focus of the Georgia Strategic Highway Safety Plan (SHSP). As addressed in the Georgia SHSP, serious injury crashes are one of the key emphasis areas, and lane departure and head-on crashes are two major crash types that often lead to severe injuries and fatalities. One of the major types of lane departure crashes on rural highways is the single-vehicle run-off road crash. Since current assessment techniques, such as the rate quality control and equivalent property damage only methods, commonly used in analysis do not include crash types, the use of predictive models can complement current procedures and help to identify locations where crash injury can be reduced with select countermeasure application. One example where crash type assessment can help clarify the expected crash conditions occurs when a median is constructed on a road to help prevent or reduce head-on collisions. If the road segment is over-represented by head-on collisions prior to median construction, then the number of severe injuries and fatalities should decrease following construction. If, on the other hand, the crashes were not associated with head-on

crashes, the median construction could conceivably have no influence on these severe crashes and may, in fact, contribute to increased speeds and more crashes. It is therefore helpful for safety engineers to know whether a candidate improvement location tends to have higher likelihood of a major fatal crash type based on the existing road design characteristics. This assessment can occur on newer roads that do not have substantial crash history if these roads are built in a manner consistent with others in the region.

As discussed in the previous chapters, Georgia state agencies can evaluate the probability of a single-vehicle fatal crash type by using the three-state combined model as depicted by Equation (5-2) or by using the Georgia-only single-vehicle crash model as presented in Equation (5-4).

Figure 133 outlines the proposed application procedure. In addition, Section 6.2 presents a sample problem that demonstrates how to apply the single-vehicle fatal crash prediction models to help engineers evaluate road safety based on existing conditions and proposed improvements.

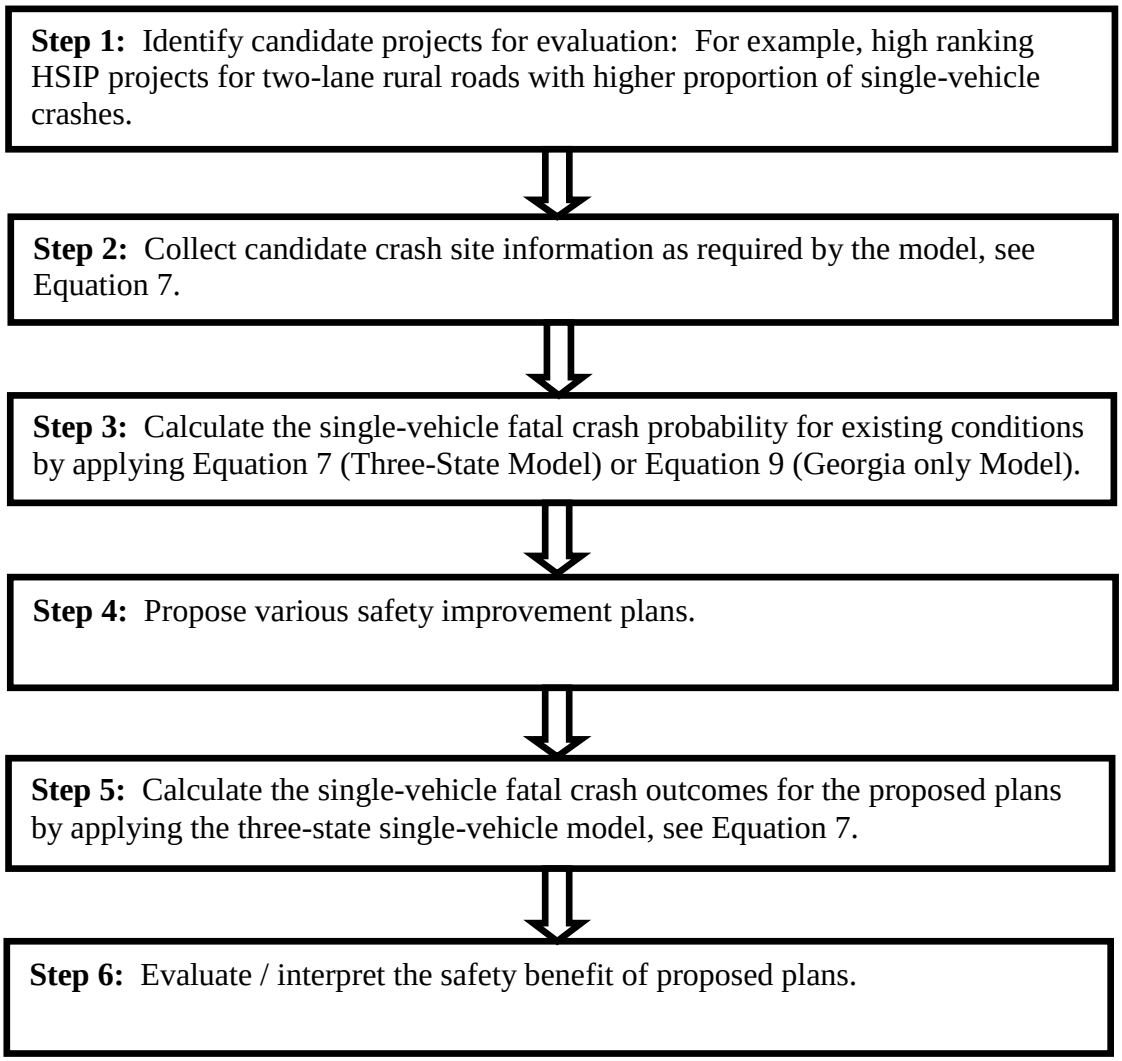


Figure 133: Single-Vehicle Fatal Crash Type Model Application Six-Step Procedure

6.2 Application Example

This section provides an example of how to apply the six-step application process (See Figure 133). This analysis will specifically target reducing single-vehicle fatal crashes for two-way rural highway locations.

Step 1 and Step 2:

Assume that a high-crash location has been previously identified using regional analysis procedures and that the road is a rural two-lane highway. This two-lane rural road segment has a known history of single-vehicle crashes that result in fatalities or serious injury. One specific location on this road has the existing characteristics as shown in Table 118.

Table 118: Sample Problem -- Existing Road Conditions for Georgia Site

Existing Condition	Status	Variables
Road segment?	Yes	JUNCTION = 0
Alabama?	No	AL = 0
South Carolina?	No	SC = 0
Lane width	11 ft	LW=11
Paved shoulder width	0 ft	PSW = 0
Graded shoulder width	8 ft	GSW = 8
Roadside hazard rating	5	RHR67 = 0
ADT	3,000 vehicles per day	ADT = 3
Land use	Driveways not for commercial use	LU_C = 0
Driving during 1am to 3am?	No	HR_DEEPSLEEP = 0
Curve to the left?	Yes	LCURV = 1
Crest?	No	CREST = 0
Daylight, dark with lighting, dusk or dawn conditions	-	DARKUNLIT = 0
Dark without supplemental street lights	-	DARKUNLIT = 1

Step 3:

With the specific site information as depicted in Table 118, the probability of a fatal crash being a single-vehicle fatal crash based on existing conditions during either the daylight, dark with lighting, dusk or dawn condition or the dark without supplemental street lights condition can be computed as follows:

Using the Three-State Combined Model (AL, GA, SC) as presented in Equation (5-2):

Let:

$$\eta_{3-state} = 6.6717 - 0.1855AL - 0.1167SC - 0.8078JUNCTION - 0.5407LW - 0.0542PSW$$
$$-0.0475GSW - 0.0676(PSW * GSW) + 0.788LCURV - 1.7264CREST$$
$$+2.5199(LCURV * CREST) + 1.1581RHR67 - 0.0965ADT$$
$$-1.3722LU\_C + 1.3101DARKUNLIT + 1.8318HR\_DEEPSLEEP$$

<u>For daylight, dark with lights, dusk, or dawn conditions (DARKUNLIT = 0):</u>

$$\eta_{3-state} = 6.6717 - (0.1855 \times 0) - (0.1167 \times 0) - (0.8078 \times 0) - (0.5407 \times 11) - (0.0542 \times 0)$$
$$-(0.0475 \times 8) - (0.0676 \times 0 \times 8) + (0.788 \times 1) - (1.7264 \times 0) + (2.5199 \times 0 \times 0) + (1.1581 \times 0)$$
$$-(0.0965 \times 3) - (1.3722 \times 0) + (1.3101 \times 0) + (1.8318 \times 0) = 0.8425$$

$$\Pr(Single - veh - runoff)_{3-state} = \frac{\exp(\eta_{3-state})}{1 + \exp(\eta_{3-state})} = \frac{e^{0.8425}}{1 + e^{0.8425}} = 0.70$$

<u>For dark without supplemental street lights (DARKUNLIT = 1):</u>

$$\eta_{3-state} = 6.6717 - (0.1855 \times 0) - (0.1167 \times 0) - (0.8078 \times 0) - (0.5407 \times 11) - (0.0542 \times 0)$$
$$-(0.0475 \times 8) - (0.0676 \times 0 \times 8) + (0.788 \times 1) - (1.7264 \times 0) + (2.5199 \times 0 \times 0) + (1.1581 \times 0)$$
$$-(0.0965 \times 3) - (1.3722 \times 0) + (1.3101 \times 1) + (1.8318 \times 0) = 2.1526$$

$$\Pr(Single - veh - runoff)_{3-state} = \frac{\exp(\eta_{3-state})}{1 + \exp(\eta_{3-state})} = \frac{e^{2.1526}}{1 + e^{2.1526}} = 0.90$$

Using the Georgia-only Model as presented in Equation (5-4):

Let:

$$\eta_{GA} = 8.9011 - 2.1473JUNCTION - 0.835LW - 0.3506PSW + 1.7437LCURV$$
$$+1.5662STRAIGHT + 1.1195DARKUNLIT - 1.1604RESTRAINT$$

<u>For at-fault driver using safety restraints (RESTRAINT = 1) and under daylight, dark with lights, dusk, or dawn conditions (DARKUNLIT = 0):</u>

$$\eta_{GA} = 8.9011 - (2.1473 \times 0) - (0.835 \times 11) - (0.3506 \times 0) + (1.7437 \times 1)$$
$$+(1.5662 \times 0) + (1.1195 \times 0) - (1.1604 \times 1) = 0.2994$$

$$\Pr(Single - veh - runoff)_{GA} = \frac{\exp(\eta_{GA})}{1 + \exp(\eta_{GA})} = \frac{e^{0.2994}}{1 + e^{0.2994}} = 0.57$$

<u>For at-fault driver using safety restraints (RESTRAINT = 1) but during dark conditions with no supplemental street lights (DARKUNLIT = 1):</u>

$$\eta_{GA} = 8.9011 - (2.1473 \times 0) - (0.835 \times 11) - (0.3506 \times 0) + (1.7437 \times 1)$$
$$+(1.5662 \times 0) + (1.1195 \times 1) - (1.1604 \times 1) = 1.4189$$

$$\Pr(Single - veh - runoff)_{GA} = \frac{\exp(\eta_{GA})}{1 + \exp(\eta_{GA})} = \frac{e^{1.4189}}{1 + e^{1.4189}} = 0.81$$

<u>For at-fault driver not using safety restraints (RESTRAINT = 0) and under daylight, dark with lights, dusk, or dawn conditions (DARKUNLIT = 0):</u>

$$\eta_{GA} = 8.9011 - (2.1473 \times 0) - (0.835 \times 11) - (0.3506 \times 0) + (1.7437 \times 1)$$
$$+(1.5662 \times 0) + (1.1195 \times 0) - (1.1604 \times 0) = 1.4598$$

$$\Pr(Single - veh - runoff)_{GA} = \frac{\exp(\eta_{GA})}{1 + \exp(\eta_{GA})} = \frac{e^{1.4598}}{1 + e^{1.4598}} = 0.81$$

<u>For at-fault driver not using safety restraints (RESTRAINT = 0) and during dark conditions with no supplemental street lights (DARKUNLIT = 1):</u>

$$\eta_{GA} = 8.9011 - (2.1473 \times 0) - (0.835 \times 11) - (0.3506 \times 0) + (1.7437 \times 1)$$
$$+(1.5662 \times 0) + (1.1195 \times 1) - (1.1604 \times 0) = 2.5793$$

$$\Pr(Single - veh - runoff)_{GA} = \frac{\exp(\eta_{GA})}{1 + \exp(\eta_{GA})} = \frac{e^{2.5793}}{1 + e^{2.5793}} = 0.93$$

The probability of single-vehicle fatal crash occurrence at this location based on the three-state combined model, Equation (5-2), is estimated as 0.70 at daylight, dark with

light, dusk, or dawn conditions, and 0.90 for dark conditions without supplemental street lights. Similarly this example includes a comparison for the Georgia-only model values based on at-fault drivers with and without safety restraints and the varying lighting conditions. For at-fault drivers who used safety restraints, the likelihood that a single-vehicle fatal crash will occur during daylight, dark with lights, dusk or dawn conditions is 0.57. For dark conditions without supplemental street lights the crash probability increases to 0.81. For at-fault drivers not using safety restraints, the Georgia-only model predicts much higher probabilities of 0.81 for the daylight, dark with lights, dusk and dawn and 0.93 for dark conditions without supplemental street lights.

The values predicted using the three-state combined model are higher than those predicted using the Georgia-only model for at-fault drivers using safety restraints and lower than those predicted for at-fault drivers not using safety restraints. Both models indicate that dark conditions without supplemental street lights are associated with higher probabilities of single-vehicle fatal crashes.

Step 4:

Based on existing road conditions, proposed improvement plans may help to reduce single-vehicle fatal crashes by considering candidate improvement Plans B1 and B2 as depicted in Table 119.

Table 119: Existing Condition and Proposed Improvement Plan

Status	Lane Width (ft)	Paved Shoulder Width (ft)	Graded Shoulder Width (ft)	Countermeasures
Existing Condition: A	11	0	8	---
Proposed Improvement Plan: B1	12	0	8	Lane Widening
Proposed Improvement Plan: B2	11	3	5	Shoulder Enhancement

Step 5:

Following a process similar to that demonstrated for Step 3, the probability of a single-vehicle fatal crash can be estimated using the three-state combined model (Equation (5-2)) and the Georgia-only model (Equation (5-4)), respectively.

Table 120, Table 121, Table 122, and Figure 134 present the estimated results for the probability of a single-vehicle fatal crash at the example study location based on the existing conditions, and the two proposed improvement conditions, B1 and B2.

Table 120: Safety Evaluation (Three-State, SV)

	Lane Width (ft)	Paved Shoulder Width (ft)	Graded Shoulder Width (ft)	Lighting Condition	
				Daylight	Dark No Lighting
Existing	11	0	8	0.70	0.90
Plan: B1	12	0	8	0.57	0.83
Plan: B2	11	3	5	0.45	0.75

Table 121: Safety Evaluation – Used Safety Restraint (GA only, SV)

	Lane Width (ft)	Paved Shoulder Width (ft)	Graded Shoulder Width (ft)	Lighting Condition	
				Daylight	Dark No Lighting
Existing	11	0	8	0.57	0.81
Plan: B1	12	0	8	0.37	0.64
Plan: B2	11	3	5	0.32	0.59

Table 122: Safety Evaluation – No Safety Restraint (GA only, SV)

	Lane Width (ft)	Paved Shoulder Width (ft)	Graded Shoulder Width (ft)	Lighting Condition	
				Daylight	Dark No Lighting
Existing	11	0	8	0.81	0.93
Plan: B1	12	0	8	0.65	0.85
Plan: B2	11	3	5	0.60	0.82

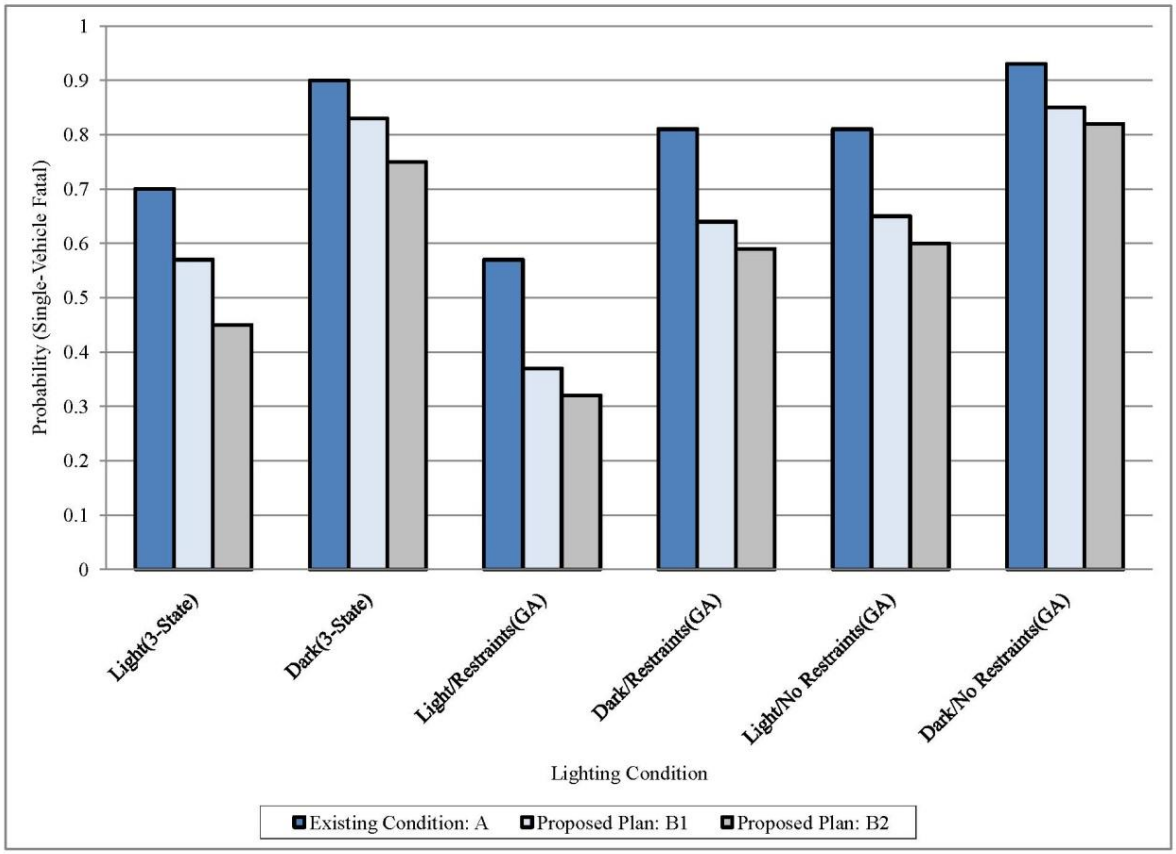


Figure 134: Safety Evaluation for Plan B1 and B2

Step 6:

The three-state combined model requires more variables than the Georgia single-vehicle fatal crash model. The combined-state model benefits from evaluating more influential factors and can potentially identify confounding influences that may not be determined by the simpler-form Georgia model. The Georgia-only model provides the analyst with the potential to further assess the impact of an at-fault drivers' safety restraint use.

The three-state combined model and the Georgia-only model provide similar predictive results from two major aspects:

- Proposed plan B1 with lane widening and B2 with shoulder enhancement both would lower the chance of a single-vehicle fatal crash when compared to the existing condition for both daylight, dark with lights, dusk, and dawn conditions as well as dark conditions.
- The proposed plan B2 with shoulder enhancements, based on both the three-state model and the Georgia model, results in a lower predicted number of single-vehicle fatal crashes when compared to estimated crashes resulting from the lane widening improvements proposed for plan B1.

Even though all models indicate a reduction in the single-vehicle fatal crashes for both daylight and dark conditions, the effectiveness of countermeasures under different lighting conditions are different. For instance, the three-state model predicts that shoulder enhancement (Plan B2) reduces the probability of single-vehicle fatal crashes by 0.25 for daylight, dark with lights, dusk and dawn conditions. The same treatment only achieves a 0.15 probability reduction for dark conditions without supplemental street lights. Plan B1 and B2 improvements are less effective during dark conditions without supplemental street lights. Therefore, countermeasures that can improve the visibility of the travel lane may also be desirable, particularly at horizontal curve locations. Effective treatments may include the installation of delineators, raised pavement markers, and rumble strips at the selected locations. Safety engineers should make decisions based on overall considerations from predictive modeling results, previous documented countermeasure recommendations, economic impact, and engineering judgment.

<u>Evaluation conclusion:</u>

- Proposed plan B2, shoulder improvement, is the recommended countermeasure under the context of single-vehicle fatal crash outcome reduction.
- Since the physical improvements have less influence on single-vehicle crashes during dark conditions, it may be appropriate to enhance the location (particularly

at horizontal curve locations) with other countermeasures that specifically increase safety during dark conditions.

- Due to the increased risk due to the lack of safety restraint use by at-fault drivers, it is recommended that the use of safety restraints be promoted in rural areas.
- Though the probability models provide indications regarding the effectiveness of improvements, the final improvement decisions should be based on cost/benefit analysis, as well as other potential conditions not available for assessment in the model development.

6.3 Application Limitation

This study focuses on fatal crashes where at least one person was fatally injured. It is not appropriate to generalize the modeling results to crashes at all injury levels. Some crash types, for example, are more commonly associated with fatalities, while others may be more likely to result in crashes common to less severe injuries. For instance, a rear-end crash is more likely to be associated with minor injury crashes instead of fatal crashes. Head-on collisions, on the other hand, are more prone to contribute to fatalities. In addition, road geometric design features and other potential contributing factors can impact the crash type differently.

The models developed for this study include a limited number of contributing factors. There are other potential factors that could influence fatal crashes, but these variables are not included in the model for a variety of reasons. For example, the random fatal crash database may have some variables that are not well populated and therefore do not provide significant effects. It is also possible that there may be influential variables that are not available in the standard crash database or the supplemental database used for this study.

As previously indicated, the model development was based on a cross-sectional dataset that included fatal crashes that occurred primarily in 1997. Though this report includes an evaluation of historic crash trends in the southeast, it is not possible to definitively conclude that the 1997 crashes suitably represent current or future crash conditions.

CHAPTER 7 CONCLUSIONS

7.1 Research Goals

The rural two-lane highway in the southeastern United States is frequently associated with a disproportionate number of serious and fatal crashes. The major research objectives are to investigate the relationships between probabilities of fatal crash type occurrence and potential contributing factors from road geometric design elements, roadside characteristics, and environmental features. The author analyzed the regional fatal crash database and successfully developed statistical models to examine these relationships and provided meaningful research findings. These findings are not only primarily consistent with previous study results based on expert panel evaluations, but also provide a quantitative assessment strategy with new insights.

This dissertation contributes to current traffic safety analysis by directly examining the connection between major fatal crash type occurrence and roadway geometrics, roadside characteristics, and environmental conditions through a regional case study. This study addresses the less understood relationship between fatal crash types and road features compared to other crash measures, such as crash frequency, crash rate, and injury severity. The developed fatal crash type prediction models not only demonstrate strong connections between crash types and road characteristics, but also provide a quantitative assessment tool for countermeasures to reduce fatal crash type occurrence. Since most countermeasures are more effective at mitigating certain types of crashes, the information revealed from the crash type prediction models help clarify the relationship between candidate countermeasures and expected crash reductions.

The intention to examine spatial transferability of fatal crash type models for four southeastern states provided limited insights, since the efforts of developing adequate fatal crash type models for each individual state with the same set of predictors was not successful. Considering the uncertain nature of fatal crashes, a larger sample size

may put a study in a better position to answer the question of whether a fatal crash type model that is developed for one state can be used in another state. Unfortunately, road feature information is limited and expensive to acquire. As a result, the data used for this research is one of the largest and most robust data sets currently available.

7.2 Research Steps

Prior to initiating an analysis, the author conducted a literature review of published pivotal studies to identify potential contributing factors on safety performance for five elements: vehicle occupant/driver, vehicle characteristics, road and roadside features, crash characteristics, and environmental conditions. Since road characteristics and the policies that establish the design of roads vary across jurisdictions, the published literature is limited to assessment of physical road features between jurisdictions and generally focuses on crashes within individual jurisdictions. Though there are indications that alcohol and drug abuse are a primary contributor to the vehicle occupant/driver influence, these speculations cannot be quantitatively confirmed due to the quality of data for this variable.

This dissertation also includes summary statistics for the available fatal crash databases. Since data from only four states included all variables needed for this analysis, the summary statistics focus on data from Alabama, Georgia, Mississippi, and South Carolina. The summary statistics (see Chapter 3) used a Chi-square test to evaluate how well the data set matched the larger fatal crash set from FARS for the year of crash. The author confirmed that the data adequately represented the larger fatal crash data set. This analysis then supported use of the data for development of probability models. The summary statistics also provided a good overview of the conditions for the crash data in each of the four states. Since the use of crash data that is not recent may raise a question as to whether models developed using that data are applicable to current conditions, the research team performed a ten-year fatal crash trend analysis. The ten-year fatal crash proportion profiles presented a generally

consistent trend based on variables including, crash types, lighting conditions, road locations types (road segments or road junctions), and crash locations (on or off active traffic way).

The use of statistical models to help predict how a candidate countermeasure can help to reduce a specific type of crash can be valuable by providing a quantitative tool to connect countermeasures and targeted crash types. Even though many other options are available to predict crashes (frequency, rate, severity, crash type), after considerable analysis, the author determined that the most meaningful models should be based on crash type. The author evaluated a wide variety of potential statistical models and determined that a logit model would be an appropriate modeling approach for determining the probability of crash type occurrence and by doing so helping to determine how to reduce the crash probability.

7.3 Research Findings

For rural two-lane roads, the single-vehicle crash and head-on crash are the over-represented fatal crash types in the southeastern region. Therefore, the author developed two fatal crash type models for combined-state data and state-specific data, respectively. One model focused on predictions of single-vehicle fatal crash type outcome; while the other one estimated the probability of head-on fatal crash occurrences for a multiple-vehicle crash. The major findings from those two types of fatal crash type models are summarized below.

<u>Single-vehicle fatal crash model:</u>

- Single-vehicle fatal crashes in Mississippi did not have similar causes for similar crashes in the other three states, so the cross-section model for single-vehicle crashes only applies to Alabama, Georgia, and South Carolina.

- Single-vehicle fatal crash type models evidently support the presumption that road geometrics as well as roadside and environmental features are associated with the probability of single-vehicle fatal crash occurrence in the southeastern region. Among the identified significant predictors, three variables, which are labeled as level one variables in Table 123, demonstrate consistent impacts on the probability of fatal crash type outcomes in state-combined models and all four state-specific models. Level two variables are those variables with significant effects in the state-combined models and at least two state-specific models, as shown in Table 123. The combined-state model also exhibited evidence of two types of significant interaction effects on safety performance. These interacting variables are (1) paved and graded shoulder width and (2) vertical and horizontal curve directions (see Table 123). These findings are generally consistent for both state and regional level models.
- For the Georgia only model, the use of safety restraints and lighting conditions were critical factors associated with single-vehicle fatal crashes.

Table 123: Significant Variables and Effects (SV)

Charac-teristics	Variables	Effects
Level One Variables	Lane Width (8-12ft)	The odds of fatal crashes as single-vehicle crashes are estimated to decrease at least by a factor of 0.65 with each 1-ft increase in lane width after accounting for the effects of other variables.
	Horizontal Curve Direction	The odds of fatal crashes as single-vehicle crashes at locations with horizontal curves to the left present are estimated to increase at least more than two folds from the odds of single-vehicle fatal crashes at locations with straight alignments or curve to the right after accounting for other variables.
	Lighting Condition	The odds of fatal crashes as single-vehicle crashes at locations under dark without supplemental lightings are estimated to increase at least more than three folds from the odds of single-vehicle fatal crashes at locations with lighting conditions as either daylight, dark with lights, dusk or dawn, after accounting for the effects of other independent variables.
Level Two Variables	Road Junction Type	The odds of fatal crashes as single-vehicle crashes at road junctions are estimated to decrease at least more than half from the odds of single-vehicle fatal crashes at road segments after accounting for the effects of other variables.
	Roadside Hazard Rating	The odds of fatal crashes as single-vehicle crashes at locations with roadside hazard rating 6 or 7 are estimated to increase at least more than three folds from the odds of single-vehicle fatal crashes occurred at locations with lower roadside hazard ratings (RHR <6) after accounting for the effects of other variables.
	Crash Time	The odds of fatal crashes as single-vehicle crashes occurred between 1am to 3am are estimated to increase at least more than six folds from the odds of single-vehicle fatal crashes occurred at other time of day after accounting for the effects of other variables.
Interaction Effects	Paved and Graded Shoulder Width	Greater safety benefits are estimated to be achieved while having both paved and graded shoulders implemented. Each 1-ft increase of paved shoulders width tend to reduce the odds of single-vehicle fatal crash occurrence more effectively while companied by wider graded shoulders. The similar effects are presented for graded shoulder width too.
	Vertical and Horizontal Curve Conditions	Locations with curve to the left tend to increase the risk of single-vehicle fatal crashes alone. Furthermore, overlapping crest and horizontal curve to the left is estimated to amplify this risk while all else are equal.

Head-on fatal crash model:

For multiple-vehicle crashes the most common crash type associated with rural two-lane highways was a head-on crash. As a result, the second modeling approach predicts head-on fatal crashes versus the likelihood of alternative multiple-vehicle crash types. For the multiple-vehicle head-on crashes, the following observations were identified:

- Multiple-vehicle head-on fatal crashes are influenced by similar characteristics in all four states, so the author developed a four-state probability model.
- The head-on fatal crash model identified considerably less significant predictors compared to the single-vehicle fatal crash models. Despite the observed differences between the state-specific models and combined-state model, the crash location (road segment) and ADT are labeled as level one variables. These key variables were determined to be significant independent variables with similar effects for the combined-state model and the state-specific models (See Table 124). The level two variables, horizontal alignment directions and lane width, were associated with head-on fatal crash occurrence in the four-state model and at least two of the state-specific models. They exhibited consistent impacts on the head-on fatal crash outcomes.
- For the Georgia only model, the use of safety restraints was a critical factor in the head-on fatal crash predictive model.

Table 124: Significant Variables and Effects (HO)

Characteristics	Variables	Effects
Level One Variables	Crash Location	The odds of multiple-vehicle fatal crashes to be head-on crashes at locations as road segments (not intersections) is estimated to increase more than 5 folds from the odds of Level Two Variables of head-on fatal crashes at road junctions while all else are equal.
	Average Daily Traffic	The odds of multiple-vehicle fatal crashes to be head-on crashes are estimated to increase by a factor of 1.3 with each 1000-vpd increase in average daily traffic while all else are equal.
Level Two Variables	Horizontal Curve Direction	The odds of multiple fatal crashes as head-on crashes at locations with curve to the right are estimated to increase at least by three folds from the odds of head-on fatal crashes at locations with curve to the left or straight alignment while all else are equal.
	Lane Width (8-12ft)	The odds of multiple-vehicle fatal crashes as head-on crashes are estimated to decrease at least by a factor of 0.5 with each 1-ft increase of lane width while all else are equal .

This study also compared the expert panel evaluation results from Georgia fatal crash data in two previous studies with the findings from the fatal crash type prediction models based on the combined-state approach. The study results were generally consistent for major findings. These separate safety studies closely aligned with the roadside hazard rating, the graded/paved shoulder condition, and the horizontal and vertical curve variables (each contributing to crashes as determined through the use of the statistical models). The corroboration of these independent assessment techniques solidifies the accuracy of both the expert opinions and the statistical models. It is worth to notice that this study is an observational study. Therefore, it is inappropriate to generalize the fatal crash type model findings from association to causation based on the statistics analysis alone.

7.4 Empirical Applications

Fatal crash type models have two empirical applications: safety improvement assessment and countermeasure recommendations.

- *Safety improvement assessment: Safety performance evaluation*
  Fatal crash type models can be applied to predict the probability of fatal crash type occurrence given a set of variables describing road geometrics, roadside features, and environment and traffic conditions. The correct use of logit model results can be problematic if it is not clear how the models should be used and what limitations should be applied to use of the models, so this research also included a practical example that demonstrated how to implement the models to help make countermeasure decisions (see Chapter 6).

  Chapter 6 presented a procedure along with a detailed example of how to conduct the assessment. The fatal crash type model quantifies safety effects based on a wide range of variables associated with individual site conditions. Those sites include locations that are identified as potential HSIP projects where a higher number of fatalities or severe injuries have been observed historically. The crash type models developed by the author also fulfill the need as a specialized tool in fatal crash analysis. Most available safety prediction models have been developed under the context of predicting total crashes only. Therefore, fatal crash type models are more suitable for evaluating the potential safety effects for crashes involved fatalities and severe injuries.
- *Countermeasure recommendations: Marginal effects of contributing factors*
  Table 125 illustrates potential effective countermeasure recommendations supported by the fatal crash type models for single-vehicle and head-on fatal crashes. The effectiveness of these countermeasures and adjustments should be evaluated based on the existing road conditions and cost-benefit analysis. It is inappropriate to extrapolate safety effects beyond the range of variables observed in the data. For example, lane widening appears to reduce single-vehicle fatal crash occurrence. Since lane width primarily ranged from 8 to 12 ft in the fatal crash data, it will be misleading to suggest that a 13 ft lane will provide more

safety benefits than a 12 ft lane. This claim is not only inappropriate, but also out of context.

Table 125: Countermeasure Recommendations from Fatal Crash Type Models

Single-Vehicle Fatal Crash	Head-on Fatal Crash
• Reduce safety hazards at locations with curve to the left or overlapping with crest (Providing adequate lane width, shoulder width, and roadside conditions, improving night visibility by adding appropriate traffic control devices)	• Reduce safety hazards at locations with curve to the right (Providing adequate lane width)
• Widen lanes	• Widen of lanes
• Implement both paved and graded shoulders as conditions allowed • Add or widen paved and graded shoulder width	--
• Improve roadside hazard rating to below 6 (Improving clear zone, flatten side slopes, removed/relocate roadside rigid objects)	--
• Enhance night visibility: ○ Improve perceptions of road geometric feature changes at high fatal crash locations ○ Promote night visibility at locations with other safety hazards	--
• Reinforce and promote driving safety education program and law enforcement for night driving safety	--

7.5 Research Limitations

As a regional study, this dissertation focuses on fatal crashes on two-lane rural highways. The study results should not be generalized to traffic crashes with all injury severity levels including property damage only crashes. Crash types are believed to distribute differently for fatal crashes versus minor injury crashes. Furthermore, this study only applies to safety performance on two-lane rural highways in the four study southeastern states. Roadways under other functional classifications, such as freeways, are constructed to different design standards. As a result, other road types are more likely to have different road and roadside geometric features and traffic conditions. Finally, it is not recommended to apply the fatal crash type models to

other regions without validation and calibration. As previously indicated, the model development was based on a cross-sectional dataset that included fatal crashes that occurred primarily in 1997.

7.6 Future Research Recommendations

Recommendations for future research:

- This study demonstrated the value of safety evaluation at the disaggregated data level. The author recommends extending the study method to other regions with enhanced crash data quality. For fatal crashes, the author suggests it would be useful to collect enhanced infrastructure information at crash locations soon after crash occurrence. However, a complicated crash police form is not practical for police officers to complete. It would be useful to find ways to obtain crash data with valuable site information and high quality.
- The author recognized the limitation of cross-sectional data analysis. Therefore, the author recommends conducting model validation with data from different years and examining potential temporal transferability in future research.
- This dissertation only incorporated fatal crash data which were available with the detailed infrastructure information. The author recommends applying crash data including various injury severity levels to predict the probability of fatal crash vs. non-fatal crash by crash type in future research activity.
- It is also recommended that a larger sample size for head-on fatal crashes will help to provide better model estimation results.

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APPENDICES

Appendix A Acronym Definitions

Acronym	Definition
AADT	Average Annual Daily Traffic
ADT	Average Daily Traffic
AIC	Akaike Information Criteria
AL	Alabama
BAC	Blood Alcohol Concentration
CMF	Crash Modification Factor
DOT	Department of Transportation
FARS	Fatality Analysis Reporting System
FHWA	Federal Highway Administration
FL	Florida
GA	Georgia
GDOT	Georgia Department of Transportation
GSW	Graded Shoulder Width
g/dl	gram per deciliter
HO	Head-on
HSIP	Highway Safety Improvement Program
KY	Kentucky
LCURV	Horizontal curve to the left
LU_C	Commercial land use
LW	Lane Width
mph	Miles per hour
MS	Mississippi
NC	North Carolina
NUMDRVWAY	Number of driveways
PDO	Property Damage Only
PSW	Paved Shoulder Width
RCURV	Horizontal curve to the right
RHR	Roadside Hazard Rating
ROC	Receiver Operating Characteristics
SC	South Carolina
SE	Southeastern United States
SHSP	Strategic Highway Safety Plan
SPFs	Safety Performance Functions
SUV	Sports Utility Vehicles
SV	Single-Vehicle

Acronym	**Definition**
TN	Tennessee
U.S.	United States
VMT	Vehicle Miles Travelled
vpd	Vehicle Per Day

Appendix B Fatal Crash Data Element

(Source: Dixon, 2005)

Crash Data Element

Vari-able #	Data Element Name	Definition	Data Type	Code (Data Items)
C1	Crash State	The FIPS code identifying the state in which the crash occurred.	Numeric Length = 2	{2 digit FIPS code} 01 Alabama 12 Florida 13 Georgia 21 Kentucky 28 Mississippi 37 North Carolina 45 South Carolina 47 Tennessee
C2	Crash Case Number	State specific unique identifier within a given year that identifies a given crash.	AlphanumericLength = 20	-
C3	Crash Date and Time	The date (year, month, and day) and time (hour and minute) at which a crash occurred.	Numeric Length = 12	YYYYMMDDHHMM
C4	Crash County	The FIPS code identifying the county in which a crash occurred.	Numeric Length = 3	{3 digit FIPS code} 888 N/A 999 Unknown
C5	Crash City/Place	The FIPS code identifying the city/place in which a crash occurred.	Numeric Length = 5	{5 digit FIPS code} 88888 N/A 99999 Unknown
C6	Number of Vehicles Involved in Crash	The total number of vehicles involved in the crash - do not include non-motorized vehicles.	Numeric Length = 2	Actual vehicle count (0-99)
C7	Number of Driver/Occupants	The total number of vehicle occupants from all vehicles including the drivers who were in the vehicle(s) at the time of the crash.	Numeric Length = 2	Actual person count (0-99)
C8	Number of Non-motorists	The total number of non-motorists involved in the crash.	Numeric Length = 2	Actual person count (0-99)

C9	Crash Roadway Location	The exact location on the roadway indicating where the crash occurred. The optimum definition uses GPS/GIS location giving latitude/longitude information. States without GPS/GIS should indicate location using current system.	Numeric or alpha/numeric **Length = ?**	• Latitude / Longitude • Road Name / Route Number / Route Signing • Mile Marker / Milepost / Mile-point • At Intersection of Road Name /Route Number • Miles, Feet (N, S, E, W) of Road Name / Route Number
C10, C11, C12	Source of Information	Identity of the source providing the information on the crash report.	Subfield 1 Numeric Length = 1 Subfield 2 Alphanumeric **Length = ?** Subfield 3 Numeric Length = 1	Subfield 1: Source of Info. 1 Police agency 2 Motorist 3 Other Subfield 2: Police Reporting Agency Identifier. Subfield 3: Type of Police Agency 1 State police/hwy patrol 2 City police 3 Sheriff department 4 Other
C13	Date and Time Crash Reported to Police Agency	The date and time at which the call was placed notifying the police agency about the crash.	Numeric Length = 12	YYYYMMDDHHMM
C14	School Bus Related	Indicates if a school bus is related to the crash. The "school bus", with or without a pupil on board, must be directly involved as a contact vehicle or indirectly involved as a noncontact vehicle. A "school bus" is a yellow vehicle, with the name "school bus" on the front and rear and lettering on both sides identifying the school, school district served, or the company operating the bus.	Numeric Length = 1	1 No 2 Yes, school bus directly involved 3 Yes, school bus indirectly involved 4 Not reported 5 Unknown

C15, C16, C17, C18	Work Zone Related	A crash which occurs in or near a construction, maintenance or utility work zone as designated by the state, whether active or inactive.	All Subfields Numeric Length = 1	**Subfield 1:** Was crash located in or near a construction, maintenance or utility work zone. 1 No 2 Unknown 3 Yes (complete subfields 2-4) **Subfield 2:** Location of Crash. 1 Advance warning area 2 Transition area 3 Adjacent to activity area 4 Activity area 5 Termination area **Subfield 3:** Type of work zone. 1 Lane closure 2 Lane shift/crossover 3 Work on shoulder or median 4 Intermittent/moving work 5 Other **Subfield 4:** Workers present 1 Yes 2 No 3 Unknown
C19	Total Fatal Injuries	The total number of fatalities (motorists and non-motorists) which resulted from injuries sustained as the result of a specific road vehicle crash. In reporting fatality statistics, a 30-day counting rule is generally used for highway safety statistics. These rules provide that only those deaths which occur within 30 days of a crash will be counted for statistical purposes.	Numeric Length = 2	Actual Count (0-99)
C20	Total Non-fatal Injuries	The total number of persons injured in a specific traffic crash.	Numeric Length = 2	Actual Count (0-99)
C21	Alcohol/Drug Involvement	Investigating police officer's assessment of whether alcohol or drug use was suspected or demonstrated to be present by test for any vehicle driver or non-motorist in the	Numeric Length = 1	1 Neither alcohol nor other drugs 2 Yes (alcohol) 3 Yes (drugs other than alcohol) 4 Yes (alcohol and drugs) 5 Not reported

		crash.		6 Unknown
C22	Hit and Run	Indicate whether or not the crash involved a hit and run.	Numeric Length = 1	1 No Hit and Run 2 Hit motor vehicle in transport 3 Hit pedestrian or non-motorist 4 Hit parked vehicle
C23	Day of Week	The day of the week on which a crash occurred.	Numeric Length = 1	1 Monday 2 Tuesday 3 Wednesday 4 Thursday 5 Friday 6 Saturday 7 Sunday
C24	Date Incident Reported	Date the call is first received by a public safety answering point (PSAP) or other designated entity.	Numeric	YYYYMMDD
C25	Time Incident Reported	Time call is first received by Public Safety Answering Point (PSAP) or other designated entity.	Numeric	HHMM
C26	Time Dispatch Notified	Time of first connection with EMS dispatch	Numeric	HHMM
C27	Date Unit Notified	Date response unit is notified by EMS dispatch	Numeric	YYYYMMDD
C28	Time Unit Notified	Time response unit is notified by EMS dispatch	Numeric	HHMM
C29	Time Unit Respondin g	Time that the response unit begins physical motion.	Numeric	HHMM
C30	Time arrival at scene	Time EMS unit stops physical motion at scene (last place that the unit or vehicle stops prior to assessing the patient).	Numeric	HHMM
C31	Time of arrival at patient	Time response personnel establish direct contact with patient.	Numeric	HHMM
C32	Time Unit Left Scene	Time when the response unit begins physical motion from scene.	Numeric	HHMM

C33	Time Arrival at Destination	Time when patient arrives at destination or transfer point.	Numeric	HHMM
C34	Incident Number	Unique number for each incident reported to dispatch.	Numeric or alpha/numeric	-
C35	Agency / Unit Number	Number that identifies the agency and unit responding to an incident.	Numeric or alpha/numeric	-

Appendix Table 1 Environment Data Element

Varia -ble #	Data Element Name	Definition	Data Type	Code (Data Items)
E1	Crash State	The FIPS code identifying the state in which the crash occurred.	Numeric Length = 2	{2 digit FIPS code} 01 Alabama 12 Florida 13 Georgia 21 Kentucky 28 Mississippi 37 North Carolina 45 South Carolina 47 Tennessee
E2	Crash Case Number	State specific unique identifier within a given year that identifies a given crash.	AlphanumericLength = 20	-
E3	Sequential Case Number	Sequential case number assigned by the university for purposes of the pooled fund study.	Alphanumeric Length = 5	2 Letter State Code followed by sequential case number (1-150) Georgia Format: GA001 - GA150
E4	Crash Date and Time	The date (year, month, and day) and time (hour and minute) at which a crash occurred.	Numeric Length = 12	YYYYMMDDHHMM
E5	Crash County	The FIPS code identifying the county in which a crash occurred.	Numeric Length = 3	{3 digit FIPS code} 888 N/A 999 Unknown

E6	First Harmful Event	The injury or damage producing event which characterizes the crash type and identifies the nature of the first harmful event, such as an explosion in the vehicle.	Numeric Length = 2	01 Overturn 02 Jackknife 03 Other Non-collision 04 Collision w/ pedestrian 05 Collision w/pedalcycle 06 Collision w/ railway vehicle 07 Collision w/ animal 08 Collision w/ motor vehicle in transport 09 Collision w/ parked vehicle 10 Collision w/ work zone equipment 11 Collision w/ other non-fixed object 12 Collision w/ bridge/culvert 13 Collision w/ guardrail/median barrier 14 Collision w/ utility pole/light support 15 Collision w/ embankment/ditch/curb 16 Collision w/ tree 17 Collision w/ other fixed object 18 Collision w/ unknown fixed object 19 Not reported 20 Unknown
E7	Relation to Roadway	The location of the First Harmful Event as it relates to its position within or outside the traffic-way.	Numeric Length = 2	01 Roadway 02 Shoulder 03 Median 04 Roadside 05 Not Reported 06 Unknown 07 Ramp 08 Gore 09 Off-Roadway – Location Unknown 10 In Parking Lane

E8	Manner of Impact	The identification in a crash of the manner in which two vehicles in transport initially came together without regard to the direction of force.	Numeric Length = 1	1 Not collision between two vehicles in transport. 2 Rear-end 3 Head-on 4 Rear-to rear 5 Angle 6 Sideswipe, same direction 7 Sideswipe, opposite direction 8 Not reported 9 Unknown
13	Force of collision	The direction of the force in a crash which caused the two vehicles to come together.	Numeric Length = 1	1 Not collision between two vehicles in transport. 2 Rear-end 3 Head-on 4 Rear-to rear 5 Angle 6 Sideswipe, same direction 7 Sideswipe, opposite direction 8 Not reported 9 Unknown
18	Weather Condition	The prevailing atmospheric conditions that existed at the time of the crash.	Numeric Length = 2	01 Clear 02 Cloudy 03 Fog, smog, smoke 04 Rain 05 Sleet, hail (freezing rain/drizzle) 06 Snow 07 Severe crosswinds 08 Blowing sand, soil, dirt, snow 09 Other 10 Not reported 11 Unknown
19	Ambient Light	The type of light that exists at the time of a motor vehicle crash.	Numeric Length = 1	1 Daylight 2 Dawn 3 Dusk 4 Dark – lighted roadway 5 Dark - roadway not lighted 6 Dark – unknown roadway lighting 7 Other 8 Not reported 9 Unknown

20	Road Surface Condition	The roadway surface condition at the time and place of a crash.	Numeric Length = 2	01 Dry 02 Wet 03 Snow 04 Ice 05 Sand, mud, dirt, oil, gravel 06 Water (standing, moving) 07 Slush 08 Other 09 Not reported 10 Unknown
21	Contributing Circumstances, Environment	Apparent environmental conditions which contributed to the crash.	Numeric Length = 1	1 None 2 Weather conditions 3 Physical obstruction 4 Glare 5 Animal in roadway 6 Other 7 Not reported 8 Unknown
22	Contributing Circumstances, Road	Apparent condition of the road which contributed to the crash.	Numeric Length = 2	01 None 02 Road surface condition (wet, icy, slush, etc.) 03 Debris 04 Rut, holes, bumps 05 Work zone(construction/ maintenance/utility) 06 Worn, travel-polished surface 07 Obstruction in Roadway 08 Traffic control device inoperative or missing 09 Shoulders (none, low, soft, high) 10 Non-highway work 11 Other 12 Not reported 13 Unknown
23	Type of Roadway Junction	A junction is either an intersection or the connection between a driveway access and a roadway other than a driveway access.	Numeric Length =12	1 Not a junction 2 Four-way intersection 3 T-intersection 4 Y-intersection 5 Traffic circle/roundabout 6 Five-point, or more 7 On ramp 8 Off ramp 9 Crossover 10 Driveway 11 Railway grade crossing 12 Shared-use paths or trails 13 Not reported 14 Unknown

Appendix Table 2 Vehicle Data Element

Variable #	**Data Element Name**	**Definition**	**Data Type**	**Code (Data Items)**
V1	Crash State	The FIPS code identifying the state in which the crash occurred.	Numeric Length = 2	{2 digit FIPS code} 01 Alabama 12 Florida 13 Georgia 21 Kentucky 28 Mississippi 37 North Carolina 45 South Carolina 47 Tennessee
V2	Crash Case Number	State specific unique identifier within a given year that identifies a given crash.	AlphanumericLength = 20	-
V3	Vehicle Unit Number	Number assigned to uniquely identify within the crash each vehicle involved in the crash.	Numeric Length = 2	Sequential number (1, 2, 3, 4…)
V4	Vehicle Registration State and Year	The state, commonwealth, territory, Indian nation, U.S. Government, foreign country, etc. issuing the registration plate and the year of registration as indicated on the registration plate displayed on the vehicle. For foreign countries, MUCC requires only the name of the country. Border states may want to collect the name of individual Canadian Provinces or Mexican States.	Numeric Length = 6	2 digit FIPS code for state and YYYY for the year.

V5	Vehicle License Plate Number	The alphanumeric identifier or other characters, exactly as displayed, on the registration plate or tag affixed to the vehicle. For combination trucks, vehicle plate number is obtained from the power unit or tractor.	Alphanumeric Length = 10?	Alphanumeric identifier assigned bythe state, foreign country, U.S. government, Indian Nation.
V6	Vehicle Make	The distinctive (coded) name applied to a group of vehicles by a manufacturer.	Text or FARS listing?	Provide in appendix
V7	Trailer Registration State and Year	The state, commonwealth, territory, Indian nation, U.S. Government, foreign country, etc. issuing the registration plate and the year of registration as indicated on the registration plate displayed on trailer. For foreign countries, MUCC requires only the name of the country. Border states may want to collect the name of individual Canadian provinces or Mexican States.	Numeric Length = 6	2 digit FIPS code for state and YYYY for the year.
V8	Trailer License Plate Number	The alphanumeric identifier exactly as displayed, on the registration plate or tag affixed to the trailer.	Alphanumeric Length = 10	Alphanumeric identifier assigned bythe state, foreign country, U.S. government, Indian Nation.

V9	Vehicle Configuration	Indicates the general configuration of vehicle.	Numeric Length = 2	1 Passenger car 2 Light truck(van, mini-van, panel, pickup, sport utility) with only four tires 3 Single-unit truck (2-axle, 6-tire) 4 Single-unit truck (3-or-more axles) 5 Truck/trailer 6 Truck tractor (bobtail) 7 Tractor/doubles 8 Tractor/triples 9 Unknown heavy truck, cannot classify 10 Motor home/recreational vehicle 11 Motorcycle 12 Bus (seats for more than 15 people, including driver) 13 Bus (seats for 7-15 people, including driver) 14 Other 15 Not reported 16 Unknown vehicle configuration
V10	Cargo Body Type	Coded for buses and trucks over 10,000 pounds GVWR.	Numeric Length = 2	01 Not applicable 02 Bus (seats for more than 15 people, including driver) 03 Bus (seats for 7-15 people, including driver) 04 Van/enclosed box 05 Grain/chips/gravel truck 06 Pole truck 07 Cargo tank 08 Flatbed 09 Dump 10 Concrete mixer 11 Auto transporter 12 Garbage/refuse 13 Other 14 Not reported 15 Unknown

V11	Weight Rating of Power Unit	A gross vehicle weight ration is a value specified by the manufacturer for a single-unit truck, truck tractor or trailer, or the sum of such values for the units which make up a truck combination. (2.2.23)	Numeric Length = 1	1 less than or equal to 10,000 lbs. 2 10,001-26,000 3 more than 26,000
V12	Vehicle Adaptive Equipment or Modificatio ns	The presence of adaptive equipment, other than that supplied by the OEM, which accomodates the vehicle functions to the capabilities of a person with disabilities. This may be for either a driver or passenger. Examples include: steering control device mounted on the steering wheel, hand controls, wheelchair lift or ramp, wheelchair tie down, additional or relocated switches for secondary controls (lights, wipers, etc.).	Numeric Length = 1	1 No—adaptive equipment/ modifications not observed 2 Yes—adaptive equipment/ modifications observed 3 Not reported 4 Unknown if adaptive equipment/modifications present
V13	Total Occupants In Vehicle	The total number of occupants in this vehicle involved in the crash, including persons in or on the vehicle at the time of the crash.	Numeric Length = 2	(1-99) Total number of occupants including the driver 00 Unknown
V14	Vehicle Role	Indicates vehicle role in single and multi-vehicle crashes. Role does not imply fault.	Numeric Length = 1	1 Noncontact 2 Noncollision 3 Striking 4 Struck 5 Both striking and struck 6 Not reported 7 Unknown

V15	Emergency Use	Indicates vehicles, such as military, police, ambulance, fire, etc., which are on an emergency response. Emergency refers to a vehicle that is traveling with physical emergency signals in use; typically red light blinking, siren sounding, etc. Code yes only if the vehicle was on an emergency response.	Numeric Length = 1	1 No 2 Yes 3 Not reported 4 Unknown
V16, V17, V18	Hazardous Materials Involvement (Cargo Only)	Indication that a motor vehicle had a hazardous material placard as required by federal regulations.	Subfield 1 Numeric Length = 1 Subfield 2 Numeric Length = 5 Subfield 3 Numeric Length = 1	Subfield 1: Did this vehicle have a hazardous materials placard? 1 Yes 2 No 3 Not reported 4 Unknown Subfield 2: If yes, record from the hazardous materials placard: 1) 4-digit placard number from the middle of the diamond or from the rectangular box; and 2) 1-digit placard number from bottom of diamond Subfield 3: Hazardous Materials, Cargo Released from the Cargo Compartment? 1 Yes – haz mat released 2 No – haz mat not released 3 Not reported 4 Unknown
V19, V20	Vehicle Authorized Speed Limit	Authorized speed limit for the vehicle at the time of the crash. The authorization may be indicated by the posted speed limit, blinking sign at construction zones, etc.	Subfield 1 Numeric Length = 3 Subfield 2 Numeric Length = 1	Subfield 1: Authorized Value Subfield 2: Unit of Measure 1 Miles per hour 2 Kilometers per hour 3 Not applicable 4 Unknown

V21	Direction of Travel Before Crash	The direction to a vehicle's normal, general travel on the roadway before the crash. Notice that this is not a compass direction but a direction consistent with the designated direction of the road. For example, the direction of a state designated north-south highway must be either northbound or southbound even though a vehicle may have been traveling due east as a result of a short segment of the highway having an east-west orientation.	Numeric Length = 1	1 Northbound 2 Southbound 3 Eastbound 4 Westbound 5 Not on roadway 6 Not reported 7 Unknown
V22	Traffic Control Device Type	The type of traffic control, if any at a crash location. This element needs to be collected at the scene because the presence of specific devices is better verified at the time of the crash.	Numeric Length = 2	01 No controls 02 Traffic control signal 03 Flashing traffic control signal 04 School zone signs 05 Stop signs 06 Yield signs 07 Warning signs 08 Railway crossing device 09 Not reported 10 Unknown
V23	Vehicle Maneuver/ Action	What the vehicle was doing prior to the crash.	Numeric Length = 2	01 Movements essentially straight ahead 02 Backing 03 Changing lanes 04 Overtaking/passing 05 Turning right 06 Turning left 07 Making u-turn 08 Entering traffic lane 09 Leaving traffic lane 10 Parked 11 Slowing or stopped in traffic 12 Other 13 Not reported 14 Unknown

V24	Point of Impact	The portion of the vehicle that impacted first in a crash.	Numeric Length = 2?	Provided in appendix
V25, V26, V27, V28	Sequence of Events	The events in sequence for this vehicle.	All Subfields Numeric Length = 2	Subfield 1: First Event Provided in Appendix Subfield 2: Second Event See codes in Subfield 1 Subfield 3: Third Event See codes in Subfield 1 Subfield 4: Fourth Event See codes in Subfield 1
V29	Most Harmful Event for this Vehicle	Event which produced the greatest property damage or most severe injury caused by this vehicle.	Numeric Length = 2	Provided in appendix
V30, V31	Underride/ Overide	An underride refers to a vehicle sliding under another vehicle during a crash. An override refers to a vehicle riding up over another vehicle. Both can occur with a parked vehicle.	All Subfields Numeric Length = 1	Subfield 1: 1 Underride 2 Override 3 No underride or override 4 Unknown if underride or override Subfield 2: 1 Compartment intrusion 2 No compartment intrusion 3 Compartment intrusion unknown
V32	Most Damaged Area	The location of most damage on vehicle and extent of total damage to vehicle from crash.	Numeric Length = 2?	Provided in appendix
V33	Extent of Damage	Estimation of total damage to vehicle from crash.	Numeric Length = 1	1 None 2 Functional damage 3 Disabling damage 4 Severe/vehicle totaled 5 Not reported 6 Unknown
V34	Vehicle Model Year	The year which is assigned to a vehicle by the manufacturer.	Numeric Length = 4	YYYY

V35	Vehicle Model	The manufacture assigned code denoting a family of vehicles (within a make) which has a degree of similarity in construction, such as body, chassis, etc.	Text or numeric list from FARS?	
V36	Vehicle Body Type	Code derived from the VIN to indicate the general configuration or shape of a vehicle distinguished by characteristics such as number of doors, seats, windows, roof line, hard top or convertible.	Numeric Length = 3	Provided in appendix
V37	Total Trailers Attached to Truck	Total number of trailers attached to a large truck.	Numeric Length = 1	Actual number of trailers (0-4)
V38	Vehicle Identificati on Number	A unique combination of alphanumeric characters assigned to a specific vehicle and formulated by the manufacturer.	Alphanumeri c Length = ?	VIN found on vehicle
V39	Registered Vehicle Owner Type	Indicate whether or not the vehicle was registered and to whom.	Numeric Length = 1	1 N/A, Vehicle not registered 2 Driver was registered owner 3 Driver not registered owner (other private owner) 4 Vehicle registered as a business, company, or government vehicle 5 Vehicle registered as a rental vehicle 6 Vehicle was stolen 7 Driverless vehicle 8 Unknown
V40	Travel Speed	An estimate of the travel speed - most likely a judgement rather than a measurement.	Numeric Length = 2	00 Stopped Vehicle 01-96 Travel Speed in MPH 97 Speed of 97 MPH or higher 99 Unknown
V41	Vehicle Towed?	Manner of leaving scene	Numeric Length = 1	1 Driven 2 Towed Away 3 Abandoned/Left Scene

				4 Unknown
V42	Fire Occurrence	Indication of fire or explosion as an involvement in the crash.	Numeric Length = 1	1 No Fire 2 Fire occurred in vehicle during crash
V43	Crash Avoidance Maneuver	The maneuver that the driver executed to attempt to avoid the crash.	Numeric Length = 1	1 No avoidance maneuver reported 2 Braking (skidmarks evident) 3 Braking (no skidmarks, driver stated) 4 Braking (other reported evidence) 5 Steering (evidence or stated) 6 Steering and Braking (evidence or stated) 7 Other avoidance maneuver 8 Not reported (by police)
V44	Number of Deaths	The number of fatalities that occurred in the specific vehicle.	Numeric Length = 2	Actual number of fatalities (0-99)

Appendix Table 3 Person Data Element

Variable #	Data Element Name	Definition	Data Type	Code (Data Items)
1	Crash State	The FIPS code identifying the state in which the crash occurred.	Numeric Length = 2	{2 digit FIPS code} 01 Alabama 12 Florida 13 Georgia 21 Kentucky 28 Mississippi 37 North Carolina 45 South Carolina 47 Tennessee
2	Crash Case Number	State specific unique identifier within a given year that identifies a given crash.	AlphanumericLength = 20	-
3	Date of Birth	The year, month, and day of birth of person involved in a crash.	Numeric Length = 8	YYYYMMDD
4	Sex	The sex of person involved in a crash.	Numeric Length = 1	1 Male 2 Female 3 Not reported 4 Unknown
5	Person Type	Type of person involved in a crash.	Numeric Length = 1	1 Driver 2 Passenger 3 Nonmotorist 4 Not reported 5 Unknown
6	Injury Status	The most severe injury to the person involved in a crash.	Numeric Length = 1	1 Fatal Injury (K) 2 Nonfatal Injury, Incapacitating (A) 3 Nonfatal Injury, Nonincapacitating (B) 4 Nonfatal Injury, Possible(C) 5 No injury (O) 6 Not reported 7 Unknown
All Vehicle Occupants				
7	Occupant's Vehicle Unit Number	The number assigned to the vehicle in which this person was an occupant.	Numeric Length = 2	(01-99)

8	Seating Position	The location for this occupant in, on, or outside of the motor vehicle prior to the impact of a crash.		01 Front seat – left side (or motorcycle driver) 02 Front seat – middle 03 Front seat – right side 04 Second seat – left side (or motorcycle passenger) 05 Second seat – middle 06 Second seat – right side 07 Third row – left side (or motorcycle passenger) 08 Third row – middle 09 Third row – right side 10 Sleeper section of cab (truck) 11 Passenger in other enclosed passenger or cargo area (non- trailing unit such as a bus) 12 Passenger in unenclosed passenger or cargo area (non-trailing unit such as a pickup) 13 Trailing unit 14 Riding on vehicle exterior (non-trailing unit) 15 Not reported 16 Unknown
9	Occupant Protection System Use	The restraint equipment in use by occupant at the time of the crash, or the helmet use by a motorcyclist.	Numeric Length = 1	1 None used – vehicle occupant 2 Shoulder belt only used 3 Lap belt only used 4 Shoulder and lap belt used 5 Child safety seat used 6 Helmet used 7 Not reported 8 Restraint use unknown

10, 11	Air Bag Deployed	Deployment status of an air bag relative to position of the occupant.	All Subfields Numeric Length = 1	**Subfield 1:** Deployment Deployed-front Deployed-side Deployed-both front/side Not-deployed Not applicable Not reported Deployment unknown **Subfield 2:** Switch Status Switch in ON position Switch in OFF position ON-OFF switch not present Unknown if ON-OFF switch present Not reported Unknown position
12	Ejection	The location of each occupant's body as being completely or partially thrown from the vehicle as a result of a crash.	Numeric Length = 1	- Not ejected - Totally ejected - Partially ejected - Not applicable - Not reported - Unknown
13	Trapped	Persons who are mechanically restrained in the vehicle by damaged vehicle components as a result of a crash, and are freed from the vehicle.	Numeric Length = 1	- Not trapped - Extricated by mechanical means (Jaws of Life, etc.) - Freed by non mechanical means - Not reported - Unknown
Driver Only				
14	Driver License State/Province	A code identifying the state or province issuing a driver license to an individual. Includes the states of the United States (including the District of Columbia and outlying areas), Indian Nation, U.S. Government, Canadian provinces, and Mexican Sates (including the Distrito Federal), as well as other jurisdictions.	Numeric Length = 2	- Not Licensed - State code (FIPS) - Indian Nation - U.S. Government - Canadian Province - Mexican State - International License (other than Mexico, Canada) - Not reported - Unknown
15	Driver License Number	A unique number assigned by the authorizing agent	Alphanumeric Length = ?	Alphanumeric identifier assigned by the state, foreign country, U.S. government,

		issuing a driver license to the individual.		Indian Nation, etc.
16	Driver Name	The full name of the individual driver.	Text Length = ?	Provided in appendix
17	Contributing Circumstances, Driver	The actions of the driver which may have contributed to the crash.	Numeric Length = 2	- No Improper driving - Failed to yield right of way - Disregarded traffic signs, signals, road markings - Exceeded authorized speed limit - Driving too fast for conditions - Made an improper turn - Wrong side or Wrong way - Followed too closely - Improper action - Failure to keep in proper lane or running off road - Operation vehicle in erratic, reckless, careless, negligent or aggressive manner - Swerving or avoiding due to wind, slippery surface, vehicle, object, nonmotorist in roadway, etc. - Overcorrecting/oversteering - Visibility obstructed - Inattention - Distracted - Fatigued/asleep - Operation defective equipment - Other - Not reported - Unknown
18	Driver Condition	The condition of the driver which may have contributed to the crash.	Numeric Length = 1	- Apparently normal - Physical impairment - Emotional (e.g., depressed, angry, disturbed) - Illness - Fell asleep, fainted, fatigued, etc. - Under the influence of medications/drugs/alcohol - Other - Not reported - Unknown

19	Cited	Driver cited for actions which contributed to the crash.	Numeric Length = 1	- Yes - No - Pending - Unknown
20, 21, 22, 23	Violation Codes	All violation codes that apply to indicate the type of violations.	All Subfields Numeric **Length = ?**	**Subfield 1:** Violation Code #1 No violation (Violation Code) Not reported Unknown **Subfield 2:** Violation Code #2 No violation (Violation Code) Not reported Unknown **Subfield 3:** Violation Code #3 No violation (Violation Code) Not reported Unknown **Subfield 4:** Violation Code #4 No violation (Violation Code) Not reported Unknown
24	Driver License Class	The type of commercial or non-commercial vehicle that a licensed driver has been examined on and approved to operate.	Numeric Length = 1	1 Class A 2 Class B 3 Class C 4 Class M 5 Unknown
25	Driver License Status, CDL	The current status of an individual's federally-approved commercial drivers license (CDL).	Numeric Length = 1	1 Eligible 2 Licensed 3 Not Eligible 4 Reported Deceased
26	Driver License Status, Non-CDL	The current status of an individual's drivers license other than a federally approved commercial driver license.	Numeric Length = 1	1 Eligible 2 Licensed 3 Not Eligible 4 Reported Deceased

27	Driver License Restrictions	Restrictions assigned to an individual's driver license by the license examiner.	Numeric Length = 2	01 None 02 Corrective Lenses 03 Mechanical devices (specialbrakes, hand controls, or other adaptive devices) 04 Prosthetic aid 05 Automatic transmission 06 Outside mirror 07 Limit to daytime only 08 Limit to employment 09 Limited - other 10 Other 11 CDL Intrastate only 12 Vehicles without air-brakes 13 Except Class A Bus 14 Except Class A and Class B bus 15 Except tractor-trailer 16 Farm waiver
28	License Endorsements	Compliance with license endorsements.	Numeric Length = 1	1 No Endorsements required for this vehicle 2 Endorsements required, complied with 3 Endorsements required, notcomplied with 4 Endorsements required, compliance unknown 5 Unknown, if required
29	License Compliance	Drivers license type compliance	Numeric Length = 1	1 Not Licensed 2 No License required for thisclass vehicle 3 No valid license for this class vehicle 4 Valid License for this class vehicle 5 Unknown if CDL Endorsement required for this vehicle 6 Unknown
30	Driver Presence	Indicate whether or not there was a driver present in the vehicle at the time of the crash as well as afterwards.	Numeric Length = 1	1 Driver Operated Vehicle 2 Driverless (No Driver) 3 Driver Left Scene 4 Unknown
31	Previous Recorded Accidents	Number of events occurring within three years of the crash.	Numeric Length = 2	00 None 01-97 Actual Value 98 CDL Disqualified 99 Unknown

32	Previous Recorded Suspensions	Number of events occurring within three years of the crash.	Numeric Length = 2	00 None 01-97 Actual Value 98 CDL Disqualified 99 Unknown
33	Previous DWI Convictions	Number of events occurring within three years of the crash.	Numeric Length = 2	00 None 01-97 Actual Value 98 CDL Disqualified 99 Unknown
34	Previous Speeding Convictions	Number of events occurring within three years of the crash. Speeding violations count going too slow, as well as, going too fast.	Numeric Length = 2	00 None 01-97 Actual Value 98 CDL Disqualified 99 Unknown
35	Previous Other Motor Vehicle Convictions	Number of events occurring within three years of the crash.	Numeric Length = 2	00 None 01-97 Actual Value 98 CDL Disqualified 99 Unknown
36	Month/Year of Last Accident		Numeric Length = 6	MMYYYY
37	Month/Year of First Accident		Numeric Length = 6	MMYYYY
38	Driver Street Address		Text **Length = ?**	Provided in appendix
39	Driver Address City	The FIPS code identifying the city/place in which the driver resides.	Numeric Length = 5	{5 digit FIPS code} 88888 N/A 99999 Unknown
40	Driver Address State	The FIPS code identifying the state in which the driver resides.	Numeric Length = 2	{2 digit FIPS code} Provided in appendix
41	Driver Zip Code		Numeric Length = 5	
Drivers and Non-motorists only				
42	Alcohol/Drug Suspected	Investigating police officer's assessment of whether alcohol or drugs were used by the vehicle driver or nonmotorist.	Numeric Length = 1	- Neither alcohol nor drugs suspected - Yes – alcohol suspected - Yes – drugs suspected - Yes – alcohol and drugs suspected - Not reported - Unknown

43, 44, 45	Alcohol	The percent of Blood Alcohol Content (BAC).	Subfields 1-2 Numeric Length = 1 Subfield 3 Numeric - decimal Length = 4	**Subfield 1:** Test Status None given Test refused Test given, results unknown Test given, contaminated sample/unusable Unknown **Subfield 2:** Type of Test Blood Breath Urine **Subfield 3:** Test Result (x.xx)
46, 47, 48	Drugs	Indication of the presence of drugs through drug testing.	All Subfields Numeric Length = 1	**Subfield 1:** Test Status Test not given Test given, no drugs reported Test given, drugs reported Test given, contaminated sample/unusable Not reported Unknown **Subfield 2:** Type of Test Blood Urine Serum **Subfield 3:** Test Result (Drugs regulated for commercial motor vehicle drivers and others) Marijuana Cocaine Opiates Amphetamines PCP
Non-motorist only				
49	Nonmotorist Number	The unique number assigned to the non motorist involved in a crash.	Numeric Length = 2	Sequential number uniquely identifying the nonmotorist involved in a crash.
50	Nonmotorist Type	A code indicating the type of nonmotorist involved in a crash.	Numeric Length = 1	- Pedestrian - Pedacyclist (bicycle, tricycle, unicycle, pedalcar) (2.2.39) - Skater - Other - Not reported - Unknown

51	Nonmotorist Action	The actions of the nonmotorist prior to the crash.	Numeric Length = 2	- Entering or crossing specified location - Improper crossing - Walking, playing, running/jogging - Working - Darting - Is lying and/or illegally in roadway - Failure to yield right of way - Not visible - Bicycle violation - Inattentive (talking, eating, etc.) - Failure to obey traffic signs, signals, or officer - Pushing vehicle - Approaching or leaving vehicle - Playing or working on vehicle - Standing - Other - Not reported - Unknown
52	Nonmotorist Condition	A code which specifies the condition of the nonmotorist immediately prior to a crash.	Numeric Length = 1	- Apparently normal - Physical impairment - Emotional (e.g., depression, angry, disturbed) - Illness - Fell asleep, fainted, fatigue, etc. - Under the influence of medications / drugs / alcohol - Other - Not reported - Unknown

53	Nonmotorist Location Prior to Impact	The nonmotorist's location with respect to the roadway prior to impact.	Numeric Length = 2	- Marked crosswalk at intersection - At intersection but no crosswalk - Nonintersection crosswalk - Driveway access crosswalk - In roadway - Not in roadway - Median (but not on shoulder) - Island - Shoulder - Sidewalk - Within 10 feet of roadway (but not shoulder, median, sidewalk, or island) - Beyond 10 feet of roadway (within trafficway) - Outside trafficway - Shared-use path or trails - Not reported - Unknown
54, 55	Nonmotorist Safety Equipment	The safety equipment(s) used by the nonmotorist.	All Subfields Numeric Length = 1	**Subfield 1:** Safety Equipment used by nonmotorist - None used - Helmet used - Protective pads used (elbows, knees, shins, etc.) - Reflective clothing - Lighting - Not applicable - Other - Not reported - Unknown **Subfield 2:** Safety Equipment used by nonmotorist - See Subfield 1
56	Number of Vehicle Striking Nonmotorist	Number assigned to identify the vehicle that struck the nonmotorist in the crash.	Numeric Length = 1	

Appendix Table 4 Site Data Element

Varia -ble #	Data Element Name	Definition	Data Type	Code (Data Items)
S1	Site Reviewer	Name of person who completed the site review.	Text	-
S2	Date of Site Review	Date on which the site review was completed.	Date/Time	-
S3	Time of Site Review	Time of day that the site review was conducted	Date/Time	-
S4	Crash State	The FIPS code identifying the state in which the crash occurred.	Numeric Length = 2	{2 digit FIPS code} 01 Alabama 12 Florida 13 Georgia 21 Kentucky 28 Mississippi 37 North Carolina 45 South Carolina 47 Tennessee
S5	Crash Case Number	State specific unique identifier within a given year that identifies a given crash. This number should be available on police reports or reports maintained by the state DOT.	AlphanumericLength = 20	-
S6	Sequential Case Number	Sequential case number assigned by the university for purposes of the pooled fund study.	Alphanumeric Length = 5	2 Letter State Code followed by sequential case number (1-150) Georgia Format: GA001 - GA150
S7, S8, S9, S10	Horizontal Alignment	The change in general horizontal alignment of a roadway.	Subfield 1 Numeric Length = 1 Subfields 2-4 Alpanumeric Length = 2	Subfield 1: General Alignment 1 Straight 2 Curved Subfield 2:Direction of Curve NA Not Applicable 01 Right 02 Left Subfield 3: Estimated Curve Radius NA Not Applicable 01 Sharp curve (requires driver speed adjustment) 02 Mild/gentle curve Subfield 4: Crash Curve

				Location NA Not Applicable 01 Inside of curve 02 Outside of curve
S11, S12, S13, S14	Grade	The inclination of a roadway, expressed as a percent of grade.	Subfield 1 Numeric Length = 1 Subfields 2-4 Alphanumeric Length = 2	Subfield 1: Direction of Slope 1 Up Down Flat Subfield 2: Estimate of the Percent of Slope NA Not Applicable 01 Level (1% ±) 02 Mild Slope (2-6% ±) 03 Steep Slope (>6% ±) Subfield 3: Crest Vertical Curve NA Not Applicable 01 Yes 02 No Subfield 4: Sag Vertical Curve NA Not Applicable 01 Yes 02 No
S15, S16	Cross-Section	Cross-section type of two-lane rural road.	Subfield 1 Numeric Length = 1 Subfield 2 Memo	Subfield 1: type Typical Rooftop 1-2% Superelevated Subfield 2: Other, (If so, indicate other type in column S13 <other.cs>)
S17, S18	National Highway System	Designation as part of the national highway system.	Subfield 1 Numeric Length = 1 Subfiled 2 Memo	Subfield 1: Designation 1 Yes 2 No Unknown Subfield 2: Other
S19	Functional Classification of Rural Roadway	The character of service or function of streets or highways.	Numeric Length = 1	1 Principal arterial 2 Minor arterial 3 Major Collector 4 Minor Collector 5 Local 6 Unknown
S20, S21	Guardrail/ Bridge Railing	Was a guardrail or bridge rail involved in crash, if so, indicate type.	Subfield 1 Numeric Length=1 Subfeild 2 Memo	Subfield 1: None Steel Breakaway Guardrail Concrete Barrier (Jersey)

				Wood Guardrail Concrete Bridge Rail Steel Bridge Rail Wood Bridge Rail Subfield 2 Indication of other type of guardrail/bridge railing.
S22, S23, S24	Lanes	Number of lanes in addition to the two main traffic-way lanes, by function , at the particular cross section of the roadway where the crash occurred.	Numeric Length = 1	Subfield 1: Number of turning lanes in addition to the two main lanes Subfield 2: Number of passing lanesin addition to the two main lanes Subfield 3: Number of emergency lanes in addtion to the two main lanes
S25, S26, S27, S28, S29, S30	Average Daily Traffic	The average number of vehicles passing a point on a trafficway per day, for some specified time period (ADT), or during a specified calendar year (AADT).	Subfield 1 Numeric Length = 1 Subfield 2 Numeric Length = 5 Subfield 3 Numeric Length = 3 Subfield 4 Numeric Length = 1 Subfield 5 Numeric Length = 8 Subfield 6 Numeric Length = 1	Subfield 1: ADT or AADT 1 Average Daily Traffic (ADT) – average daily traffic averaged over a period less than one year 2 Annual Average Daily Traffic (AADT) –average daily traffic averaged over a continuous count period of one year Subfield 2: Daily Traffic Count Subfield 3: Length of Count Subfield 4: Time Increment of Count Hours Days Months 4 Years Subfield 5: Date Collection Began MMDDYYYY Subfield 6: Counts obtained from 1 Actual Roadway 2 Similar Roadway
S31	Lane Width	Width of lane where crash occurred.	Alphanumeric Length = 2	Width (feet) (NA = Not Applicable)

S32, S33, S34	Shoulder Type/Width	Type of shoulder adjacent to lane in which crash occurred.	Subfield 1 Numeric Length = 1 Subfield 2 Alphanumeric Length = 2 Subfield 3 Alphanumeric Length = 2	Subfield 1: Shoulder Type Paved Graded Combination Paved and Graded Raised Curb, Traversable Raised Curb, Barrier No Shoulder Subfield 2: Paved Shoulder Width (NA = Not Applicable) Subfield 3: Graded Shoulder Width (NA = Not Applicable)
S35, S36	Nature of Adjacent Influences	The type of visual content of abutting land, air, or view in connection with a roadway (within 500 ft. laterally of crash site).	Subfield 1 Numeric Length = 1 Subfield 2 Memo	Subfield 1: Type 1 Billboards 2 Driveways, residential 3 Driveways, commercial 4 Driveways, industrial Subfield2: Other, (If so, indicate other type in column S30 <other.ai>)
S37, S38	Driveways/ Intersections	Number of driveways and intersections surrounding crash site which provide sources of vehicular conflict.	Numeric Length = 2	Subfield 1 – Indicate number of driveways within 250 ft upstream and 250 ft downstream of the crash site. Circular drives that have two access points are counted as two. Driveways directly across the street from each other count as two driveways. Subfield 2 – Indicate the number of intersection with 250 ft upstream and 250 ft downstream of the crash site. A four-way intersection will count as two intersections to determine conflict patterns.
S39	Bridge or Railroad Involvement	Indication of whether or not a bridge or railroad was involved in the crash.	Numeric Length = 1	Not Applicable Bridge Railroad Bridge and Railroad

S40	Bridge/Structure Identification	A unique code assigned to a bridge, underpass, overpass ,or tunnel.	Alphanumeric Length = 10	- (NA = Not Applicable)
S41	Railroad Crossing ID	A unique number assigned to a railroad crossing by a state highway agency in cooperation with the American Association of Railroads for identification purposes	Alphanumeric Length = 10	- (NA = Not Applicable)
S42	Roadside Illumination	The type of roadway illumination within 250 ft longitudinally of crash site.	Numeric Length = 1	1 No illumination fixtures 2 Spot illumination 3 Continuous illumination
S43	Pavement Markings, Longitudinal	The longitudinal markings (paint, plastic, or other) used on the roadway surface to guide or control the path followed by drivers at crash site.	Numeric Length = 2	Function and Color 01 Centerline, skip-dash, yellow 02 Centerline, solid, yellow 03 Centerline, solid double, yellow 04 No passing barrier, right or left, yellow 05 Lane line, skip-dash, white 06 Lane line, solid, white 07 Edge line, left, yellow 08 Edge line, right, white 09 Left turn lane lines, combination of solid and skip-dash, yellow 10 Turn arrow symbols, right, through, left, or combination of two 11 Unknown
S44	Bikeway	Any road, path, or way which in some manner is specifically designated as being open to bicycle travel, regardless of whether such facilities are designated for the exclusive use of bicycles or are to be shared with other transportation modes. Select only one value – closest to actual configuration.	Numeric Length = 1	1 No Bikeway 2 Bicycle Route (signed only) 3 Bicycle Lane (striped) - right only 4 Bicycle Lane (striped) - both sides 5 Bicycle Lane (striped) - left only 6 Separate Bicycle Path/Trail Unknown

S45, S46	Delineator Presence	The presence or absence of a series of reflecting devices mounted at regular intervals along the side, center, or lane lines of the road to assist in directing drivers along the alignment of the roadway.	Subfield 1 Numeric Length = 1 Subfield 2 Alphanumeric Length = 2	Subfield 1: Delineator Presence 1 None 2 Delineators, right 3 Delineators, left 4 Delineators, both sides 5 Unknown Subfield 2: Type of Delineator Directional chevron signs Mounted reflectors NA Not Applicable

S47, S48, S49, S50, S51, S52, S53	Traffic Control Device	Traffic control devices present at the crash site at the time of the crash.	Subfields 1,3,5 Alphanumeric Length = 2 Subfields 2,4,6 Memo Subfield 7 Alphanumeric Length = 50	Subfield 1: Highway Traffic Signals 1 Traffic control signal (operating green, yellow, red) without pedestrian signal 2 Traffic control signal (operating green, yellow, red) with pedestrian signal 3 Traffic control signal (operating green, yellow, red) pedestrian signal not known 4 Flashing traffic control signal 5 Flashing beacon 6 Flashing highway traffic signal, type unknown, or other 7 Lane use control signal 8 Unknown highway traffic signal NA Not Applicable Subfield 2: Other Traffic Signals Subfield 3: Regulatory Signs 1 Stop Sign 2 Yield Sign 3 Unknown type regulatory sign NA Not Applicable Subfield 4: Other type regulatory sign Subfield 5: School Zone Signs 1 School speed limit sign 2 School advance or crossing sign 3 Unknown type school zone sign NA Not Applicable Subfield 6: Other school related sign Subfield 7: Warning Signs – Indicate type (NA Not Applicable)
S54, S55	Speed Limit	Posted speed limit at the location of the crash.	Subfield 1 Numeric Length = 1 Subfield 2 Numeric Length = 2	Subfield 1: Speed Limit Type 1 Regulatory 2 Warning Subfield 2: Posted Speed Limit

S56	Roadside Parking	Presence of adjacent roadside parking.	Numeric Length = 1	1 No Roadside Parking 2 Parallel parking 3 Head-in parking 4 Unknown
S57	Roadside Hazard Rating	A subjective measure of the hazard associated with the roadside environment. The rating values indicate the crash damage likely to be sustained by errant vehicles on a scale from one (low likelihood of an off-roadway collision or overturn) to seven (high likelihood of an accident resulting in a fatality or severe injury). For more clarification see Zegeer, FHWA-RD-87-008.	Numeric Length = 1	(1-7) Ratings are determined from a 7-point rural pictorial scale as shown in Appendix S1.
S58, S59	Surface Type	Roadway surface material at the crash site.	Subfield 1: Numeric Length = 1 Subfield 2: Memo	Subfield 1: Type 1 Concrete 2 Blacktop 3 Brick or block 4 Slag, gravel or stone 5 Dirt 6 Unknown Subfield 2: Other
S60, S61	Roadside Barrier	A roadside barrier is a longitudinal barrier used to shield motorists from natural or man-made obstacles located along either side of a traveled way.	Subfield 1: Numeric Length = 2 Subfield 2: Memo	Subfield 1: Type 1 None 2 3-Strand Cable 3 W-Beam (weak post) 4 Thrie-Beam (weak post) 5 Box Beam (weak post) 6 Blocked-out W-Beam (strong post) 7 Blocked-out Thrie-Beam (strong post) 8 Modified Thrie-Beam 9 Self-Restoring Barrier 10 Steel-Backed Wood Rail 11 Concrete Safety Shape 12 Stone Masonry Wall Subfield 2: Other See appendix S2 for more details on Barrier types.

S62	Raised Pavement Reflectors	Were raised pavement reflectors used to accent or replace painted pavement markings?	Numeric Length = 1	Yes No
S63	Terrain	Indicate the general terrain surrounding the crash site.	Numeric Length = 1	Flat Rolling Mountainous

Appendix C Roadside Hazard Ratings 1-7

Roadside Hazard Rating Pictorial Codes

(Source: Zegeer et al., 1988)

Roadside Hazard Rating – A subjective measure of the hazard associated with the roadside environment. The rating values indicate the accident damage likely to be sustained by errant vehicles on a scale from one (low likelihood of an off-roadway collision or overturn) to seven (high likelihood of an accident resulting in a fatality or severe injury).

The ratings are determined from a 7-point rural pictorial scale, as shown in Figures 1 through 7. The data collector should choose the rating value (1 through 7) that most closely matches the roadside hazard level for the roadway section in question. In many cases, the roadside hazard along a section will vary considerably, so the roadside hazard rating should represent a “middle” value (e.g., if ratings generally range from 4 to 6 along a section, a rating of 5 should be used to best represent the roadside hazard rating of the section).

Roadside Hazard Rating = 1

Figure 1. Rural roadside hazard rating of 1.

- Wide clear zones greater than or equal to 9 m (30 ft) from the pavement edgeline
- Sideslope flatter than 1:4
- Recoverable

Roadside Hazard Rating = 2

Figure 2. Rural roadside hazard rating of 2.

- Clear zone between 6 and 7.5 m (20 and 25 ft) from pavement edgeline
- Sideslope 1:4
- Recoverable

Roadside Hazard Rating = 3

Figure 3. Rural roadside hazard rating of 3.

- Clear zone about 3 m (10 ft) from pavement edgeline
- Sideslope about 1:3 or 1:4
- Rough roadside surface
- Marginally recoverable

Roadside Hazard Rating = 4

Figure 4. Rural roadside hazard rating of 4.

- Clear zone 1.5 to 3 m (5 to 10 ft) from pavement edgeline
- Sideslope about 1:3 or 1:4
- May have guardrail (1.5 to 2 m [5 to 6.5 ft] from pavement edgeline)
- May have exposed trees, poles, or other objects (about 3 m or 10 ft from pavement edgeline)
- Marginally forgiving, but increased chance of a reportable roadside collision

Roadside Hazard Rating = 5

Figure 5. Rural roadside hazard rating of 5.

- Clear zone 1.5 to 3 m (5 to 10 ft) from pavement edgeline
- Sideslope about 1:3
- May have guardrail (0 to 1.5 m [0 to 5 ft] from pavement edgeline)
- May have rigid obstacles or embankment within 2 to 3 m (6.5 to 10 ft) of pavement edgeline
- Virtually non-recoverable

Roadside Hazard Rating = 6

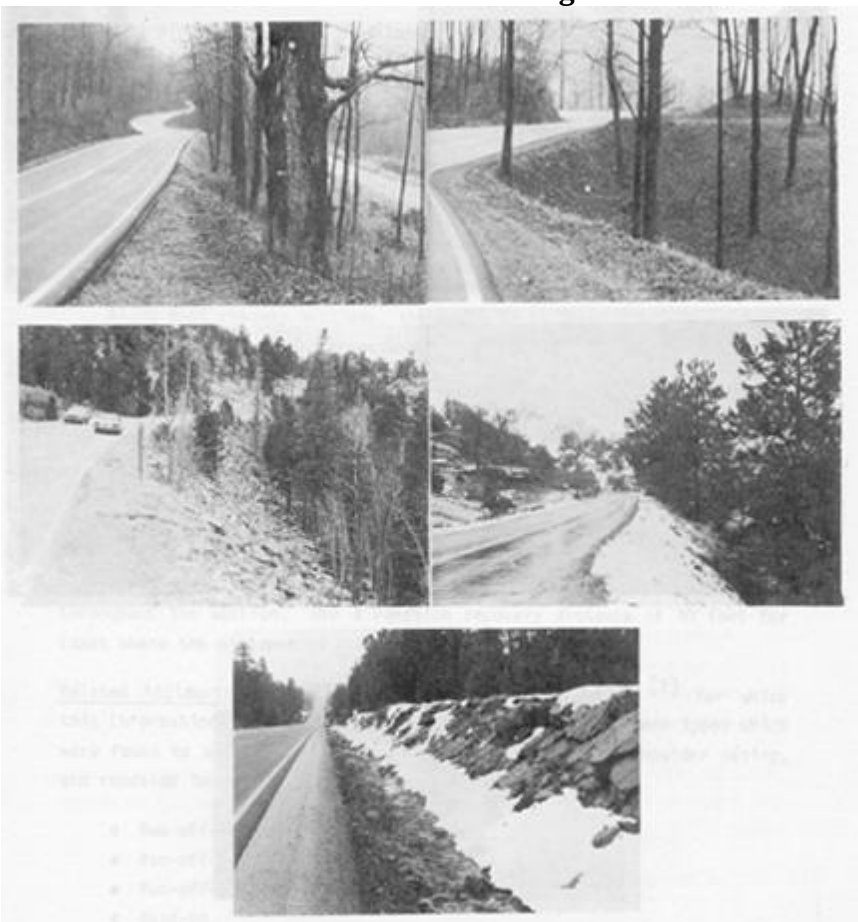

Figure 6. Rural roadside hazard rating of 6.

- Clear zone less than or equal to 1.5 m (5 ft)
- Sideslope about 1:2
- No guardrail
- Exposed rigid obstacles within 0 to 2 m (0 to 6.5 ft) of the pavement edgeline
- Non-recoverable

Roadside Hazard Rating = 7

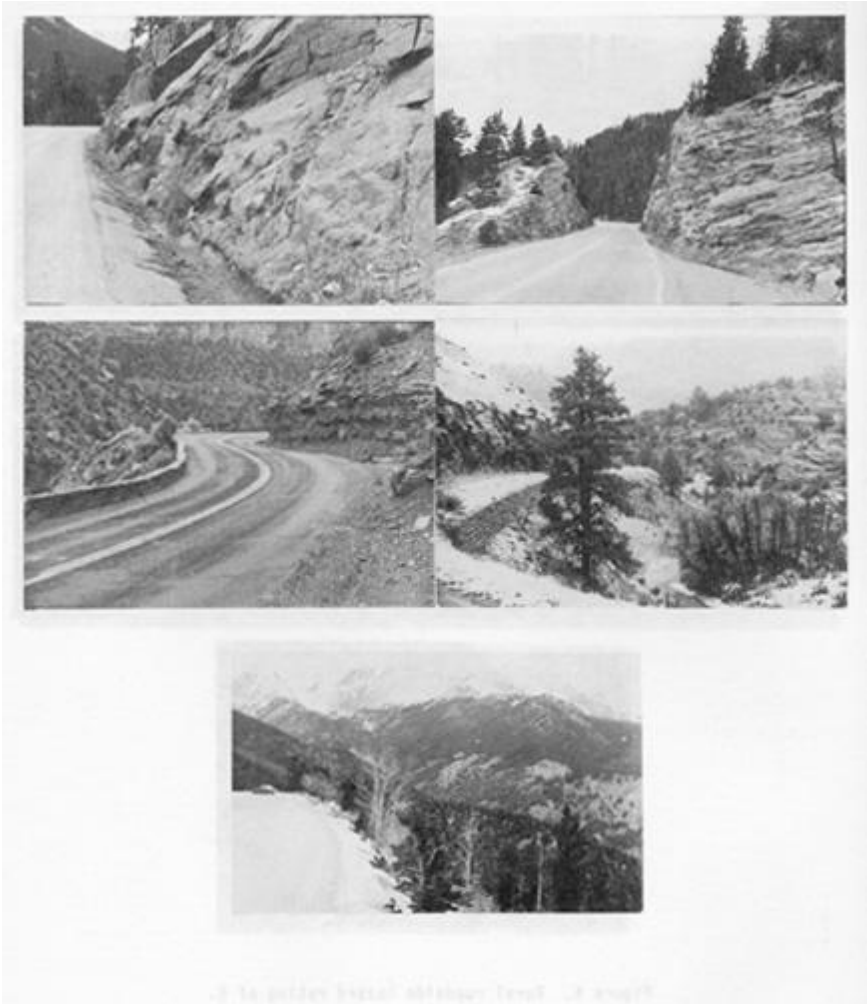

Figure 7. Rural roadside hazard rating of 7.

- Clear zone less than or equal to 1.5 m (5 ft)
- Sideslope 1:2 or steeper
- Cliff or vertical rock cut
- No guardrail
- Non-recoverable with high likelihood of severe injuries from roadside collision