AN ABSTRACT OF THE DISSERTATION OF

Jason C. Anderson for the degree of Doctor of Philosophy in Civil Engineering presented on July 18, 2018.

Title: Unobserved Heterogeneity and Spatial Correlation: Statistical and Econometric Analyses of Heavy-Vehicle Hard Braking and Crash Frequency by Crash Type

Abstract approved:

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This dissertation provides a comparison of statistical and econometric frameworks, using a previously unused freight data source, to study crash frequency by crash type and heavy-vehicle hard braking in Oregon. Hard braking can serve as a proxy for several factors, one of which is safety. Therefore, with the hard braking literature being limited to regenerative braking of electric vehicles, behavior modeling, and stopping performance, this dissertation uniquely fills the gap in literature as it pertains to hard braking of heavy-vehicles explicitly in a safety context. Hence, based on the data, the four most occurring crash types at areas prone to heavy-vehicle hard braking are analyzed: rear-end crashes, turning movement crashes, fixed-object crashes, and sideswipe (overtaking) crashes.

The new norm in transportation safety analyses is to account for the unobserved heterogeneity (unobservables) in the crash data. However, specific events may be linked spatially, which can result in spatial correlation. With this in mind, this dissertation seeks to analyze each crash type by fitting a model that accounts for unobserved heterogeneity and a model that accounts for spatial correlation. This is accomplished through a detailed data process and spatial analysis. To compare these analytic methods, overall model fit (log-likelihood values) and the rate of correctly predicted crash frequencies are assessed. With crash frequencies being non-negative integer count values, specific count-data models are applied: Poisson regression if the data is not over- or under-dispersed, Negative Binomial regression if the data is over- or under-dispersed, and Spatial Lag of X variants of these models if there is significant spatial correlation. Results show that three of the four crash frequency models have a better fit when accounting for spatial autocorrelation. But, the rate of correctly predicted crash frequencies for each crash type is substantially higher when accounting for unobserved heterogeneity.

As stated previously, through the comparison of the crash frequency analysis frameworks, the predictability power of the "heterogeneity" models outperformed the predictability of the spatial models. In addition to identifying a preferred method to model crash frequency, this dissertation shows the viability of a new freight data source for transportation research. More, the importance of studies regarding hard braking and crash frequency have been presented. This dissertation uniquely fills this gap in literature.

Finally, an analytical foundation and recommendations have been provided. With regard to the analytical method, several Departments of Transportation (DOT) use traditional crash frequency analysis methods; but, they typically do not account for unobserved heterogeneity. This work has shown that the Oregon DOT (location of the current study) can generate a higher rate of prediction by accounting for these unobservables in crash data. For recommendations, this dissertation identifies methods to monitor hard braking (both for heavy-vehicles and other classes of vehicles). In addition, the locations of heavy-vehicle hard braking hot spots, along with the significant crash frequency contributing factors, can assist the Oregon DOT in identifying specific countermeasures to mitigate hard braking events and crash frequency by crash type.

Unobserved Heterogeneity and Spatial Correlation: Statistical and Econometric Analyses of Heavy-Vehicle Hard Braking and Crash Frequency by Crash Type

by
Jason C. Anderson

A DISSERTATION

submitted to

Oregon State University

in partial fulfillment of
the requirements for the
degree of

Doctor of Philosophy

Presented July 18, 2018
Commencement June 2019

Doctor of Philosophy dissertation of Jason C. Anderson presented on July 18, 2018

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

Jason C. Anderson, Author

ACKNOWLEDGEMENTS

Before thanking anyone, I want to thank my advisor, Dr. Sal Hernandez. I have been with Dr. Hernandez for several years, during which I have been given many opportunities to succeed, publish papers, and obtain the ultimate goal of earning a Ph.D. I will forever be grateful to Dr. Hernandez for what he has done for me and I hope to repay him by becoming a successful faculty member and continuing to conduct high quality research. Through this journey, Dr. Hernandez has become more than just an academic advisor, but a lifelong friend. I look forward to many collaborations and publications over the years. Dr. Hernandez, thank you.

I also want to thank Dr. David Hurwitz. Although not a student of Dr. Hurwitz, he is willing to help in any way that he can and is readily available when that help is needed. The way you have helped me, I hope to help students the same once I become a faculty member. I will always remember the many recommendations you have made on my behalf. Dr. Hurwitz, thank you.

Being that I have been at Oregon State University for a decade (B.S. through Ph.D.), I want to thank Dr. Chris Bell and Dr. Shane Brown. During my undergrad, you were always available to talk about career paths and where I might see myself after graduation. These talks lead to this moment, and for that, I sincerely thank both of you.

I want to thank all the faculty at Oregon State, within the Transportation Department and outside the Transportation Department (if I named everybody that has impacted me, it may be a dissertation in itself). Oregon State has been so good to me and I will make it a life's goal to represent Oregon State in the way it deserves. I will

certainly visit this campus and give back in any way that I can. There's something special about the Civil Engineering Department at Oregon State and I am proud to say I'm from Oregon State University.

Lastly, and probably most importantly, I want to thank all my loved ones: my wife FeiFei, my mother Felicia, my brother James, and my brother Rybo. They love to give me a hard time about becoming a "Dr.", but when it comes to it, they have been very supportive through this entire process. I have grown both professionally and personally, and this is because you. Now, let's go get that faculty position!

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1.0 INTRODUCTION

In heavy-vehicles (a truck with a gross vehicle weight rating of greater than 10,000 pounds), a hard braking occurrence is often described as an event that prompts the "black box" to record an abrupt change in speed (Fried, 2015). This occurs when the driver of the heavy-vehicle applies excess force to the vehicle's brake and can serve as a proxy for several factors (Telogis, 2014). In economic terms, hard braking can impact overall gas mileage and has the potential to cost trucking firms up to three miles per gallon of gas (GPSTrackit, 2013, Telogis, 2014). Hard braking is also bad for the environment, as it increases pollutants due to higher fuel consumption and particle emissions due to brake wear (Telogis, 2014, Grigoratos and Martini, 2015). Specifically, wear due to hard braking can contribute to non-exhaust related PM_{10} emissions up to 55% by mass (Harrison et al., 2012) and up to 21% by mass for total PM_{10} emissions (Bukowieki et al., 2009, Gasser et al., 2009, Lawrence et al., 2013). Lastly, hard braking can be a sign of aggressive driving behavior (Telogis, 2014), in which approximately one-third of heavy-vehicle-caused crashes in 2014 were contributed to faulty brakes (EMC, 2014). The latter, hard braking as a sign of aggressive driving behavior, can directly impact safety and can be used by trucking fleets to better monitor driving behavior.

Considering braking, it is widely known that stopping distances for heavy-vehicles are substantially longer than passenger vehicles, and even more so when road surface conditions are wet and slippery (Mannering and Washburn, 2013, Insurance Institute for Highway Safety, 2017). This is illustrated in Figure 1.1, in which stopping distances for heavy-vehicles can be nearly double that of passenger vehicles. In addition to stopping distances being longer, heavy-vehicles have brake lag (Utah Department of Transportation, 2018). To illustrate the differences in total stopping distance at different speeds, refer to Figure 1.2.

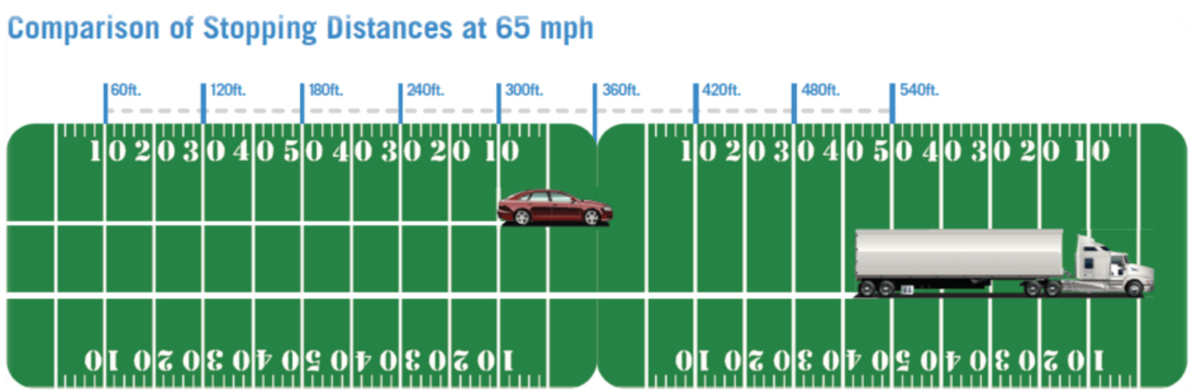

Figure 1.1: Comparison of Stopping Distances Between Passenger Vehicles and Heavy-Vehicles (Source: Utah Department of Transportation, 2018)

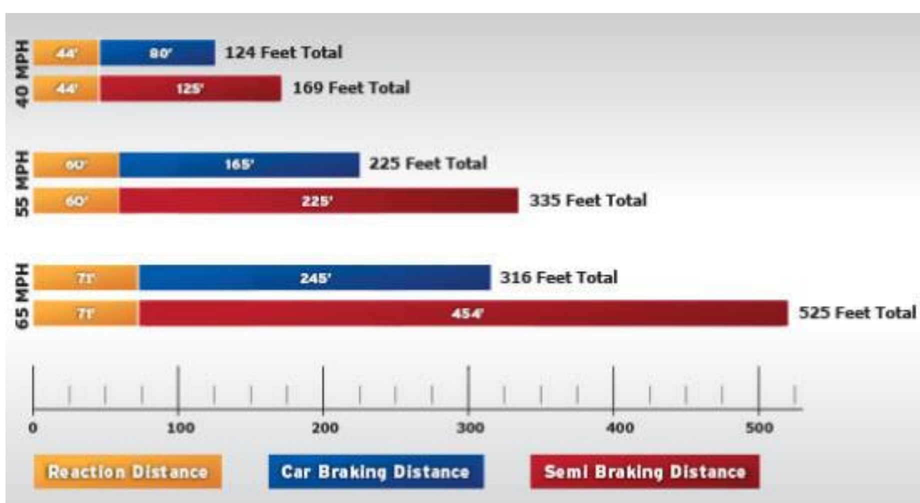

Figure 1.2: Total Stopping Distances at Various Speeds (Source: Utah Department of Transportation, 2018)

Although antilock brake systems improve driver control during a hard braking event, there is still a likelihood of jackknifing, rear-end crashes, fixed-object crashes, etc. (Dziuk, 2015, Insurance Institute for Highway Safety, 2017, Magoci, 2017). Therefore, the issue of hard braking, and the potential implications of such an event, was addressed in 2009 through a Federal Motor Vehicle Safety Standard amendment regarding air brake systems. Specifically, this rule required that the majority of new heavy-vehicles achieve a 30% reduction in stopping distance, where heavy-vehicles were to stop *"not in more than 250 feet when loaded to their gross vehicle weight rating and tested at a speed of 60 miles per hour (mi/hr)"* (National Highway Traffic Safety Administration, 2009). According to the National Highway Traffic Safety Administration (NHTSA), the intention of this amendment was to reduce the number of fatalities and injuries associated with heavy-vehicle braking. However, as will be shown through the current study, several crashes (and, therefore, injuries and fatalities) still occur (for all traffic mixes) in areas that are prone to a high number of heavy-vehicle hard braking events.

In light of this, the current research utilizes a previously unused freight data source to investigate crash frequency of all traffic mixes by crash type at heavy-vehicle hard braking hot spots in Oregon:[1] EROAD. EROAD is a fully integrated regulatory technology provider, which through the use of their electronic logging device (ELD) system, collects unique data, such as heavy-vehicle hard braking locations. For the

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[1] Heavy-vehicle hard braking hot spots are described in detail in Section 4.2.

purposes of this study, EROAD has provided its data in an unidentifiable aggregated form. Using this data, a kernel density analysis is performed to identify high density areas of heavy-vehicle hard braking. Upon identification of these high density areas, a hot spot analysis is conducted to determine and locate statistically significant heavy-vehicle hard braking hot spots (i.e., locations prone to heavy-vehicle hard braking events). After the hot spot analysis, several datasets are merged before being spatially joined to the heavy-vehicle hard braking hot spots. Next, the four crash types that occurred most frequently at these locations (i.e., hard braking hot spots) are identified: rear-end crashes, turning movement crashes, fixed-object crashes, and sideswipe (overtaking) crashes. The four crash types are then modeled using an econometric approach, random parameters Poisson and Negative Binomial models, to determine significant contributing crash frequency factors by crash type. At last, a spatial analysis is performed to determine if spatial autocorrelation is present among hard braking hot spots and a Spatial Lag of X (SLX) model for each crash type is then estimated and compared to the random parameters models. It is hypothesized that both unobserved heterogeneity and spatial autocorrelation are present in the utilized datasets. Therefore, this dissertation seeks to determine if these are in fact present. Further, if present, the current research will determine if accounting for data-variation or spatial autocorrelation provides better overall fit and correctly predicted crash frequencies for the given dataset.

1.1 National Crash Statistics

As stated previously, the four crash types that occurred most often at the heavy-vehicle hard braking hot spots are analyzed: rear-end crashes, turning movement crashes, fixed-object crashes, and sideswipe (overtaking) crashes.

Over the past few years there have been more than 6 million police-reported crashes in the United States (National Highway Traffic Safety Administration, 2016, 2017). In addition, crashes by injury severity have also experienced an increase over the last couple of years (National Highway Traffic Safety Administration, 2016, 2017, 2018). From 2014 to 2015, there was a 3.03% increase in the number of injury crashes (1.65 million to 1.7 million) (National Highway Traffic Safety Administration, 2016, 2017). In terms of fatalities, there was a 8.26% increase from 2014 to 2015 (29,989 to 32,166) and a 7.07% increase from 2015 to 2016 (32,166 to 34,439) (National Highway Traffic Safety Administration, 2016, 2017, 2018).[2] As seen from these statistics, there is a clear upward trend in terms of injury and fatal crashes in the United States.

In terms of the crash types considered in the current study, rear-end crashes (all injury severities) experienced a 6.87% increase from 2014 to 2015 (1,966,000 to 2,101,000) (National Highway Traffic Safety Administration, 2016, 2017). In regards to fatalities, the only crashes compiled in the newest document from NHSTA, there was a 12.05% increase in fatal rear-end crashes from 2014 to 2015 (1,966 to 2,203)

[2] Due to the change in collecting data (Crash Report Sampling System was adopted in 2016), crash statistics for injury and no injury crashes are not yet available (National Highway Traffic Safety Administration, 2018). Therefore, only the number of fatal crashes can be provided for 2016.

(National Highway Traffic Safety Administration, 2016, 2017). Then, from 2015 to 2016, there was another increase of 6.67% in fatal rear-end crashes (2,203 to 2,350) (National Highway Traffic Safety Administration, 2018).

The next crash type considered in the present study is turning movement. Based on national statistics, there was a slight decrease of 0.67% in the total number of turning movement crashes (essentially no change in the total number of turning movement crashes). However, when considering fatalities (the only crashes compiled in the newest document from NHSTA), there was an 8.67% increase from 2014 to 2015 and an 11.16% increase from 2015 to 2016 (National Highway Traffic Safety Administration, 2016, 2017, 2018). As shown, a significant increase in the frequency of turning movement crashes is observed over recent years.

The third crash type considered for the current study is fixed-object. From 2014 to 2015, there was an increase of 2.21% in the total number of fixed-object crashes (906,000 to 926,000) (National Highway Traffic Safety Administration, 2016, 2017). Again, considering fatalities (the only crashes compiled in the newest document from the NHSTA), there was an increase of 2.04% from 2014 to 2015 and an increase of 4.9% from 2015 to 2016 (9,939 to 10,426) (National Highway Traffic Safety Administration, 2016, 2017, 2018). Once more, an increase in a specific crash type is observed.

The final crash type occurring most often at heavy-vehicle hard braking hot spots is sideswipe (overtaking). According to national statistics, sideswipe crashes experienced an 8.85% increase from 2014 to 2015 (712,000 to 775,000) (National

Highway Traffic Safety Administration, 2016, 2017). But, yet again, when considering fatalities (the only crashes compiled in the newest document from NHSTA), an increase of 1.73% was observed for sideswipe crashes from 2014 to 2015 (810 to 824) and an increase of 14.08% was observed from 2015 to 2016 (824 to 940) (National Highway Traffic Safety Administration, 2016, 2017, 2018).

To visualize the trend in rear-end crashes since 2011, refer to Figure 1.3. Other than a slight decrease in the total number of rear-end crashes and the number of fatal rear-end crashes from 2012 to 2013, there is a steady increase in the number of rear-end crashes (both in total and fatal). Next is the trend for turning movement crashes since 2011, as shown in Figure 1.4. Similar to that of rear-end crashes, a steady increase in the total number of turning movement crashes is observed, with the exception of a slight decrease from 2014 to 2015. As for fatal turning movement crashes, there is a noticeable increase from 2011 to 2016. Turning to fixed-object crashes (shown in Figure 1.5), there is an increasing trend in the total number of fixed-object crashes from 2011 to 2015. However, when considering the number of fatal fixed-object crashes, the trend is not as consistent. Although there was a significant decrease from 2012 to 2014, there has been a significant increase since (2014 to 2016). To conclude, sideswipe crash trends from 2011 to 2016 are shown in Figure 1.6. In terms of the total number of sideswipe crashes, there is a constant increase from 2011 to 2015. In general, regarding fatal sideswipe crashes, there is an increasing trend from 2011 to 2016; but, there was a slight decrease in the number of fatal sideswipe crashes from 2012 to 2013.

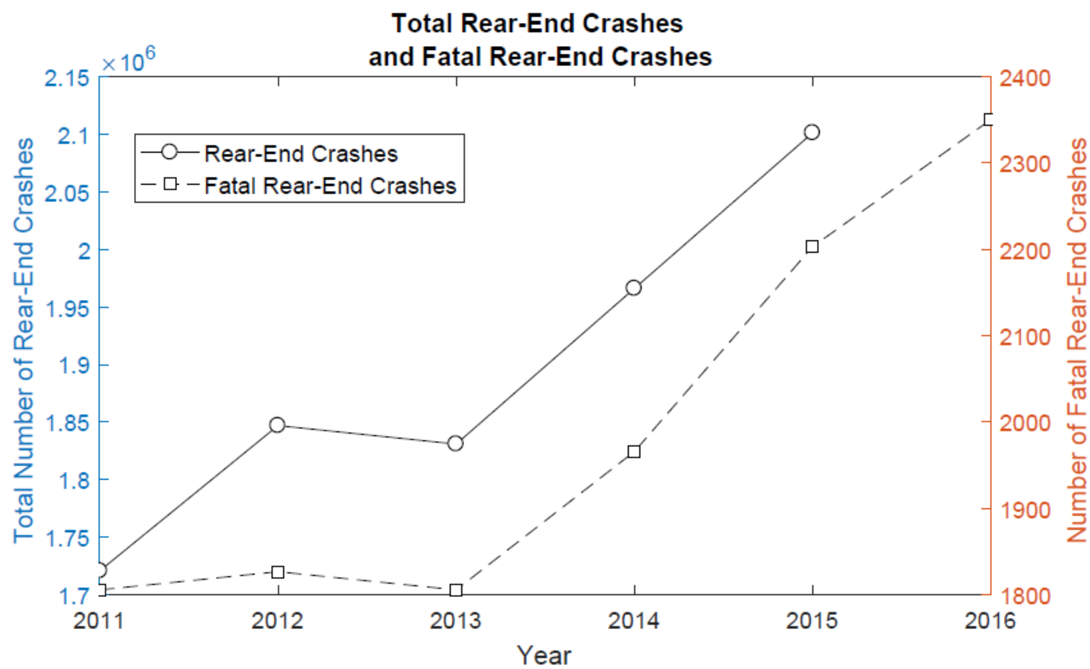

Figure 1.3: Nationwide Rear-End Crash Trends From 2011 to 2016

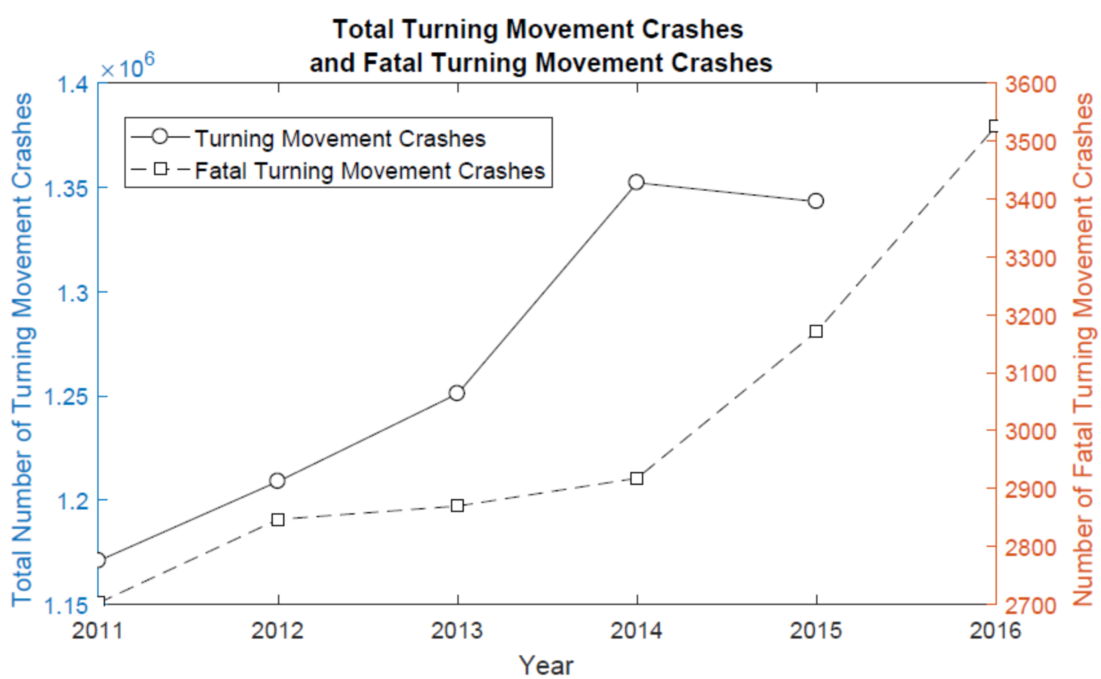

Figure 1.4: Nationwide Turning Movement Crash Trends From 2011 to 2016

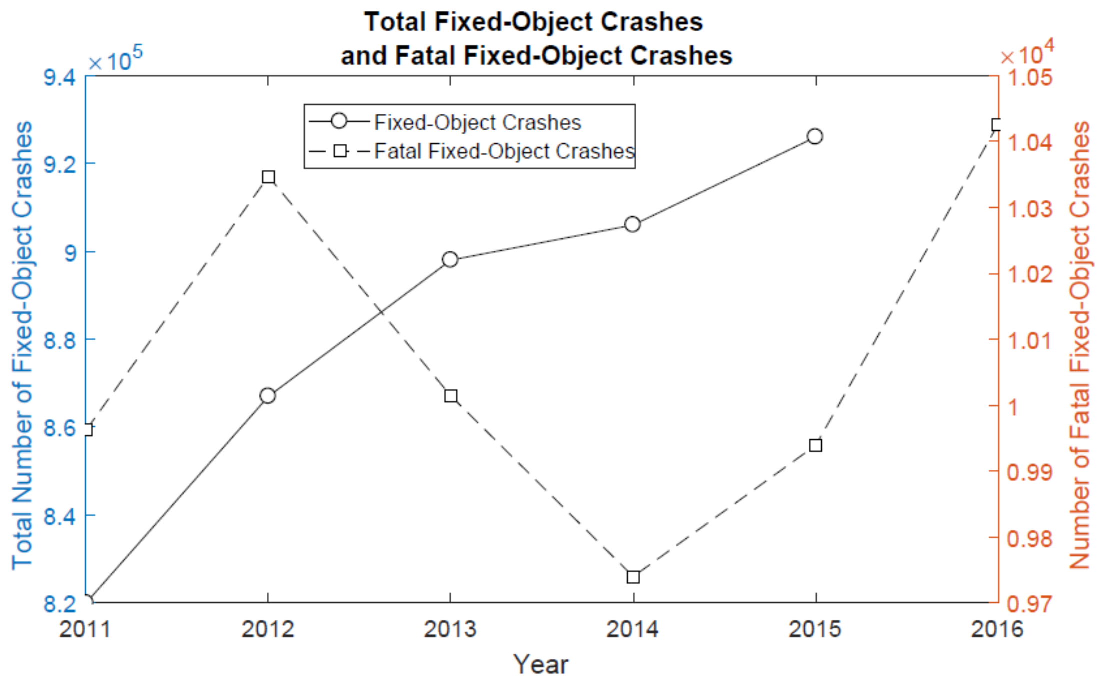

Figure 1.5: Nationwide Fixed-Object Crash Trends From 2011 to 2016

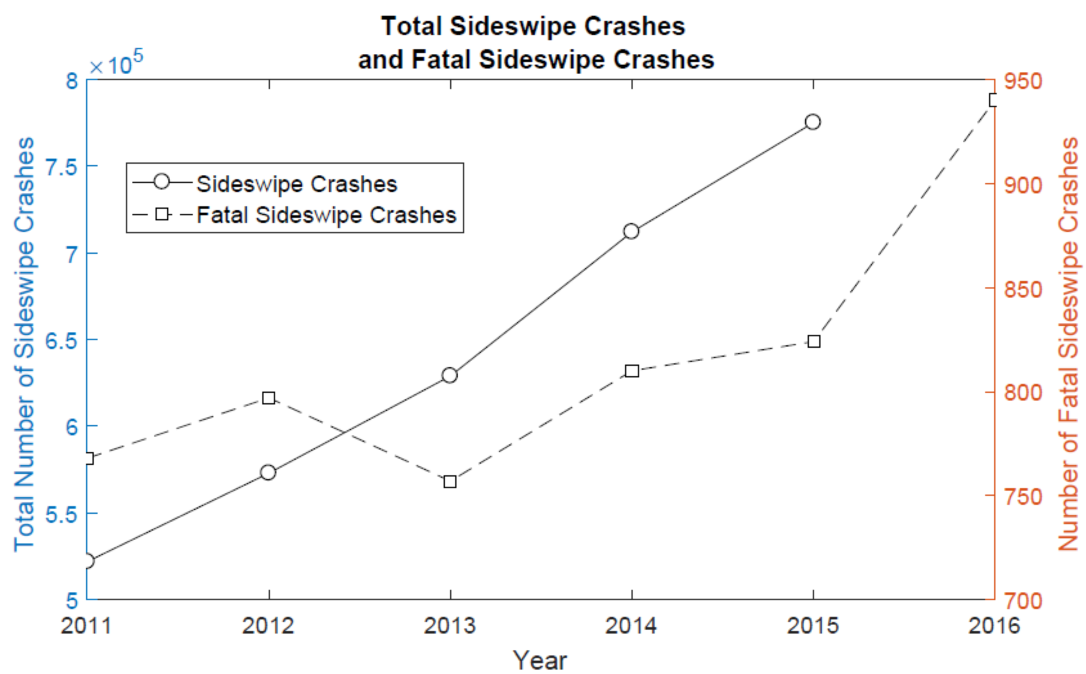

Figure 1.6: Nationwide Sideswipe Crash Trends From 2011 to 2016

The presented trends show that the crash types which occurred most often at heavy-vehicle hard braking hot spots are crashes that, nationwide, have been increasing in recent years (i.e., the frequency of these crashes is getting higher). These statistics illustrate a need to better understand the exposure-based factors that contribute to a respective crash frequency. More, considering these crashes are the most occurring crashes at heavy-vehicle hard braking hot spots in Oregon, the implications of these crashes can be more severe.

1.2 Oregon Crash Statistics

Because the current study takes place in Oregon, the crash trends in Oregon for the crash types considered are also presented. As discussed previously, the first crash type considered is rear-end. Therefore, referring to Figure 1.7, rear-end crash trends in Oregon are shown. In terms of the total number of rear-end crashes, there is a steady increase from 2011 to 2015, with a significant increase from 2014 to 2015. In particular, from 2011 to 2014, Oregon experienced a 4.49% increase (17,618 to 18,409) in the total number of rear-end crashes. Then, from 2014 to 2015, there was an increase of 9.07% (18,409 to 20,079) in the total number of rear-end crashes in Oregon. With regard to fatal rear-end crashes in Oregon, there was a decrease of 33.3% (15 to 10) from 2011 to 2013. However, this was followed by a significant increase of 150% (10 to 25) from 2013 to 2014.

The following crash type is turning movement, in which trends are shown in Figure 1.8. For this crash type, in terms of total turning movement crashes, there has been a steady increase since 2013. Pointedly, Oregon experienced a 9.57% increase (9,884 to 10,830) in the total number of turning movement crashes from 2013 to 2014 and a 7.5% increase (10,830 to 11,642) from 2014 to 2015 (this is an increase of 17.8% from 2013 to 2015). In regards to fatal crashes, there was an increase of 47.4% (19 to 28) in the number of fatal turning movement crashes from 2012 to 2013. This was then followed by a decrease of 21.4% (28 to 22) from 2013 to 2014, which was again followed by a significant increase. Notably, from 2014 to 2015, Oregon had a 50% increase (22 to 33) in the number of fatal turning movement crashes.

Fixed-object crashes is the next crash type, in which trends in Oregon are presented in Figure 1.9. As shown, in terms of total fixed-object crashes, there was not much movement in the trend from 2011 to 2013. However, from 2013 to 2014, there was a 1.97% increase (8,214 to 8,376) in the total number of fixed-object crashes and a 3.75% increase in the total number of fixed-object crashes from 2014 to 2015 (8,376 to 8,690) (a 5.79% increase from 2013 to 2015). Regarding fatal crashes, there has been an increase each year since 2012. From 2012 to 2013, there was an 8.26% increase (109 to 118) in the number of fatal fixed-object crashes. Then, from 2013 to 2014, there was a 2.54% increase (118 to 121) in the number of fatal fixed-object crashes. Finally, from 2014 to 2015, there was a 26.45% increase (121 to 153) in the number of fatal fixed-object crashes. In total, from 2012 to 2015, there has been a 40.4% increase in the number of fatal fixed-object crashes.

The final crash type is sideswipe (overtaking), where trends for these crashes in Oregon can be seen in Figure 1.10. With regard to the total number of sideswipe (overtaking) crashes, Oregon has experienced an increase each year since 2012. Specifically, from 2012 to 2013, there was a 5.89% increase (3,106 to 3,289). Next, from 2013 to 2014, Oregon had a 3.77% increase (3,289 to 3,413) in the total number of sideswipe (overtaking) crashes. And, lastly, from 2014 to 2015, there was a 10.5% increase in the total number of sideswipe (overtaking) crashes in Oregon. This results in a total increase of 21.4% from 2012 to 2015.

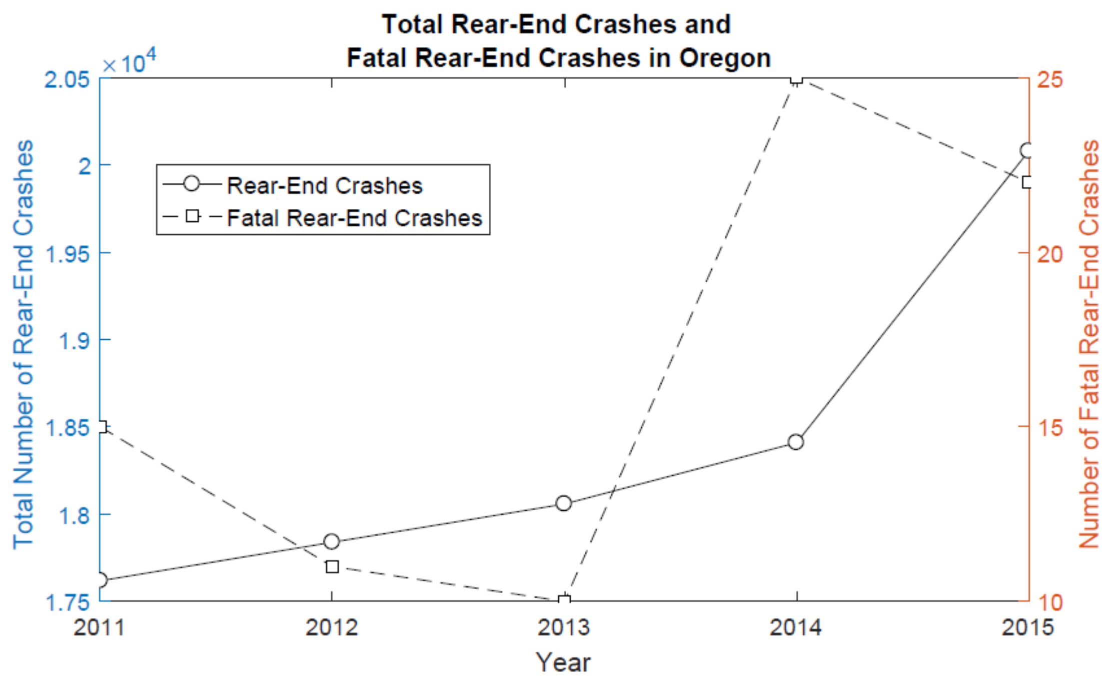

Figure 1.7: Rear-End Crash Trends in Oregon From 2011 to 2015

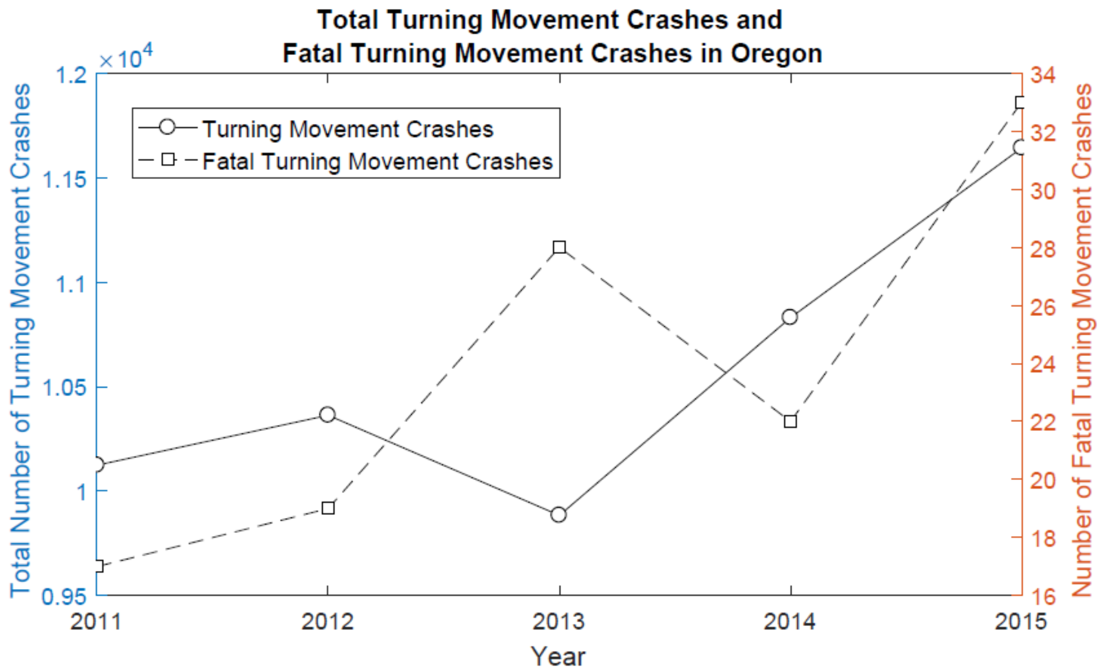

Figure 1.8: Turning Movement Crash Trends in Oregon From 2011 to 2015

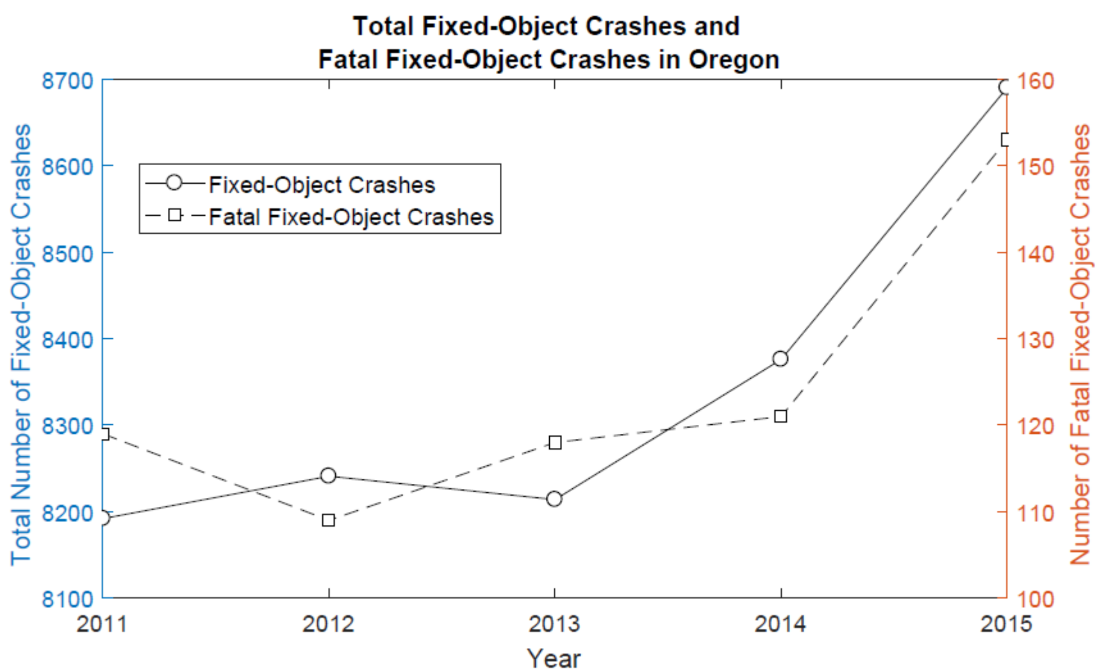

Figure 1.9: Fixed-Object Crash Trends in Oregon From 2011 to 2015

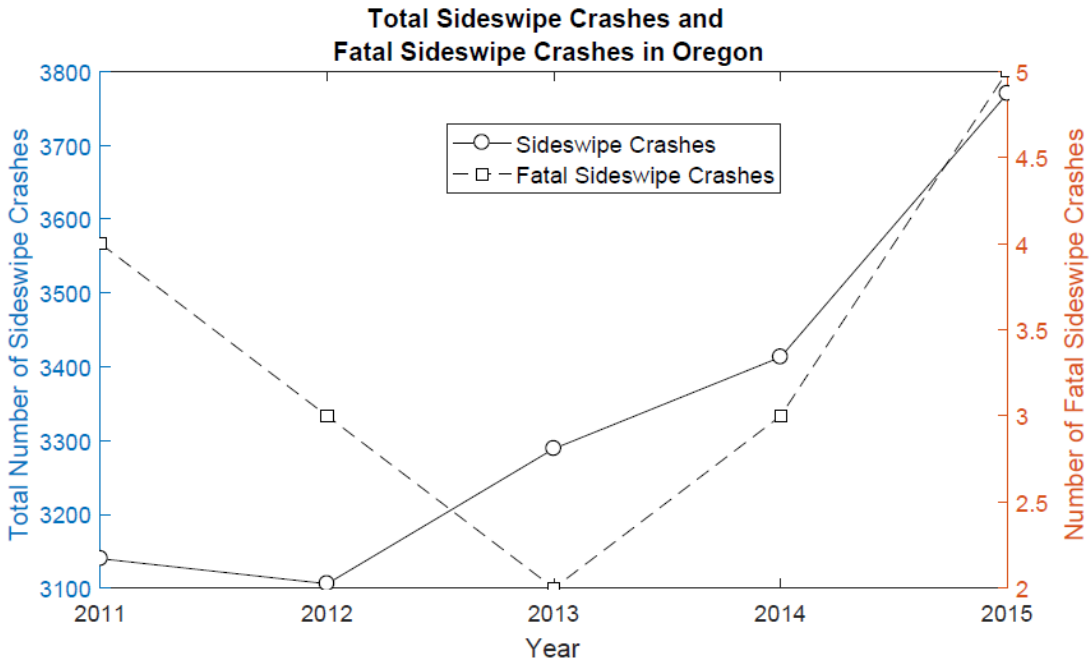

Figure 1.10: Sideswipe (Overtaking) Crash Trends in Oregon From 2011 to 2015

Once more, the trends in Oregon show that the crash types which occurred most often at heavy-vehicle hard braking hot spots have been increasing in recent years, some significantly (i.e., the frequency of these crashes is getting higher). These statistics illustrate a need to better understand the exposure-based factors that contribute to a respective crash frequency in Oregon. Considering these crashes are the most occurring crashes at heavy-vehicle hard braking hot spots, the implications of these crashes can be more severe.

1.3 Dissertation Objectives

There are several objectives of this dissertation, with the primary one being the exploration and comparison of two analytic methods for transportation safety (i.e., crash frequency) analysis. The proposed methods include an approach to account for unobserved heterogeneity (unobservables) often present in crash data and an approach to account for spatial autocorrelation. The motivation for these analyses stem from the research question: *"Does accounting for unobserved heterogeneity or spatial autocorrelation provide better overall model fit and/or a higher rate of correctly predicted crash frequencies?"* Therefore, to answer this question, the crash frequency analyses are accomplished through a detailed statistical analysis and econometric modeling approach. To achieve this dissertation object, several intermediate objectives are addressed:

a) Review current and relevant literature as it pertains to hard braking and crash frequency analysis. Review of hard braking literature will be used to identify gaps as it relates to hard braking safety analyses, with a specific focus on heavy-vehicles. Next, the crash frequency literature will reveal state-of-the-art methods used to analyze crash frequency while addressing specific data limitations (e.g., unobserved heterogeneity, spatial correlation). This will also consist of identifying a gap in literature in regards to heavy-vehicle crash frequency analysis.

b) Use a previously unused freight data source to determine areas that are prone to heavy-vehicle hard braking (i.e., heavy-vehicle hard braking hot spots). Being this data has yet to be used in a research context within the United States, this particular objective will also focus on the viability of using this data source and conclude if this freight data source can be used in future freight research ventures.

c) Utilizing the previously unused freight data source, merge with crash data and several exposure-based datasets to obtain the most comprehensive dataset to be used for the crash frequency analysis.

d) Develop a method to conduct a kernel density and hot spot analysis for heavy-vehicle hard braking locations. The primary focus of this objective is to identify high density areas of heavy-vehicle hard braking and identify heavy-vehicle hard braking hot spots. The hot spots will be used to aggregate the crash data. That is, the crash frequency analyses will be conducted at the heavy-vehicle hard braking hot spots.

e) Develop an econometric modeling approach to determine statistically significant crash frequency contributing factors by crash type. This will also include a method to account for the unobserved heterogeneity often present in crash data, as well as several other types of data. If unobserved heterogeneity is present and not accounted for, model estimates can be biased and result in incorrect inferences and corresponding recommendations.

f) Develop a spatial econometric modeling approach to account for spatial autocorrelation. If there is significant spatial autocorrelation, parameter estimates can be biased and result in incorrect inferences and corresponding recommendations.

g) Compare analysis results from the two analytical approaches. This will include assessing overall model fit and the number of correctly predicted crash frequencies. This comparison will identify a preferred method, for the given data, for conducting crash frequency analysis. In addition, comparison of results can motivate future work to consider accounting for unobserved heterogeneity and spatial autocorrelation.

1.4 Dissertation Organization

This dissertation is comprised of seven chapters, each of which addresses one of the aforementioned dissertation objectives. Chapter 2.0 reviews the current and relevant literature as described in Chapter 1.3. As discussed, hard braking studies will be reviewed to identify a gap in regards to hard braking and transportation safety analysis. Next, state-of-the-art methodologies for transportation crash frequency analysis will be reviewed.

Chapter 3.0 presents and discusses, in detail, the data used for the current study. First, the source of the previously unused freight data source is described, as well as how this data will be used for this dissertation. Next, the merging of several datasets will be explained, after which a full discussion on the variables included in the comprehensive dataset is provided. During this section, several figures are provided to further illustrate the extent of the data and present key variables within the data. This chapter also exhibits the four most occurring crash types that will be used for the crash frequency analysis.

Chapter 4.0 presents the methodological approaches used in the current study. First, the methodology for the kernel density analysis is presented and, as stated previously, is used to identify high density heavy-vehicle hard braking areas. Second, the methodology for the hot spot analysis is detailed. This analysis plays an important role in the overall objective of this dissertation, as the heavy-vehicle hard braking hot spots are the crash locations being used for the crash frequency analysis (i.e., crashes are aggregated at these locations). Thirdly, the econometric modeling approach for data that is not over- or under-dispersed is shown: the Poisson regression model (the integration of random parameters used to account for unobserved heterogeneity is also presented). Fourthly, the econometric modeling approach for data that is over- or under-dispersed is shown: the Negative Binomial regression model. Again, the integration of random parameters used to account for unobserved heterogeneity is also shown. Fifth, the methods used to test for spatial autocorrelation are thoroughly discussed. This method is used to determine if a spatial econometric modeling approach is appropriate. Finally, the spatial econometric modeling approach is presented for both the Poisson and Negative Binomial models. As discussed formerly, this method is the SLX model and is used to account for spatial autocorrelation.

Chapter 5.0 presents the results from all analyses. Chapter 5.0 begins with the results from the kernel density analysis, which shows high density heavy-vehicle hard braking areas. Next, results from the hot spots analysis are shown. Both the results for the kernel density analysis and hot spot analysis are portrayed via maps created in ArcGIS®. Once more, the results shown for the hot spot analysis are the locations used for the crash frequency analyses. In regards to the crash frequency analyses, the results (by crash type) from the method used to account for unobserved heterogeneity are presented first. After the modeling results accounting for unobserved heterogeneity are given, the test results for spatial autocorrelation are provided. These results show that spatial autocorrelation is, in fact, present in the crash datasets considered in the current study. Lastly, modeling results from the spatial econometric modeling approach are reported.

Chapter 6.0 includes a full discussion of results for each of the aforesaid analyses. This includes a discussion of the kernel density analysis, a discussion of the heavy-vehicle hard braking hot spot analysis, a discussion of the unobserved heterogeneity modeling results, a discussion of the spatial autocorrelation tests, and a discussion of the spatial econometric modeling results. Chapter 6.0 continues by a discussion comparing the various models in terms of overall model fit and rate of correctly predicted crash frequencies. This particular discussion is supplemented by figures that illustrate the rate of correctly predicted crash frequencies. Upon completing the comparison of modeling approaches, a summary of the comparisons is reported. To conclude Chapter 6.0, a discussion on the difference in significant crash frequency contributing factors is provided. This shows that exposure-based contributing factors differ by crash type.

Chapter 7.0 summarizes the work completed in this dissertation. This includes summary remarks regarding insights from analysis results, as well as recommendations to reduce crash frequency by crash type. This section also provides a recommendation for all vehicles to monitor their hard braking. Chapter 7.0 concludes by identifying significant contributions and avenues for future research as a result of the current study.

2.0 RELEVANT LITERATURE

Review of current and relevant literature for the current study consists of three specific categories: (1) literature pertaining to braking, (2) literature regarding heavy-vehicle braking, and (3) literature concerning crash frequency analysis. Therefore, Chapter 2.0 is divided into subsections to review each category of literature separately. This chapter will conclude by illustrating the gaps in literature and how the current study aims to fill these gaps.

2.1 Vehicular Braking Work

2.1.1 Braking Performance

In terms of braking research, recent years have shown that the primary focus is on regenerative braking of electric vehicles (Nian et al., 2014, Zou et al., 2015, Lv et al., 2015, Maia et al., 2015, Björnsson and Karlsson, 2016, Pan et al., 2016, Qiu and Wang, 2016, Li, Li, et al., 2016, Li, Zhang, et al., 2016, Itani et al., 2017, Liu et al., 2017, Mehta and Hemamalini, 2017, Chen et al., 2018). These works focus solely on the performance of regenerative braking, but some do investigate the effects of regenerative braking on safety (Oleksowics et al., 2013, Oleksowicz et al., 2013, Patel et al., 2015, Lian et al., 2016, Xu et al., 2016, Qiu et al., 2018) and the effects of regenerative braking on the environment (Wayne et al., 2004, Sovran and Blaser, 2006, Clarke et al., 2010, Boretti, 2011, Lorf et al., 2013). Unfortunately, this abundance of literature available for regenerative braking is not comparable to the limited literature in regards to hard braking.

As stated previously, work as it pertains to hard braking is substantially limited when compared to other areas of braking research. On that note, there have been recent works on braking performance, in which some attempt to integrate the idea of hard braking. For example, Hamid et al. (2012) investigate the effects of hard particles on friction coefficients and particle embedment during hard braking events. Hamid et al. (2012) used silica sands grit between 180 and 355 micrometers during their experiment, then compared results using the grit to results in which no grit was present. In doing experiments with and without the grit, the authors were able to assess the change in friction coefficients, fluctuation of frictional oscillation amplitude, and the percentage of particle embedment. In addition, Hamid et al. (2012) applied different sliding speeds to investigate the relationship between particle embedment with a friction coefficient and the friction oscillation amplitude. Through their experiments, Hamid et al. (2012) concluded that the presence of hard particles of different grit size do significantly affect friction coefficients and oscillation amplitude during a hard braking event.

Still considering braking performance, Hamersma and Els (2014) explored the improvement of braking performance of a vehicle with an anti-lock brake system (ABS) with a semi-active suspension. The authors, while motivating their work, state that ABS have contributed to significant advances in vehicle braking and directional control. However, ABS can have opposite effects (i.e., longer stopping distances) if a vehicle is traveling on an undulating road. Through a simulation-based approach, Hamersma and Els (2014) discovered that suspension systems play a pivotal role in braking performance on hard, rough roadways. Ultimately, the impact of suspension systems on braking performance can lead to differences in stopping distances of up to 9 meters (roughly 29.5 feet).

Also investigating braking performance, Fitch et al. (2010) considered driver braking performance to surprise and expected events. It has been shown that driver braking characteristics can vary as a result of research methodologies (Green, 2000, Summala, 2000, Muttart, 2005); therefore, Fitch et al. (2010) contribute to the literature by classifying driver behavior during surprise events and expected events (an investigation into gender, age, and vehicle type is also explored). With 64 drivers performing surprise and expected braking events at 45 mi/hr, in two different vehicle types, Fitch et al. (2010) found that braking performance varied by gender, age, and vehicle driven.

Continuing with braking performance, Harbluk et al. (2007) performed an on-road assessment of cognitive distraction and its effects on braking performance (the authors also assessed visual behavior as a result of cognitive distraction). Drivers traveling an 8 kilometer (approximately 4.97 miles) segment were assessed under three conditions: (1) no additional task, (2) an easy cognitive task, and (3) a difficult cognitive task. Harbluk et al. (2007) observed braking performance differences among the three conditions. Specifically, under the most difficult cognitive tasks, a higher number of hard braking events were detected. During their study, these hard braking events (roughly 85%) happened at signalized intersections.

To conclude the braking performance review, Smith et al. (2003) analyzed braking (and steering) performance in different car-following scenarios. The authors begin by defining four specific driving states: (1) low risk, (2) conflict, (3) near crash, and (4) crash imminent. These four driving states are used to assess driver braking (and steering) performance in two car-following scenarios: (1) lead vehicle stopped and (2) lead vehicle moving. Smith et al. (2003), utilizing experimental data collected from test track studies, discovered that braking performance (specifically, "last-second" braking) was contingent on one of the four dynamic scenarios defined formerly. Lastly, Smith et al. (2003) found that drivers in the two car-following scenarios initiated their "last-second" braking at longer distances when compared to their steering maneuvers.

2.1.2 Brake Behavior Modeling

During the literature review, three specific studies regarding brake behavior modeling were relevant to hard braking. In the first study, Delaigue and Eskandarian (2004) develop a comprehensive braking model to predict stopping distances. As part of their study, they integrate hard braking (in some cases, they refer to hard braking as emergency braking). One of their first steps in model development was to correct for drum brakes. Delaigue and Eskandarian (2004) explain that during a hard braking event, drum brakes often gain less effective heat dissipation compared to disc brakes. As such, Delaigue and Eskandarian (2004) state that this difference results in substantial braking potential differences during a hard braking event. To account for this, the authors introduce a correction factor conditional on the heat dissipated in the brakes. Upon their simulation, they validated their model using sets of experimental braking data. As this relates to hard braking, Delaigue and Eskandarian (2004) assumed a hard brake pedal application. Under this assumption, high brake application rates and final force values were executed by the driver of the vehicle (this ensured that the ABS was triggered as quickly as possible). The results from their work showed that their simulation adequately modeled hard braking events and their corresponding stopping distances during NHSTA tests (variations were always with $\pm$ 9%).

The second study regarding brake modeling was conducted by Fancher et al. (2001). In their study, they developed a human-centered design of an ACC-with-braking and a forward-crash-warning system. In their model, however, Fancher et al. (2001) elected to avoid hard braking events by forfeiting some of the time-headway. Their argument in doing so was predicated on the difficulty in separating mandatory and discretionary braking events. Namely, drivers can perform a hard braking event because they want to stop or slow down quickly (Fancher et al., 2001). Or, drivers can perform a hard braking event due to mistakes in observation or prediction (Fancher et al., 2001). In the end, Fancher et al. (2001) state that modeling hard braking events could be attainable if researchers were able to measure what drivers are thinking during their braking maneuvers.

The final reviewed modeling work considers a safety and capacity analysis of automated and manual highway systems. In particular, Carbaugh et al. (1998) compares the safety of automated and manual highway systems as it relates to rear-end crash frequency and severity. Of specific focus to Carbaugh et al. (1998), is modeling the probability and severity of the first rear-end crash due to a hard braking disturbance in the traffic flow. To do this, the authors model the behavior of two vehicles in a hard braking event using six parameters, in which each parameter represents an initial condition where a hard braking event can begin. Utilizing these parameters and a simulation framework, Carbaugh et al. (1998) discovered that automated driving is safer (i.e., reduces probability of frequency and severity during a hard braking event) compared to most alert manual drivers.

2.1.3 Naturalistic, Simulator Braking Studies

Of all the braking research, excluding regenerative braking of electric vehicles, several works focus on braking behavior using naturalistic or simulator driving studies. The first reviewed work considers the real world safety benefits of brake assistance systems (Breuer et al., 2007). Making use of a Mercedes-Benz test car, several simulator and practice trials were conducted. Breuer et al. (2007) gathered 110 male and female drivers to take part in a series of tests, in which they were exposed to various common critical situations on motorways and country roads based on findings from previous work. In their study, they observed that drivers were able to avoid crashes by hard braking alone. Breuer et al. (2007) attributed this to the new Brake Assist PLUS system in the test vehicle, where the crash rate decreased by 75%.

The next study with a consideration of hard braking investigated the effects of Intelligent Cruise Control (ICC) on driver braking behavior (Hogema and Janssen, 1996). The primary focus of Hogema and Janssen (1996) was to assess driver behavior with the ICC system that automatically regulates speed and can maintain an appropriate following distance behind a leading vehicle. In their study, Hogema and Janssen (1996) found that the ICC would deliver a warning sound (i.e., an alarm) if the following vehicle was approaching the leading vehicle too fast. As a result, it was found that the ICC was unable to slow the following vehicle to avoid a rear-end crash. In other words, Hogema and Janssen (1996) discovered that drivers had to take control of the vehicle (i.e., deactivate the ICC) in situations that required a hard braking event to avoid a crash.

Continuing, the following study attempted to detect real-time drivers' stress in a potentially stress occurring event (Rigas et al., 2012). Rigas et al. (2012) argue that more knowledge on causes of a driver's stress can assist in future navigation systems. To illustrate this, Rigas et al. (2012) state that if a hard braking event causes a driver's stress level to increase, it can be used by a collision warning system to alter driving strategy appropriately. In their work, the authors propose using a GPS system and a vehicles Controller Area Network-bus to extract features that can identify hard braking events, as this may cause a stress event for a driver. Rigas et al. (2012) found that hard braking can result in a low-to-medium stress event incurred by the driver.

The subsequent study utilized naturalistic driving data to determine if vehicle longitudinal jerk can be used to identify aggressive drivers. In regards to braking, Feng et al. (2017) use vehicle sensor data from a naturalistic driving study to examine jerk-based metrics of a driver's frequency of having large negative jerk when the brake pedal is applied. To do this, drivers were classified into an aggressive group and a normal group. Feng et al. (2017) used brake cylinder pressure to determine how hard the brake pedal was pressed, where all measurements were made with a sampling rate of 10 Hz. Based on their naturalistic driving data, results showed that the frequency of large negative jerks (i.e., hard braking) had a significantly better performance in identifying aggressive drivers. In addition, a sensitivity analysis was conducted and determined that the findings were consistent with varying parameters.

Also using naturalistic driving data, Kiefer et al. (2005) developed a crash alert timing approach based on last-second braking judgements. In their study, drivers performed both normal and hard braking maneuvers. Regarding hard braking, drivers were instructed to maintain their speed and brake at the last possible second to avoid a crash. Upon developing their model for time-to-collision (TTC), Kiefer et al. (2005) found that drivers fail to use detailed knowledge on the lead vehicle deceleration when making the decision to hard brake. More, it was determined that their inverse-TTC model can serve as a vital element when considering the underlying mental process of drivers when determining if they are in their normal braking or hard braking range.

In a study that utilized both a simulator and a test track, Lee et al. (2002) instructed some drivers to brake normally and others to perform hard braking events. The objective of the study was to compare braking responses in the simulator to those on the test track. Lee et al. (2002) found that braking instructions did not impact the drivers in the simulator. However, during the test track experiment, required deceleration in the normal braking scenario was significantly less compared to hard braking events. Lee et al. (2002) state that these differences provide crucial information, as they reflect driver response before the braking maneuver has begun. In addition, the authors infer that these differences between the simulator and the test track must be a result of limited visual and vestibular cues in the simulator and a combination of extended practice with an artificial lead vehicle on the test track.

The next naturalistic driving study related to hard braking was aimed towards novice teenage drivers by passenger characteristics. In particular, Simons-Morton et al. (2009) use 42 teenage drivers over the first six months of being licensed and assess hard braking events. For this work, Simons-Morton et al. (2009) defined a hard braking event as a braking event that results in ≤ -0.45 g. Through their study, a total of 1,721 hard braking events were recorded and video footage of the study was used to determine validity and reasons for the hard braking events. It was found that hard braking rates per 10 trips were substantially higher when newly licensed drivers had a teenage passenger, while the hard braking rates were lower if the passengers were adults. In the end, based on the examination of hard braking events, Simons-Morton et al. (2009) determined that novice teenage drivers' performance is not as safe when driving alone or with teenage passengers.

2.2 Heavy-Vehicle Braking Studies

In terms of heavy-vehicle braking research, work is limited. For the current study, four relevant works were found. The first study reviewed analyzed an experimental measurement for the stopping performance of a tractor-semitrailer at multiple speeds. Specifically, Garrott et al. (2011) use a single tractor towing a 28-foot long, un-braked control trailer. The authors elected to modify the loading (referred to as the modified gross vehicle weight rating), where the truck was tested at maximum load and light load. The modified loading was done to achieve the 60 mi/hr stopping distance (250 feet) discussed in Chapter 1.0. Through their experiment, Garrott et al. (2011) demonstrated that as initial speed decreased from 60 mi/hr, the average measured corrected stopping distance decreases faster than the maximum permitted stopping distance. This finding holds true until an initial speed of 30 mi/hr, where the margin of compliance is largest. Then, as initial speed decreased from 30 mi/hr, the maximum permitted stopping distance decreases faster than the average measured corrected stopping distance. Finally, at 20 mi/hr, the test ruck had a negative margin of compliance.

As stated previously, Garrott et al. (2011) also tested a lightly loaded truck. During these tests, it was determined that the maximum permitted stopping distance was greater than the average measured corrected stopping distance for all tested initial speeds. This made the lightly loaded truck have a relatively constant margin of compliance from 60 mi/hr to 35 mi/hr. Unlike the maximum loaded truck, at 20 mi/hr, the lightly loaded truck still had a positive margin of compliance (although, it was the smallest margin of all initial speeds). The preceding results lead Garrott et al. (2011) to conclude that at an initial speed of 20 mi/hr, measured average corrected stopping distance surpassed the required maximum stopping distance.

In another heavy-vehicle braking study, Kubo et al. (2016) quantified the vertical load applied to the roadway surface as a result of heavy-vehicle braking. Kubo et al. (2016) equipped a heavy-vehicle with strain gauges and one accelerometer, and by using the heavy-vehicles springs as cells, evaluated the vertical load to the roadway surface under various braking situations. Through statistical measures, the authors measured statistical differences regarding the transferred load to the roadway surface based on the heavy-vehicle's initial speed and brake pedal position. Kubo et al. (2016) concluded, in their specific experiment, that initial speed does not impact the vertical load applied to the roadway surface during braking. On the other hand, they did discover that the brake pedal position had a significant impact on the vertical, dynamic, load applied to the roadway surface. Kubo et al. (2016) finish by emphasizing that these findings apply only to brake pedal positions that are greater than or equal to 60%.

The third relevant heavy-vehicle braking study consisted of a mediation model linking dispatcher leadership and work ownership. In this study, Zohar et al. (2014) use safety climate as predictors for heavy-vehicle driver safety performance. The idea of the mediation model is to link psychological safety climate antecedents and consequences as predictors for driving safety of long-haul heavy-vehicle drivers. Zohar et al. (2014) administered a survey, then over a six month period, collected data on hard braking frequency. In their work, Zohar et al. (2014) utilized a zero-inflated Poisson log-link generalized linear model to model hard braking events as the dependent variable. Results suggested that climate perceptions mediated effects on safety behavior and hard braking frequency.

The fourth, and final, relevant study to heavy-vehicle braking is also related to safety climate scales. Specifically, Huang et al. (2013) developed and validated safety climate scales for lone workers using heavy-vehicle drivers. In their study, one of the objective safety criteria is hard braking, as the frequency of hard braking can represent the number of near miss crashes for heavy-vehicles. As such, Huang et al. (2013) received hard braking frequency data from a participating company. During analysis, the authors found that organization-level safety climate scores could predict hard braking frequency, while group-level safety climates scores could not. Then, as the authors introduced driving safety behavior as a mediator, both organization- and group-level safety climate scores were found to have significant indirect effects on hard braking frequency.

2.3 Crash Frequency Analyses

Crash frequency analyses are among the most common transportation safety analyses for state and federal agencies, and often lead to the development of safety performance functions (American Association of State Highway and Transportation Officials, 2010). That said, as discussed in Chapter 4.0, crash frequencies are non-negative integer count values; therefore, a specific modeling framework for this type of dependent variable must be used. As such, the remainder of this section will review the most common types of these models in the context of crash frequency analysis and the current work.

2.3.1 Poisson Regression Crash Frequency Studies

One of the earliest crash frequency studies dates back to 1976 (Gustavsson and Svensson, 1976). Since then, Poisson regression has been used to study crash frequency of roadway classifications with small frequencies, heavy-vehicle accident rate, freeway accidents, accidents with respect to highway geometric design relationships, truck accidents and geometric design of roadway sections, underreporting and signalized intersections, Bayesian methods for underreporting on two-lane highways, and crash frequency by severity level on freeway sections with simultaneous equations. For a summary of these studies, see Table 2.1. However, it was later discovered that the distribution of crash frequencies can often lead to a violation of the key assumption for Poisson regression. This assumption, described in detail in Chapter 4.0, is the assumption of equal mean and variance ($\mathrm{E}[y_i] = \mathrm{Var}[y_i]$). To account for this and improve crash frequency analysis results, researchers began to apply the Negative Binomial regression model and variants of the Poisson-gamma regression model. These models are discussed in the following section.

Table 2.1: Summary of Poisson Regression Crash Frequency Studies

Authors	Study
Gustavsson and Svensson (1976)	A Poisson Regression Model Applied to Classes of Road Accidents With Small Frequencies
Joshua and Garber (1990)	Estimating Truck Accident Rate and Involvements Using Linear and Poisson Regression Models
Jones et al. (1991)	Analysis of the Frequency and Duration of Freeway Accidents in Seattle
Miaou and Lum (1993)	Modeling Vehicle Accidents and Highway Geometric Design Relationships
Miaou (1994)	The Relationship Between Truck Accidents and Geometric Design of Road Sections: Poisson Versus Negative Binomial Regressions
Kumara and Chin (2005)	Application of Poisson Underreporting Model to Examine Crash Frequencies at Signalized Three-Legged Intersections
Ma (2009)	Bayesian Analysis of Underreporting Poisson Regression Model With an Application to Traffic Crashes on Two-Lane Highways
Ye et al. (2013)	A Simultaneous Equations Model of Crash Frequency by Severity Level for Freeway Sections

2.3.2 Negative Binomial and Poisson-Gamma Regression Crash Frequency Studies

As stated in the previous section, crash frequency distributions are often found to violate the key assumption of the Poisson regression model; that is, the data is over- or under-dispersed (i.e., the mean and variance are not equal). As such, researchers began to apply a new analytical framework to model and predict crash frequencies, the Negative Binomial regression model or variants of the Poisson-gamma regression model. Specifically, these models relax the assumption of the Poisson model and allow the mean to differ from the variance. Being that the assumption of the Poisson model often does not hold true, the number of studies using Negative Binomial regression and variants of Poisson-gamma regression is substantially larger when compared to traditional Poisson regression studies.

In the case of crash frequency models (Negative Binomial or variants of the Poisson-gamma) that address the over- or under-dispersion issue, these date back to as early as 1984 (Maycock and Hall, 1984). Subsequently, these methods have been used to study crash frequency at intersections, crash frequency on freeway segments, junctions, crash frequency and its relationship to geometrics/environmental factors/traffic-related elements, heterogeneity considerations, effect of ice warning signs, Bayesian methods, traffic crash-flow relationships, sources of error, developing predictive crash frequency models, endogeneity issues, highway design exceptions, single- and multi-vehicle crashes, roundabouts, animal-vehicle crashes, site collection criteria, safety effects of wider edge lines, rear-end crash frequencies in tunnels, and safety effects of a fuel cost increase measure. As shown in Table 2.2, the number of studies addressing over- or under-dispersion is substantially larger.

However, as is the case with the traditional Poisson regression model, the models accounting for over- or under-dispersion also have their limitations. Of these limitations, there are two primary ones that remain a focus of researchers: (1) unobserved heterogeneity and (2) spatial (and/or temporal) correlation. Therefore, researchers have applied and developed methods to address these two key limitations, as discussed in the succeeding sections.

Table 2.2: Summary of Negative Binomial and Poisson-Gamma Crash Frequency Studies

Authors	Study
Maycock and Hall (1984)	TRR Laboratory Report 1120: Accidents at 4-Arm Roundabouts
Bonneson and McCoy (1993)	Estimation of Safety at Two-Way Stop-Controlled Intersections
Shankar et al. (1995)	Effect of Roadway Geometrics and Environmental Factors on Rural Freeway Accident Frequencies
Poch and Mannering (1996)	Negative Binomial Analysis of Intersection-Accident Frequencies
Maher and Summersgill (1996)	A Comprehensive Methodology for the Fitting of Predictive Accident Models
Mountain et al. (1996)	Accident Prediction Models for Roads With Minor Junctions
Milton and Mannering (1998)	The Relationship Among Highway Geometrics, Traffic-Related Elements and Motor-Vehicle Accident Frequencies
Mountain et al. (1998)	The Influence of Trend on Estimates of Accidents at Junctions
Karlaftis and Tarko (1998)	Heterogeneity Considerations in Accident Modeling
Carson and Mannering (2001)	The Effect of Ice Warning Signs on Ice-Accident Frequencies and Severities
Heydecker and Wu (2001)	Identification of Sites for Road Accident Remedial Work by Bayesian Statistical Methods: An Example of Uncertain Inference
Miaou and Lord (2003)	Modeling Traffic Crash-Flow Relationships for Intersections: Dispersion Parameter, Functional Form, and Bayes Versus Empirical Bayes Methods
Amoros et al. (2003)	Comparison of Road Crashes Incidence and Severity Between Some French Counties
Hirst et al. (2004a)	Sources of Error in Road Safety Scheme Evaluation: A Method to Deal With Outdated Accident Predictions Models
Hirst et al. (2004b)	Sources of Error in Road Safety Scheme Evaluations: A Quantified Comparison of Current Methods

Table 2.2: Summary of Negative Binomial and Poisson-Gamma Crash Frequency Studies

Authors	Study
Abbas (2004)	Traffic Safety Assessment and Development of Predictive Models for Accidents on Rural Roads in Egypt
Lord et al. (2005)	Modeling Crash-Flow-Density and Crash-Flow-V/C Ratio Relationships for Rural and Urban Freeway Segments
El-Basyouny and Sayed (2006)	Comparison of Two Negative Binomial Regression Techniques in Developing Accident Prediction Models
Kim and Washington (2006)	The Significance of Endogeneity Problems in Crash Models: An Examination of Left-Turn Lanes in Intersection Crash Models
Lord (2006)	Modeling Motor Vehicle Crashes Using Poisson-Gamma Models: Examining the Effects of Low Sample Mean Values and Small Sample Size on the Estimation of the Fixed Dispersion Parameter
Lord and Mahlawat (2009)	Examining Application of Aggregated and Disaggregated Poisson-Gamma Models Subjected to Low Sample Mean Bias
Malyshkina and Mannering (2010)	Empirical Assessment of the Impact of Highway Design Exceptions on the Frequency and Severity of Vehicle Accidents
Geedipally and Lord (2010)	Investigating the Effect of Modeling Single-Vehicle and Multi-Vehicle Crashes Separately on Confidence Intervals of Poisson-Gamma Models
Daniels et al. (2010)	Explaining Variation in Safety Performance of Roundabouts
Cafiso et al. (2010)	Development of Comprehensive Accident Frequency Models for Two-Lane Rural Highways Using Exposure, Geometry, Consistency and Context Variables
Lao et al. (2011)	Modeling Animal-Vehicle Collisions Considering Animal-Vehicle Interactions
Geedipally and Lord (2011)	Examination of Crash Variances Estimated by Poisson-Gamma and Conway-Maxwell-Poisson Models
Lord and Kuo (2012)	Examining the Effects of Site Collection Criteria for Evaluating the Effectiveness of Traffic Safety Countermeasures
Park et al. (2012)	Safety Effects of Wider Edge Lines on Rural, Two-Lane Highways
Vieira Gomes et al. (2012)	Estimating the Safety Performance of Urban Intersections in Lisbon, Portugal
Meng and Qu (2012)	Estimation of Rear-End Vehicle Crash Frequencies in Urban Road Tunnels
Pirdavani et al. (2013)	Evaluating the Road Safety Effects of a Fuel Cost Increase Measure by Means of Zonal Crash Prediction Modeling

2.3.3 Random Parameters Crash Frequency Studies

As stated in Chapter 2.3.2, a key limitation during analysis is due to unobserved heterogeneity (i.e., unobserved factors that can cause crash-specific variation). In recent years, the most common method to account for unobserved heterogeneity is to fit a model with random parameters. In doing so, parameter estimates can vary across observations and account for crash-specific variations.

In attempt to address this issue, works have focused on explaining the importance of using random parameters, created crash prediction models with random corridor parameters, modeled the relationship between crash frequency and geometrics, investigated the effects of built-environment characteristics on pedestrian crash frequency, crash frequency analysis by severity, number of vehicles involved, collision and location type, impacts of signal-warning flashers at high-speed intersections, roadway lighting, endogeneity, heterogeneity-in-means for evaluating effects of interchange type, and modeling safety of highway work zones. Again, for a summary of these works, refer to Table 2.3.

Although these studies address the issue of unobserved heterogeneity, the second key issue is still not addressed, spatial correlation. Therefore, beginning in the early 2000s, researchers began to address this issue by applying and developing methods to account for spatial correlation. Studies that focus on spatial correlation will be discussed in the next section.

Table 2.3: Summary of Random Parameters Crash Frequency Studies

Authors	Study
Anastasopoulos and Mannering (2009)	A Note on Modeling Vehicle Accident Frequencies With Random-Parameters Count Models
El-Basyouny and Sayed (2009)	Accident Prediction Models With Random Corridor Parameters
Ukkusuri et al. (2011)	Random Parameter Model Used to Explain Effects of Built-Environment Characteristics on Pedestrian Crash Frequency
Venkataraman et al. (2011)	Model of Relationship Between Interstate Crash Occurrence and Geometrics: Exploratory Insights from Random Parameter Negative Binomial Approach
Garnowski and Manner (2011)	On Factors Related to Car Accidents on German Autobahn Connectors
Venkataraman et al. (2013)	Random Parameter Models of Interstate Crash Frequencies by Severity, Number of Vehicles Involved, Collision and Location Type
Wu et al. (2013)	Safety Impacts of Signal-Warning Flashers on Speed Control at High-Speed Signalized Intersections
Bullough et al. (2013)	To Illuminate or Not to Illuminate: Roadway Lighting as it Affects Traffic Safety at Intersection
Bhat et al. (2014)	A Count Data Model with Endogenous Covariates: Formulation and Application to Roadway Crash Frequency at Intersections
Venkataraman et al. (2014)	A Heterogeneity-in-Means Count Model for Evaluating the Effects of Interchange Type on Heterogeneous Influences of Interstate Geometrics on Crash Frequencies
Chen and Tarko (2014)	Modeling Safety of Highway Work Zones With Random Parameters and Random Effects Models

2.3.4 Spatial Correlation Crash Frequency Studies

The final issue to address in crash frequency analyses is spatial (or temporal) correlation (a full discussion of spatial correlation is provided in Chapter 4.4). Real attention to spatial correlation began as early as 1998, in which a random-effects model was initially used (Shankar et al., 1998).[3] From this time forward, there have been

[3] For a full discussion on how random- or fixed-effects models can account for unobserved spatial or temporal correlations, see Wooldridge (2010) and Greene (2018).

several works that focus on crash frequency spatial analyses. Of these works, some develop new methodologies while others apply existing techniques.

With this in mind, spatial analysis in the context of crash frequency have been used for roadway traffic crash mapping, identifying black zones, small-area crash and injury analysis, ranking sites for engineering safety improvements, rear-end crashes at signalized intersections, analysis of fatal and injury crashes, roadway crash frequency, examining the choice of statistical model in road safety countermeasure effectiveness, multilevel crash frequency, signalized intersections with corridor-level spatial correlation, latent variable to predict crash frequency at intersections, significance of omitted variables, comparing precision of crash frequency estimates, multivariate spatial models, spatial dependence in bicycle and pedestrian injury counts, geographically weight Poisson regression, multivariate spatial analysis of pedestrian crash frequency, signalized intersections in a high-density urban roadway network, spatial heterogeneity, crash frequency and severity with spatiotemporal dependence, effects of spatial correlation in random parameters crash frequency models, multivariate spatial analysis to identify sites with promise based on crash types, multivariate random parameters crash frequency models with spatial heterogeneity, multivariate spatial model of crash frequency by transportation mode, multivariate space-time model of crash frequency by severity, and comparison of models to identify hot spots of intersections. Once more, to summarize the spatial analysis works as it pertains to crash frequency analysis, Table 2.4 has been provided.

Table 2.4: Summary of Spatial Correlation Crash Frequency Studies

Author	Study
Shankar et al. (1998)	Evaluating Median Crossover Likelihoods with Clustered Accident Counts: An Empirical Inquiry Using the Random Effects Negative Binomial Model
Miaou et al. (2003)	Roadway Traffic Crash Mapping: A Space-Time Approach
Mouchart et al. (2003)	The Local Spatial Autocorrelation and the Kernel Method for Identifying Black Zones: A Comparative Approach
MacNab (2004)	Bayesian Spatial and Ecological Models for Small-Area Accident and Injury Analysis
Miaou and Song (2005)	Bayesian Ranking of Sites for Engineering Safety Improvements: Decision Parameter, Treatability Concept, Statistical Criterion, and Spatial Dependence
Wang and Abdel-Aty (2006)	Temporal and Spatial Analyses of Rear-End Crashes at Signalized Intersections
Aguero-Valverde and Jovanis (2006)	Spatial Analysis of Fatal and Injury Crashes in Pennsylvania
Aguero-Valverde and Jovanis (2008)	Analysis of Road Crash Frequency with Spatial Models
Li et al. (2008)	The Choice of Statistical Models in Road Safety Countermeasure Effectiveness Studies in Iowa
Aguero-Valverde and Jovanis (2010)	Spatial Correlation in Multilevel Crash Frequency Models: Effects of Different Neighboring Structures
Guo et al. (2010)	Modeling Signalized Intersection Safety With Corridor-Level Spatial Correlations
Castro et al. (2012)	A Latent Variable Representation of Count Data Models to Accommodate Spatial and Temporal Dependence: Application to Predicting Crash Frequency at Intersections
Mitra and Washington (2012)	On the Significance of Omitted Variables in Intersection Crash Modeling
Aguero-Valverde (2013a)	Full Bayes Poisson Gamma, Poisson Lognormal, and Zero Inflated Random Effects Models: Comparing the Precision of Crash Frequency Estimates
Aguero-Valverde (2013b)	Multivariate Spatial Models of Excess Crash Frequency at Area Level: Case of Costa Rica
Narayanamoorthy et al. (2013)	On Accommodating Spatial Dependence in Bicycle and Pedestrian Injury Counts by Severity Level
Li et al. (2013)	Using Geographically Weight Poisson Regression for County-Level Crash Modeling in California
Wang and Kockelman (2013)	A Poisson-Lognormal Conditional-Autoregressive Model for Multivariate Spatial Analysis of Pedestrian Crash Counts Across Neighborhoods
Xie et al. (2014)	Crash Frequency Modeling for Signalized Intersections in a High-Density Urban Road Network

Table 2.4: Summary of Spatial Correlation Crash Frequency Studies

Author	Study
Xu and Huang (2015)	Modeling Crash Spatial Heterogeneity: Random Parameters Versus Geographically Weighting
Chiou and Fu (2015)	Modeling Crash Frequency and Severity With Spatiotemporal Dependence
Barua et al. (2015)	Effects of Spatial Correlation in Random Parameters Collision Count-Data Models
Aguero-Valverde et al. (2016)	A Multivariate Spatial Crash Frequency Model for Identifying Sites With Promise Based on Crash Types
Barua et al. (2016)	Multivariate Random Parameters Collision Count Data Models With Spatial Heterogeneity
Huang et al. (2017)	A Multivariate Spatial Model of Crash Frequency by Transportation Modes for Urban Intersections
Ma et al. (2017)	Multivariate Space-Time Modeling of Crash Frequencies by Injury Severity Levels
Cheng et al. (2017)	Comparison of Multivariate Poisson Lognormal Spatial and Temporal Crash Models to Identify Hot Spots of Intersections Based on Crash Types

2.4 Gap in Heavy-Vehicle Hard Braking and Crash Frequency Studies

Based on the review of current and relevant literature regarding braking research, it was found that the majority of braking research focuses on the regenerative braking of electric vehicles. However, of the literature that does focus on braking of manually driven vehicles, the emphasis is on braking performance, brake behavior modeling, and naturalistic or simulator braking studies. Of these studies, few address safety explicitly, and of the ones that do, the objective is identifying aggressive driving behavior.

With regard to heavy-vehicle braking research, the literature is quite limited. For the current study, four relevant works are found. The first used an experiment to measure stopping performance and the second investigated the impact of heavy-vehicle braking on vertical dynamic loads to roadway surfaces. The final two, although in a safety context, explored the safety climate of drivers of heavy-vehicles through recorded heavy-vehicle hard braking events.

Pertaining to crash frequency, several different methodologies to account for various issues within crash data, have been conducted over the years. Of these works, few emphasize heavy-vehicles and the majority analyze crash frequency at intersections or on roadway segments (mostly freeways or two-lane rural roads). Likewise, there have been several works on the issue of spatial correlation and crash frequency, but again with little attention paid to heavy-vehicles or locations outside of intersections and roadway segments.

Therefore, based on the demonstrated gaps, the current study attempts to uniquely fill these gaps by considering crash frequency at new locations: heavy-vehicle hard braking hot spots. To the best of the authors' knowledge, a crash frequency analysis at these locations has not been attempted. Further, of the spatial crash frequency analyses, few have a heavy-vehicle context and few relate spatial correlation to areas that are prone to heavy-vehicle hard braking. In the referenced study that attempts to compare random parameters versus geographically weighting (Xu and Huang, 2015), the authors emphasize that similar studies be conducted to confirm their findings. Although the analytic framework in the current study is not unambiguously the same, the current work will compare random parameters estimates and SLX estimates of crash frequency by crash type at heavy-vehicle hard braking hot spots. This uniquely fills gaps in the literature in all sections discussed in Chapter 2.0.

3.0 DATA

3.1 Data Massaging and Identification

Data for the current study began with data that had previously been unused in transportation research in the United States (it has been used in applications in New Zealand): EROAD. EROAD is a fully integrated regulatory technology, tolling, and services provider, based in Auckland, New Zealand. EROAD has a growing presence in the United States by developing products in response to the various regulatory changes, such as the introduction of electronic logging devices (ELD) . Through their systems, as discussed previously, several unique data are collected (for further information on EROAD and the data their systems are capable of collecting, the reader is referred to http://www.eroad.com). But, for the current study, only unidentifiable aggregated data was provided to enable hard braking events to be considered for analysis.

The hard braking data obtained from EROAD consisted of 2,993 hard braking events that occurred in Oregon from December 31, 2016, to June 25, 2017. Per EROAD, a hard braking event is recorded as a reduction in speed of greater than 10 kilometers per hour (km/hr) (approximately 6.21 mi/hr) in 1 second. This reduction equates to a 0.28 g-force. Included in the data were posted speed limits at the hard braking location (in km/hr), vehicle speed at the time of the hard braking event (in km/hr), bearing of the heavy-vehicle, and hard braking event coordinates so the data could be geocoded in ArcGIS®. To begin, the heavy-vehicle hard braking events were geocoded (shown in Figure 3.1) and plotted in ArcGIS®. At first glance, it can be seen that the majority of hard braking events occurred in metropolitan-type areas with larger populations. To further investigate heavy-vehicle hard braking locations, additional analyses are conducted (see Chapter 4.0).

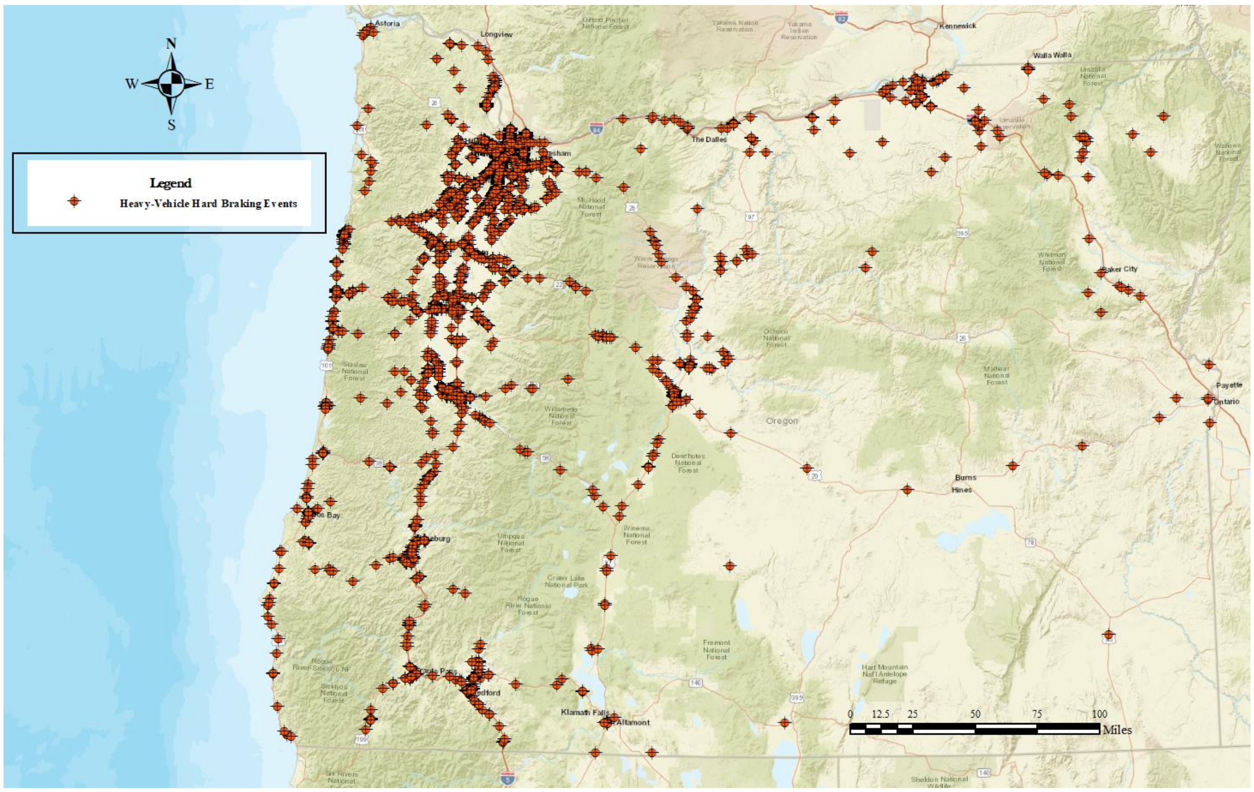

Figure 3.1: Heavy-Vehicle Hard Braking Events in Oregon (December 31, 2016, to June 25, 2017)

To continue the analysis, a comprehensive crash database provided by Oregon's Department of Transportation Crash Analysis and Reporting Unit is used.[4] This data consists of all police- and self-reported crashes from 2011 to 2015 that occurred in Oregon. Each year is comprised of three specific datasets: (1) a crash file, (2) a vehicle

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[4] For further information on Oregon crash data and the Crash Analysis and Reporting Unit, refer to http://www.oregon.gov/ODOT/Data/Pages/Crash.aspx.

file, and (3) a participant file. To merge these files, the crash and vehicle data were merged based on a crash ID, then that merged dataset was merged with the participant file based on a crash ID and vehicle ID. This resulted in five datasets (one for each year, 2011 to 2015) that included detailed information about the crash, vehicle, and driver.

However, due to the nature of the current analysis (i.e., crash frequency), many of the aforementioned characteristics cannot be used. To explain, crash frequency analyses utilize a segment or intersection (in the case of this work, a heavy-vehicle hard braking hot spot), in which the number of crashes are aggregated. That is, for example, if 10 crashes occurred at a heavy-vehicle hard braking hot spot, these 10 crash observations are aggregated to create a single crash observation with a new variable labeled "frequency" (the number of crashes that occurred at this location). Because of this aggregation procedure, characteristics relating to the driver, weather, crash, etc., cannot be included. That is to say, 10 different characteristics (e.g., 10 different ages, 10 different weather conditions, 10 different vehicle types, etc.) cannot be aggregated to a single characteristic without introducing severe bias into the crash frequency analysis, or any statistical/econometric analysis (Cameron and Trivedi, 2005, Kennedy, 2008, Angrist and Pischke, 2009, Wooldridge, 2010, 2016, Greene, 2018). Therefore, to further expand the usable data and corresponding characteristics for analysis, several additional datasets consisting of exposure-based variables are merged with each year of crash data.

As explained previously, aggregating observations with different characteristics will result in extreme bias during analysis. However, the aggregation of exposure-based variables mitigates this bias, as these are characteristics that are assumed to not change from observation-to-observation. For example, if 10 crashes occurred at a heavy-vehicle hard braking hot spot on a segment of roadway with a posted speed limit of 45 mi/hr, that posted speed limit will be the same for each of the 10 observations. As such, aggregating the 10 observations to a single observation with a speed limit of 45 mi/hr is permitted (Shankar et al., 1997, Park and Lord, 2007, Xie and Zhang, 2008, Ye et al., 2009, Lord and Mannering, 2010, Anastasopoulos et al., 2012, Zhang et al., 2012, Chen and Tarko, 2012, Chiou and Fu, 2013, Xie et al., 2014, Bhat et al., 2014, Dong et al., 2014, Anderson and Hernandez, 2017, Huang et al., 2017). Therefore, six additional datasets consisting of exposure-based variables are merged with each year of crash data.

The first dataset was comprised of lane characteristics; specifically, lane widths for each lane along a given roadway segment and the road surface type. The next dataset provided information on the width of the roadway surface in feet (i.e., from edge of surface to edge of surface). Continuing, the next dataset gave information regarding the shoulder of the roadway. Included in this data are characteristics about both the left- and right-side shoulders of the roadway, such as shoulder width and shoulder type (e.g., asphalt concrete, Portland cement concrete, etc.). Surface conditions are provided in the next dataset, where conditions are ranked from “Very Good” to “Very Poor.” The next dataset is a comprehensive dataset on traffic barriers for roadway segments in

Oregon. This included a generalized barrier type based on material (rail, concrete, or cable), specific barrier type (e.g., galvanized steel, three-strand wire, jersey barrier, tall-F barriers, timber barriers, etc.), construction method, roadside post type, height of barrier, barrier condition, and barrier connection to the roadway for both the left- and right-side of the roadway.

The final datasets merged with each year of crash data are datasets on traffic volume. In this dataset, average-annual-daily-traffic (AADT) volumes were provided for various roadway segments across Oregon. Also included are heavy-vehicle AADT (HV-AADT) volumes, heavy-vehicle percentage, and the percentage of vehicles by class. In regards to vehicles by class, see Table 3.1 and Figure 3.2 for a definition of each vehicle class included in the traffic volume data and crash frequency analysis (not all classes are found to be significant during analysis, however).

Table 3.1: Vehicle Class and Vehicle Description

Vehicle Class	Vehicle Description
Class 01	Motorcycle
Class 02	Passenger Cars
Class 03	Four-Tire, Single Unit
Class 04	Buses
Class 05	Two Axle, Six-Tire, Single Unit
Class 06	Three Axle, Single Unit
Class 07	Four or More Axle, Single Unit
Class 08	Four or Less Axle, Single Trailer
Class 09	5-Axle Tractor Semitrailer
Class 10	Six or More Axle, Single Trailer
Class 11	Five or Less Axle, Multi-Trailer
Class 12	Six Axle, Multi-Trailer
Class 13	Seven or More Axle, Multi-Trailer

Source: (Federal Highway Administration, 2016)

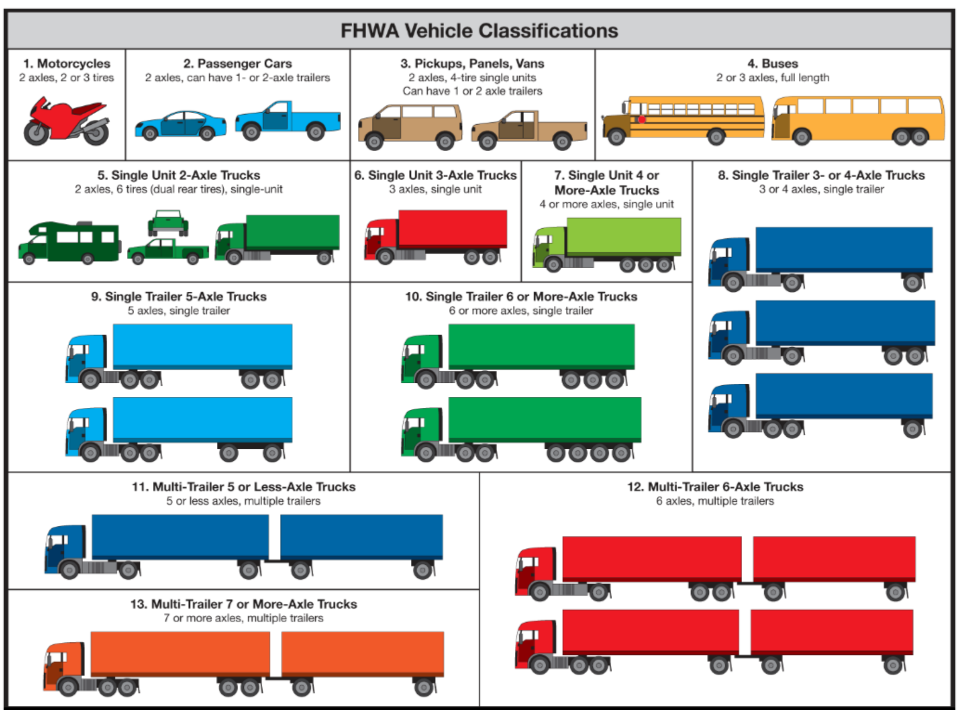

Figure 3.2: Federal Highway Administration 13-Category Scheme for Vehicle Classifications (Source: Federal Highway Administration, 2016)

The final step in the data process, after merging all relevant datasets, is to associate crashes with heavy-vehicle hard braking hot spots. To do this, the merged datasets are spatially joined to heavy-vehicle hard braking hot spots. Due to hard braking event locations being a point on a segment or network, they are treated like intersections when the crash data is spatially joined. In general, previous work and transportation practitioners adopt a 250 feet radius when aggregating and considering these types of crashes (Wang et al., 2008, American Association of State Highway and Transportation Officials, 2010). However, applying a 250 feet buffer to all crashes and crash types can result in statistical errors during the safety analysis (American Association of State Highway and Transportation Officials, 2010). Therefore, following the work of Fambro et al (1997) and Dolatsara (2014), the highest observed posted speed limit is used to determine an adequate buffer area. In Oregon, the 85th percentile speed ranges from 67 mi/hr to 70 mi/hr (Oregon Department of Transportation, 2017); therefore, based on this highest observed speed, a 500 feet buffer is adopted. As such, crashes (and corresponding exposure-based variables) are spatially joined to heavy-vehicle hard braking hot spots if they occurred at or within 500 feet of the hot spot (i.e., a 500 feet buffer is applied).[5]

Now that all crash data has been merged and spatially joined to heavy-vehicle hard braking hot spots, the four crash types that occurred most at these hot spots are identified: (1) rear-end crashes, (2) turning movement crashes, (3) fixed-object crashes,

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[5] If this analysis were considering only intersections, for example, in urban areas where speed limits are generally lower, the buffer zone can be taken as low as 250 feet.

and (4) sideswipe (overtaking) crashes. To see the distribution of crashes by crash type at heavy-vehicle hard braking hot spots, see Figure 3.3. From these 12 different crash types, the four most occurring crash types are chosen for analysis, as previously stated (see Figure 3.4). A total of 13,734 crashes from 2011 to 2015 occurred at, or within 500 feet, of a heavy-vehicle hard braking hot spot. Of the 13,734 crashes, the four most occurring crashes accounted for 12,420 (roughly 90% of all crashes).

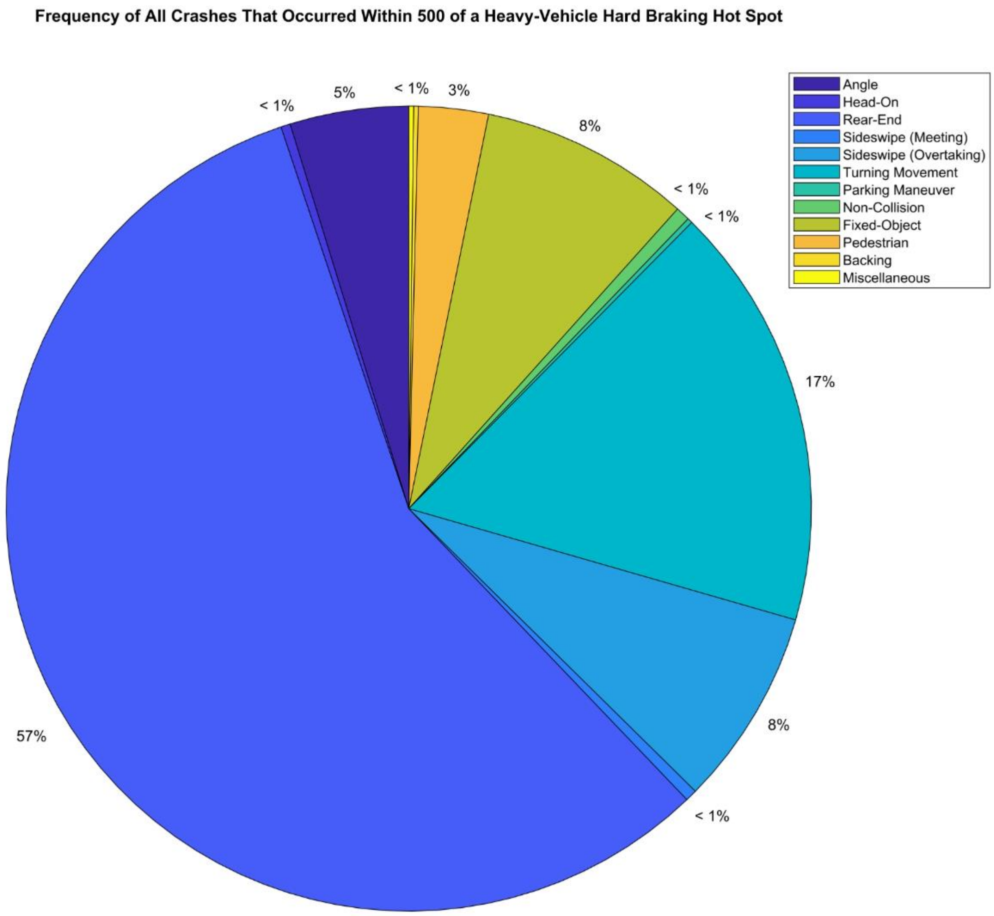

Figure 3.3: Crash Frequency Distribution by Crash Type at Heavy-Vehicle Hard Braking Hot Spots

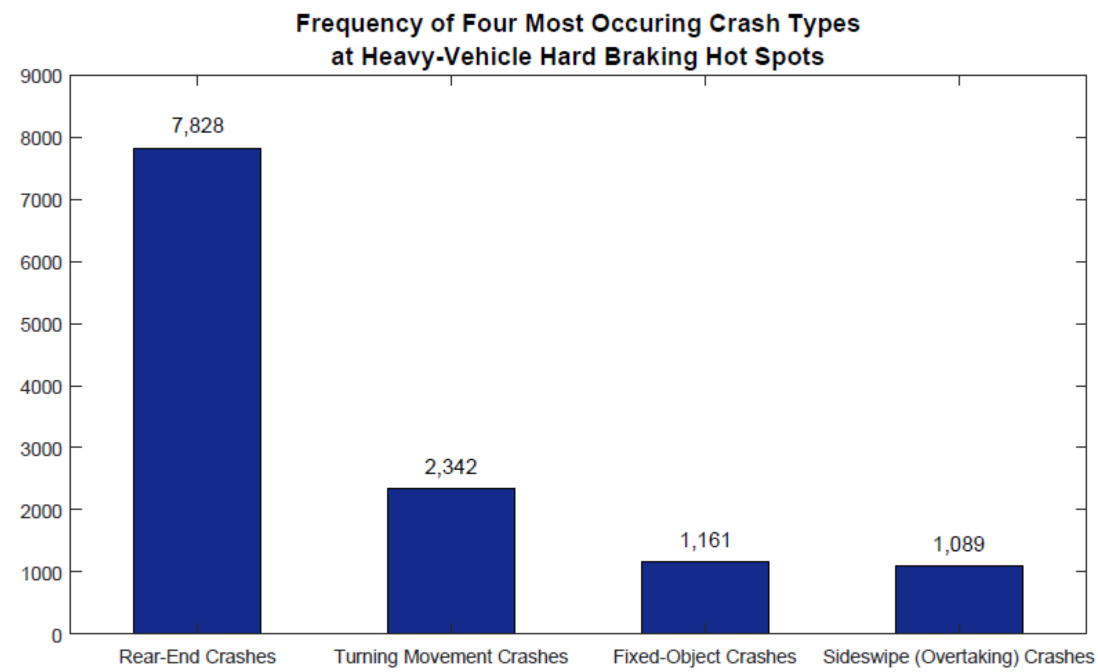

Figure 3.4: Four Most Occurring Crash Types at Heavy-Vehicle Hard Braking Hot Spots

3.2 Rear-End Crashes

Upon disaggregating the data by rear-end crashes, the next step in the data process is to aggregate the crashes to the corresponding number of hot spots. For rear-end crashes, 7,828 crashes occurred at 565 heavy-vehicle hard braking hot spots across Oregon (i.e., 565 observations for the safety analysis). As shown in Figure 3.5, the majority of rear-end crashes occurred at hot spots located in urban areas. However, there is a stretch of US-101 along the Oregon Coast and US-199 that had some rear-end crashes occur at heavy-vehicle hard braking hot spots.

Next, to gain a better understanding of rear-end crashes in the context of the current research, several characteristics are assessed.[6] The first two are injury severity and vehicle type, as shown in Figure 3.6. Greater than 75% of the rear-end crashes resulted in no injury, roughly 21% result in a possible injury, and nearly 3% were non-incapacitating injuries (fatal crashes and incapacitating crashes account for less than 1% of the total injuries each).

The next set of characteristics, shown in Figure 3.7, include AADT, HV-AADT, roadway surface width, and lane width. As seen in Figure 3.7a, the distribution of AADT is skewed left with a mean of 30,153 and substantially high standard deviation of 32,461. More, the range in AADT is quite large, as there is a minimum of 10 and maximum of 164,200. In regards to HV-AADT, Figure 3.7b, the distribution is also skewed left. For HV-AADT, there is a mean of 2,205 and another large standard deviation of 3,388. HV-AADT also has a large range, where the minimum HV-AADT is 1 and the maximum is 23,240. Based on these traffic volumes, it is clear that these represent both highly trafficked urban areas and rural areas with minimal traffic. The next characteristic, Figure 3.7c, is roadway surface width. The distribution of surface widths is much closer to normal with a mean of 60 feet and standard deviation of 21 feet (the range of surface widths varies from a minimum of 12 feet to a maximum of 130 feet). The final characteristic shown in Figure 3.7 is lane width. There is not much variation for this characteristic, as the mean is 12 feet (also the width with the highest

[6] Although injury severity did not get analyzed in the current research, these statistics show a need for future work in regards to injury severity analysis at heavy-vehicle hard braking hot spots.

frequency) and standard deviation is 1 feet. The variation for lane width is also less, with a minimum lane width of 8 feet and maximum width of 25 feet.

The next set of characteristics, displayed in Figure 3.8, are related to pavement condition and functional class of roadway. As for pavement condition, excluding “Very Poor” (only 2% of rear-end crashes occurred on “Very Poor” pavement condition, the distribution of pavement conditions are quite similar. For instance, 20% of rear-end crashes happened on “Very Good” pavement, 24% took place on “Good” pavement, 29% occurred on “Fair” pavement, and 24% happened on “Poor” pavement. Regarding functional class of roadway, the majority of rear-end crashes occurred on three functional classifications: urban principal arterials (44%), urban interstates (22%), and urban freeways and expressways (12%). The next classification with the most crashes are urban minor arterials (8%), while of the remaining classifications, no more than 4% of rear-end crashes happened. Being that the current research focuses on crashes at heavy-vehicle hard braking hot spots, it is not surprising to see that the majority of rear-end crashes took place on urban roadways.

Referring to Figure 3.9, the final set of exposure characteristics are road character and posted speed limit. As shown in Figure 3.9a, greater than 90% of rear-end crashes happened at an intersection (34%) or on a straight roadway segment (58%). 3% of rear-end crashes occurred on grades and 3% on bridge structures, while no more than 1% happened on the remaining road characters. Lastly, the number of rear-end crashes by posted speed limit is assessed (Figure 3.9b). Of the posted speed limits, 38% of rear-end crashes happened at a hot spot with a posted speed limit of 55 mi/hr, 17% occurred at a hot spot with a posted speed limit of 35 mi/hr, and 16% took place at a hot spot with a posted speed limit of 45 mi/hr. More, 8% happened at hot spots with posted speed limits of both 30 mi/hr and 40 mi/hr, while 7% happened at a hot spot with a posted speed limit of 65 mi/hr.

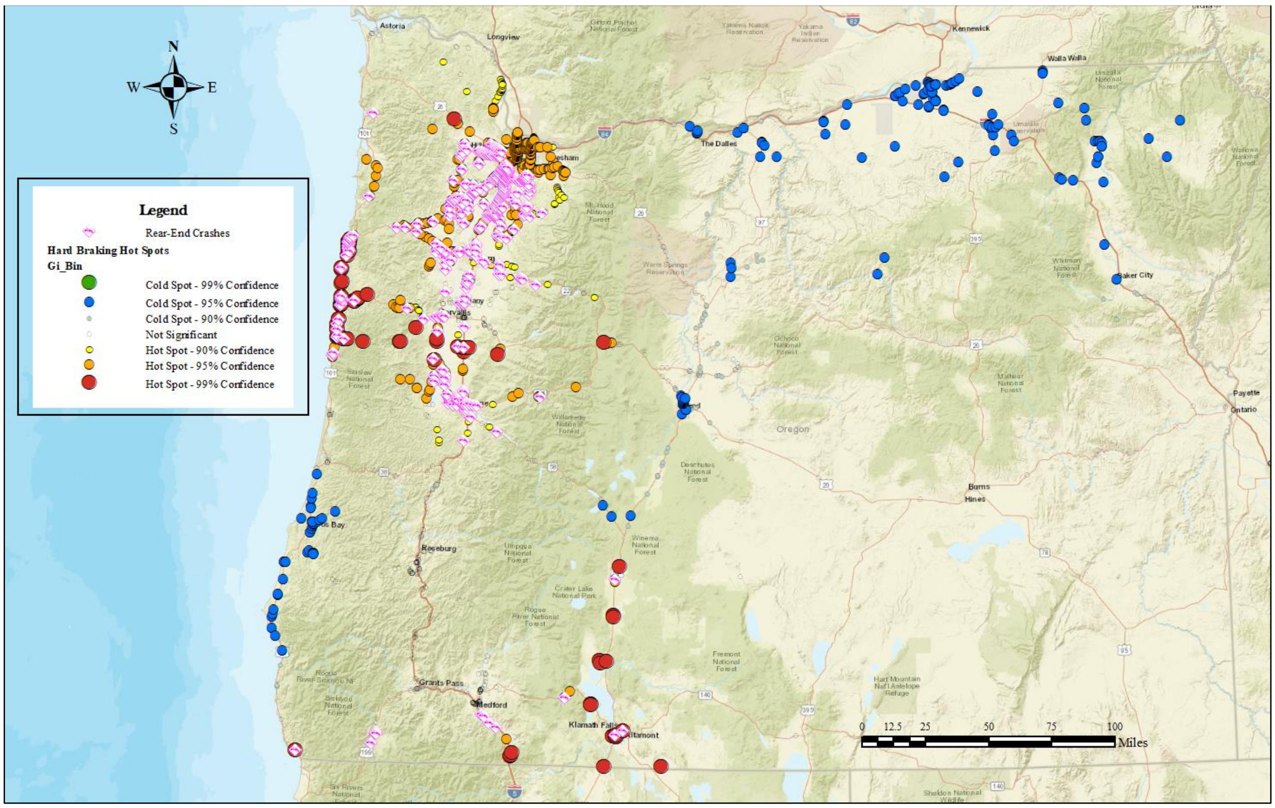

Figure 3.5: Rear-End Crashes at Heavy-Vehicle Hard Braking Hot Spots

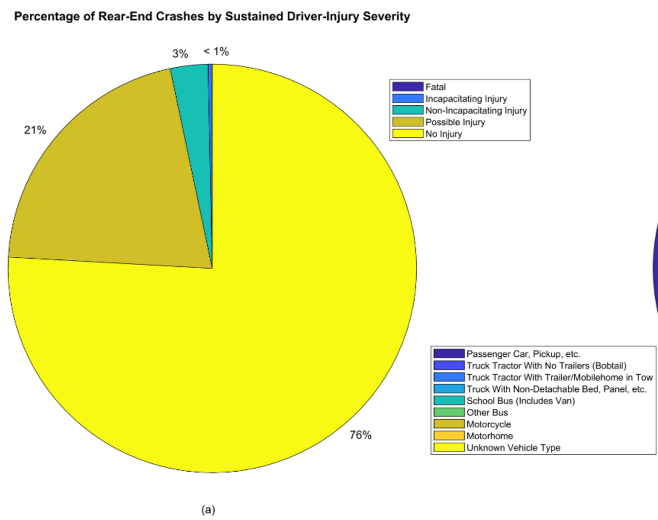

Figure 3.6: Percentage of Rear-End Crashes at Hard Braking Hot Spots by (a) Injury Severity and Vehicle Type

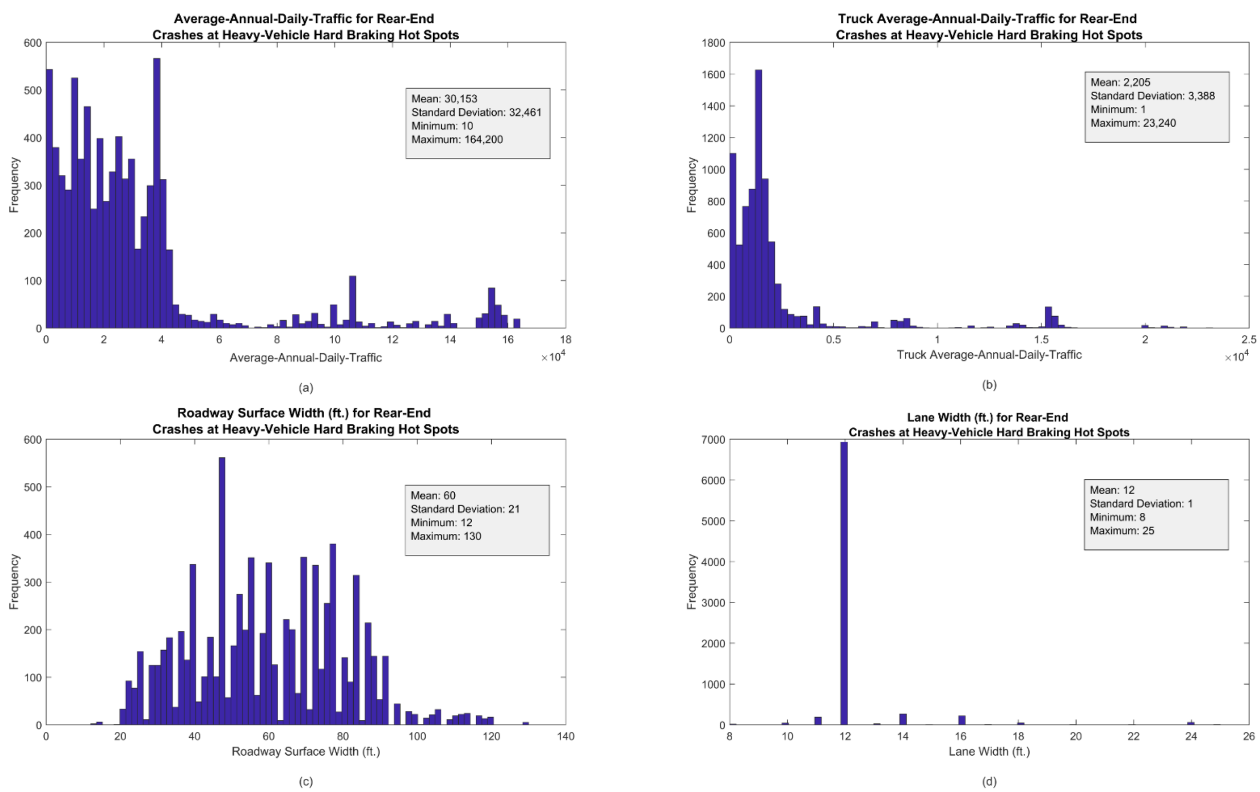

Figure 3.7: (a) AADT, (b) T-AADT, (c) Roadway Surface Width, and (d) Lane Width for Rear-End Crashes

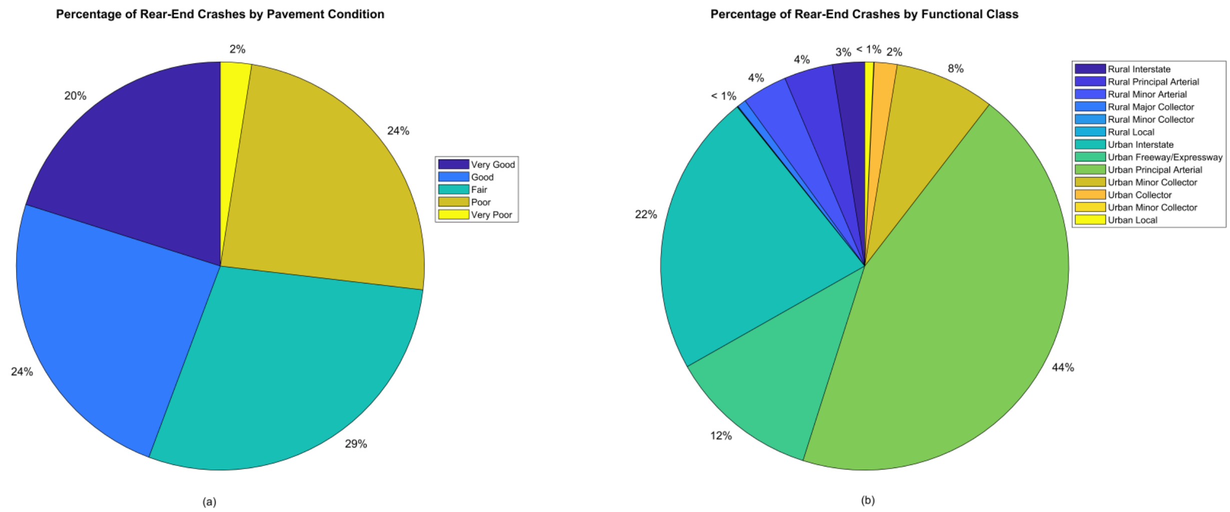

Figure 3.8: Rear-End Crashes by (a) Pavement Condition and (b) Functional Class of Roadway

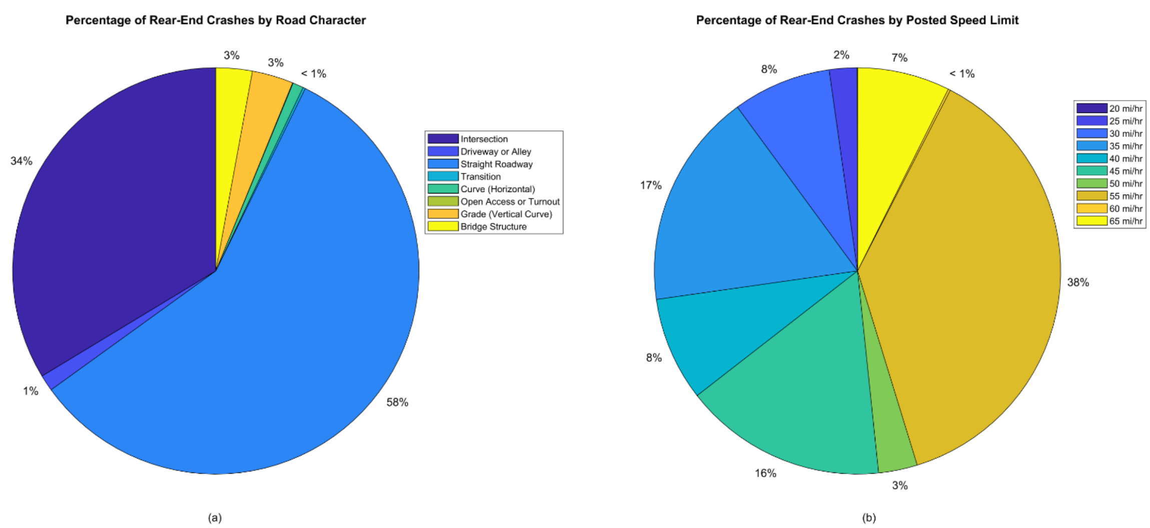

Figure 3.9: Rear-End Crashes by (a) Road Character and (b) Posted Speed Limit

3.3 Turning Movement Crashes

The next crashes to aggregate to the corresponding number of hot spots are turning movement crashes. For turning movement crashes, 2,342 crashes occurred at 411 heavy-vehicle hard braking hot spots across Oregon (i.e., 411 observations for the safety analysis). As shown in Figure 3.10, similar to that of rear-end crashes, the majority of turning movement crashes occurred at hot spots located in urban areas. However, tantamount to rear-end crashes there is a stretch of US-101 along the Oregon Coast (both northern and southern), in addition to crashes that happened at hot spots along I-5 near the California border and along the southern segment of US-97, that had turning movement crashes occur at heavy-vehicle hard braking hot spots.

As with rear-end crashes, to gain a better understanding of turning movement crashes in the context of the current research, the same characteristics discussed in Chapter 3.2 are assessed. The first two are injury severity and vehicle type, as shown in Figure 3.11. Nearly 75% of the turning movement crashes resulted in no injury, roughly 18% result in a possible injury, 8% in a non-incapacitating injury, and 1% in an incapacitating injury (3 of the turning movements crashes involved a fatality). In regard to vehicle type, once again the majority of vehicles involved are passenger cars and pickups (approximately 96%). However, unlike rear-end crashes, a larger percentage of heavy-vehicles are involved in turning movement crashes. Specifically, roughly 3% of turning movement crashes involved a truck tractor with a trailer/mobilehome in tow. Motorcycles account for less than 1% (22 crashes), while no other vehicle type accounts for more than 0.5% of the crashes.

The next set of characteristics, shown in Figure 3.12, include AADT, HV-AADT, roadway surface width, and lane width. As seen in Figure 3.12a, the distribution of AADT is again skewed left with a mean of 21,679 and a high standard deviation of

19,394. Similar to AADT for rear-end crashes, the range in AADT is quite large, as there is a minimum of 20 and maximum of 164,200. In regards to HV-AADT, Figure 3.12b, the distribution is also skewed left (as it is for rear-end crashes). For HV-AADT, there is a mean of 1,506 and a standard deviation of 2,021. HV-AADT also has a large range, where the minimum HV-AADT is 4 and the maximum is 20,900. As is the case for rear-end crashes, these traffic volumes suggest that turning movement crashes happened in both highly trafficked urban areas and rural areas with minimal traffic. The next characteristic, Figure 3.12c, is roadway surface width. The distribution of surface widths follows a normal distribution much closer than the other characteristics with a mean of 60 feet and standard deviation of 21 feet. The range of surface widths for turning movement crashes is also large, where there is a minimum of 14 and maximum of 119. The final characteristic shown in Figure 3.12 is lane width (Figure 3.12d). There is not much variation for this characteristic, as the mean is 12 feet (also the width with the most frequency) and standard deviation is 2 feet. The variation for lane width is also less, with a minimum lane width of 8 feet and maximum width of 25 feet. The summary statistics for lane widths at turning movement crashes is nearly identical to that of rear-end crashes.

The next set of characteristics, displayed in Figure 3.13, are related to pavement condition (Figure 3.13a) and functional class of roadway (Figure 3.13b). As for pavement condition, excluding “Very Poor” (only 1% of turning movement crashes occurred on “Very Poor” pavement conditions), the distribution of pavement conditions are not as similar as they are for rear-end crashes. For instance, 30% of turning movement crashes happened on “Poor” pavement and 29% of crashes occurred on “Fair” pavement. On the other hand, 22% of turning movement crashes took place on “Good” pavement conditions and 18% happened on “Very Good” pavement conditions. Excluding “Very Poor” conditions, the highest percentage of crashes occurred on “Poor” pavement and the least percentage of crashes (18%) happened on “Very Good” pavement conditions. Regarding functional class of roadway, there is a wider variety of roadway classifications and turning movement crashes. The classifications with the largest number of crashes are urban principal arterials (55%), urban minor arterials (14%), rural principal arterials (7%), rural minor arterials (7%), and urban collectors (6%). This is noticeably different than rear-end crashes, in which the majority of rear-end crashes occurred on three functional classifications. The next classification with the most crashes are urban freeways/expressways (5%) and urban interstates (3%), while of the remaining classifications, no more than 2% of turning movement crashes happened. For rear-end crashes, it was seen that the majority of crashes happened on urban roadways. However, for turning movement crashes, several crashes happened on both urban roadways and rural roadways.

The final set of exposure characteristics assessed, shown in Figure 3.14, are road character and posted speed limit. As shown in Figure 3.14a, and similar to that of rear-end crashes, the majority of turning movement crashes occurred at intersections (approximately 76% of crashes). Being that these are turning movement crashes, it is not surprising to see that driveways or alleys accounted for 20% of turning movement crashes. While straight roadways accounted for 3% of turning movement crashes, no other road character accounted for greater than 1%; grades have 1 crash, open access or turnouts have 1 crash, and bridge structures have 3 crashes.

Lastly, the number of turning movement crashes by posted speed limit is assessed (Figure 3.14b). Of the posted speed limits, 27% of turning movement crashes happened at a hot spot with a posted speed limit of 35 mi/hr, 24% occurred at a hot spot with a posted speed limit of 55 mi/hr, and 19% took place at a hot spot with a posted speed limit of 45 mi/hr. 30 mi/hr and 40 mi/hr posted speed limits account for 11% and 10% of turning movement crashes, respectively, while posted speed limits of 25 mi/hr and 50 mi/hr have 6% and 3% of turning movement crashes.

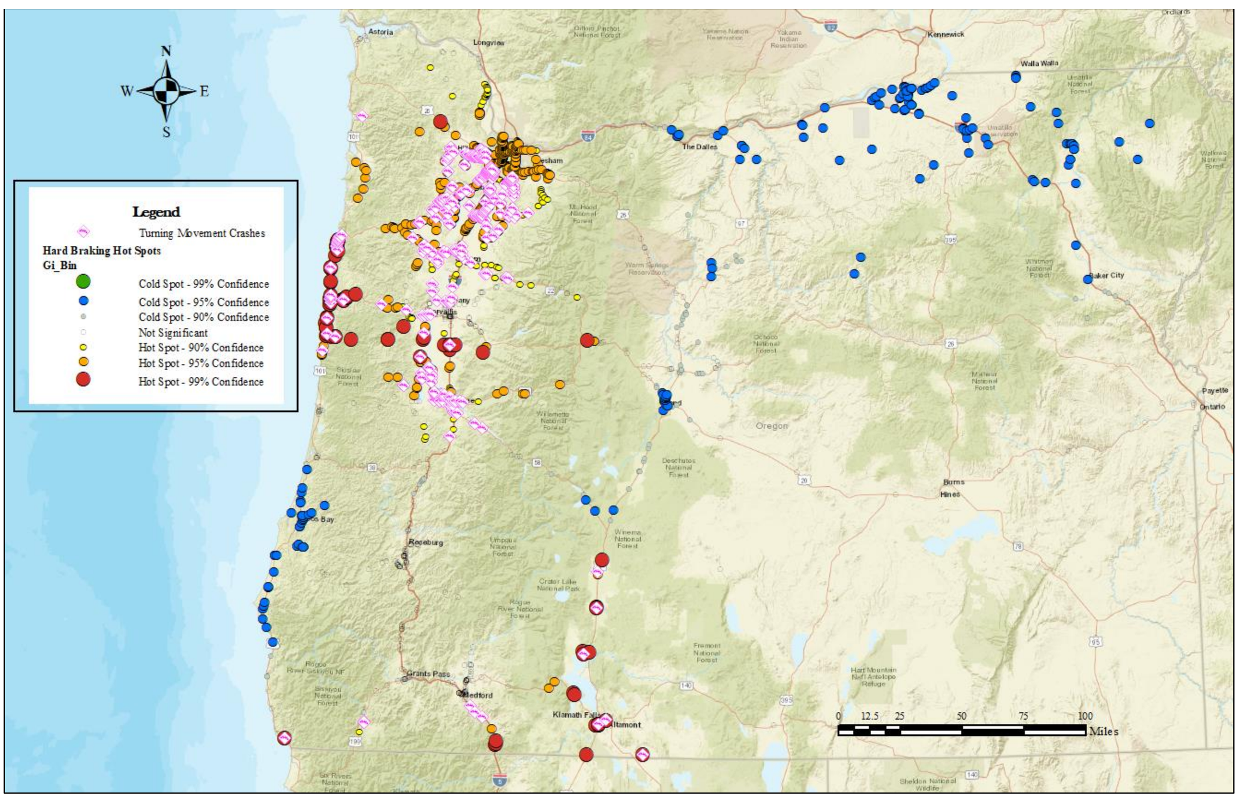

Figure 3.10: Turning Movement Crashes at Heavy-Vehicle Hard Braking Hot Spots

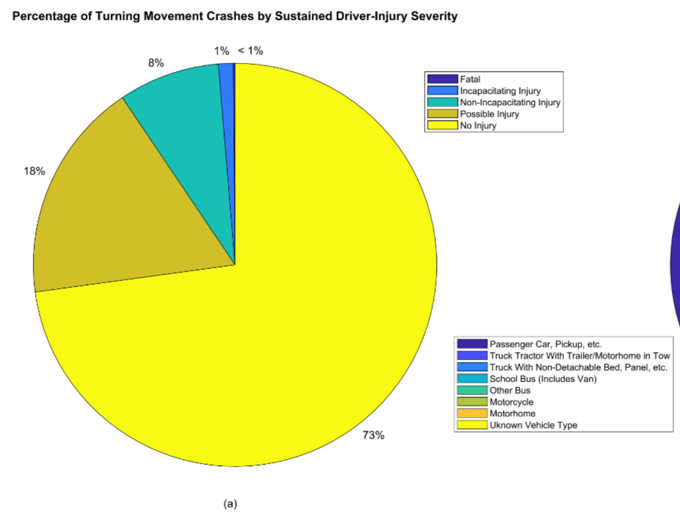

Figure 3.11: Percentage of Turning Movement Crashes at Hard Braking Hot Spots by (a) Injury Severity and (b) Vehicle Type

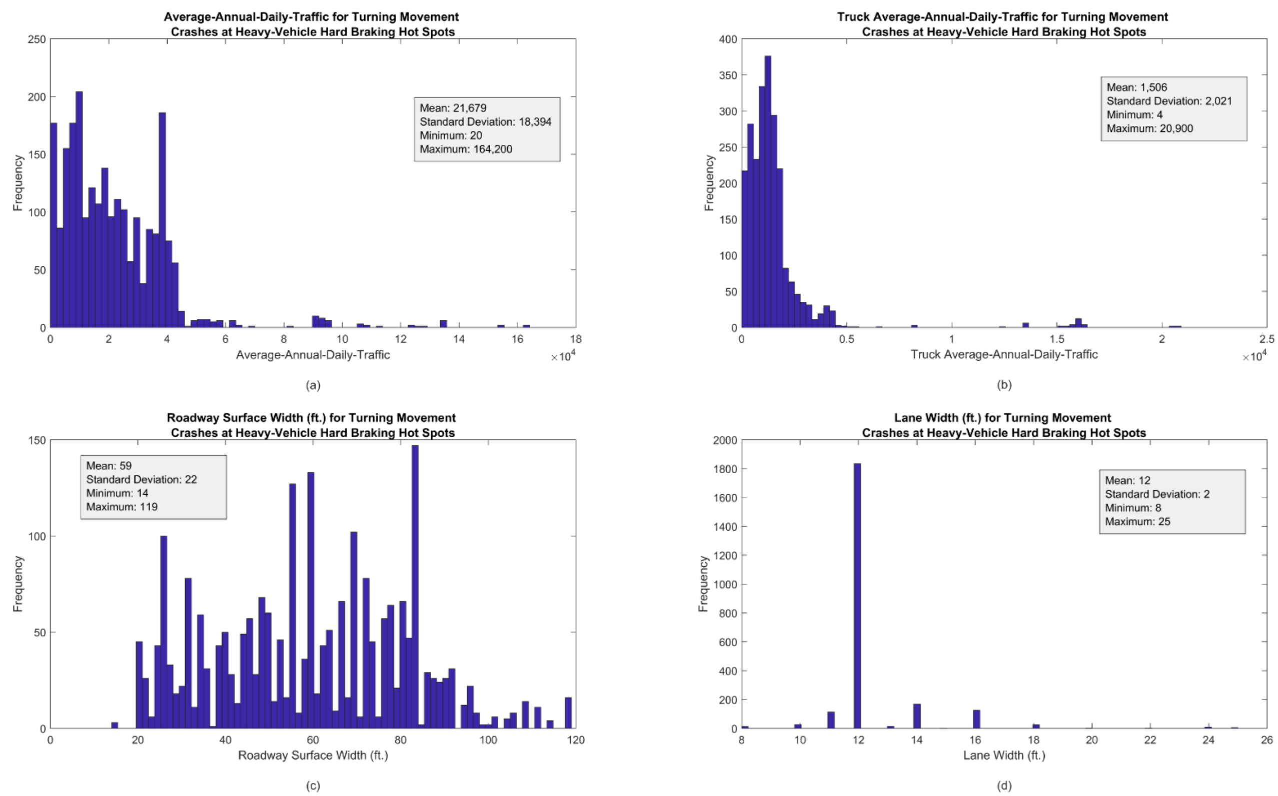

Figure 3.12: (a) AADT, (b) HV-AADT, (c) Roadway Surface Width, and (d) Lane Width for Turning Movement Crashes

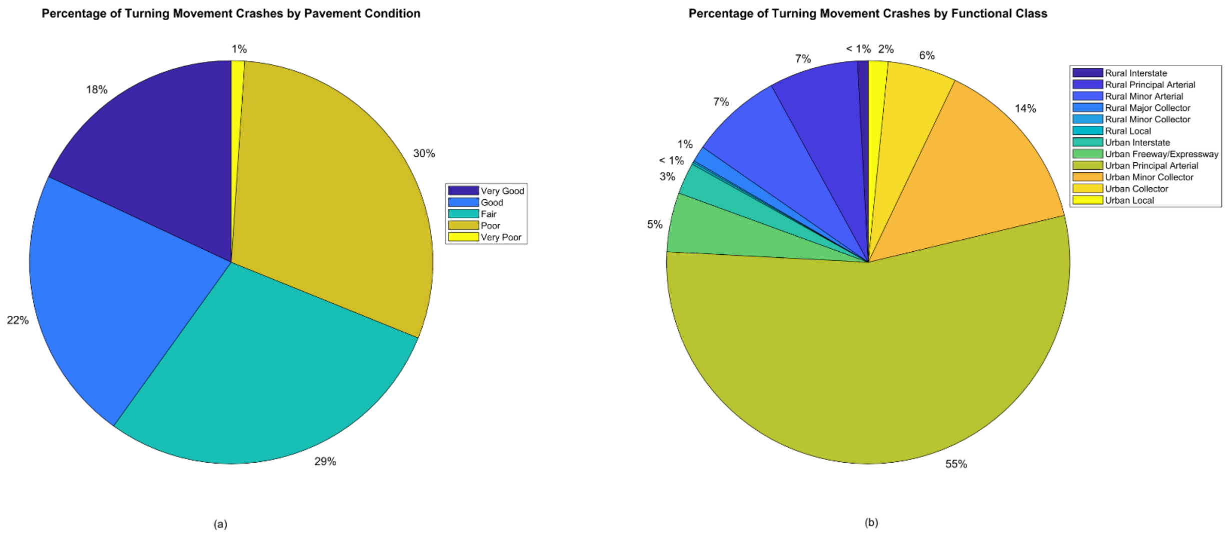

Figure 3.13: Turning Movement Crashes by (a) Pavement Condition and (b) Functional Class of Roadway

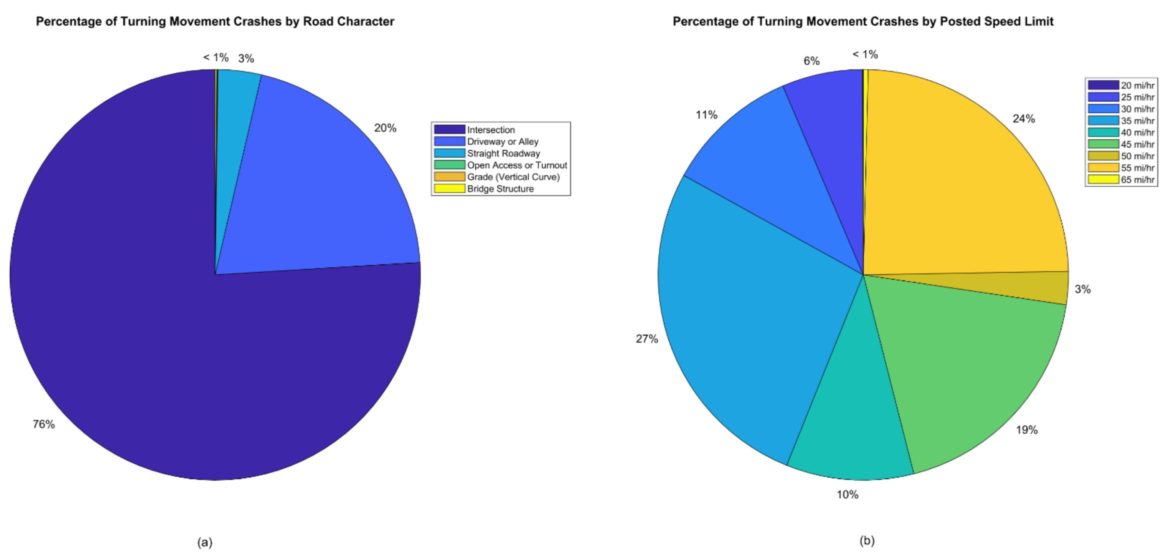

Figure 3.14: Turning Movement Crashes by (a) Road Character and (b) Posted Speed Limit

3.4 Fixed-Object Crashes

Continuing with the crash types considered for analysis, the next crashes to aggregate to the corresponding number of hot spots are fixed-object crashes. For fixed-object crashes, 1,161 crashes occurred at 479 heavy-vehicle hard braking hot spots across Oregon (i.e., 479 observations for the safety analysis). As shown in Figure 3.15, similar to that of rear-end crashes and turning movement crashes, the majority of fixed-object crashes occurred at hot spots located in urban areas (in addition to the hot spots located along US-101 on the Oregon Coast). Fixed-object crashes also occurred at hot spots along US-199 from Grants Pass, OR, to Crescent City, CA, the southern segment of I-5 near the California border, and the southern segment of US-97.

As with the previous crash types (rear-end crashes and turning movement crashes), to gain a better understanding of fixed-object crashes in the context of the current research, the same characteristics discussed in Chapter 3.2 and Chapter 3.3 are assessed. The first two, as discussed previously, are injury severity and vehicle type (shown in Figure 3.16). Once more, the majority of fixed-object crashes resulted in no injury (roughly 63%), but fixed-object crashes did see larger percentages of the other injury severities. To highlight, 19% of fixed-object crashes resulted in a possible injury, 14% a non-incapacitating injury, 2% an incapacitating injury, and 10 crashes involved a fatality (approximately 1%). However, unlike the other crash types, there is one fixed-object crash in which the driver died prior to the crash. In regard to vehicle type, once again the majority of vehicles involved are passenger cars and pickups (approximately 95%). However, unlike the previous crashes, a larger percentage of heavy-vehicles and motorcycles are involved in fixed-object crashes. Specifically, roughly 3% of fixed-object crashes involved a truck tractor with a trailer/mobilehome in tow and 2% of fixed-object crashes involved a motorcycle. No other vehicle type accounts for more than 0.5% of the crashes.

The next set of characteristics, shown in Figure 3.17, include AADT, HV-AADT, roadway surface width, and lane width. As seen in Figure 3.17a, the distribution of AADT is again skewed left (as are rear-end and turning movement crashes) with a mean of 22,035 and a significantly high standard deviation of 32,820. Similar to AADT for the previous crashes (rear-end and turning movement), the range in AADT is quite large, as there is a minimum of 10 and maximum of 162,800. In regards to HV-AADT, Figure 3.17b, the distribution is also skewed left (as is the case for the previous crash types, rear-end and turning movement). For HV-AADT, there is a mean of 2,033 and a large standard deviation of 3,730. HV-AADT also has a large range, where the minimum HV-AADT is 1 and the maximum is 21,900. As is the case for rear-end crashes and turning movement crashes, these traffic volumes suggest that fixed-object crashes happened at hot spots located in both highly trafficked urban areas and rural areas with minimal traffic. The next characteristic, Figure 3.17c, is roadway surface width. Once more, the distribution of roadway surface width follows a normal distribution much closer than the other characteristics with a mean of 49 feet and standard deviation of 18 feet. The range of surface widths for fixed-object crashes is also large, where there is a minimum of 12 and maximum of 118. The final characteristic shown in Figure 3.17 is lane width (Figure 3.17d). There is not much variation for this characteristic (also seen in the previous two crash types, rear-end and turning movement), as the mean is 12 feet (also the width with the most frequency) and standard deviation is 2 feet. The variation for lane width is also less, with a minimum lane width of 8 feet and maximum width of 30 feet; however, the previous crash types did not have a lane width of greater than 25 feet. In general, the summary statistics for lane widths and fixed-object crashes is nearly identical to that of rear-end and turning movement crashes.

The next set of characteristics, displayed in Figure 3.18, are pavement conditions (Figure 3.18a) and roadway classifications (Figure 3.13b). As for pavement conditions, excluding “Very Poor” (only 2% of turning movement crashes occurred on “Very Poor” pavement conditions), the distribution of pavement conditions are similar to that of turning movement crashes. In particular, 17% of turning movements crashes happened on “Very Good” pavement and 30% of crashes occurred on “Good” pavement. On the other hand, 35% of fixed-object crashes took place on “Fair” pavement conditions and 15% happened on “Poor” pavement conditions. Excluding “Very Poor” conditions, the highest percentage of crashes (35%) occurred on “Fair” pavement and the least percentage of crashes (15%) happened on “Very Good” pavement conditions.

Regarding functional class of roadway, more fixed-object crashes happened on rural roadways than the previous two crash types (rear-end crashes and turning movement crashes). To illustrate, 8% of fixed-object crashes occurred on rural interstates, 8% took place on rural principal arterials, 12% happened on rural minor arterials, and 4% occurred on rural major collectors. However, as is the case with the previous crash types, the majority of fixed-object crashes did occur on urban roadways. Specifically, 32% of fixed-object crashes happened on urban interstates, 8% took place on urban freeways/expressways, 16% happened on urban principal arterials, and 6% occurred on urban minor arterials.

The final set of exposure characteristics discussed, shown in Figure 3.19, are road character and posted speed limit. As shown in Figure 3.19a, unlike the previous two crash types, the majority of fixed-object crashes did not happen at an intersection. For fixed-object crashes, the majority (53%) occurred along straight roadway segments, while horizontal curves account for the next largest percentage of crashes at 19%. Of the remaining road characters, intersections account for 17% of fixed-object crashes, grades account for 4%, bridge structures account for 5%, and driveways or alleys account for 2%. To finish the assessment of exposure characteristics and fixed-object crashes, posted speed limits are evaluated (Figure 3.19b). Of the posted speed limits, the majority of fixed-object crashes occurred at hot spots with a posted speed limit of 55 mi/hr (44%). Also accounting for a significant portion of fixed-object crashes (16%) are hot spots with a posted speed limit of 65 mi/hr. Of the remaining crashes, 10% occurred at hot spots with a posted speed limit of 45 mi/hr, 5% with a posted speed limit of 40 mi/hr, 14% with a posted speed limit of 35 mi/hr, and 4% with a posted speed limit of 30 mi/hr.

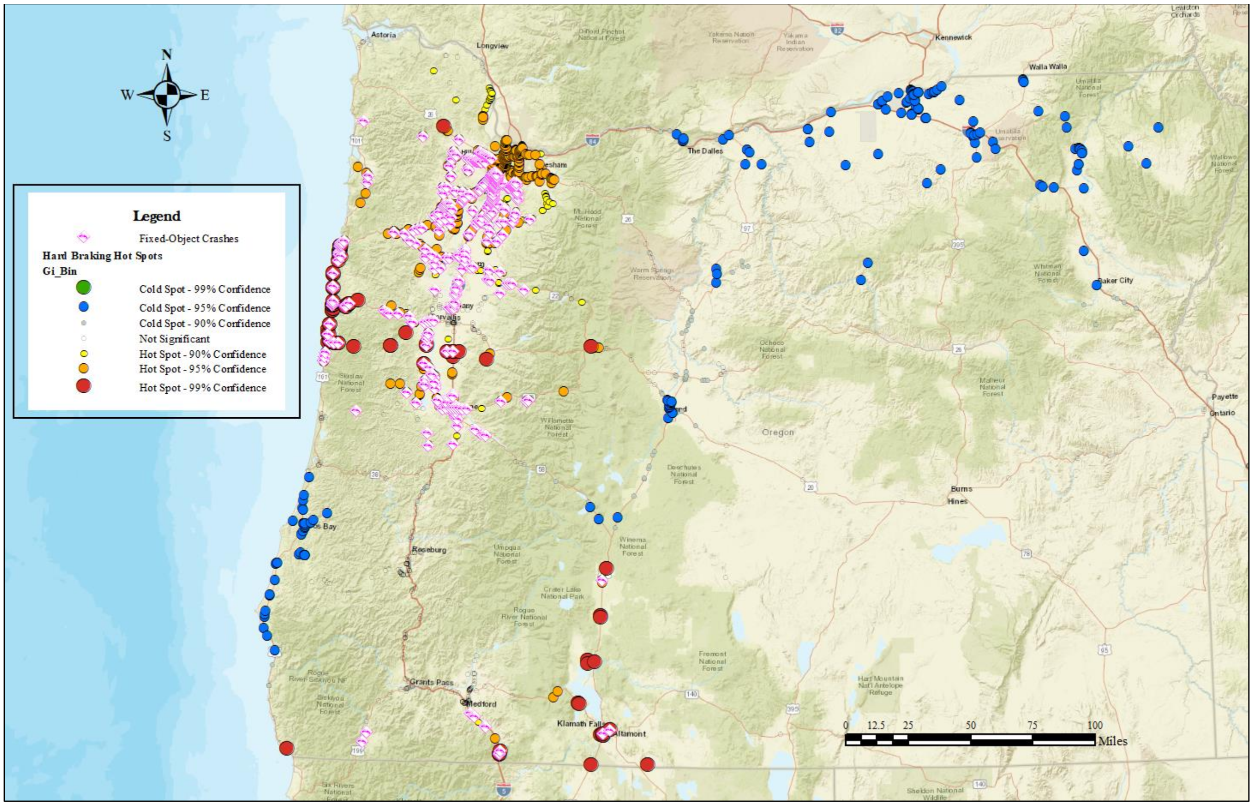

Figure 3.15: Fixed-Object Crashes at Heavy-Vehicle Hard Braking Hot Spots

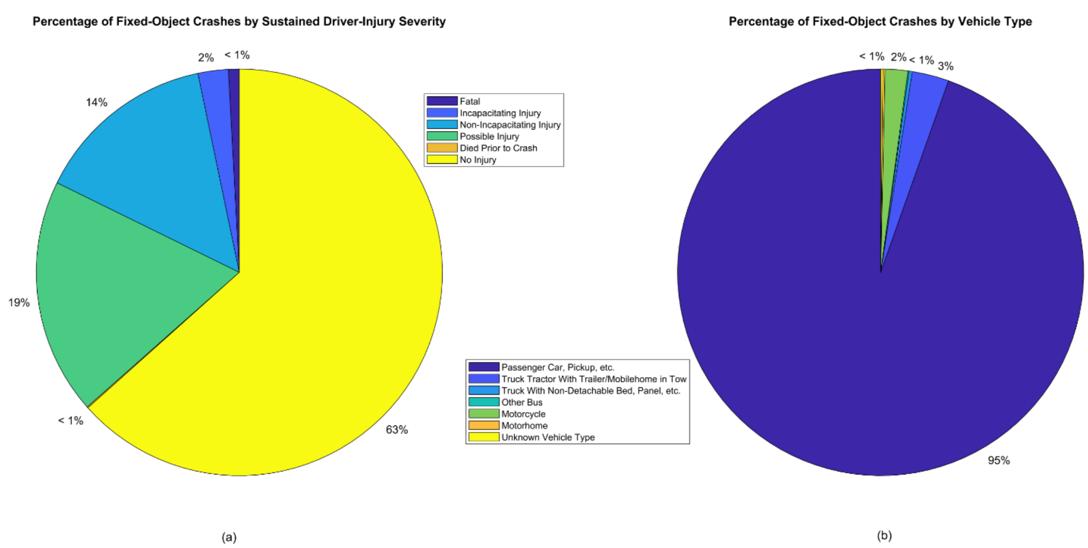

Figure 3.16: Percentage of Fixed-Object Crashes at Hard Braking Hot Spots by (a) Injury Severity and (b) Vehicle Type

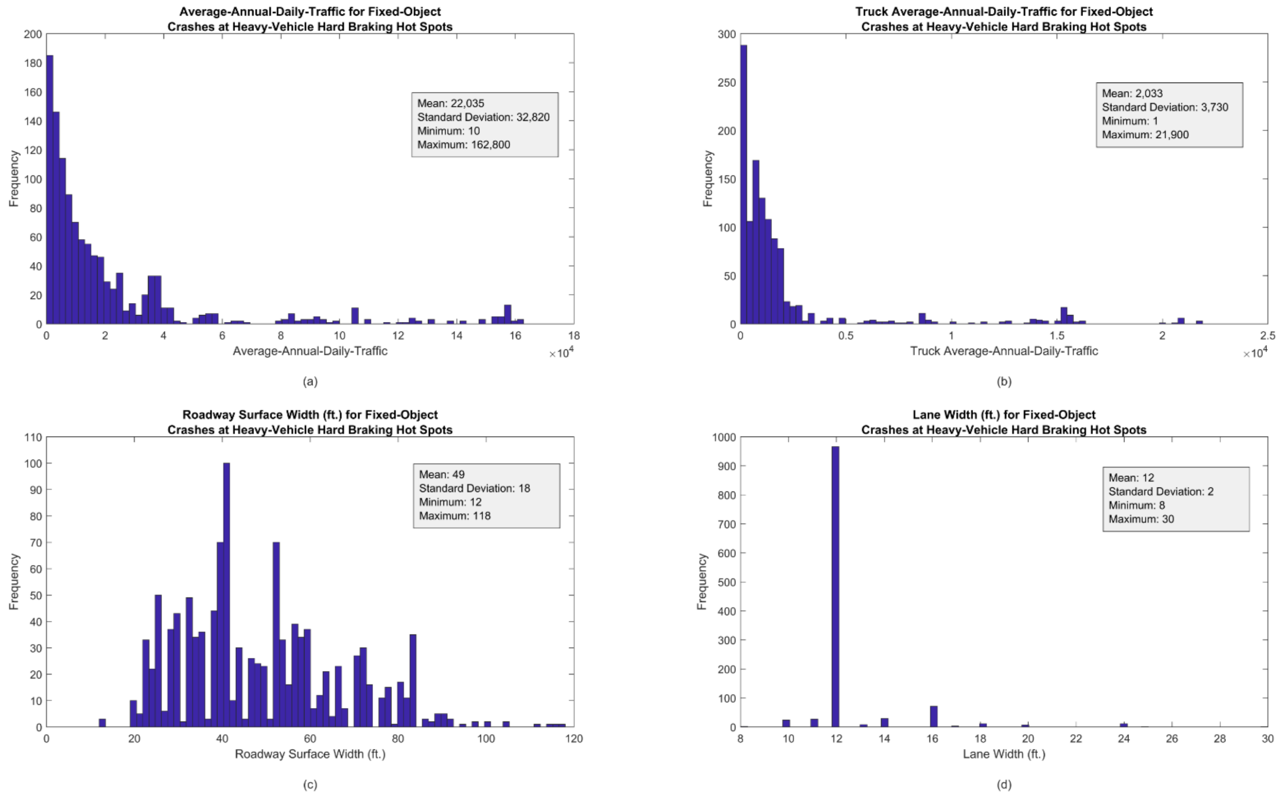

Figure 3.17: (a) AADT, (b) HV-AADT, (c) Roadway Surface Width, and (d) Lane Width for Fixed-Object Crashes

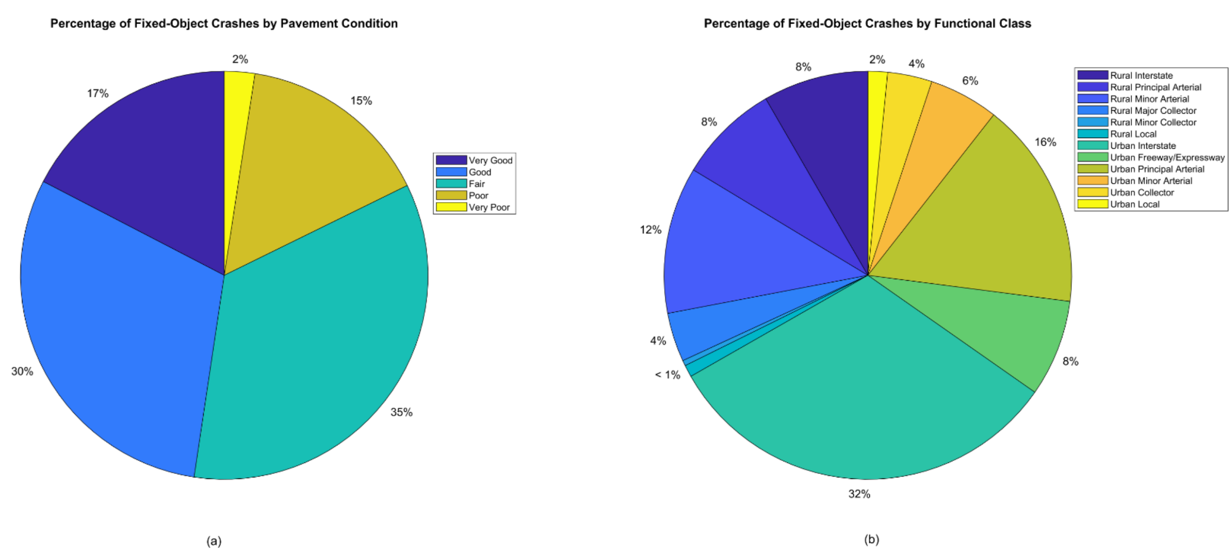

Figure 3.18: Fixed-Object Crashes by (a) Pavement Condition and (b) Functional Class of Roadway

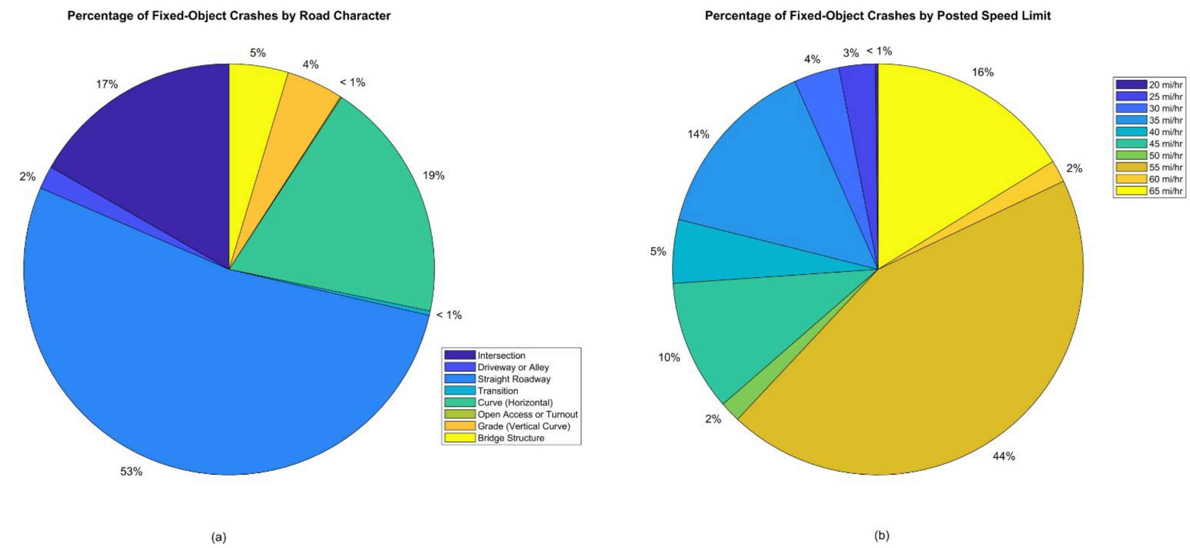

Figure 3.19: Fixed-Object Crashes by (a) Road Character and (b) Posted Speed Limit

3.5 Sideswipe (Overtaking) Crashes

The final crash type considered for analysis, and the final crash type to aggregate based on heavy-vehicle hard braking hot spots, are sideswipe (overtaking) crashes. For sideswipe (overtaking), 1,089 crashes occurred at 306 heavy-vehicle hard braking hot spots across Oregon (i.e., 306 observations for the safety analysis). As shown in Figure 3.20, sideswipe (overtaking) crashes occurred primarily at hot spots within urban areas. Further, as is the case with the previous three crash types, sideswipe (overtaking) crashes did occur at hot spots along US-101. However, unlike the previous crash types, no sideswipe (overtaking) crashes occurred at hot spots in Southern Oregon (i.e., no crashes along the southern segment of I-5 and no crashes along the southern segment of US-97).

As with the previous three crash types, the same characteristics discussed in Chapter 3.2 to Chapter 3.4 are assessed. The first two, as described previously, are injury severity and vehicle type (shown in Figure 3.21). Once more, the majority of fixed-object crashes resulted in no injury (roughly 88%), but this is the largest percent of no injury crashes for the four crash types considered in the current study. In addition, 9% of sideswipe (overtaking) crashes resulted in a possible injury, 3% a non-incapacitating injury, and less than 1% in an incapacitating. Lastly, unlike the previous crash types, sideswipe (overtaking) crashes had no fatalities. Regarding vehicle type, the majority of vehicles involved are passenger cars and pickups (approximately 91%). For sideswipe (overtaking) crashes, there is a larger percentage of heavy-vehicles. Pointedly, roughly 6% of sideswipe (overtaking) crashes involved a truck tractor with a trailer/mobilehome in tow and 2% involved a truck with a non-detachable bed. In the case of sideswipe (overtaking) crashes, no other vehicle type accounts for more than 0.5% of the crashes.

The next set of characteristics, shown in Figure 3.22, include AADT, HV-AADT, roadway surface width, and lane width. As seen in Figure 3.22a, the distribution of AADT is again skewed left (as are rear-end, turning movement, and fixed-object crashes) with a mean of 37,238 and a substantially high standard deviation of 43,447 (this is the largest mean and standard deviation of AADT for the four crash types). Similar to AADT for the previous crashes, the range in AADT is quite large, as there is a minimum of 10 and maximum of 164,200. In regards to HV-AADT, shown Figure 3.22b, the distribution is also skewed left (as it is for the previous crash types). For HV-

AADT, there is a mean of 3,245 and a large standard deviation of 4,991 (these, too, are also the largest mean and standard deviation of HV-AADT for the four crash types). HV-AADT also has a large range, where the minimum HV-AADT is 1 and the maximum is 23,500. The next characteristic, Figure 3.22c, is roadway surface width. Once more, the distribution of roadway surface width follows a normal distribution much closer than the other characteristics with a mean of 61 feet and standard deviation of 18 feet. The range of surface widths for sideswipe (overtaking) crashes is also large, where there is a minimum of 12 and maximum of 119. The final characteristic shown in Figure 3.22 is lane width (Figure 3.22d). There is not much variation for this characteristic (also observed in the previous crash types), as the mean is 12 feet (also the width with the most frequency) and standard deviation is 1 foot. The range for lane width is also less (the least of the four crash types), with a minimum lane width of 10 feet and maximum width of 24 feet. This is the only crash type to not have a lane width of 8 feet.

The subsequent set of characteristics, displayed in Figure 3.23, are pavement conditions (Figure 3.23a) and roadway classifications (Figure 3.23b). As for pavement conditions, excluding “Very Poor” (less than 1%, also the least of all crash types, of sideswipe (overtaking) crashes occurred on “Very Poor” pavement conditions), the distribution of pavement conditions is centered around the “middle” conditions. That is, 33% of sideswipe (overtaking) crashes happened on both “Good” pavement conditions and “Fair” pavement conditions. Of crashes that occurred on “Poor” pavement, there is 17%, and crashes that happened on “Very Good” pavement conditions account for 16% of crashes.

Regarding functional class of roadway, the majority of sideswipe (overtaking) crashes occurred on urban roadways. To demonstrate, 39% of sideswipe (overtaking) crashes happened on urban interstates, 36% took place on urban principal arterials, 10% happened on urban freeways and expressways, and 5% occurred on urban minor arterials (this is the case for all crash types, the majority of crashes occurred on urban roadways). With regard to rural roadways, small percentages of crashes happened on these classifications. In particular, 5% of sideswipe (overtaking) crashes occurred on rural interstates, 2% on rural minor arterials, and 1% on rural principal arterials.

The final set of exposure characteristics discussed, shown in Figure 3.24, are road character and posted speed limit. As shown in Figure 3.24a, unlike the rear-end and turning movement crashes, the majority of sideswipe (overtaking) crashes did not happen at an intersection. For sideswipe (overtaking) crashes, the majority (77%) occurred along straight roadway segments, while intersections account for the next largest percentage of crashes at 10%. Of the remaining road characters, horizontal curves account for 3% of sideswipe (overtaking) crashes, grades account for 4%, bridge structures account for 3%, and transitions account for 2%. To finish the assessment of exposure characteristics and sideswipe (overtaking) crashes, posted speed limits are evaluated (Figure 3.24b). Of the posted speed limits, the most sideswipe (overtaking) crashes occurred at hot spots with a posted speed limit of 55 mi/hr (42%). Also accounting for a significant portion of sideswipe (overtaking) crashes (17%) were hot spots with a posted speed limit of 65 mi/hr. Of the remaining sideswipe (overtaking) crashes, 14% occurred at hot spots with a posted speed limit of 35 mi/hr, 11% with a posted speed limit of 45 mi/hr, and 5% with a posted speed limit of 40 mi/hr (25 mi/hr, 30 mi/hr, and 50 mi/hr each accounted for 3%).

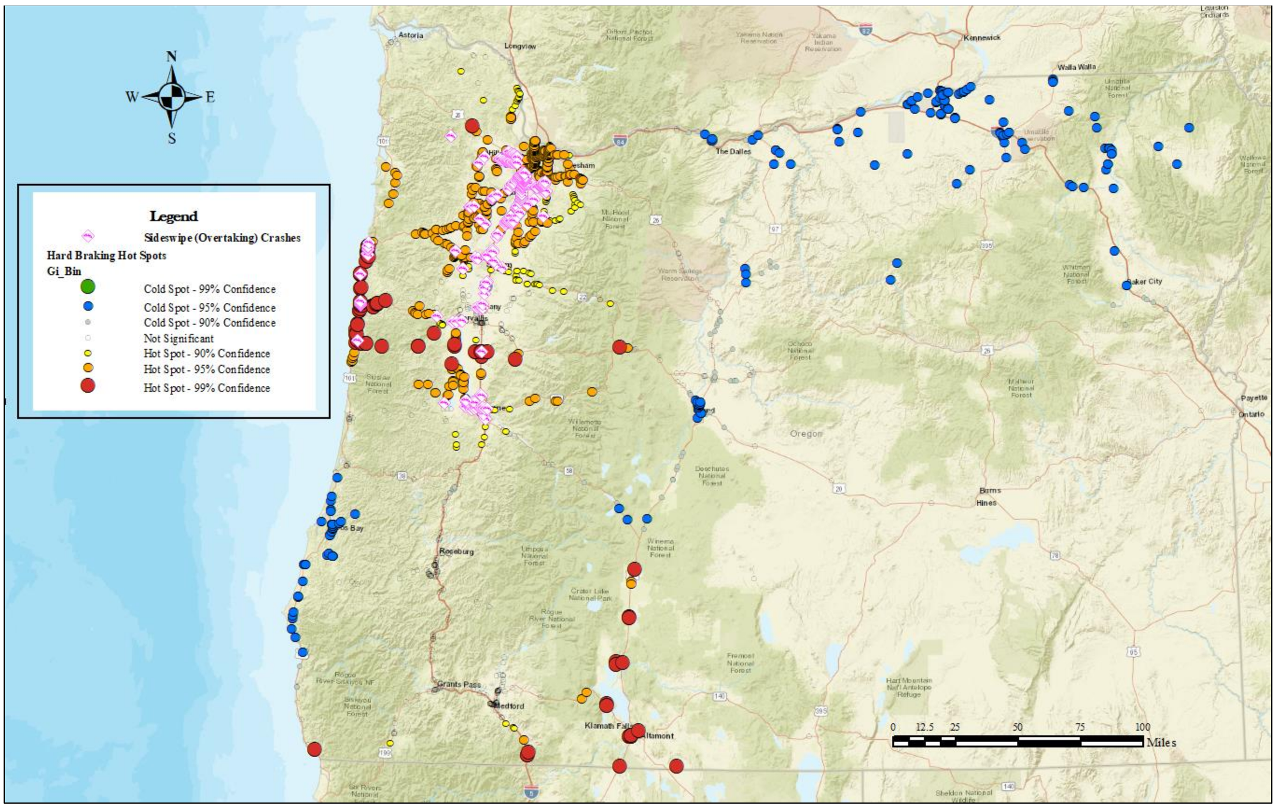

Figure 3.20: Sideswipe (Overtaking) Crashes at Heavy-Vehicle Hard Braking Hot Spots

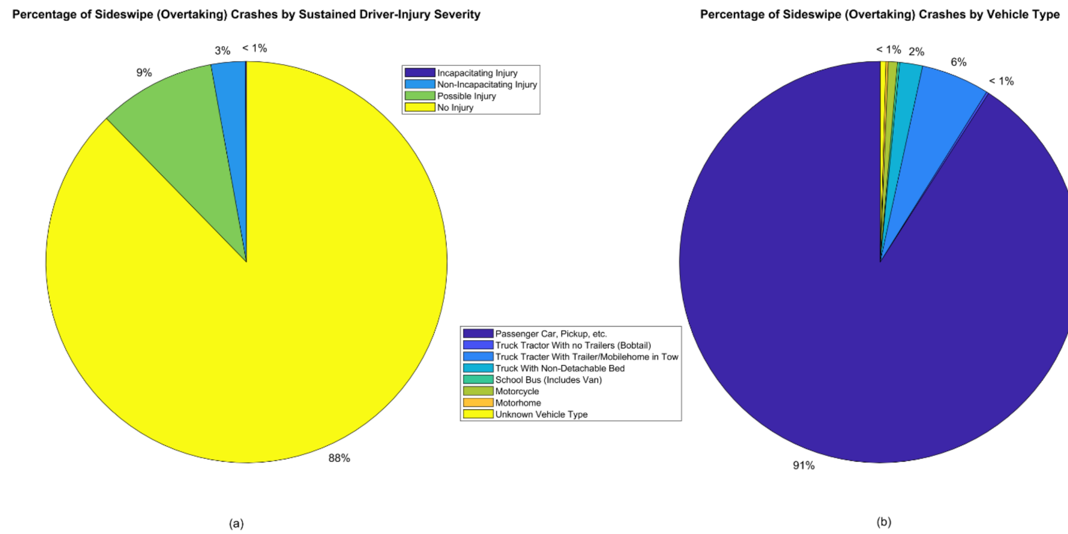

Figure 3.21: Percentage of Sideswipe (Overtaking) Crashes at Hard Braking Hot Spots by (a) Injury Severity and Vehicle Type

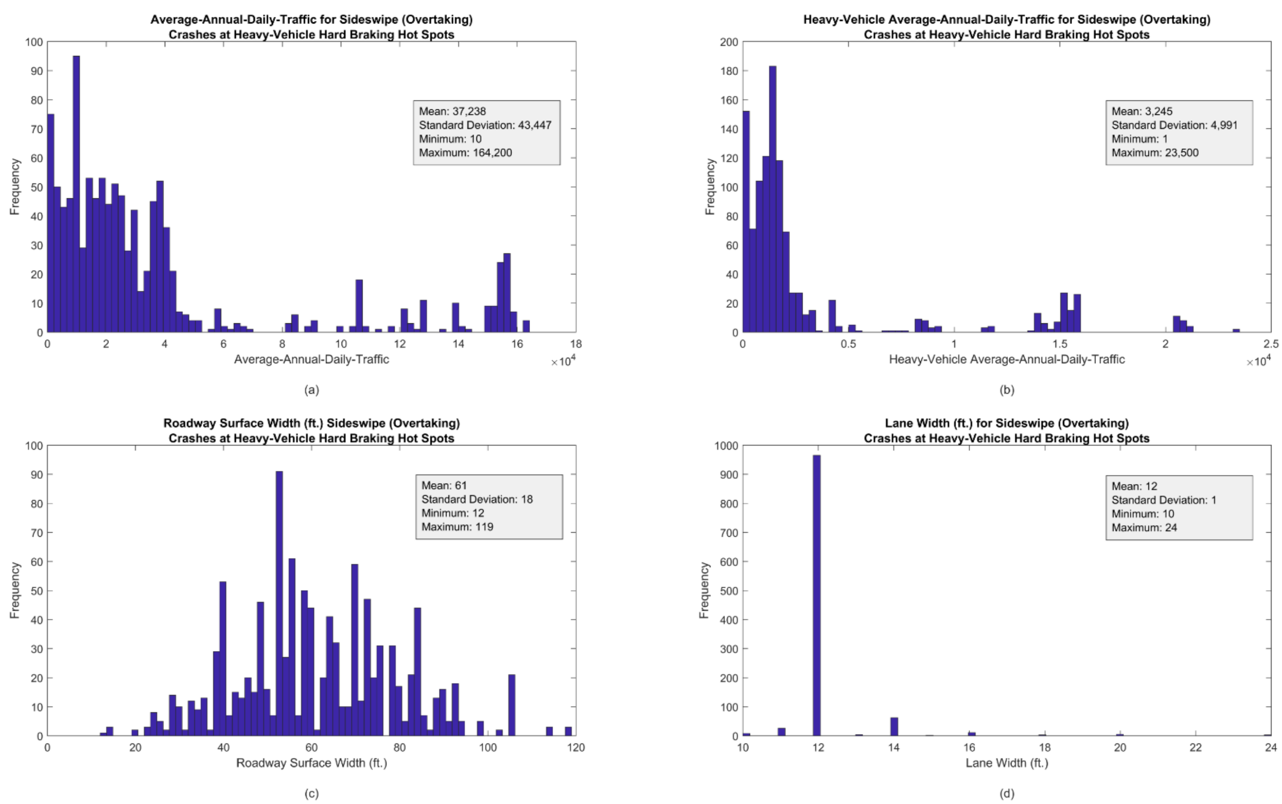

Figure 3.22: (a) AADT, (b) T-AADT, (c) Roadway Surface Width, and (d) Lane Width for Sideswipe (Overtaking) Crashes

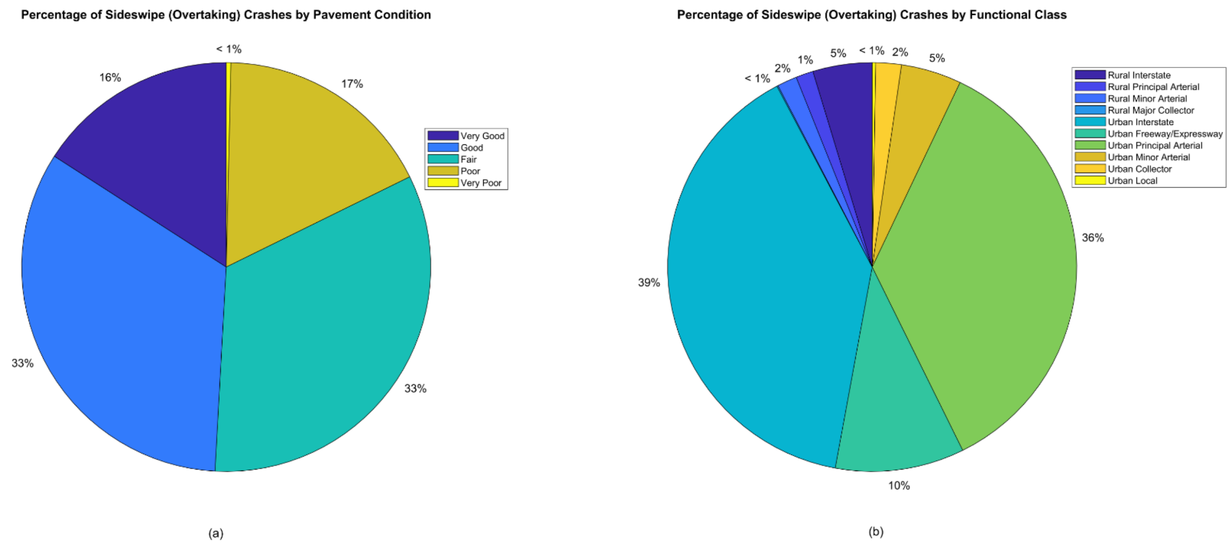

Figure 3.23: Sideswipe (Overtaking) Crashes by (a) Pavement Condition and (b) Functional Class of Roadway

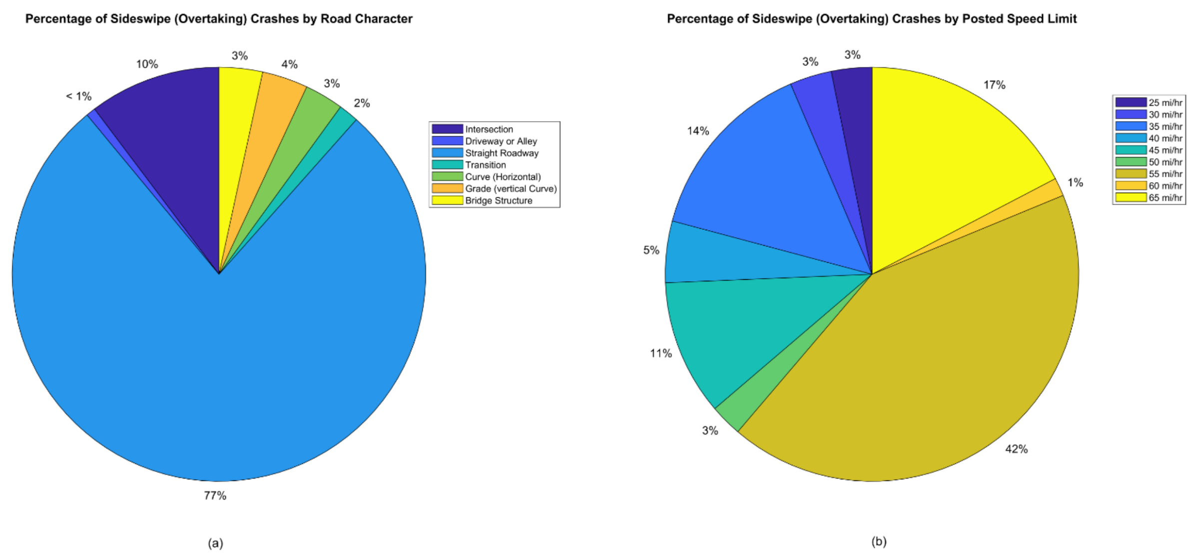

Figure 3.24: Sideswipe (Overtaking) Crashes by (a) Road Character and (b) Posted Speed Limit

4.0 METHODOLOGY

For the present study, several specific methodologies are applied to investigate heavy-vehicle hard braking and crash frequency by crash type. The first method is to conduct a kernel density analysis to get a holistic view of high density areas in regard to heavy-vehicle hard braking. Following the kernel density analysis, the heavy-vehicle hard braking data is used to conduct a hot spot analysis to identify statistically significant heavy-vehicle hard braking hot spots (as well as cold spots) throughout Oregon. Then, as described previously, several datasets are merged together to conduct a crash frequency analysis by crash type. These analyses utilize a random parameters Poisson model (framework used when there is no under- or over-dispersion in the data) and a random parameters Negative Binomial model (framework to account for under- or over-dispersion in the data).

Upon conducting the crash frequency analysis with the aforementioned methods, the data is then tested for spatial autocorrelation. It is determined, as discussed in the following sections, that spatial autocorrelation is present. Therefore, to address the spatial autocorrelation and compare model estimates to that of the random parameters model, a spatial lag model is conducted using a spatial weights matrix obtained during the test for spatial autocorrelation. In the end, the two frameworks (i.e., accounting for unobserved heterogeneity and accounting for spatial correlation) are compared via overall model fit (log-likelihood values) and model predictions (actual crash frequencies versus predicted crash frequencies).

Accordingly, the remainder of the methodology section is organized as follows: the method for the kernel density analysis will be presented, the method for the hot spot analysis will be discussed, the random parameters Poisson and Negative Binomial models will be presented, the method used to test for spatial autocorrelation will be provided, and the methodology for the SLX models will be given.

4.1 Methodology for Kernel Density Analysis

To conduct the kernel density analysis, ArcGIS® is used. First, the hard braking data is geocoded and projected to the coordinate system used by ODOT's Crash Analysis and Reporting Unit: "NAD_1983_Oregon_Statewide_Lambert_Feet_Intl."

Regarding the kernel density analysis, in ArcGIS®, this calculates the magnitude-per-unit area from point features (ESRI, 2018a). Specifically, the Kernel Density tool computes the density of events in a neighborhood around said event. For the current study, this is applied to point events, heavy-vehicle hard braking. In general, the kernel density analysis within ArcGIS® is direct, as presented in the ensuing paragraphs.

To begin, ArcGIS® utilizes a radius (i.e., bandwidth) algorithm to determine a default search radius for the given problem. The first step calculates the mean center of heavy-vehicle hard braking events and is followed by computing the distance from the mean center for all heavy-vehicle hard braking events (ESRI, 2018b). Next, the median of the distances is calculated. Lastly, the standard distance is calculated. After these values have been determined, the following equation is used to determine the search radius in regard to heavy-vehicle hard braking events (ESRI, 2018b):

$$\text{Search Radius} = (0.9) \times \min\left(SD, \sqrt{\frac{1}{\ln(2)}}(D_m)\right) \times n^{-0.2} \tag{4.1}$$

where SD is the standard distance, D_m is the median distance, and n is the number of hard braking events. For this work, hard braking events (i.e., point features in ArcGIS®), the density at each output raster cell is computed by summing all values that overlay the raster cell center (ESRI, 2018b). The computations within ArcGIS® are based on the quartic kernel function (Silverman, 1986).

4.2 Methodology for Hot Spot Analysis

Using the geocoded and projected hard braking data, a hot spot analysis is conducted. The hot spot analysis is contingent on several factors, the first being to aggregate hard braking events based on the accuracy of the data. In the case of the current work, it is possible that hard braking events within a certain distance of each other are likely at the same location (Bennett, 2012). There are several methods to do this, but being that the data for the current study are likely to have coincident points and almost coincident points (this is common in point data collected via GPS), the integration tool and collect events tool are used (Bennett, 2012). To account for GPS accuracy, the XY tolerance (i.e., the distance in which hard braking events are integrated) used to integrate the hard braking events is 50 feet. Using the integrate tool with a XY tolerance of 50 feet has now snapped any hard braking event within 50 feet of each other to a single "stack" (i.e., location) of coincident points with the same coordinates (Bennett, 2012). Then, running the collect events tool, a single point at each hard braking location is created with a count field (denoted "ICOUNT" in ArcGIS®). This count field returns the number of hard braking events at that location (i.e., the number of hard braking events the integrate tool snaps to a location).

The next step is to determine an adequate distance band or threshold distance to use for the hot spot analysis. For this particular step, there is no "right" way to select a distance (Bennett, 2012). In general, the distance is chosen based on the scale of analysis (e.g., distance reflecting a neighborhood, distance reflecting a region, etc.). In the case of the current study, the State of Oregon is the scale of analysis. If the analyst knows the geographic extent of the spatial processes that promote clustering, it is suggested that the analyst select a distance based on this; however, this is most often unknown (Bennett, 2012). Therefore, as recommended by Bennett (2012), the Incremental Spatial Autocorrelation tool is used to find a distance that accounts for maximum spatial autocorrelation.[7]

Lastly, using the distance corresponding to maximum spatial autocorrelation identified from the Incremental Spatial Autocorrelation tool, a hot spot analysis is conducted to identify statistically significant locations in which heavy-vehicle hard braking events occur; these statistically significant locations can be either hot spots or cold spots. In the ArcGIS® framework, hot spots are determined by statistical significance of a z-statistic. The tool within ArcGIS® utilizes a Getis-Ord Gi* statistic

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[7] Several other distances were also tested, such as mean distances, averages distances, minimum distances, etc. However, following Bennett (2012), these distances did not account for maximum spatial autocorrelation.

that works by investigating each heavy-vehicle hard braking event within the context of neighboring heavy-vehicle hard braking events and produces corresponding z-statistics (ESRI, 2014). To be significant, the Getis-Ord Gi* statistic is calculated as (ESRI, 2014):

$$G_i = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \acute{X} \sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{\left[n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}} \tag{4.2}$$

where x_j is the attribute values for heavy-vehicle hard braking events j, $w_{i,j}$ is the spatial weight between hard braking event i and hard braking event j, n is the total number of hard braking events, and:

$$\acute{X} = \frac{\sum_{j=1}^{n} x_j}{n} \tag{4.3}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \left(\acute{X}\right)^2} \tag{4.4}$$

Upon completion of analysis, a map is produced that illustrates hot and cold spots in regards to heavy-vehicle hard braking. This map can be seen in Chapter 5.2.

4.3 Methodology for Crash Frequency Analysis

The current study analyzes crash frequency of all traffic mixes at heavy-vehicle hard braking hot spots in Oregon. Crash frequencies are considered non-negative integer count values; therefore, specific methodologies must be applied to correctly model the relationships between exposure-based variables and the expected number of crashes. Although there are several techniques to model these relationships, the current study adopts two explicit modeling frameworks: (1) Random parameters Poisson regression and (2) Random parameters Negative Binomial regression.

4.3.1 Random Parameters Poisson Regression

Poisson regression is commonly used to model relationships between independent variables and a count dependent variable (i.e., crash frequency). In the Poisson model, y_i is drawn from a Poisson population with parameter λ_i, where the model can be formulated as (Greene, 2012):

$$P(y_i) = \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!} \tag{4.5}$$

where $P(y_i)$ is the probability of heavy-vehicle hard braking hot spot i having y_i crashes and λ_i is the Poisson parameter for heavy-vehicle hard braking hot spot i (the Poisson parameter for heavy-vehicle hard braking hot spot i is also equal to the expected number of crashes, $\mathrm{E}[y_i]$, at hot spot i) (Washington et al., 2011). Poisson models are estimated by specifying the Poisson parameter as a function of covariates (i.e., explanatory variables), which most often takes the form of a log-linear model (Greene, 2012):

$$\ln(\lambda_i) = \beta X_i \tag{4.6}$$

or, equally (Washington et al., 2011, Greene, 2012):

$$\lambda_i = e^{\beta X_i} \tag{4.7}$$

where X_i is a vector of explanatory variables (i.e., exposure-based variables) and β is a vector of estimable parameters. Based on the formulation shown in Eq. (4.7), the expected number of crashes at heavy-vehicle hard braking hot spot i can be shown as (Greene, 2012):

$$\mathrm{E}[y_i \mid X_i] = \mathrm{Var}[y_i \mid X_i] = \lambda_i = e^{\beta X_i} \tag{4.8}$$

Although, in principal, the Poisson model is simply a non-linear regression model, it is substantially easier to estimate parameters using maximum likelihood estimation (Greene, 2012). Therefore, parameters in the Poisson model are estimated using the following log-likelihood function (Washington et al., 2011, Greene, 2012):

$$LL(\beta) = \sum_{i=1}^{n} [-\lambda_i + y_i \beta X_i - \ln(y_i!)] \tag{4.9}$$

or, substituting $e^{\beta X_i}$ for the Poisson parameter:

$$LL(\beta) = \sum_{i=1}^{n} \left[-e^{\beta X_i} + y_i \beta X_i - \ln(y_i!)\right] \tag{4.10}$$

Lastly, to interpret parameter estimates, the current study follows the Poisson parameter estimates interpretation from Ramsey and Schafer (2012). This is done by calculating a multiplicative change in the expected number of crashes at heavy-vehicle hard braking hot spot i, similar to that of calculated odds ratios for a logit model parameter.[8] That is (Ramsey and Schafer, 2012):

$$MC = e^{\beta} \tag{4.11}$$

where MC is the multiplicative change in the expected number of crashes and β is the estimated parameter from the Poisson regression.

4.3.2 Random Parameters Negative Binomial Regression

Although the Poisson regression model is basic and easy to estimate, it has a major shortcoming: it cannot handle over- or under-dispersion. That is, the Poisson model and Poisson distribution operates under the assumption that the mean and variance be equal, $\mathrm{E}[y_i] = \mathrm{Var}[y_i]$. If this equality is untrue in the data being analyzed, the data is said to be under-dispersed ($\mathrm{E}[y_i] > \mathrm{Var}[y_i]$) or over-dispersed ($\mathrm{E}[y_i] < \mathrm{Var}[y_i]$) (Washington et al., 2011, Greene, 2012). If this is the case and measures are not taken to correct for it, the parameter estimates will no longer be unbiased and standard errors of the parameters will be incorrect (Wooldridge, 2010, 2016, Washington et al., 2011, Greene, 2012).

To determine if dispersion is present in the data, it must be tested for. In most statistical software, a dispersion parameter will be provided to determine if the data is significantly over- or under-dispersed (Greene, 2016). For the current study, this

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[8] This type of interpretation is permitted, as the Poisson model and Poisson parameter take on the form of a log-linear model.

parameter (the parameter provided by the statistical software) is used along with manually calculating for over- or under-dispersion based on Poisson estimates (Wooldridge, 2016):

$$(n-k-1)^{-1}\sum_{i=1}^{n}\frac{\hat{u}_i^2}{\hat{y}_i} \tag{4.12}$$

where $\hat{y}_i$ is the exponential of the fitted value ($\hat{y}_i = e^{\hat{\beta}_0+\hat{\beta}_1 X_{i1}+\cdots+\hat{\beta}_k X_{ik}}$), $\hat{u}_i^2$ is the squared-residual ($\hat{u}_i = y_i - \hat{y}_i$), and $(n-k-1)$ is the degrees of freedom given n observations and $k+1$ estimates (Wooldridge, 2016). If the result from Eq. (4.12) is equal to 1, the said data meets the requirements of the Poisson regression model. However, if the result from Eq. (4.12) is less than or greater than 1, then an alternate modeling framework must be applied (i.e., there is over- or under-dispersion). For the current study, the method considered to account for over- or under-dispersion is the random parameters Negative Binomial model.

To begin, the functional form of the Negative Binomial model remains the same as the functional form of the Poisson model shown in Eq. (4.5). However, the form of the Poisson parameter is now changed by rewriting it as (Washington et al., 2011, Greene, 2012):

$$\ln(\lambda_i) = \beta X_i + \varepsilon_i \tag{4.13}$$

or, equally (Washington et al., 2011, Greene, 2012):

$$\lambda_i = e^{\beta X_i + \varepsilon_i} \tag{4.14}$$

where ε_i is a Gamma-distributed disturbance term with mean 1 and variance α. With the addition of this Gamma-distributed disturbance term, ε_i, the variance is now allowed to differ from the mean to overcome the limitation of the Poisson regression model (Washington et al., 2011):

$$\mathrm{Var}[y_i] = \mathrm{E}[y_i]\big[1 + \alpha\mathrm{E}[y_i]\big] = \mathrm{E}[y_i] + \alpha\mathrm{E}[y_i]^2 \tag{4.15}$$

where α is often referred to as the over-dispersion parameter, in which model selection is contingent on. Due to the addition of ε_i, and resulting variance α, the probability density function changes to the Negative Binomial probability density function (Anastasopoulos and Mannering, 2009, Washington et al., 2011):

$$P(y_i) = \prod_i \frac{\Gamma\left(\frac{1}{\alpha} + y_i\right)}{\Gamma\left(\frac{1}{\alpha}\right) y_i!} \left(\frac{\frac{1}{\alpha}}{\frac{1}{\alpha} + \lambda_i}\right)^{\frac{1}{\alpha}} \left(\frac{\lambda_i}{\frac{1}{\alpha} + \lambda_i}\right)^{y_i} \tag{4.16}$$

where $\Gamma(\cdot)$ is a gamma function, which results in the likelihood function (Washington et al., 2011, Greene, 2012):

$$L(\lambda_i) = \prod_i \frac{\Gamma\left(\frac{1}{\alpha} + y_i\right)}{\Gamma\left(\frac{1}{\alpha}\right) y_i!} \left(\frac{\frac{1}{\alpha}}{\frac{1}{\alpha} + \lambda_i}\right)^{\frac{1}{\alpha}} \left(\frac{\lambda_i}{\frac{1}{\alpha} + \lambda_i}\right)^{y_i} \tag{4.17}$$

To interpret parameter estimates, the current study follows the Negative Binomial parameter estimates interpretation from Ramsey and Schafer (2012). This is done by calculating a multiplicative change in the expected number of crashes at heavy-vehicle hard braking hot spot i, similar to that of calculated odds ratios for a logit model parameter.[9] That is (Ramsey and Schafer, 2012):

$$MC = e^{\beta} \tag{4.18}$$

where MC is the multiplicative change in the expected number of crashes and β is the estimated parameter from the Negative Binomial regression.

Lastly, to account for variation within the data (often referred to as unobserved heterogeneity), the Poisson and Negative Binomial regression models are extended to include the estimation of random parameters. If unobserved heterogeneity is present and not accounted for, parameter estimates will be biased and the corresponding inferences incorrect (see Mannering et al. (2016) for a full discussion of unobserved heterogeneity and the implications of not accounted for it). In the context of crash data, unobserved heterogeneity is most often a result of variation within existing variables and "missing" variables. In the case of variation within existing variables, think of variation among people. For example, people have different visual acuity, ability to hear, different perception-reaction-times, etc. These characteristics are not captured within typical demographic variables in crash data, yet are likely to influence the outcome of a crash. In the case of the current work, where only exposure-based variables are used, there is likely unobserved heterogeneity due to the exclusion of all non-exposure-based variables. As such, the proposed modeling framework accounts

[9] This type of interpretation is permitted, as the Negative Binomial model and Negative Binomial parameter take on the form of a log-linear model.

for this. In regards to “missing” variables, this is most notably attributed to crash data collection forms. For instance, when police- or self-reporting crashes, not each and every factor that lead to a crash is on the data collection forms; therefore, the data is not collected. This, too, is accounted for through the proposed modeling framework. Now, to allow for the estimation of random parameters and account for unobserved heterogeneity in the data, Greene (2012) developed a simulated maximum likelihood estimation procedure to include random parameters estimation in Poisson and Negative Binomial regressions[10]. To estimate random parameters and allow β to vary across observations (i.e., account for crash-specific variation), estimable parameters are now:

$$\beta_i = \beta + \varphi_i \tag{4.19}$$

where φ_i is a randomly distributed term, such as normally distributed with mean 0 and variance σ^2 (the distribution of this term is chosen and tested by the analyst for statistical significance). Considering random parameters estimation, the Poisson parameter in the Poisson model can now be written as (Anastasopoulos and Mannering, 2009, Greene, 2012):

$$\lambda_i \mid \varphi_i = e^{\beta X_i} \tag{4.20}$$

[10] According to Cameron and Trivedi (1986), an alternative to estimating random parameters (for the negative binomial model) would be to let α vary as a function of the mean, λ. However, although this simplifies the estimation procedure, this method is more restrictive in the ability to account for heterogeneity across heavy-vehicle hard braking hot spots (Anastasopoulos and Mannering, 2009).

where λ_i is now conditional on φ_i. Likewise, the Poisson parameter for the Negative Binomial model can now be written as (Anastasopoulos and Mannering, 2009, Greene, 2012):

$$\lambda_i \mid \varphi_i = e^{\beta X_i + \varepsilon_i} \tag{4.21}$$

where λ_i is now conditional on φ_i for the Negative Binomial model. With the addition of the randomly distributed term, φ_i, the probabilities of the Poisson and Negative Binomial models is now $P(y_i \mid \varphi_i)$. Finally, the log-likelihood function of the random parameters Poisson or Negative Binomial model is represented as (Anastasopoulos and Mannering, 2009, Greene, 2012):

$$\sum_{\forall i} \ln \int_{\varphi_i} f(\varphi_i)\, P(y_i \mid \varphi_i) d\varphi_i \tag{4.22}$$

where $f(\varphi_i)$ is the probability density function of φ_i. To finish, Eq. (4.22) is simulated via simulation-based maximum likelihood estimation due to the complex integral. This works by estimating parameters that maximize the simulated log-likelihood function while allowing for heterogeneity (i.e., crash-specific variation) (Anastasopoulos and Mannering, 2009). This particular simulation is accomplished by utilizing Halton draws, where Halton draws are sequences used to deterministic, nearly uniformly distributed points (between 0 and 1) that appear to be random (Halton, 1960). More recent work has shown that this simulation procedure results in a more efficient, preferred distribution of draws if compared to purely random draws (Train, 2000, Bhat, 2003).

4.4 Methodology for Spatial Econometric Analysis

Being that the current study utilizes spatial data (i.e., heavy-vehicle hard braking events and their corresponding hot spots), the data is assessed for spatial autocorrelation. This is exhibited by Tobler (1979), in which he states "everything is related to everything else, but near things are more related than distant things." This idea (i.e., spatial effects) is the reason for a field of spatial econometrics (Anselin, 1988). Therefore, if spatial effects are present, there is said to be spatial dependence. Spatial dependence can be thought of as the presence of a fundamental relationship between events at one point in space and events at another (Anselin, 1988). This particular relationship is often generalized by two classes of conditions, in which the second condition most accurately describes the spatial dependence observed in the current work. That said, the second condition is a fundamental aspect of regional science and geography where there is presence of a variety of spatial interaction phenomena (Anselin, 1988).

As such, considering spatial interaction phenomena, the location of events and the distance between them matter (Anselin, 1988). As a result, there may be a variety of interdependencies between events in space-time (Anselin, 1988).

4.4.1 Test for Spatial Autocorrelation

If spatial dependence (also to referred to as spatial autocorrelation) is present, a methodology to account for such autocorrelation is needed. In the context of the current study, this methodology is spatial econometrics. Therefore, tests for spatial autocorrelation for each crash type considered are conducted.

The first step is to import the spatial data into a statistical software to test for spatial autocorrelation (R-Studio is used in the present study). Upon importing the ArcGIS® shapefiles, the number of k-nearest neighbors must be determined before continuing. In the context of transportation safety, nearest neighbors is a useful tool when conducting spatial analyses (Spiegelman et al., 2011). In many cases, analysts begin with a number of k-nearest neighbors equal to $\sqrt{n}$, where n is the number of observations (Silverman, 1986, Duda et al., 2001). However, the number of k-nearest neighbors is highly data-dependent, contingent on the knowledge of the geographical region being studied, and consideration of the bias-variance tradeoff (Formann-Roe, 2012, Vanderplas, 2017). For the current study, $\sqrt{n}$ was assessed, but the resulting plots suggest that areas in Portland, OR, are neighbors with events that occurred several hundred miles away. To illustrate, Figure 4.1 shows $\sqrt{n}$ nearest neighbors for each crash type considered in the current study. Therefore, the current work begins with 1 nearest neighbor and continues until the number of nearest neighbors properly reflects the geography of Oregon.

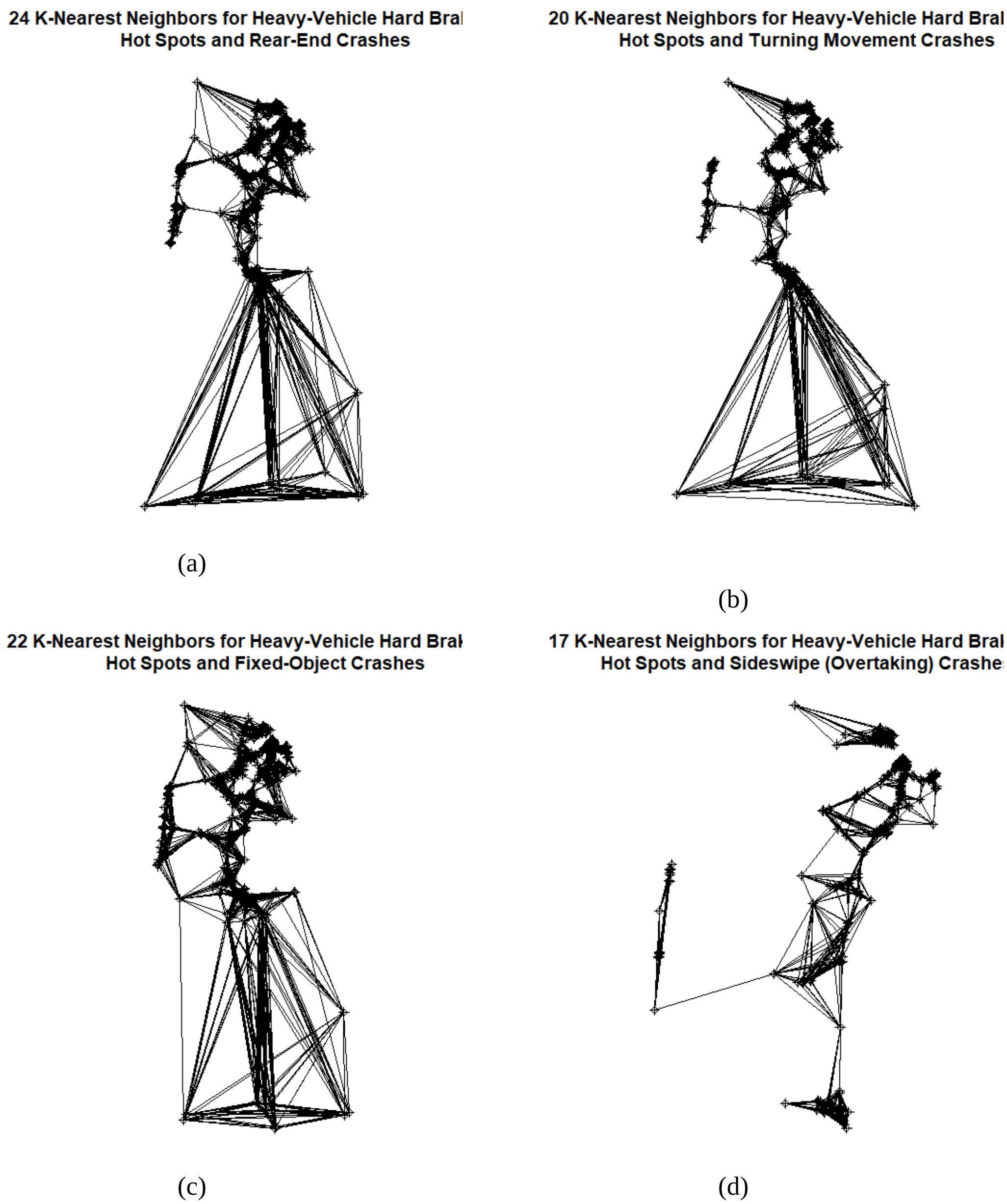


Figure 4.1: Number of Nearest Neighbors for Heavy-Vehicle Hard Braking Hot Spots Based on $\sqrt{n}$ for: (a) Rear-End Crashes, (b) Turning Movement Crashes, (c) Fixed-Object Crashes, and (d) Sideswipe (Overtaking) Crashes

The first crash type first assessed is rear-end crashes. As mentioned previously, the current work begins with 1 nearest neighbor and continues until the number of nearest neighbors properly reflects the geography of Oregon. To demonstrate the difference in the number of k-nearest neighbors for rear-end crashes, see Figure 4.2. As seen, once 4-nearest neighbors is applied, hard braking hot spots that span a significant distance across Oregon are defined as neighbors. Based on the geography and topography of Oregon, these likely do not share specific spatial characteristics that would make them spatial neighbors. Therefore, for rear-end crashes, 3-nearest neighbors is used to conduct the spatial autocorrelation test; and, if significant, used to conduct the spatial econometric analysis.

Next, the number of k-nearest neighbors needs to be determined for turning movement crashes. Again, plots are used to assess and determine a representative number of nearest neighbors, as shown in Figure 4.3. Seen in Figure 4.3, the first set of nearest neighbors to define neighbors than span a significant distance across Oregon is 5-nearest neighbors. Southern Oregon shares similar geographic and topographic features; therefore, the neighbors seen defined “horizontally” at the bottom of the plots are reasonable. However, the features between Southern Oregon and mid- to Northern Oregon likely do not share specific spatial characteristics that would make them spatial neighbors. Therefore, for turning movement crashes, 4-nearest neighbors is used to conduct the spatial autocorrelation test; and, if significant, used to conduct the spatial econometric analysis.

The next crash type in which the number of k-nearest neighbors needs to be determined is fixed-object. Once more, plots are provided and used to assess the relationship between the number of nearest neighbors and the geographical region of Oregon. For fixed-object nearest neighbor plots, refer to Figure 4.4. For heavy-vehicle hard braking hot spots and fixed-object crashes, 3-nearest neighbors is the first to show that events spanning a significant distance across Oregon are defined as neighbors. As with the previous three crash types, specific spatial characteristics among these neighbors are likely different based on knowledge of the area. Therefore, for fixed-object crashes, 2-nearest neighbors are used to conduct the spatial autocorrelation test; and, if significant, used to conduct the spatial econometric analysis.

The final crash type assessed to determine the number of k-nearest neighbors is sideswipe (overtaking). 1-nearest neighbor to 3-nearest neighbors do not represent neighbors based on the geographical characteristics of Oregon; therefore, only 4-nearest neighbors to 7-nearest neighbors are shown (Figure 4.5). Seen in Figure 4.5, 7-nearest neighbors is too many neighbors, as it defines events in Northern Oregon to Southern Oregon as neighbors. Now, both 6-nearest neighbors and 5-nearest neighbors appear to accurately reflect natural clustering based on geographical characteristics of Oregon (i.e., either can be chosen). In the case of sideswipe (overtaking) crashes, the number is chosen based on the preference of the analyst; that is, whether the analyst wants to mitigate bias or variance (Formann-Roe, 2012, Vanderplas, 2017). Therefore, for sideswipe (overtaking) crashes, the decision was based on two factors: (1) the clustering of nearest neighbors that more accurately reflects the geography of Oregon[11]

[11] The difference is marginal, but can be seen if comparing the plots between 5- and 6-nearest neighbors. For instance, all events that occurred on US-101 (the left-side of the plot) are defined as neighbors with 6-nearest neighbors; but, with 5-nearest neighbors they are more naturally clustered based on the geography and topography along this route. Likewise, a similar situation is seen along I-5 (the center of the plot). Although subtle differences in the plot, the difference in geographical characteristics need to be accounted for when considering the number of nearest neighbors.

and (2) mitigate bias (Formann-Roe, 2012, Vanderplas, 2017). Therefore, for sideswipe (overtaking) crashes, 5-nearest neighbors are used to conduct the spatial autocorrelation test; and, if significant, used to conduct the spatial econometric analysis.

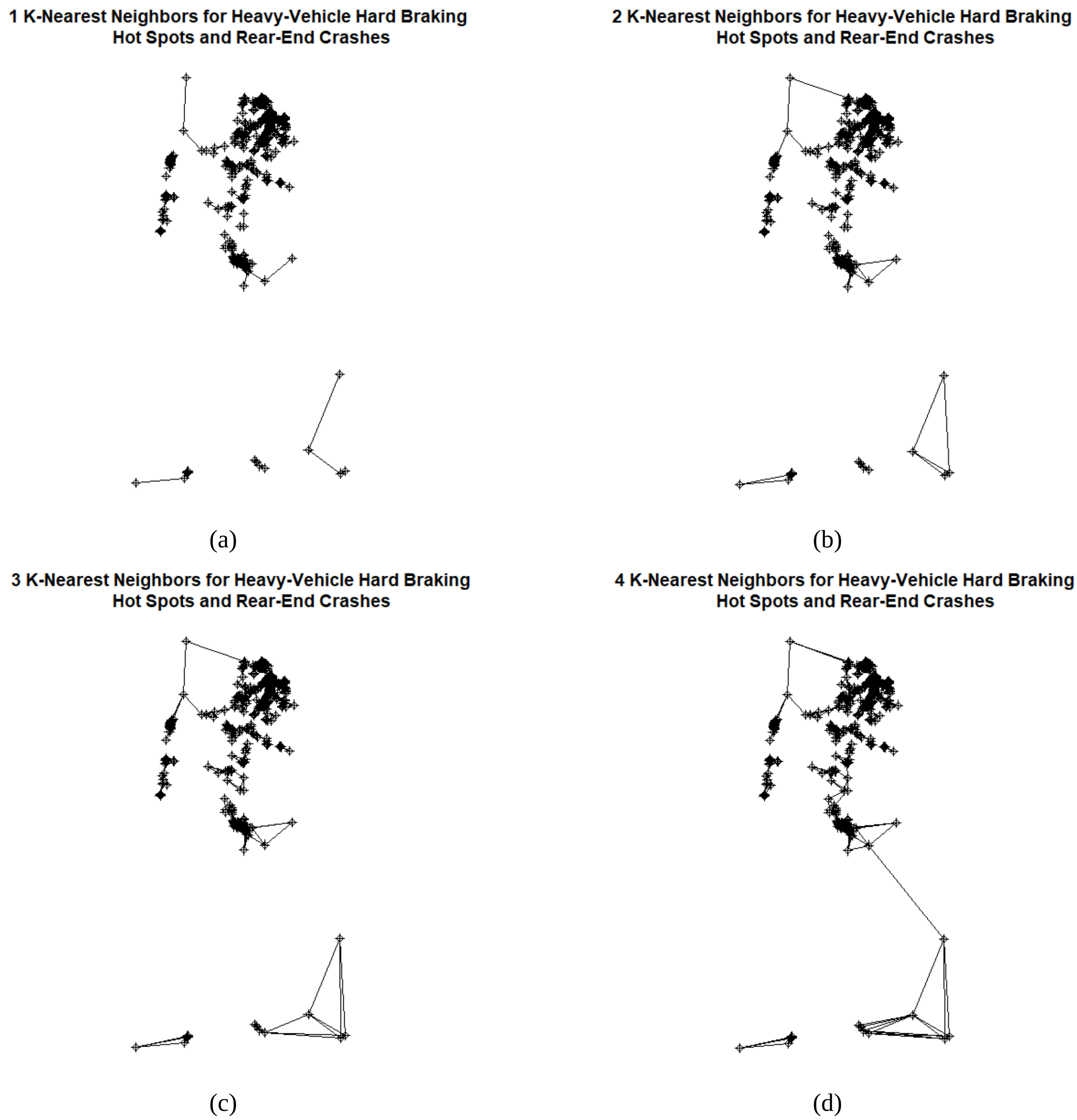


Figure 4.2: (a) 1-Nearest Neighbors, (b) 2-Nearest Neighbors, (c) 3-Nearest Neighbors, and (d) 4-Nearest Neighbors for Heavy-Vehicle Hard Braking Hot Spots and Rear-End Crashes

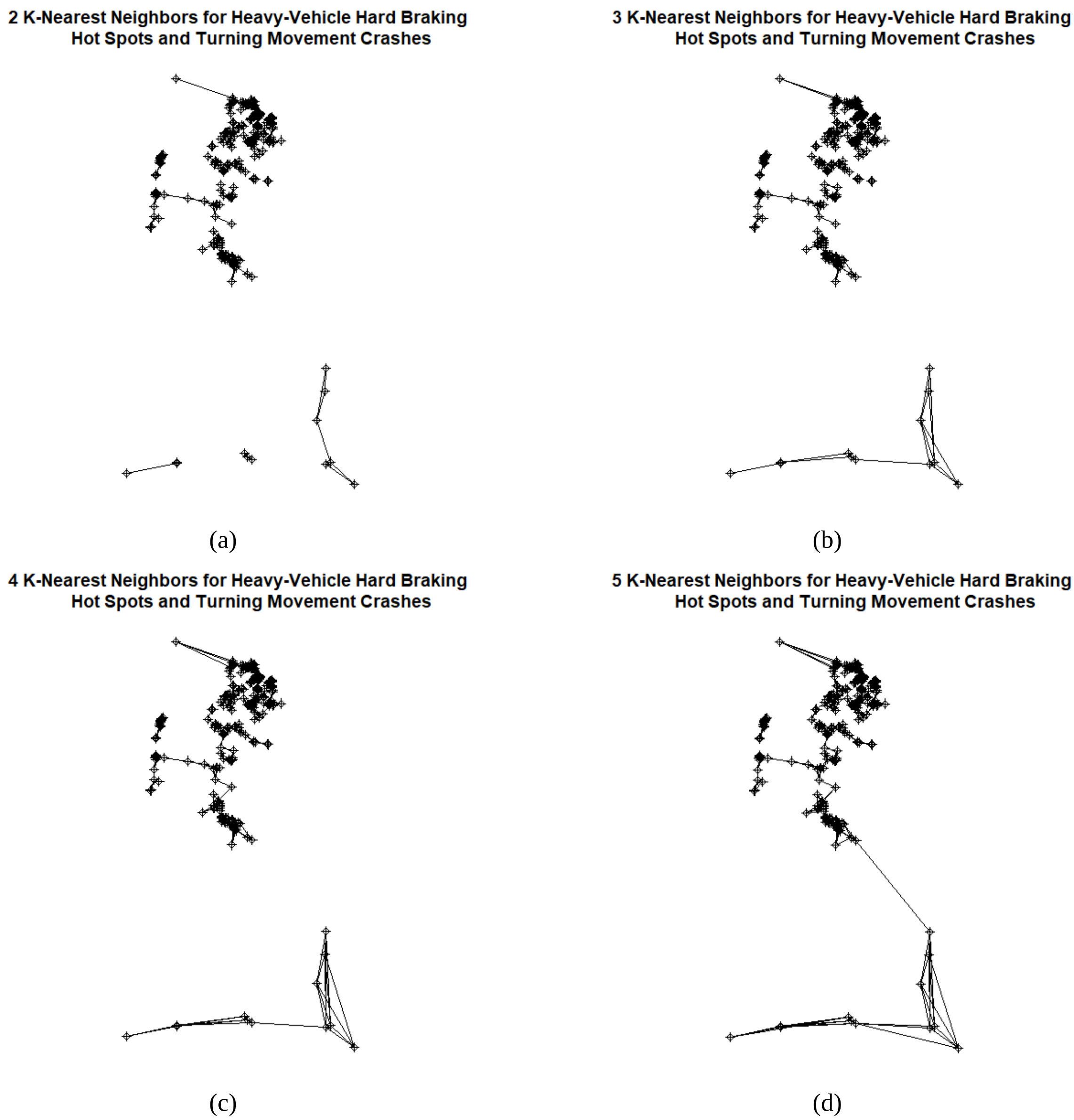


Figure 4.3: (a) 2-Nearest Neighbors, (b) 3-Nearest Neighbors, (c) 4-Nearest Neighbors, and (d) 5-Nearest Neighbors for Heavy-Vehicle Hard Braking Hot Spots and Turning Movement Crashes

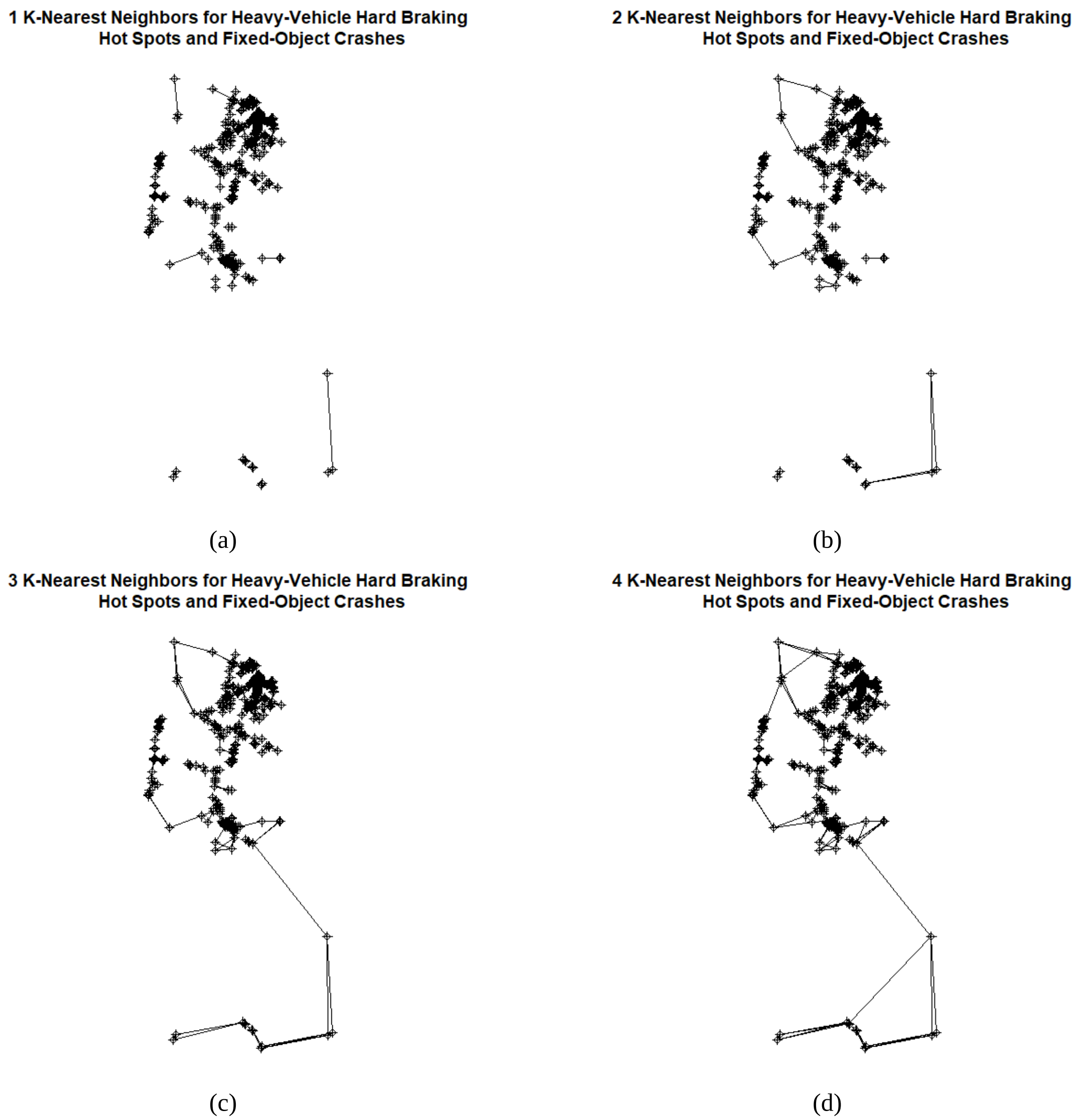


Figure 4.4: (a) 1-Nearest Neighbors, (b) 2-Nearest Neighbors, (c) 3-Nearest Neighbors, and (d) 4-Nearest Neighbors for Heavy-Vehicle Hard Braking Hot Spots and Fixed-Object Crashes

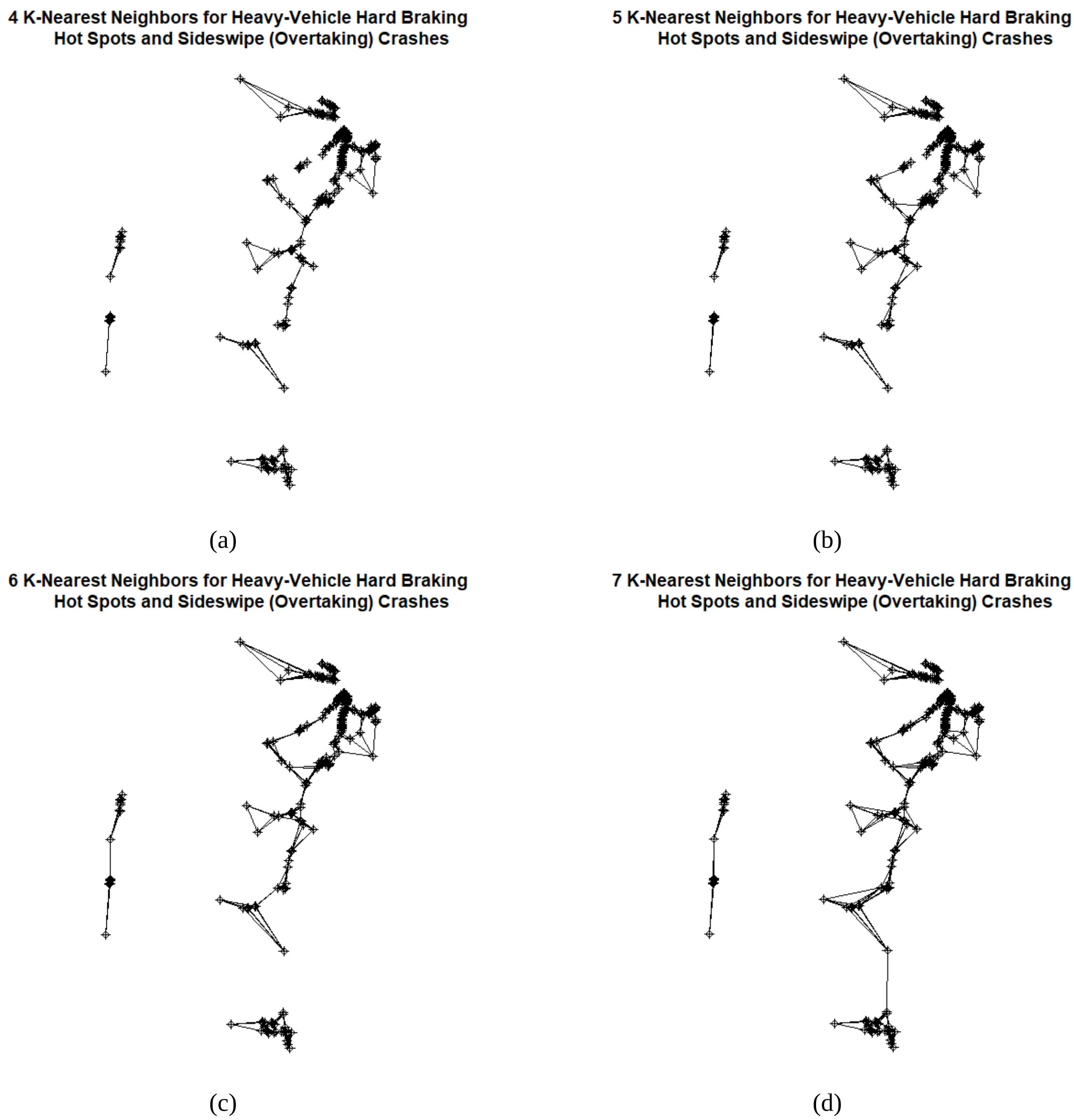


Figure 4.5: (a) 4-Nearest Neighbors, (b) 5-Nearest Neighbors, (c) 6-Nearest Neighbors, and (d) 7-Nearest Neighbors for Heavy-Vehicle Hard Braking Hot Spots and Sideswipe (Overtaking) Crashes

Using the number of nearest neighbors for each crash type, a spatial weights matrix is calculated and used to compute a Moran's I-statistic for spatial autocorrelation. The Moran's I-statistic has been widely accepted and used to test for spatial autocorrelation

(Goodchild, 1987, Anselin, 1988, Anselin and Bera, 1998, LeSage, 2008, Bivand et al., 2013, Loo and Anderson, 2016). Therefore, the current work utilizes this statistic to test for spatial autocorrelation.

The Moran's I-statistic, specifically, measures spatial autocorrelation by focusing on feature hard braking locations and their feature values simultaneously. In doing so, the Moran's I-statistic determines whether the spatial data (point features in the case of the current study) is clustered, dispersed, or random. The Moran's I-statistic is then calculated as (Moran, 1948, 1950, Goodchild, 1987, Griffith, 1987, Getis and Ord, 1992):

$$I = \left[\frac{N}{S_0}\right] \frac{\left(\sum_{i=1}^{N} \sum_{j=1}^{N} w_{i,j} z_i z_j\right)}{\left(\sum_{i=1}^{N} z_i^2\right)} \tag{4.23}$$

where z_i and z_j is the deviation of an attribute for feature i and j, respectively, from its mean (this is represented as $X_i - \acute{X}$ and $X_j - \acute{X}$, and when multiplied is the covariance matrix), $w_{i,j}$ is the spatial weights between i and j and represented by the spatial weights matrix discussed previously, N is the sample size (i.e., total number of hard braking hot spots), and S_0 is a standardization factor corresponding to the sum of all spatial weights for non-zero cross-products:

$$S_0 = \sum_{i=1}^{N} \sum_{j=1}^{N} w_{i,j} \tag{4.24}$$

Now, to determine significance, as the Moran's I-statistic is asymptotically distributed normal (i.e., $z_I N(0,1)$), a z-statistic is calculated to determine statistical significance:

$$z_I = \frac{I - \mathrm{E}[I]}{\sqrt{\mathrm{Var}[I]}} \tag{4.25}$$

where the expected value of I, the mean of I, and the variance of I are determined as follows (based on the null hypothesis that there is no spatial autocorrelation):

$$\mathrm{E}[I] = \frac{-1}{(N-1)} \tag{4.26}$$

$$\mathrm{Var}[I] = \mathrm{E}[I^2] - \mathrm{E}[I]^2 \tag{4.27}$$

Using this test for spatial autocorrelation, results will be discussed in Chapter 5.4.1.

4.4.2 Spatial Econometric Modeling Framework

If there is spatial autocorrelation present, not accounting for it can result in severe model misspecification (Anselin, 1988). As such, the current work extends the Poisson and Negative Binomial regression models discussed in Chapter 4.3 to account for spatial autocorrelation. To do this, there are specific frameworks that can be applied, most notable the spatial lag model (SLM) and spatial error model (SEM) (Aguero-Valverde and Jovanis, 2008). For a summary and comparison of different spatial econometric model specifications, refer to Figure 4.6. Of the model specifications shown, the most commonly used is the SLM, which is a special case of the simultaneous spatial autoregressive process (Tiefelsdorf, 2000).

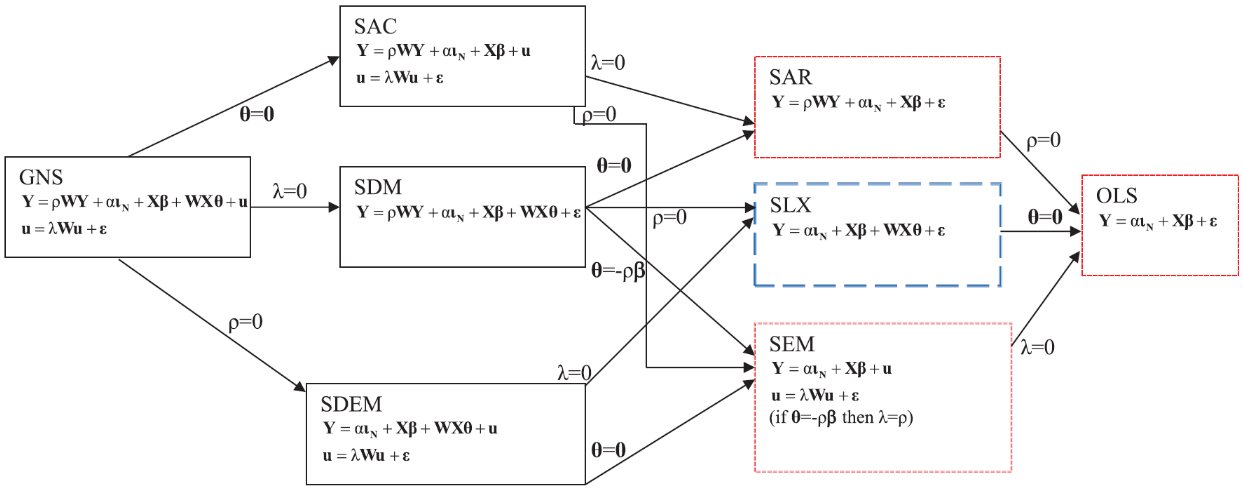


Figure 4.6: Comparison of Different Spatial Econometric Models (Source: Elhorst, 2010)

*Note: GNS = General Nesting Spatial Model; SAC = Spatial Autoregressive Combined Model; SDM = Spatial Durbin Model; SDEM = Spatial Durbin Error Model; SAR = Spatial Autoregressive Model; SLX = Spatial Lag of X Model; SEM = Spatial Error Model; OLS = Ordinary Least Squares Model

This special case is predicated on lagging the dependent variable, which has been common in the econometric literature (Anselin and Bera, 1998, LeSage, 2008, LeSage and Pace, 2009) and is often referred to as the “lagged-response model” (Dormann et al., 2007). Although SLM models have been the primary method in regards to spatial econometric research, models where the explanatory variables are lagged (SLX models) have become more prevalent in recent years (Gibbons and Overman, 2012, Grubesic and Rosso, 2014, Vega and Elhorst, 2015). This is attributed to a couple different factors, the first of which is spatially lagged explanatory variables can serve as important tools when conducting an econometric model and is in striking contrast to the lagged dependent variable models (Grubesic and Rosso, 2014). Another factor leading to this paradigm is the identification of spatial spillovers, or spillover effects; specifically, the effect of an explanatory variable in location i on the dependent variable in location j (where $j \neq i$) (Vega and Elhorst, 2015).[12] In addition, unlike the SLM, the elements in the spatial weights matrix, W, in the SLX model can be parameterized (Vega and Elhorst, 2015). In other words, there is greater flexibility with the specification of W, an aspect with a concentration of criticism within the spatial econometric literature (Corrado and Fingleton, 2012, Mcmillen, 2012). Lastly, in the SLM, simultaneity results in the lagged dependent variable being endogenous; therefore, alternate techniques to account for endogeneity are required (Grubesic and Rosso, 2014). In the SLX model, this is not the case.

There have been previous studies in which SLX models have been applied (Boarnet, 1994a, 1994b, 1998, Holtz-Eakin and Schwartz, 1995, Dalenberg et al., 1998, Fischer et al., 2009), but they are still considered to be "left out of the picture" (Vega and Elhorst, 2015). Therefore, the current study utilizes a SLX model. In addition to the listed deficiencies in the traditional SLM, this is based on the premise that the spatial average of crashes at neighboring heavy-vehicle hard braking hot spots could have a direct role in determining the number of crashes at hot spots in the dependent variable vector, Y.

[12] This particular type of effect is not attainable with the traditional method in which the dependent variable is spatially lagged.

Therefore, the SLX model for the Poisson regression model can be formulated as (Gibbons and Overman, 2012, Grubesic and Rosso, 2014, Vega and Elhorst, 2015, Wu and Chvosta, 2016):

$$\lambda_i = e^{\beta_i X_i + W\beta_i X_i} \tag{4.28}$$

where λ_i is the Poisson parameter for the SLX model, W is the spatial weights matrix based on the number of k-nearest neighbors, and $X = [X_i W X_i]$. Likewise, the SLX variant of the Negative Binomial regression model can be represented as:

$$\lambda_i = e^{\beta_i X_i + W\beta_i X_i + \varepsilon_i} \tag{4.29}$$

where all terms have been defined previously. Essentially, variables are now allowed to lag to account for the spatial autocorrelation. In the context of this model, there is a parameter estimate for both the non-lagged and lagged explanatory variable. As such, the interpretation of direct and spillover effects (i.e., indirect effects) do not require further calculation compared to other spatial econometric models (Vega and Elhorst, 2015). That is, the direct effects are the parameter estimates for the non-lagged explanatory variables and the spillover effects (indirect effects) are the parameter estimates for the lagged explanatory variables (Vega and Elhorst, 2015). Lastly, the parameters are interpreted in the same manner as the random parameters models, as a multiplicative change in the expected number of crashes.

5.0 RESULTS

5.1 Kernel Density Results

Before conducting a more in-depth analysis, the kernel density analysis provides a holistic view of high density areas in regards to heavy-vehicle hard braking. Referring to Figure 5.1, the majority of high density areas are along the I-5 corridor. This corridor also runs through the most populated areas in Oregon. Therefore, it is not surprising to see high density areas in the Portland Metropolitan area, Salem, Eugene, Albany, and Roseburg. As for the high density area in Medford, the topography of this section of I-5 is mountainous and can certainly lead to hard braking (this section includes the highest point on I-5 from the Canadian border to the Mexican border). Interestingly, there are no high density areas along the coastal route (US-101) and only one high density area along US-97 (a major north/south freight corridor in Oregon)

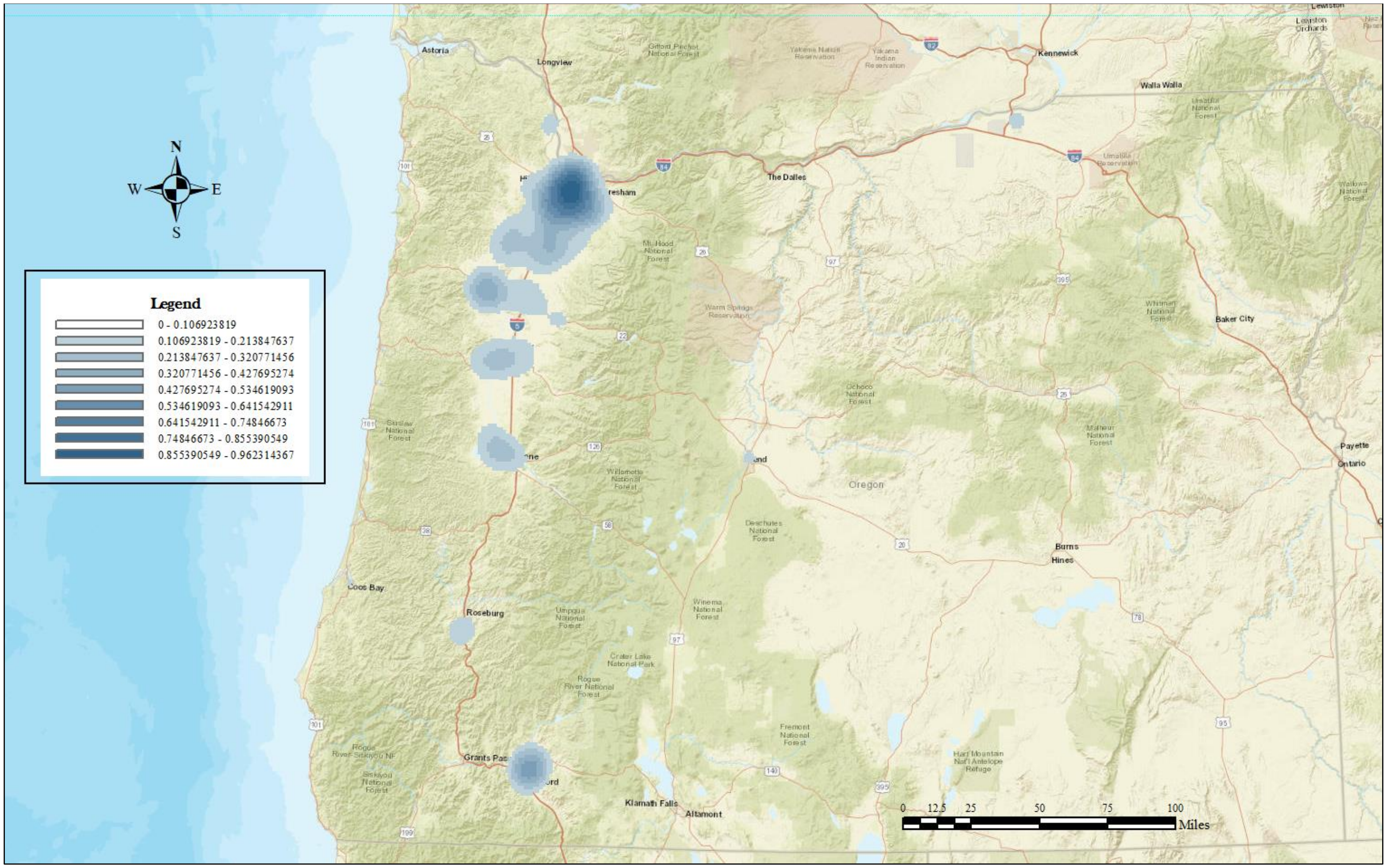


Figure 5.1: Results From Kernel Density Analysis of Heavy-Vehicle Hard Braking Events

5.2 Hot Spot Analysis Results

As discussed previously, identifying statistically significant hot spots is a primary part of the current study. The importance of the hot spots is due to the crash frequency analysis, as crashes are aggregated to these hot spots. Therefore, the results of the hot spot analysis are shown in Figure 5.2.

In total, there are 1,280 hard braking hot spots, of which the majority are in the Portland Metropolitan area. In addition to the more populated areas of Oregon, there are several highly significant hot spots along the coastal highway of US-101. These findings are not surprising, as the topography and roadway geometrics along this highway can certainly lead to hard braking events. There are also hard braking hot spots observed along routes connected US-101 and I-5, all of which include topography and roadway geometrics that could lead to hard braking.

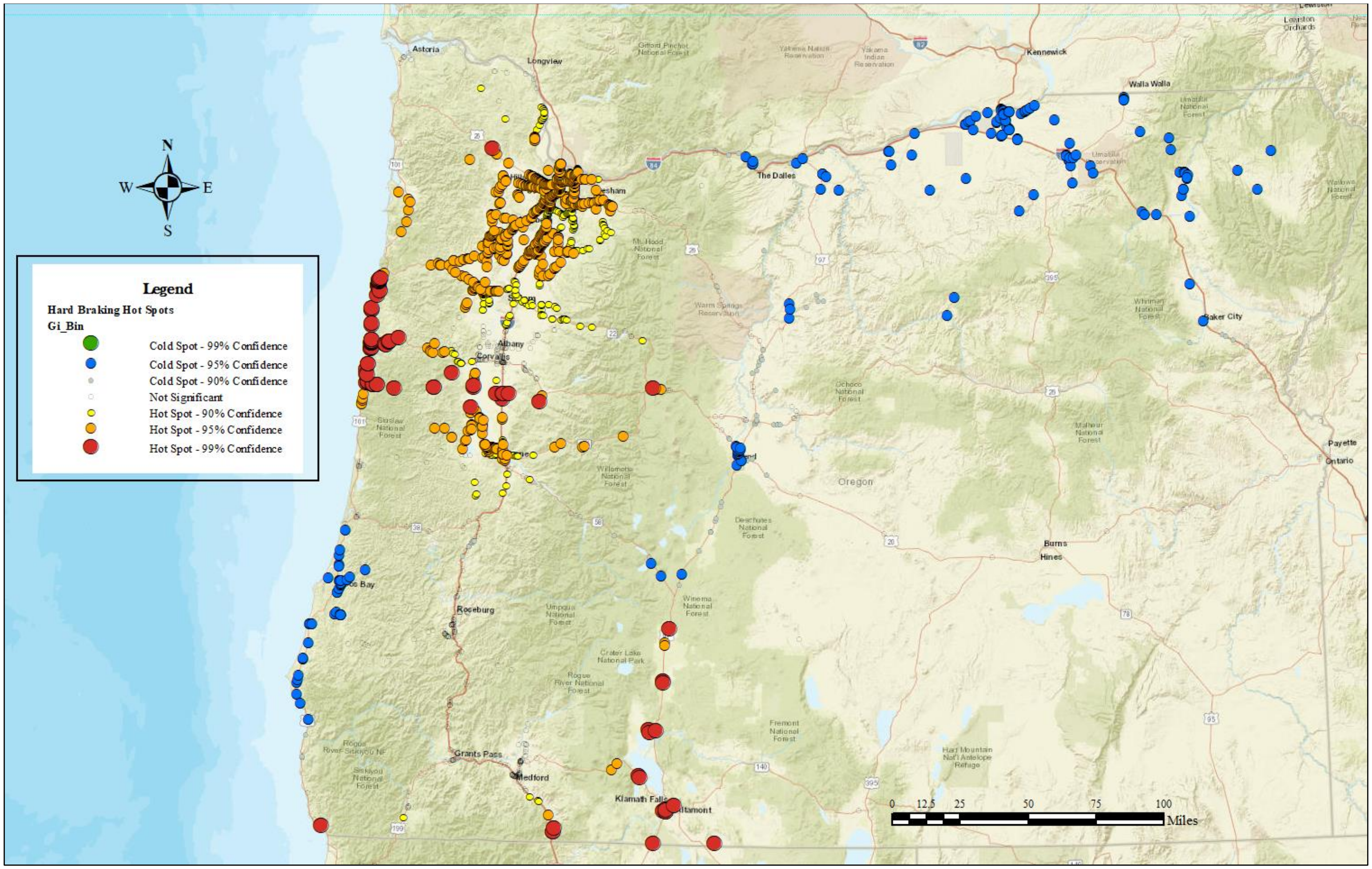


Figure 5.2: Results From Hot Spot Analysis of Heavy-Vehicle Hard Braking Events

5.3 Crash Frequency Analysis Results

As described in Chapter 3.0, four crash types are considered for analysis: (1) rear-end crashes, (2) turning movement crashes, (3) fixed-object crashes, and (4) sideswipe (overtaking) crashes. To ease the presentation of analysis results, model specifications for the random parameters Poisson and Negative Binomial models will be presented first. Then, results from the spatial autocorrelation tests will be shown. And, finally, the results from the SLX Poisson and Negative Binomial models will be presented.

5.3.1 Rear-End Crash Frequency Results

For model specifications of the rear-end crash analysis, refer to Table 5.1. Of the 90 variables created for this model, 16 are found to be statistically significant. As shown, the dispersion parameter is significantly different from zero; therefore, the negative binomial model is the appropriate model. Further, Poisson estimates (following Eq. (4.12)) indicated a θ value of 12.95. This confirms the dispersion parameter being statistically different from zero. In other words, there is high over-dispersion. Lastly, when conducting a log-likelihood ratio test to determine if the fixed or random parameters model is statistically preferred, it is determined that the random parameters model is preferred over the fixed parameters model with well over 99% confidence (χ^2 of 29.03 with 9 degrees of freedom, the number of estimated random parameters). Discussion of these results are presented in Chapter 6.1.1.

Table 5.1: Negative Binomial Model Specifications for Rear-End Crashes

Variable	Coefficient	Std. Error	*t*-statistic	IRR	% Change
Constant	1.892	0.19	9.77		
Hard Braking					
Number of Hard Braking Events	0.075	0.01	6.10	-	-
(St. Dev. of Normally Distributed Random Parameter)	*(0.050)*	*(0.01)*	*(5.08)*	-	-
Roadway Characteristics					
Roadway Classification (1 if Rural Minor Arterial, 0 Otherwise)	-0.661	0.13	-5.16	0.52	-48%
Roadway Classification (1 if Rural Major Collector, 0 Otherwise)	-0.974	0.19	-5.23	0.38	-62%
Posted Speed Limit (1 if Less Than or Equal to 25 mi/hr, 0 Otherwise)	0.358	0.09	3.92	1.43	-
(St. Dev. of Normally Distributed Random Parameter)	*(0.680)*	*(0.09)*	*(7.69)*	-	-
Posted Speed Limit (1 if Greater Than or Equal to 60 mi/hr, 0 Otherwise)	-0.673	0.11	-6.37	0.51	-49%
Type of Median (1 if Solid Median, 0 Otherwise)	0.404	0.09	4.47	1.50	-
(St. Dev. of Normally Distributed Random Parameter)	*(0.318)*	*(0.07)*	*(4.26)*	-	-
Width of Roadway in Inches	0.005	0.00	3.11	1.01	-
(St. Dev. of Normally Distributed Random Parameter)	*(0.008)*	*(0.00)*	*(14.43)*	-	-
Number of Lanes (1 if Two Lanes, 0 Otherwise)	-0.562	0.09	-6.14	0.57	-
(St. Dev. of Normally Distributed Random Parameter)	*(0.435)*	*(0.08)*	*(5.47)*	-	-
Roadway Geometrics (1 if Grade, 0 Otherwise)	0.351	0.11	3.12	1.42	-
(St. Dev. of Normally Distributed Random Parameter)	*(0.216)*	*(0.10)*	*(2.06)*	-	-
Traffic Characteristics					
Natural Log of AADT	0.061	0.02	3.46	-	-
Vehicle Class Percentage (1 if Class 01, 0 Otherwise)	-0.342	0.11	-3.08	0.71	-29%
Vehicle Class Percentage (1 if Class 04, 0 Otherwise)	-0.342	0.06	-5.46	-	-
(St. Dev. of Normally Distributed Random Parameter)	*(0.331)*	*(0.04)*	*(8.30)*	-	-
Vehicle Class Percentage (1 if Class06, 0 Otherwise)	-0.555	0.08	-7.16	0.57	-
(St. Dev. of Normally Distributed Random Parameter)	*(0.231)*	*(0.03)*	*(6.74)*	-	-
Vehicle Class Percentage (1 if Class 07, 0 Otherwise)	2.303	0.38	6.01	10.01	-
(St. Dev. of Normally Distributed Random Parameter)	*(1.542)*	*(0.27)*	*(5.72)*	-	-
Vehicle Class Percentage (1 if Class 12, 0 Otherwise)	0.471	0.28	1.66	1.60	60%
Traffic Control Characteristics					
Traffic Control (1 if Traffic Signal, 0 Otherwise)	0.534	0.09	5.94	1.71	71%
Dispersion Parameter for Negative Binomial Model					
α	3.030	0.26	11.55	-	-
Model Summary					
Number of Observations	565				
Log-Likelihood at Zero	-2,062.47				
Log-Likelihood at Convergence	-1,890.23				
McFadden Pseudo R-Squared	0.08				

5.3.2 Turning Movement Crash Frequency Results

For model specifications of the rear-end crash analysis, refer to Table 5.2. Of the 94 variables created for this model, 13 are found to be statistically significant. As shown, the dispersion parameter is significantly different from zero; therefore, the negative binomial model is the appropriate model. Further, Poisson estimates (following Eq. (4.12)) indicated a θ value of 3.52. This confirms the dispersion parameter being statistically significant different from zero. In other words, there is high over-dispersion in the turning movement crash data. Lastly, when conducting a log-likelihood ratio test to determine if the fixed or random parameters model is statistically preferred, it is determined that the random parameters model is preferred over the fixed parameters model with well over 99% confidence (χ^2 of 27.17 with 6 degrees of freedom, the number of estimated random parameters). Discussion of these results are provided in Chapter 6.1.2.

Table 5.2: Negative Binomial Model Specifications for Turning Movement Crashes

Variable	Coefficient	Std. Error	*t*-statistic	IRR	% Change
Constant	0.402	0.25	1.61		
Roadway Characteristics					
Roadway Classification (1 if Rural Minor Arterial, 0 Otherwise)	-0.540	0.12	-4.37	0.58	42%
Roadway Classification (1 if Urban Collector, 0 Otherwise)	-0.646	0.20	-3.28	0.52	48%
Roadway Classification (1 if Urban Local Road, 0 Otherwise)	-1.201	0.25	-4.74	0.30	70%
Posted Speed Limit (1 if 50 mi/hr to 60 mi/hr, 0 Otherwise)	-0.310	0.09	-3.58	0.73	27%
Width of Roadway in Inches	0.014	0.00	8.40	-	
(St. Dev. of Normally Distributed Random Parameter)	*(0.003)*	*(0.00)*	*(6.06)*	-	
Lane Width (1 if 12 Feet, 0 Otherwise)	-0.168	0.08	-2.12	0.85	15%
Intersection Characteristics					
Intersection Type (1 if Cross Intersection, 0 Otherwise)	0.450	0.07	6.54	-	-
(St. Dev of Normally Distributed Random Parameter)	*(0.394)*	*(0.04)*	*(9.10)*	-	-
Pavement Characteristics					
Pavement Condition (1 if Very Good, 0 Otherwise)	-0.446	0.11	-4.13	0.64	36%
Traffic Characteristics					
Natural Log of AADT	0.062	0.02	2.52	-	-
Truck AADT (1 if Greater Than 5,000, 0 Otherwise)	0.238	0.12	1.92	-	-
(St. Dev of Normally Distributed Random Parameter)	*(0.644)*	*(0.13)*	*(5.15)*	-	-
Vehicle Class (1 if Class 08, 0 Otherwise)	-0.123	0.03	-3.71	-	-
(St. Dev of Normally Distributed Random Parameter)	*(0.054)*	*(0.03)*	*(2.13)*	-	-
Vehicle Class (1 if Class 12, 0 Otherwise)	0.748	0.34	2.20	-	-
(St. Dev of Normally Distributed Random Parameter)	*(2.055)*	*(0.25)*	*(8.18)*	-	-
Traffic Control Characteristics					
Refuge (1 if Left-Turn Refuge, 0 Otherwise)	0.551	0.15	3.64	-	-
(St. Dev of Normally Distributed Random Parameter)	*(0.910)*	*(0.16)*	*(5.85)*	-	-
Dispersion Parameter for Negative Binomial Model					
α	5.932	0.95	6.27	-	-
Model Summary					
Number of Observations	411				
Log-Likelihood at Zero	-1,154.94				
Log-Likelihood at Convergence	-1,029.19				
McFadden Pseudo R-Squared	0.11				

5.3.3 Fixed-Object Crash Frequency Analysis

For model specifications of the fixed-object crash analysis, refer to Table 5.3. Of the 94 variables created for this model, 11 are found to be statistically significant. As shown, fixed-object crashes are estimated using the Poisson regression model. That is, the dispersion parameter in the Negative Binomial model is not statistically different from zero; therefore, the Poisson regression model is the appropriate model for the fixed-object crash data. Further, Poisson estimates (following Eq. (4.12)) indicated a θ value of 1.08. This confirms the dispersion parameter not being significantly different from zero. In other words, there is no significant over- or under-dispersion in the fixed-object crash data. Lastly, when conducting a log-likelihood ratio test to determine if the fixed or random parameters model is statistically preferred, it is determined that the random parameters model is preferred over the fixed parameters model with over 99% confidence (χ^2 of 13.54 with 4 degrees of freedom, the number of estimated random parameters). Discussion of these results are presented in Chapter 6.1.3.

Table 5.3: Poisson Model Specifications for Fixed-Object Crashes

Variable	Coefficient	Std. Error	*t*-statistic	IRR	% Change
Constant	1.379	0.13	10.26		
Roadway Characteristics					
Roadway Classification (1 if Urban Interstate, 0 Otherwise)	0.347	0.08	4.09	1.41	41%
Type of Roadway (1 if Bridge Structure, 0 Otherwise)	0.954	0.11	8.85	2.59	159%
Roadway Geometrics (1 if Grade, 0 Otherwise)	0.309	0.12	2.49	1.36	36%
Work Zone (1 if Yes, 0 Otherwise)	0.670	0.15	4.62	-	-
(St. Dev. of Normally Distributed Random Parameter)	*(0.247)*	*(0.14)*	*(1.77)*	-	-
Roadway Geometrics (1 if Horizontal Curve, 0 Otherwise)	0.510	0.10	5.35	-	-
(St. Dev. of Normally Distributed Random Parameter)	*(0.194)*	*(0.07)*	*(2.71)*	-	-
Roadway Surface Characteristics					
Pavement Condition (1 if Good, 0 Otherwise)	0.189	0.08	2.43	1.21	21%
Surface Type (1 if Asphalt Concrete, 0 Otherwise)	-0.344	0.09	-3.95	0.71	-29%
Median Type (1 if Solid Median Barrier, 0 Otherwise)	-0.464	0.09	-5.07	-	-
(St. Dev. of Normally Distributed Random Parameter)	*(0.479)*	*(0.08)*	*(5.67)*	-	-
Traffic Characteristics					
Percentage of Heavy-Vehicles	-0.048	0.01	-4.78	0.95	-5%
Vehicle Class (1 if Class 03, 0 Otherwise)	-0.009	0.00	-2.59	0.99	-1%
Vehicle Class (1 if Class 09, 0 Otherwise)	0.042	0.02	2.71	-	-
(St. Dev. of Normally Distributed Random Parameter)	*(0.038)*	*(0.01)*	*(5.79)*	-	-
Model Summary					
Number of Observations	479				
Log-Likelihood at Zero	-1,019.22				
Log-Likelihood at Convergence	-832.45				
McFadden Pseudo R-Squared	0.18				

5.3.4 Sideswipe (Overtaking) Crash Frequency Results

For model specifications of the sideswipe (overtaking) crash analysis, refer to Table 5.4. Of the 99 variables created for this model, 10 are found to be statistically significant. As shown, the dispersion parameter is significantly different from zero; therefore, the negative binomial model is the appropriate model. Further, Poisson estimates (following Eq. (4.12)) indicated a θ value of 1.71. This confirms the dispersion parameter being statistically different from zero. In other words, there is over-dispersion in the sideswipe (overtaking) crash data. Lastly, when conducting a log-likelihood ratio test to determine if the fixed or random parameters model is statistically preferred, it is determined that the random parameters model is preferred over the fixed parameters model with well over 95% confidence (χ^2 of 8.35 with 3 degrees of freedom, the number of estimated random parameters). Discussion of these results are given in Chapter 6.1.4.

Table 5.4: Negative Binomial Model Specifications for Sideswipe (Overtaking) Crashes

Variable	Coefficient	Std. Error	*t*-statistic	IRR	% Change
Constant	1.286	0.13	10.28	-	-
Roadway Characteristics					
Number of Lanes	0.094	0.02	5.00	1.10	10%
Median Type (1 if Earth, Grass, or Paved Median, 0 Otherwise)	-0.560	0.12	-4.66	0.57	-43%
Roadway Classification (1 if Urban Principal Arterial, 0 Otherwise)	0.319	0.10	3.07	1.38	38%
Median Type (1 if Jersey Barrier, 0 Otherwise)	0.833	0.16	5.14	-	-
(St. Dev. of Normally Distributed Random Parameter)	*(0.361)*	*(0.16)*	*(2.30)*	-	-
Roadway Geometrics (1 if Straight Segment, 0 Otherwise)	-0.314	0.09	-3.34	-	-
(St. Dev. of Normally Distributed Random Parameter)	*(0.261)*	*(0.04)*	*(6.23)*	-	-
Traffic Characteristics					
Vehicle Class (1 if Class 04, 0 Otherwise)	-0.369	0.14	-2.70	0.69	-31%
Vehicle Class (1 if Class 12, 0 Otherwise)	-1.500	0.52	-2.90	0.22	-78%
Vehicle Class (1 if Class 10, 0 Otherwise)	0.104	0.06	1.69	-	-
(St. Dev. of Normally Distributed Random Parameter)	*(0.176)*	*(0.03)*	*(5.74)*	-	-
Traffic Control Characteristics					
One Way Street (1 if Yes, 0 Otherwise)	-0.621	0.11	-5.66	0.54	-46%
Refuge (1 if Left-Turn Refuge, 0 Otherwise)	0.360	0.11	3.28	1.43	43%
Dispersion Parameter for Negative Binomial Model					
α	15.200	6.35	2.39		
Model Summary					
Number of Observations	306				
Log-Likelihood at Zero	-702.21				
Log-Likelihood at Convergence	-630.98				
McFadden Pseudo R-Squared	0.10				

5.4 Spatial Lag Crash Frequency Analysis Results

This section will begin by presenting the results of the spatial autocorrelation tests. Then, if the tests indicate the presence of spatial autocorrelation, this section will conclude by presenting the results from the spatial econometric analysis.

5.4.1 Results From Spatial Autocorrelation Tests

5.4.1.1 Rear-End Crashes

Using the methodology presented in Chapter 4.4.1, rear-end crashes at heavy-vehicle hard braking hot spots are tested for spatial autocorrelation. This is done in two specific steps: (1) test for spatial correlation on the geographic location and (2) test for spatial autocorrelation based on the residuals of the Negative Binomial model estimates.

Using 3-nearest neighbors, as discussed previously, the first test for spatial correlation is conducted. As shown in Table 5.5, with a p-value of 0.005, the null hypothesis that there is no spatial correlation is rejected. That is to say, there is significant spatial correlation among heavy-vehicle hard braking hot spots and rear-end crashes. To illustrate this correlation, refer to Figure 5.3. As seen in Figure 5.3, there is clustering in the “low-low” quadrant of the plot. This indicates that there is positive spatial correlation among heavy-vehicle hard braking hot spots in the rear-end crash data. Now, testing the residuals of the Negative Binomial model for spatial autocorrelation results in the statistics shown in Table 5.6. With a p-value of 0.000, the null hypothesis that there is no spatial autocorrelation among regression residuals is rejected. In other words, based on these results, there is high positive spatial autocorrelation and the spatial econometric methodology presented in Chapter 4.4.2 will be used.

Table 5.5: Moran I Test for Rear-End Crashes and Heavy-Vehicle Hard Braking Hot Spots

Moran I Statistic Standard Deviate	p-value	Alternative Hypothesis
2.554	0.005	Greater
Sample Estimates		
Moran I Statistic	Expectation	Variance
0.07350	-0.00177	0.00087

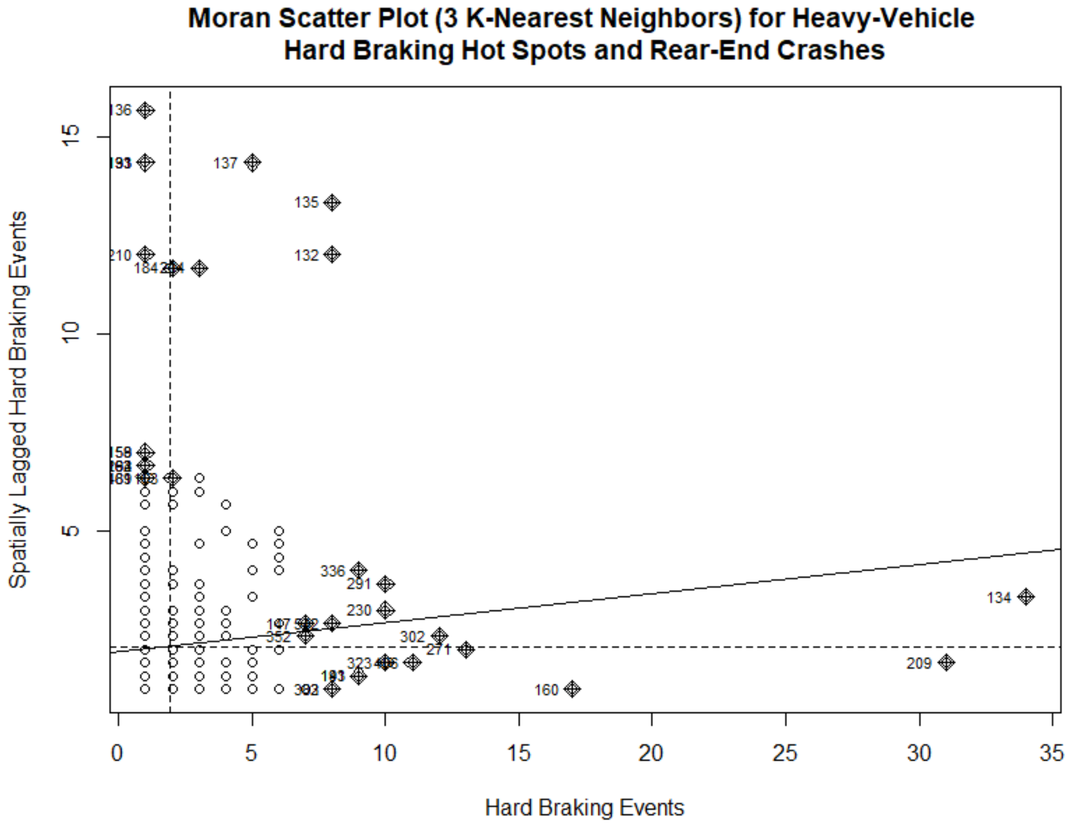


Figure 5.3: Moran Scatter Plot for Heavy-Vehicle Hard Braking Hot Spots and Rear-End Crashes

Table 5.6: Moran I Test for Rear-End Crash Negative Binomial Regression Residuals

Moran I Statistic Standard Deviate	p-value	Alternative Hypothesis
12.358	0.000	Greater
Sample Estimates		
Moran I Statistic	Expectation	Variance
0.37203	-0.01241	0.00097

5.4.1.2 Turning Movement Crashes

Again, using the methodology presented in Chapter 4.4.1, turning movement crashes at heavy-vehicle hard braking hot spots are tested for spatial autocorrelation. This, too, is done in two specific steps: (1) test for spatial correlation on the geographic location and (2) test for spatial autocorrelation based on the residuals of the Negative Binomial model estimates.

Using 4-nearest neighbors, as discussed previously, the first test for spatial correlation is conducted. As shown in Table 5.7, with a p-value of 0.000, the null hypothesis that there is no spatial correlation is rejected. That is to say, there is significant spatial correlation among heavy-vehicle hard braking hot spots and turning movement crashes. To illustrate this correlation, refer to Figure 5.4. As seen in Figure 5.4, there is again clustering in the "low-low" quadrant of the plot (akin to the Moran scatter plot for heavy-vehicle hard braking hot spots and rear-end crashes). This indicates that there is positive spatial correlation among heavy-vehicle hard braking hot spots in the turning movement crash data. Now, testing the residuals of the Negative Binomial model for spatial autocorrelation results in the statistics shown in Table 5.8. With a p-value of 0.000, the null hypothesis that there is no spatial autocorrelation among regression residuals is rejected. In other words, based on these results, there is high positive spatial autocorrelation and the spatial econometric methodology presented in Chapter 4.4.2 will be used.

Table 5.7: Moran I Test for Turning Movement Crashes and Heavy-Vehicle Hard Braking Hot Spots

Moran I Statistic Standard Deviate	p-value	Alternative Hypothesis
4.9378	0.000	Greater
Sample Estimates		
Moran I Statistic	Expectation	Variance
0.14600	-0.00244	0.00090

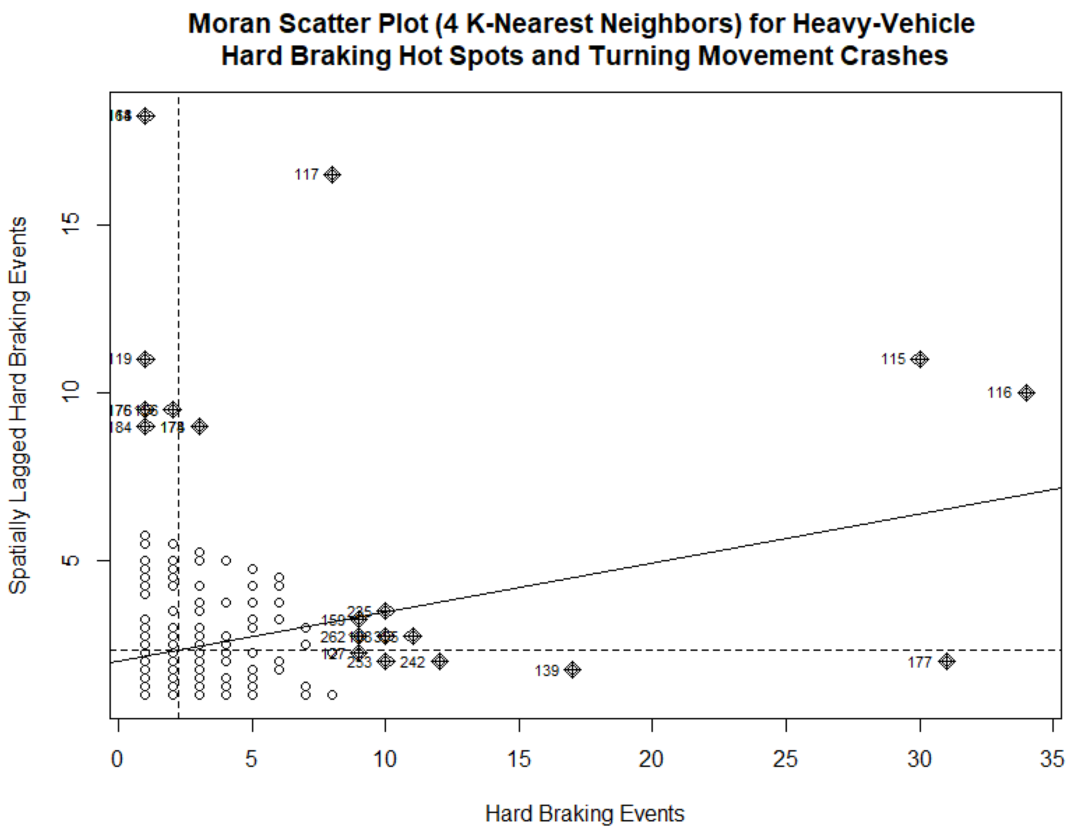


Figure 5.4: Moran Scatter Plot for Heavy-Vehicle Hard Braking Hot Spots and Turning Movement Crashes

Table 5.8: Moran I Test for Turning Movement Crash Negative Binomial Residuals

Moran I Statistic Standard Deviate	p-value	Alternative Hypothesis
5.6997	0.000	Greater
Sample Estimates		
Moran I Statistic	Expectation	Variance
0.17283	-0.00901	0.00102

5.4.1.3 Fixed-Object Crashes

Continuing with the next crash type, the methodology presented in Chapter 4.4.1 is used to test fixed-object crashes and heavy-vehicle hard braking hot spots are tested for spatial autocorrelation. Once more, this is done in two specific steps: (1) test for spatial correlation on the geographic location and (2) test for spatial autocorrelation based on the residuals of the Poisson model estimates.

Using 2-nearest neighbors, as discussed previously, the first test for spatial correlation is conducted. As shown in Table 5.9, with a p-value of 0.024, the null hypothesis that there is no spatial correlation is rejected. That is to say, there is significant spatial correlation among heavy-vehicle hard braking hot spots and turning movement crashes. To illustrate this correlation, refer to Figure 5.5. As seen in Figure 5.5, there is again clustering in the “low-low” quadrant of the plot (the same clustering seen in the Moran plots for rear-end crashes and turning movement crashes). This indicates that there is positive spatial correlation among heavy-vehicle hard braking hot spots in the fixed-object crash data. Now, testing the residuals of the Poisson model for spatial autocorrelation results in the statistics shown in Table 5.10. With a p-value of 0.000, the null hypothesis that there is no spatial autocorrelation among regression residuals is rejected. In other words, based on these results, there is high positive spatial autocorrelation and the spatial econometric methodology presented in Chapter 4.4.2 will be used.

Table 5.9: Moran I Test for Fixed-Object Crashes and Heavy-Vehicle Hard Braking Hot Spots

Moran I Statistic Standard Deviate	p-value	Alternative Hypothesis
1.9732	0.024	Greater
Sample Estimates		
Moran I Statistic	Expectation	Variance
0.07283	-0.00209	0.00144

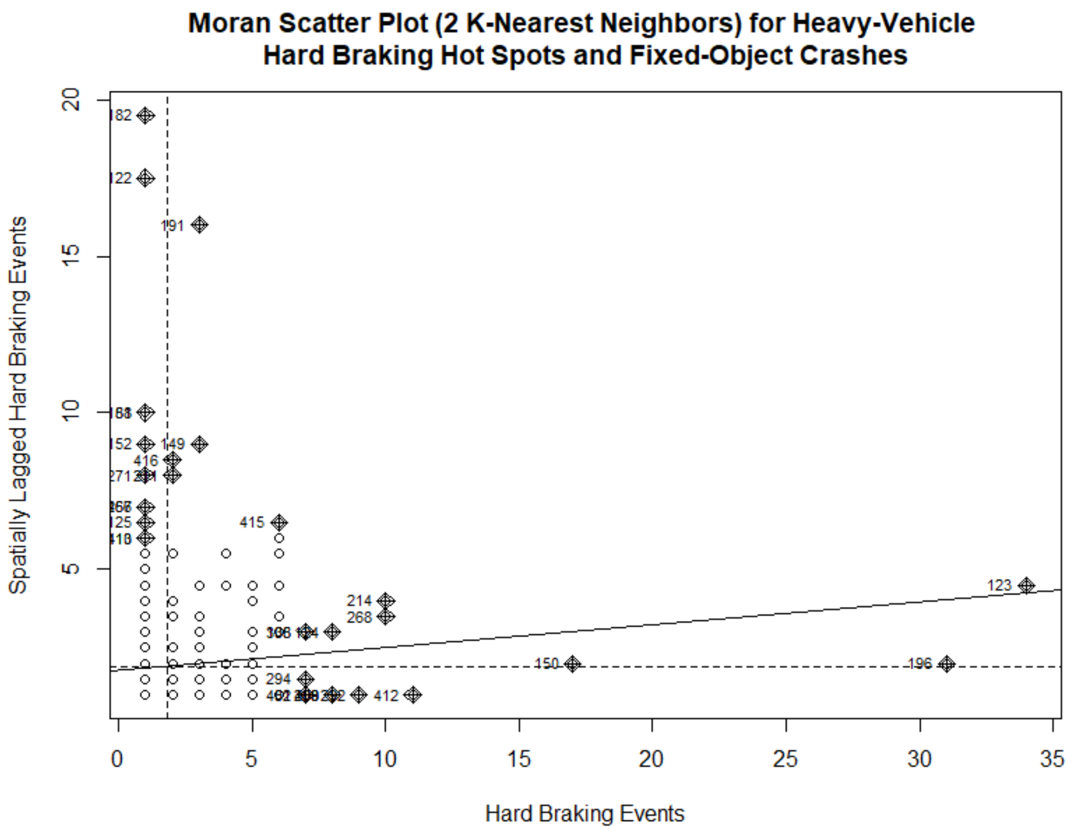


Figure 5.5: Moran Scatter Plot for Heavy-Vehicle Hard Braking Hot Spots and Fixed-Object Crashes

Table 5.10: Moran I Test for Fixed-Object Crash Poisson Residuals

Moran I Statistic Standard Deviate	p-value	Alternative Hypothesis
5.1932	0.000	Greater
Sample Estimates		
Moran I Statistic	Expectation	Variance
0.21383	-0.00518	0.00178

5.4.1.4 Sideswipe (Overtaking) Crashes

The final crash type considered, and tested for spatial autocorrelation, is sideswipe (overtaking). As with the previous tests, the methodology presented in Chapter 4.4.1 is used to test sideswipe (overtaking) crashes and heavy-vehicle hard braking hot spots for spatial autocorrelation. As stated previously, this is done in two specific steps: (1) test for spatial correlation on the geographic location and (2) test for spatial autocorrelation based on the residuals of the Negative Binomial model estimates.

Using 5-nearest neighbors, as discussed previously, the first test for spatial correlation is conducted. As shown in Table 5.11, with a p-value of 0.089, the null hypothesis that there is no spatial correlation is rejected (however, this is the least significant spatial correlation at just over 90% significance). To illustrate this correlation with lower significance, refer to Figure 5.6. As seen in Figure 5.6, the clustering is not as profound as it is in the previous three crash types (this corresponds to the higher p-value of 0.089). However, the clustering that is present is still in the "low-low" quadrant of the plot. This indicates, although not as significant, that there is positive spatial correlation among heavy-vehicle hard braking hot spots in the sideswipe (overtaking) crash data. Now, testing the residuals of the Negative Binomial model for spatial autocorrelation results in the statistics shown in Table 5.12. With a p-value of 0.000, the null hypothesis that there is no spatial autocorrelation among regression residuals is rejected with a high level of significance. Based on these results, specifically the results from the model residuals, there is high positive spatial autocorrelation and the spatial econometric methodology presented in Chapter 4.4.2 will be used.

Table 5.11: Moran I Test for Sideswipe (Overtaking) Crashes and Heavy-Vehicle Hard Braking Hot Spots

Moran I Statistic Standard Deviate	p-value	Alternative Hypothesis
1.3497	0.089	Greater
Sample Estimates		
Moran I Statistic	Expectation	Variance
0.03566	-0.00328	0.00083

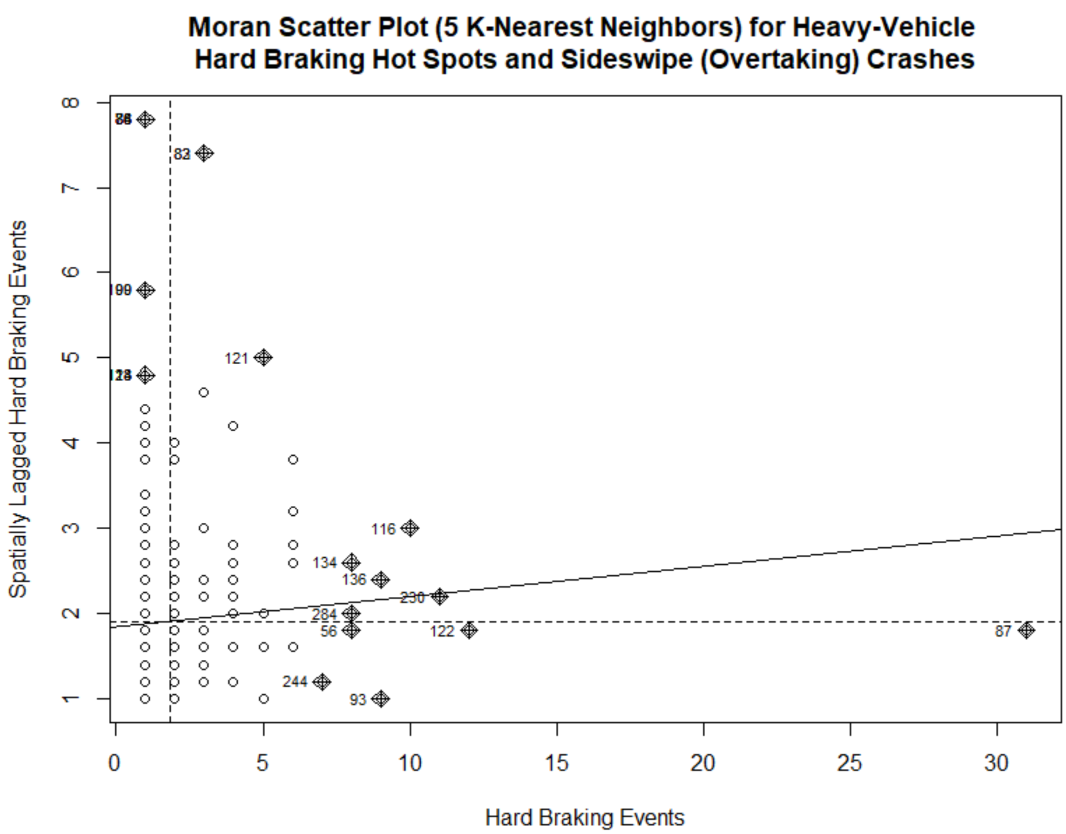


Figure 5.6: Moran Scatter Plot for Heavy-Vehicle Hard Braking Hot Spots and Sideswipe (Overtaking) Crashes

Table 5.12: Moran I Test for Sideswipe (Overtaking) Crash Negative Binomial Residuals

Moran I Statistic Standard Deviate	p-value	Alternative Hypothesis
4.4913	0.000	Greater
Sample Estimates		
Moran I Statistic	Expectation	Variance
0.13931	-0.00919	0.00109

5.4.2 Rear-End Spatial Lag Crash Frequency Results

Based on results of the spatial autocorrelation tests, spatial econometrics are used to determine significant contributing factors to rear-end crash frequency at heavy-vehicle hard braking hot spots while accounting for spatial autocorrelation. Specifically, a model in which the explanatory variables are spatially lagged is used: the SLX model. Utilizing 3-nearest neighbors to generate a spatial weights matrix, the model specifications for the Negative Binomial SLX model are shown in Table 5.13. As seen, some variables are significant in their direct effect and insignificant in their spillover effect (i.e., indirect effect), insignificant in their direct effect and significant in their indirect effect, significant in both direct and indirect effects with the same sign, or significant in both direct and indirect effects with different signs (for further discussion on these results, see Chapter 6.2.1).

In terms of model fit, the final Negative Binomial SLX model has a McFadden Pseudo R-Squared value of 0.09 (full model compared to model with only the constant).

This values falls just short of the adequate range of values (0.10 to 0.20) (McFadden, 1973, 1977, 1981). In addition, the lagged explanatory variables are tested to determine if their beta estimate is statistically different from zero. To do this, three different tests are conducted: (1) Wald Test, (2) Likelihood Ratio Test, and (3) Lagrange Multiplier Test. As shown in Table 5.14, each lagged explanatory variable should be included in the final model specifications, as their beta estimates are statistically different from zero.

Table 5.13: Negative Binomial SLX Model Specifications for Rear-End Crashes

Variable	Non-Lagged					Lagged				
	Coefficient	Std. Error	*t*-statistic	IRR	% Change	Coefficient	Std. Error	*t*-statistic	IRR	% Change
Constant	0.832	0.40	2.08	-	-	-	-	-	-	-
Hard Braking										
Number of Hard Braking Events	0.059	0.02	3.14	1.06	6%	-	-	-	-	-
Roadway Characteristics										
Roadway Classification (1 if Rural Minor Arterial, 0 Otherwise)	-0.573	0.21	-2.71	0.56	-44%	-	-	-	-	-
Roadway Classification (1 if Rural Major Collector, 0 Otherwise)	-0.509	0.30	-1.70	0.60	-40%	-0.875	0.40	-2.20	0.42	-58%
Posted Speed Limit (1 if Less Than or Equal to 25 mi/hr, 0 Otherwise)	0.275	0.13	2.11	1.32	32%	-	-	-	-	-
Posted Speed Limit (1 if Greater Than or Equal to 60 mi/hr, 0 Otherwise)	-0.514	0.22	-2.33	0.60	-40%	-	-	-	-	-
Median Type (1 if Solid Median Barrier, 0 Otherwise)	-	-	-	-	-	0.613	0.19	3.26	1.85	85%
Width of Roadway in Inches	-	-	-	-	-	0.015	0.00	4.06	1.01	1%
Number of Lanes (1 if Two Lanes, 0 Otherwise)	-0.508	0.12	-4.11	0.60	-40%	-	-	-	-	-
Roadway Geometrics (1 if Grade, 0 Otherwise)	0.315	0.16	1.98	1.37	37%	-	-	-	-	-
Traffic Characteristics										
Natural Log of AADT	-	-	-	-	-	0.126	0.04	3.32	-	13%
Vehicle Class Percentage (1 if Class 01, 0 Otherwise)	-	-	-	-	-	-0.399	0.23	-1.76	0.67	-33%
Vehicle Class Percentage (1 if Class 04, 0 Otherwise)	-0.277	0.11	-2.50	0.76	-24%	-	-	-	-	-
Vehicle Class Percentage (1 if Class 06, 0 Otherwise)	-0.354	0.15	-2.43	0.70	-30%	-	-	-	-	-
Vehicle Class Percentage (1 if Class 07, 0 Otherwise)	1.452	0.75	1.93	4.27	327%	-	-	-	-	-
Vehicle Class Percentage (1 if Class 12, 0 Otherwise)	-	-	-	-	-	2.471	0.86	2.86	11.83	1,083%
Traffic Control Characteristics										
Traffic Control (1 if Traffic Signal, 0 Otherwise)	0.545	0.12	4.48	1.73	73%	-0.458	0.20	-2.34	0.63	-37%

Table 5.13: Negative Binomial SLX Model Specifications for Rear-End Crashes

Variable	Non-Lagged					Lagged				
	Coefficient	Std. Error	*t*-statistic	IRR	% Change	Coefficient	Std. Error	*t*-statistic	IRR	% Change
Negative Binomial Dispersion Parameter										
α	0.652	0.044	14.96							
Model Summary										
Number of Observations	565									
Log-Likelihood at Zero	-2,062.47									
Log-Likelihood at Convergence	-1,871.00									
McFadden Pseudo R-Squared	0.09									

Table 5.14: Tests for Lagged Explanatory Variables in Rear-End Crash Analysis

Test	χ^2	$\mathrm{Pr.} > \chi^2$	Variables
Wald Test	71.85	0.000	All Lagged Variables
Likelihood Ratio Test	67.44	0.000	All Lagged Variables
Lagrange Multiplier Test	83.41	0.000	All Lagged Variables

5.4.3 Turning Movement Spatial Lag Crash Frequency Analysis

Based on results of the spatial autocorrelation tests, spatial econometrics are used to determine significant contributing factors to turning movement crash frequency at heavy-vehicle hard braking hot spots while accounting for spatial autocorrelation. Again, a model in which the explanatory variables are spatially lagged is used: the SLX model. Using 4-nearest neighbors to generate a spatial weights matrix, the model specifications for the Negative Binomial SLX model are shown in Table 5.15. As seen, some variables are significant in their direct effect and insignificant in their spillover effect (i.e., indirect effect), insignificant in their direct effect and significant in their indirect effect, significant in both direct and indirect effects with the same sign, or significant in both direct and indirect effects with different signs (for further discussion on these results, see Chapter 6.2.2).

In terms of model fit, the final Negative Binomial SLX model has a McFadden Pseudo R-Squared value of 0.11 (full model compared to model with only the constant). This values falls between the range of adequate values (0.10 to 0.20) (McFadden, 1973, 1977, 1981). In addition, as with the rear-end crash analysis, the lagged explanatory variables are tested to determine if their beta estimate is statistically different from zero. To do this, the same three tests shown in Table 5.14 are conducted. As shown in Table 5.16, each lagged explanatory variable should be included in the final model specifications, as their beta estimates are statistically different from zero.

Table 5.15: Negative Binomial SLX Model Specifications for Turning Movement Crashes

Variable	Non-Lagged					Lagged				
	Coefficient	Std. Error	*t*-statistic	IRR	% Change	Coefficient	Std. Error	*t*-statistic	IRR	% Change
Constant	-0.220	0.42	-0.52	-	-	-	-	-	-	-
Roadway Characteristics										
Roadway Classification (1 if Rural Minor Arterial, 0 Otherwise)	-0.540	0.17	-3.11	0.58	-42%	-	-	-	-	-
Roadway Classification (1 if Urban Collector, 0 Otherwise)	-0.769	0.21	-3.71	0.46	-54%	0.676	0.34	2.01	1.97	97%
Roadway Classification (1 if Urban Local Road, 0 Otherwise)	-1.325	0.34	-3.90	0.27	-73%	-	-	-	-	-
Posted Speed Limit (1 if 50 mi/hr to 60 mi/hr, 0 Otherwise)	-0.371	0.11	-3.34	0.69	-31%	0.322	0.16	2.00	1.38	38%
Width of Roadway in Inches	0.010	0.00	3.60	1.01	1%	0.009	0.00	2.46	1.01	1%
Lane Width (1 if 12 Feet, 0 Otherwise)	-	-	-	-	-	-	-	-	-	-
Intersection Characteristics										
Intersection Type (1 if Cross Intersection, 0 Otherwise)	0.525	0.09	6.06	1.69	69%	-	-	-	-	-
Pavement Characteristics										
Pavement Condition (1 if Very Good, 0 Otherwise)	-0.492	0.15	-3.36	0.61	-39%	-	-	-	-	-
Traffic Characteristics										
Natural Log of AADT	-	-	-	-	-	-	-	-	-	-
Truck AADT (1 if Greater Than 5,000, 0 Otherwise)	0.456	0.17	2.64	1.58	58%	-	-	-	-	-
Vehicle Class Percentage (1 if Class 08, 0 Otherwise)	-0.180	0.06	-3.07	0.84	-16%	-	-	-	-	-
Vehicle Class Percentage (1 if Class 12, 0 Otherwise)	1.178	0.56	2.09	3.25	225%	-	-	-	-	-
Traffic Control Characteristics										
Refuge (1 if Left-Turn Refuge, 0 Otherwise)	0.842	0.19	4.44	2.32	132%	-	-	-	-	-

Table 5.15: Negative Binomial SLX Model Specifications for Turning Movement Crashes

	Non-Lagged					Lagged				
Variable	Coefficient	Std. Error	*t*-statistic	IRR	% Change	Coefficient	Std. Error	*t*-statistic	IRR	% Change
Negative Binomial Dispersion Parameter										
α	0.360	0.04	9.48							
Model Summary										
Number of Observations	411									
Log-Likelihood at Zero	-1,154.94									
Log-Likelihood at Convergence	-1,033.00									
McFadden Pseudo R-Squared	0.11									

Table 5.16: Tests for Lagged Explanatory Variables in Turning Movement Crash Analysis

Test	χ^2	$\Pr. > \chi^2$	Variables
Wald Test	21.16	0.070	All Lagged Variables
Likelihood Ratio Test	20.51	0.083	All Lagged Variables
Lagrange Multiplier Test	22.31	0.051	All Lagged Variables

5.4.4 Fixed-Object Spatial Lag Crash Frequency Analysis

Based on results of the spatial autocorrelation tests, spatial econometrics are used to determine significant contributing factors to fixed-object crash frequency at heavy-vehicle hard braking hot spots while accounting for spatial autocorrelation. Once more, a model in which the explanatory variables are spatially lagged is used: the SLX model. Using 2-nearest neighbors to generate a spatial weights matrix, the model specifications for the Poisson SLX model are shown in Table 5.17. As seen, some variables are significant in their direct effect and insignificant in their spillover effect (i.e., indirect effect), insignificant in their direct effect and significant in their indirect effect, significant in both direct and indirect effects with the same sign, or significant in both direct and indirect effects with different signs (for further discussion on these results, see Chapter 6.2.3).

In terms of model fit, the final Poisson SLX model has a McFadden Pseudo R-Squared value of 0.19 (full model compared to model with only the constant). This values falls between the range of adequate values (0.10 to 0.20) (McFadden, 1973, 1977, 1981). In addition, as with the rear-end crash and turning movement crash analyses, the lagged explanatory variables are tested to determine if their beta estimate is statistically different from zero. To do this, the same three tests shown in Table 5.14 are conducted. As shown in Table 5.18, each lagged explanatory variable should be included in the final model specifications, as their beta estimates are statistically different from zero.

Table 5.17: Poisson SLX Model Specifications for Fixed-Object Crashes

Variable	Non-Lagged					Lagged				
	Coefficient	Std. Error	*t*-statistic	IRR	% Change	Coefficient	Std. Error	*t*-statistic	IRR	% Change
Constant	1.278	0.21	6.00	-	-	-	-	-	-	-
Roadway Characteristics										
Roadway Classification (1 if Urban Interstate, 0 Otherwise)	0.353	0.12	2.88	1.42	42%	-	-	-	-	-
Type of Roadway (1 if Bridge Structure, 0 Otherwise)	0.665	0.14	4.86	1.94	94%	0.467	0.18	2.66	1.59	59%
Roadway Geometrics (1 if Grade, 0 Otherwise)	0.232	0.14	1.64	1.26	26%	0.366	0.17	2.10	1.44	44%
Work Zone (1 if Yes, 0 Otherwise)	0.679	0.15	4.42	1.97	97%	-	-	-	-	-
Roadway Geometrics (1 if Horizontal Curve, 0 Otherwise)	0.514	0.09	5.64	1.67	67%	-	-	-	-	-
Pavement Characteristics										
Pavement Condition (1 if Good, 0 Otherwise)	-	-	-	-	-	0.199	0.10	2.03	1.22	22%
Roadway Surface Characteristics										
Surface Type (1 if Asphalt Concrete, 0 Otherwise)	-	-	-	-	-	-	-	-	-	-
Median Type (1 if Solid Median Barrier, 0 Otherwise)	-0.394	0.11	-3.43	0.67	-33%	-	-	-	-	-
Traffic Characteristics										
Percentage of Heavy-Vehicles	-0.035	0.01	-3.63	0.97	-3%	-0.019	0.01	-1.85	0.98	-2%
Vehicle Class Percentage (1 if Class 03, 0 Otherwise)	-	-	-	-	-	-	-	-	-	-
Vehicle Class Percentage (1 if Class 09, 0 Otherwise)	0.055	0.02	3.04	1.06	6%	-	-	-	-	-
Model Summary										
Number of Observations	479									
Log-Likelihood at Zero	-1,019.22									
Log-Likelihood at Convergence	-821.81									
McFadden Pseudo R-Squared	0.19									

Table 5.18: Tests for Lagged Explanatory Variables in Fixed-Object Crash Analysis

Test	χ^2	$\mathrm{Pr.} > \chi^2$	Variables
Wald Test	34.02	0.000	All Lagged Variables
Likelihood Ratio Test	34.82	0.000	All Lagged Variables
Lagrange Multiplier Test	34.28	0.000	All Lagged Variables

5.4.5 Sideswipe (Overtaking) Spatial Lag Crash Frequency Results

Based on results of the spatial autocorrelation tests, spatial econometrics are used to determine significant contributing factors to sideswipe (overtaking) crash frequency at heavy-vehicle hard braking hot spots while accounting for spatial autocorrelation. As with the previous three crash types, a model in which the explanatory variables are spatially lagged is used: the SLX model. Using 5-nearest neighbors to generate a spatial weights matrix, the model specifications for the Negative Binomial SLX model are shown in Table 5.19. As seen, some variables are significant in their direct effect and insignificant in their spillover effect (i.e., indirect effect), insignificant in their direct effect and significant in their indirect effect, significant in both direct and indirect effects with the same sign, or significant in both direct and indirect effects with different signs (for further discussion on these results, see Chapter 6.2.4).

In terms of model fit, the final Negative Binomial SLX model has a McFadden Pseudo R-Squared value of 0.12 (full model compared to model with only the constant). This value falls between the range of adequate values (0.10 to 0.20) (McFadden, 1973, 1977, 1981). In addition, as with the previous three crash analyses, the lagged explanatory variables are tested to determine if their beta estimate is statistically different from zero. To do this, the same three tests shown in Table 5.14 are conducted. As shown in Table 5.20, each lagged explanatory variable should be included in the final model specifications, as their beta estimates are statistically different from zero.

Table 5.19: Negative Binomial SLX Model Specifications for Sideswipe (Overtaking) Crashes

	Non-Lagged					Lagged				
Variable	Coefficient	Std. Error	*t*-statistic	IRR	% Change	Coefficient	Std. Error	*t*-statistic	IRR	% Change
Constant	0.612	0.22	2.84	-	-	-	-	-	-	-
Roadway Characteristics										
Number of Lanes	0.060	0.02	2.58	1.06	6%	0.118	0.04	3.17	1.13	13%
Roadway Classification (1 if Urban Principal Arterial, 0 Otherwise)	0.415	0.12	3.51	1.51	51%	-	-	-	-	-
Roadway Geometrics (1 if Straight Segment, 0 Otherwise)	-0.259	0.10	-2.57	0.77	-23%	-	-	-	-	-
Roadway Surface Characteristics										
Median Type (1 if Jersey Barrier, 0 Otherwise)	0.688	0.19	3.72	1.99	99%	1.458	0.32	4.51	4.30	330%
Median Type (1 if Earth, Grass, or Paved Median, 0 Otherwise)	-0.362	0.14	-2.67	0.70	-30%	-	-	-	-	-
Traffic Characteristics										
Vehicle Class Percentage (1 if Class 04, 0 Otherwise)	-0.370	0.12	-3.12	0.69	-31%	-	-	-	-	-
Vehicle Class Percentage (1 if Class 12, 0 Otherwise)	-1.401	0.42	-3.32	0.25	-75%	-	-	-	-	-
Vehicle Class Percentage (1 if Class 10, 0 Otherwise)	0.152	0.08	1.83	1.16	16%	-	-	-	-	-
Traffic Control Characteristics										
One Way Street (1 if Yes, 0 Otherwise)	-	-	-	-	-	-0.564	0.26	-2.15	0.57	-43%
Refuge (1 if Left-Turn Refuge, 0 Otherwise)	0.383	0.14	2.74	1.47	47%	0.473	0.34	1.39	1.61	61%
Dispersion Parameter for Negative Binomial Model										
α	0.115	0.03	3.92							
Model Summary										
Number of Observations	306									
Log-Likelihood at Zero	-702.21									
Log-Likelihood at Convergence	-618.10									
McFadden Pseudo R-Squared	0.12									

Table 5.20: Tests for Lagged Explanatory Variables in Sideswipe (Overtaking) Crash Analysis

Test	χ^2	$\mathrm{Pr.} > \chi^2$	Variables
Wald Test	36.41	0.000	All Lagged Variables
Likelihood Ratio Test	34.10	0.000	All Lagged Variables
Lagrange Multiplier Test	41.21	0.000	All Lagged Variables

6.0 DISCUSSION OF RESULTS

To ease discussion, results will be discussed by method and crash type. That is, the random parameters models will first be discussed by crash type. Then, the SLX models will be discussed by crash type. To conclude this section, a comparison of the two presented methods will be provided. This will include comments on model fit, accuracy of prediction, and a recommendation of the preferred method for the given datasets.

6.1 Discussion of Crash Frequency Analyses

6.1.1 Rear-End Crash Frequency Discussion

Referring to Table 5.1, 16 factors are found to contribute to rear-end crash frequency at heavy-vehicle hot spots. Of the 16 significant factors, nine have normally distributed random parameters (i.e., the factors are heterogeneous across crash observations). The first of these with an estimated random parameter is the number of hard braking events. Specifically, with a mean of 0.075 and a standard deviation of 0.050, the estimated parameter mean is less than zero for 6.7% of hard braking hot spots and greater than zero for 93.3%. In particular, the number of hard braking events decreases the expected number of crashes at 6.7% of heavy-vehicle hard braking hot spots and increases the expected number of crashes at 93.3% of heavy-vehicle hard braking hot spots.

The second factor with a normally distributed random parameter is posted speed limits less than or equal to 25 mi/hr. This estimated parameter, with a mean of 0.358

and a standard deviation of 0.980, has an estimated mean of less than zero for 35.7% of heavy-vehicle hard braking hot spots and an estimated mean of greater than zero for 64.3% of heavy-vehicle hard braking hot spots.

Next, the estimated parameter for solid median barriers is found to be random and normally distributed. This indicates, based on a mean of 0.404 and a standard deviation of 0.318, that the estimated parameter mean for solid median barriers is less than zero for 10.2% of heavy-vehicle hard braking hot spots and greater than zero for 89.8%.

The fourth factor with an estimated random parameter, also normally distributed, is the width of the roadway (measured in feet). Based on model estimations, roadway width has a mean of 0.005 and a standard deviation of 0.008. Using the normal distribution curve, these estimates indicate that for 26.6% of heavy-vehicle hard braking hot spots the estimated parameter mean for roadway width is less than zero, whereas 73.4% have an estimated parameter mean greater than zero.

The next factor with a normally distributed random parameter pertains to hard braking hot spots with two lanes (i.e., one lane in each direction). With a mean of -0.562 and a standard deviation of 0.435, the estimated parameter mean for two lanes is greater than zero for 9.8% of heavy-vehicle hard braking hot spots and less than zero for 90.2% of hot spots.

Another roadway characteristic with a normally distributed random parameter are rear-end crashes that occurred at hot spots with a grade. According to model estimations, there is a parameter mean of 0.351 and a parameter standard deviation of

0.216. This indicates, based on the normal distribution curve, that 5.2% of heavy-vehicle hard braking hot spots with a grade have a decrease in the expected number of crashes and 94.8% have an increase.

The final three factors with normally distributed estimated random parameters are traffic characteristics. The first, the estimated parameter for percentage of Class 04 vehicles. Referring to Figure 3.2, Class 04 vehicles are buses (this includes 2 or 3 axles and full length). Therefore, with a mean of -0.342 and a standard deviation of 0.331, buses increase the expected number of crashes for 15.1% of heavy-vehicle hard braking hot spots and decrease the expected number of crashes for 84.9%.

The second traffic characteristic found to be heterogeneous is also a percentage of vehicle class; specifically, Class 06 vehicles. Again, referring to Figure 3.2, Class 06 vehicles are defined as single-unit 3-axle trucks (depending on load, these vehicles may meet the requirements of a heavy-vehicle, a gross vehicle weight rating of greater than 10,000 pounds). From model estimations, this parameter has a mean of -0.555 and a standard deviation of 0.231. This specifies that the percentage of single-unit 3-axle trucks increases the expected number of crashes for 0.8% of heavy-vehicle hard braking hot spots and decreases the expected number of rear-end crashes for 99.2% of heavy-vehicle hard braking hot spots.

The final traffic characteristic, and final factor in the rear-end crash analysis, with a normally distributed random parameter is the percentage of Class 07 vehicles. According to Figure 3.2, FHWA defines Class 07 vehicles as single-unit 4 or more axle trucks. Then, with a mean of 2.303 and a standard deviation of 1.542, single-unit 4 or more axle trucks decrease the expected number of crashes for 6.8% of heavy-vehicle hard braking hot spots and increase the expected number of rear-end crashes for 93.2% of heavy-vehicle hard braking hot spots.

In regards to factors with a large impact on the expected number of rear-end crashes, hot spots with a traffic signal and hot spots located on rural major collectors have the largest impact. A one-unit increase in traffic signals, while holding all other factors constant, results in a 71% increase in the expected number of crashes. As for rural major collectors, a one-unit increases results in a 62% decrease in the expected number of rear-end crashes.

6.1.2 Turning Movement Crash Frequency Discussion

Referring to Table 5.2, 13 factors are found to contribute to turning movement crash frequency at heavy-vehicle hot spots. Of the 13 significant factors, six have normally distributed random parameters (i.e., the factors are heterogeneous across crash observations). The first of these factors with an estimated random parameter is a roadway characteristic, width of roadway (in feet). Although this parameter has a statistically significant standard deviation, the standard deviation is close to zero; as such, when using the normal distribution curve, no variation across crash observations is observed.

The next factor with a normally distributed random parameter is an intersection characteristic. Specifically, with a mean of 0.450 and a standard deviation of 0.394, cross intersections decrease the expected number of turning movement crashes for 12.7% of heavy-vehicle hard braking hot spots and increase the expected number of turning movement crashes for 87.3% of heavy-vehicle hard braking hot spots.

The following three factors with normally distributed random parameters are traffic characteristics. The first of these traffic characteristics is HV-AADT greater than 5,000. Therefore, HV-AADT greater than 5,000, with a parameter mean of 0.238 and a parameter standard deviation of 0.644, decreases the expected number of turning movement crashes for 35.6% of heavy-vehicle hard braking hot spots and increases the expected number of crashes for 64.4%.

The second traffic characteristic with a normally distributed random parameter is the percentage of Class 08 vehicles, defined as single trailer 3- or 4-axle trucks (Figure 3.2). A mean of -0.123 and a standard deviation of 0.054 show that single trailer 3- or 4-axle trucks increase the expected number of turning movement crashes for 1.1% of heavy-vehicle hard braking hot spots and decrease the expected number of turning movement crashes for 98.9% of heavy-vehicle hard braking hot spots.

The third, and final, traffic characteristic with a normally distributed random parameter is the percentage of Class 12 vehicles; Figure 3.2 shows that Class 12 vehicles are defined as multi-trailer 6-axle trucks. Based on model estimates, multi-trailer 6-axle trucks have a parameter mean of 0.748 and a standard deviation of 2.055.

These values, according to the normal distribution curve, indicate that multi-trailer 6-axle trucks decrease the expected number of turning movement crashes for 35.8% of heavy-vehicle hard braking hot spots and increase the expected number of turning movement crashes for 64.2% of heavy-vehicle hard braking hot spots.

The final factor found to be heterogeneous in the turning movement crash frequency analysis is related to traffic control. In particular, the parameter for left-turn refuges is found to be random and normally distributed with a mean of 0.551 and a standard deviation of 0.910. This indicates that left-turn refuges decrease the expected number of turning movement crashes for 27.2% of heavy-vehicle hard braking hot spots and increase the expected number of turning movement crashes for 72.8% of heavy-vehicle hard braking hot spots.

6.1.3 Fixed-Object Crash Frequency Discussion

Referring to Table 5.3, 11 factors are found to contribute to turning movement crash frequency at heavy-vehicle hard braking hot spots. Of the 11 significant factors, four have normally distributed random parameters (i.e., the factors are heterogeneous across crash observations). The first of these factors with an estimated random parameter are hot spots in which a work zone was present. Based on model estimations, the parameter for work zones has a mean of 0.670 and a standard deviation of 0.247. Using the normal distribution curve, this mean and standard deviation imply that work zones decrease the expected number of fixed-object crashes for 0.3% of heavy-vehicle hard braking hot spots and increase the expected number of fixed-object crashes for 99.3% of heavy-vehicle hard braking hot spots. Work zones typically have fixed-objects present, which would certainly increase the expected number of fixed-object crashes (if a crash were to occur). However, a small percentage of work zones may have less (or no) fixed-objects; therefore, resulting in a decrease in the expected number of fixed-object crashes.

The next contributing factor to fixed-object crash frequency, with a normally distributed random parameter, is related to roadway characteristics. Specifically, hard braking hot spots located on horizontal curves have heterogeneous effects on fixed-object crash frequency. With a mean of 0.510 and a standard deviation of 0.194, 0.4% of heavy-vehicle hard braking hot spots on horizontal curves have a decrease in the expected number of fixed-object crashes and 99.6% have an increase in the expected number of fixed-object crashes.

The third contributing factor to fixed-object crash frequency at heavy-vehicle hard braking hot spots, with a normally distributed random parameter, is median type. Specifically, solid median barriers have an estimated parameter mean of -0.464 and an estimated standard deviation of 0.479. This indicates, based on the normal distribution curve, that solid median barriers increase the expected number of fixed-object crashes for 16.6% of heavy-vehicle hard braking hot spots and decrease the expected number of crashes for 83.4% of heavy-vehicle hard braking hot spots.

The fourth, and final, contributing factor with a normally distributed random parameter is the percentage of Class 09 vehicles. FHWA, referring to Figure 3.2, defines Class 09 vehicles as single trailer 5-axle trucks. Based on the significance of the estimated standard deviation, the percentage of single trailer 5-axle trucks have a heterogeneous effect on fixed-object crash frequency at heavy-vehicle hard braking hot spots. Namely, with a mean of 0.042 and a standard deviation of 0.038, the percentage of single trailer 5-axle trucks decrease the expected number of fixed-object crashes for 13.5% of heavy-vehicle hard braking hot spots and increase the expected number of crashes for 86.5% of heavy-vehicle hard braking hot spots.

6.1.4 Sideswipe (Overtaking) Crash Frequency Discussion

The final crash type considered for analysis is sideswipe (overtaking). Referring to Table 5.4, 10 factors are found to contribute to turning movement crash frequency at heavy-vehicle hot spots. Of the 10 significant factors, three have normally distributed random parameters (i.e., the factors are heterogeneous across crash observations). The first of these factors with an estimated random parameter are hot spots in which a jersey barrier was present. Based on model estimations, the parameter for jersey barrier has a mean of 0.833 and a standard deviation of 0.361. Using the normal distribution curve, this mean and standard deviation imply that jersey barriers decrease the expected number of sideswipe (overtaking) crashes for 1.1% of heavy-vehicle hard braking hot spots and increase the expected number of sideswipe (overtaking) crashes for 98.9% of heavy-vehicle hard braking hot spots.

The second contributing factor, with a normally distributed random parameter, to sideswipe (overtaking) crash frequency at heavy-vehicle hard braking hot spots is roadway geometrics. The roadway geometrics that have heterogeneous effects on sideswipe (overtaking) crash frequency are straight roadway segments. Thus, with an estimated parameter mean of -0.314 and an estimated standard deviation of 0.261, straight roadway segments increase the expected number of sideswipe (overtaking) crashes for 11.5% of heavy-vehicle hard braking hot spots and decrease the expected number of crashes for 88.5% of heavy-vehicle hard braking hot spots. The heterogeneous nature in this contributing factor may be attributed to hot spots that have straight roadway segments with and without broken yellow centerlines; that is, segments that allow passing and segments that do not allow passing. Depending on the nature of the roadway, passing (even if permitted) can result in sideswipe (overtaking) crashes.

The third, and final, factor with a normally distributed random parameter that contributes to sideswipe (overtaking) crash frequency at heavy-vehicle hard braking hot spots is the percentage of Class 10 vehicles. According to FHWA (Figure 3.2), Class 10 vehicles are defined as single trailer 6 or more-axle trucks. Therefore, with a mean of 0.104 and a standard deviation of 0.176, the percentage of single trailer 6 or more-axle trucks decrease the expected number of sideswipe (overtaking) crashes for

27.7% of heavy-vehicle hard braking hot spots and increase the expected number of sideswipe (overtaking) crashes for 72.3% of heavy-vehicle hard braking hot spots.

6.2 Discussion of Spatial Lag Crash Frequency Analyses

As discussed previously, it has been determined that spatial autocorrelation is present and needs to be accounted for during the econometric analysis for crash frequency. As such, the following subsections will discuss the findings from the corresponding SLX models (models in which explanatory variables are lagged to account for spatial autocorrelation). Now, to compare apples-to-apples, the same models presented in Table 5.1 to Table 5.4 are fit using spatially lagged explanatory variables. In addition, the lagged explanatory variables provide the analyst with a spillover (i.e., indirect) effect of a given explanatory variable on neighboring hard braking hot spots.

6.2.1 Rear-End Spatial Lag Crash Frequency Discussion

Being that the same model used for the random parameters rear-end crash frequency analysis is used for the SLX analysis, 16 factors are used. For the spatial econometric analysis of rear-end crash frequency at heavy-vehicle hard braking hot spots, some factors are significant in only their direct effects, some are significant in only their indirect effects, some are significant in both direct and indirect effects with the same sign, and some are significant in both direct and indirect effects with different signs.

To illustrate, 9 factors are found to be significant in only their direct effect. The first of these factors is the number of heavy-vehicle hard braking events. According to model estimations, the number of hard braking events is associated with a 6.1% increase in the expected number of rear-end crashes at heavy-vehicle hard braking hot spots. This finding is intuitive, as the number of hard braking events increase, there is likely to be an increase in the expected number of rear-end crashes. Rear-end crashes are most common with braking events, and this is seen in this parameter estimate.

The next factor found to be significant only in its direct effect is rural minor arterials. Based on model estimations, rural minor collectors are associated with a 43.6% decrease in the expected number of rear-end crashes at heavy-vehicle hard braking hot spots. This may be a result of traffic volumes and posted speed limits on minor rural arterials. If traffic volumes are lower, vehicles may be hard braking with no vehicles traveling in front of them (i.e., no vehicle to rear-end). Likewise, if posted speed limits are lower, vehicles are able to decrease their speed less abruptly. This allows surrounding traffic to respond adequately without causing a rear-end crash.

Continuing, posted speed limits less than or equal to 25 mi/hr is significant in only its direct effect on rear-end crash frequency. Specifically, posted speed limits less than or equal to 25 mi/hr are associated with a 31.7% increase in the expected number of rear-end crashes at heavy-vehicle hard braking hot spots. This finding may be attributed to vehicles traveling faster than the posted speed limit, which can increase the expected number of rear-end crashes if a vehicle is forced to slow down.

Another posted speed is also found to be significant in only its direct effect, posted speed limits greater than or equal to 60 mi/hr. According to model estimations, posted speed limits greater than or equal to 60 mi/hr are associated with a 40.2% decrease in the expected number of rear-end crashes at heavy-vehicle hard braking hot spots.

Two additional roadway characteristics are also found to have only significant direct effects on rear-end crash frequency. The first of these are roadways with two lanes. In particular, two lane roadways are associated with a 39.8% decrease in the expected number of rear-end crashes at heavy-vehicle hard braking hot spots. Although there are only two lanes, this may provide additional roadway surface that vehicles can use to avoid a rear-end collision.

The final roadway characteristic found to have only a significant direct effect on rear-end crash frequency is grade. Based on model estimations, crashes that occurred at heavy-vehicle hard braking hot spots with a grade are associated with a 37.1% increase in the expected number of rear-end crashes. This could be attributed to a couple of factors, the first of which would be visibility. If a vehicle is approaching the top of the grade, it is sometimes difficult to see traffic beyond the crest. Therefore, if a vehicle is approaching this location of the grade at a high rate of speed, it may not be able to slow before causing a rear-end crash. Alternatively, rear-end crashes may be more likely when traveling down the grade, in which speeds are typically higher and stopping requires a longer distance.

Next, there are five factors found to have only a significant indirect effect on rear-end crash frequency. The first factor to be significant in its indirect effect only is solid median barrier. Based on model estimations, solid median barriers are associated with an 84.6% increase in the expected number of rear-end crashes on neighboring heavy-vehicle hard braking hot spots.

The following factor to have only a significant indirect effect is width of the roadway (in feet). Width of the roadway (in feet), based on model estimations, is associated with a 1.5% increase in the expected number of rear-end crashes on neighboring heavy-vehicle hard braking hot spots.

The next factor found to have only a significant indirect effect on rear-end crash frequency is related to traffic volumes. Specifically, AADT is associated with a 12.6% increase in the expected number of rear-end crashes on neighboring heavy-vehicle hard braking hot spots.

Continuing, another traffic characteristic is found to have only a significant indirect effect on rear-end crash frequency. This traffic characteristic is the percentage of Class 01 vehicles, which are defined by FHWA as motorcycles (2-axle, 2 or 3 tires) (see Figure 3.2). Now, based on model estimations, motorcycles are associated with a 32.9% decrease in the expected number of rear-end crashes on neighboring heavy-vehicle hard braking hot spots.

The final factor to be significant in only its indirect effect is also a traffic characteristic, Class 12 vehicles. FHWA defines Class 12 vehicles as multi-trailer 6-axle trucks (see Figure 3.2). Therefore, according to model estimations, multi-trailer 6-axle trucks are associated with a 1,083% increase in the expected number of rear-end crashes on neighboring heavy-vehicle hard braking hot spots.

In regards to factors with both a significant direct effect and indirect effect, one is a roadway characteristic and the other is a traffic control characteristic. In terms of the roadway characteristic, rural major collectors are found to have both significant direct and indirect effects on rear-end crash frequency. Specifically, according to model estimations, rural major collectors are associated with 39.9% decrease in their direct effect in the expected number of rear-end crashes. On the other hand, in its indirect effect, rural major collectors are associated with a 58.3% decrease in the expected number of rear-end crashes on neighboring heavy-vehicle hard braking hot spots.

As for the traffic control characteristic found to have significant direct and indirect effects, traffic signals have a positive estimated parameter mean in its direct effect and a negative estimated parameter mean in its indirect effect. To illustrate, model estimations show that traffic signals are associated with a 72.5% increase in the expected number of rear-end crashes. More, model estimations show that traffic signals are associated with a 367% decrease in the expected number of rear-end crashes on neighboring heavy-vehicle hard braking hot spots.

6.2.2 Turning Movement Spatial Lag Crash Frequency Discussion

Once more, the same model used for the random parameters turning movement crash frequency analysis is used for the SLX analysis. As such, 13 factors are included in the Negative Binomial SLX turning movement crash frequency model. For the spatial econometric analysis of turning movement crash frequency at heavy-vehicle hard braking hot spots, some factors are significant in only their direct effects, no factors are significant in only their indirect effects, one factor is significant in both direct and indirect effects with the same sign, and two factors are significant in both direct and indirect effects with different signs.

Regarding factors that are significant in only their direct effects, there are eight factors related to roadway characteristics, intersection characteristics, pavement characteristics, traffic characteristics, and traffic control characteristics. As for roadway characteristics, rural minor arterials and urban local roads have only a significant direct effect on turning movement crash frequency. First, model estimations indicate that rural minor arterials are associated with a 41.7% decrease in the expected number of turning movement crashes. Secondly, based on model estimations, urban local roads are associated with a 73.4% decrease in the expected number of turning movement crashes.

In terms of intersection characteristics, cross intersections are found to have only a significant direct effect on turning movement crash frequency. In particular, based on model estimations, cross intersections are associated with a 69.1% increase in the expected number of turning movement crashes. This finding is rather intuitive, as intersections are prone to several turning movements and conflict points, which can result in an increase in turning movement crashes.

For pavement characteristics, very good pavement conditions are found to be significant in only their direct effect. Very good pavement conditions, according to model estimations, are associated with a 69.1% increase in the expected number of turning movement crashes.

Three traffic characteristics have only a significant direct effect on turning movement crash frequency. The first is HV-AADT greater than 5,000, which according to model estimations, is associated with a 57.8% increase in the expected number of turning movement crashes.

The following two traffic characteristics are related to vehicle percentage by vehicle classification. The first vehicle percentage is the percentage of Class 08 vehicles, which are defined as single trailer 3- or 4-axle trucks (refer to Figure 3.2). Model estimations show that single trailer 3- or 4-axle trucks are associated with a 16.5% decrease in the expected number of turning movement crashes. The second vehicle percentage to have only a significant direct effect is the percentage of Class 12 vehicles. As discussed previously, FHWA defines Class 12 vehicles as multi-trailer 6-axle trucks. Then, according to model estimations, multi-trailer 6-axle trucks are associated with a 225% increase in the expected number of turning movement crashes.

The final factor with only a significant direct effect on turning movement crash frequency are left-turn refuges as traffic control devices. This factor has a large impact on the expected number of crashes, as model estimations indicate that left-turn refuges are associated with a 132% increase in the expected number of turning movement crashes.

Three factors are found to have both significant direct effects and significant indirect effects, with no factors being significant only in their indirect effects. Of the three significant factors, one had the same impact directly and indirectly: width of the roadway (in feet). In terms of direct effects, roadway width (in feet) is associated with a 1% increase in the expected number of turning movement crashes. In regards to indirect effects, model estimations show that width of the roadway (in feet) is associated with a 0.9% increase in the expected number of turning movement crashes at neighboring heavy-vehicle hard braking hot spots.

The remaining two factors, significant in both their direct and indirect effects, are found to have different effects directly and indirectly. Both of these factors are related to roadway characteristics, the first of which is a roadway classification. Specifically, regarding direct effects, model estimations indicate that urban collectors are associated with 53.7% decrease in the expected number of turning movement crashes. Yet, as it pertains to indirect effects, model estimations show that urban collectors are associated with a 96.6% increase in the expected number of turning movement crashes at neighboring heavy-vehicle hard braking hot spots.

The final factor, also with different direct and indirect effects, is a posted speed limit. Particularly, in terms of direct effects, model estimations demonstrate that posted speed limits between 50 mi/hr and 60 mi/hr are associated with a 30.9% decrease in the expected number of turning movement crashes. On the other hand, in terms of indirect effects, model estimations indicate that posted speed limits between 50 mi/hr and 60 mi/hr are associated with a 37.9% increase in the expected number of turning movement crashes at neighboring heavy-vehicle hard braking hot spots.

6.2.3 Fixed-Object Spatial Lag Crash Frequency Discussion

Again, the same model used for the random parameters fixed-object crash frequency analyses is used for the SLX analysis. Therefore, 11 factors are included in the Poisson SLX fixed-object crash frequency model. For the spatial econometric analysis of fixed-object crash frequency at heavy-vehicle hard braking hot spots, some factors are significant in only their direct effects, one factor is significant in only their indirect effects, and three factors are significant in both direct and indirect effects with the same sign.

Of the 11 factors, six are found to have only significant direct effects on fixed-object crash frequency. Three of the six are related to roadway characteristics: (1) urban interstates, (2) work zone, and (3) horizontal curves. The first, urban interstates, are associated with a 42.3% increase in the expected number of fixed-object crashes. Next, model estimations show that work zones are associated with a 97.2% increase in the expected number of fixed-object crashes. Thirdly, according to model estimations, horizontal curves are associated with a 67.1% increase in the expected number of fixed-object crashes.

The remaining two factors found to have only a significant direct effect are related to roadway surface characteristics and traffic characteristics. Regarding roadway surface characteristics, model estimations show that solid median barriers are associated with a 32.6% increase in the expected number of fixed-object crashes.

The final factor significant only in its direct effect, as stated previously, is related to traffic characteristics. This factor is the percentage of Class 09 vehicles, in which FHWA defines Class 09 vehicles as single trailer 5-axle trucks. Referring to model estimations, the percentage of single trailer 5-axle trucks is associated with a 5.7% increase in the expected number of fixed-object crashes.

Only one factor has been found to be significant in only its indirect effects, good pavement condition. According to model estimations, good pavement conditions are associated with a 22% increase in the expected number of fixed-object crashes on neighboring heavy-vehicle hard braking hot spots.

Regarding the three factors that are significant in both their direct effects and indirect effects (with the same sign), roadway characteristics increase the expected number of fixed-object crashes and traffic characteristics decrease the expected number of fixed object crashes. First, if the roadway is a bridge structure, there are significant direct and indirect effects. For direct effects, model estimations show that bridge structures increase the expected number of fixed-object crashes by 94.4%. If a crash were to occur on a bridge structure, it is likely that a fixed-object is involved; therefore, an increase in the expected number of fixed-object crashes can be expected. As for indirect effects, model estimations show a 59.5% increase in the expected number of fixed-object crashes on neighboring heavy-vehicle hard braking hot spots.

The second significant roadway characteristic with a positive direct and indirect effect is grade. That is, in terms of direct effects, hard braking hot spots with a grade are associated with a 26.1% increase in the expected number of fixed-object crashes. On the other hand, indirectly, hard braking hot spots with a grade are associated with an increase of 44.1% in the expected number of fixed-object crashes on neighboring heavy-vehicle hard braking hot spots.

The final factor to have both significant direct and indirect effects (with the same sign) is the percentage of heavy-vehicles. In its direct effect, the percentage of heavy-vehicles is associated with a 3.4% decrease in the expected number of fixed-object crashes. Also with a decrease in the expected number of fixed-object crashes, the indirect effect of the percentage of heavy-vehicles. Based on model estimations, indirectly, the percentage of heavy-vehicles is associated with a decrease of 1.9% in the expected number of fixed-object crashes on neighboring heavy-vehicle hard braking hot spots.

6.2.4 Sideswipe (Overtaking) Spatial Lag Crash Frequency Discussion

Lastly, the same model used for the random parameters sideswipe (overtaking) crash frequency analysis is used for the SLX analysis. Accordingly, 10 factors are included in the Negative Binomial SLX sideswipe (overtaking) crash frequency model. For the spatial econometric analysis of sideswipe (overtaking) crash frequency at heavy-vehicle hard braking hot spots, seven factors are significant in only their direct effects, one factor is significant in only their indirect effects, and two factors are significant in both direct and indirect effects with the same sign.

To begin, urban principal arterials are found to have statistically significant direct effects on sideswipe (overtaking) crash frequency at heavy-vehicle hard braking hot spots. Referring to model estimations, urban principal arterials are associated with a 51.4% increase in the expected number of sideswipe (overtaking) crashes.

The next factor to have only a significant direct effect on sideswipe (overtaking) crash frequency is also a roadway characteristic. Specifically, straight roadway segments, based on model estimations, are associated with a 22.8% decrease in the expected number of sideswipe (overtaking) crashes.

A roadway surface characteristic is also found to have only a significant direct effect, median type. According to model estimations, earth, grass, or paved medians are associated with a decrease of 30.4% in the expected number of sideswipe (overtaking) crashes.

The next three factors with only a significant direct effect on sideswipe (overtaking) crash frequency are all related to traffic characteristics. The first factor is the percentage of Class 04 vehicles. Referring to Figure 3.2, FHWA defines Class 04 vehicles as 2- or 3-axle full length buses. Then, according to model estimations, 2- or 3-axle full length buses are associated with a 31% decrease in the expected number of sideswipe (overtaking) crashes.

The following traffic characteristic with only a significant direct effect on sideswipe (overtaking) crash frequency is the percentage of Class 12 vehicles. Again, referring to Figure 3.2, FHWA defines Class 12 vehicles as multi-trailer 6-axle trucks. Therefore, based on model estimations, multi-trailer 6-axle trucks are associated with a 75.4% decrease in the expected number of sideswipe (overtaking) crashes. Such truck configurations are often linked to lower posted speed limits, which can deter them from passing (or overtaking) other vehicles. As a result, if multi-trailer 6-axle trucks are not passing (or overtaking) other vehicles, the expected number of sideswipe (overtaking) crashes can be expected to decrease.

The final traffic characteristic with only a significant direct effect on sideswipe (overtaking) crash frequency is the percentage of Class 10 vehicles. Once more, from Figure 3.2, FHWA defines Class 10 vehicles as single trailer 6- or more-axle trucks. As follows, based on model estimations, single trailer 6- or more-axle trucks are associated with a 16.4% increase in the expected number of sideswipe (overtaking) crashes.

To conclude the factors with only a significant direct effect on sideswipe (overtaking) crash frequency, left-turn refuges are significant and increase the expected number of sideswipe (overtaking) crashes. To be specific, model estimations show that left-turn refuges are associated with a 46.7% increase in the expected number of sideswipe (overtaking) crashes.

Regarding indirect effects, just one factor is found to have significant indirect effects, one-way streets. Referring to model estimations, one-way streets are associated with a 43.1% decrease in the expected number of sideswipe (overtaking) crashes on neighboring heavy-vehicle hard braking hot spots.

As stated previously, just two factors are found to be significant in both their direct effects and indirect effects. The first of these factors is the number of lanes. Referencing Table 5.19, model estimations show that the direct effect of number of lanes is associated with a 6.2% increase in the expected number of sideswipe (overtaking) crashes. This finding is plausible, as an additional lane provides more opportunity for vehicles to pass (or overtake) other vehicles. If vehicles have more opportunity to pass (or overtake) other vehicles, the expected number of sideswipe (overtaking) may increase, and this is what model estimations show. Likewise, in its indirect effect, the number of lanes is associated with a 12.6% increase in the expected number of sideswipe (overtaking) crashes on neighboring heavy-vehicle hard braking hot spots. A possible explanation for this indirect effect may be linked to a lane drop at neighboring hard braking hot spots. A lane drop results in vehicles traveling in the same direction to converge to a single lane, which can increase the expected number of sideswipe (overtaking) crashes.

The second, and final, factor with both a significant direct effect and indirect effect is median type. Specifically, in terms of direct effects, jersey barriers are associated with a 99.1% increase in the expected number of sideswipe (overtaking) crashes. In the same manner, regarding indirect effects, jersey barriers are associated with a 330% increase in the expected number of sideswipe (overtaking) crashes at neighboring heavy-vehicle hard braking hot spots.

6.3 Comparison Between Random Parameters and Spatial Lag Models

Taking into account that two specific methodologies are used to conduct crash frequency analyses, results of the two different analytic methods are compared. To compare the results from the random parameters and SLX models, overall model fit based on log-likelihood values and the rate of correctly predicted crash frequencies will be assessed. As with the previous sections, comparison of analysis methods will be done by crash type.

6.3.1 Comparison of Rear-End Crash Frequency Models

In regards to overall model fit, the random parameters model for rear-end crash frequency converged at a log-likelihood value of -1,890.23 and has a McFadden Pseudo R-Squared value of 0.08. Now, turning to the SLX rear-end crash frequency model, the log-likelihood at convergence is marginally better at -1,871.00 with a slightly better McFadden Pseudo R-Squared value of 0.09. If considering only overall model fit, the SLX model (model accounting for spatial autocorrelation) is preferred. However, when considering the rate of correctly predicted crash frequencies, the results are substantially different. To illustrate, see Figure 6.1 and Figure 6.2. As seen, accounting for unobserved heterogeneity (for this specific data) results in a significantly higher prediction rate.

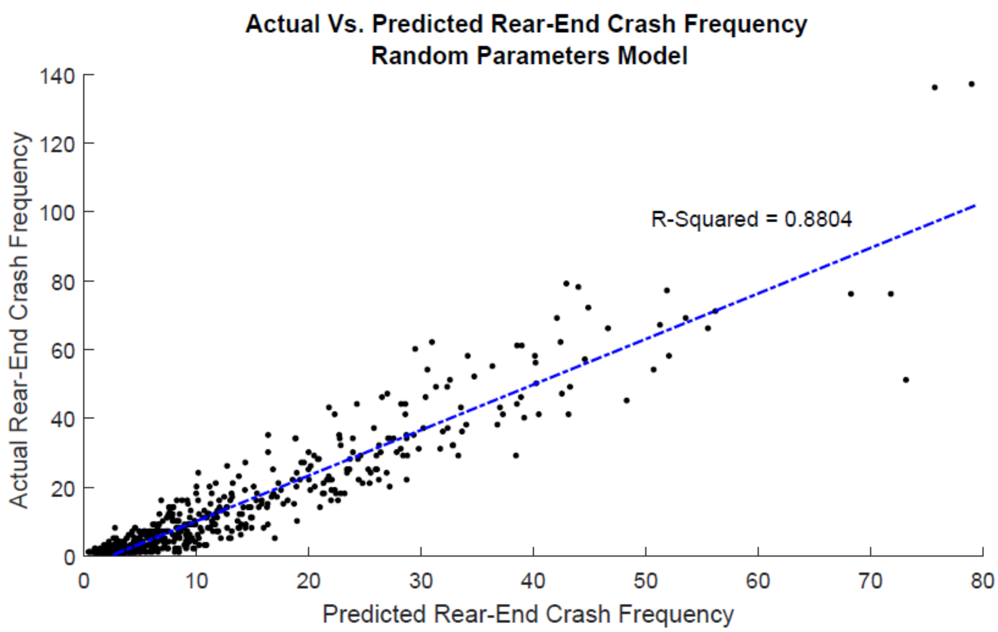


Figure 6.1: Actual Versus Predicted Rear-End Crash Frequency for Random Parameters Negative Binomial Model

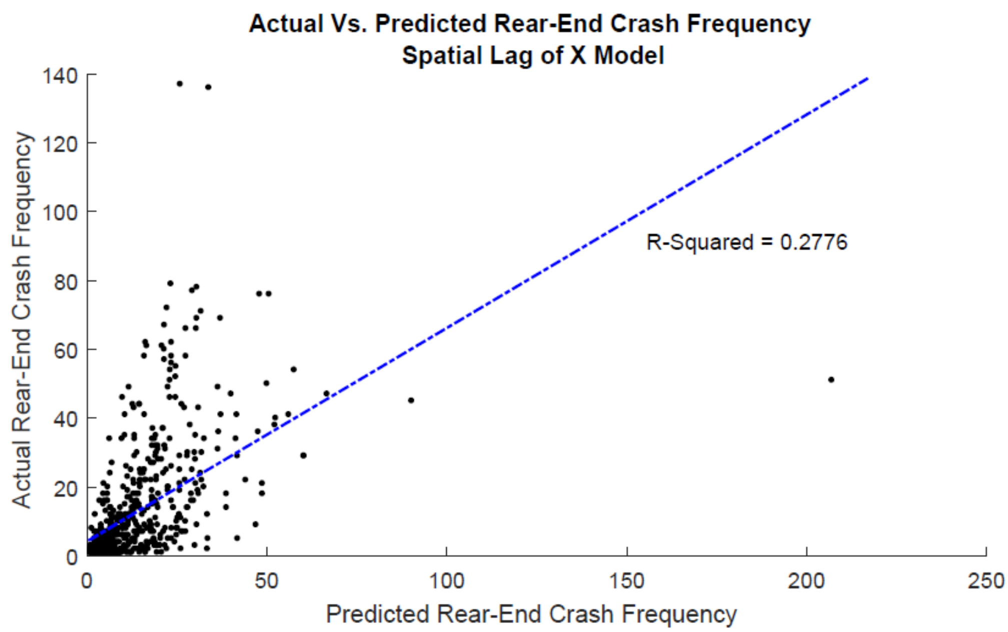


Figure 6.2: Actual Versus Predicted Rear-End Crash Frequency for SLX Negative Binomial Model

Although there is significant spatial autocorrelation present, as shown previously, the prediction rate is substantially lower for the SLX model. Based on these results, if one is looking for better overall model fit, the SLX model marginally outperforms the random parameters model. However, if one is looking for correctly predicted crash frequencies, the random parameters model is statistically superior when compared to the SLX model. This suggests that although there is significant spatial autocorrelation, there is more unobserved heterogeneity present in the rear-end crash data.

6.3.2 Comparison of Turning Movement Crash Frequency Models

In regards to overall model fit, the random parameters model for turning movement crash frequency converged at a log-likelihood value of -1,029.19 and has a McFadden Pseudo R-Squared value of 0.11. Now, turning to the SLX turning movement crash frequency model, the log-likelihood at convergence is marginally worse at -1,033.00 with the same McFadden Pseudo R-Squared value of 0.11. If considering only overall model fit, the random parameters model (model accounting for unobserved heterogeneity) is preferred. Next, when considering the rate of correctly predicted crash frequencies, the results of the random parameters model are substantially better in terms of predicted crash frequencies. To illustrate, see Figure 6.3 and Figure 6.4. As seen, accounting for unobserved heterogeneity (for this specific data) results in a significantly higher prediction rate (R^2 of 0.8167 to 0.3769).

Although there is significant spatial autocorrelation present, as shown previously, the prediction rate is substantially lower for the SLX model. Based on these results, accounting for unobserved heterogeneity provides both a better overall model fit and more correctly predicted crash frequencies. For the turning movement crash data, the random parameters method is preferred.

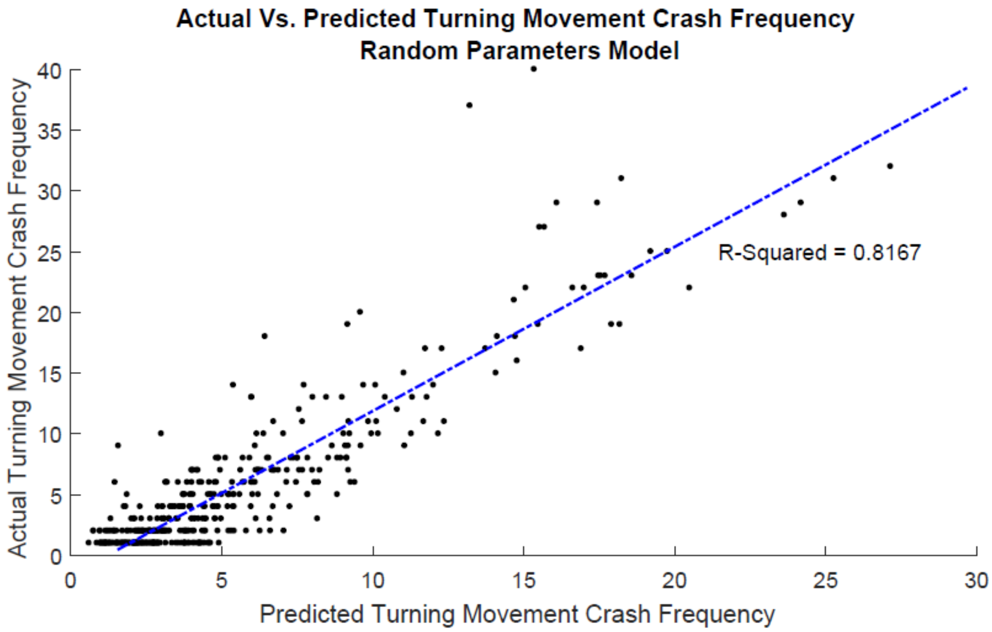


Figure 6.3: Actual Versus Predicted Turning Movement Crash Frequency for Random Parameters Negative Binomial Model

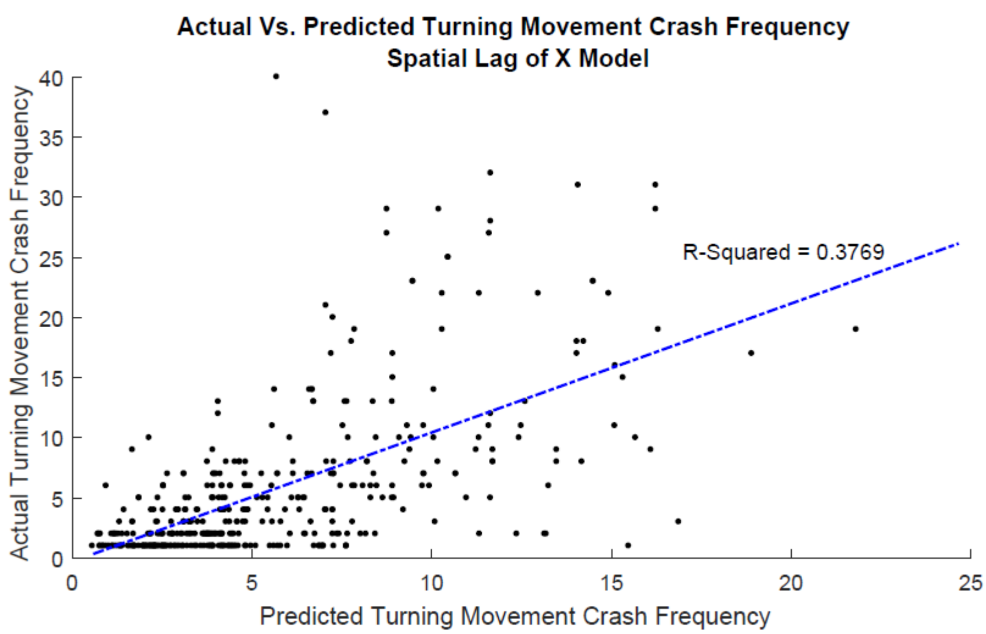


Figure 6.4: Actual Versus Predicted Turning Movement Crash Frequency for SLX Negative Binomial Model

6.3.3 Comparison of Fixed-Object Crash Frequency Models

Continuing with model comparison, the fixed-object crash frequency models are compared via overall model fit and rate of correctly predicted crash frequencies. Pertaining to overall model fit, the random parameters model for turning movement crash frequency converged at a log-likelihood value of -832.45 and has a McFadden Pseudo R-Squared value of 0.18 (the best fit of all the random parameters crash frequency models). When considering the SLX fixed-object crash frequency model, the log-likelihood at convergence is marginally better at -821.81 with a slightly better McFadden Pseudo R-Squared value of 0.19. If considering only overall model fit, the SLX model (model accounting for spatial autocorrelation) is slightly better. However, when considering the rate of correctly predicted crash frequencies, the results of the random parameters model are a bit better in terms of predicted crash frequencies. To illustrate, see Figure 6.5 and Figure 6.6. As seen, accounting for unobserved heterogeneity (for this specific data) results in a marginally higher prediction rate (R^2 of 0.6312 to 0.5559). To this point, this is the closest the prediction rate has been between the two econometric methods. This suggests there may be similar amounts of heterogeneity and spatial autocorrelation in the fixed-object crash data.

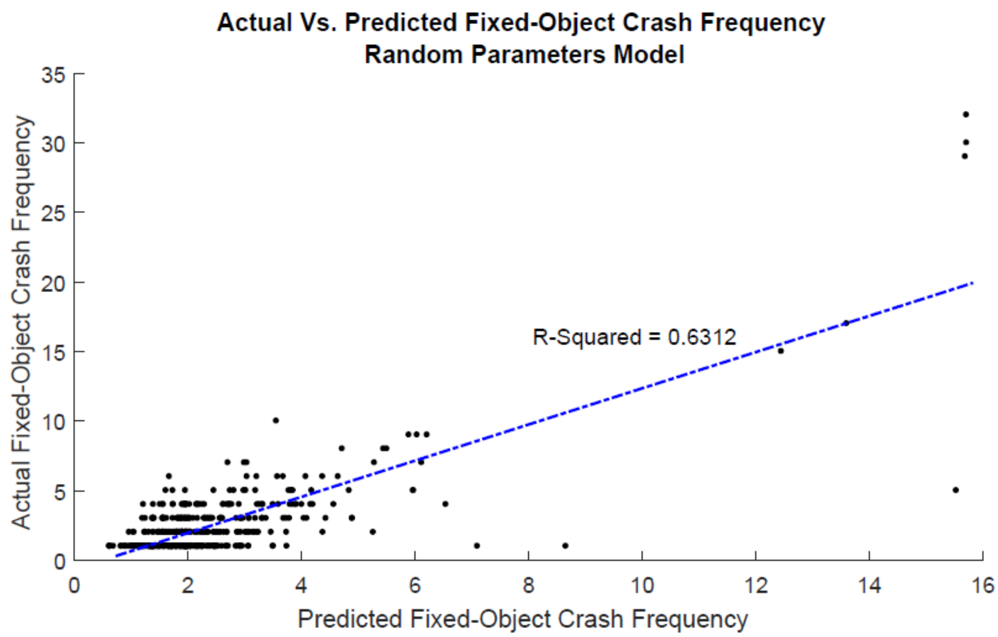


Figure 6.5: Actual Versus Predicted Fixed-Object Crash Frequency for Random Parameters Poisson Model

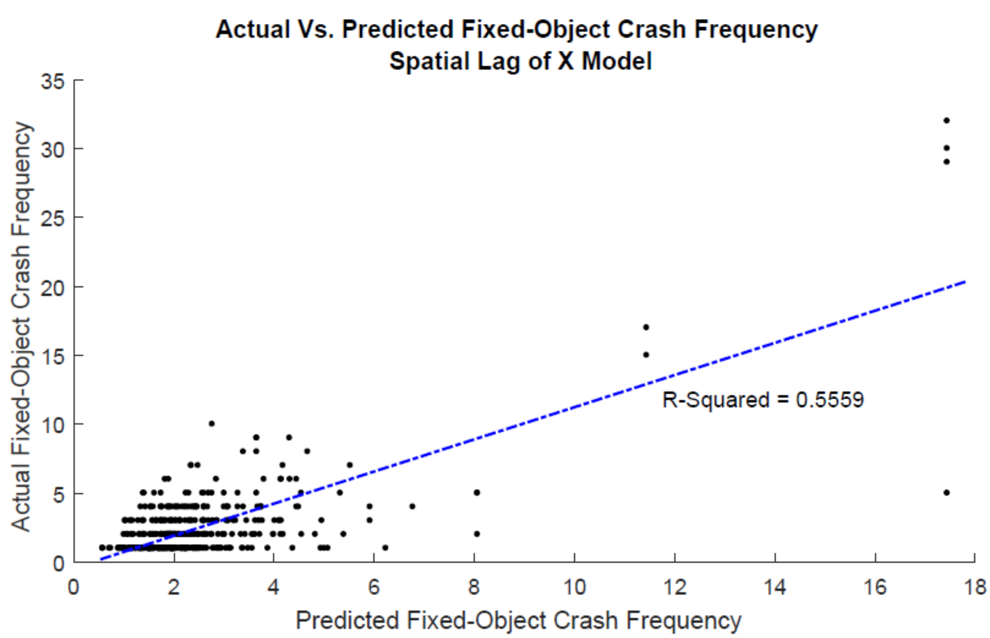


Figure 6.6: Actual Versus Predicted Fixed-Object Crash Frequency for SLX Poisson Model

6.3.4 Comparison of Sideswipe (Overtaking) Crash Frequency Models

The final crash type analysis to compare is the analysis of sideswipe (overtaking) crashes. As with the previous three crash type models, overall model fit and the rate of correctly predicted crash frequencies are compared. Regarding overall model fit, the random parameters model for sideswipe (overtaking) crash frequency converged at a log-likelihood value of -630.98 and has a McFadden Pseudo R-Squared value of 0.10. When considering the SLX sideswipe (overtaking) crash frequency model, the log-likelihood at convergence is marginally better at -618.10 with a better McFadden Pseudo R-Squared value of 0.12. Therefore, if considering only overall model fit, the SLX model (model accounting for spatial autocorrelation) is slightly better. However, when considering the rate of correctly predicted crash frequencies, the results of the random parameters model are superior. To illustrate, see Figure 6.7 and Figure 6.8. As seen, accounting for unobserved heterogeneity (for this specific data) results in a significantly higher prediction rate (R^2 of 0.6734 to 0.4335).

Although the prediction rates are not as close to one another as the fixed-object analysis, these are much closer than rear-end crashes or turning movement crashes. Once more, these results suggest that the crash data for this crash type has larger amounts of heterogeneity than spatial autocorrelation.

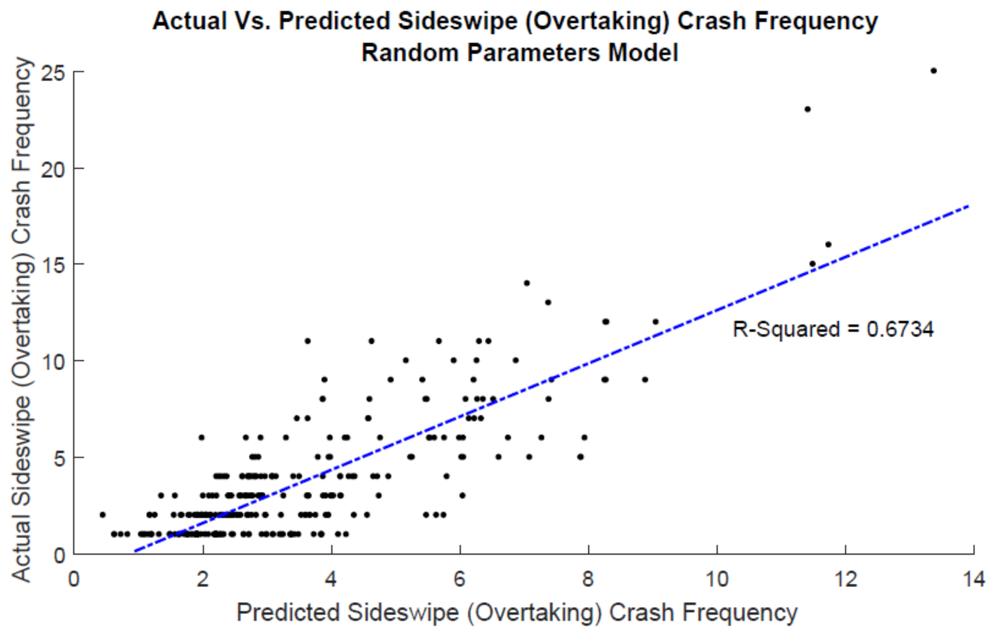


Figure 6.7: Actual Versus Predicted Sideswipe (Overtaking) Crash Frequency for Random Parameters Negative Binomial Model

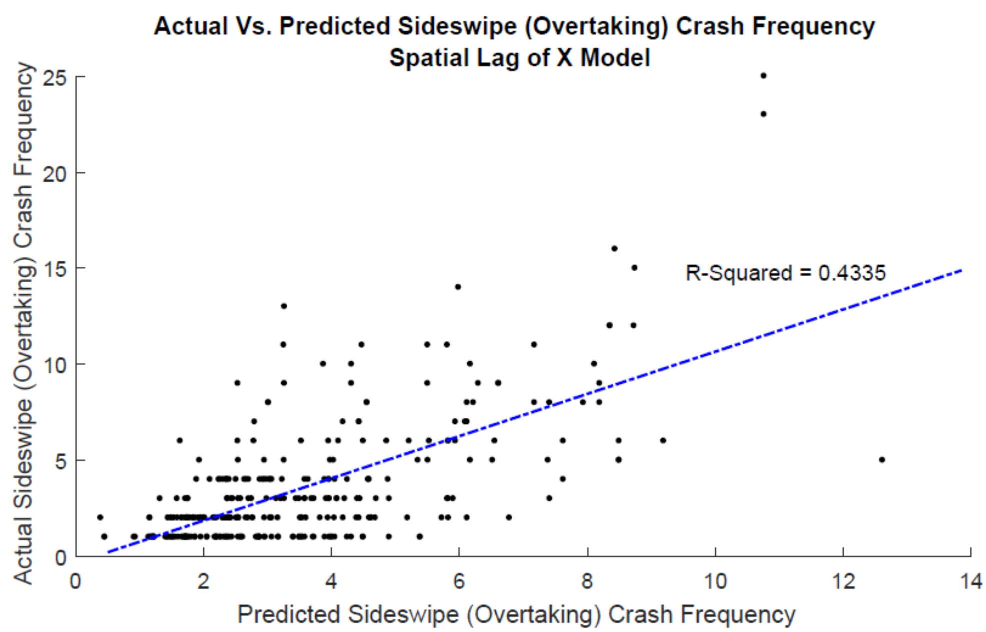


Figure 6.8: Actual Versus Predicted Sideswipe (Overtaking) Crash Frequency for SLX Negative Binomial Model

6.4 Summary of Model Comparisons

To summarize the comparisons between analytic methods, refer to Table 6.1. In three of the four crash frequency analyses, the SLX variants provided a slightly better overall fit in terms of log-likelihood values and McFadden Pseudo R-Squared values. For rear-end crashes, the difference in overall model fit is just 1.02%. This difference in overall model fit is essentially negligible, but the difference in correctly predicted crash frequencies is not. That is, the difference in correctly predicted crash frequencies is 214.3%.

The turning movement crash frequency analysis is the only analysis in which the random parameters model provided a better overall model fit; still, the percent change is essentially negligible at 0.37%. Again, the percent difference in correctly predicted crash frequencies is very significant with a 115.8% difference.

The fixed-object crash frequency analysis, like the rear-end analysis, had a better overall model fit with the SLX variant. However, once again, the difference in overall model fit is marginal at 1.29%. However, the random parameters and SLX models for the fixed-object analysis provided the closest prediction rate of the four crash type analyses with a difference of just 12.5%. As stated previously, this may suggest similar amounts of heterogeneity and spatial autocorrelation in the fixed-object crash data.

The final crash type, sideswipe (overtaking), has a better overall model fit with the SLX variant when compared to the random parameters model. Yet, as is the case with each crash type in which the SLX variant provided a better overall model fit, the difference is minimal at 2.08%. As it pertains to correctly predicted crash frequencies, the random parameters method still outperformed the SLX model. But, the SLX model was closer to the random parameters model in correctly predicted crash frequencies compared to the rear-end and turning movement analyses, where the difference for the sideswipe (overtaking) analysis is 55.8%.

Table 6.1: Summary of Model Comparisons by Crash Type

Crash Type	Model Type	Log-Likelihood at Convergence	McFadden Pseudo R-Squared	R-Squared (Rate of Correctly Predicted Crash Frequencies)
Rear-End	Random Parameters	-1,890.23	0.08	**0.88**
	SLX	**-1,871.00**	**0.09**	0.28
Turning Movement	Random Parameters	**-1,029.19**	**0.11**	**0.82**
	SLX	-1,033.00	0.11	0.38
Fixed-Object	Random Parameters	-832.45	0.18	**0.63**
	SLX	**-821.81**	**0.19**	0.56
Sideswipe (Overtaking)	Random Parameters	-630.98	0.10	**0.67**
	SLX	**-618.10**	**0.12**	0.43

6.5 Comparison of Factors by Crash Type

The final comparison is to compare significant contributing crash frequency factors by crash type. No factor has been found to be significant in each of the four crash frequency models, but one factor is significant among three of the crash frequency models. This factor is the percentage of Class 12 vehicles, defined by FHWA as multi-trailer 6-axle trucks. Although significant in three of the crash frequency models, the percentage of multi-trailer 6-axle trucks had different effects on crash frequency for each type. For rear-end crashes, the percentage of multi-trailer 6-axle trucks increased the expected number of crashes, while decreasing the expected number of sideswipe (overtaking) crashes. Then, for turning movement crashes, the percentage of multi-trailer 6-axle trucks is heterogeneous (i.e., increases the expected number of crashes for a proportion of heavy-vehicle hard braking hot spots and decreases the expected number of crashes for the remaining hot spots). Although this is the only vehicle class significant for more than two crash types, Class 04 (2- or 3-axle full length buses) vehicles are significant for two crash types and various other vehicle classes are significant across the four crash types.

Significant across three crash types are roadway geometrics; however, different geometrics are significant for each of the three crash types. For instance, grades are significant for rear-end crashes (heterogeneous) and fixed-object crashes (increases the expected number of crashes), horizontal curves are significant for fixed-object crashes (heterogeneous), and straight segments are significant for sideswipe (overtaking) crashes (heterogeneous). In addition, as shown in parentheses, grades for rear-end crashes, horizontal curves for fixed-object crashes, and straight segments for sideswipe (overtaking) crashes are all heterogeneous across heavy-vehicle hard braking hot spots.

The next set of characteristics significant across three of the crash type models are related to median type. Solid median barriers are significant in both rear-end crashes and fixed-object crashes, in which both are heterogeneous. Then, for sideswipe (overtaking) crashes, two different median types are significant. The first is jersey barrier, where this is also heterogeneous across hard braking hot spots. The second, and decreases the expected number of sideswipe (overtaking) crashes, is an earth, grass, or paved median.

The final set of characteristics, in which a different classification is significant in each of the four crash type models, is roadway classifications. The only crash types, however, to have rural classifications significant are rear-end and turning movement. For rear-end crashes, both rural minor arterials and rural major collectors decrease the expected number of crashes (rural minor arterials also decrease the expected number of turning movement crashes). The remaining classifications are urban classifications, in which different urban classifications are significant for turning movement, fixed-object, and sideswipe (overtaking) crashes. Urban collectors and urban local roads decrease the expected number of turning movement crashes, urban interstates increase the expected number of fixed-object crashes, and urban principal arterials increase the expected number of sideswipe (overtaking) crashes.

To summarize and compare the impacts of various exposure-based factors by crash type, see Table 6.2 to Table 6.5.

Table 6.2: Summary of Roadway Characteristics by Crash Type

Characteristic	Rear-End Crashes	Turning Movement Crashes	Fixed-Object Crashes	Sideswipe (Overtaking) Crashes
Rural Roadway Classifications	↓	↓	-	-
Urban Roadway Classifications	-	↓	↑	↑
Low Posted Speed Limits	↓↑	-	-	-
High Posted Speed Limits	↓	↓	-	-
Solid Median Barriers	↓↑	-	↓↑	-
Jersey Barrier	-	-	-	↓↑
Earth, Grass, or Paved Median	↓			
Width of Roadway (In Feet)	↓↑	↓↑	-	-
Number of Lanes	↓↑	-	-	↑
Vertical Geometrics (Grade)	↓↑	-	↑	
Horizontal Curve	-	-	↓↑	-
Straight Segments	-	-	-	↓↑
Lane Width	-	↓	-	-
Bridge Structure	-	-	↑	-
Work Zone	-	-`	↓↑	-

* ↓ = Decrease in Expected Number of Crashes, ↑ = Increase in Expected Number of Crashes, ↓↑ = Heterogeneous Across Heavy-Vehicle Hard Braking Hot Spots

Table 6.3: Summary of Intersection and Traffic Control Characteristics by Crash Type

Characteristic	Rear-End Crashes	Turning Movement Crashes	Fixed-Object Crashes	Sideswipe (Overtaking) Crashes
Cross Intersections	↓↑	-	-	-
Traffic Signal	↑	-	-	-
Left-Turn Refuge	-	↓↑	-	↑
One-Way Street	-	-	-	↓

* ↓ = Decrease in Expected Number of Crashes, ↑ = Increase in Expected Number of Crashes, ↓↑ = Heterogeneous Across Heavy-Vehicle Hard Braking Hot Spots

Table 6.4: Summary of Roadway Surface Characteristics by Crash Type

Characteristic	Rear-End Crashes	Turning Movement Crashes	Fixed-Object Crashes	Sideswipe (Overtaking) Crashes
Very Good Pavement Condition	-	↓	-	-
Good Pavement Condition	-	-	↑	-
Asphalt Concrete Surface	-	-	↓	-

* ↓ = Decrease in Expected Number of Crashes, ↑ = Increase in Expected Number of Crashes, ↓↑ = Heterogeneous Across Heavy-Vehicle Hard Braking Hot Spots

Table 6.5: Summary of Traffic Characteristics by Crash Type

Characteristic	Rear-End Crashes	Turning Movement Crashes	Fixed-Object Crashes	Sideswipe (Overtaking) Crashes
AADT	↑	↑	-	-
High HV-AADT	-	↓↑	-	-
Percentage of Heavy-Vehicles	-	-	↓	-
Class 01 Vehicles	↓	-	-	-
Class 03 Vehicles	-	-	↓	-
Class 04 Vehicles	↓↑	-	-	↓
Class 06 Vehicles	↓↑	-	-	-
Class 07 Vehicles	↓↑	-	-	-
Class 08 Vehicles	-	↓↑	-	-
Class 09 Vehicles	-	-	↓↑	-
Class 10 Vehicles	-	-	-	↓↑
Class 12 Vehicles	↑	↓↑	-	↓

* ↓ = Decrease in Expected Number of Crashes, ↑ = Increase in Expected Number of Crashes, ↓↑ = Heterogeneous Across Heavy-Vehicle Hard Braking Hot Spots

7.0 SUMMARY AND INSIGHTS

Utilizing a previously unused freight data source, the current dissertation explored heavy-vehicle hard braking events in a safety context for all traffic mixes. This began by obtaining heavy-vehicle hard braking data from EROAD, a fully integrated regulatory technology, tolling and services provider. Per EROAD, a hard braking event was recorded as a reduction in speed greater than 10 kilometers per hour (6.21 mi/hr) in 1 second. Such events were then collected over a six month period and used for the statistical and econometric analyses of crash frequency by crash type.

To begin, a kernel density analysis was conducted using the heavy-vehicle hard braking event data. The kernel density analysis showed that the majority of high density heavy-vehicle hard braking areas are in urban areas, mostly along the I-5 corridor that runs north-to-south through Oregon. Upon completing the kernel density analysis, a hot spot analysis was conducted to determine statistically significant hot spots in regard to heavy-vehicle hard braking. Results determined that several heavy-vehicle hard braking hot spots are located throughout Oregon, both in urban and rural areas.

To continue the data-driven analysis, crash data and several exposure-based datasets were obtained from ODOT. Before spatially joining the crash data to the heavy-vehicle hard braking hot spots, the exposure-based datasets were merged with the crash data (a detailed discussion of these datasets can be found in Chapter 3.0). This resulted in a comprehensive dataset that could be spatially joined to heavy-vehicle hard braking hot spots and used for a crash frequency analysis. Using a 500 feet buffer, the crash data (with all the exposure-based data) were spatially joined to the hard braking hot spots, in which crashes were aggregated by hard braking hot spot. The final step determined that the four most occurring crash types at heavy-vehicle hard braking hot spots in Oregon are: rear-end crashes, turning movement crashes, fixed-object crashes, and sideswipe (overtaking) crashes.

After disaggregating the data by crash type, various statistical and econometric analyses were completed. Before the spatial analyses took place, a set of random parameters models were estimated to determine significant contributing crash frequency factors by crash type. In each model, factors were found to have normally distributed random parameters (i.e., their effects were heterogeneous across heavy-vehicle hard braking hot spots). No factor was found to be significant in each crash type model, but there were some characteristics found significant in as many as three. One of these characteristics to be significant in three of the four models were urban roadway classifications. Specifically, urban roadway classifications decreased the expected number of turning movement crashes while increasing the expected number of fixed-object and sideswipe (overtaking) crashes. The other characteristic significant in three of the crash models is the percentage of Class 12 vehicles (multi-trailer 6-axle trucks). The impact of Class 12 vehicles was different for each crash type they were significant in. For rear-end crashes, Class 12 vehicles were found to increase the expected number of crashes. For turning movement crashes, the effect of Class 12 vehicles on the expected crash frequency was found to be heterogeneous. And, for sideswipe (overtaking) crashes, Class 12 vehicles were found to decrease the expected number of crashes.

After fitting four random parameters crash frequency models, tests for spatial autocorrelation were conducted. Using the number of k-nearest neighbors, spatial weights matrices were developed and used to test for spatial autocorrelation. It was determined that each crash type dataset was susceptible to spatial autocorrelation with a high level of significance. Therefore, using the spatial weights matrix corresponding to each crash type dataset, four Spatial Lag of X (SLX) models were fit using the significant variables found in the random parameters analysis. This was done to ensure the comparison between the model types had no bias in one way or the other. That is, the variables remain the same and the only change is the data limitation the model is accounting for.

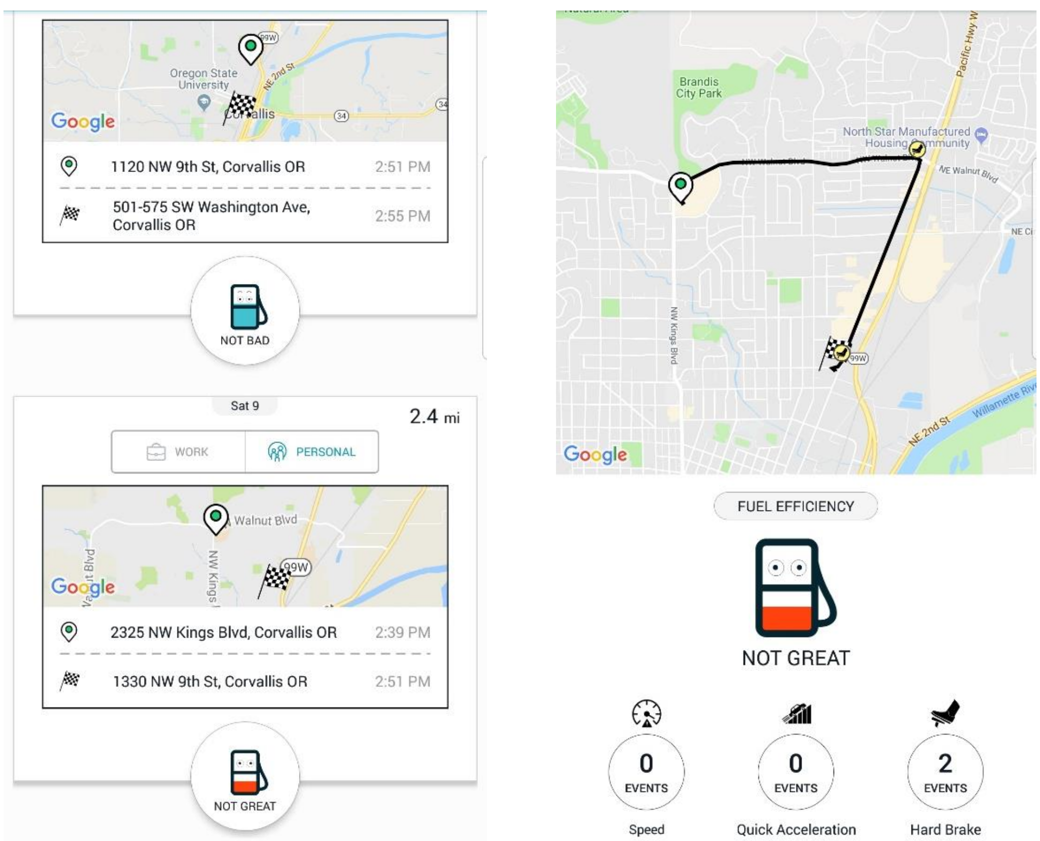
After fitting the SLX models, it was determined that some variables have significant direct effects on expected crash frequency and insignificant indirect effects, some variables have insignificant direct effects on expected crash frequency and significant indirect direct effects, some variables have both significant direct and indirect effects with the same sign (increase in both or decrease in both), and others have both significant direct and indirect effects with different signs (increase in one effect and decrease in the other, or vice-versa). In three of the four models, the overall model fit of the SLX models (compared to the random parameters models) was slightly better (i.e., log-likelihood value closer to zero). However, when comparing crash frequency prediction, the random parameters models substantially outperformed the SLX models. Therefore, based on these results, accounting for unobserved heterogeneity is the preferred method for the crash type datasets considered in the current study.

7.1 Recommendations Based on Analysis Results

Using the analysis results, the current section will propose recommendations that can be used to mitigate/monitor hard braking events and address specific exposure-based characteristics that lead to an increase in expected number of crashes.

In regards to mitigating and monitoring hard braking events of heavy-vehicles, this can be achieved as the mandate for electronic logging devices is here. As is, several trucking firms equip their trucks with technology that records several aspects of the drivers' trips. This study can be used to prompt trucking firms to equip their trucks (if not already equipped) with units that can record these types of events. Further, trucking firms can put more emphasis on addressing hard braking within their firm, being that it impacts safety and, potentially, the firm's profits. This work shows that several crashes among several crash types occur at locations that are prone to heavy-vehicle hard braking; therefore, if heavy-vehicle hard braking can be reduced, so may the crashes at these locations.

In addition, monitoring hard braking is something drivers of all vehicles can do. As stated previously, hard braking can be a sign of aggressive driving behavior or distracted driving; therefore, if a person can monitor their hard braking events, they may be able to adapt their driving behavior. One such way comes with a smart phone application: GasBuddy.[13] This app can be downloaded on both iPhone and Android, and be used to track hard braking events (as well as hard accelerating) along a driver's trip. As seen in Figure 7.1, the overall trip is rated and the number of events that lead to a bad a rating are recorded. In this case, it was a short trip and the bad ranking is given due to the number of hard braking events.



(a) (b)

Figure 7.1: Example of Smart Phone Application to Monitor Hard Braking

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13 https://www.gasbuddy.com/

In regards to recommendations based on analysis results, ODOT can use the results from the hot spot analysis as a starting point regarding areas that are prone to heavy-vehicle hard braking. In addition, it is possible that these locations are vulnerable to hard braking of all traffic mixes. ODOT can focus on these areas to determine if any exposure-based characteristics are contributing to hard braking. For example, visibility may be limited, not enough lighting, or signage for horizontal curves can be improved. More, poor pavement conditions may be causing drivers to brake suddenly to avoid bumps or extreme potholes. Understanding why these locations may lead to hard braking events can help decrease the number of hard braking events and, therefore, improve traffic safety.

As for exposure-based characteristics, traffic signals and left-turn refuges increase the expected number of crashes. This can prompt an investigation into the locations of these traffic control devices. There may be insignificant signage informing the driver that a traffic signal or a left-turn refuge is approaching. Or, they may be in locations such as speed drop zones, following horizontal curves, or at crests of vertical curves.

Very good pavement conditions decrease the expected number of crashes; therefore, investing in projects to improve pavement conditions may lead to a decrease in crash frequency. Several of the heavy-vehicle hard braking hot spots are located in the Portland metropolitan area, in which several segments of local streets, highways, and interstates have poor to very poor pavement conditions.

7.2 Moving Forward

Based on the current study, several avenues for future work were identified. The first of these pertains to the freight data source used. The present work has shown the viability of using this data, both for research and in a safety context. As such, ODOT and other transportation agencies can use this data source moving forward. It can be used to conduct safety studies, not just for heavy-vehicles, but for all traffic mixes (as shown in the current work). More, it can be used to develop statewide freight plans and generate supply-chain analyses.

Regarding the analytical methods, this work has shown that accounting for heterogeneity better predicts crash frequency. However, there is still spatial correlation that is not being accounted for. Therefore, future work should focus on accounting for both unobserved heterogeneity and spatial correlation. This will likely consist of algorithm development that can estimate random parameters while accounting for the spatial weights between events (this may or may not consists of spatial lag variables, as was the case for this study).

Lastly, hard braking studies are still limited and especially so in the explicit context of crash frequency. With full penetration of connected and autonomous vehicles still years away, research into hard braking in a safety context can benefit the public as a whole. Other areas could include, but not limited to, the effect of roadway classification on hard braking, injury severity and hard braking, and hard braking as it relates to weather and lighting conditions.

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