2019

Exploring the relationship between interstate crashes and various speed metrics based upon probe vehicle data

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Recommended Citation

Zhou, Chao, "Exploring the relationship between interstate crashes and various speed metrics based upon probe vehicle data" (2019). *Graduate Theses and Dissertations*. 17132.
https://lib.dr.iastate.edu/etd/17132

Exploring the relationship between interstate crashes and various speed metrics based upon probe vehicle data

by

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A thesis submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Major: Civil Engineering (Transportation Engineering)

Program of Study Committee:
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Peter T. Savolainen, Co-major Professor
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Iowa State University

Ames, Iowa

2019

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NOMENCLATURE

AADT	Annual Average Daily Traffic
ATR	Automatic Traffic Recorder
AVG	Average
CTRE	Center for Transportation Research and Education
DOT	Department of Transportation
FARS	Fatality Analysis Reporting System
FHWA	Federal Highway Administration
GIMS	Geographic Information Management System
HMVMT	Hundred Million Vehicle Miles Traveled
IEM	Iowa Environmental Mesonet
MPH	Miles per Hour
NMSL	National Maximum Speed Law
PDO	Property Damage Only
QA/QC	Quality Assurance/Quality Control
RAMS	Roadway Asset Management System
SD	Standard Deviation
Std. Error	Standard Error
TMC	Traffic Message Channel
VMT	Vehicle Miles Traveled

ACKNOWLEDGMENTS

I would like to thank my committee members, Dr. Christopher M. Day, Dr. Peter T. Savolainen, and Dr. Kristen S. Cetin, for their guidance and support throughout the course of this research.

In addition, I would also like to thank the Iowa Department of Transportation and the members of the Technical Advisory Committee for the financial and technical support of this study.

Finally, I would like to offer my appreciation to my friends, colleagues, the department faculty and staff for making my time at Iowa State University a wonderful experience.

ABSTRACT

In recent years, a considerable amount of research has been aimed at discerning the determinants of traffic crashes and those circumstances under which crash risk is increased. This is particularly important when considering the potential safety impacts of geometric design or transportation policy decisions. For example, research has consistently demonstrated that crashes are affected by various factors related to the roadway, the surrounding environment, and the involved drivers. This study has two principal goals. The first is to understand how driver speed selection varies with respect to traffic and roadway geometric characteristics. The second goal is to explore the relationship between traffic crashes, operating speeds (i.e., mean speed, 85th percentile speed, speed variance) and other pertinent factors (e.g., traffic, roadway, weather). To achieve these goals, the study utilized traffic, roadway, weather, and speed data (i.e., automatic traffic recorder, INRIX) for Iowa interstates. Simple descriptive statistics are documented to illustrate crash trends on the Iowa interstate network during the study period. A series of regression models were estimated to investigate relationships between various speed metrics and crash rates with respect to traffic, roadway, and weather characteristics. The study suggests that speed measures, such as mean speed, 85th percentile speed, and speed variance, are found to correlate with the roadway geometry. In addition, higher speed variance is associated with more crashes, while the absolute speed of traffic does not necessarily correspond to higher crash occurrences.

CHAPTER 1. INTRODUCTION

Balancing transportation efficiency and traffic safety has long been a crucial issue. One policy issue with substantive impacts on both safety and efficiency is the establishment of maximum statutory speed limits. Various research studies have indicated that increased speed limits are associated with increased crashes. From a policy standpoint, it is critical to understand how the frequency and severity of traffic crashes may be influenced by speed limits and other roadway and environmental factors.

In 1974, a national maximum speed limit (NMSL) was introduced in the United States, which established a consistent 55 mph limit on all high-speed roadways. Subsequent legislation in 1987 allowed states to increase limits up to 65 mph on rural interstates. In 1995, states were provided with full autonomy to establish maximum speed limits on all roads under their jurisdiction. Figure 1 shows the current maximum posted speed limit map on rural interstates for all 50 states and the District of Columbia. In particular, 19 states have raised their maximum speed limit to 75 mph or above, with Texas having the highest posted speed limit (85 mph) on selected road segments.

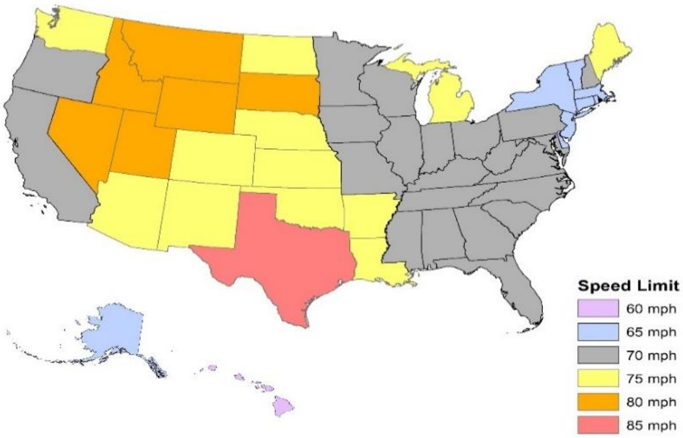

Figure 1. Maximum Posted Rural Interstate Speed Limits

In Iowa, the most recent speed limit change took place on July 1, 2005, when the maximum speed limit was raised from 65 mph to 70 mph on rural interstates. A series of subsequent studies evaluated the short-term impacts of the speed limit increases (Souleyrette et al., 2009; Souleyrette et al., 2010). The results showed that crashes increased following the speed limit change, though this change was not statistically significant at a 95-percent confidence level. The researchers suggested that further study is required to understand the relationship better, including whether drivers may have adapted to the new speed limit over time.

This study builds upon these initial analyses and leverages the additional crash data that are now available, allowing for a comparison of changes in the crash frequency, rate, and severity between the periods before and after the speed limit change was introduced. In addition, comprehensive analyses are conducted using an integrated database that includes traffic volumes, roadway geometry, and weather data, as well as detailed speed information from automatic traffic recorders and probe vehicles. The objective of this study is to understand the relationship between different speed measures (e.g., mean speed, 85th percentile speed, speed variance) and roadway geometric characteristics. The study also examines how safety on Iowa interstates is influenced by operating speeds while controlling for the effects of other site-specific factors that may affect both speeds and safety.

This thesis consists of six chapters. Chapter 1 introduces the background and objectives of the research problem. A comprehensive literature review shows previous studies and their findings of how speed, traffic, weather condition, and roadway geometry affect transportation safety in Chapter 2. Chapter 3 provides a detailed description of the datasets and the processes of integrating data. The statistical methods utilized in this study and research findings are summarized in Chapter 4 while the results of these analyses are detailed in Chapter 5. Finally, Chapter 6 provides a summary and discussion of key findings.

CHAPTER 2. LITERATURE REVIEW

Numerous prior studies have investigated the impacts of speed limit changes. The introduction in 1974 of the national maximum speed limit (NMSL) of 55 mph resulted in speed limit reductions on various high-speed facilities. Several research studies tried to evaluate the impacts of the NMSL (Enustun, 1974; Borg, 1975; Johnson et al., 1980). A study conducted in Indiana found that the NMSL led to a 67% decrease in fatalities, 32% decrease in personal injury, and 13% decrease in property damage on rural highways in the first half of 1974 when compared to the same period of 1971, 1972, and 1973 (Borg, 1975). Similar reductions were also observed in Michigan over the first half of 1974 (Enustun, 1974).

When the NMSL was relaxed in 1987 and 1988, some states increased their maximum speed limit on rural interstates from 55 mph to 65 mph. One study in Washington used crash and traffic data between 1970 and 1997 to investigate the impacts of the increased speed limit on rural freeways. The results suggest that the increased speed limit was associated with an increase of 26.4 fatalities per year (Ossiander et al., 2002). Some additional research compared traffic safety between states that raised their speed limit to 65 mph and states that retained the speed limit of 55 mph. A national analysis found a 15 percent increase in fatalities on rural interstates in 38 states that set higher speed limits in 1987 than the expected fatalities if the states had retained the 55 mph speed limit, while states that retained the 55 mph speed limit experienced 6 percent fewer fatalities than expected (Baum et al., 1989). The study was extended two years later and it was found that the fatality risk on rural interstates had increased 29% for states that increased the speed limit and had decreased 12% for states that retained 55 mph speed limit when adjusting the vehicle miles traveled and vehicle occupancy rates (Baum et al., 1991). A before-after study was performed for Iowa and surrounding Midwestern states to study the consequence of raising speed limits to 65 mph for all road types. This study used fatality data for eight years preceding the speed limit change (1988-1995) and eight years after (1997-2004). It was found that collectively the rate of fatalities per 100 million vehicle miles traveled rose by 10 percent in states that increased the speed limit, and decreased by 7 percent in states that did not raise their speed limits (Falb, 2006).

Other research on the impacts of speed limit increases to 65 mph found similar results. Research from Virginia analyzed data from two years before and two years after the 1987 speed limit change. They asserted that rural interstate fatalities increased by 42.2% after the speed limit increase (Lynn & Jernigan, 1992). Another study conducted in Illinois used data from five years before and four years after the speed limit increase. The researchers estimated that the increased speed limit resulted in 345 additional crashes, 15 more deaths, and 150 more injuries per month on rural Illinois highways. This negative impact was not only apparent on 65 mph rural road segments, but also on 55 mph rural highways (with a smaller impact). The results implied that speed spillover effects may have occurred, wherein the higher speeds on the 65-mph roadways induced increases on other facilities where the limits had not been increased (Rock, 1995).

A study in Michigan took a more in-depth look at the impact of raising speed limits to 65 mph on crash severity on limited access freeways. The study indicated the speed limit change led to a 19.2% increase in fatalities, 39.8% increase in serious injuries, 25.4% increase in moderate injuries, 16.1% increase in PDO crashes, and no significant change in minor injuries. The fatalities on limited access freeways with 55 mph speed limit also increased by 38.4%, suggesting further evidence of speed spillover effects (Wagenaar et al., 1990). Streff and Schultz performed a similar study for Michigan rural limited-access highways in 1990. The results of the monthly time-series intervention analyses estimated that the rates of fatality, A-level injuries, and B-level injuries were raised by 28.4% (31 additional deaths), 38.8% (420 additional injuries), and 24.0% (491 additional injuries) respectively over the 25-month study period, resulting in a total societal cost of $98 million (Streff & Schultz, 1990).

An Iowa study explored the safety impact of the increased 65 mph limit on rural interstates from 1981 to 1991. Researchers claimed that higher speed limits led to a higher fatality rate as the speed limit change was associated with about 20% more fatal crashes statewide, though major injury crashes did not change significantly (Ledolter & Kwai, 1994). The study was expanded two years later, using the same years of data but more selective sample locations, comprising 18 locations including rural interstates, rural primary roads, rural secondary roads, and urban interstates. The same 20% increase in fatal crashes was seen using the same years of data. Additionally, it was found that adverse effects of increasing speed limit to 65 mph was most apparent on rural interstates, causing a 57% increase in the number of fatal crashes on this road type, while the effect was negligible on urban interstates, as the new speed limit was not implemented on urban interstates. Consistent results were found on the number of major-injury crashes, suggesting that this type of crash was insensitive to the speed limit increase (Ledolter & Kwai, 1996). Additional research on the 65 mph speed limit increase on rural Iowa interstate highways used fatal crash data from 1980 to 1993. The predictions from a dynamic model showed an average increase of four fatal crashes per quarter on rural Iowa interstate highways due to the increase in speed limit (Raju et al., 1998).

Research also unveiled the relationship between speed limit, operating speed change, and traffic safety. One study used fatal crash and speed data for five years preceding and one year following the increase in the national maximum speed limit to 65 mph for all states. Results showed that increasing the speed limit caused 48% more speeders and 22% more fatal crashes on rural interstates. Even in states that retained lower speed limits, the fatal crashes still increased by 10% and 13% for rural interstates and other 55 mph highways respectively, which was explained by the increasing number of speeders coinciding with the change in speed limit. Although it seemed that negative impacts were found for increasing the speed limit, the authors believed that increasing speed limits on rural interstates may benefit safety by diverting some speeders to highways that better accommodated their desired speed, since the non-compliance rate with the 55 mph speed limit was high (McKnight & Klein, 1990).

Another study produced different findings, and claimed that the proportion of people driving at high speeds were considerably lower in states with 55 mph speed limit than in states with 65 mph speed limit (Freedman & Williams, 1992). Meanwhile, a study from Washington evaluated the impacts of raising speed limits to 65 mph on high-speed roads. According to the study, a 3-mph increase in average speed was expected for a 10-mph speed limit increase. Also, the raised speed limit led to a 3% increase in crash rate and 24% increase in the probability of an occupant being fatally injured in a crash (Kockelman et al., 2006). A later study collected rural interstate speed and crash data from 61 stations in California, 51 stations in Oregon, and 6 stations in Washington. It was concluded that a 1-

mph increase in speed limit was associated with a 0.3 to 0.4 mph increase in travel speed, and increasing the speed limit by 10 mph resulted in 9-15% more crashes and 34-60% more fatal crashes (Van Benthem, 2015).

A study in Virginia utilized both urban and rural interstate speed data and fatal crash data from 1986 to 1989 to assess the effects of increasing speed limits from 55 mph to 65 mph on rural interstates. A significant positive relationship was found between average speed and the annual number of fatalities on Virginia's rural interstates. A 1-mph increase in the annual average speed corresponded to about 2-6 deaths. Average and 85th-percentile speeds, fatal crashes, and fatalities all increased on Virginia's rural interstates after raising the speed limit. Negligible impacts were observed on urban interstates (Jernigan & Lynn, 1989). Research from Illinois examined the safety impact of the 65 mph speed limit on rural interstate highways using speed and crash data for 15 rural interstate highway segments, and data were obtained for 52 months before and 15 months after the speed limit increase. Results illustrated that the 85th-percentile speed for cars was 4 mph higher than before, but there was no change in the rate of all crashes except for a statistically non-significant increase (18.5%) in the rate for fatal and injury crashes (Pfefer et al., 1991).

Other research indicated positive effects of increasing the speed limit to 65 mph. One study assessed the 65 mph speed limit for all states. For the states that increased their speed limit, the growth of VMT for rural interstate highways was 1.73 times greater than the overall VMT growth rate, implying that interstates took traffic away from the more dangerous highway types. When aggregating all states that raised their speed limits and all that did not, the states with increased speed limits experienced a 3.62% greater decrease in fatality rates from 1986 to 1988 than states with the unchanged speed limit (Lave & Elias, 1997). Another study calculated the fatality rate per VMT from January 1976 to December 1990 for each state and fitted a linear regression while controlling state-specific characteristics such as percent unemployment and seat belt use. The results demonstrated that the states that raised the speed limit to 65 mph experienced 3.4% to 5.1% drop in fatality rates compared to the states that remained the same speed limit (Lave & Elias, 1994).

Mixed results were found in several studies regarding raising the speed limit from 55 mph to 65 mph. A state-by-state analysis was done for rural highway fatalities using the Fatality Analysis Reporting System (FARS) data from January 1976 to November 1988. Researchers asserted that the new 65 mph speed limit had quite disparate effects on rural highway fatalities, and the speed change affected both rural interstates and rural non-interstate highways. Among all states, some experienced increasing rural interstate fatalities, while others saw decreases or had no detectable effect. However, the number of states observing increased fatalities exceeded the number of states experiencing reduced fatalities, leading to a median effect of about 15% more fatalities. The researchers speculated that the new 65 mph speed limit may contribute to traffic diversion as well as speed spillover effects on rural non-interstates. The median effects of the new speed limit on rural non-interstate fatalities was an approximately 5% increase (Garber & Graham, 1990).

Preliminary evaluation of the increased speed limit on rural interstates was conducted in Illinois by comparing fatal crashes and personal injury crashes as proportions of total crashes for the before (May 1982 through April 1987) and after periods (May 1987 through April 1988). No significant differences were found. From this, the researcher concluded that the severity of crashes on Illinois rural interstates did not worsen and no noticeable adverse effects because of the speed limit increase were observed, at least for the first year after the increase (Sidhu, 1990). In the same year, another study in Alabama yielded similar results. The study assessed the impact of the 65 mph speed limit on the entire Alabama roadway system using two years of data from before and one year after the change. They pointed out that the proportion of PDO to injury to fatal crashes remained the same, meaning there was no evident change in crash severity, although the crash frequency was found to be increased by 18.88% on rural interstates in the first 12-month period after the change (Brown et al., 1990).

Some studies observed different effects of the speed limit increase on different road types. An Ohio study used 36 months of crash data both before and after the speed limit increase, and claimed that the fatal crash rate did not significantly change on rural interstate highways with 65 mph speed limits and non-interstate highways with 55 mph speed limits. However, the injury and PDO crash rates increased by 16% and 10% respectively on 65 mph rural interstates, while the injury and PDO crash rates decreased by 5% and 3% respectively on 55 mph rural interstates. Additionally, crash severity decreased on 55 mph non-interstate highways, which researchers believed to be associated with the effects of a recent seat belt law, speed enforcement, and geometric and operational improvements (Prahlad et al., 1992). According to a study that examined the impact of the increased speed limit on rural interstates of 48 states excluding the District of Columbia, Delaware, and Alaska, raising the speed limit resulted in a significant increase in fatalities nationwide. However, this increase decayed after about one year. Larger states, such as Texas, California, Florida, and Illinois were insensitive to the speed limit increase, while smaller states reacted to the speed limit increase more dramatically (Chang et al., 1993).

Since the repeal of NMSL, the speed limit setting authority was fully returned to the individual states, and many states decided to further increase their speed limit to 70 mph. Studies in several states have observed the outcomes of increasing the posted speed limit from 65 to 70 miles per hour. A study in Iowa found increases in fatal crashes and in serious nighttime crashes over a 2.5 year period after the change, but the increases were not statistically significant at the 95% confidence level. (Souleyrette et al., 2009). A study in Florida evaluated drivers' compliance to posted speed limits and studied the average speeds at locations where the speed limit increase was applied. At sites where the increase was applied, the average speed increased by 5 miles per hour, reaching 72 miles per hour over a 6 year period. Researchers argued that speed variation might cause the majority of crashes analyzed in this study (Muchuruza & Mussa, 2004).

Studies in Indiana also evaluated the increase in the speed limit from 65 to 70 miles per hour and the outcomes of that change. One of the studies examined drivers' perceptions of their driving speed after the state applied the speed limit increase on its rural interstates. The study found that socioeconomic variables, such as age, gender, and income, correlate with driver speed choice. It was also found that drivers do not believe that driving above the speed limit significantly threatens their safety (Mannering, 2007). Another study performed in Indiana evaluated the effects of the speed limit increase on crash severity. Researchers found that the change did not have a statistically-significant effect on the severity of crashes for interstate highways; for some non-interstate highways, a positive correlation was observed between higher speed limits and the severity of crashes (Malyshkina & Mannering, 2007). A study in the state estimated the crash-injury severity on interstate highways after the speed limit increase and did not find a significant correlation between them. However, the crash data showed that higher speed limits were associated with a greater likelihood of injury, fatality, or both on some non-interstate highways (Malyshkina & Mannering, 2008).

Since the state of Michigan increased its speed limit on freeways in 1997 from 65 to 70 miles per hour, several studies have examined the effects of that change. One of them evaluated the effects of increasing the speed limit from 65 to 70 miles per hour for passenger cars. The study found that fatal crashes increased by 5% and total crashes increased by 10.5% after the change. It was observed that A-crashes decreased by 9% after the increase in speed limit and a higher percentage of statewide crashes occurred on freeways after 1997. The study also found a decrease in severe truck crashes, but found an increase in the total amount of truck crashes after the speed limit change (Taylor, 2000). Another study in Michigan studied the results of the speed limit change on crash frequency. The study observed a 16.4% increase in crashes over one month after the speed limit change at sites where the speed limit increased. Crashes decreased by 2.4% over the same period in sites where the speed limit did not increase (Taylor & Maleck, 1996). A study in the same state observed drivers' speeds after the change. It did not find meaningful speed changes for sites where the speed limit increase was not applied and did not observe a spillover effect of increased speeds for locations near those sites. The 50th and 85th percentile speeds respectively increased by 1 mph and 0.8 mph for sites where the change was applied (Binkowski et al., 1998).

A study in Alabama evaluated vehicle crash frequency for rural interstate highways after the speed limit increase from 65 to 70 miles per hour and found significant increases in the number of fatal crashes. However, state and federal highways did not have significant changes (Bartle et al., 2003). A study conducted in Iowa evaluated the effects of the speed limit increase from 65 to 70 miles per hour on crash frequency in the state. It found a 52% increase in nighttime fatal crashes and a 25% increase in severe cross median crashes. The increases were more than normal variation, but were not statistically significant at 90% confidence level. The research found a 25% increase in the total crashes in the state after the speed limit increase, which was significant at the 90% confidence level (Souleyrette et al., 2010).

Instead of focusing on the impact of one speed limit change, additional studies considered several speed limit changes over a longer period of time. One national study used a time series model to investigate the impacts of two speed limit increases on the Interstate network, one in 1987 when some states increased speed limit to 65 mph, and another in 1996 when some states implemented speed limits over 65 mph. The numbers of fatal crashes for each month from January 1975 to December 1998 were collected. The results indicated that a significant increase in fatal crashes on rural interstates was found in 19 of 40 states in the first speed limit increase in 1987, while in the second speed limit increase in 1996, 10 out of 36 states witnessed a significant increase in fatal crashes on rural interstates (Balkin & Ord, 2001).

Research in California studied speed limit changes on state highway segments. Three groups that remained the same speed limits and increased speed limits were identified: remained at 55mph, increased from 55 to65 mph, and increased from 65 to 70 mph. It was found that for groups that experienced a speed limit increase, there was a significant increase in fatal collisions, although the 65-70 mph group had a level of significance of less than 10% (Haselton et al., 2002). A study in Utah analyzed crash data on rural/urban interstates, rural non-interstates, and high-speed non-interstates between 1992 and 1999. Within these roadway categories, various speed limit changes were experienced, such as 55-60 mph, 65-65 mph, 55-65 mph, 65-70 mph, and 65-75 mph. Researchers asserted that the total crash rates on urban interstates where the speed limit was raised from 60 to 65 mph and fatal crash rates on high-speed rural non-interstates where speed limit increased from 60 to 65 mph had increased sharply. Meanwhile, the study observed that other statistics remained stable after the speed limit change, such as the total, fatal, and injury crash rates on rural interstates; fatal and injury crash rates on urban interstates, and total and injury crash rates on high-speed non-interstate (Vernon et al., 2004). Another study included 41 states that at least had 10 billion VMT in each year in the analysis. All roadway types were included in the analysis, and the study period was between 1993 and 2013, during which some states increased speed limits from 55 to 65 mph or from 65 to 70 mph. The study results revealed that the fatality rate generally decreased over the study period; however, increasing the maximum speed limit was associated with higher fatality rates. On all roads, a 1-mph increase in the maximum speed limit resulted in a 0.9% increase in the fatality rate, while this positive relationship was almost doubled to 1.6% on interstates and freeways (Farmer, 2016).

Apart from the impacts of the speed limit, traffic and roadway geometry also play significant roles in traffic safety. Several prior studies have provided observations in regard to these factors. Preliminary conclusion was made that the number of crashes had been observed to increase with traffic volume, while crash rates tend to decrease as traffic volumes increase. Further research was warranted to study the relationship extensively (Duivenvoorden, 2010). Crash odds have been found to decrease as the shoulder width increases (Gross et al, 2009). A recent study examined several risk factors, including highway traffic and roadway design collectively. It was concluded that higher traffic volume consistently led to higher crash frequencies. As for geometry characteristics, a 1% increase in the left shoulder width on interstates is related to a 1.72% decrease in fatal crashes and a 2.97% decrease in non-fatal crashes, while crash frequencies were less sensitive to the right shoulder width. Increasing the median width by 1% reduces fatal crashes by 0.50% and non-fatal crashes by 0.65% (Chen et al., 2019). Researchers conducted a study on the effectiveness of a cable median barrier system on an Oregon highway. Although more crashes were observed on the cable median barrier roadway sections, the severity of crashes decreased significantly (Burns & Bell, 2016). A more recent study in Iowa evaluated the performance of median cable barriers and concluded that the countermeasure decreased K, A, and B crashes while increasing C and PDO crashes. The reason was that the median cable barrier system might effectively convert more severe crashes to less severe crashes. It was also found that the frequencies in fatal, injury, and PDO crashes decreased with a wider median width (Savolainen et al., 2018).

Adverse weather has always been associated with increases in crashes, and many studies have evaluated the impacts of adverse weather on traffic safety. Abdel-Aty et al. (2011) analyzed the fatal crash data in the US from 2000 to 2007 using FARS and reported that there were 4,972 fatal crashes during snow events, and 31,514 fatal crashes during all inclement weather including rain, snow, and fog/smoke. Adverse weather reduced visibility and caused slippery roadway pavement surfaces, which in turn led to increased accident risks. Khattak and Knapp (2001) considered crash, weather, and roadway geometry information on selected Iowa interstate segments to compare crashes during snow events with crashes that occurred during non-snow events. They reported that the winter snow event injury and non-injury crash rates were significantly higher than the equivalent winter nonsnow event injury and non-injury crash rates. However, the crash severity was lower during snow events, which might be caused by slower speeds and more cautious driving during a snow event. Another study showed that the accident risk increased by four times on slushy road conditions and two times on slippery and very slippery road conditions (Malin et al., 2019). Similar results were also demonstrated in a study conducted by Yu et al. (2015), where increased crash rates in large precipitation (above 0.02 in/h) conditions were observed.

Although considerable effort has been extended to make highway travel safer, understanding how travel speed and speed variation affects crash rates and crash severity can help further improve roadway safety. A previous study reported that a driver would have a higher risk of experiencing a crash if the difference between the vehicle speed and the average traffic speed increases (Solomon, 1964). Lave (1985) concluded that no evident relationship was observed between fatality rate and average speed, but speed variance was highly correlated with the fatality rate. He claimed that the safest driving speed was the median speed, and deviations from this speed in either direction would increase the crash risk, meaning both slower and faster vehicles were more likely to be involved in crashes. Later, Garber and Gadiraju (1989) studied the factors that caused the increased speed variance and the relationship between speed variance and crash rates. They reported that the minimum speed variance was observed when the posted speed limit was 5 to 10 mph lower than the design speed, and the speed variance increased with the increased differential between design speed and posted speed limit. They explained that drivers chose their driving speed based on the roadway geometric characteristics, and higher driving speed was anticipated on improved roadway geometry regardless of the posted speed limit. Also, similar to the previous findings, they argued that crash rates increased with higher speed variance and no significant relationship was found between crash rates and average speed. Oh et al. (2005) also identified that the standard deviation of speed was the most significant variable when estimating the likelihood of crashes. A research conducted by Abdel-Aty et al. (2004) determined that the average lane occupancy at the upstream station and variation of speed downstream were the most significant variables in predicting the likelihood of crash occurrences.

Contrary results have been seen in other studies. Another study in Australia quantified the relationship between free traveling speed and fatal crash risk using a case control study. They concluded that vehicles traveling 10 km/h above the average speed doubled the risk of being involved in a fatal crash and this risk increased to six times greater when the vehicle speed was 20 km/h higher than average speed. The results indicated that slower vehicles did not have significantly higher risks. The researchers suggested that reducing traffic speed was more effective in reducing crash frequency than reducing speed differences (Kloeden et al., 2001). A year later, a study conducted by the same researchers asserted similar findings that crash frequency was correlated with vehicle speed rather than speed variations and other factors. They indicated that a small reduction in absolute traveling speed could lead to decreased fatal crash frequency (Kloeden et al., 2002).

Overall, there remains some ambiguity as to the relationship between crashes, travel speed, and speed variance. Some studies have found that speed variance had greater impacts on crash risk than average speed while others report that crashes were affected more by mean speed than by speed variance. Ultimately, traffic crashes occur due to a complex combination of factors including traffic flow, roadway condition and geometry, human behavior, etc. This study aims to provide further research in support of continuing policy debates regarding maximum statutory speed limits.

CHAPTER 3. DATA COLLECTION

This study involves an investigation of the safety performance of Iowa interstates, with an emphasis on changes that have occurred since the most recent speed limit increase from 65 to 70 mph, which occurred in 2005. These analyses rely on information from several different datasets, outlined in the following sections.

3.1 Roadway Information

The interstate roadway network used in the Iowa-specific analysis was obtained from the Iowa DOT online Geographic Information Management System (GIMS) portal, which provides traffic control and geometric characteristics of state-maintained roadways. A unique identifier, known as "MSLINK", is assigned for each segment.

In order to evaluate the potential impacts of the speed limit policy on Iowa highways, various roadway geometric and traffic characteristics were extracted from the GIMS database. To obtain the Iowa interstate segments, the ROAD_INFO_2015 file, which had the most current data at the time of study, was imported into ArcMap. Several fields such as "INTERSTATE" and "FUNCTION" were utilized to identify the interstate segments. The "INTERSTATE" field indicates whether or not a road system is classified as an interstate; however, solely relying on this attribute would result in additional unwanted road segments such as ramps. Therefore, another attribute was introduced to filtering only mainline segments, which was the "FUNCTION" field. This field distinguishes mainline and non-mainline road sections, the following values were selected by applying filter under attribute "FUNCTION": mainline normal (00), mainline - 1st innerleg (09), mainline - 2nd innerleg (10), mainline - 3rd innerleg (11), mainline - 4th innerleg (12), mainline - 5th innerleg (13), mainline - 6th innerleg (14), mainline - 7th innerleg (22), mainline - 8th innerleg (23), mainline - 9th innerleg (24), mainline - 10th innerleg (25). After this process, there were still some redundant segments. They were then removed manually using ArcMap's Editing tool. Eventually a total of 4164 interstate segments were selected. Furthermore, because the GIMS database was updated annually, in order to include more years of data, the information collected was disaggregated by year. "MSLINK" was used as an identifier to link roadway and traffic characteristics. The information obtained from the GIMS database for this study includes the following:

- Location of the roadway segments
- Segment length
- Data year
- Indicator for urban/rural area
- Median type, presence of median barrier, and median width
- Number of lanes, lane type, and acceleration/deceleration lane
- Annual average daily traffic (AADT)
- Shoulder width
- Presence of rumble strip
- Speed limit

It should be noted that some variables of interest were not provided by GIMS directly, and some manipulations were made to obtain the information. For example, the indicator for the urban/rural area was derived from the "URBANAREA" attribute, which identifies whether the road segment is within a specific urban area assigned by the FHWA. Segments with predefined codes were treated as urban segments and were given "1" as an indicator for the urban area, while segments with code “9999” were given “0”, indicating its presence in a rural area. The presence of the median barrier was identified by median type where medians were categorized in different groups. Segments with acceleration/deceleration lanes were identified by lane type attribute where the type of each lane from the left side of the road segment to the right side is specified. Since the information was disaggregated by year, new construction or resurfacing of the roadway might have taken place throughout the years. A new “MSLINK” would have been assigned to the roadway segment where works had been done. Thus, 208 out of 4164 segments had missing values in 2008, which was the start of the study period and the year that had the largest number of missing values. To verify whether the road segments had previously existed or completely new constructed, QA/QC was conducted for those segments using Google street view. Eventually, it was found that there were no completely new interstate segments constructed. Therefore, in order to add those missing values, ArcMap was used to locate the nearest segment on either side of the null segments, and then the values were filled in by taking the average values of the data from the two adjacent segments. The same process was repeated for all nine years of data.

Additionally, there were a large number of short segments that had lengths of less than 0.1 miles. To eliminate potential bias that the short segments might create when developing crash prediction models, segments shorter than 0.095 miles (i.e., those that do not round up to 0.1 miles) were merged in with the nearest adjacent segments. Given that two segments that were being merged might have different characteristics, in order to better represent the characteristics of newly combined segments, a weighted average by length was taken for all corresponding variables. By merging the short segments (<0.095 miles), the number of interstate segments was reduced from 4164 to 2578.

Summary statistics for these interstate segments are given in Table 1. Note that all the low-speed interstate roadways with speed limits of 55 mph and 60 mph are in urban areas. It was found that only 22% of interstate miles are within urban areas while the average annual VMT on urban interstate accounts for 38% of the total VMT on all interstate.

Table 1. Summary Statistics for Average Interstate Bi-directional Mileage and Vehicle Miles Traveled, 2008 to 2016

Interstate Type	Mileage (bi-directional)	Vehicle Miles Traveled (100 M)
55mph	55	5.129
60 mph	32	4.083
65 mph (urban)	190	15.735
65 mph (rural)	34	1.365
70 mph (urban)	65	4.043
70 mph (rural)	1187	45.272

3.2 Crash Information

Another essential database used in this study was the Iowa statewide crash database maintained by the Iowa DOT, which includes information regarding crashes that occurred on the Iowa roadway network, such as vehicle characteristics, driver characteristics, crash environment, roadway characteristics, injury/protective devices, etc. For the purpose of this study, crash information was collected from 2008 to 2016. Aggregate data for years prior to 2008 were obtained from a prior short-term evaluation of the 2005 speed limit increases (Souleyrette et al., 2009; Souleyrette & Cook, 2010).

The variables of interest in the crash database included crash keys, crash location, type of roadway/ramp identifier, crash severity, weather/road surface condition, year of crash, manner of collision, and first harmful event. In order to obtain crashes that occurred on a mainline interstate, the interstate network layer derived previously and crash layer were both added into ArcMap. A 100-foot buffer on both sides was created along the interstate network to include only crashes that were within the buffer. However, this method could have possibly included some crashes that occurred on interstate ramp segments as well. To remove ramp crashes, the ramp identifier in the crash database was used. The crash severities for individual crashes were also collected to study the severity-specific crash rate.

3.3 Weather Data

Weather data was requested from the Iowa Environmental Mesonet (IEM). IEM provides access to the raw observations from the National Weather Service Cooperative Observer Program (NWS COOP) network, and daily reports could be downloaded. In this dataset, there are 115 stations spread across Iowa, from which data were obtained between January 2008 and December 2016. The variables requested include latitude and longitude coordinates, daily high temperature, daily low temperature, daily precipitation, and daily snowfall.

After downloading the weather data, a data cleaning process was performed by eliminating the stations that had zero or unusual low values for the yearly total. If a station had a value of zero or a value that was three standard deviations away from the average of all observed stations in any one of the variables of interest, that value was counted as an outlier and removed from the dataset. Yearly average values for temperature, precipitation, and snowfall for each station were then calculated, and the data was imported into ArcMap. Since the weather stations were point data and can only represent weather condition in its surrounding region, the stations that were within 20 miles from the interstate network were first selected to ensure better representation of the weather characteristics, then a 25-mile buffer was created around every weather station, which established total coverage of the interstate network. The weather stations with an interstate within the 25-mile buffer were joined to the nearest interstate segments. Because some weather stations were close to each other and the 25-mile buffer might have created some overlap, when integrating the data into the interstate segments, an average was taken for overlapping stations. Among nine years of data, different weather stations were eliminated for every year due to the missing records. Hence, the joining process was repeated for nine years of weather data. Figure 2 illustrates the selected weather stations and buffers for 2016.

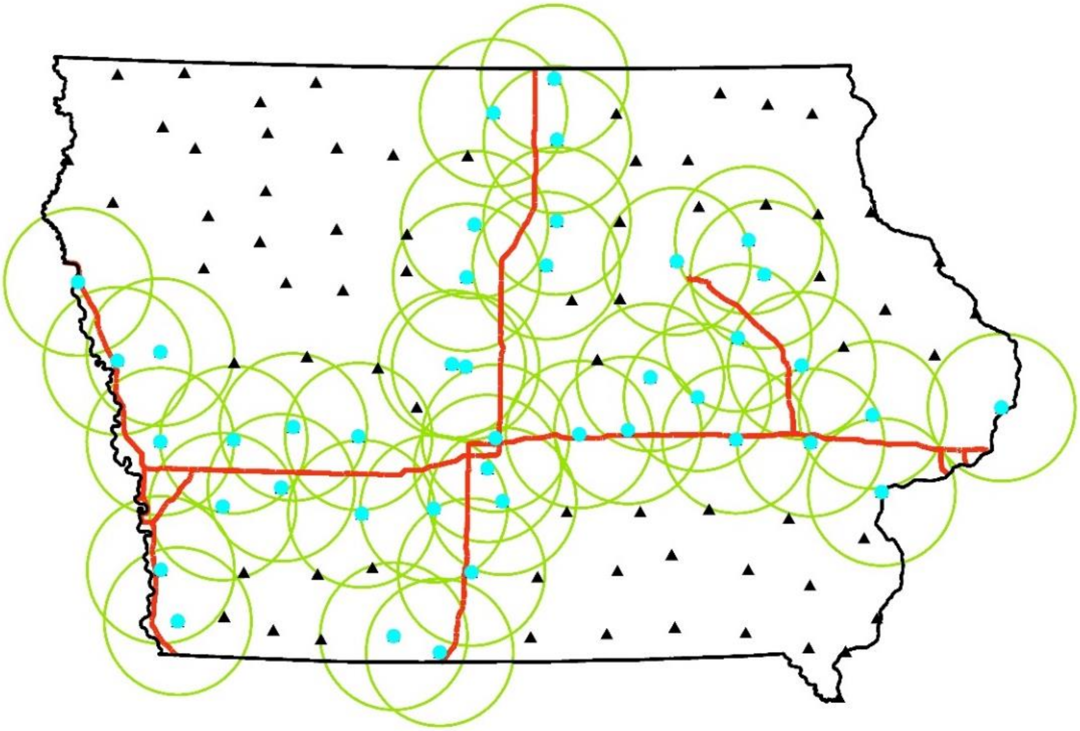

Figure 2. Selected Weather Stations and Buffers along Iowa Interstate, 2016

3.4 Automatic Traffic Recorder (ATR) Data

Iowa Department of Transportation collects vehicle speed data using automatic traffic recorder (ATR) equipment at permanent sites across Iowa's highway system. Speed reports for Iowa highways were generated on a quarterly basis. The quarterly speed reports for Iowa were requested from Iowa DOT from 2013 to 2016, however, three quarterly reports were missing during this four-year period, which were second quarter in 2014, second and third quarters in 2015. Forty ATR locations are listed on the reports where ten of them are on interstates, and seven of them are on rural interstates. The estimated locations of the interstate ATR stations were mapped out manually in ArcMap according to the location description provided along with the reports. Figure 3 shows the Iowa interstate network with the ATR stations.

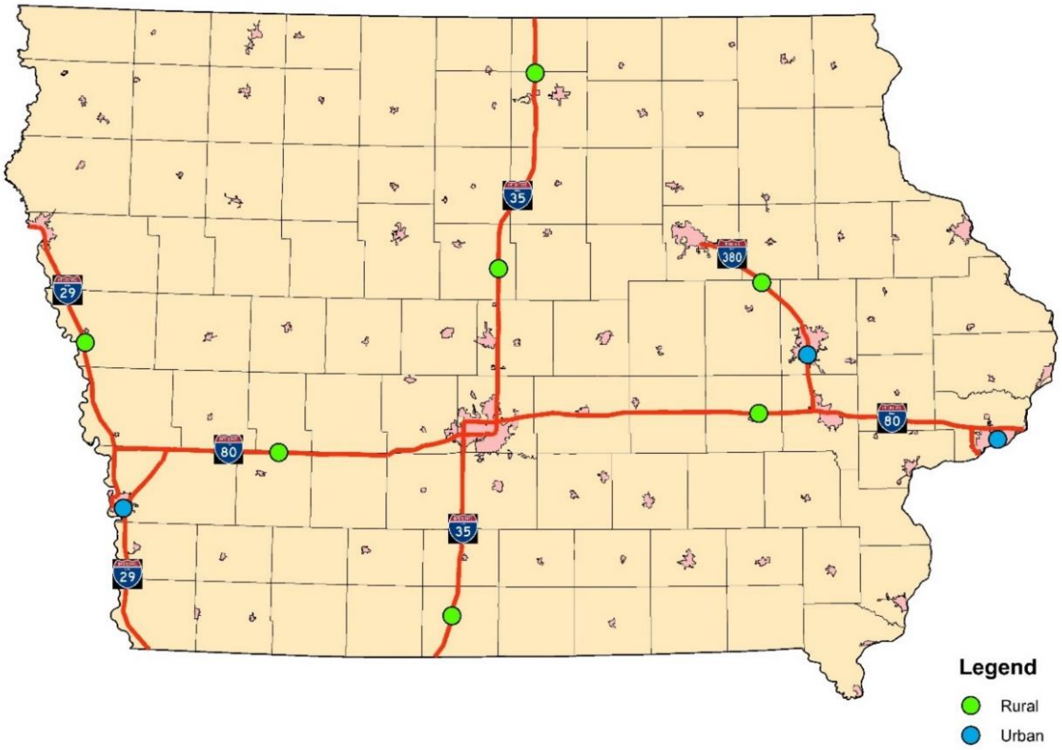

Figure 3. ATR Stations on Iowa Interstates.

Since the quarterly speed reports only recorded the count of vehicles that fell into each speed ranges, it was necessary to apply some techniques to estimate the average speeds as well as percentile speeds. To estimate average speed, a mid-point was applied to each speed ranges. It should be noted that for speed at 40 mph and below and at 86 mph and above, mid-points were not applicable. As each speed range increments by five, 2.5 was deducted from the higher speed boundary or added to the lower speed boundary thus 37.5 mph and 87.5 mph were used as the mid points of these speed ranges respectively. The number of vehicles operated under these two speed ranges were generally low; therefore it should not significantly alter the average speed estimation. The average speeds were then calculated by multiplying the count of vehicles in each speed ranges by the corresponding mid points, adding up all the products and divide the sum by the total number of vehicles. In terms of estimating 85th percentile speed, the percentage of exceeding the lower bound of all speed ranges were calculated and logical functions were applied to locate which speed range contained the 85th percentile speed. The proportion was then taken to estimate the 85th percentile speed.

3.5 INRIX Data

Conventionally, freeway traffic data are collected through fixed location detectors by state DOTs and transportation agencies. In recent years, though, several companies have started to collect traffic data by using probe vehicle technology. The data is obtained through the collection of vehicle position data from fleet navigation services, smartphone apps, and other sources. The raw vehicle position data is aggregated to average speeds on predefined segments; that data is sold to transportation agencies and others. INRIX is one of the leading providers of this type of data. Compared to traditional fixed-location sensors, INRIX probe data provide more comprehensive coverage of roadway systems and do not require costs for sensor deployment and maintenance.

INRIX provides speed data at a one-minute reporting interval. There are two segment formats, which are TMC and XD segments. Traffic Message Channel (TMC) segmentation is defined by an industry consortium. On controlled-access highways, TMC segments generally span distances between interchanges, which can be several miles long. There are often many shorter segments as well, particularly in sections with complex interchange geometry. INRIX develops the XD segmentation scheme. The segments are more consistent in length, with mostly 1- to 1.5-mile long segments. In this study, TMC data were used because of the availability of more years of data. INRIX provides both real-time data and historical data. Generally, INRIX has excellent coverage of interstate highways and was able to collect real-time data on the entire interstate system in Iowa. INRIX TMC real-time data were acquired for Iowa interstates from 2013 to 2016. The quality of the data was first evaluated by extracting and analyzing one month of raw data (July 2016) for one segment from each type of interstate segments, which were urban 55-mph (TMC: 118+04661), urban 60-mph (TMC: 118+04643), urban 65-mph (TMC: 118+04644), urban 70-mph (TMC: 118+04859), rural 65-mph (TMC: 118+05030), and rural 70-mph (TMC: 118+04815). Table 2 summarizes the one- month raw data on different types of sample interstate segments.

Table 2. Summary Statistics of Sample INRIX Operational Speed for One Month (July 2016)

	Min	**Max**	**Mean**	**Std. Dev.**	**Percentage Below Speed Limit (%)**
Urban 55 mph	10	75	58.65	3.79	6
Urban 60 mph	13	75	60.47	3.64	42
Urban 65 mph	7	75	61.26	3.99	82
Urban 70 mph	5	75	67.39	3.7	75
Rural 65 mph	43	75	66.72	2.55	16
Rural 70 mph	37	75	67.28	2.41	83

According to the data, the maximum speed was capped at 75 mph, and the standard deviation of the raw speed data was suspected of being higher in urban areas than rural areas. The percentages of one-minute raw speeds that were below the speed limit over the one month period were high, especially on urban 65-mph, urban 70-mph, and rural 70-mph segments, which were also reflected on the much lower mean speed than the actual speed limits. One reason might be that the vast majority of INRIX data are collected from the fleet and commercial vehicles which are more consistent and reliable in nature as these vehicles travel the same routes on a regular basis (Travers, 2010). Although only one sample segment was selected from each type of interstate, the large proportion of the operating speeds that were below the speed limit indicates that the overall speed data was potentially skewed by freight vehicles, which generally operate at or below the speed limit on high-speed rural interstates. This likely reflects the sourcing of the raw data from navigation services used by the trucking industry and other fleet operators.

Additional investigation was performed to assess the upper bound of speeds from INRIX data. Five segments were selected, all rural interstates with a speed limit of 70 mph: one from I-29 (TMC: 118-04967), two from I-80 (TMC: 118+04747 and 118+04815), one from I-35 (TMC: 118-04843), and one from I-380 (TMC: 118N04932). These specific segments were chosen because they are relatively straight and far away from an urban area. Figure 4 indicates the locations of the selected segments.

Figure 4. Selected 70 mph Rural Interstate Segments

To begin the investigation, five probability density functions were plotted for the selected 70 mph segments to determine whether the speed distribution stay relatively stable over the course of a month (July 2016).

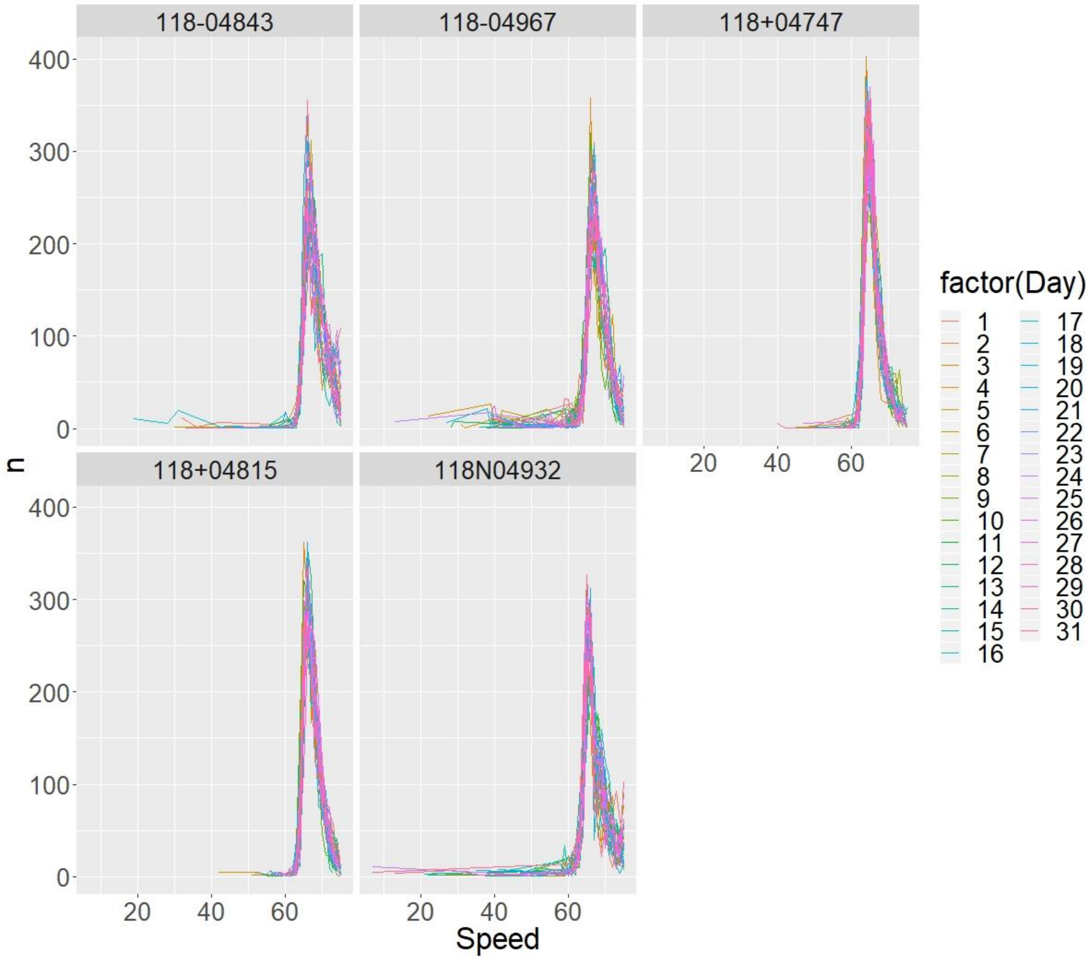

Figure 5. Probability Density Function Plots for One Month

The graphs shown in Figure 5 indicate that the speed with the highest frequency falls between 62 mph to 65 mph. The speed characteristics are generally consistent between days of the month. However, traffic patterns typically vary between weekdays and weekends because of the greater proportion of recreational traffic on weekends (Pigman, Rolands, & Donald, 1978). Thus, filters were applied to the raw data to exclude weekends and holidays. Speed profiles also vary by time of day. To study this, modified boxplots were created for the selected segments to visualize and understand the characteristics of the speed data using the filtered raw data. The boxplots, shown in Figure 14, were modified to show minimum, 15th percentile, 50th percentile, 85th percentile, and maximum speeds. The red horizontal line indicates the speed limit, which is 70 mph.

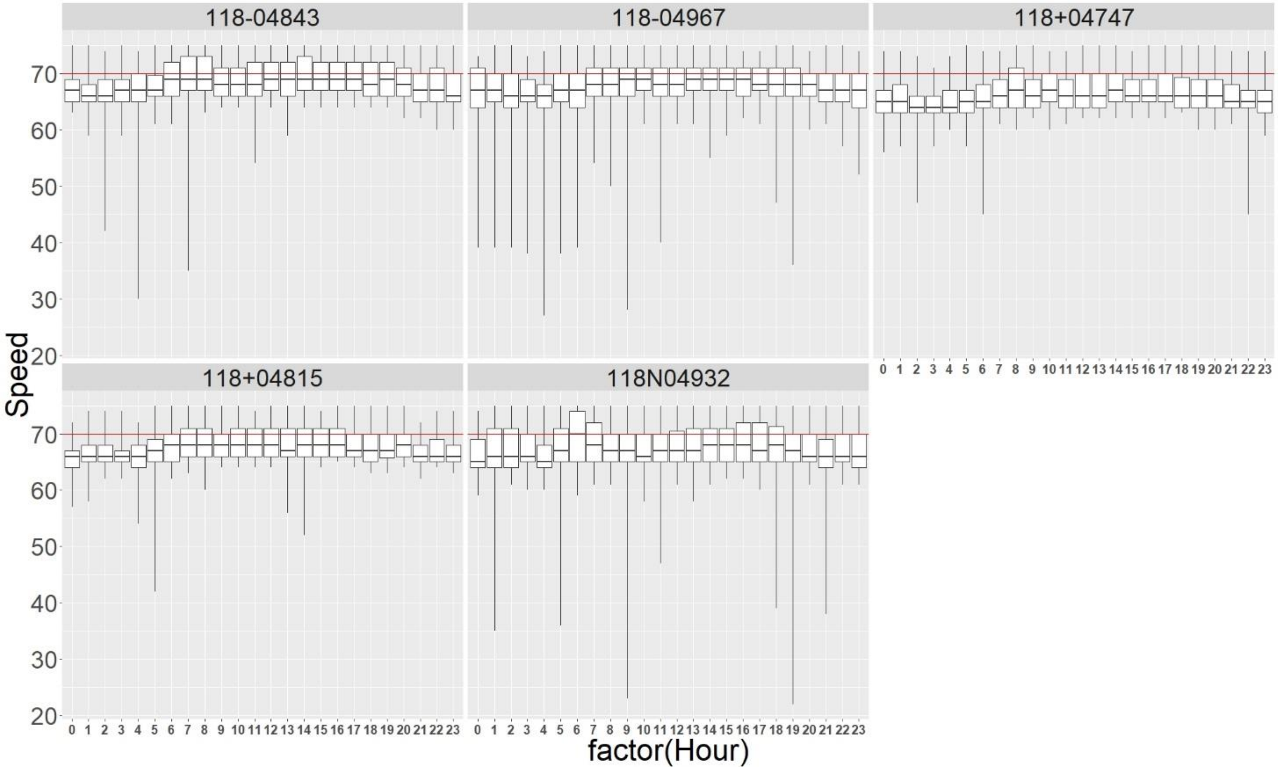

Figure 6. Modified Box Plots by Time of Day

As shown in Figure 6, the speeds during the overnight periods (9 p.m. to 5 a.m.) tended to be lower than other times of the day. Although the composition of the raw data is unknown, it seems likely that lower overnight speeds could be caused by a higher proportion of trucks during that time period. A previous study also claimed that the speed bias was higher during the overnight period compared to other times of a day (Sharma et al. 2017). To better represent typical speed characteristics of interstate segments, it was decided to select data only on weekdays from 6 a.m. to 8 p.m. Monthly average values of percentile speeds, average speed, standard deviation and variance of speed for all interstate TMC segments were obtained from 2013 to 2016. Mean speeds were calculated per month by segment, by simply averaging all available 1-minute speed records for that segment within each month. However, standard methods of calculating percentile speed and standard deviation of speed were not feasible due to the format of INRIX data (one-minute average speed on a segment). The one-minute interval average speed for the segment now replaces the individual vehicle speed. For each month, the 85th percentile speed was calculated for the sample of one-minute average speed measurements for each segment. The speeds were ordered from smallest to highest, and 85th percentile rank was calculated using Equation 1.

$$Rank_{85} = \frac{85}{100} * n + 0.5 \qquad (1)$$

The integer calculated in Equation 1 was used to locate the data. If the number was a whole number, the corresponding data point was the 85th percentile speed. If the number was a decimal, the data points below and above the number were selected, and Equation 2 was applied to calculate the 85th percentile speed.

$$Percentile_{85} = (1 - d) * X_{below} + d * X_{above} \qquad (2)$$

Where d is the decimal from the result of Equation 1, X_{below} and X_{above} are the data points corresponding to the integers below and above the rank calculated in Equation 1 respectively. Similarly, the standard deviation was calculated across these one-minute speed measurements over a monthly basis.

3.6 Comparison of ATR and INRIX Data

In order to understand how the recorded speed data collected by fixed location sensors (ATR) and vehicle probe (INRIX) vary, a speed comparison was conducted for Iowa rural interstates. Seven ATR stations are located at rural interstates: one on I-29, two on I-80, three on I-35, and one on I-380. The nearest corresponding INRIX TMC segments were identified for comparison purposes. Since ATR only reports quarterly data, to be consistent INRIX data were averaged by quarter. Figure 7 and Figure 8 show the differences between ATR and INRIX for the overall rural interstate in average speed and 85th percentile speed respectively.

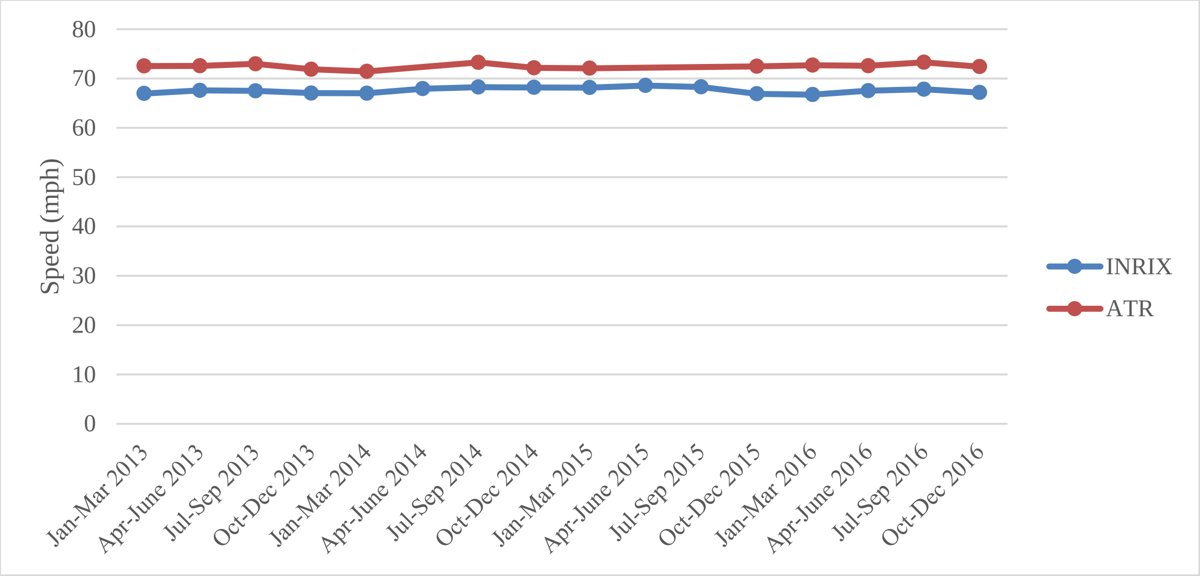

Figure 7. Average Speed Comparison between INRIX and ATR

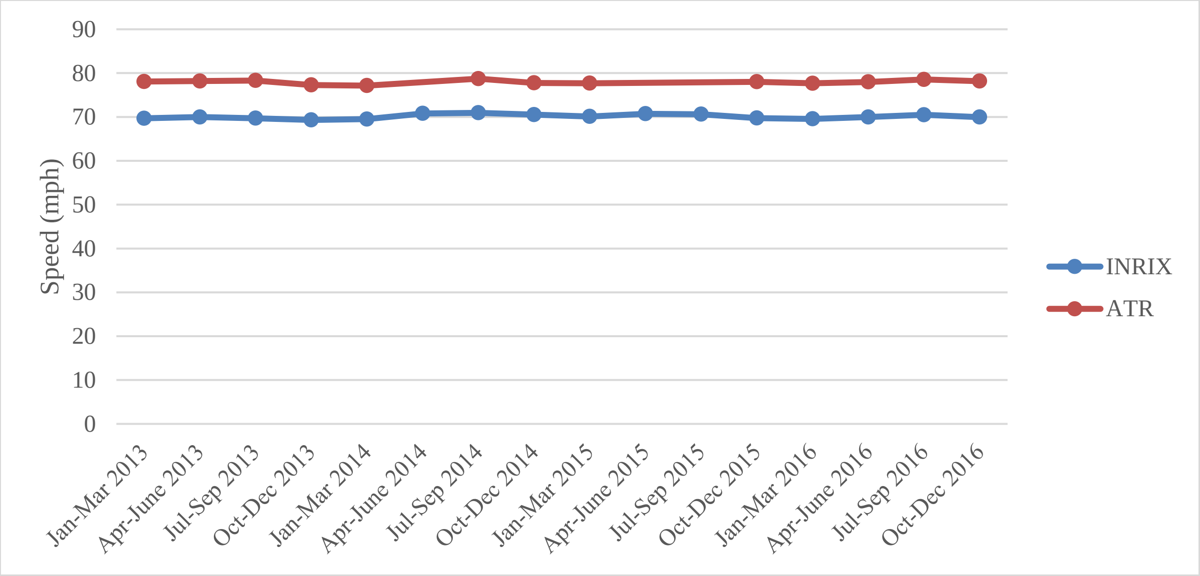

Figure 8. 85th Percentile Speed Comparison between INRIX and ATR

The comparison shows that the INRIX speeds are consistently lower than ATR reported speeds at these selected sites. The average speeds are about 5 mph lower while the 85th percentile speeds are about 8 mph lower. However, it should be noted these differences are relatively stable over the study period for both speed characteristics. Again, these differences might reflect the distinct mechanisms of how data were collected from these two sources. Probe data is provided as the average speed of vehicles over a one-minute interval across segments, whereas the fixed-location sensors calculate speeds by averaging spot speeds. In a previous study, researchers compared the speed data from probes and traditional sensors and noted a consistent difference between the two sources (Sharma et al., 2017). Other research has compared INRIX speeds against loop detector speeds as well, and also found around five mph consistent difference between two reported speeds (Kim & Coifman, 2014). Also, INRIX collects speed data through the probe, most of which were located on freight vehicles while ATR collects all the passing vehicle speeds. The lower speeds reported by INRIX was potentially affected by the lower freight vehicle speed. Another finding is that both datasets indicate that the speeds peaked at summer months and declined at winter months. This is typically true for Iowa.

Two disaggregated plots, Figure 9 and Figure 10, were produced by separating interstate numbers. Note that average was taken for an interstate that has more than one station on it.

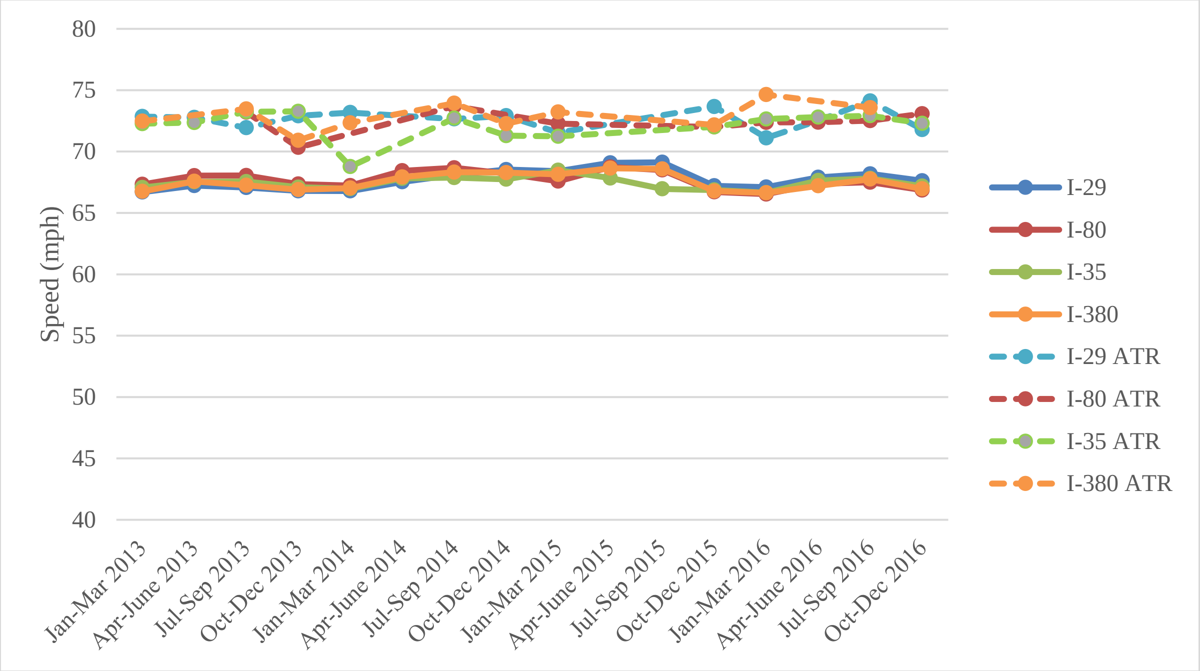

Figure 9. Average Speed Comparison by Interstates between INRIX and ATR

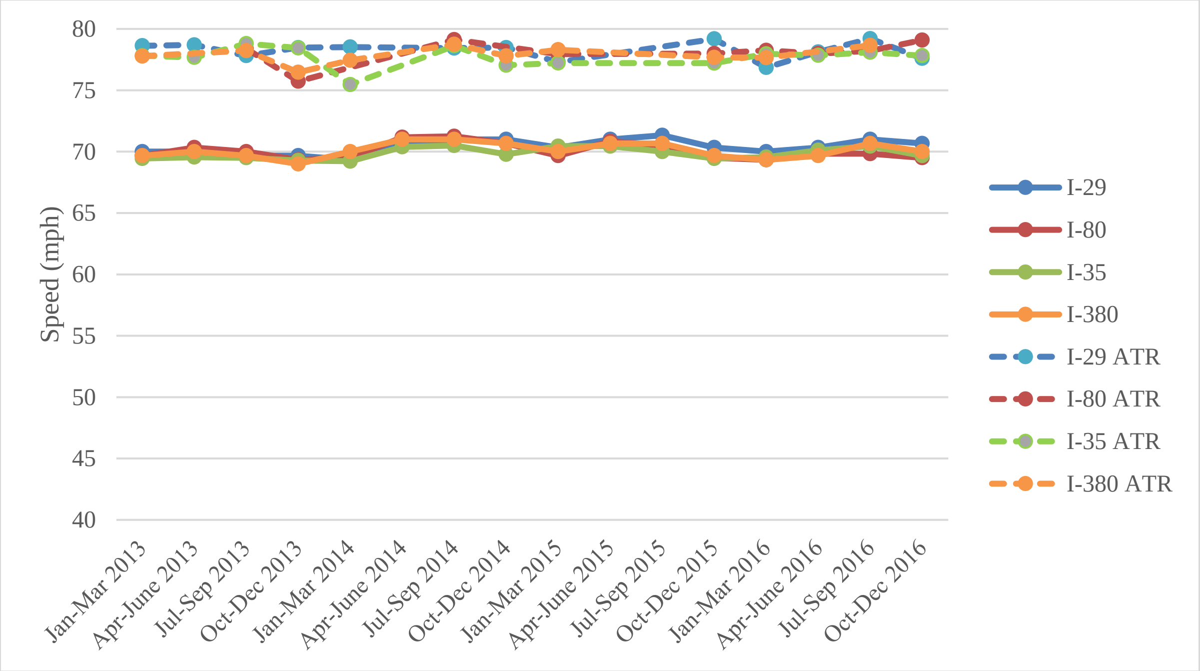

Figure 10. 85th Percentile Speed Comparison by Interstates between INRIX and ATR

As expected, the discrepancies persist comparably steady between ATR and INRIX. The abrupt jumps of speeds for ATR could be caused by the absence of data for several months, however, the INRIX reported speeds show more consistency among all rural interstates.

3.7 Data Integration

When analyzing crash data, The Highway Safety Improvement Program Manual provided by FHWA recommends using at least three years of historical/observed crash data (Herbel et al., 2010). For the purposes of this study, nine years of data (2008-2016) were obtained from the Iowa DOT's Geographic Information Management System (GIMS).

Two combined datasets were assembled for analysis and building statistical models, achieved with the aid of ArcMap. The first dataset was developed for assessing how the crash, injury, and fatality rates vary across the limited-access highway network and what roadway geometrics led to increased crash rate. The geospatial data for the Iowa interstate network, crash data, and weather station data between 2008 and 2016 were imported into ArcMap as layers. Crashes were spatially joined onto the nearest Iowa interstate segments, and the 25-mile buffers around the selected weather stations were joined into the roadway segments that they intersected. The final dataset has each row representing one segment in a particular year with all the geometric, traffic, and weather information. As previously mentioned, a total of 2578 interstate segments were examined over the nine-year period study period, resulting in 23,202 segment-years of data from Iowa interstates. Table 3 shows the summary statistics for these segments.

Table 3. Summary Statistics for Iowa Interstates (n=23202, segment-year)

Variable	Min	Max	Mean	Std. Dev
Presence of Median Barrier (1=yes, 0=no)	0	1	0.22	0.41
Median Width (ft)	1	100	52.77	15.52
Four Lanes (1=yes, 0=no)	0	1	0.64	0.48
Five Lanes (1=yes, 0=no)	0	1	0.15	0.35
Six Lanes (1=yes, 0=no)	0	1	0.14	0.35
Seven Lanes (1=yes, 0=no)	0	1	0.03	0.16
Eight Lanes (1=yes, 0=no)	0	1	0.03	0.16
Nine Lanes (1=yes, 0=no)	0	1	0.01	0.09
Acceleration/Deceleration Lane (1=yes, 0=no)	0	1	0.28	0.45
Presence of Rumble Strips (1=yes, 0=no)	0	1	0.35	0.48
Right Shoulder Width (ft)	0	40	9.85	1.28
Left Shoulder Width (ft)	0	16	6.27	1.75
Speed Limit 55 mph (1=yes, 0=no)	0	1	0.06	0.24
Speed Limit 60 mph (1=yes, 0=no)	0	1	0.04	0.19
Speed Limit 65 mph (1=yes, 0=no)	0	1	0.19	0.39
Speed Limit 70 mph (1=yes, 0=no)	0	1	0.71	0.45
Length (mile)	0.1	1.38	0.3	0.25
Annual Average Daily Traffic (AADT)	2258	135300	28655	20455
ln(AADT)	7.72	11.82	10.07	0.61
Urban Area (1=yes, 0=no)	0	1	0.31	0.46
Annual Average High Temperature (°F)	51.81	66.56	59.78	2.76
Annual Average Low Temperature (°F)	32.28	44.07	38.38	2.33
Annual Average Temperature (°F)	42.05	55.21	49.08	2.45
Annual Precipitation (in)	20.5	57.87	38.72	7.93
Annual Snowfall (in)	8.78	63.8	31.89	11.32
Total Crashes	0	29	1.57	2.29
K-injury Crashes	0	2	0.01	0.11
A-injury Crashes	0	3	0.03	0.19
B-injury Crashes	0	6	0.13	0.39
C-injury Crashes	0	9	0.2	0.55
O-injury Crashes	0	21	1.2	1.82

The shoulder width was averaged across the left (inside) and right (outside) shoulders. Median width was also determined, and 82 out of 2578 segments had extremely large median widths (over 100 feet). For analysis purposes, the median width was capped at 100 feet.

Other datasets were assembled that incorporated operational speed data from INRIX. Since INRIX data were only available after 2013, the new dataset was reduced to four years of data that was from 2013 to 2016. Additional operational speed data were added into the datasets to capture the speed characteristics of each interstate segment. The speed data from INRIX was aggregated by month; therefore the new datasets were created to include INRIX speed data as well as all traffic weather, and geometric characteristics variables. The final datasets have each row representing one segment in a specific month with all the geometric, traffic, weather information, and speed data. It should be noted that GIMS data does not allow for any directional analysis while INRIX provides speed data for each direction; therefore the speed data were averaged across opposing directions of travel. The INRIX TMC segments were separated into two layers based on the directions: one containing northbound or eastbound segments, and the other with southbound or westbound segments. In ArcMap, two line datasets cannot be spatially joined to one another, so additional work was required to integrate INRIX data with GIMS and crash data. It was found that in general, INRIX segments were longer than GIMS segments; thus the center point of each GIMS roadway segment was computed, and the two directional INRIX TMC segment layers were joined into the GIMS roadway centers separately. The average across the two directions of travel was then taken to calculate the speed characteristics of the GIMS segments. Ultimately, the dataset was prepared and analyzed for the entire Iowa interstate network. Table 4 indicates the descriptive statistics for the dataset.

Table 4. Summary Statistics for All Interstate Speed Model (n=123744, segment-month)

Variable	**Min**	**Max**	**Mean**	**Std. Dev**
Presence of Median Barrier	0	1	0.43	0.49
Median Width	1	100	44.27	24.86
Right Shoulder Width	0	13	9.17	2.8
Left Shoulder Width	0	12.5	6.24	2.8
AADT	6777	130500	52764.36	26700.46
ln(AADT)	8.82	11.78	10.72	0.58
Urban Area (1=yes, 0=no)	1	1	1	0
KA-injury Crashes	0	1	0.01	0.07
B-injury Crashes	0	2	0.02	0.15
C-injury Crashes	0	3	0.05	0.23
O-injury Crashes	0	6	0.17	0.45
85th Percentile Speed	51.5	71	61.22	2.52
Speed Standard Deviation	1.54	16.99	3.66	1.52
Average Speed	40.03	68.3	58.7	2.76
Speed Limit 55 mph (1=yes, 0=no)	0	1	0.060	0.240
Speed Limit 60 mph (1=yes, 0=no)	0	1	0.040	0.190
Speed Limit 65 mph (1=yes, 0=no)	0	1	0.190	0.390
Speed Limit 70 mph (1=yes, 0=no)	0	1	0.710	0.450

CHAPTER 4. STATISTICAL METHODOLOGY

4.1 Random Effects Negative Binomial Regression Model

To study how crash, injury, and fatality rates vary across the Iowa Interstate network and identify those characteristics associated with these crash rates, a series of regression models were estimated. Ultimately, crash data are comprised of non-negative integers. When dealing with such count data, Poisson and negative binomial are the two most commonly used models in the extant literature. The analyses conducted as a part of this study considered the number of crashes across different severity levels as the dependent variable, and a set of traffic, geometry characteristics, and other factors were introduced as independent variables. Starting with the Poisson model, the probability of the number of crashes equals y_i at specific segment during a one-year period is shown in Equation 3.

$$P(Y = y_i) = \frac{EXP(-\lambda_i)\lambda_i^{y_i}}{y_i!}, y_i = 0,1,2, \ldots \qquad (3)$$

Where λ_i is the mean or expected value of a Poisson distribution, which in this case stands for the expected number of crashes that could occur in a segment at a given year. The expected number of crashes is given by Equation 4 to introduce the set of explanatory variables:

$$\lambda_i = exp(\beta X_i) \text{ Or } Ln\lambda_i = \beta X_i \qquad (4)$$

Where X_i is the explanatory variable and β is the estimated parameter.

The limitation of the Poisson model is that it assumes that the variance is equal to mean, which is often not true in real data. The assumption of the Poisson model makes it unable to address overdispersion. As our analysis suggests that the crash data are overdispersed, a negative binomial model is preferred over the Poisson model. Negative binomial models handle overdispersion by adding an unobserved heterogeneity term u_i to the log linear as shown in Equation 5:

$$Lny_i = Ln\lambda_i + Ln\mathrm{u}_i = \beta X_i + \varepsilon_i \tag{5}$$

Thus, the probability of the number of crashes, y_i, which occurs at specific segment in a year can be rewritten as Equation 6:

$$P(Y = y_i) = \frac{EXP(-\lambda_i \mathrm{u}_i)(\lambda_i \mathrm{u}_i)^{y_i}}{y_i!}, y_i = 0,1,2, \ldots \tag{6}$$

Unlike the Poisson model, the negative binomial model adds parameter α in the formula that describes the relationship between variance and mean, which can be expressed as Equation 7:

$$VAR(y_i) = E[y_i]\{1 + \alpha E(Y_i)\} \tag{7}$$

From this equation, it is observed that when α is equal to zero, the negative binomial model is transformed to the Poisson model.

For achieving good results with the Poisson and the negative binomial models, the crash data should be uncorrelated in time. In this study, both models seem to be inappropriate as unobserved heterogeneity and serial correlation are present in the crash data. The random effects negative binomial (RENB) model is a more suitable alternative. It can deal with the spatial and temporal effects in the data set by treating the data in a time-series cross-section panel. The RENB model is expressed as follow:

$$E(\lambda_{it}) = exp(\beta X_{it} + \mu_i + \varepsilon_{it}) \tag{8}$$

Where $E(\lambda_{it})$ stands for the predicted number of crashes in segment i in year t, X_{it} is a vector of explanatory variables, β is a vector of estimable parameters, ε_{it} is the vector of residual errors, and μ_i is the random effects for the i^{th} segment.

As for the interpretation of coefficients, if X_i is continuous, the percent change in mean response when X_i is increased by one unit and the other X variables are held constant, is given as:

$$100 \times \left[exp(\hat{\beta}_1) - 1\right] \tag{9}$$

If X_i is binary, the percent change in mean response when X_i is equal to one, and other X variables are held fixed is also expressed as Equation 9.

4.2 Seemingly Unrelated Regression Equations Model

In addition to impacts on crash rates and severity, it is also important to consider the impact of speed limit policy on driver speed selection and how this correlates to crashes. Three common speed measures, the mean speed, 85th percentile speed, and speed variance, were compared with crash frequencies while controlling for the effects of roadway geometry and traffic volumes. Typically, separate models are developed for various speed measures such as average speed and percentile speed. However, the model results might be biased due to the recursive or endogenous relationship between speed measures. To account for this issues, a seemingly unrelated regression equations (SURE) model was introduced.

In this study, the SURE model consists of three single equations that simultaneously predict the mean speed, 85th percentile speed, and speed variance.

$$MS_i = \beta_{1i}X + \varepsilon_{1i} \tag{10}$$

$$SP85_i = \beta_{2i}X + \varepsilon_{2i} \tag{11}$$

$$SDS_i = \beta_{3i}X + \varepsilon_{3i} \tag{12}$$

Where: MS_i is the mean speed at segment I; $SP85_i$ represents the 85th percentile speed at segment I; SDS_i is calculated standard deviation of speeds at segments I; The β terms are the estimated regression coefficients; X is a vector of crash, traffic, roadway geometry, weather characteristics; and the ε terms represent unobserved characteristics.

Although Equation 10, 11, and 12 are seemingly unrelated and do not directly interact with each other (e.g., the mean speed does not directly affect the 85th percentile speed or speed variance), there are some unobserved shared characteristics since all three values are calculated for the same segment. This cross-equation correlation is captured in the error term. SURE provides efficient parameter estimates by considering the contemporaneous correlation of disturbances, ε_1, ε_2, and ε_2. A detailed discussion on SURE can be found in *Statistical and Econometric Methods for Transportation Data Analysis* (Washington et al., 2010). Separate models were created for mean speeds, 85th percentile speeds, and speed standard deviations for all interstate segments.

CHAPTER 5. RESULTS AND DISCUSSION

5.1 Historical Crash Trend on Iowa Interstates

Iowa most recently raised its maximum speed limit from 65 mph to 70 mph in 2005. A previous study conducted evaluated the short-term impacts of this speed limit increase on traffic safety (Souleyrette & Cook, 2010). In this report, annual fatal and serious injury crashes were examined from 1991 to 2009 across those interstate sections where speed limits were increased to 70 mph. As a continuation of that study, these same plots were extended to 2017, the most current year for which data were available. There were two years of overlap between the previous study period and the current study period, 2008 and 2009. These were used to verify that the number of crashes was consistent across the two datasets.

Instead of merely plotting the number of fatal and serious crashes over the years, changes in vehicle-miles traveled (VMT) were also taken into consideration. The VMT information was collected from 30-year historical VMT by system table provided on the Iowa DOT website (Iowa DOT, 2018). As a result, plots for the crash rate over the years were produced, shown in Figure 11 and Figure 12.

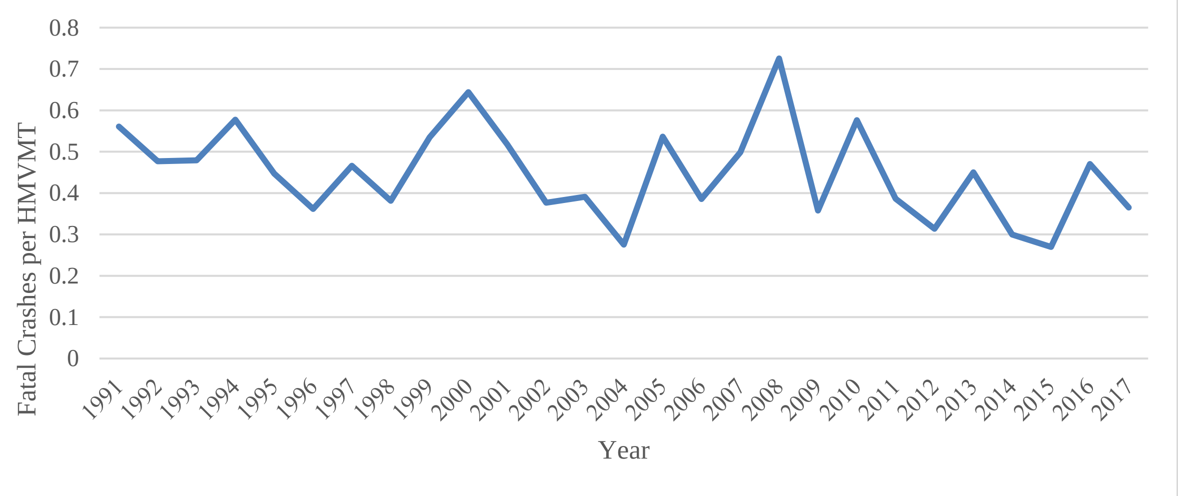

Figure 11. Fatal Crash Rate from 1991 to 2017 on Sections Increased to 70 mph

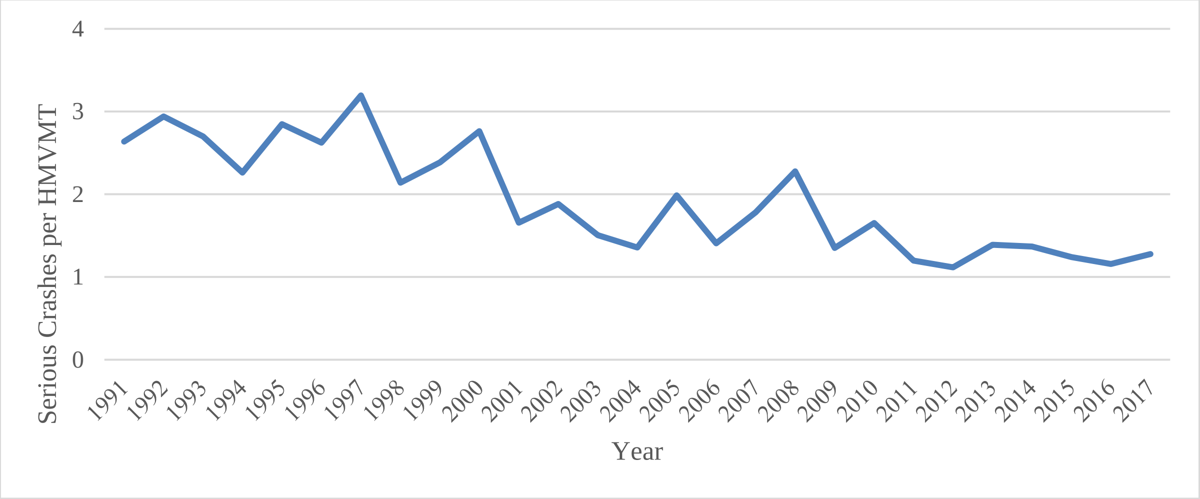

Figure 12. Serious Crash Rate from 1991 to 2017 on Sections Increased to 70 mph

These plots show that the fatal crash rate fluctuated significantly over the study period, ranging from between 0.2 and 0.8 crashes per hundred million vehicle-miles traveled (HMVMT). Between the periods before and after the speed limit change (excluding data from the calendar year 2005), it was found that the average number of fatal crashes per year increased from 20.8 to 22.2, resulting in a 6.7 percent increase. However, when normalizing the data by VMT, the average crash rate declined by 8.3 percent, or from 0.46 to 0.42 fatal crashes per HMVMT. In terms of serious crash rate (i.e., fatal (K) or serious injury (A) crashes), as Figure 20 shows, there was a general declining trend. Upon examining the raw data, the average number of serious crashes per year decreased from 104.1 to 74.9 (a decrease of 28 percent), while serious crashes per HMVMT dropped by 39 percent from 2.35 to 1.44.

In both fatal and serious injury rates, a short-term increase occurred in the years immediately following the speed limit increases. Subsequently, crashes tended to trend downward over time, which is broadly reflective of national trends over this same time period. This declining trend in both fatal and serious crash rates might be a result of the traffic safety countermeasures implemented and more advanced motor vehicle technologies over the years.

Table 5 presents the average number of total, fatal, and serious (fatal and severe) interstate crashes over the nine-year period (2008 to 2016). Despite that much larger portion (78%) of the interstate network locates on rural areas, the yearly average number of total crashes are nearly the same for both rural interstate (2098) and urban interstate (1985) and 43% of serious interstate crashes occurred on the urban interstate.

Table 5. Summary Statistics for Annual Average Number of Total, Fatal, and Serious Crashes by Interstate Type, 2008 to 2016

Interstate Type	**Total Crashes**	**Fatal Crashes**	**Serious Crashes (fatal + severe)**
55mph	446	2	11
60 mph	277	1	7
65 mph (urban)	1,033	7	26
65 mph (rural)	63	1	2
70 mph (urban)	198	1	6
70 mph (rural)	2,034	21	67

Table 6 shows the serious crash percentage by collision types on the different types of interstates in Iowa. The percentage was calculated using data from 2008 to 2016, and the collision types were classified into four groups, which were single-vehicle, rear-end, head-on or opposite direction sideswipe, same direction sideswipe, and other.

Table 6. Crash Type Distribution for Various Interstate Types, 2008 to 2016

Interstate Type	**Single Vehicle**	**Rear End**	**Head-On/Opposite Direction Sideswipe**	**Same Direction Sideswipe**	**Other**
55mph	52.0	25.5	5.9	10.8	5.9
60 mph	46.2	29.2	6.2	16.9	1.5
65 mph (urban)	53.8	22.0	9.7	11.8	2.7
65 mph (rural)	56.5	18.8	7.2	15.9	1.4
70 mph (urban)	69.4	16.3	4.1	6.1	4.1
70 mph (rural)	56.8	20.1	12.6	7.6	2.8

The results suggest that the interstate segments with lower speed limits (55 mph and 60 mph) had a higher percentage of serious rear-end collisions. These lower-speed segments are located within urban areas. Higher traffic volumes and greater density of interchanges may lead to a higher risk of rear-end collisions. Meanwhile, the head-on or opposite direction sideswipe serious crashes were found to be most prevalent on rural interstates with 70 mph speed limit. Head-on collisions are more likely to include fatalities and serious injuries because of the destructive nature of such crashes. Compared to other types of interstates, 70 mph rural interstate has more roadway miles lacking median barriers, making it easier for vehicles to cross the median and collide with vehicles in the opposite direction.

Three plots detailing crash rates over time were constructed distinguishing the speed limits where crashes happened. Since these plots required more disaggregated information such as VMT on the roadway with different speed limits, it was only possible to form the graphs for the nine-year period with the assembled dataset. Crashes that occurred on roadways with different speed limits were counted separately, and the VMT on roads with different speed limits was calculated by multiplying the annual average daily traffic (AADT) by the length of the segment, then adding all the segments’ VMT on each speed limit.

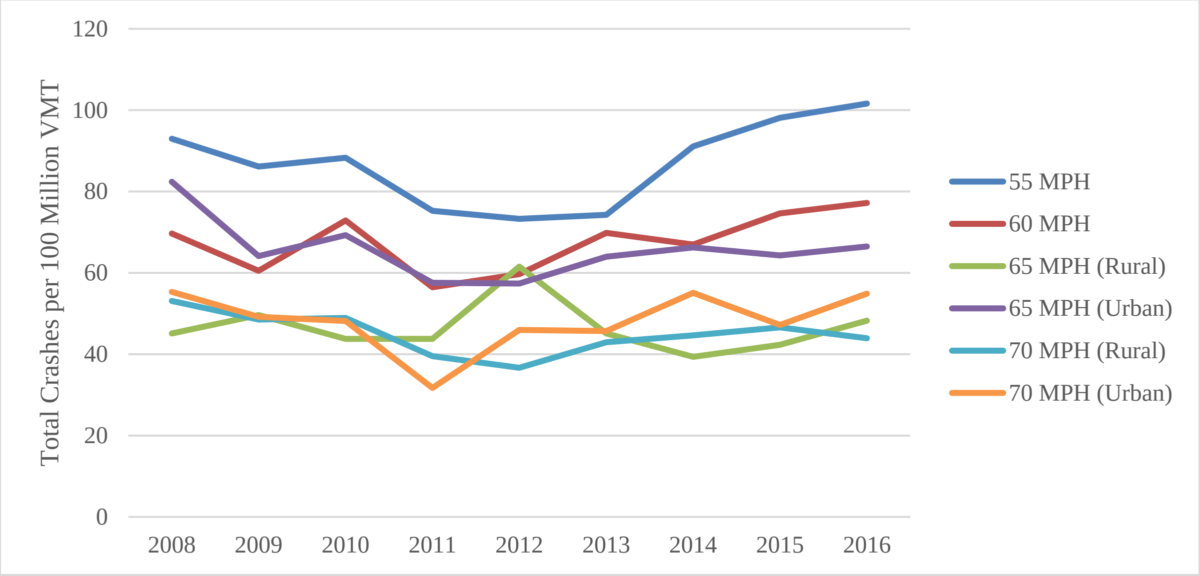

Figure 13. Total Crash Rate by Interstate Types from 2008 to 2016

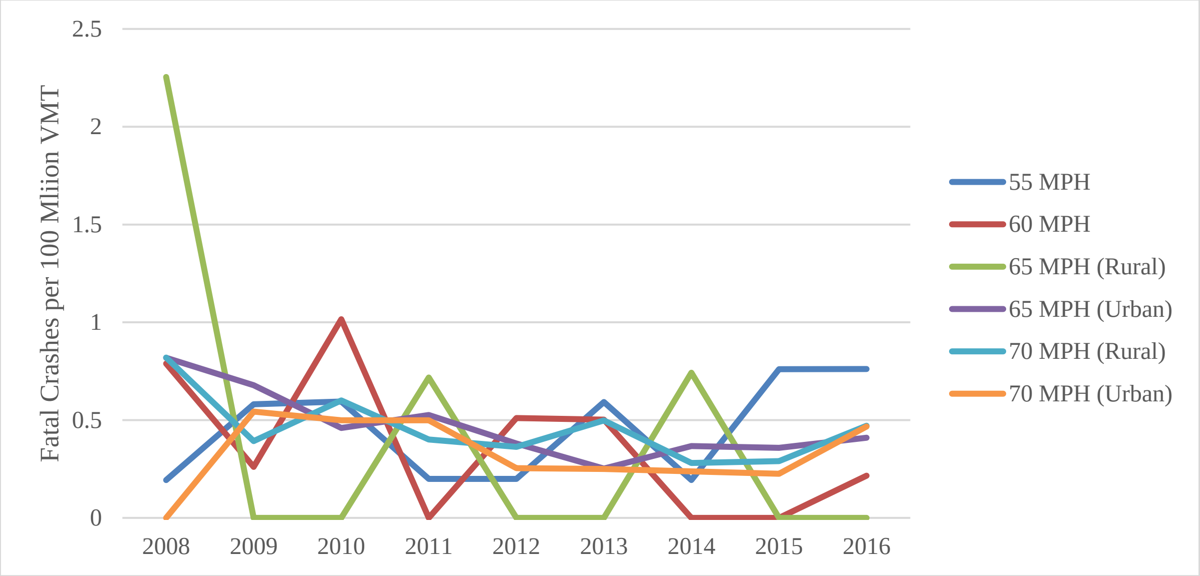

Figure 14. Fatal Crash Rate by Interstate Types from 2008 to 2016

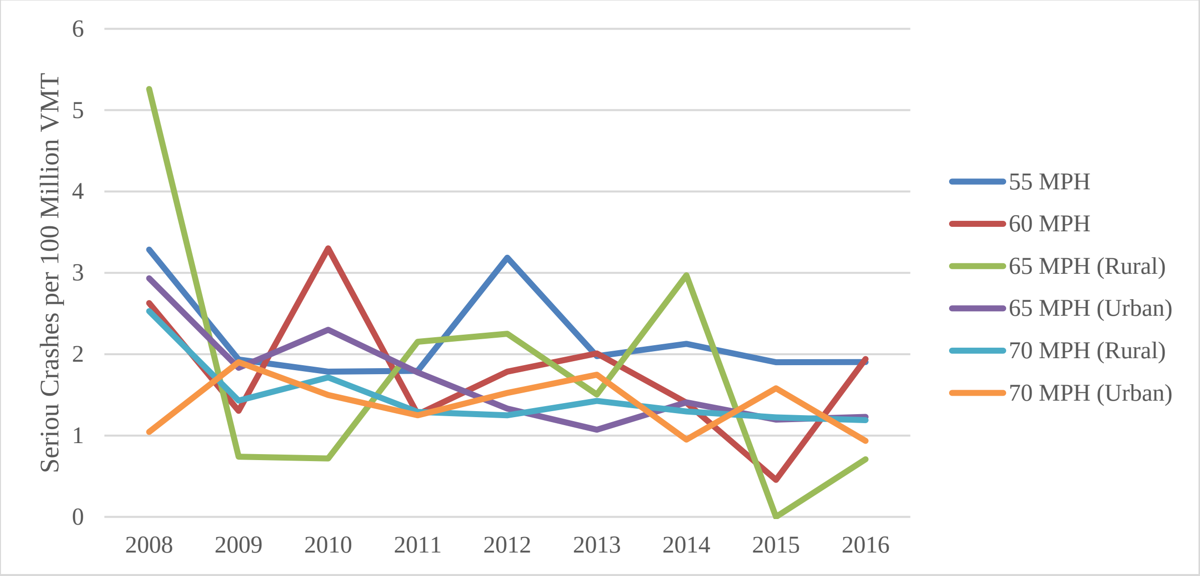

Figure 15. Serious Crash Rate by Interstate Types from 2008 to 2016

Figure 13 shows that total crash rates were consistently higher on 55 mph segments than other segments. These segments are typically located in urban areas with higher amounts of traffic, lower design speeds, and a higher density of entry and exit ramps, which would both tend to increase the risk of crashes. Although 70 mph segments tend to have lower total crash rates than segments with lower speed limits, this does not necessarily mean the overall interstate crash rate would be reduced by simply increasing the speed limits of all segments to 70 mph. Here again, the selection of the speed limit relates to the segment characteristics—such roadways would likely have less traffic, higher design speeds, and lower densities of entry and exit ramps. Other segment-specific control variables, such as safety countermeasures (median barriers, rumble strips, etc.), roadway geometry, weather information, and operating speeds, should be taken into consideration to reveal the factors contributing to the change of the number of crashes and crash rates.

No apparent trends were found by examining the number of fatal (Figure 14) and serious crashes (Figure 15) for segments of different speed limits over the study period.

5.2 Iowa Interstates Safety Assessment

Upon examining the historical crash trends on Iowa interstates, the datasets that contained nine years of crash data (2008-2016) were leveraged to study the relationship between safety and various factors. The Iowa-specific analysis features a series of RENB models that were developed to study how crash, injury, and fatality rates vary across the Iowa interstate network and the characteristics that lead to increased crash rate. Segment-level ID and year were used as the random effects in the models and segment length was treated as an offset term. Five different crash frequency prediction models were estimated: the first was a total crash frequency prediction model, followed by four severity-specific crash frequency prediction models that were constructed separately. The four different severity models predicted the number of combined fatal or major injury crashes (KA), minor injury crashes (B), possible injury crashes (C), and property-damage-only (PDO) crashes (O). The results of these five models are found in Table 7.

Table 7. Regression Model Results for Annual Segment Crashes by Severity Level (2008-2016)

Severity	Parameter	Estimate	Std. Error	Pr(>|z|)
Total	Intercept	-8.300	0.330	<0.001
	Ln AADT	1.034	0.029	<0.001
	Presence of Median Barrier (1=yes, 0=no)	0.132	0.022	<0.001
	Median Width (ft)	-0.002	0.001	0.003
	Right Shoulder Width (ft)	-0.046	0.008	<0.001
	Speed Limit 60 mph (1=yes, 0=no)	-0.436	0.073	<0.001
	Speed Limit 65 mph (1=yes, 0=no)	-0.225	0.052	<0.001
	Speed Limit 70 mph (1=yes, 0=no)	-0.468	0.052	<0.001
	Annual Snowfall (in)	0.005	0.001	<0.001
	Acceleration/Deceleration Lane (1=yes, 0=no)	0.068	0.028	0.016
KA	Intercept	-8.514	0.963	<0.001
	Ln AADT	0.744	0.087	<0.001
	Presence of Median Barrier (1=yes, 0=no)	-0.167	0.095	0.078

Table 7. (continued)

	Median Width (ft)	-0.002	0.002	0.422
	Right Shoulder Width (ft)	-0.042	0.020	0.036
	Speed Limit 60 mph (1=yes, 0=no)	-0.139	0.175	0.427
	Speed Limit 65 mph (1=yes, 0=no)	-0.232	0.133	0.080
	Speed Limit 70 mph (1=yes, 0=no)	-0.604	0.135	<0.001
	Annual Snowfall (in)	0.000	0.004	0.977
B	Intercept	-9.114	0.652	<0.001
	Ln AADT	0.896	0.059	<0.001
	Presence of Median Barrier (1=yes, 0=no)	-0.094	0.058	0.105
	Median Width (ft)	-0.003	0.002	0.084
	Right Shoulder Width (ft)	-0.037	0.014	0.006
	Speed Limit 60 mph (1=yes, 0=no)	-0.430	0.116	<0.001
	Speed Limit 65 mph (1=yes, 0=no)	-0.482	0.085	<0.001
	Speed Limit 70 mph (1=yes, 0=no)	-0.860	0.088	<0.001
	Annual Snowfall (in)	0.007	0.002	0.001
C	Intercept	-10.946	0.585	<0.001
	Ln AADT	1.144	0.053	<0.001
	Presence of Median Barrier (1=yes, 0=no)	-0.002	0.050	0.975
	Median Width (ft)	-0.007	0.001	<0.001
	Right Shoulder Width (ft)	-0.040	0.012	<0.001
	Speed Limit 60 mph (1=yes, 0=no)	-0.537	0.098	<0.001
	Speed Limit 65 mph (1=yes, 0=no)	-0.628	0.073	<0.001
	Speed Limit 70 mph (1=yes, 0=no)	-1.116	0.076	<0.001
	Annual Snowfall (in)	0.008	0.002	<0.001
O	Intercept	-9.014	0.354	<0.001
	Ln AADT	1.065	0.031	<0.001
	Presence of Median Barrier (1=yes, 0=no)	0.176	0.024	<0.001
	Median Width (ft)	-0.001	0.001	0.093
	Right Shoulder Width (ft)	-0.050	0.008	<0.001
	Speed Limit 60 mph (1=yes, 0=no)	-0.420	0.077	<0.001
	Speed Limit 65 mph (1=yes, 0=no)	-0.104	0.055	0.058
	Speed Limit 70 mph (1=yes, 0=no)	-0.310	0.055	<0.001
	Annual Snowfall (in)	0.005	0.001	<0.001

In interpreting the model results, a positive estimate indicates a positive correlation with crash frequencies while a negative estimate is associated with an inverse relationship with crash frequencies. It was evident that higher AADT is associated with higher crash frequencies for all types of severities. Higher traffic volume would likely increase the risk of being involved in a collision. Also, a study has shown that conflict risk would potentially increase with higher traffic density (Kuang et al., 2017).

The segments with median barrier installed were found to experience 14 percent more total crashes, which might result from the fact that median barriers are designed to convert some potential fatal or severe crashes to less severe crashes or PDO crashes. As the KA and O model results show, the segments with median barriers were subject to statistically significantly fewer fatal or severe crashes (15 percent decrease) and more PDO crashes (19 percent increase).

Other roadway geometric configurations, such as median width and right shoulder width, also had impacts on the crash frequencies. In general, the wider the median width and shoulder width, the lower the crash frequencies per mile. Compared to the segments with narrow shoulders and medians, segments with wider shoulders and medians would have adequate space for the drivers to adjust vehicles or sometimes get back to the traffic lane when the cars depart the roadway. In addition, the model results illustrate that interstate segments near interchanges that have acceleration or deceleration lanes were associated with a 7 percent higher crash frequency per mile.

The impacts of weather conditions on crash frequencies were also captured in these models by including an annual snowfall term. A previous study conducted by Eisenberg and Warner (2005) argued that compared to dry days, snow days had fewer fatal crashes and more non-fatal injury and PDO crashes. The results from the present study agree with these claims, as it was found that higher annual cumulative snowfall was correlated with higher crash frequencies for all severity types except fatal crashes. A reason for this is that although one might think that driving in snow increases the risk of having a severe traffic crash due to less friction and visibility issues, it might also encourage drivers to drive slower and more cautiously in snowy days, and the traffic volume might also be lower in those days.

The model results were also graphically displayed to visualize how crash frequency varies across roadways with different speed limits. Each line was plotted by inputting the average characteristics of each specific speed limit group into the estimated crash prediction function.

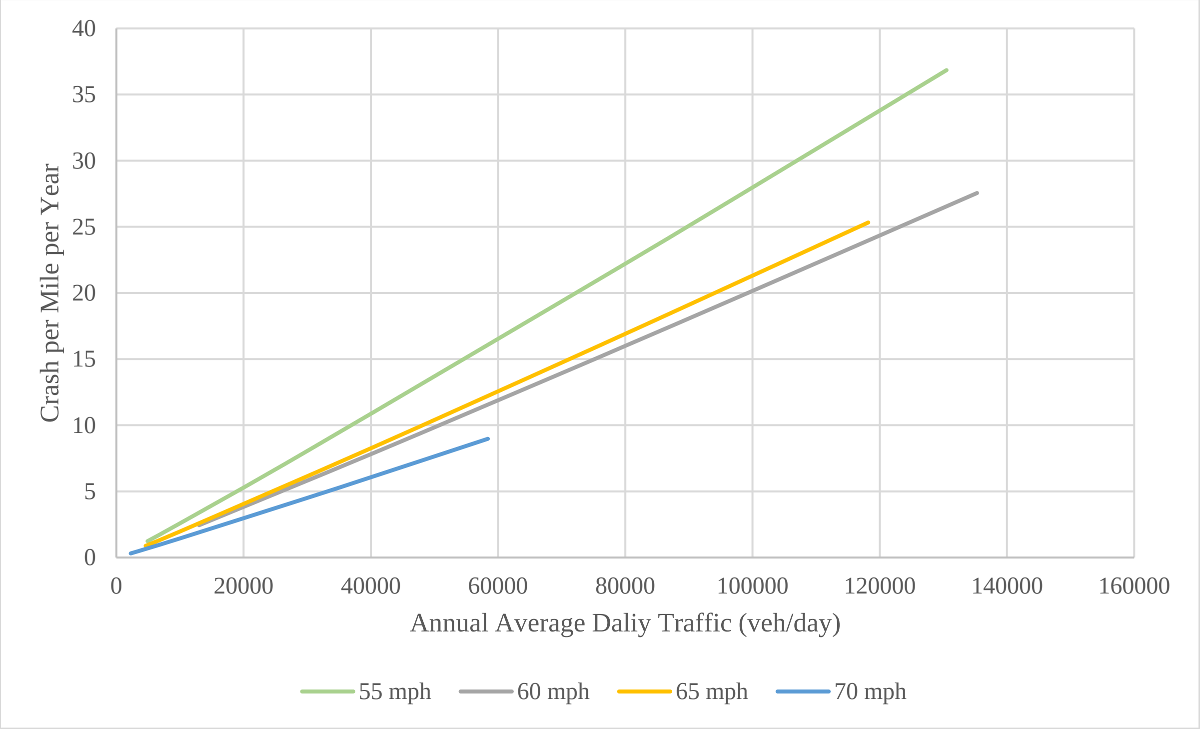

Figure 16. Expected Number of Total Crash with Different AADT

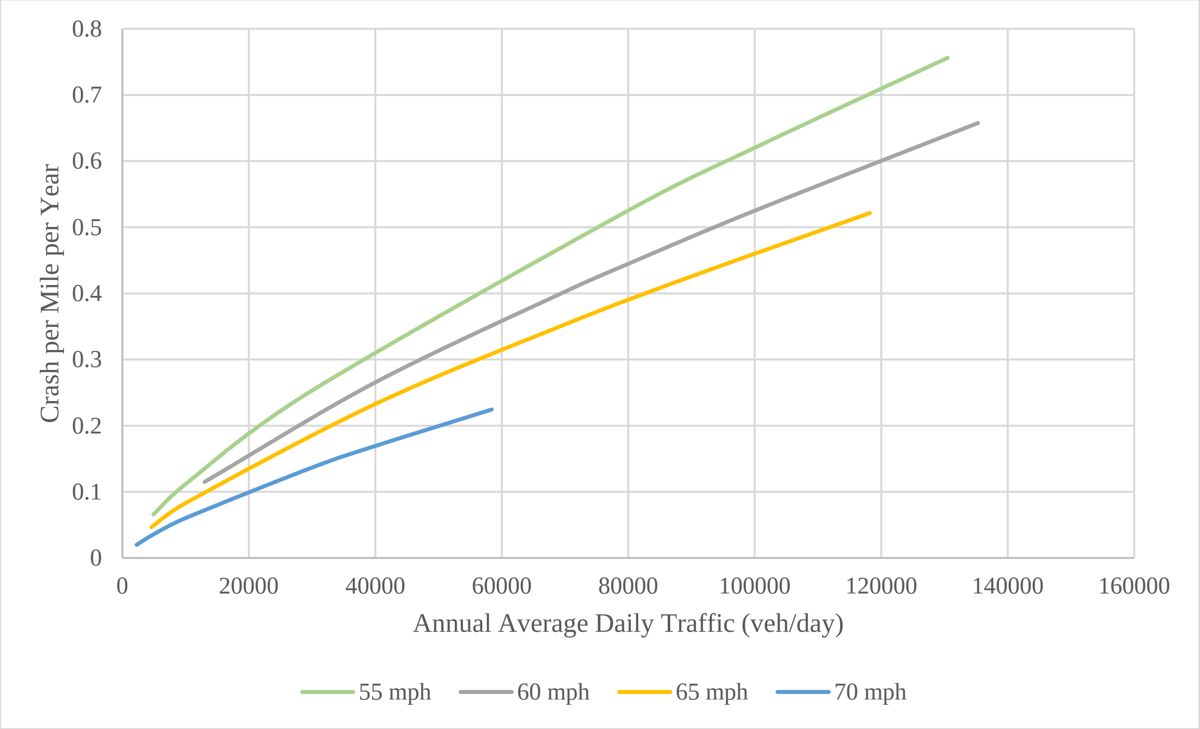

Figure 17. Expected Number of KA-Injury Crash with Different AADT

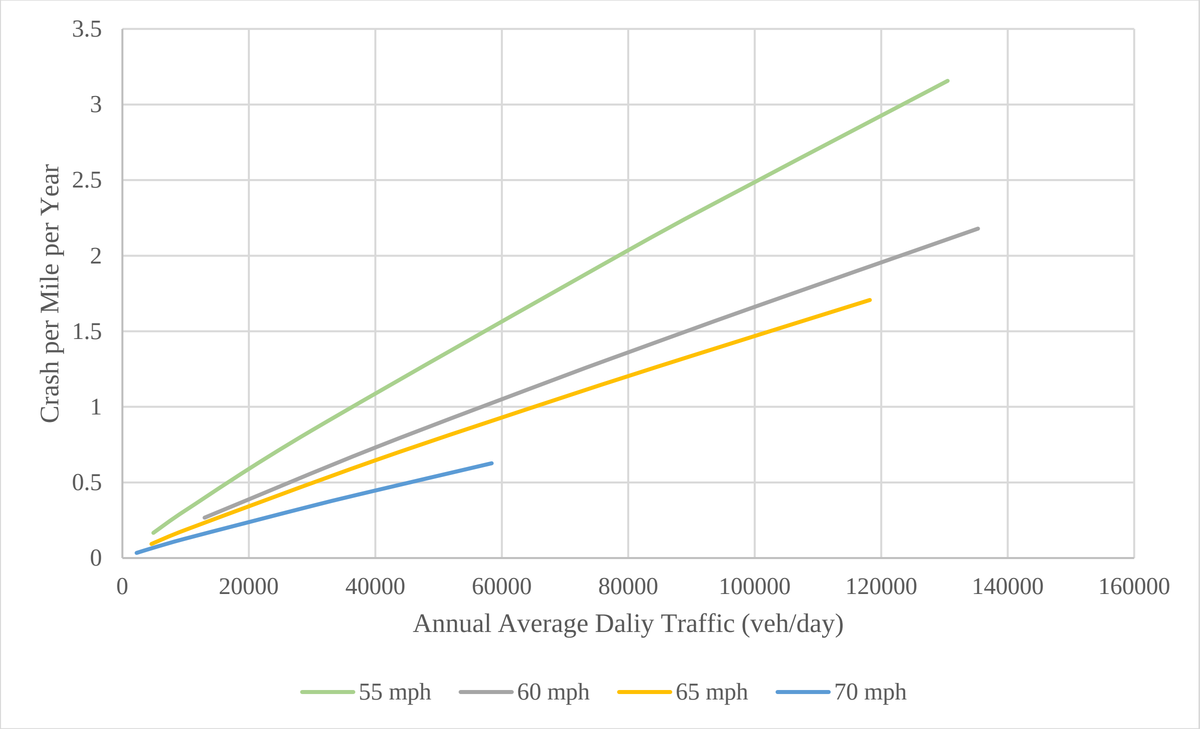

Figure 18. Expected Number of B-Injury Crash with Different AADT

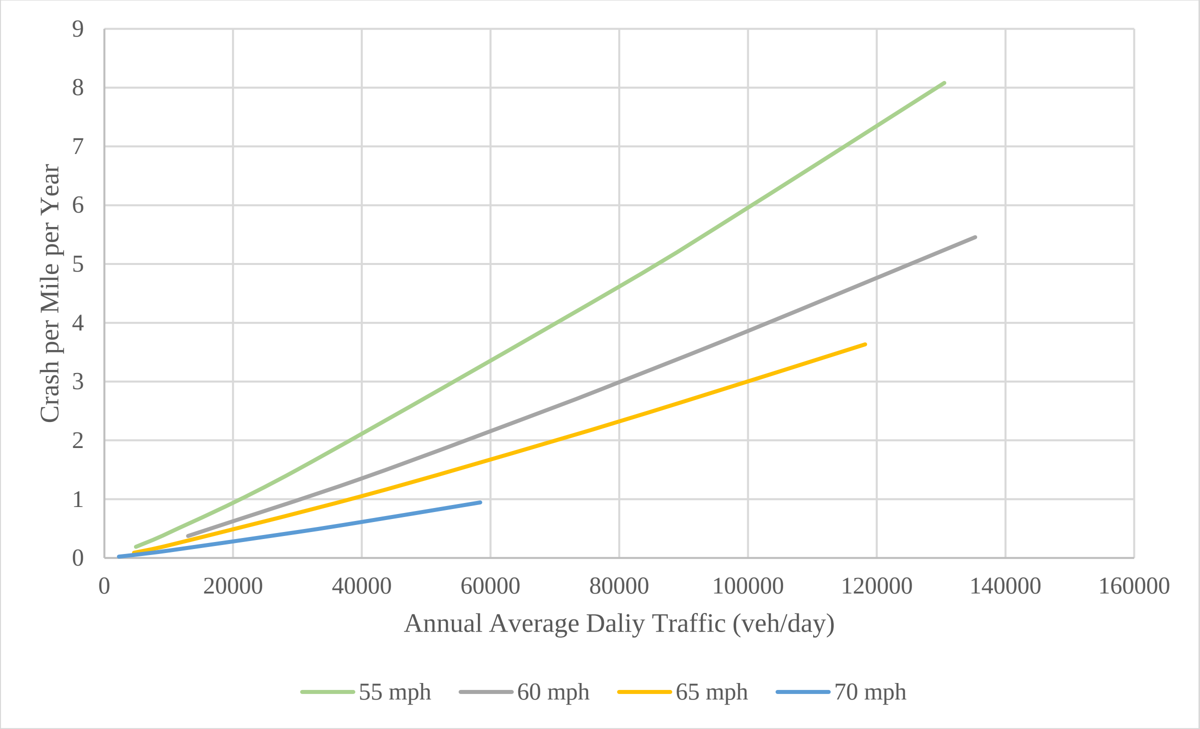

Figure 19. Expected Number of C-Injury Crash with Different AADT

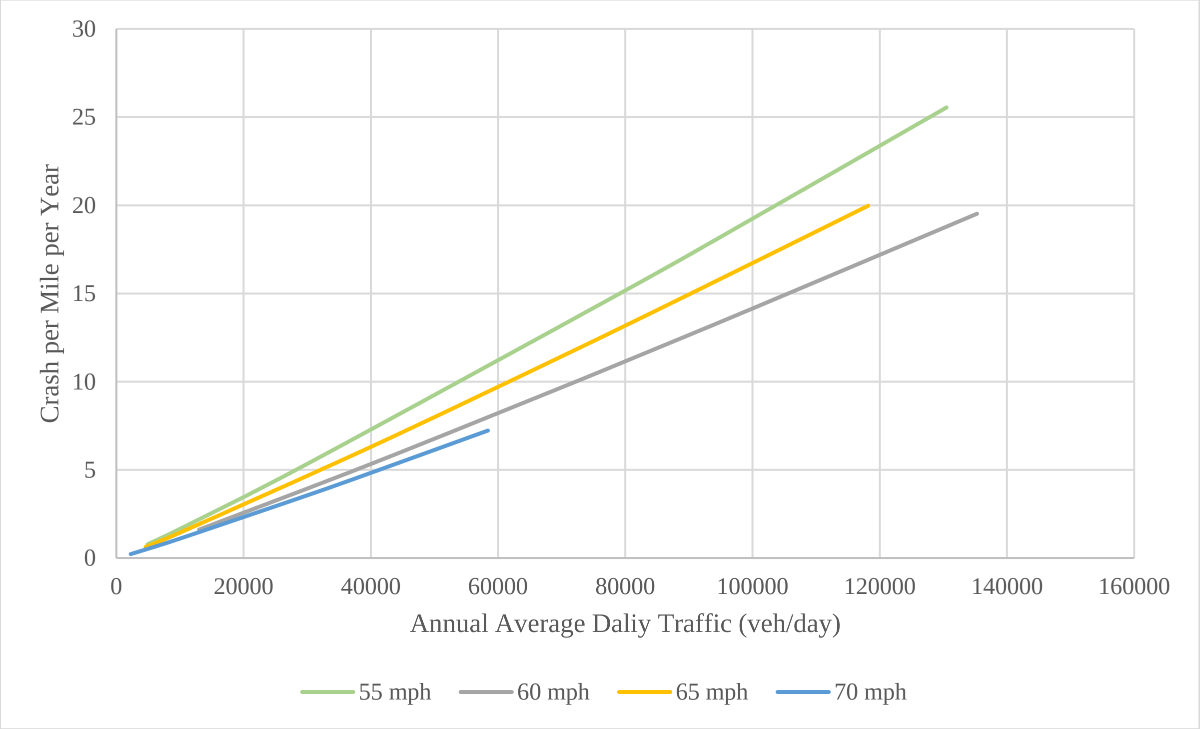

Figure 20. Expected Number of O-Injury Crash with Different AADT

Figure 16 through Figure 20 demonstrate that higher crash frequencies were expected on lower-speed portions of the Iowa interstate network, which are typically located near urban or suburban areas where more complicated traffic patterns and roadway configurations would be anticipated. For all crash severities, 55-mph roadways had the highest crash frequencies while 70-mph roadways had the lowest. The estimated coefficients and graphs for speed limits were intuitive. However, some caution is needed when interpreting these results due to the complicated interactions between traffic conditions, roadway conditions, and driver behavior.

In addition to the crash frequencies calculated from the model estimates, crash rates were also predicted by dividing the crash frequency by roadway HMVMT. The RENB models predicted crashes per mile per year, it was then converted to an equivalent rate of crashes per 100 million vehicle miles traveled. Crash rates were estimated for the entire interstate network as well as each speed limit group for total and severity-specific crashes as shown in Table 8.

Table 8. Predicted Number of Crashes per Hundred Million Vehicle Miles Traveled

Predicted Crash per HMVMT	**All Interstate**	**55 mph Roadway**	**60 mph Roadway**	**65 mph Roadway**	**70 mph Roadway**
Total	45.2	74.6	54.4	56.4	40.5
KA	1.5	2.1	1.6	1.6	1.4
B	3.7	7.4	4.8	4.5	3.3
C	4.8	14.5	10.0	7.1	3.8
O	34.5	50.0	37.7	43.0	31.5

Table 8 illustrates that 55-mph roadways had about 84 percent more traffic crashes than 70-mph roadways. Additionally, the injury (type B) and more severe (type KA) crashes per HMVMT were nearly doubled on the 55-mph roadways compared to the 70-mph roadways. The crash, injury, and fatality rates were similar on 60- and 65-mph roadways, and the general decreasing trend of crash rate as the posted speed limit increase was observed on almost all type of crashes.

Ultimately, the results indicate that the increased crash rate on the lower speed segments is likely caused by the lower design speed and roadway geometry standards. The findings suggest that extensive reconstruction and improvements are required to decrease the crash rate on those lower speed segments. These might include redesigning horizontal and vertical alignments, adding guardrails, increasing the lengths of merging tapers, purchasing right of ways, and implementing new signs and markings.

One limitation of the analyses is that the operational speed information was lacking. Although the regression models included the maximum speed limit as explanatory variables to control for the speed characteristics to some extent, the actual operating speed characteristics might still vary on different roadway segments. Therefore, it is essential to discern how speed changes on different roadway segments and how the operating speed affects safety as well.

5.3 Relationship between Speed and Roadway Characteristics

To examine the impacts of roadway geometric characteristics on speed measures, and how the drivers react to the roadway features on average, SURE models were estimated using the speed data between 2013 and 2016. The analysis included geometric and traffic volume related variables. Three speed measures were investigated, which are average speed, 85th percentile speed, and standard deviation of speed. Table 9 indicates the results of the SURE models for the entire interstate network.

Table 9. Seemingly Unrelated Regression Equations (SURE) Results for All Interstates (2013-2016)

	Mean Speed Model		
Parameter	**Estimate**	**Std. Error**	**Pr(>|t|)**
Intercept	49.009	0.136	<0.001
Ln AADT	0.806	0.012	<0.001
Urban Area (1=yes, 0=no)	-1.038	0.019	<0.001
Presence of Median Barrier (1=yes, 0=no)	0.112	0.013	<0.001
Right Shoulder Width	0.106	0.004	<0.001
Left Shoulder Width	0.059	0.003	<0.001
Median Width	0.016	0.000	<0.001
Speed Limit 60 mph (1=yes, 0=no)	2.665	0.032	<0.001
Speed Limit 65 mph (1=yes, 0=no)	5.880	0.023	<0.001
Speed Limit 70 mph (1=yes, 0=no)	8.037	0.026	<0.001
	85th Percentile Speed Model		
Parameter	**Estimate**	**Std. Error**	**Pr(>|t|)**
Intercept	49.765	0.134	<0.001
Ln AADT	1.004	0.012	<0.001
Urban Area (1=yes, 0=no)	-0.933	0.019	<0.001
Presence of Median Barrier (1=yes, 0=no)	0.073	0.012	<0.001
Right Shoulder Width	0.087	0.004	<0.001
Left Shoulder Width	0.033	0.003	<0.001
Median Width	0.013	0.000	<0.001
Speed Limit 60 mph (1=yes, 0=no)	2.619	0.031	<0.001
Speed Limit 65 mph (1=yes, 0=no)	5.971	0.022	<0.001
Speed Limit 70 mph (1=yes, 0=no)	8.330	0.026	<0.001
	Speed Standard Deviation Model		
Parameter	**Estimate**	**Std. Error**	**Pr(>|t|)**
Intercept	0.970	0.076	<0.001
Ln AADT	0.309	0.007	<0.001
Urban Area (1=yes, 0=no)	0.278	0.011	<0.001
Presence of Median Barrier (1=yes, 0=no)	-0.118	0.007	<0.001
Right Shoulder Width	-0.053	0.002	<0.001
Left Shoulder Width	-0.026	0.002	<0.001
Median Width	-0.005	0.000	<0.001
Speed Limit 60 mph (1=yes, 0=no)	0.277	0.018	<0.001
Speed Limit 65 mph (1=yes, 0=no)	-0.051	0.012	<0.001
Speed Limit 70 mph (1=yes, 0=no)	-0.161	0.015	<0.001

The coefficient estimates of the binary indicator for urban areas are negative for mean speed and 85th percentile speed models, while the estimate is positive in the standard deviation of speed model. This demonstrates that drivers are likely to choose lower speeds in an urban environment due to the complex traffic and roadway conditions. However, different people react to the urban environment in different ways, and traffic congestion is more likely to occur in urban areas than in rural areas, leading to more variation in speed. Another binary indicator for the presence of median barrier suggests that segments with a median barrier tend to have a higher average and 85th percentile speed and lower speed variance. Similar trends are observed for the continuous variables, which are right shoulder width, left shoulder width, and median width. As the right shoulder width, left shoulder width, and median width increase, the average and 85th percentile increase as well while the standard deviation of speed decreases. This could be explained by that drivers perceive the safer roadway features and choose a higher traveling speed accordingly. Also, drivers might have a more consistent speed selection on safer roads suggested by the lower speed variation observed. The binary indicators for speed limits demonstrate that how the speed measures vary on roadways with different speed limits. The 55 mph speed limit was treated as the base scenario. As the mean speed and 85th percentile speed models show, compared to segments with 55 mph speed limit, roadways with higher speed limit generally are associated with higher average speed and 85th percentile speed. Interestingly, the parameter estimates illustrate that compared to 55 mph interstates, the mean speed is 2.7 mph, 5.9 mph, and 8.0 mph higher on 60 mph, 65 mph, and 70 mph roadways respectively. The increase in the mean speeds is much lower than the actual posted speed limit increase. Similar trend is also found in the 85th percentile speed model. In the speed standard deviation model, it was found that the 60 mph interstates are associated with the highest speed standard deviation, followed by 55 mph, 65 mph, and 70 mph interstates.

Ultimately, the SURE models show that driver speed choice is impacted by roadway geometric characteristics. The mean speed and 85th percentile speed models show that drivers are suspected to generally select a higher speed on the interstate with good geometry design standards, such as broader shoulder width and wider median width. Besides, drivers are likely to select faster speeds where the median barrier has been installed. The standard deviation of speed measures the variability of the operating speeds. As the speed standard deviation models indicate, the speed variance is typically the highest in the urban areas with a lower speed limit, narrower right and left shoulder widths and median width, and no median barrier installed.

5.4 Relationship between Speed and Safety

To further study the relationship between operational speeds and crash frequencies, an additional set of RENB models were created by including speed measures, such as speed variance and average speed, as the explanatory variables. Additional variables, such as traffic, roadway geometry, were added in the model as the control variables. These models utilized the segment-month datasets prepared from 2013 to 2016. Three random effect terms, segment-level ID, year, and month, were introduced to account for spatial and temporal effects. These random effects accounted for the unobserved site-specific heterogeneity and allowed the fixed effects to vary for each segment in certain years. Since GIMS segments do not have a uniform length, segment length was included in the models as an offset term. This enables the models to estimate the crash rate on a per-mile basis. Five RENB models were developed for the entire interstate network. One used the total number of crashes as the dependent variable, while the other four used different severity types. Table 10 shows the model results.

Table 10. Regression model Results for Monthly Crashes with Different Severity Types (2013-2016)

Severity	**Parameter**	**Estimate**	**Std. Error**	**Pr(>|z|)**
Total	Intercept	-11.080	0.545	<0.001
	Ln AADT	1.117	0.037	<0.001
	Standard deviation of speed	0.201	0.010	<0.001
	Average speed	-0.023	0.007	0.002
	Median Width	-0.001	0.001	0.211
	Right Shoulder Width	-0.023	0.009	0.016
	Presence of Median Barrier (1=yes, 0=no)	0.059	0.034	0.085
	Speed Limit 60 mph (1=yes, 0=no)	-0.418	0.083	<0.001
	Speed Limit 65 mph (1=yes, 0=no)	-0.127	0.073	0.083
	Speed Limit 70 mph (1=yes, 0=no)	-0.196	0.087	0.025
KA	Intercept	-11.891	2.377	<0.001
	Ln AADT	0.388	0.154	0.012
	Standard deviation of speed	0.290	0.048	<0.001
	Average speed	0.043	0.035	0.228
	Median Width	-0.004	0.004	0.306
	Right Shoulder Width	0.033	0.038	0.381
	Presence of Median Barrier (1=yes, 0=no)	-0.028	0.145	0.846
	Speed Limit 60 mph (1=yes, 0=no)	-0.383	0.330	0.245
	Speed Limit 65 mph (1=yes, 0=no)	-0.734	0.313	0.019
	Speed Limit 70 mph (1=yes, 0=no)	-0.994	0.380	0.009
B	Intercept	-13.830	1.312	<0.001
	Ln AADT	0.934	0.087	<0.001
	Standard deviation of speed	0.216	0.027	<0.001
	Average speed	0.015	0.019	0.455
	Median Width	-0.001	0.002	0.782
	Right Shoulder Width	-0.017	0.018	0.350
	Presence of Median Barrier (1=yes, 0=no)	-0.060	0.078	0.437
	Speed Limit 60 mph (1=yes, 0=no)	-0.393	0.157	0.013
	Speed Limit 65 mph (1=yes, 0=no)	-0.539	0.162	<0.001
	Speed Limit 70 mph (1=yes, 0=no)	-0.807	0.205	<0.001
C	Intercept	-13.123	1.104	<0.001
	Ln AADT	1.153	0.076	<0.001

Table 10. (continued)

	Standard deviation of speed	0.197	0.022	<0.001
	Average speed	-0.020	0.016	0.210
	Median Width	-0.007	0.002	<0.001
	Right Shoulder Width	-0.003	0.015	0.864
	Presence of Median Barrier (1=yes, 0=no)	-0.035	0.070	0.614
	Speed Limit 60 mph (1=yes, 0=no)	-0.577	0.133	<0.001
	Speed Limit 65 mph (1=yes, 0=no)	-0.655	0.135	<0.001
	Speed Limit 70 mph (1=yes, 0=no)	-1.031	0.172	<0.001
O	Intercept	-11.310	0.585	<0.001
	Ln AADT	1.160	0.040	<0.001
	Standard deviation of speed	0.184	0.011	<0.001
	Average speed	-0.034	0.008	<0.001
	Median Width	-0.0001	0.001	0.889
	Right Shoulder Width	-0.023	0.010	0.019
	Presence of Median Barrier (1=yes, 0=no)	0.081	0.036	0.024
	Speed Limit 60 mph (1=yes, 0=no)	-0.374	0.089	<0.001
	Speed Limit 65 mph (1=yes, 0=no)	0.091	0.079	0.248
	Speed Limit 70 mph (1=yes, 0=no)	0.098	0.095	0.302

Similar to the previous findings, higher AADT is associated with higher crashes. Additionally, based on the model results, it could be found that there were strong positive correlations between the number of crashes in all severity types and standard deviation of speed. The estimates indicate that a one-unit increase in standard deviation of speed would result in a 22.2% increase in the total number of crashes, a 33.6% increase in the number of serious crashes (fatal and serious injury), a 24.1% increase in the number of B-injury crashes, a 21.8% increase in the number of C-injury crashes, and a 20.1% increase in the number of O-injury crashes. The results demonstrate that severe crashes are likely to be more sensitive to the speed standard deviation. Some prior research presented similar findings that speed variance was highly correlated with crash frequencies (Lave, 1985; Garber & Gadiraju, 1989). Segments with wider shoulder widths and median width were generally associated with fewer crashes. The presence of the median barrier was suspected of lowering the severe crash frequencies but increasing the PDO crash frequencies.

Table 11 shows the descriptive statistics of the speed measures in each speed limit group. One interesting finding is that the mean value for the speed standard deviation is the lowest in the 70 mph group, suggesting that traffic speed was more uniform in the high-speed segments.

Table 11. Descriptive Statistics for Speed Measures under Different Speed Limit Groups

Segment	**Variable**	**Min**	**Max**	**Mean**	**Std. Dev**
55 mph	85th Percentile Speed	51.5	71.0	61.2	2.5
	Speed Standard Deviation	1.5	17.0	3.7	1.5
	Average Speed	40.0	68.3	58.7	2.8
60 mph	85th Percentile Speed	58.0	70.5	64.1	1.5
	Speed Standard Deviation	1.6	8.4	4.1	1.6
	Average Speed	54.9	68.2	61.5	1.7
65 mph	85th Percentile Speed	54.5	73.5	67.4	2.2
	Speed Standard Deviation	1.6	12.7	3.4	1.2
	Average Speed	50.2	69.7	64.9	2.4
70 mph	85th Percentile Speed	59.0	73.5	69.8	1.4
	Speed Standard Deviation	1.4	10.2	2.9	0.7
	Average Speed	58.0	70.5	67.2	1.3

Ten graphs were created to visually illustrate how crashes change with respect to the standard deviation of speed and the mean speed. Each line was plotted by five points which were calculated by changing the variable of interest while keeping other variables at the mean in each speed limit group. Within each speed limit group, the five points used the mean value of the variable of interest as well as one standard deviation and two standard deviations away from the mean in both directions. The values were inputting into the regression equations estimated in Table 10 to get the predicted crash frequencies.

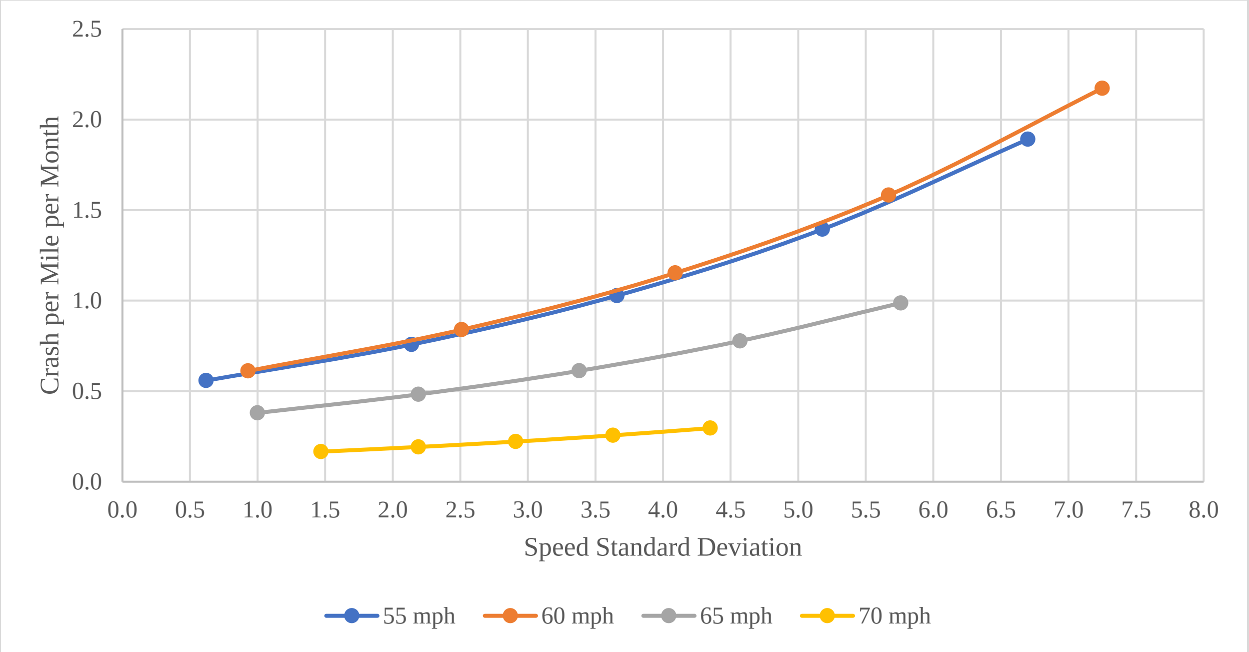

Figure 21. Relationship between Total Crash Frequency and Speed Standard Deviation

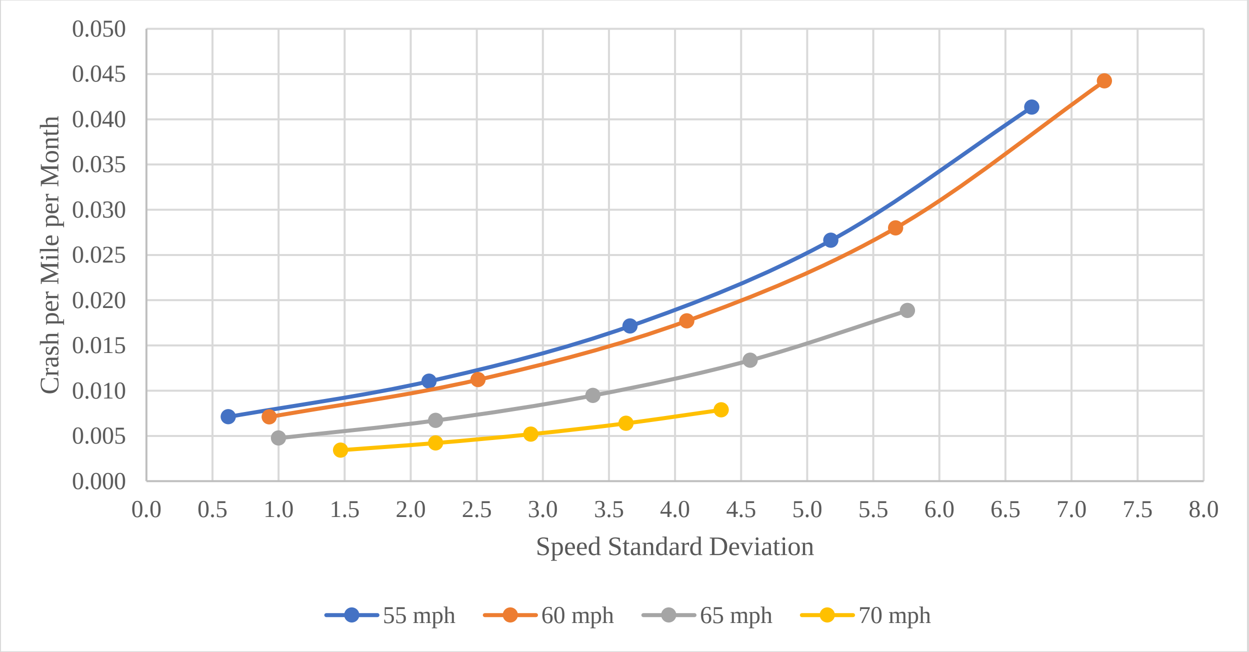

Figure 22. Relationship between KA-Injury Crash Frequency and Speed Standard Deviation

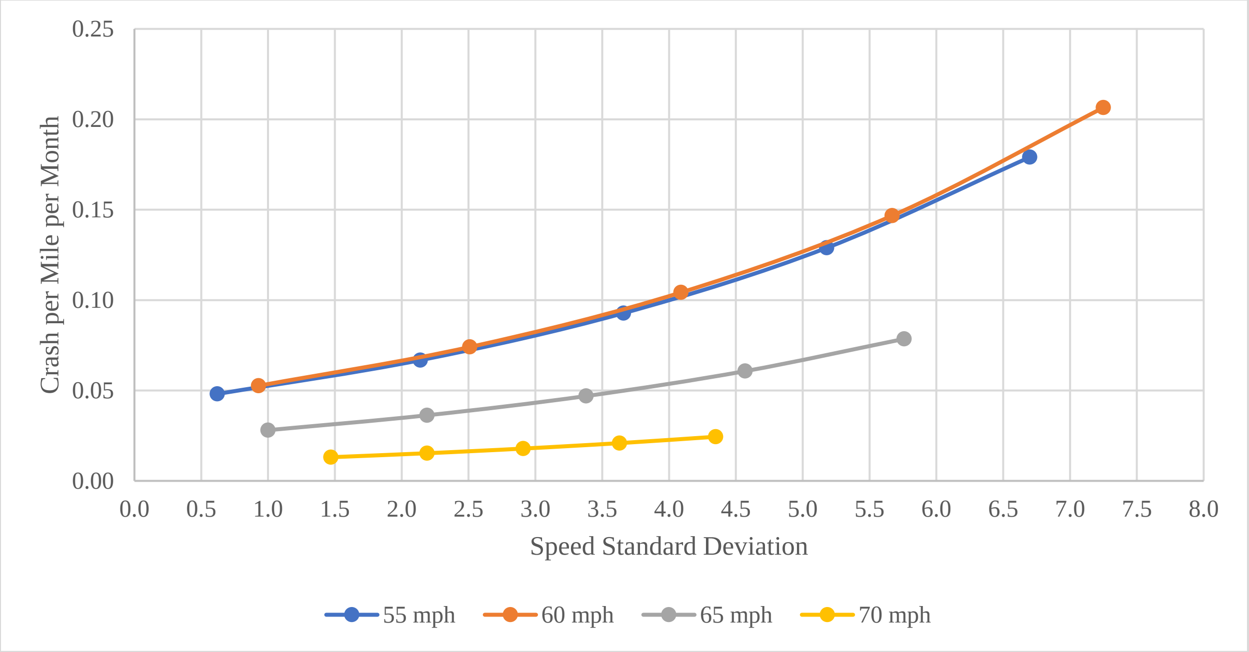

Figure 23. Relationship between B-Injury Crash Frequency and Speed Standard Deviation

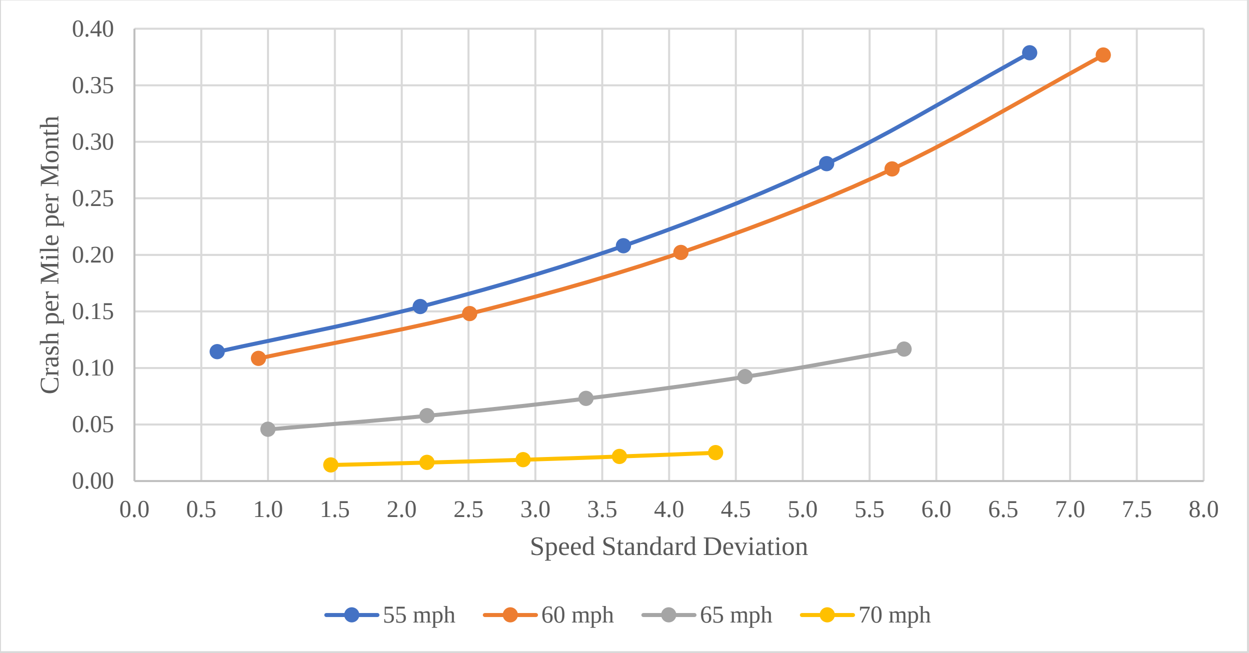

Figure 24. Relationship between C-Injury Crash Frequency and Speed Standard Deviation

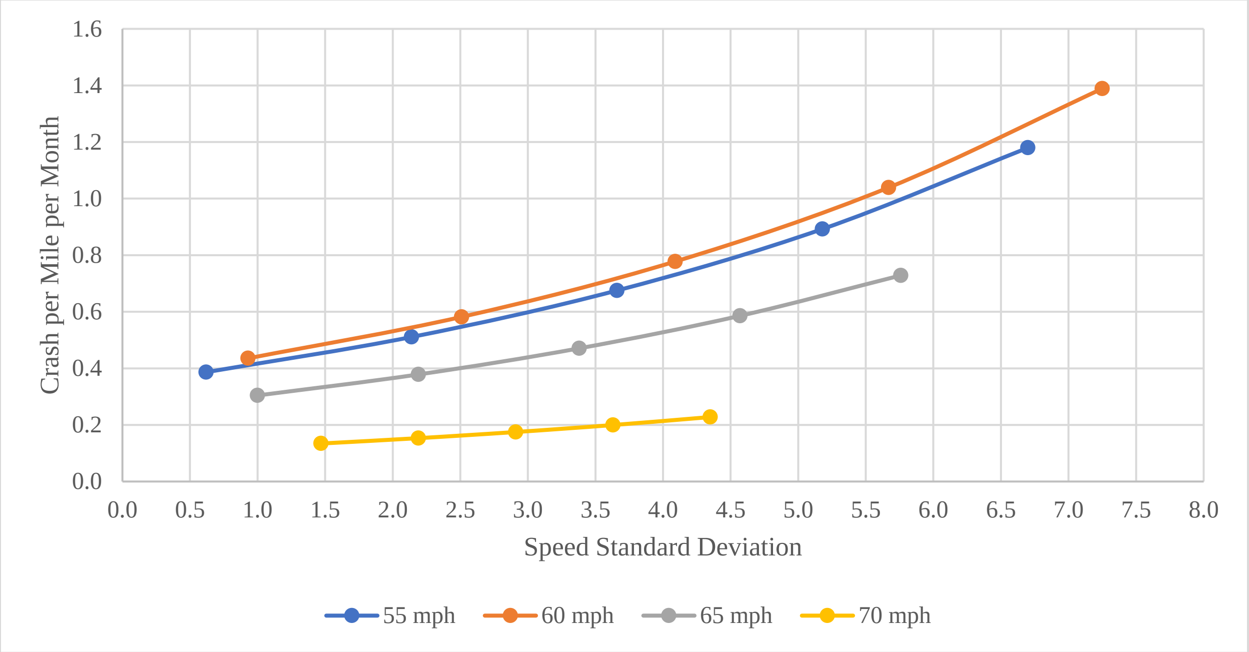

Figure 25. Relationship between O-Injury Crash Frequency and Speed Standard Deviation

From these charts, a consistent increasing trend was observed in the crash frequencies for all speed limits as speed standard deviation increased. Based on the plots, the crash frequencies were found to be always higher on the slower speed segments, and 70 mph segments had the lowest crash frequencies in all crash severity types. The slope of 55 mph and 60 mph segments were steeper than the slope of 65 mph and 70 mph segments, indicating that the lower speed segments were associated with more variability in the speed standard deviation and the safety impact of speed standard deviation was likely to be stronger in the lower speed interstates.

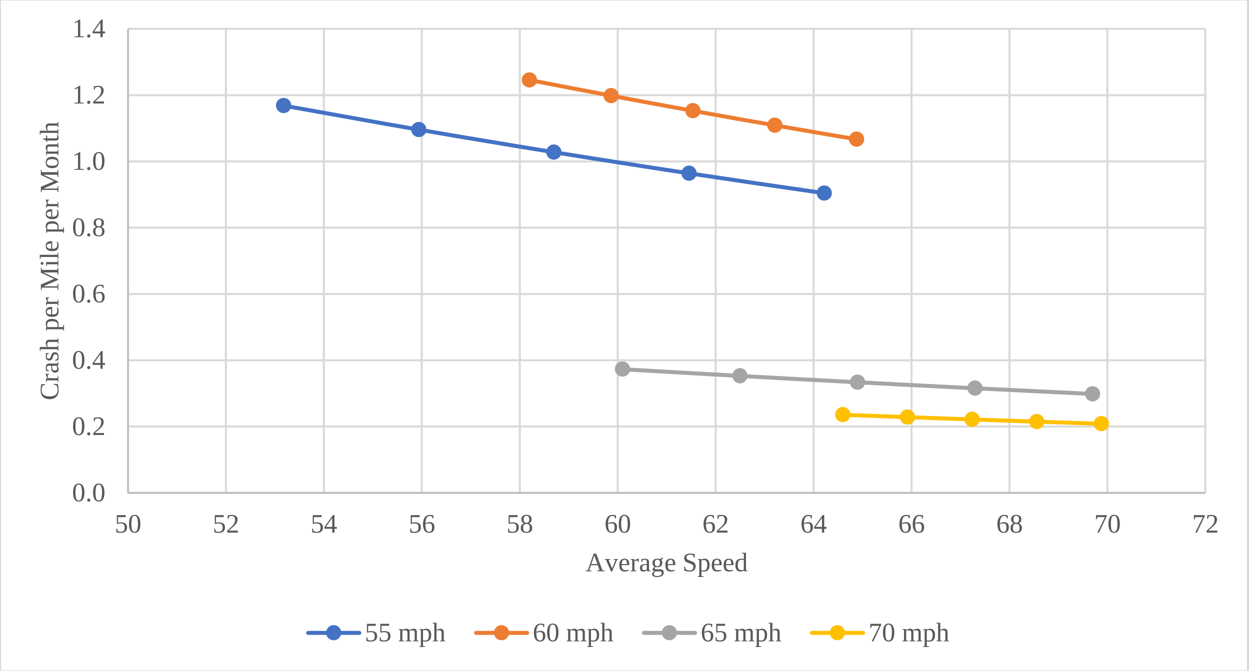

Figure 26. Relationship between Total Crash Frequency and Average Speed

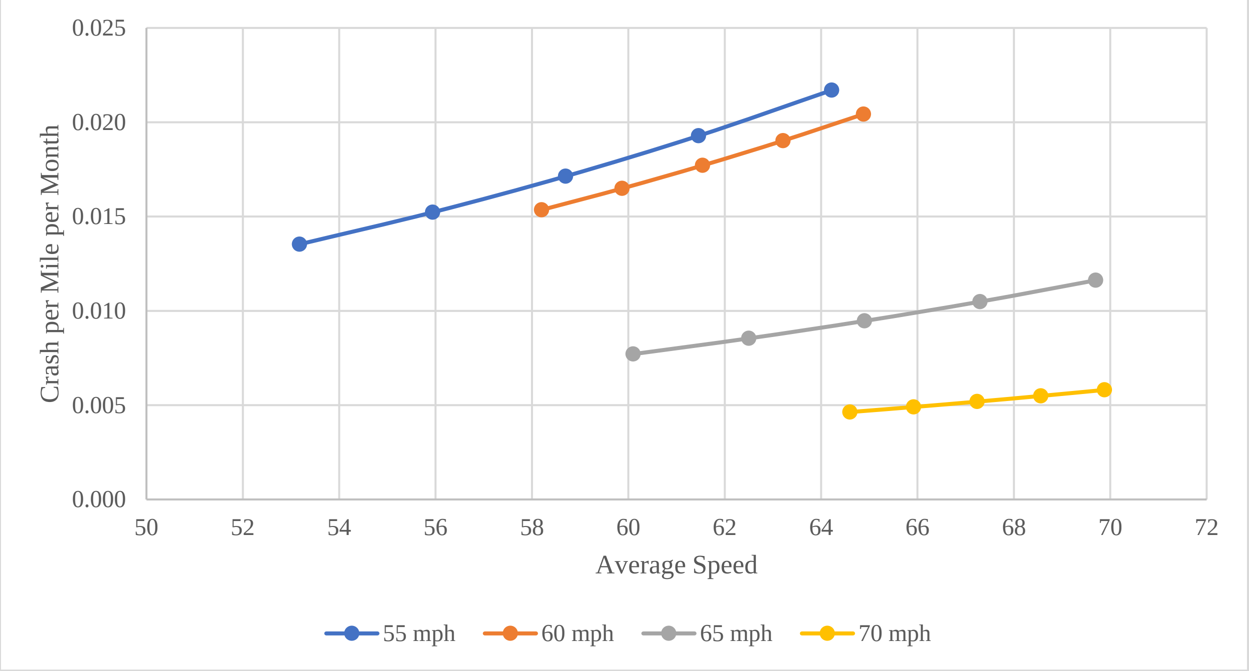

Figure 27. Relationship between KA-Injury Crash Frequency and Average Speed

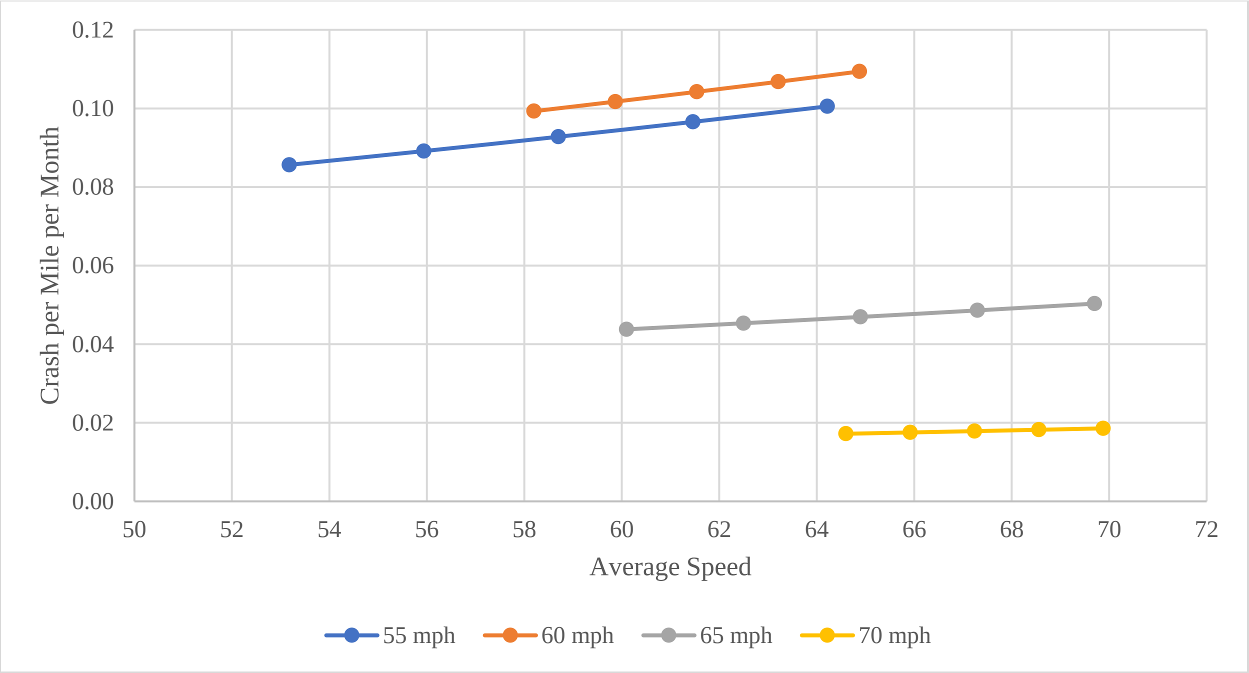

Figure 28. Relationship between B-Injury Crash Frequency and Average Speed

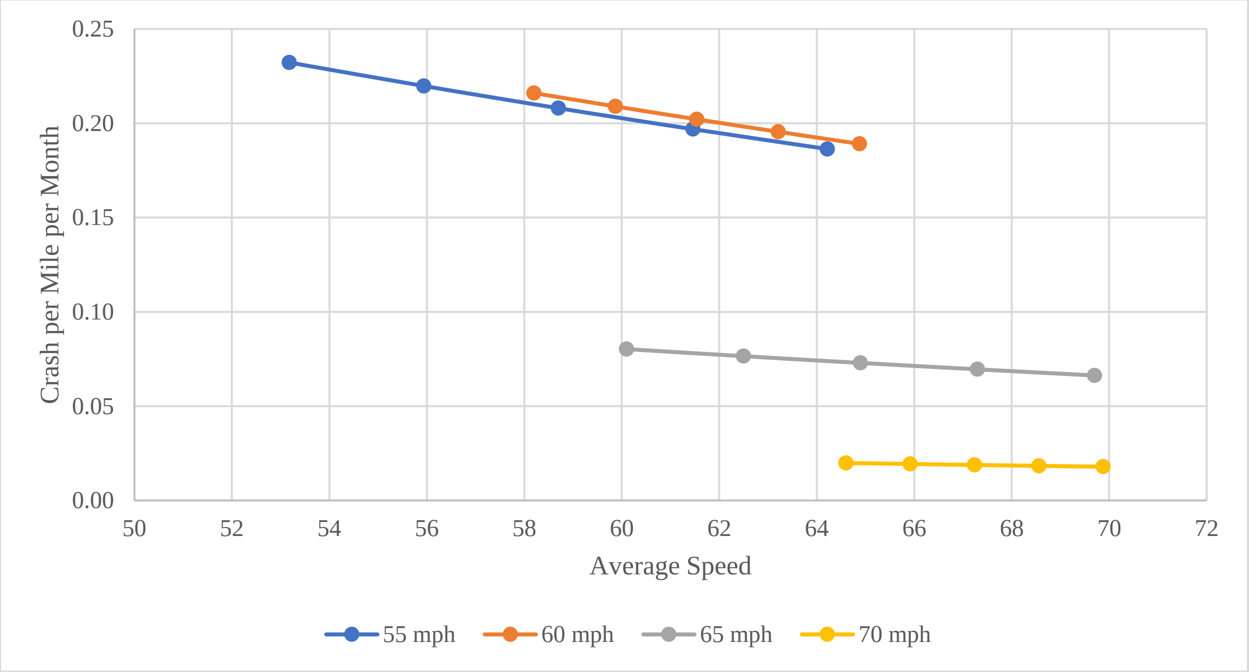

Figure 29. Relationship between C-Injury Crash Frequency and Average Speed

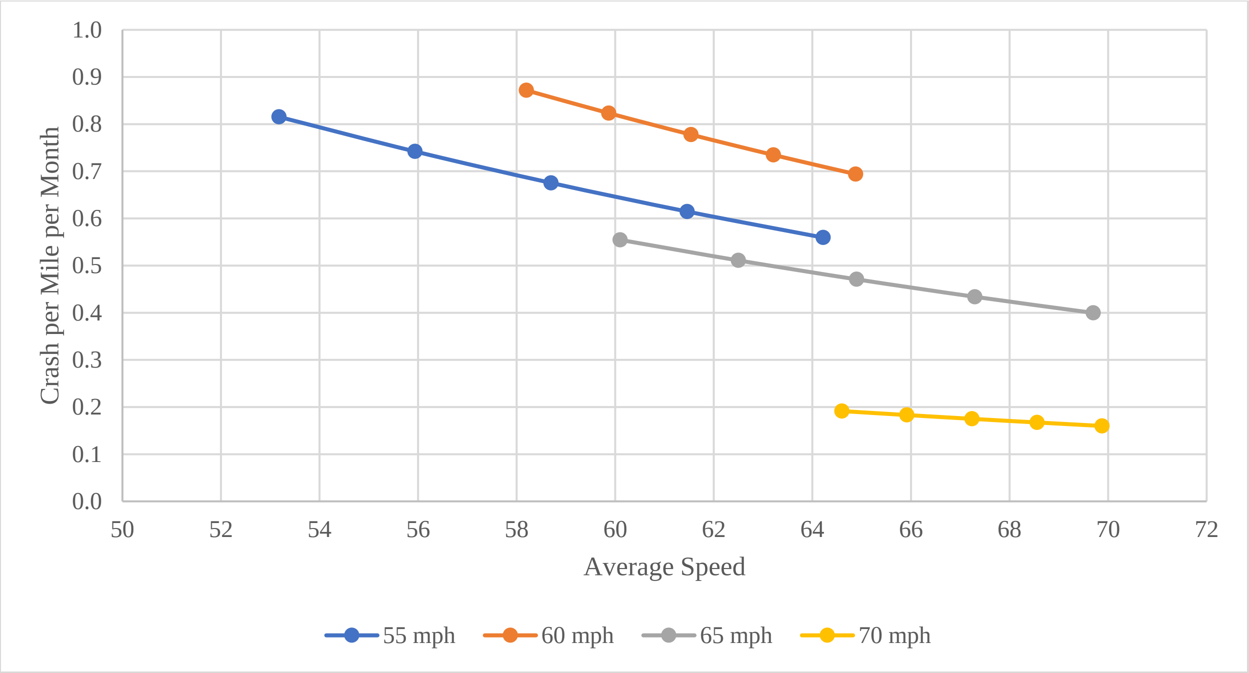

Figure 30. Relationship between O-Injury Crash Frequency and Average Speed

Based on these results, crash frequencies for the serious (KA) and the B-injury were positively proportional to the average speed, although these correlations were not statistically significant in a 95% confidence level. Conversely, the total crash and less severe crash (C-injury, O-injury) frequencies were trended downward as the average speed increased. Other studies also showed a negative relationship between average speed and crash frequencies (Lave, 1985; Baruya, 1998). One explanation of why roadways with higher average speeds seem to be overall safer is that the roadway geometric characteristics or design standards are typically higher on those high speeds segments. With good roadway and traffic characteristics, drivers might choose higher travel speeds. Besides, longer following distances typically used by vehicles traveling at higher speeds might also help reduce the crash risk (Imprialou et al., 2016). Nevertheless, many before-and-after studies have shown that increasing speed limits leads to an increase in crashes, as discussed in the literature review. It is evident that average speeds will increase with higher maximum speed limits. However, raising the maximum speed limit without increasing the minimum speed limit might also introduce higher speed variance. Further studies are required to understand the interrelationship between average speed, speed variation, speed limits, and roadway geometry.

Compared to the analyses in Chapter 5.1, the analyses presented in this chapter provide more detailed models that include additional speed information. Based on the model results, higher speed variance is associated with more crashes, while the absolute speed of traffic does not necessarily correspond to higher crash occurrences. The impacts of speed variance are likely to be higher for more severe crashes on lower speed segments.

CHAPTER 6. CONCLUSION

6.1 Summary of Findings

This study provides valuable insights into the relationship between driver speed selection and crash risk. The variables assessed in this study include traffic volume, weather conditions, roadway geometry, and various operating speed measures. Separate analyses were conducted which leveraged Iowa roadway information, crash information, weather, ATR, and INRIX data.

A simple before-and-after comparison of fatal and serious crash rates on Iowa Interstates from 1991 to 2017 shows that crashes increased in the few years after the 2005 speed limit increase, but crashes have generally declined since that time. This is likely due to many factors, including the implementation of roadway crash countermeasures that were implemented over these years such as median cable barrier, and rumble strips, among others. In general, crashes tended to be higher on segments with lower speed limits. However, it is essential to acknowledge that these lower speed limits are often in place due to the more complex urban environments that are subject to higher traffic volumes, more frequent interactions between vehicles (particularly near exit/entrance ramps), and lower design speeds than would be observed in rural environments. Indeed, the 55-mph segments, which were all located in urban areas, were found to consistently have the highest total crash rates over the study period.

Further study was conducted to better understand the relationship between different factors and increased crash rate. The findings suggested that traffic, roadway, and weather characteristics were correlated with the occurrence of crashes. The annual average daily traffic was positively correlated with crashes in all severity types. As for the roadway geometry variables, the presence of median barrier was suspected to significantly reduce the fatal and severe crashes while increasing property damage only crashes. The overall total number of crashes was expected to be higher on segments with a median barrier installed. The result demonstrated that the median barrier could likely mitigate crash severity effectively. In addition, the wider median width and right shoulder width also might help reduce the crash frequency with all different severity levels on a roadway segment. The segments that had deceleration or acceleration lanes were expected to experience more total crashes compared to others, which may be likely caused by the frequent merging activities and increased speed variance on such roadway segments. Another variable examined in the analyses was the annual snowfall. The model results illustrated that all crash types except fatal and serious crashes were likely to increase with higher accumulated snowfall.

Upon assessing the operating speed data from INRIX, speeds were generally lower in urban areas, which was measured by average and 85th percentile speeds, while the standard deviation of speeds on urban interstates was greater. The higher mean and 85th percentile speeds occurred on rural interstates with broader shoulders and median widths. In term of the speed variance, as measured by the standard deviation of speed models, the higher standard deviations were predicted to take place under the following circumstance: urban areas that have 60 mph speed limit, narrow shoulder widths and median widths, and no median barrier present.

After investigating the impact of roadway geometry on speed measures, it was necessary to evaluate whether operating speed measures influence the crash frequencies as well. Separate models were estimated for interstate crashes with different severity types. Two speed measures were included in the models, which were mean speed and speed variance, while controlling for the effects of geometry and traffic that may affect both speeds and safety. It was suspected that speed variance were the major contributing factors that lead to increased crash rate, and the effects were stronger on lower speed segments. The intensity of the speed variance impacts gradually increased with more severe crashes. Meanwhile, the mean speed seemed to have insignificant effects or sometimes negative correlations with crashes, which was in line with some prior studies. It was proposed that the lower crash frequency observed on the segments with high mean speed was largely associated with the higher design standards and overall safer roadway geometry.

The findings of this study demonstrate that traffic safety is impacted by a combination of various factors including operational speeds, roadway geometry, environmental conditions, and traffic volumes. The results provide empirical support of prior research, which suggest that the average speed might be less influential than speed variance on safety and higher standard deviation of speed is associated with the higher crash rates. These findings provide policymakers insights to help support the establishment of maximum statutory speed limits. Also, this study examines how speed measures are influenced by roadway geometric characterizes as well as how the site-specific factors can affect safety. The results of these analyses provide roadway designers insights on the design of a safer interstate system. In addition, this study demonstrates that the lower speed interstate segments are subjected to higher crash risk where substantial reconstruction might be needed in order to meet the higher design speed.

6.2 Limitations and Future Research

Ultimately, this study provides important information on how various factors can impact traffic safety on interstates. However, there were several limitations worth mentioning to understand the nature of these relationships better. One limitation of this study was that the Geographic Information Management System (GIMS) database maintained by Iowa DOT was utilized for integrating traffic, roadway, and crash data. The disadvantage of this database was that directional analysis was not supported. Therefore all the specific site features were aggregated by averaging two directions. Additionally, it was challenging to integrate INRIX data into the GIMS roadway segments, as INRIX not only provides directional speeds but it divides the interstate segments in a different way than GIMS.

Note that a new database, the Roadway Asset Management System (RAMS), has been adopted by Iowa DOT. RAMS will allow for the collection and maintenance of roadway asset data on a directional basis. As such, with more data available over the years, future research should leverage this dataset for directional analysis to examine the interrelationships with better resolution. Furthermore, the weather data was collected from the weather stations across the state and was integrated into the adjacent interstate segments. These weather stations might not be able to provide great accuracy in representing the weather conditions at each segment as relatively large buffers around weather stations were generated to ensure entire coverage of the interstate network.

Moving forward, several additional analyses could provide further insight as to correlate the crashes with a variety of factors. For example, a crash level analysis could be performed with the higher resolution speed data from INRIX. The speed measures before crash events could be compared to the regular periods to quantify how traffic conditions affect the occurrence of crashes. Moreover, separate analyses could be conducted for various collision types (i.e., head-on, rear-end, etc.). Also, this study focuses on the interstate network, and future research efforts are warranted to assess how these findings can transfer to non-interstate highways.

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