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Statewide Heavy-Truck Crash Assessment

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MATC

Statewide Heavy-Truck Crash Assessment

Center for Transportation Research and Education

Final Report
September 2014

Iowa State University
Institute for Transportation

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16. Abstract

In 2010, 16.5 percent of all fatal vehicle crashes in Iowa involved large trucks compared to the national average of 7.8 percent. Only about 16 percent of these fatalities involved the occupants of the heavy vehicles, meaning that a majority of the fatalities in fatal crashes involve non-heavy-truck occupants. These statistics demonstrate the severe nature of heavy-truck crashes and underscore the serious impact that these crashes can have on the traveling public. These statistics also indicate Iowa may have a disproportionately higher safety risk compared to the nation with respect to heavy-truck safety.

Several national studies, and a few statewide studies, have investigated large-truck crashes; however, no rigorous analysis of heavy-truck crashes has been conducted for Iowa. The objective of this study was to investigate and identify the causes, locations, and other factors related to heavy-truck crashes in Iowa with the goal of reducing crashes and promoting safety. To achieve this objective, this study used the most current statewide data of heavy-truck crashes in Iowa.

This study also attempted to assess crash experience with respect to length of commercial driver's license (CDL) licensure using the most recent five years of CDL data linked to the before mentioned crash data. In addition, this study used inspection and citation data from the Iowa Department of Transportation (DOT) Motor Vehicle Division and Iowa State Patrol to investigate the relationship between enforcement activities and crash experience.

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STATEWIDE HEAVY-TRUCK CRASH ASSESSMENT

Final Report
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The authors would like to thank the Iowa Department of Transportation (Iowa DOT) and Mid-America Transportation Center (MATC), and U. S. Department of Transportation (DOT) Research and Innovative Technology Administration (RITA) for sponsoring this research.

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EXECUTIVE SUMMARY

Objective

The objective of this study was to investigate and identify the causes, locations, and other factors related to heavy-truck crashes in Iowa with the goal of reducing crashes and promoting safety.

Background

In 2010, 16.5 percent of all fatal vehicle crashes in Iowa involved large trucks compared to the national average of 7.8 percent. Only about 16 percent of these fatalities involved the occupants of the heavy vehicles, meaning that a majority of the fatalities in fatal crashes involve non-heavy-truck occupants.

These statistics demonstrate the severe nature of heavy-truck crashes and underscore the serious impact that these crashes can have on the traveling public. These statistics also indicate Iowa may have a disproportionately higher safety risk compared to the nation with respect to heavy-truck safety.

Problem Statement

Several national studies, and a few statewide studies, have investigated large-truck crashes. However, no rigorous analysis of heavy-truck crashes has been conducted for Iowa.

Research Description

This study used the most current statewide crash data to perform an in-depth analysis of heavy-truck crashes in Iowa. This study also attempted to assess crash experience with respect to commercial driver’s license (CDL) licensure. In addition, this study used citation data from the Iowa Department of Transportation (DOT) Motor Vehicle Division and Iowa State Patrol to investigate the possible relationship between past enforcement efforts and crash experience.

Research Methodology

To conduct the crash analysis, Iowa crash data for 2007 through 2012 were used to prepare descriptive statistics and to develop statistical models for single- and multiple-vehicle heavy-truck crash severity. Single-vehicle crashes were modeled using a binary probit model with outcomes of injury (fatal, major, minor, or possible injury) or no injury (property damage only). Multiple-vehicle crashes were modeled using a nested logit model with severity outcomes of severe injury (fatal or major injury), minor injury (minor or possible injury), and no injury (property damage only), with the two injury outcomes placed in a nest.

The analysis of CDL licensure data used 2008 through 2012 CDL new licensure and licensure renewal information linked to the crash data. Both descriptive statistics and negative binomial model estimates were utilized to investigate license characteristics, driver experience, and crash frequency.

In an effort to investigate the relationship between enforcement activities and crashes, the most recent four years of commercial motor vehicle-related public enforcement data (2009 through 2012) were used to conduct a statewide analysis, which included descriptive statistics and a test of proportions for time of day, day of week, month, road system, and county. Selected descriptive results are also presented geographically in the final report at the county and primary-road segment levels.

Key Findings

Findings from the two statistical crash severity models were both complimentary and contradictory. Both models found older drivers to be associated with more severe injuries. Both models also indicated crashes that have an impact on and damage the front of both heavy and non-heavy trucks play a significant role in the severity outcome of the crash.

The findings were consistent with previous research identifying the importance of the heavy-truck frontal structure as well as other safety features, such as stability control, air bags, collision and lane departure warning systems, and improved braking systems.

The main disparity of the two statistical crash models relates to the effect that single-unit and combination trucks have on crash severity, with combination trucks being associated with a higher probability of a severe injury in multiple-vehicle collisions and single-unit trucks being associated with a higher probability of an injury in single-vehicle crashes.

Other factors found to be significant in either of the two models relate to the manner of the collision, temporal factors (season, day of week, time of day), vehicle characteristics, roadway characteristics, and environmental factors. Here are a few highlights of these results:

- Posted speed limits were found to have potentially great influence on heavy-truck crash-severity outcomes, with higher speeds being associated with more severe crash outcomes
- Severe crashes were more likely during morning (5 a.m. to 8 a.m.) and midday (11 a.m. to 2 p.m.)
- Severe crashes were more likely toward the beginning of the week (Monday or Tuesday) and over the weekend (Saturday or Sunday)

Other findings based on model results, descriptive statistics, and a test of proportions included the following:

- While the majority of crashes occurred with dry surface conditions, a higher proportion of multiple-vehicle crashes occurred with snow and slush surface conditions
- The majority of multiple-vehicle and single-vehicle crashes occurred in daylight conditions, but a statistically significant greater proportion occurred with dark, unlighted road conditions
- Younger heavy-truck drivers (ages 20 to 34) had proportionally higher involvement in single-vehicle crashes than in multiple-vehicle crashes
- The proportion of heavy-truck drivers under the age of 30 involved in a crash was higher than the proportion of Iowa CDL license holders under the age of 30, not considering vehicle miles of travel of these drivers
- Heavy-truck driver age distribution is far more concentrated than non-heavy-truck driver age distribution, with a greater percentage of heavy-truck drivers who are 30 to 64 and with percentage differences between heavy-truck drivers and non-heavy-truck drivers most pronounced between the ages of 40 and 59, and particularly between the ages of 45 and 54

Descriptive statistics and the results from test proportions indicated differences in proportions between law enforcement contacts and crashes both temporally and spatially for time of day, day of week, month, road classifications, and individual counties.

Temporally, contact proportions were much less during the early morning hours from 2:00 a.m. to 8:00 a.m. and mid- to late-afternoon hours from 2:00 p.m. to 6:00 p.m. along with Saturdays and Sundays.

Enforcement contact proportions were generally lower for non-primary (state) roadways. Lower proportions of crashes were consistently observed with higher proportions of enforcement contacts.

No significant differences were found between the electronic citation component (ECCO) and commercial motor vehicle inspections (VSIS) contacts, and their statewide proportions were generally consistent, possibly suggesting that either ECCO or VSIS contacts may be used as a proxy for law enforcement activity.

Implementation Readiness and Benefits

The findings of this research may benefit the areas of heavy-truck design, driver education and licensing, and law enforcement resource allocation. In addition, the findings support education of heavy-truck drivers about the importance of being alert after extended off-duty periods and also susceptibility to fatigue in the morning. Finally, the findings may be used, in part, by law enforcement agencies in developing schedules, establishing enforcement priorities, and monitoring enforcement impacts.

INTRODUCTION

In 2010, 16.5 percent of all fatal vehicle crashes in Iowa involved large trucks compared to the national average of 7.8 percent and averages for similar states of 10.3 percent (South Dakota), 19.7 percent (Nebraska), 12.4 percent (Kansas), and 6.6 percent (Missouri) (NHTSA 2011a). In the same year, heavy vehicles represented only 11.8 percent of the VMT in Iowa, indicating heavy vehicles may be overrepresented in fatal crashes.

Furthermore, between 2006 and 2010 in Iowa, there were on average 74 heavy vehicles involved fatal crashes annually (NHTSA 2011b). Only about 16 percent of these fatalities involved the occupants of the large trucks, meaning that a majority of the fatalities in fatal crashes involve non-heavy-truck occupants (NHTSA 2011b).

These statistics demonstrate the severe nature of heavy-truck crashes and underscores the serious impact that these crashes can have on the traveling public. The statistics presented above also indicate that Iowa may potentially have a disproportionately higher safety risk compared to the rest of the nation and neighboring states (except for Nebraska) with respect to heavy-truck safety. Several national studies, and a few statewide studies, have investigated large-truck crashes; however no rigorous analysis of heavy-truck crashes has been conducted for Iowa. This report uses the most current statewide crash data to perform an in-depth analysis of heavy-truck crashes in Iowa.

The goal of this report is to investigate the causes, locations, and other factors related to heavy-truck crashes in Iowa. Descriptive analysis, statistical tests, and statistical modeling were used to discover what factors contribute to heavy-truck crashes. Findings of this research will be of interest to multiple parties—particularly law enforcement agencies. Law enforcement agencies will be able to utilize this study's results to establish enforcement priorities and make determinations on how to best allocate their limited resources to promote safety and reduce crashes.

As mentioned previously, this report is the first attempt to conduct an in-depth analysis of heavy-truck safety for Iowa. Additionally, no extensive work has been conducted on heavy trucks utilizing the same data set used for this study and as such there is no pre-established definition of what a heavy truck is. The vehicles considered for this analysis were carefully selected. A review of similar studies revealed that the definition of what constitutes a heavy truck is quite variable. A heavy truck could be based on the vehicle's weight, the licensure requirements to operate the vehicle, or the vehicle's department of transportation (DOT) registration. For this analysis, the choice what of constitutes a heavy truck was based solely on configuration as suggested by members of the Iowa Motor Vehicle Enforcement (Iowa MVE) and the Federal Motor Carrier Safety Administration (FMCSA). The vehicles suggested and used in the study include both single-unit and combination trucks. A sample of the vehicles and categories of vehicles considered can be seen in Figure 1 (FMCSA 2005). It should be mentioned that a majority of these vehicles, but not all of these vehicles, require a commercial driver's license (CDL) to operate.

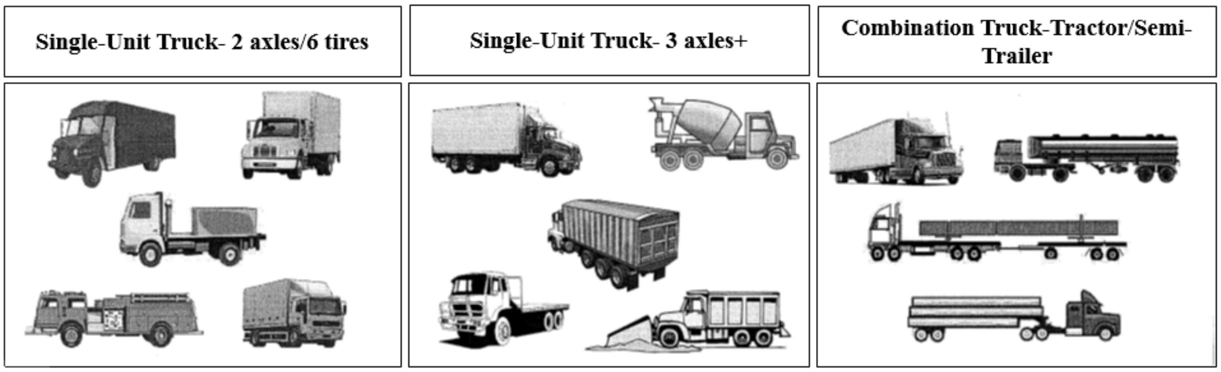


Figure 1. Vehicles considered to be heavy trucks

The data set itself and the sources of the data used for this study should also be defined here. The data used for this study, which will be discussed in greater detail later, comes from law enforcement crash reports and includes information on the driver involved, the vehicle involved, the crash location, the time of the crash, the environmental conditions present at the time of the crash, the severity outcome of the crash, and various other factors related to the crash and its possible causes. It should be noted that some of the information populated in the crash reports is subjective and left to the discretion of the officer completing the crash form. All information included in the crash report is populated after the crash has taken place and is based on the observations of trained law enforcement personnel and the information the law enforcement personnel gather from eyewitnesses.

The remainder of this report is divided into five chapters:

Literature Review provides an overview of past studies related to vehicle and heavy-truck safety. This chapter mainly focuses on various methods of modeling heavy-truck crashes and the results of the various studies reviewed. A review of possible countermeasures is also included in this chapter.

Crash Analysis presents an overview of the crash data obtained for analysis as well as notable estimation results from the crash severity models developed.

Commercial Driver's License Data Analysis offers a look at licensure trends over the most recent five years and attempts to establish a link between licensure information and crash frequency.

Citation and Inspection Analysis compares the characteristics of citation and inspection data to the crash data to identify any similarities or differences among the two data sets.

Conclusions summarizes the finding of the project.

LITERATURE REVIEW

Literature Review Overview

There have been several national-level and state-level studies on commercial motor vehicle (CMV) crash severity. These studies vary in methodology and range from observational/field studies to more rigorous studies involving statistical modeling. From the review of existing literature, it became apparent that traffic crashes are the result of a complex interaction of numerous factors including driver characteristics, vehicle condition/configuration, environmental characteristics, roadway features/geometrics, and traffic characteristics. Additionally, an analysis of countermeasures aimed at improving commercial motor vehicle safety through changes in roadways, vehicles, and enforcement was conducted and reported. A comprehensive overview of the review findings is presented next.

Descriptive Studies of Heavy-Truck Crash Frequency and Severity

The Federal Motor Carrier Safety Administration's (FMCSA) 2006 Report to Congress on the Large Truck Crash Causation Study (FMCSA 2006) outlined and identified factors of large-truck crashes that needed investigation. The study looked at a nationally representative sample of large-truck-involved fatal and injury crashes in the US between 2001 and 2003. Vehicles considered to be large trucks included single-unit trucks (two and three axles) and combination trucks (truck trailers, tractor trailers). The standard, single tractor trailer configuration accounted for more than 60 percent of the trucks included in the study. From the study it was indicated that trucks were at fault in 55 percent of all crashes (single- and multiple-vehicle crashes) and 44 percent of all truck/passenger vehicle crashes. The study also noted that driver- related factors accounted for 87 to 89 percent of the crashes analyzed. The most common factors being traveling too fast for conditions, making an illegal maneuver, legal drug use, unfamiliarity with the roadway, and fatigue. It was noted that fatigue was recorded twice as often for the passenger vehicle driver than for the truck driver. The study also found certain vehicle and roadway characteristics to contribute to large-truck crash occurrence, but such factors were far less common than driver related factors. The most common vehicle-associated factor was brake problems and the most common roadway factor was interruptions in traffic flow. The outcome of the study drew no clear conclusions on the causes of large-truck crashes, but provided a multitude of guidance that was used in many of the studies discussed within the remainder of this literature review.

A study by Blower and Kostyniuk (2007) used 2001-2005 data from the Michigan Vehicle Crash Files, Trucks Involved in Fatal Accidents file (TIFA), the Motor Carrier Management Information System (MCMIS), and the Michigan FACT file to conduct a descriptive study aimed at identifying the issues that contributed most to commercial vehicle crashes, fatalities, and injuries in Michigan. The result of their analysis indicated that numerous factors, ranging from the driver to the roadway to the vehicle and even the location contributed to severe commercial vehicle crashes. It was found that younger driver crashes were more likely to be coded with hazardous actions such as following too closely or speeding. Younger drivers were also found to be more likely to be involved in backing-up crashes than older drivers. It was also noted that in approximately half of the CMV crashes, the hazardous action contributing to the crash was coded for the driver of the other vehicle (non CMV). It was also found that fatigue-related CMV crashes tended to be rear-end and single-vehicle crashes, with most crashes occurring at night on interstate roads between midnight and 6 a.m. Additionally, when all levels of severity were considered, angle crashes, rear-end crashes, head-on crashes, same-direction sideswipes, and single-vehicle crashes tended to, in the order presented, contribute the most to CMV crash costs and harm to society. Vehicle defects and inspection violations were also analyzed by Blower and Kostyniuk. It was noted that lighting and brake violations were the most frequent violations in CMV inspections with both smaller fleet carriers and intrastate carriers tending to have higher violation rates in their inspections. It was also observed that intrastate carriers had more serious violations then did interstate carriers. The results provide no clear solution, but suggest strategies to improve commercial vehicle safety will have to work on many fronts, ranging programs to improve the conditions of the vehicles themselves, to programs educating all drivers sharing the road.

Statistical Modeling of Crash Frequency, Occurrence, and Severity

Crash Frequency and Occurrence Models

Multiple studies have investigated which driver factors contribute to heavy-vehicle crashes. A study by Cantor et al. (2009) applied a Poisson regression model on national CDL and crash data to investigate the relationship between driver characteristics and heavy-vehicle crashes. The results showed that poor driver safety performance (expressed as number of previous crashes), driver out of service violations, driver body mass index, driver gender, driver age, and past employment were significant characteristics in the prediction of heavy-vehicle crash rates. In particular, the model estimated males and drivers under 25 years old to be associated with higher crash rates.

Another study by Park and Jovanis (2010) looked at the effect hours of service and schedules had on the probability of a crash occurring (crash odds). For their study, they collected detailed crash and driving schedule data from three national companies, with varying operations, for a total of 231 crashes. Their primary method of analysis utilized time-dependent logistic regression models to assess the relationship between hours of service/schedule and crash risk. From their models, it was found that the odds of a crash occurring was, indeed, associated with the hours of driving, with particular emphasis placed on times after the sixth hour of driving. With respect to the first hour of driving, the odds of a crash occurring increased by 56 percent after the 6th hour and more that 200 percent after the 10th and 11th hours. The study also found that off duty times of more than 46 hours were associated with an increase in crash risk. These findings are of great interest and provide ample guidance; however, these findings were obtained based on a limited sample size.

A similar study conducted by the U.S. Department of Transportation and the Virginia Tech Transportation Institute (Barr et al. 2011) analyzed driver drowsiness to assess the impact that drowsiness had on commercial motor vehicle driving performance. Their research objectives included characterizing the occurrence of drowsiness and its cause(s); exploring the effects of drowsiness on safe driving performance; and identifying relationships between drowsiness, distraction, and performance. Data were collected as part of a naturalistic field study. Cameras filmed drivers and lane position. A total of 908 hours of video footage was collected and then processed. Drowsiness events observed from the videos were then documented, described, and entered into a data set. Analysis of Variance (ANOVA) tests, stepwise linear regression, and logistic regression were then used to analyze the collected data. Generally, all three of the data analysis methods produced consistent results. Each analysis method showed evidence of a strong correlation between drowsiness and the time of day, with early morning time periods between 6 a.m. and 9 a.m. being particularly problematic. The opposite finding was observed between the hours of 12 p.m. and 3 p.m. when drivers appeared to be alert. These findings indicate that drivers may not be fully refreshed or awake in the early hours of their work shift and special precautions during these hours may be of great aid to the drivers and the traveling public. Drowsiness was also found to be related to age and experience. Younger drivers in the 19-25-year-old age group were found to be nine times more likely to be classified in the "high fatigue" group of drivers. Similarly, inexperienced drivers with less than one year of commercial driving experience were found to be seven times more likely to be grouped in the "high fatigue" category. The results of this study provided some interesting results with important implications especially related to younger and inexperienced drivers.

A study by Blower et al. (2010) used the data and findings from the Large Truck Crash Causation study to examine the relationship between vehicle condition and crash involvement in more detail. More specifically, the study attempted to test two different hypotheses. The first hypothesis tested was that trucks with defects and out of service (OOS) conditions are statistically more likely to be in the role of actuating a crash then trucks with no defects. The second hypothesis tested was that defects in specific systems are associated with crash roles in which those systems are paramount in crash avoidance (a physical mechanism links the vehicle defect to the crash). To test these hypotheses, multiple logistic regression models were developed to show if any statistical association was present. From the models it was found that the critical reason for the crash was mostly associated with driver factors and less likely due to a mechanical defect. Among all mechanical systems, only brakes were shown to be significantly statistically related to the crash cause. More specifically brake adjustment was found to be most significant mechanical defect associated with the cause of a crash. The results of this study, though limited, do identify two key aspects. First, drivers are clearly a critical factor in truck crashes. Second, mechanical conditions do, to a lesser extent than drivers, also play a role in truck crashes with a key emphasis placed on the brake systems.

A study conducted by Giuliano et al. (2009) used both descriptive statistics and statistical modeling to analyze the factors and trends associated with commercial motor vehicle crashes in California. From the descriptive investigation, it was observed that the fewest crashes occur in the winter and early spring (January, February, and April) and crashes peak during the late summer and early fall (August, September, and October). It was also observed that few crashes occur during the late night and early morning, but crash occurrences tended to rise throughout the morning, peak in the early afternoon, and then dramatically reduce in occurrence after 6 p.m. Additionally the researches also noticed a crash pattern by day of the week. The data indicated that crashes tended to be most frequent on Tuesday and Friday and minimal over the weekend. In an effort to gain further insight into the crash phenomenon both a Poisson and a Weighted Least

Squares (WLS) model were developed based on county level data. Both models contained the same variables and reported similar findings. From the models it was interpreted that precipitation, the percentage of elderly residents, and the percentage of foreign born residents were all strongly and significantly related to an increase in the number of crashes. One surprising result of the models was the indication that heavily urbanized areas are actually less dangerous for trucks than more rural areas. The only variables the two models reported different signs for were variables related to road usage and the percentage of young residents. The WLS model indicated that increases in road usage and the proportion of younger residents in the population would lead to an increase in crash frequency, but the opposite relationship was expressed in the Poisson model. However, no conclusions were drawn as to whether one model was preferred to the other.

Crash Severity Models

Binary Models

A study published by the National Center for Statistics and Analysis (Moonesinghe et al. 2003) looked at how the environment and the characteristics of the vehicle impact a truck's propensity to roll over or jackknife in single-vehicle collisions. To conduct the analysis, data from the TIFA survey was used. From the TIFA data a binary logit model was developed to estimate the probability of a large-truck rollover or jackknife. The model's results suggested that a speed limit of 55mph or higher, poor weather, and a curved road all substantially increases the odds of both a rollover or a jackknife occurring. Additionally, it was found that the odds of a rollover increased with increasing the weight of the large truck and cargo, but the odds of a jackknife actually decreased with increasing the weight of the large truck and cargo. However, opposite results were found for increases in truck length. These results are specific to just rollover and jackknife occurrences, but the findings and methodology are still of use in analyzing heavy-vehicle crashes.

Bham et al. (2012) used a multinomial logit (MNL) model to examine the differences in crash contributing factors for six collision types and a binary logit model to identify factors that contribute to crash injury severity (severe and non-severe crashes) for motor vehicles in Arkansas. The multinomial model's estimation results suggested that the risk of a multi-vehicle crash was higher during weekdays while the risk of a single-vehicle collision was higher over the weekend. It was also deduced that single-vehicle collisions were significantly associated with nighttime and wet conditions. The binary logit model of injury severity showed that drivers who did not wear a seatbelt and those under the influence of alcohol were more prone to severe crashes. The binary model also indicated that roadway grades and the presence of curves also increased the severity of crashes. Another notable finding from the binary severity model was that the severity of crashes actually declined under wet roadway conditions, which is likely due to drivers being more attentive and cautious under such conditions.

Ordered Models

Lemp et al. (2011) used both and ordered probit and heteroskedastic ordered probit (HOP) model to study the impact of vehicle, occupant, driver, and environmental characteristics on the injury severity outcome of large-truck crashes. Data used for this study came from the United States' Large Truck Crash Causation Study, General Estimates System, and Vehicle Inventory and Use Survey. Factors, found by both models, to increase the severity outcome of a large-truck crash include multiple-vehicle crashes, multiple occupant vehicles, crash involving more than one truck, and crashes occurring under dark lighting conditions. Generally, both models produced consistent results; however. it was determined that the more flexible HOP model performed significantly better.

A study by Abdel-Aty (2003) used multiple ordered probit models to investigate motor vehicle crash severity for roadway sections, signalized intersections, and toll plazas in Florida. The four levels of severity incorporated in the models were no injury, possible injury, evident injury, and severe/fatal injury crashes. Several factors were common across all the models and those factors were driver age, gender, seatbelt use, vehicle type, point of impact, and speed. From the models developed it was found that elderly drivers, those not wearing seatbelts, and male drivers all have a higher probability of severe injuries. The modeling results also highlight that other factors related to the location of the crash contribute to higher severity levels. Such location specific factors associated with high severity include characteristics such as roadway curves, dark lighting conditions, and rural areas. Other modeling approaches such as multinomial logit models and nested logit models were attempted, but the results of these models were rather poor in comparison to the ordered probit model discussed previously.

A different study by O'Donnell and Connor (1996) utilized both an ordered probit and an ordered logit model to model the relationship between crash severity and the attributes of motor vehicle users in New South Wales, Australia . The study found that higher speeds, high blood alcohol content, older vehicles, and older drivers were highly linked to greater crash severity. It was also found that the vehicle type and vehicle manufacturers (brand) were also significant determinants of crash severity.

A similar study for heavy vehicles conducted by Kockelman and Kweon (2002) also employed an ordered probit model to estimate crash severity. From the model's results, a variety of implications could be drawn. It was determined that the manner of collision, number of vehicles involved, driver gender, vehicle type, and alcohol use all played a significant role in crash severity. The results also corresponded well with the works discussed earlier by O'Donnell and Connor on motor vehicle users.

Unordered Models

Environmental factors such as the weather, the type of roadway, and the area surrounding a roadway also contribute to heavy-vehicle crashes and crash severities. In one study conducted by Khorashadi et al. (2005), heavy-vehicle crash severity was examined in urban and rural areas. This study used a MNL model to model four outcomes of heavy-vehicle crash severity (no injury, complaint of pain, visible injury, and severe/fatal injury) in urban and rural conditions, with severe crashes being more prevalent in rural areas. Their study found some striking differences between the two area types and their respective models. Most notable was that the different models contained different variables. Multiple variables found to be significant in the urban model, turned out to be insignificant in the rural model and vice versa. Additionally, variables shared by both models typically possessed signs of different magnitude and impact. These findings underscore the difference between urban and rural large-truck crash severities and suggest that complex interactions between driver and other measurable environmental factors are playing a significant role in the demands placed on the driver in rural versus urban areas.

Cheng and Mannering (1999) used two nested logit models to determine the influence that certain factors have on the injury severity outcome of both truck and non-truck involved accidents. The data used for the project was for King County in Washington State and included information regarding injury, weather, alcohol use, restraint use, roadway conditions, and factors contributing to the accident. Both the truck and non-truck models were compared for similarities and differences. One variable that was unique to impact trucks was a variable for speeds of 55 mph. The speed variable increased the likelihood of possible injury and injury/fatality outcomes, but was found to be insignificant in the non-truck model, highlighting the critical relationship between speed and truck crash severity. Other variables found to only be significant in the truck model included variables for left or right turns and rear-end crashes. To supplement the comparison between trucks and non-trucks, elasticity's were computed and compared. From the elasticity analysis it was found that the variables common to both models generally had a much larger impact on the outcome of the truck model which underscores the great importance and potential impact of truck safety countermeasures.

Other discrete outcome models such as latent class logit models (LCL) have also shown to be effective. A study by Xie et al. (2012) examined motor vehicle driver severity in rural single-vehicle collisions. For this study researchers created both an MNL and LCL model to analyze the same data set. Both models were run with the same 31 explanatory variables that included information on traffic, roadway geometry, driver characteristics, vehicle characteristics, and environmental characteristics. Variables for driver age, alcohol use, lighting conditions, speed, and ethnicity were all significant variables in the determination of crash severity in both models. It was also noted that the variables in both models were consistent in both the signs and trends of their marginal effects. To further compare the two model types, a prediction experiment was conducted to evaluate the goodness of fit of both models. From the experiment it was determined that the LCL model generated a satisfactory fit and prediction ability, and when compared to the MNL model, the LCL model improved prediction accuracy by 37 percent. This result is encouraging, but the authors suggest additional testing be performed before a conclusion can be drawn on the use of LCL models over MNL models.

Non-parametric modeling methods have also been used to establish a relationship between injury/severity outcome and driver, vehicle, environmental, and roadway conditions. A study conducted by Chang and Chien (2012) used a non-parametric Classification and Regression Tree (CART) model to investigate the factors associated with truck involved crash severity. The benefit of the CART model is that it is not susceptible to the assumption violations and the associated erroneous estimation results that can plague parametric regression models such as

MNL models and ordered regression models. The results of the CART model were comparable to many past studies and, for the most part, reinforce many of the findings already discussed. However, despite the misspecification advantage, the CART model was limited in usefulness. Elasticity's and marginal effects for each injury outcome cannot be calculated from a CART model's output and as such CART models are not able to fully and correctly evaluate the relative impact of each variable in the model.

In summary, a review of the literature clearly shows that statistical modeling is a proven tool capable of analyzing vehicular crashes and the factors that contribute to the crashes themselves. However, once contributing factors are identified, the next challenge becomes implementing practices that can favorably alter these factors. Practices targeted toward improving roadways, vehicles, and enforcement have been developed and show promise at reducing both the occurrence and severity outcome of crashes. An overview of these potential countermeasures follows.

Countermeasures

Roadway Improvements

One strategy for improving truck safety involves making changes to the existing roadway and roadway regulations. In a study conducted by Harwood et al. (2003) researchers used findings from interviews and literature reviews to analyze the interaction between commercial trucks and busses with highway features. The researchers found that traffic control devices and traffic regulations play a significant role in the safe movement of heavy vehicles. In particular, the researches mentioned safety benefits are capable through the use of differential speed limits, lane use restrictions, exclusive lanes, and modified signal timing. The researchers also noted that the increased use of intelligent transportations systems (ITS) has also been of great benefit to improvements in heavy-truck safety. Such ITS systems mentioned were downgrade warning signs, dynamic curve warning systems, and improved weigh stations.

A different report by McMurty et al. (2007) identified some additional roadway design and operations problem areas. Truck's high centers of gravity, longer braking distances, and articulation all contribute to trucks having an increased rollover risk at curves, particularly curves on exit ramps. One countermeasure suggested was truck specific warnings/advisory speeds (both before and during the curve) that incorporate dynamic signing. Vehicles at risk are identified by sensors and dynamic signage is then used to notify the drivers of the impending danger with enough time for corrective measures to be taken. In addition to curves, work zones also present an increased safety risk for heavy vehicles. Some possible work zone countermeasures to consider include rumble stripes, highway advisory radio, and queue detection and warning systems. As with many new technologies there is little work to draw conclusions on effectiveness of any of the improvements mentioned, but none the less there are a multitude of countermeasures available for consideration.

Potter et al. (2013) analyzed heavy-truck crashes in urban areas and identified multiple ITS technologies that could potentially decrease the occurrence of heavy-truck collisions. From crash data it was noticed that a majority of heavy-truck crashes in urban areas were rear-end crashes taking place at intersections. Intersections of interest were then selected and site investigations were conducted to indicate potential causes and identify practical ITS solutions.

Commonly reported infrastructure ITS improvements included the following:

- Activated warning signs for queuing and end of green
- Intersection collision avoidance systems using short range radio
- "Dilemma zone" activated clearance time extension
- Various other vehicle to infrastructure communication systems (speed, rail, clearance, etc.)

Vehicle Improvements

Technological improvements to vehicles have the ability to influence heavy-vehicle safety in two ways:

- Improve the performance of the vehicle (avoid or survive crashes better)
- Improve the performance of the driver

A report by Blower and Woodrooffe (2012) outlines an emerging set of new technologies available to help a driver control their vehicle. One technology under development for large trucks is electronic stability control (ESC). ESC is a technology that helps drivers maintain control and prevent a rollover of the vehicle should the driver lose lateral control and begin to roll. In an effort to reduce rear-end collisions, both forward collision warning (FCW) systems and collision mitigation braking (CMB) systems are also being considered for use in large trucks. If a driver fails to react to a collision, both systems work to alert the driver in an attempt to avoid the collision. The CMB system will actually apply the brakes without input from the driver in an effort to reduce the severity of the crash should the driver not respond to the FCW system. Another system mentioned was the lane departure warning (LDW) system. LDW systems alert a driver should the vehicle inadvertently leave the lane of travel. LDW systems are believed to have the ability to reduce sideswipe crashes as well as reduce crashes resulting from drowsy drivers. In addition to new technologies, improvement of some existing technologies also shows promise. Underride guards presently equipped on trucks in the US are not strong or low enough to be effective and as such, it is suggested that more work be done with respect to new improvements and regulations relating to current underride prevention systems.

Perrin et al. (2007) discussed many other technological improvements on the horizon to improve heavy-vehicle safety. One technology currently under review is the use of electronically controlled braking systems (ECBS). ECBS controls a vehicle's brakes electronically rather than pneumatically. Electronic control of the brakes provides for better response, more precise control, and a better platform to introduce the ESC, FCW, and CMB systems mentioned in the previous report. Other improvements discussed include monitoring the driver and driver behaviors. Most of these systems are conceptual at this point, but the idea is to provide the driver feedback if the driver presents a risky behavior (drowsiness, speeding, tailgating, etc.) and monitor driver hours of service and tendencies in an effort to reduce unsafe behaviors. Preliminary studies in Belgium and the Netherlands showed such systems were capable of reducing crashes by 20 percent, but the issue of intrusion of privacy is a large hurdle to overcome before such technologies are considered for widespread use. Another conceptual technology being considered is the use of wireless communications to support vehicle-to-vehicle and vehicle-to- infrastructure communications in an effort to heighten driver awareness. Details of the possible applications are provided in Table 1.

Table 1. Sample applications of vehicle wireless communications (TRC May 2007)

Public Safety Applications	Private Sector Applications
Vehicle-to-Vehicle Approaching emergency vehicle (warning) Cooperative collision warning Cooperative adaptive cruise control	*All Vehicles* Access control Onboard diagnostic data Repair-service record Vehicle ECU program updates Enhance route planning and guidance
Vehicle-to-Infrastructure Road condition warning Low bridge warning Toll collection Traffic information Green light- optimal speed advisory	*Commercial Motor Vehicles (CMV)* Automated vehicle safety inspections Border clearance information (credentialing) Electronic manifests (hazmat) Unique CVO fleet management applications

Other vehicle improvements mentioned were focused on surviving the crash and protecting the occupants. Many of the technologies discussed for the occupants of the large trucks already exist widely. Many trucks are already equipped with seatbelts and front impact air bags and years of testing has shown both of these mechanisms, when used in conjunction, to be rather effective. The use of side impact airbags is rather new; however, they show promise. Studies in Europe have shown side airbags to be a rather effective means in the prevention of ejection and vehicle rollover.

Further improvements discussed were focused on protecting those in the other, light vehicle(s) involved in the collision with the large truck(s). Such technologies under consideration include front underride prevention improvements (also mention by Blower and Woodrooffe), crash-attenuating front structures, and deflecting front structures. Measures taken to improve front underride are rather simple and include modifying existing frontal structures or creating new frontal structures for trucks that are low enough to ensure the truck’s structure engages the crash absorbing mechanism of the light vehicle. Another means of improving the crash outcome of a collision with a heavy vehicle involve the dissipation of collision energy either through crash attenuation structures or energy deflecting structures. Crash attenuation structures dissipate crash energy by allowing the heavy vehicle to crush, collapse, and absorb a crash’s energy and thus reduce the severity of the injuries sustained by the humans involved in the crash. Energy deflection, on the contrary, uses structures that manage a collision’s energy by deflecting the impacting vehicle through the use of properly designed truck structures. Deflecting a crash’s energy reduces the collision energy absorbed by the light vehicle, which reduces the resulting injury outcomes, but does increase the possibility of a secondary collision. Many of these proposed systems or structures are theoretical, and development and testing is necessary before any definitive conclusions are drawn.

Enforcement

Another alternative counter measure involves modifying enforcement practices. A study by Strathman et al. (2010) looked to identify program strategies and practices that could potentially be implemented by the Oregon Department of Transportation Motor Carrier Transportation Division in an effort to reduce commercial motor vehicle crashes. To conduct their study, a cluster analysis was implemented to establish peer states with geographic, development, travel, and safety enforcement conditions similar to those found in Oregon. Once peer states were established, structured interviews of each state's Motor Carrier Safety Assistance Program representative were conducted. The states included in the study were Oregon, Colorado, Michigan, Minnesota, Nevada, Washington, Kentucky, and Florida. From the peer interviews a multitude of suggestions were compiled and reported. Though protocols for conducting driver and vehicle inspections are fixed, the interviews did offer some tactics that benefit the effectiveness of inspection activities:

- Having troopers prepare their own regional safety plans
- Placing special enforcement in places where there are no inspection/weigh stations
- Increasing the number of inspectors by using the private sector (e.g., truck repair businesses)
- Using aircraft to spot trucks attempting to bypass stops

The interviews also supplied additional useful tactics with respect to traffic enforcement practices, some of the findings are listed below:

- Joining top performing troopers with inspectors
- Targeting high-risk highway segments
- Using data tools to identify at risk drivers
- Patrolling in unmarked vehicles to identify unsafe automobile drivers around commercial vehicles

Additionally, the interviews also revealed various tactics to improve the overall effectiveness of compliance reviews:

- Extending compliance reviews to intrastate carriers
- Maintaining the training of inspectors
- Focusing on "at risk" carriers identified by the Federal Motor Carrier Safety Administration

Relocating enforcement efforts also has the potential to impact road safety. Huges (2000) conducted a study in North Carolina to evaluate a change in enforcement practices and a reallocation of efforts. Between the years of 1998 and 1999, the North Carolina Department of Transportation identified 21 counties as having the most truck involved crashes and as such reallocated and increased CMV enforcement in those 21 targeted counties. The increased CMV enforcement consisted of an increase in roadside inspections, an increase in driver and vehicle out of service violations, an increase in CDL citations, and an increase in public education efforts. The product of these combined efforts produced a 17.7 percent reduction in fatal truck involved crashes for the 21 county area and a 5 percent decrease in truck involved crashes statewide between the years of 1998 and 1999. Counties outside the 21 target counties actually saw a 7.6 percent increase in heavy-vehicle-involved fatal crashes which highlights the resource dependent nature of CMV enforcement practices and underscores a need for improvements geared toward offsetting manpower and personnel limitations. The study suggests that improvements through a systematic reallocation of enforcement efforts is possible; however, other methods of improvement should also be considered in the future to ensure available resources are optimally utilized.

McCartt et al. (2007) offered even more suggestions for advancing enforcement techniques. For the most part, the suggestions presented focused on compliance programs and a select list of those suggestions is presented below.

- Identifying and focusing on problematic carriers and drivers with relatively poor safety records
- Building databases to support problem identification
- Increasing oversight of new drivers and carriers
- Electronic screening bypass systems that allow qualifying carriers, vehicles, and drivers to bypass weigh stations, port-of-entry facilities, and roadside inspections
- Automated vehicle performance monitoring (i.e., brakes, tires)

A related study by Lucke (1999) used a team of federal, state and industry representatives to survey and assesses the effectiveness and uniformity of roadside vehicle inspections in the US. Site visits took place in seven states: Illinois, Arizona, California, Tennessee, Connecticut, Minnesota, and West Virginia. From these site visits observations were reported and best practices were then identified by the project team. Overall, the team found that a majority of the inspections observed to be uniformly conducted from state-to-state and some of the best practices the team found were:

- Use of an inspector evaluation process that focuses on the quality rather than quantity of inspections.
- Working with seasonal carriers during their off season to inspect their vehicles thoroughly.
- More outreach programs to make both the commercial vehicle industry and the general public more aware of commercial vehicle safety.
- Further utilization of technology to permit both the entry and access to real-time commercial vehicle information.
- Requiring drivers placed out of service to sign a form that explains the penalties of an out-of-service order and that they are aware of these penalties.

The best practices identified by Lucke, though broadly detailed, do offer areas for enforcement agencies to focus on and possibly re-evaluate their current practices. This concludes the discussion on countermeasures. A summary and synthesis of all the findings presented throughout the literature review follows.

Literature Review Summary

Traffic crashes are the result of a complex interaction of numerous factors. One pattern consistently noticed in a review of past studies was that factors relating to the drivers of both large trucks and other vehicles appear to play a disproportionally large role in crash occurrence. Of all the driver factors considered, age, experience, and behavior (speeding, following too closely, etc.) tended to be the most common and most statistically significant factors. Other variables such as gender, physical condition, and ethnicity, though pertinent in some studies, gave mixed and varying results.

Location, environmental, and mechanical factors appear to also contribute to crash occurrence, but to a much lesser extent than driver-related variables. Numerous studies indicated lighting and brake defects to be common mechanical defects on large trucks, with brake defects actually showing a significant correlation to crash occurrence. Other vehicle factors noted to be significant by other studies include vehicle age, load characteristics (weight and length), and carrier type (small/large, interstate/intrastate, long haul/short haul).

Significant spatial and temporal factors were also revealed by past works. Severe heavy-vehicle crashes were found to be more likely to occur in rural areas, at night/dark light conditions, at early times of the day, during peak traffic hours, and on curves. Precipitation, though likely to increase crash frequency, was not found to be associated with severe crashes. This finding is likely attributed to drivers being more cautious during adverse weather conditions.

Also discussed was the current and future countermeasures the transportation industry is considering or should consider implementing to improve heavy-truck safety. Countermeasures mentioned relate to improving driver performance, vehicle performance, roadway ease of use, and enforcement techniques. A majority of the improvements for drivers focused on identifying drowsiness, improving reaction time, and monitoring driving schedules. Improvements to vehicles were concentrated mostly on improving a vehicle’s stability and braking efficiency. Other suggestions were directed toward adaptations of enforcement methods and were rather ubiquitous. Some improvement measures suggested were targeted enforcement, mandated preventive maintenance programs, strengthened CDL programs, and increased campaigns to broaden public understanding of the hazards associated with heavy vehicles in the traffic stream.

This concludes the discussion on the literature reviewed for this report. The results of the crash analysis, both summary statistics and model estimates, are presented next.

CRASH ANALYSIS

Data Overview/Summary Statistics

Heavy-truck crash data were obtained through the Iowa Traffic Safety Data Service (ITSDS) at the Institute for Transportation (InTrans) at Iowa State University. The data are a collection of crash reports completed by state and local law enforcement agencies that are aggregated by the Iowa DOT before becoming available at the ITSDS. The crash data consists of crash, vehicle, driver, and passenger-level characteristics of all vehicles involved in reported fatal, major injury, minor injury, possible injury, and property damage only (PDO) crashes in Iowa from 2002 through 2012. To gain a better understanding of the current nature of heavy-truck crashes in Iowa, it was desired to use the most recent data available; however, the 2012 data, in particular, were recent enough that imperfections and missing information were of concern. In an effort to balance the effect of these possible imperfections a six-year analysis period (2007 through 2012) was chosen over the more traditional five-year analysis period. Appendix A: Summary Statistics of Select Variables provides a comprehensive overview of the crash data by number of vehicles involved (single- versus multiple-vehicle crash).

Heavy-Truck Crash Distribution

Table 2 shows that the majority of the crashes analyzed involved a standard semi/tractor trailer combination-truck while single-unit trucks accounted for less than 35 percent the heavy trucks analyzed.

Table 2. Heavy-truck crash distribution 2007 through 2012

Vehicle Description	Number in Crashes	Percentage in Crashes
Single-Unit Trucks	**8,735**	**34.9%**
Single-Unit Truck (2-axle/6-tire)	5,732	22.9%
Single-Unit Truck (>= 3 axles)	3,003	12.0%
Combination Trucks	**16,268**	**65.1%**
Truck/Trailer	1,669	6.68%
Truck Tractor (bobtail)	270	1.08%
Tractor/Semi-trailer	13,789	55.1%
Tractor/Doubles	264	1.06%
Tractor/Triples	11	0.04%
Other Heavy Truck (cannot classify)	265	1.06%
All Heavy Trucks	**25,003**	**100%**

All crashes and all vehicles involved in a crash with a heavy truck, as identified in Table 2, from 2007 through 2012 were extracted for a total of 23,538 crashes involving 25,003 heavy trucks and 18,414 other vehicles. The distribution of the other vehicles involved in a crash with a heavy truck can be seen in Table 3.

Table 3. Non-heavy-truck crash distribution 2007 through 2012

Vehicle Description	Number of Vehicles in Crashes	Percentage of Vehicles in Crashes
Small Passenger Vehicle	**17,851**	**96.94**
Passenger Car	10,315	56.02
Four-Tire Light Truck	3,262	17.71
Van or Mini-Van	1,716	9.32
SUV	2,558	13.89
Recreational Vehicle	**129**	**0.70**
Motor Home	34	0.18
Motorcycle	82	0.45
Moped/All-Terrain Vehicle	13	0.07
Bus	**83**	**0.45**
School Bus (>15 seats)	30	0.16
Small School Bus (9-15 seats)	3	0.02
Other Bus (>15 seats)	41	0.22
Other Small Bus (9-15 seats)	9	0.05
Other Vehicle Type	**351**	**1.91**
Farm Vehicle/Equipment	143	0.78
Maintenance/Construction Vehicle	28	0.15
Train	55	0.30
Not Reported	79	0.43
Unknown	46	0.25
All Non-Heavy Trucks	**18,414**	**100**

More than 96 percent of the non-heavy-truck vehicles in a collision involving a heavy truck involve some type of a small passenger vehicle, with more than half of the collisions involving a passenger car.

Descriptive Analysis

Crash Characteristics

The manner in which a crash occurs, as well as and the number and type of vehicles involved, are significant determinants of the severity outcome of a crash. A distribution of crash severity and vehicle involvement is shown in Figure 2.

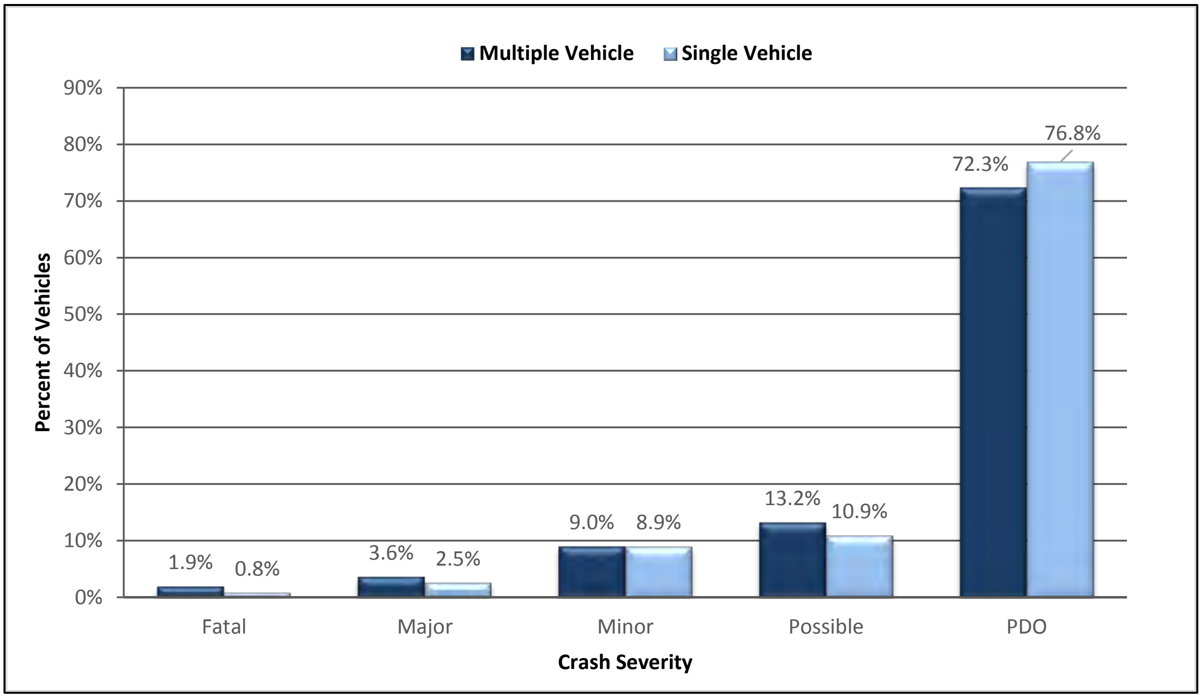


Figure 2. Severity distribution of single- and multiple-vehicle crashes 2007 through 2012

Both multiple- and single-vehicle crashes show a similar distribution by severity with more severe outcomes being slightly more prevalent in multiple-vehicle crashes.

Though the severity distribution is similar, multiple- and single-vehicle crashes are quite different with respect to many other crash-specific characteristics. With multiple-vehicle crashes there is much greater diversity in the manner in which vehicles collide, as can be seen by comparing Figure 3 to Figure 4

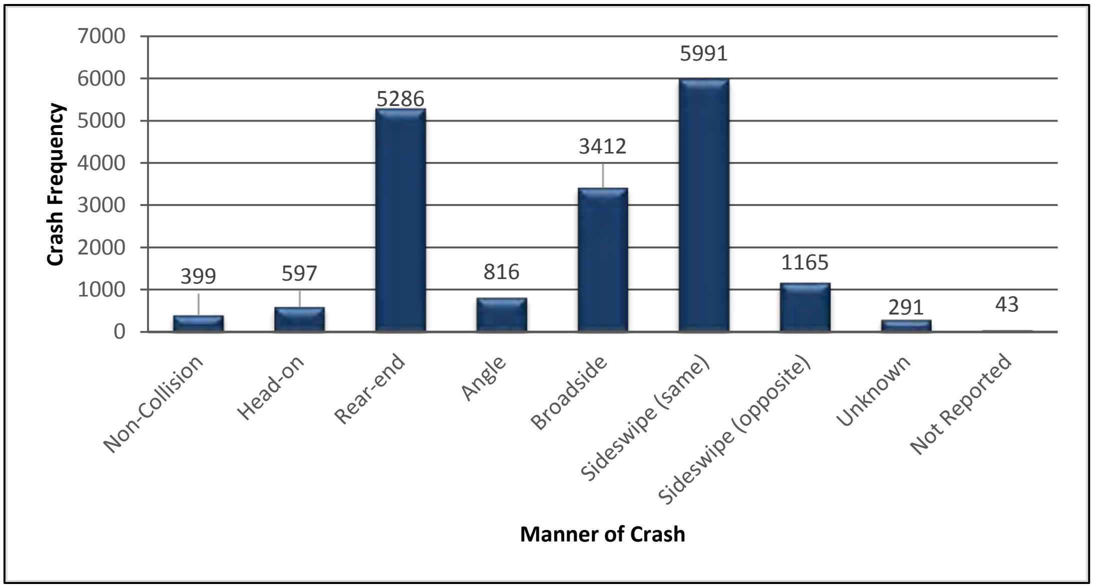


Figure 3. Multiple-vehicle crashes: manner of crash frequency distribution 2007 through 2012

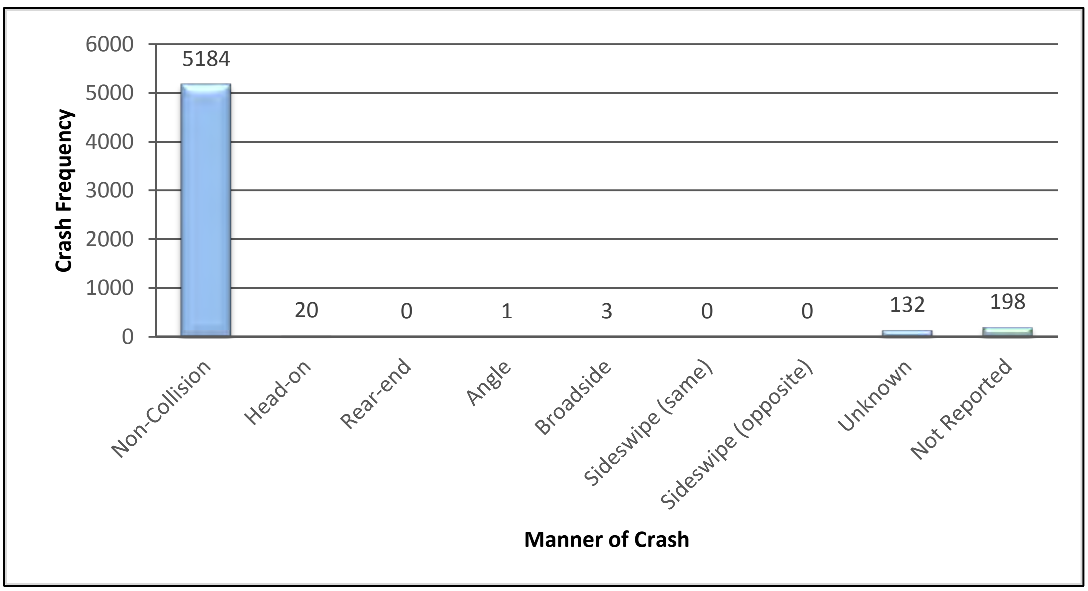


Figure 4. Single-vehicle crashes: manner of crash frequency distribution 2007 through 2012

Sideswipe, rear-end, and broadside crashes tend to be the most common manner of collision for multiple-vehicle crashes, while single-vehicle crashes are almost exclusively non-collision events.

The most harmful event of a heavy-truck crash is also likely to be highly related to the severity outcome of the crash. Figure 5 and Figure 6 show the distribution of the most harmful event reported in multiple- and single-vehicle crashes, respectively.

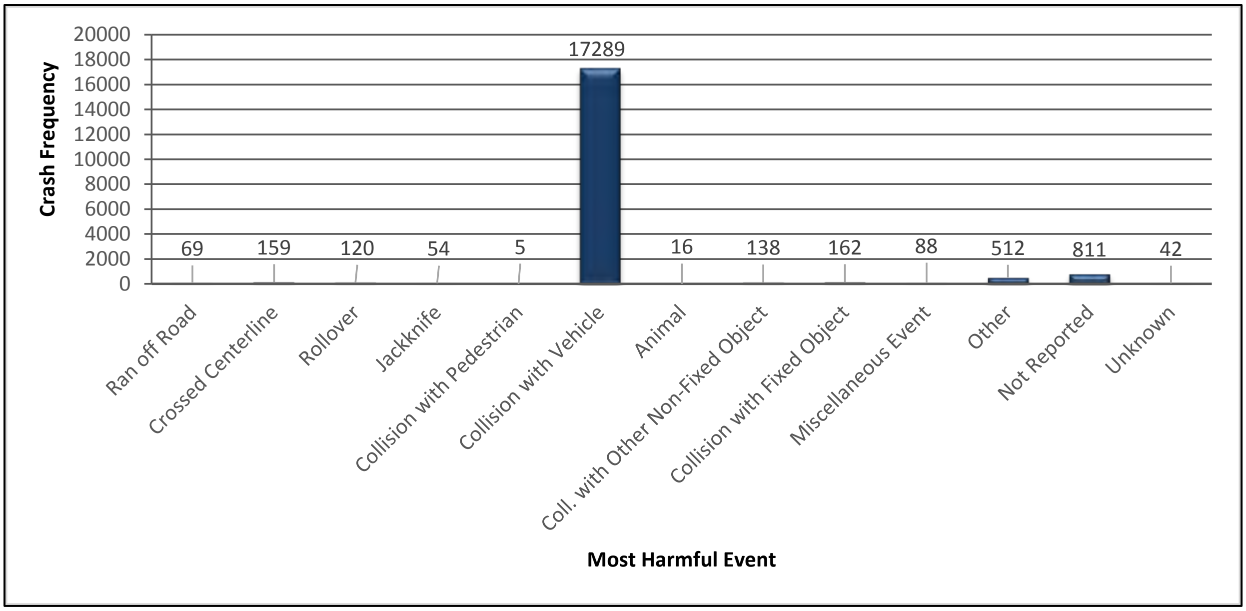


Figure 5. Multiple-vehicle crashes: most harmful event frequency distribution 2007 through 2012

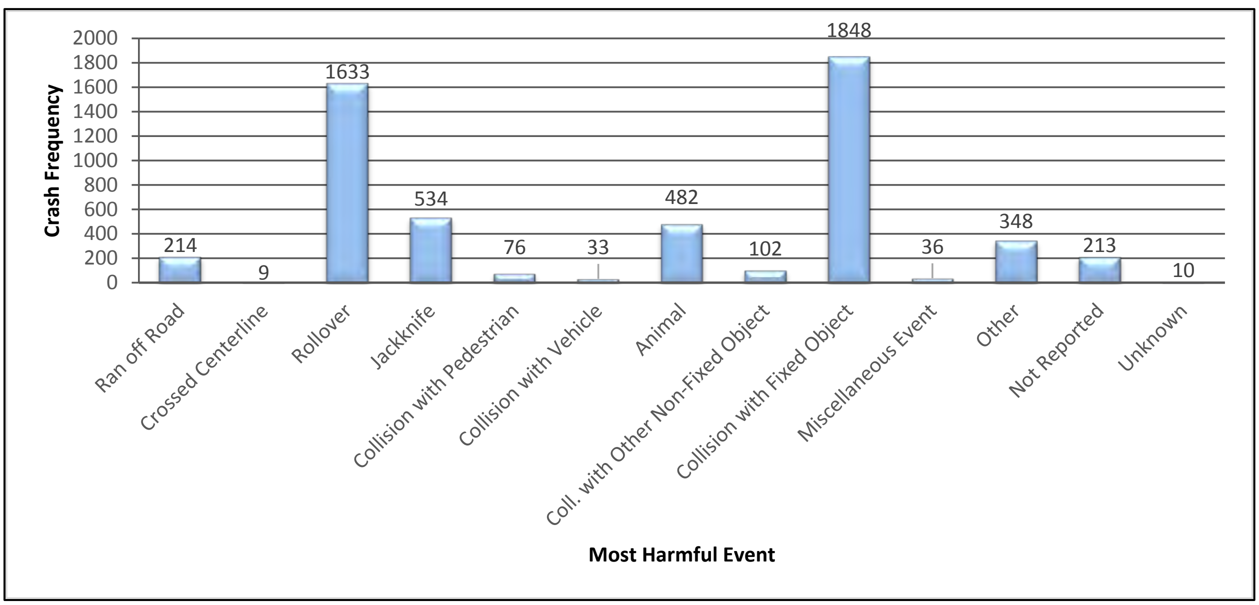


Figure 6. Single-vehicle crashes: most harmful event frequency distribution 2007 through 2012

For multiple-vehicle collisions the most harmful event is predominately a collision with another vehicle, while for single-vehicle collisions the most harmful event is rather variable, with collisions with fixed objects, rollovers, jackknifes, and collisions with animals occurring the most frequently.

Driver Characteristics

As mentioned in the literature review, driver-related factors are commonly cited as the major cause of the crash and, as such, a desirable attribute to examine. The data set used for analysis included information on heavy-truck and non-heavy-truck driver age, gender, condition, crash contributing action, and state of licensure. The age distribution of heavy-truck drivers involved in a single- and multiple-vehicle crashes is similar, with younger drivers appearing to be slightly more involved in single-vehicle crashes than multiple-vehicle crashes, as can be seen in Figure 7.

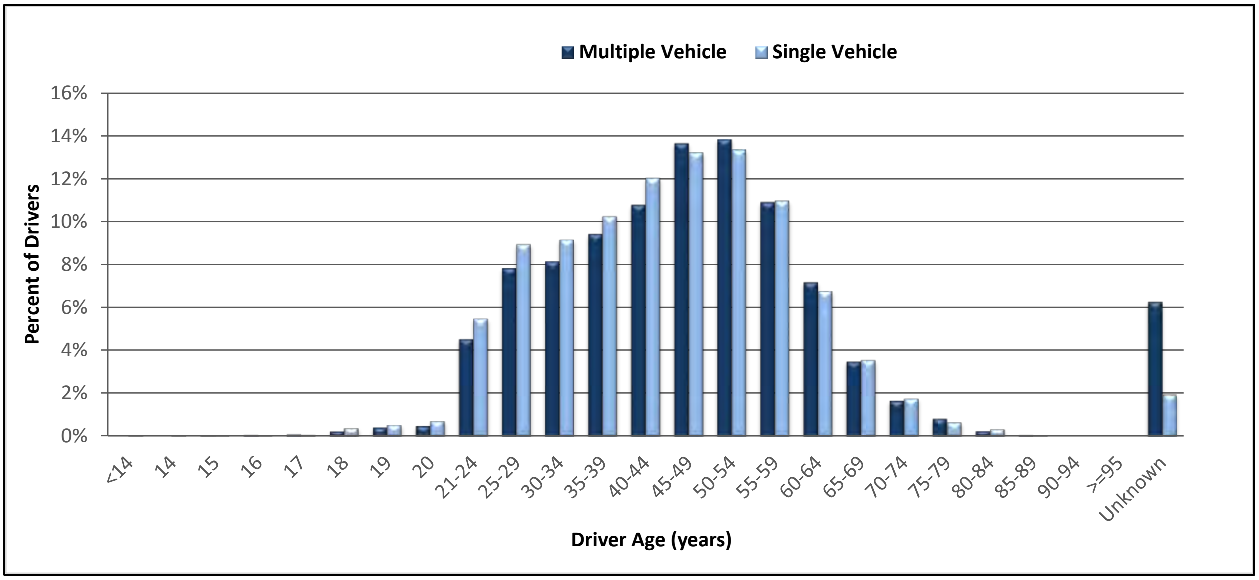


Figure 7. Heavy-truck driver age distribution in multiple- and single-vehicle crashes 2007 through 2012

This observation was also verified by a test of proportions ($p < 0.05$), with the significance tested using the z-statistic for a standard normal random variable. The test of proportions was used because the frequency of crashes was greater than five, and the two population proportions being compared were independent. The results of this test indicated that drivers from 20 to 34 years old were proportionally higher in single-vehicle crashes. Trends and differences in the age distribution of heavy-truck drivers in crashes and the age distribution of all heavy-truck drivers in the population were also analyzed. Information on the age of all heavy-truck drivers in Iowa was not readily available, so, as a substitute, the age distribution of drivers getting their CDL renewed from 2008 through 2012 was used to represent the heavy-truck driver population. The approximate age distribution of the heavy-truck driver population and heavy-truck drivers in crashes can be seen in Figure 8.

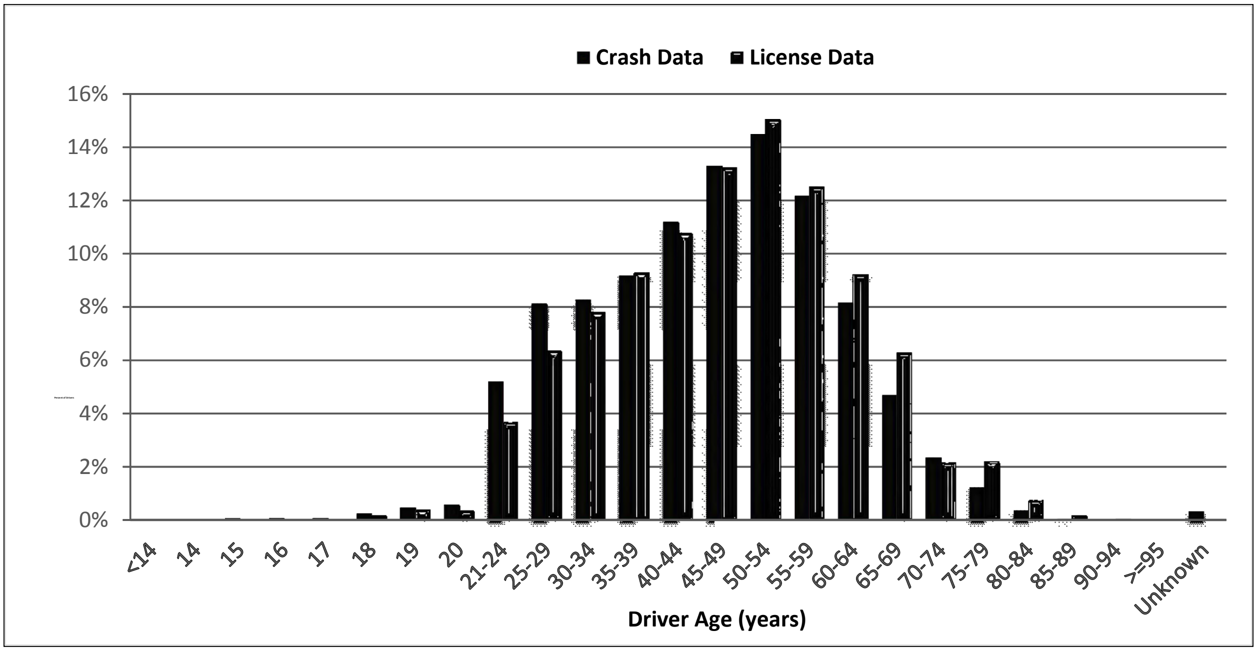


Figure 8. Heavy-truck driver age distribution for drivers in crashes and drivers renewing their CDLs 2008 through 2012 (Licensure data obtained through Iowa Motor Vehicle Enforcement)

For a fair comparison between the CDL data and the crash data, only drivers licensed in Iowa and operating vehicles that require a CDL (all combination trucks) were used for comparison purposes. From the figure one can see that younger drivers appear proportionally higher in crashes. This observation was also verified by a test of proportions ($p < 0.01$), indicating that drivers under the age of 30 were, indeed, proportionally higher in crashes.

Both the gender and age distribution of heavy-truck and non-heavy-truck drivers varies greatly. As can be seen in Figure 9, more than 90 percent of the heavy-truck drivers in crashes are male, while the gender split of the non-heavy-truck drivers is close to even.

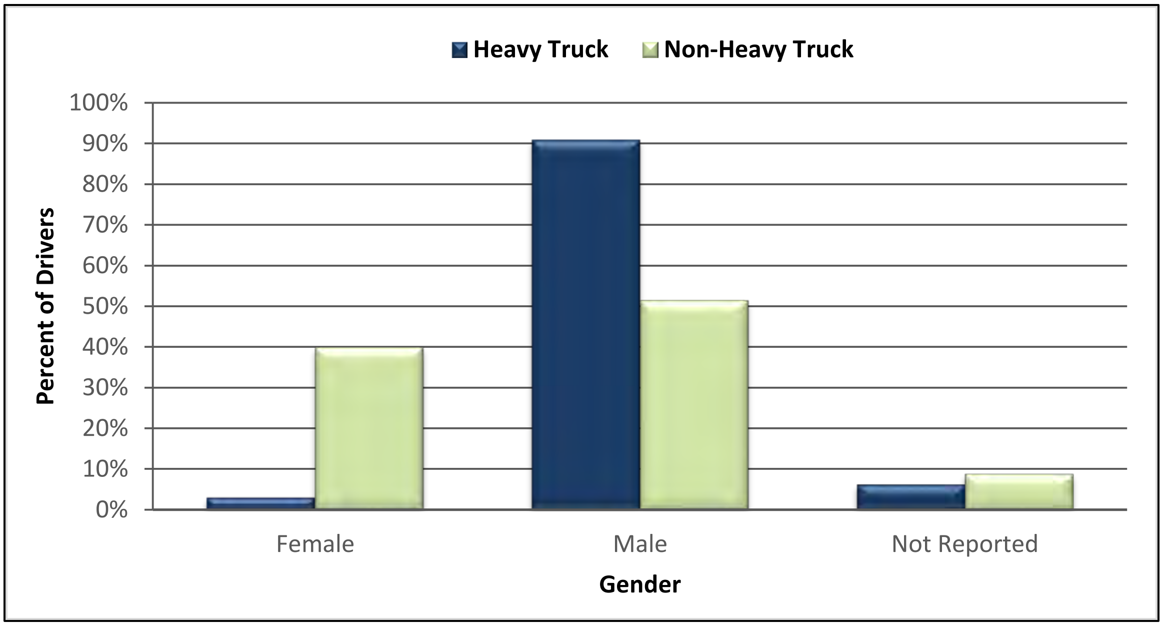


Figure 9. Heavy- and non-heavy-truck driver gender distribution 2007 through 2012

The approximate gender distribution of heavy-truck drivers renewing their license and heavy-truck drivers in crashes between 2008 and 2012 can be seen in Figure 10.

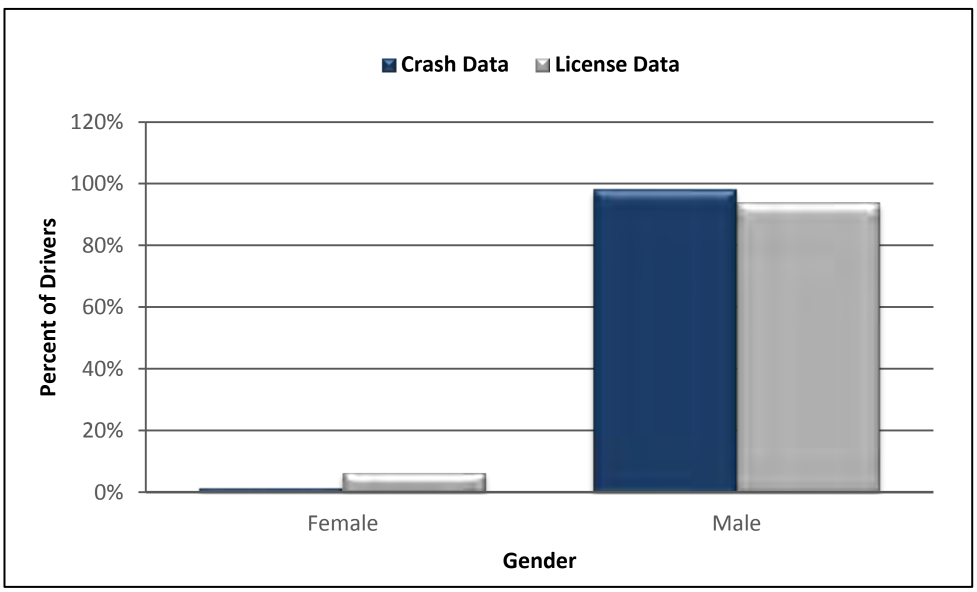


Figure 10. Heavy-truck driver gender distribution for drivers in crashes and drivers renewing their CDLs 2008 through 2012 (Licensure data obtained through Iowa Motor Vehicle Enforcement)

Again, for a fair comparison between the CDL data and the crash data, only drivers licensed in Iowa and operating vehicles that require a CDL (all combination trucks) were used for comparison purposes. The figure shows that the gender distribution of drivers in crashes and drivers renewing their license is similar with males appearing to be proportionally higher in crashes as also verified by a test of proportions ($p < 0.01$).

The age distribution of heavy- and non-heavy-truck drivers is also dissimilar and can be seen Figure 11.

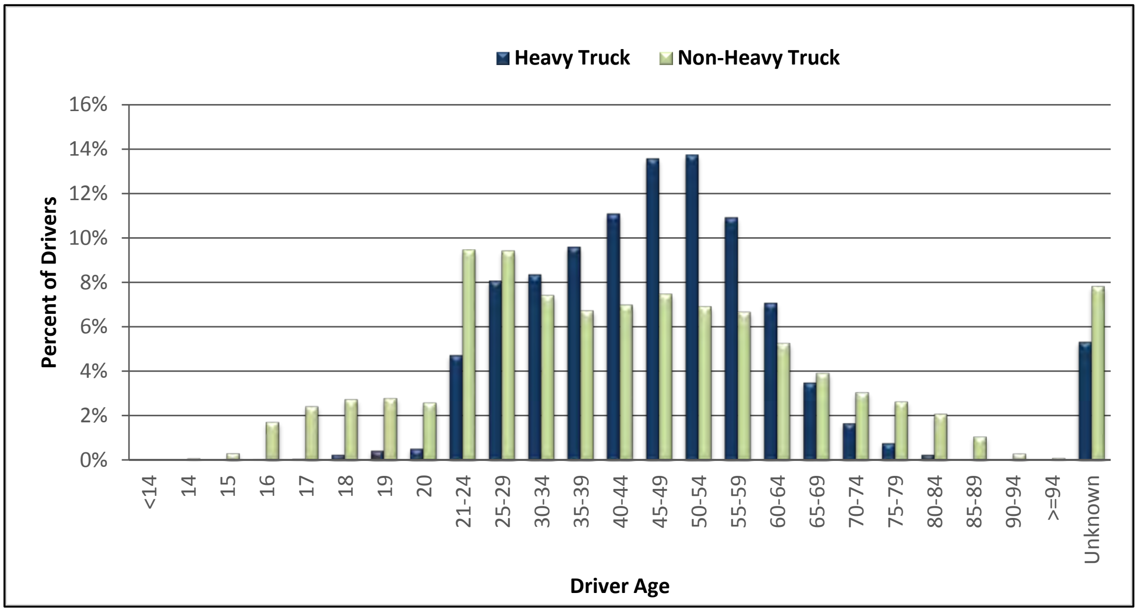


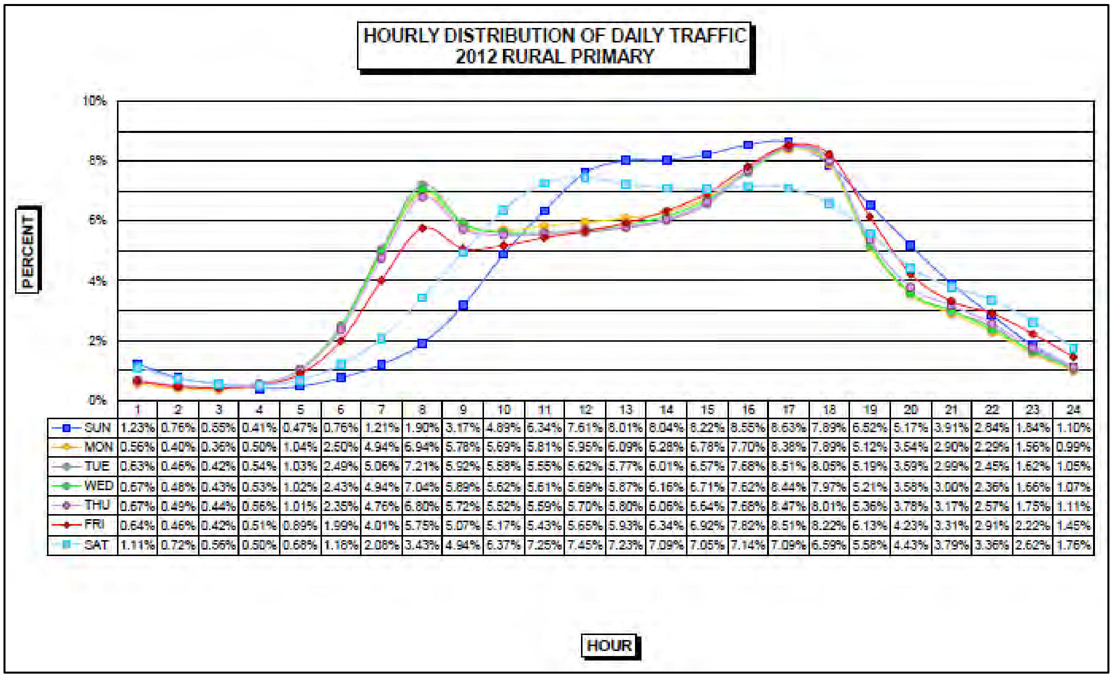
Figure 11. Heavy- and non-heavy-truck driver age distribution 2007 through 2012

Non-heavy-truck driver age distribution is widely dispersed with greater representation in both older and younger age groups, when compared to the heavy-truck driver age distribution. Heavy-truck driver age distribution is far more concentrated than non-heavy-truck driver age distribution, with a majority heavy-truck drivers being middle-aged.

Other driver specific attributes of interest such as alcohol use, drug use, and distraction were reported in such low frequency that it is of little benefit to report such occurrences and attempt to discern a relationship to crash occurrence or crash severity. The temporal and spatial characteristics of heavy-truck crashes are discussed next.

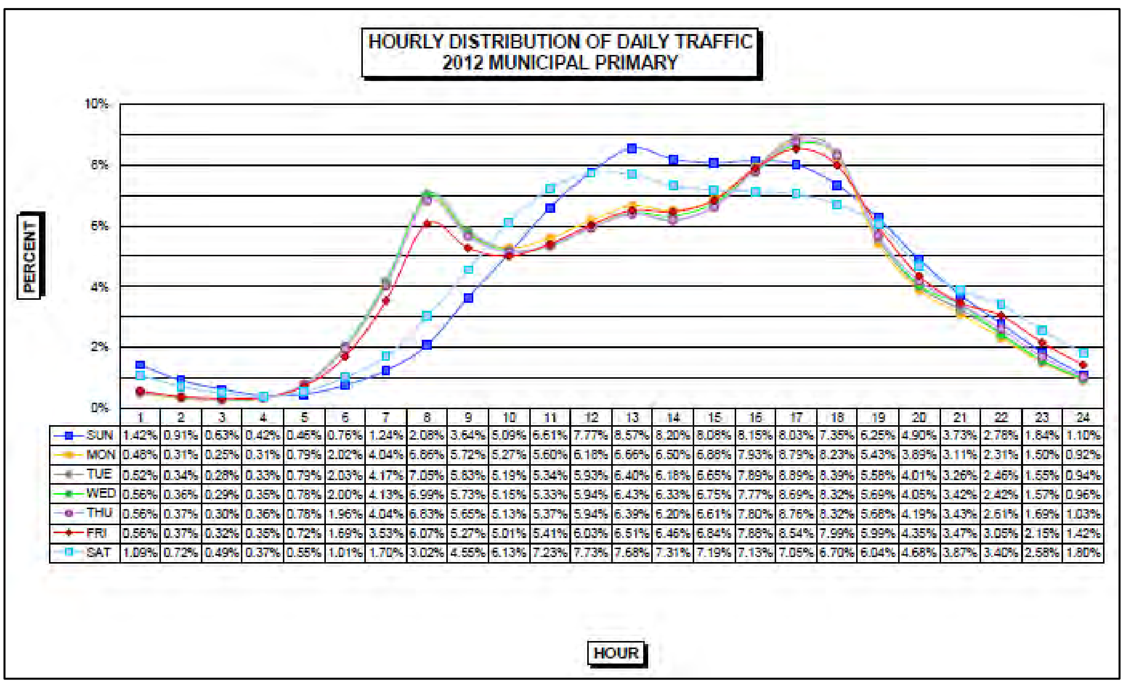
Time and Location Characteristics

The time and location at which crashes occur is of great importance in the development of appropriate countermeasures. Insight into temporal and spatial trends is also necessary to fully assess safety in a region or associated with a specific demographic group. Traffic on Iowa roadways follows a temporal pattern, with traffic peaking on weekdays during the morning, afternoon, and evening peak hours as can be seen in Figure 12 and Figure 13.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
SUN	1.23%	0.76%	0.55%	0.41%	0.47%	0.76%	1.21%	1.90%	3.17%	4.89%	6.34%	7.61%	8.01%	8.04%	8.22%	8.55%	8.63%	7.89%	6.52%	5.17%	3.91%	2.84%	1.84%	1.10%
MON	0.56%	0.40%	0.36%	0.50%	1.04%	2.50%	4.94%	6.94%	5.78%	5.69%	5.81%	5.95%	6.09%	6.28%	6.78%	7.70%	8.38%	7.89%	5.12%	3.54%	2.90%	2.29%	1.56%	0.99%
TUE	0.63%	0.46%	0.42%	0.54%	1.03%	2.49%	5.06%	7.21%	5.92%	5.58%	5.55%	5.62%	5.77%	6.01%	6.57%	7.68%	8.51%	8.05%	5.19%	3.59%	2.99%	2.45%	1.62%	1.05%
WED	0.67%	0.48%	0.43%	0.53%	1.02%	2.43%	4.94%	7.04%	5.89%	5.62%	5.61%	5.69%	5.87%	6.16%	6.71%	7.62%	8.44%	7.97%	5.21%	3.58%	3.00%	2.36%	1.66%	1.07%
THU	0.67%	0.49%	0.44%	0.56%	1.01%	2.35%	4.76%	6.80%	5.72%	5.52%	5.59%	5.70%	5.80%	6.06%	6.64%	7.68%	8.47%	8.01%	5.36%	3.78%	3.17%	2.57%	1.75%	1.11%
FRI	0.64%	0.46%	0.42%	0.51%	0.89%	1.99%	4.01%	5.75%	5.07%	5.17%	5.43%	5.65%	5.93%	6.34%	6.92%	7.82%	8.51%	8.22%	6.13%	4.23%	3.31%	2.91%	2.22%	1.45%
SAT	1.11%	0.72%	0.56%	0.50%	0.68%	1.16%	2.08%	3.43%	4.94%	6.37%	7.25%	7.45%	7.23%	7.09%	7.05%	7.14%	7.09%	6.59%	5.58%	4.43%	3.79%	3.36%	2.62%	1.76%

Figure 12. 2012 VMT by time of day for rural primary roads in Iowa (Iowa DOT Automatic Traffic Recorder Yearly Report for 2012)



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
SUN	1.42%	0.91%	0.63%	0.42%	0.46%	0.76%	1.24%	2.08%	3.64%	5.09%	6.61%	7.77%	8.57%	8.20%	8.08%	8.15%	8.03%	7.35%	6.25%	4.90%	3.73%	2.78%	1.84%	1.10%
MON	0.48%	0.31%	0.25%	0.31%	0.79%	2.02%	4.04%	6.86%	5.72%	5.27%	5.60%	6.18%	6.66%	6.50%	6.88%	7.93%	8.79%	8.23%	5.43%	3.89%	3.11%	2.31%	1.50%	0.92%
TUE	0.52%	0.34%	0.28%	0.33%	0.79%	2.03%	4.17%	7.05%	5.83%	5.19%	5.34%	5.93%	6.40%	6.18%	6.65%	7.89%	8.89%	8.39%	5.58%	4.01%	3.26%	2.46%	1.55%	0.94%
WED	0.56%	0.36%	0.29%	0.35%	0.78%	2.00%	4.13%	6.99%	5.73%	5.15%	5.33%	5.94%	6.43%	6.33%	6.75%	7.77%	8.69%	8.32%	5.69%	4.05%	3.42%	2.42%	1.57%	0.96%
THU	0.56%	0.37%	0.30%	0.36%	0.78%	1.96%	4.04%	6.83%	5.65%	5.13%	5.37%	5.94%	6.39%	6.20%	6.61%	7.80%	8.76%	8.32%	5.68%	4.19%	3.43%	2.61%	1.69%	1.03%
FRI	0.56%	0.37%	0.32%	0.35%	0.72%	1.69%	3.53%	6.07%	5.27%	5.01%	5.41%	6.03%	6.51%	6.46%	6.84%	7.88%	8.54%	7.99%	5.99%	4.35%	3.47%	3.05%	2.15%	1.42%
SAT	1.09%	0.72%	0.49%	0.37%	0.55%	1.01%	1.70%	3.02%	4.55%	6.13%	7.23%	7.73%	7.68%	7.31%	7.19%	7.13%	7.05%	6.70%	6.04%	4.68%	3.87%	3.40%	2.58%	1.80%

Figure 13. 2012 VMT by time of day for municipal primary roads in Iowa (Iowa DOT Automatic Traffic Recorder Yearly Report for 2012)

During these peak times of the day the exposure to other vehicles on the roadway is the greatest. As the exposure increases so to should the likelihood of a collision. This trend in exposure needs to be taken into account when interpreting any trends noticed in the data.

Figure 14 and Figure 15 show the hourly distribution of multiple- and single-vehicle heavy-truck crashes, respectively.

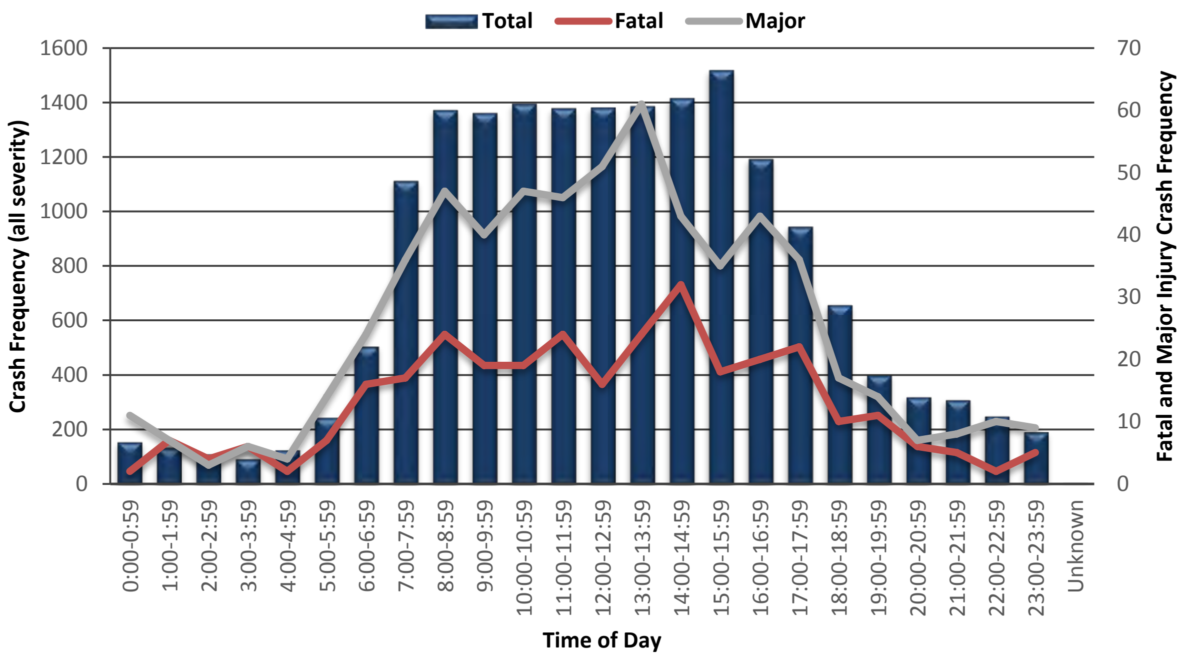


Figure 14. Multiple-vehicle crash frequency versus time of day 2007 through 2012

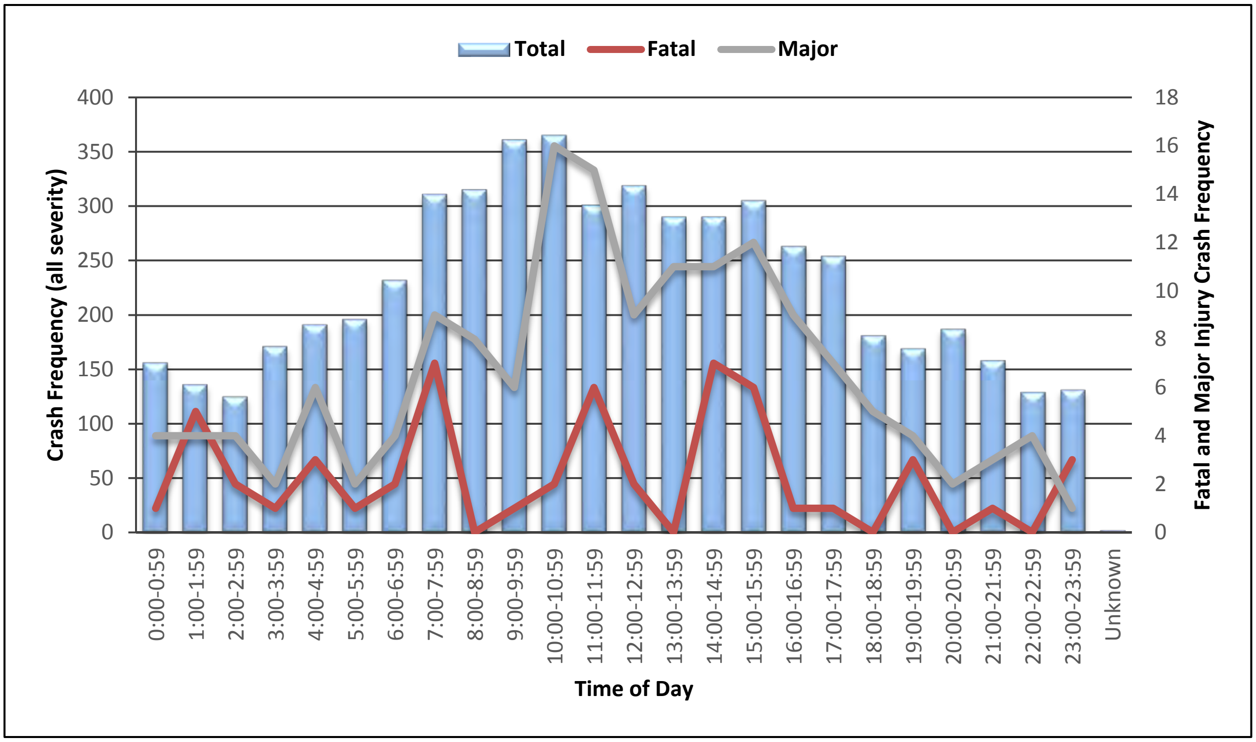


Figure 15. Single-vehicle crash frequency versus time of day 2007 through 2012

Typically, one would expect the frequency of vehicular crashes to be highest during peak traffic hours, with peaks in the morning, afternoon, and evening as shown in Figure 12 and Figure 13. Multiple-vehicle heavy-truck crashes appear to peak throughout the daylight hours between 7 a.m. and 5 p.m., with the frequency of crashes remaining consistent throughout the day, aside from a slight peak in the late afternoon. Single-vehicle heavy-truck crash frequency is less stable, with the crash frequency peaking throughout the morning peak hours, and varying throughout the remainder of the 24-hour cycle. Also, single-vehicle crashes do not display the same level of concentration of crashes around the workday, as is observed for multiple-vehicle crashes. Figure 14 and Figure 15 also display individual heavy-truck crash severity outcomes versus the time of day.

It can be observed that severe, multiple-vehicle crashes, such as fatal and major injury crashes, appear to steadily increase in frequency throughout the day with a prominent peak during afternoon before frequency then declines. Figure 15 shows that severe, crash occurrence is highly irregular throughout the day, with discernable peaks occurring in the morning, afternoon, and early evening, with the late morning peak being the most prominent.

Individual days of the week were also taken into consideration. Multiple-vehicle and single-vehicle crash frequency and their relation to the days of the week can be seen in Figure 16 and Figure 17, respectively.

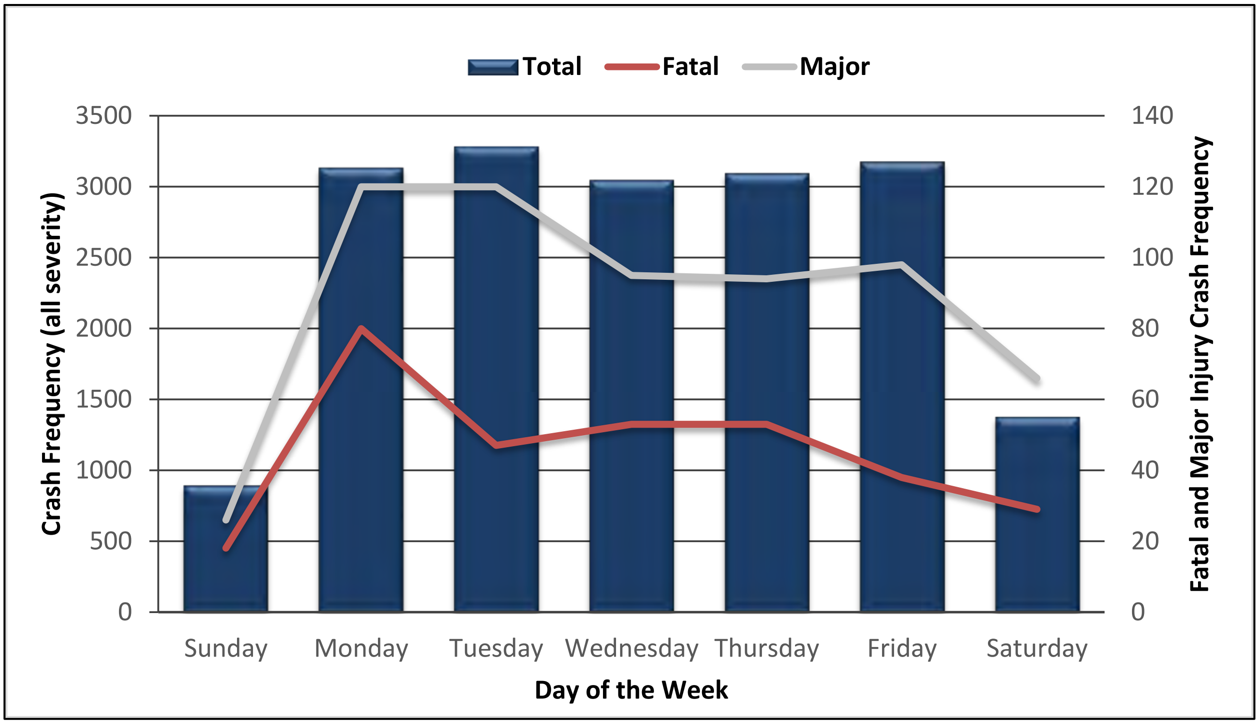


Figure 16. Multiple-vehicle crash frequency versus day of the week 2007 through 2012

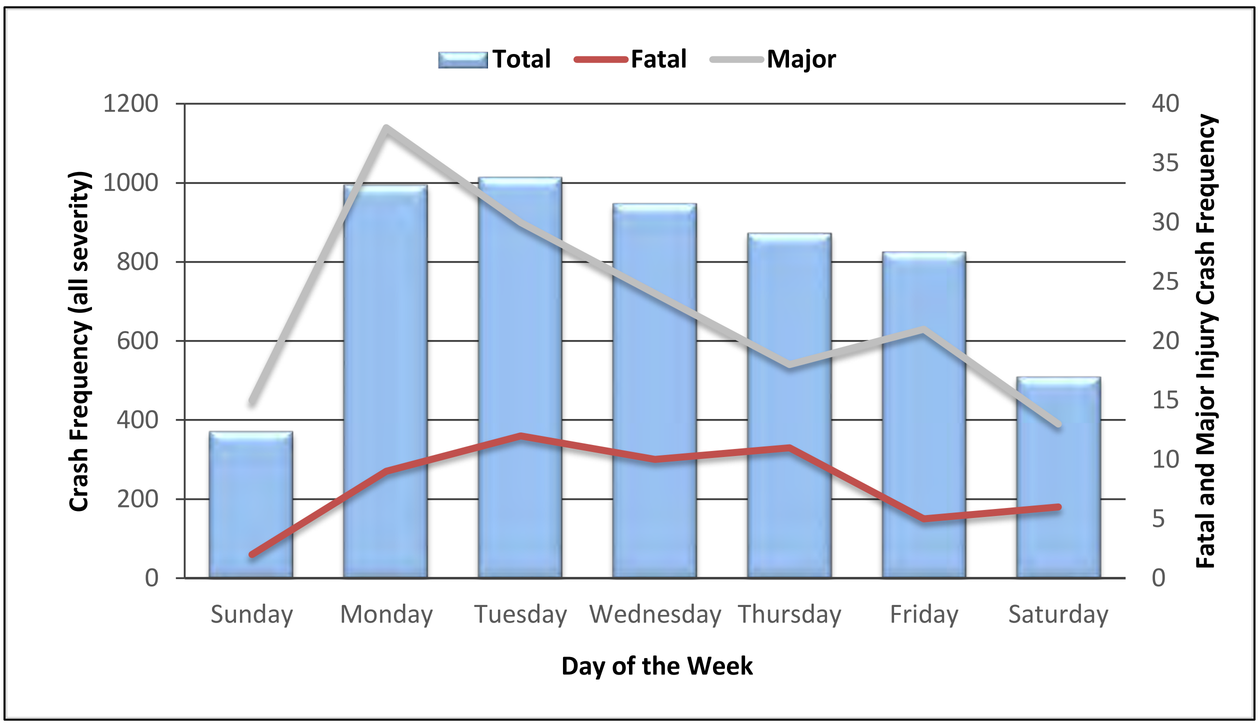


Figure 17. Single-vehicle crash frequency versus day of the week 2007 through 2012

Figure 16 shows that overall, multiple-vehicle heavy-truck crash frequency tends to be the highest during weekdays, with the crash frequency being fairly stable from Monday to Friday.

Similarly, Figure 17 shows single-vehicle heavy-truck crash frequency to be highest during weekdays, but with the frequency of crashes declining as the week progresses from Monday to Friday. From Figure 16 it can be seen that severe, multiple-vehicle collisions tend to be more frequent toward the beginning of the work week than at the end of the work week. A similar, but much more irregular trend is present for severe, single-vehicle collisions, as can be seen in Figure 17. To gain further insight into any trends present over the weekend, a test of proportions ($p < 0.01$), was conducted to see if fatal and major injuries were proportionally higher on Saturday or Sunday. The test of proportions concluded that for multiple-vehicle collisions, severe crashes were proportionally higher on Saturday; however, no significant difference in representation over the weekend was found for single-vehicle collisions.

The multiple- and single-vehicle heavy-truck crash distribution by month can be seen in Figure 18 and Figure 19, respectively.

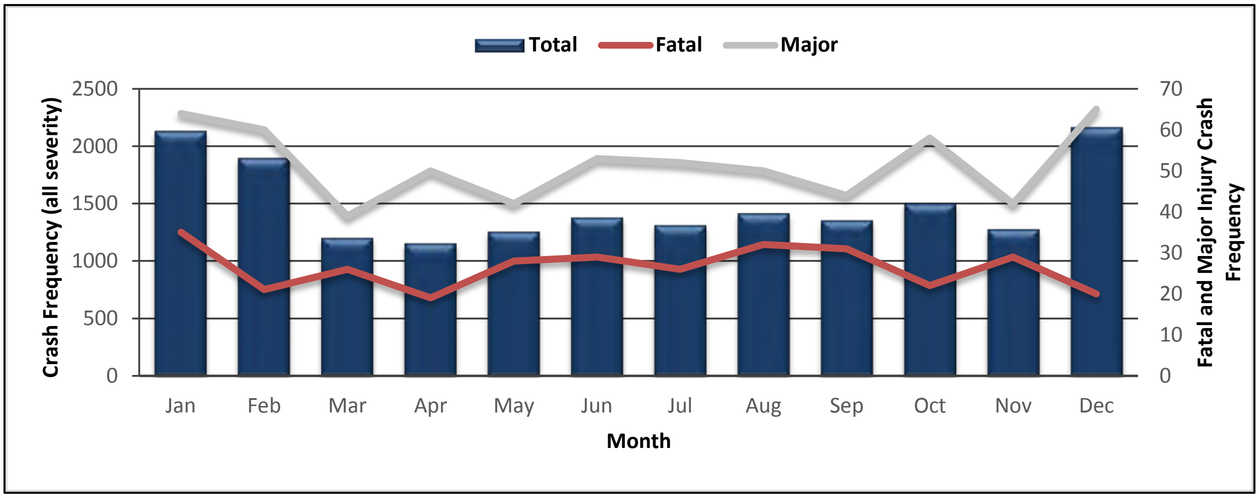


Figure 18. Multiple-vehicle crash frequency versus month 2007 through 2012

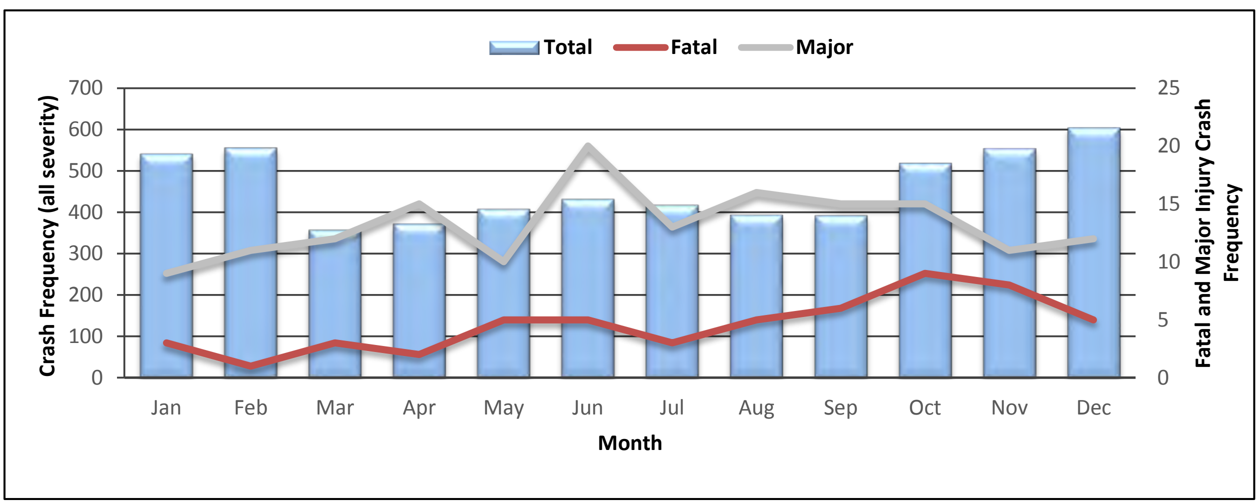


Figure 19. Single-vehicle crash frequency versus month 2007 through 2012

It can be observed that heavy-truck crash frequency is highest during the winter months and lowest during the spring, with a slight increase in crash frequency over the summer months. More notable are the differences in the frequency of severe crashes from month to month. Severe, multiple-vehicle crashes tend to occur rather irregularly over the year, while severe, single-vehicle crash occurrence appears to fluctuate much less from month-to-month, aside from a prominent peak during the summer months.

The location of a crash is also critical to the complete understanding of heavy-truck crash occurrence. Figure 20 shows the rural and urban crash distribution of multiple- and single-vehicle heavy-truck crashes.

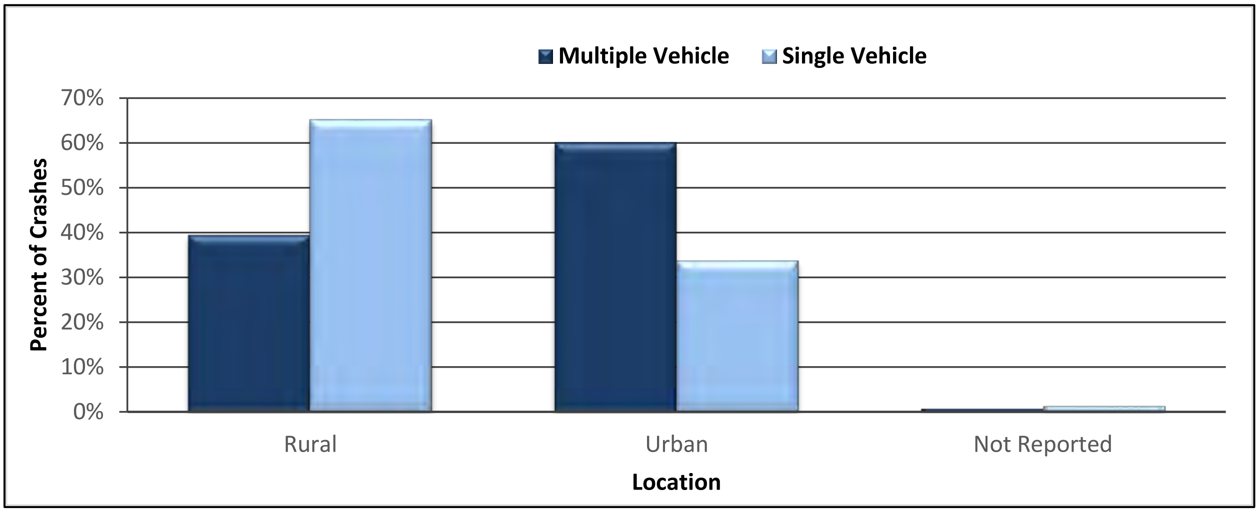


Figure 20. Multiple- and single-vehicle heavy-truck crash distribution by location 2007 through 2012

It can be observed that single-vehicle crashes appear to be predominantly rural events, while multiple-vehicle crashes appear to occur most frequently in urban areas. Other factors considered, such as roadway characteristics, are discussed next.

Roadway and Environmental Characteristics

Information on the type of roadway and characteristics of the roadway where a crash involving a heavy truck occurred were also examined. Figure 21 and Figure 22 show multiple- and single-vehicle crash distribution by road classification, respectively.

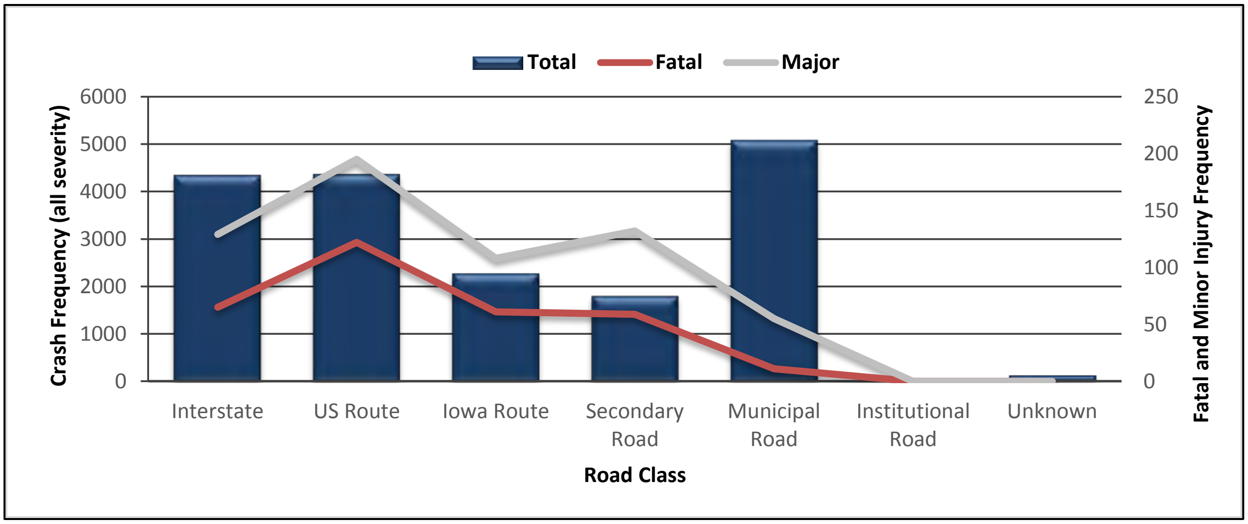


Figure 21. Multiple-vehicle crash frequency by road classification 2007 through 2012

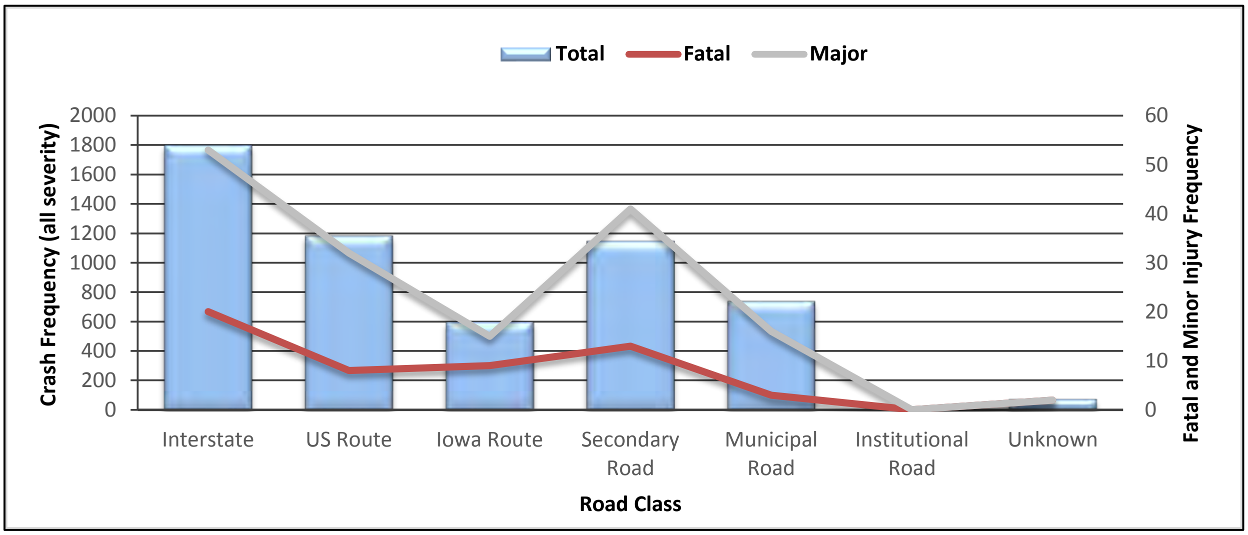


Figure 22. Single-vehicle crash frequency by road classification 2007 through 2012

Overall, multiple-vehicle crashes occur predominately on municipal roads, interstates, and US routes, with more severe crashes taking place on US routes and interstates. Single-vehicle crashes, on the other hand, occur predominately on interstates, secondary roads, and US routes, with the more severe crashes occurring primarily on interstates and secondary roads. The final category of factors considered were environmental characteristics and they are discussed next.

The environmental conditions present at the time of a heavy-truck crash are likely to play a role in the frequency and severity of the crash itself. Figure 23 shows the crash distribution of multiple- and single-vehicle heavy-truck crashes with respect to the surface conditions present at the time of the crash.

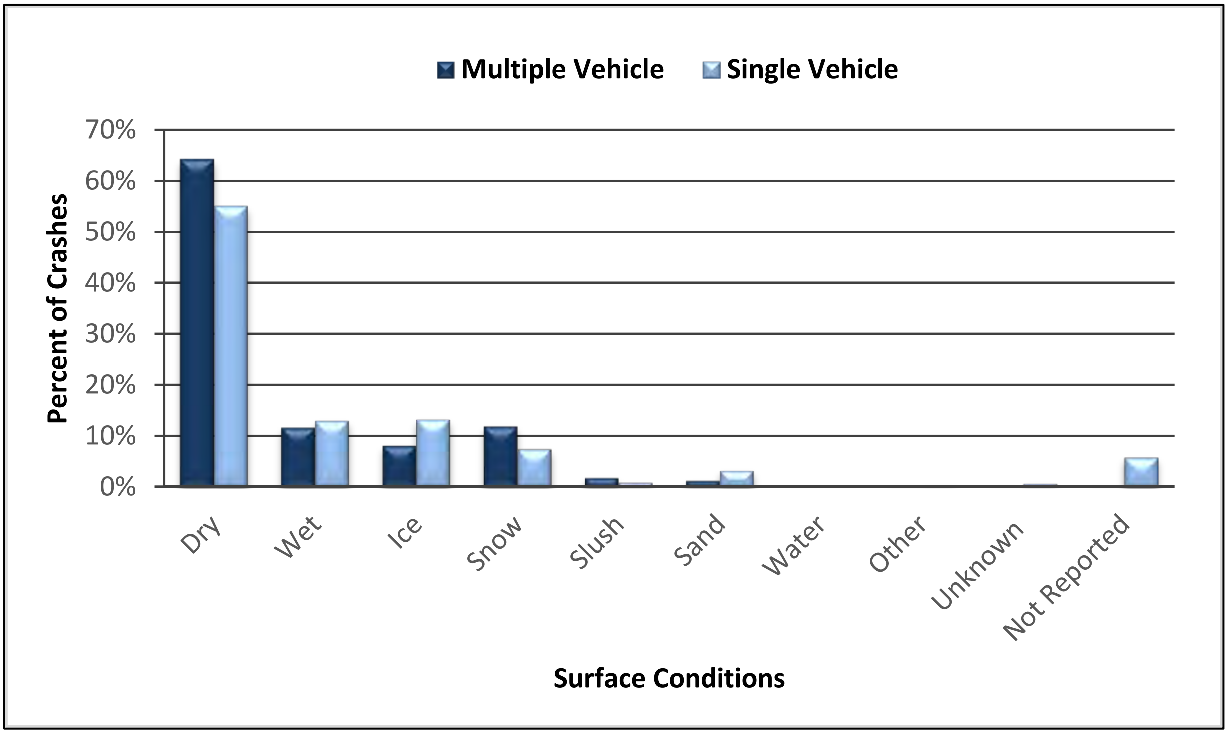


Figure 23. Multiple- and single-vehicle crash distribution by surface condition 2007 through 2012

From Figure 23 it can be seen that a majority of both single- and multiple-vehicle crashes occur under dry conditions. This observation could be an artifact of the prevalence of dry surface conditions with respect to the other alternative surface conditions reported or related to risk-compensating behavior in which drivers drive more aggressively as they perceive dry conditions as safer. Of greater importance is the observation that a higher proportion of single-vehicle crashes appear to occur on wet and icy surfaces, while a higher proportion of multiple-vehicle crashes occur under snowy and slushy conditions. A test of proportions also supports these observations ($p < 0.01$).

The lighting conditions present at the time of crash occurrence are likely to play a role in the occurrence of a heavy-truck crash. Figure 24 shows the distribution of multiple- and single-vehicle heavy-truck crashes with respect to the lighting conditions present at the time of the crash.

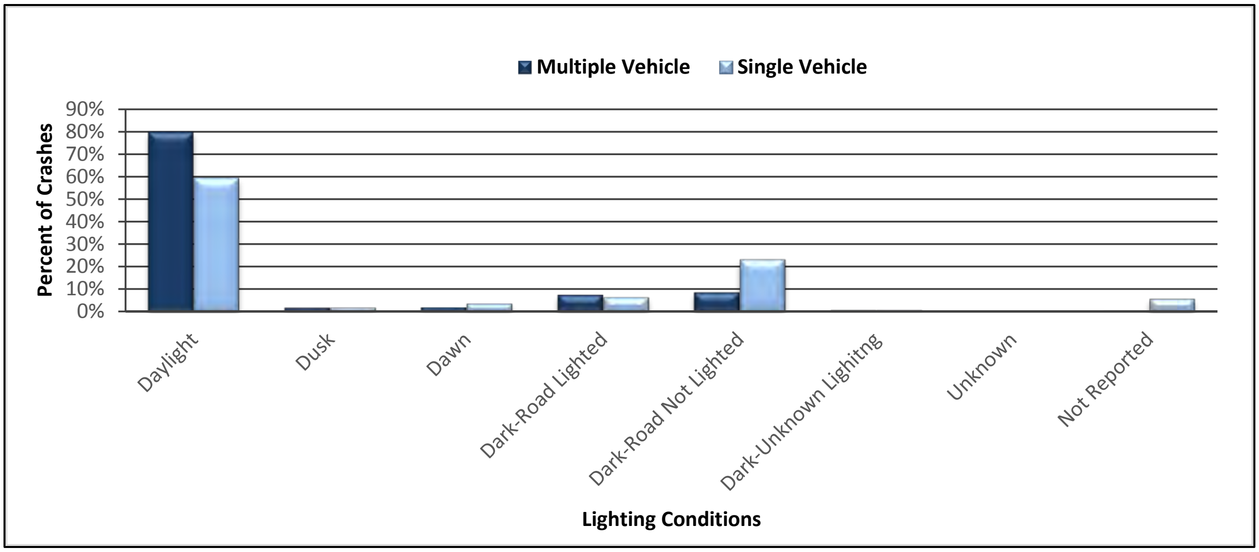


Figure 24. Multiple- and single-vehicle crash distribution by lighting condition 2007 through 2012

From Figure 24, it can be seen that a majority of both multiple- and single-vehicle crashes occur during daylight lighting conditions with the next highest proportion crashes occurring under dark conditions where the road is not lighted. From the same figure, the disparity of multiple- and single-vehicle collisions under dark, unlighted, road conditions is rather notable, with a much greater proportion of single-vehicle crashes occurring under these conditions as verified by a test of proportions ($P < 0.01$). This concludes descriptive analysis of heavy-truck crashes investigated in this report. The statistical models developed from the data just described is presented next.

Statistical Model Estimates

The literature review revealed that crash severity can be estimated by employing either ordered or unordered discrete outcome models. For this study, heavy-truck severity was estimated using unordered discrete outcome models because of the associated flexibility and goodness of fit. Separate models for single- and multiple-vehicle crashes were estimated. Single-vehicle crash severity was estimated using a binary probit model with outcomes of injury (fatal, major, minor, or possible injury) or no injury (PDO), while multiple-vehicle crash severity was estimated using a nested logit model with fatal or major injury and minor or possible injury outcomes nested to compensate for their shared unobserved effects. Elasticities and marginal effects were computed to assess the magnitude of the impact of the significant factors on crash severity. The estimation results (shown in Appendix B) and implications of the findings from both models are summarized next.

Crash Characteristics

The type of collision involving a heavy truck was found to have a great impact (based on elasticity) on the severity outcome of multiple-vehicle crashes. Head-on and broadside crashes were found to increase the probability of an injury while sideswipe crashes were found to increase the probability of no injury. Vehicular rollover too had a large effect (based on marginal effect) on the severity outcome of single-vehicle crashes.

Time and Location Characteristics

Time of the day, day of the week, and seasons were all found to have a relationship to multiple-vehicle crash severity. Both early morning (5 a.m. to 8 a.m.) and midday hours of the day (11 a.m to 2 p.m.) where found to increase the probability of severe crashes, while late afternoon and early evening hours (3 p.m. to 6 p.m.) were found to increase the probity of no injury crashes. These findings may be of use to law enforcement agencies in developing schedules and establishing enforcement priorities. Crashes at the beginning of the week (Monday or Tuesday) and over the weekend were also found to increase the probability of a severe crash. Additionally, the finding of an increase in crash severity toward the beginning of the week supports the finding by Park and Jovanis (2010) that heavy-truck drivers tend to be at more risk for a crash after extended off duty times over 46 hours, such as the weekend. Both models predicted higher probability of injury crashes during the summer and lower probability toward the end of the work week. However, the effect of these variables, in comparison to the other temporal variables discussed, is rather small (see Appendix B).

Vehicle Characteristics

Vehicle characteristics were also found to be associated with crash severity. The elasticity analysis for the multiple-vehicle crash severity model showed that indicator variables for frontal impacts generated the highest elasticity with respect to severe crash outcomes, suggesting that improvements in the frontal structures of both heavy trucks, in particular, and non-heavy trucks could impact heavy-truck crash safety the most. This effect was also significant but less pronounced in the single-vehicle crash severity model.

The type of heavy truck involved in the crash was found to have different effects on the severity outcomes of a single-vehicle compared to a multiple-vehicle crash. Collisions of combination trucks with other vehicles increases the severity of multiple-vehicle crashes, while single-vehicle collisions involving a single-unit truck increases the probability of an injury. This finding suggests that combination trucks potentially pose a greater hazard to the traveling public however exposure should also be factored in before any definitive conclusions are drawn.

Driver Characteristics

Both the single- and multiple-vehicle models found older drivers to be more likely to sustain an injury in crashes involving heavy trucks. This finding is more likely a reflection of the physiological differences between older and younger drivers. Younger drivers, in comparison to older drivers, are likely more resilient in crashes and as such, less likely to sustain a major or fatal injury. Additional information on the associated driving training and experience would help evaluate this finding.

Roadway and Environmental Characteristics

Environmental and roadway factors were also significant in both the multiple- and crash severity models. Higher posted speed limits increase the probability of an injury in single- and multiple-vehicle crashes. This is likely related to heavy-truck energy and momentum dynamics and suggests that improvements in the performance of heavy trucks can greatly influence heavy-truck safety.

Finally, both models found winter road conditions to decrease the probability of severe crash outcomes. This finding is consistent with past research findings (Lemp et al. 2011; Bham et al. 2012) and is attributable to drivers being more cautious and attentive under such conditions. Moreover, the severity of multiple-vehicle crashes was found to increase during dark, un-lit lighting conditions and decrease under rainfall events. Again these findings are in line with past work (Lemp et al. 2011; Bham et al. 2012; Abdel-Aty 2003), further validating the results of the models developed. For additional details on the methodology used for model specification, and details on both the single- and multiple-vehicle models estimated, see Appendix B: Crash Severity Models.

COMMERCIAL DRIVER'S LICENSE DATA ANALYSIS

In an effort to investigate the relationship between CDL licensure and crashes, the most recent five years of CDL licensure data (2008 through 2012) was obtained through the Iowa DOT Motor Vehicle Division (MVD). Additionally a memorandum of understanding was obtained to link the licensure data to the crash data. This link facilitated an investigation of the frequency of driver involvement as well as an investigation into the relationship between driver experience and crash involvement. The results of this data integration are presented next.

Descriptive Analysis

License Type Trends

Figure 25 and Figure 26 show the temporal CDL distribution by license type of all CDLs issued from 2008 through 2012 and all drivers with a CDL involved in a crash from 2008 through 2012, respectively.

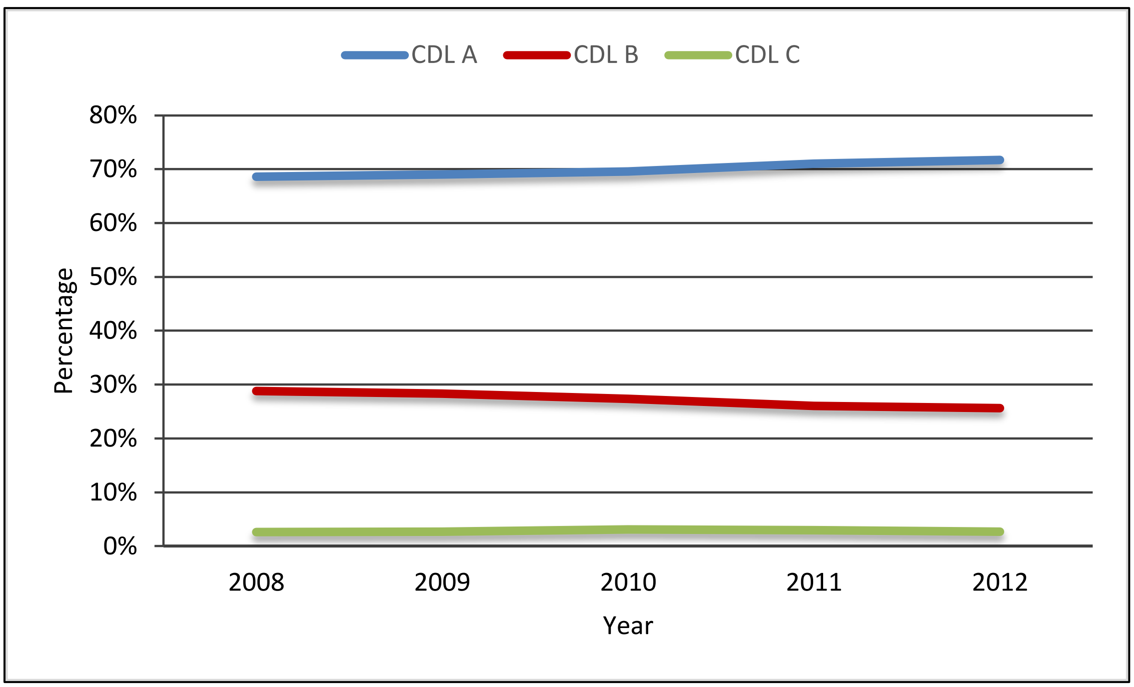


Figure 25. CDL license type distribution 2008 through 2012

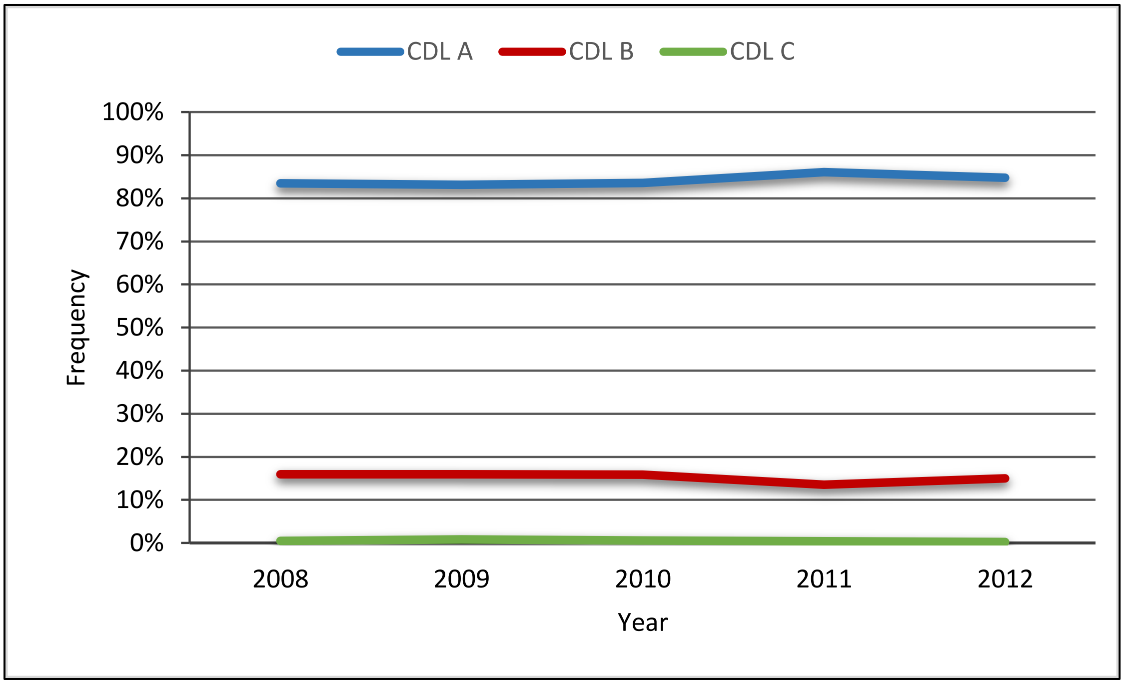


Figure 26. CDL license type distribution for drivers with a CDL involved in a crash 2008 through 2012

The figures show that the most common license type issued is a CDL A followed by CDL B and CDL C. Over the past five years it can also be observed that the proportion of CDL A licenses issued and involved in crashes has increased, while the proportion of CDL B licenses issued and involved in crashes has declined. Comparing Figure 25 to Figure 26 yields that CDL A drivers appear proportionally higher in crashes as was also verified by a test of proportions ($p<0.01$).

CDL license type distribution by gender was also reviewed. Figure 27 and Figure 28 show the license type distribution for females and males respectively.

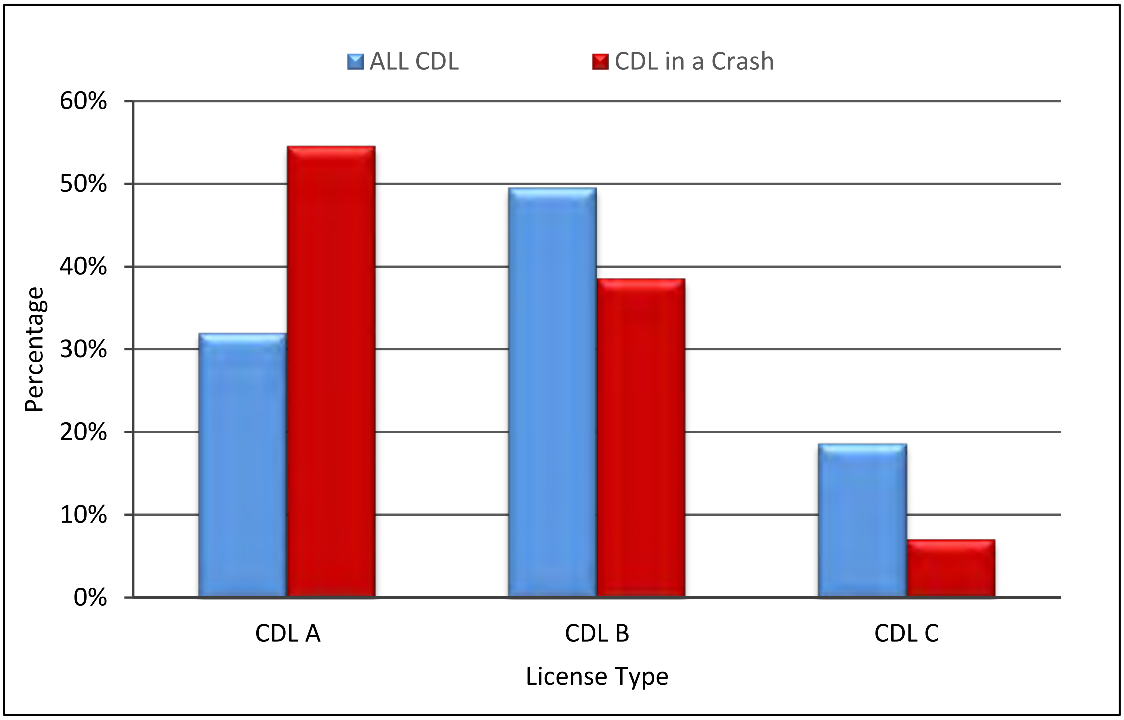


Figure 27. Female CDL license type distribution 2008 through 2012

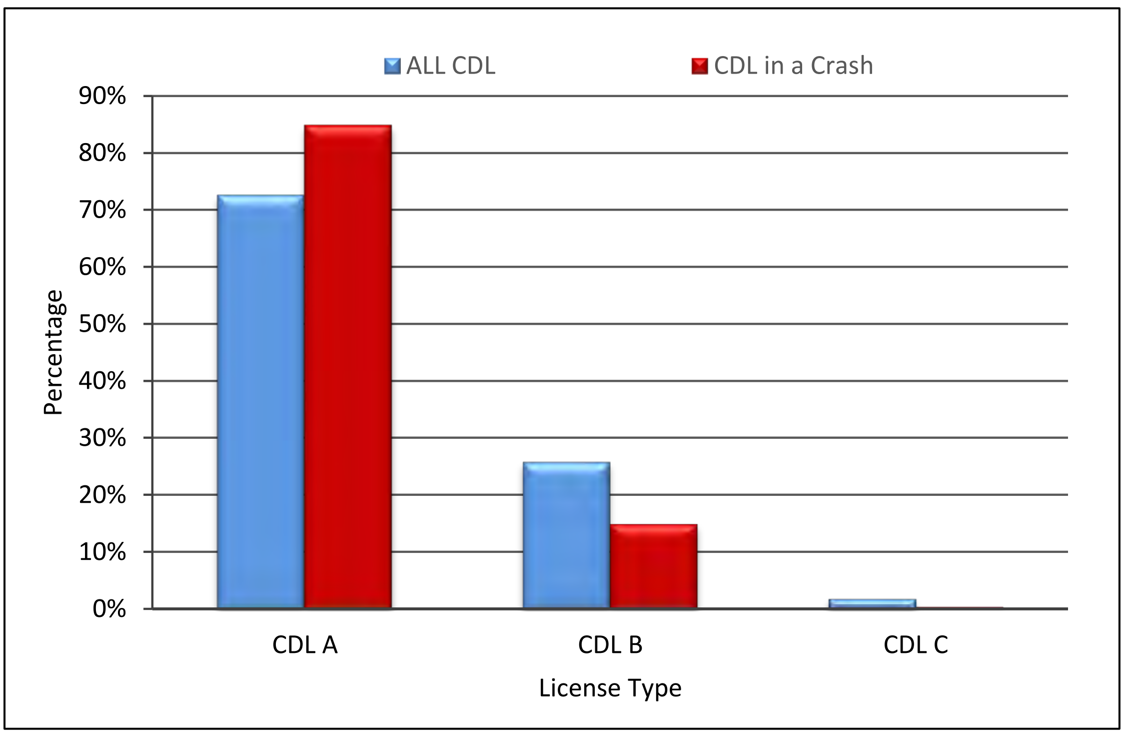


Figure 28. Male CDL license type distribution 2008 through 2012

Figure 27 shows that a majority of females possess a CDL B license; however, a majority of females in crashes possess a CDL A license. Males on the other hand mostly possess a CDL A license, with a majority of the male drivers involved in crashes also possessing a CDL A license. From Figure 27 and Figure 28 it appears that both females and males possessing a CDL A license are proportionally higher in crashes as was also verified by a test of proportions ($P<0.01$).

The distribution of CDL license restrictions for all licenses issued and drivers with a CDL involved in a crash from 2008 through 2012 can be seen in Figure 29.

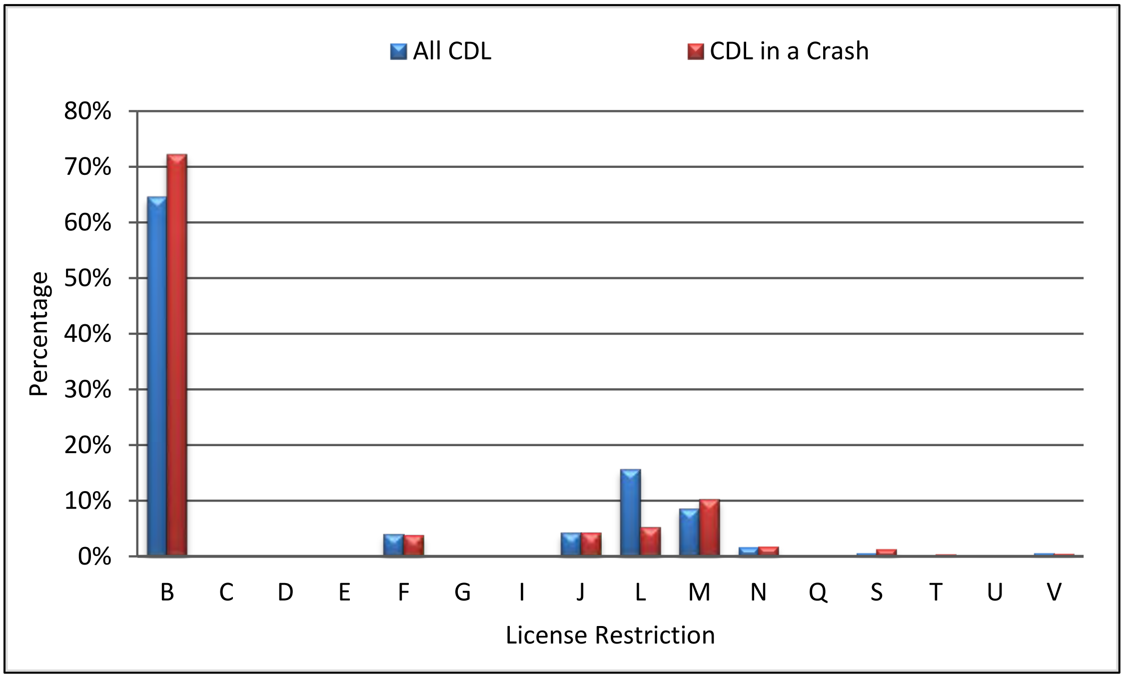


Figure 29. Distribution of license restrictions for all CDL licenses issued and all CDL licensed drivers 2008 through 2012

Overall the distribution of restrictions for licenses issued and drivers in crashes appears to be similar. Drivers possessing restriction B (corrective lenses) or restriction M (class B passenger vehicle) are the only restrictions proportionally higher in crashes as verified by a test of proportions ($p<0.01$). A list of the Iowa license restrictions is provided in Appendix C.

Crash Frequency Trends

To examine the relationship between driver characteristics and crash frequency a negative binomial crash frequency model was estimated using the data obtained through the MVD. Observations from 10,225 crashes involving 9,332 drivers were used for model estimation. After multiple trials utilizing a variety of variables, no useful results were obtained from the model estimates. No explanatory variables relating to driver age, license endorsements, license restrictions, license type, and gender were found to be significantly related to crash frequency.

CITATION AND INSPECTION ANALYSIS

In an effort to investigate the relationship between enforcement activities and crashes, the most recent four years of commercial motor vehicle-related public enforcement data (2009 through 2012) were obtained from Iowa DOT Motor Vehicle Enforcement (MVE) and Iowa State Patrol (ISP). Both agencies utilize Traffic and Criminal Software (TraCS) and its Incident Location Tool (ILT) module to record and geospatially locate citations and inspections, known as Electronic Citation Component (ECCO) and commercial motor vehicle inspections (VSIS), respectively. Of primary interest was the location and temporal components of the enforcement activities. While the ECCO and VSIS data do not comprehensively represent commercial motor vehicle-related law enforcement activities, such as patrolled routes not resulting in a citation or inspection, or the length of time a location or route was occupied, they were the best available data for assessment, serving as an adequate proxy of activities.

While citations are often inspection-related, they may also involve general traffic violations, including non-commercial motor vehicles. Multiple citations may be issued at a single law enforcement intervention or inspection, with each citation represented as a unique record in the database. To avoid overrepresentation of citation-based law enforcement activity, a single record (or contact record) was created for each event, regardless of the number of citations issued. This yielded approximately 96,400 MVE and 10,600 ISP contacts. ISP contacts were limited to full time, Motor Carrier Safety Program (MCSAP) funded troopers. The two resulting databases were combined and are referred to as “ECCO” through the remainder of this report. Inspection records were only available from MVE, with a single record representing a unique inspection. Nearly 191,300 inspections (referred to as “VSIS” through the remainder of this report) were included in the analysis.

ECCO and VSIS data, referred to as contacts, were independently compared to crash data, and based on proportional distribution from 2009 through 2012. Statewide analyses included descriptive statistics and a test of proportions ($p < 0.01$) of time of day, day of week, month and road system. County-level comparisons (99) were conducted for the same analysis period as well as a one year offset (lag) between crash and enforcement data. Specifically, enforcement data were compared to crash data from the prior year. Counties were ranked based on the percent difference in enforcement activity and crashes and further refined by road jurisdiction (i.e., primary or state, secondary or county, and municipal). The results of these analyses are presented in the following sections (also see Appendix D: Citation and Inspection Analysis).

Time of Day

Figure 30 presents the hourly distribution of law enforcement contacts and crashes during the four-year analysis period.

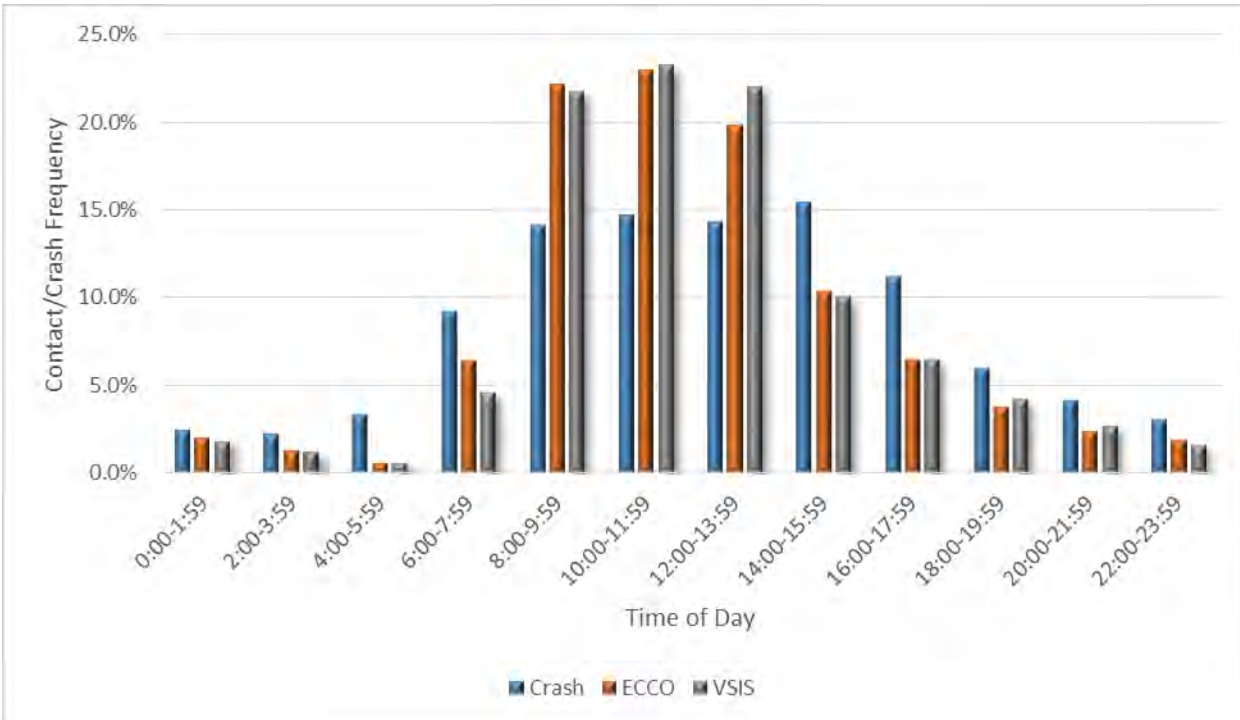


Figure 30. Contact and crash frequency by time of day 2009 through 2013

As discussed previously, crash occurrence was greatest during typical daylight hours between 7:00 a.m. and 5:00 p.m. The percentage of law enforcement contacts was also highest during a similar period from 6:00 a.m. to 6:00 p.m. A test of proportions ($p < 0.01$) indicated that the percentage of contacts and crashes were statistically different during all time periods of the day. Overall, the greater differences occurred between 8:00 a.m, to 6:00 p.m. Contacts were much higher during the peak hours from 8:00 a.m. to 2:00 p.m., and much less during the early morning hours from 2:00 a.m. to 8:00 a.m. and late afternoon hours from 2:00 p.m. to 6:00 p.m. Lower proportions of crashes were consistently observed during time periods with higher proportions of enforcement contacts. The converse was also observed (i.e., higher proportion of crashes with lower proportion of enforcement contacts).

In general, the distributions of the ECCO and VSIS contacts were consistent during the analysis period, as may be expected. The greatest differences between their distributions and crash distribution were also consistent. Annual (year-by-year) comparisons yielded consistent results as well. Table 4 presents the two-hour time periods with the greatest differences between VSIS contacts and crash experience. A negative difference indicates a higher crash proportion compared to VSIS contacts.

Table 4. Greatest time of day differences between VSIS and crash distributions 2009 through 2013

Rank	Time of day	Difference (%)
1	10:00-11:59	8.60
2	12:00-13:59	7.64
3	8:00-9:59	7.59
4	14:00-15:59	-5.36

Day of Week

Annual law enforcement contact and heavy-truck crash distributions by day of week are presented in Figure 31.

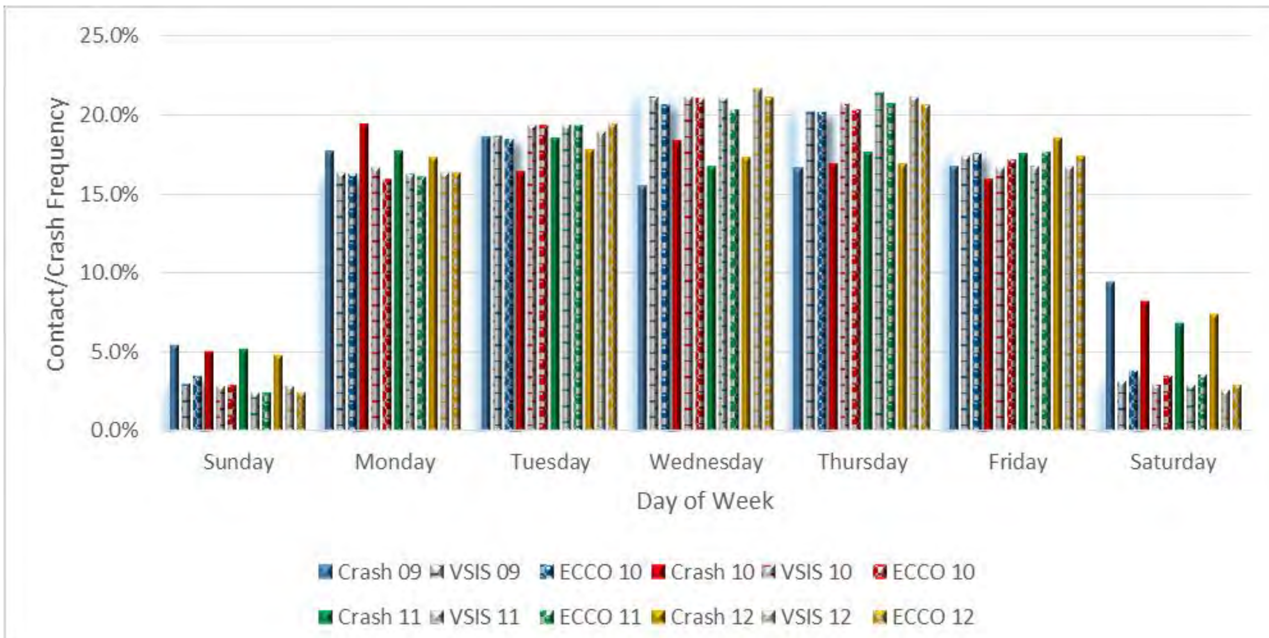


Figure 31. Annual contact and crash frequency by day of week 2009 through 2013

Truck crash frequency tended to be the highest, and relatively uniform, during weekdays. Contacts displayed similar characteristics. However, a test of proportions ($p < 0.01$) of the entire analysis period indicated that the distribution of contacts for most days of a week were significantly different from crash experience, except for Friday. Annually, the VSIS and crash proportions were not statistically different on Tuesday or Friday in three of the four years.

Greater differences were found during the weekend, with lower contact proportions on Saturday and Sunday. On the other hand, contacts on Thursday were greater than crash experience. The top differences in the day of week proportions are presented in Table 5. A negative difference indicates a higher crash proportion compared to VSIS contacts.

Table 5. Greatest day of week differences between VSIS and crash distributions 2009 through 2013

Rank	Day of Week	Difference (%)
1	Saturday	-5.11
2	Wednesday	4.24
3	Thursday	3.88

Month of Year

Figure 32 presents the distribution of crashes and law enforcement activities from 2009 through 2013.

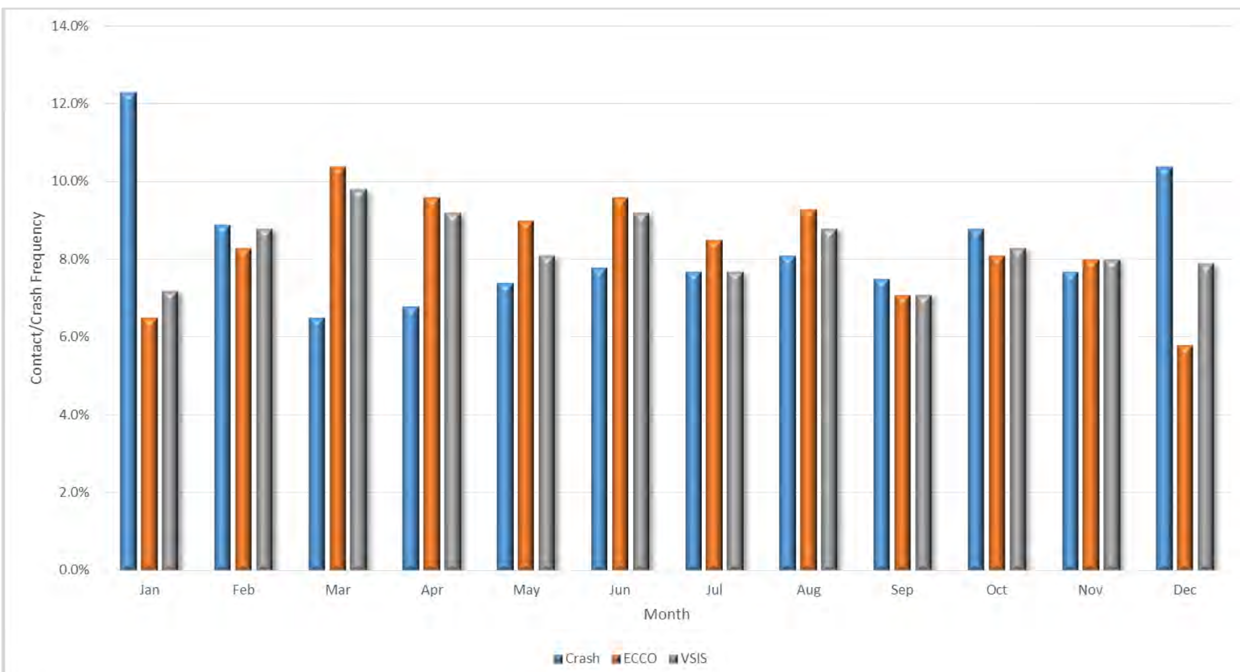


Figure 32. Contact and crash frequency by month of year 2009 through 2013

As discussed previously, heavy-truck crash frequency was highest during the winter months and lowest during the spring. A slight increase in crash frequency was observed over the summer months. In contrast, the contact frequency was generally highest in the spring months, lowest in winter and consistent during summer. Test of proportions ($p < 0.01$) results for the entire analysis period revealed that the distribution of contacts was comparable to crash distribution in only February, July, and November. March, April, and June were found a disproportionately higher number of crashes compared to contacts, while January and December had disproportionately higher contacts (see Table 6).

Table 6. Greatest month of year differences between VSIS and crash distributions 2009 through 2013

Rank	Month	Difference (%)
1	January	-5.08
2	March	3.22
3	December	-2.53
4	April	2.38
5	June	1.40

Differences did exist among the individual years. For example, in 2009, contacts were not significantly different from crashes in several of the summer and fall months (May through November), with the exception of June. In each of the other three following years, no statistically different proportions existed for at least three months, typically one in each in each season other than winter. Most recently, in 2012, no statistically significant proportions were observed for six total months (i.e., February, May, August, October, November, and December).

Road System

Based on the geocoded locations of enforcement and crash data, the Iowa DOT-based road system of occurrence was derived. Iowa consists of approximately 116,600 centerline miles of public roadways. Five systems were considered: Interstate, US route, Iowa route, farm-to-market route, and local route. The first three systems represent approximately 9,500 centerline miles of state-maintained (primary) roads, of which 16 percent are located within cities. Farm-to-market and local routes are under the jurisdiction of a county or municipality (city), representing nearly 31,800 and 74,400 centerline miles, respectively. Only four percent of the farm-to-market system is municipal compared to approximately 20 percent of the local system. Table 7 presents an estimated distribution of centerline mileage and total vehicle miles of travel (VMT) by road system and location.

Table 7. Iowa public road centerline mileage and VMT 2011

Road System	Location	Centerline Mileage (%)	Total VMT (%)
Interstate	Rural	0.7	16.2
	Urban	0.2	7.9
US Route	Rural	2.7	15.4
	Urban	0.6	6.7
Iowa Route	Rural	3.5	10.1
	Urban	0.5	4.6
Farm To Market	Rural	26.4	13.5
	Urban	1.1	5.0
Local	Rural	51.8	3.2
	Urban	12.5	17.3
Total		100.0	100.0

Total VMT was used because truck VMT is not available for all public roads in Iowa. As is clear in Table 7, the mileage and VMT may be quite different, which should be taken into consideration when evaluating crash experience and enforcement activities.

Figure 33 presents the annual frequency of contacts and crashes from 2009 through 2012.

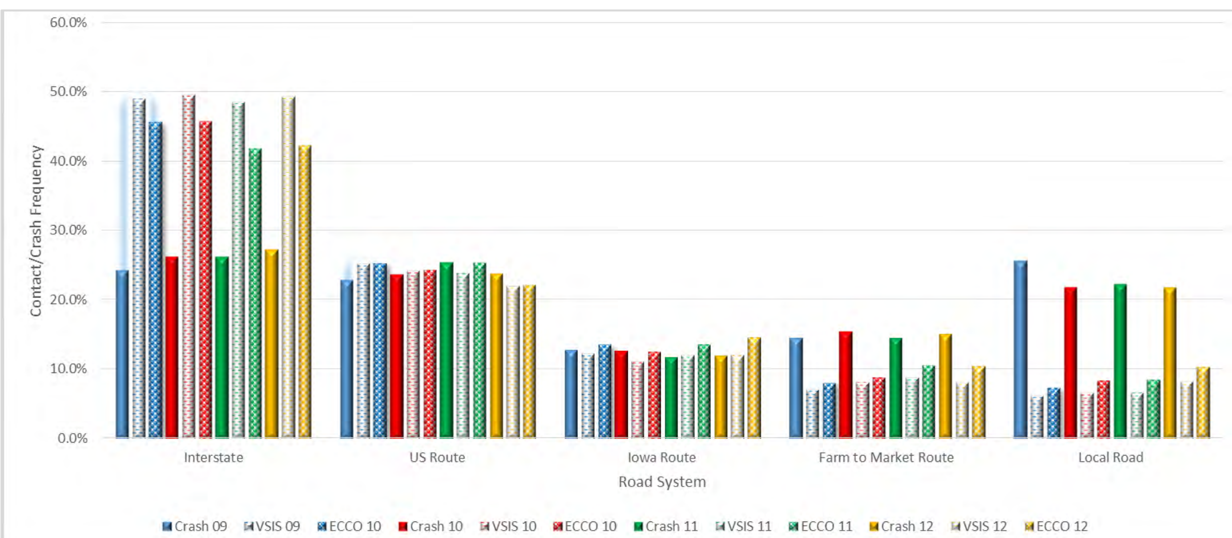


Figure 33. Annual contact and crash frequency by road system 2009 through 2012

As indicated previously, heavy-truck crashes occurred predominately on interstates and US routes. The frequency of contacts was also observed highest on these systems. A test of proportions ($p < 0.01$) for the entire analysis period indicated that the proportion of contacts were statistically different on interstate, farm-to-market, and local routes. In three of the four years, proportions were not statistically different only on the Iowa routes. Overall, statistical differences indicated that contacts are much greater, compared to crashes, on interstates and much less on local roads. Comparisons of the VSIS and ECCO data yielded similar results.

Table 8 presents a comparison of the VSIS contact, truck crash, and total VMT proportions.

Table 8. Comparison of VSIS, truck crashes and total VMT by road system

	2009-2012		2011
Road System	**VSIS Contacts (%)**	**Truck Crashes (%)**	**Total VMT (%)**
Interstate	49.1	25.9	24.1
US Route	23.9	23.9	22.0
Iowa Route	12.0	12.4	14.8
Farm-to-Market	8.1	14.9	18.5
Local	7.0	22.9	20.5
Total	100.0	100.0	100.0

The proportion of truck crashes and total VMT are generally consistent. In addition, the proportion of VSIS contacts is similar to truck crashes and total VMT for US and Iowa routes. The greatest differences between VSIS contacts and total VMT appear on the interstate, farm-to-market, and local routes. While the farm-to-market and local systems represent about 40 percent of the total statewide VMT, they also account for nearly 92 percent of the centerline miles in the state—which is a very extensive network to enforce.

County-Level Assessment - Annual

Iowa consists of 99 counties. Understanding the relationship between law enforcement activities and crashes within individual counties may provide preliminary insight into the impact of law enforcement as well as resource allocation. The counties that had the highest proportion of heavy-truck crashes statewide during 2009 through 2012, not considering exposure, are presented in Figure 34.

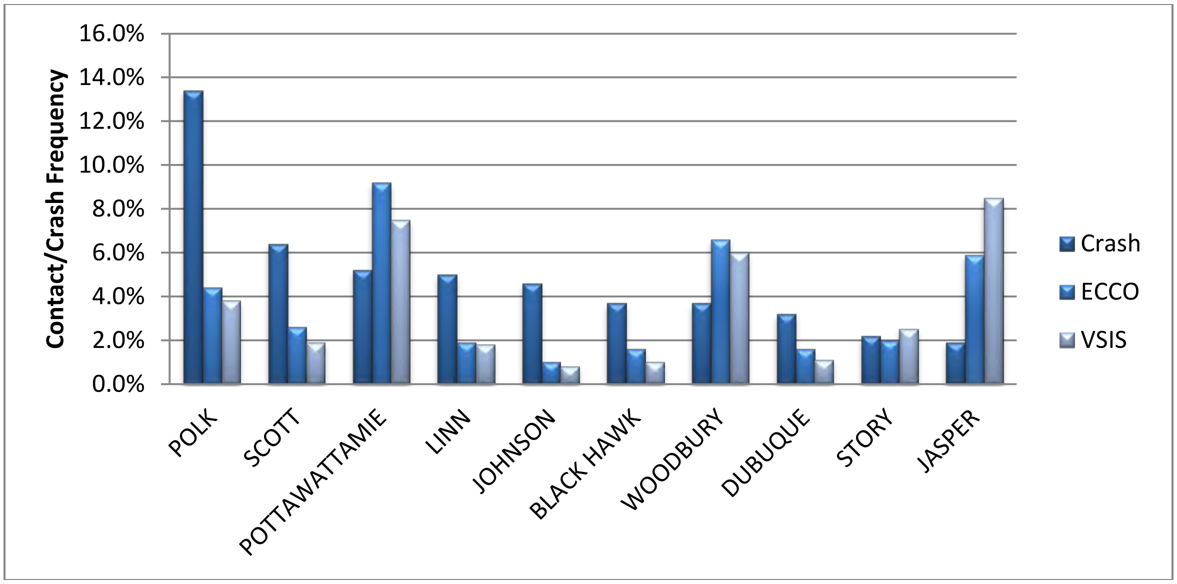


Figure 34. County-level proportion of crashes and contracts 2009 through 2012

The highest counties were Polk, Scott, Pottawattamie, Linn, Johnson, Black Hawk, Woodbury, Dubuque, Story, and Jasper. Figure 35 presents the 10 counties with the highest proportion of contacts during this same time period: Dallas, Buchanan, Jasper, Pottawattamie, Woodbury, Polk, Clarke, Lee, Sac, and Worth.

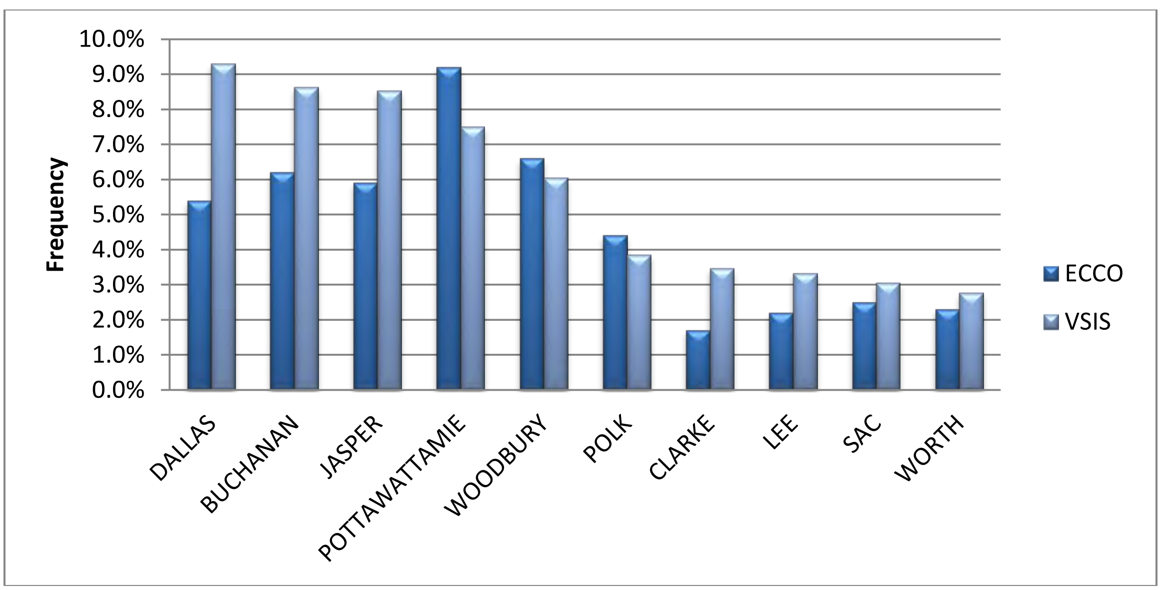


Figure 35. County-level proportion of contacts 2009 through 2012

Five counties were present in both the high-crash and high-contact lists: Pottawattamie, Woodbury, Scott, Polk and Jasper. A test of proportions ($p < 0.01$) indicated that the differences between the proportion of contacts and crashes during 2009 through 2012 were statistically significant among counties such as Polk, Scott, and Pottawattamie. The greatest difference was observed for Polk County, which includes the Des Moines metropolitan area and major interstates. The crashes were proportionally much greater than contacts in Polk, Scott, Black Hawk, and Linn counties. The converse was true in other counties, such as Pottawattamie, Jasper, Fremont, Dallas, and Buchanan. Similar trends were observed when comparing the annual contact and crash data over the same period.

The 16 counties with the greatest differences, of at least one percent, between VSIS contact and crash proportions are presented in Table 9.

Table 9. Counties with greatest differences in contact and crash proportions same year

Rank	County (VSIS)	Difference (%)	County (ECCO)	Difference (%)
1	Polk	-9.59	Polk	-9.00
2	Buchanan	8.06	Buchanan	5.60
3	Dallas	7.73	Jasper	4.03
4	Jasper	6.65	Pottawattamie	4.00
5	Scott	-4.50	Dallas	3.85
6	Johnson	-3.81	Scott	-3.77
7	Linn	-3.16	Johnson	-3.61
8	Sac	2.73	Fremont	3.08
9	Clarke	2.71	Linn	-3.03
10	Black Hawk	-2.67	Woodbury	2.95
11	Lee	2.46	Sac	2.20
12	Worth	2.36	Black Hawk	-2.06
13	Woodbury	2.36	Worth	1.89
14	Pottawattamie	2.29	Dubuque	-1.56
15	Dubuque	-2.02	Lee	1.33
16	Fremont	1.95	Hamilton	-0.95

A negative sign indicates that the percentage of VSIS contacts was lower than the percentage of crashes. The results of ECCO contact and crash percentages mirror these results, with the 15 counties with the greatest differences being the same.

These results may be interpreted and utilized in several different ways. For example, higher statewide proportions of contacts on a county-level appear to yield lower proportions of crashes. Similarly, lower statewide proportions of contacts appear to result in higher proportions crashes. This may indicate that greater law enforcement efforts improve traffic safety. These results may also be potentially utilized to identify counties in which increased enforcement efforts may be warranted or where reallocation of resources can occur. However, exposure, i.e. truck traffic, in these counties should also be taken into consideration when interpreting these data and before making any final determinations.

County-Level Assessment – Annual Offset (Lagged Year)

Similar to the annual county-level assessment, the relationship between the statewide proportion of crashes in a given year and the statewide proportion of contacts the following year was analyzed. This was done to assess possible crash experience-based changes in enforcement activities.

A county-level test of proportions ($p < 0.01$) was first performed for the 2008 crash and 2009 contact proportions. Approximately 70 percent of the counties (70 of 99) had statistically significant differences in proportions, suggesting that contact frequency may not have been entirely driven by prior year's crash experience. More consistency was observed in the 2010 contact proportions, with fewer statistically significant differences from the 2009 crash proportions, i.e. 64 of 99 counties. Moreover, the counties with statistically significant differences decreased to 57 counties for the 2011 contact/2010 crash comparison and 51 counties for the 2012 contact/2011 crash comparison.

The results of the offset (lagged) year analyses were similar to the annual analyses, with Polk, Johnson, Scott, Black Hawk, Linn having a higher proportion of crashes, while counties such as Buchanan, Dallas, Jasper, Woodbury, and Fremont had a higher proportion of contacts. The difference of proportions was at least one percent for 19 counties in 2009 (see Table 10). A negative sign indicates that the contact proportion was less than the crash proportion.

Table 10. Counties with greatest differences in 2009 contact and 2008 crash proportions (offset/lagged year)

Rank	County (VSIS)	Difference (%)	County (ECCO)	Difference (%)
1	Polk	-10.51	Polk	-10.35
2	Buchanan	7.67	Pottawattamie	5.28
3	Dallas	7.62	Buchanan	5.09
4	Jasper	7.35	Jasper	4.94
5	Scott	-4.85	Fremont	4.33
6	Johnson	-4.04	Dallas	4.33
7	Black Hawk	-3.62	Scott	-4.31
8	Fremont	3.30	Johnson	-4.22
9	Linn	-3.08	Woodbury	3.87
10	Woodbury	3.07	Linn	-3.46
11	Sac	2.64	Black Hawk	-2.97
12	Worth	2.37	Sac	2.39
13	Lee	2.25	Worth	1.91
14	Clarke	1.96	Iowa	-1.27
15	Iowa	-1.58	Lee	1.23
16	Dubuque	-1.45	Dubuque	-1.19
17	Story	1.42	Hamilton	-1.13
18	Pottawattamie	1.29	Harrison	1.03
19	Hamilton	-1.20	Monona	0.97

A comparison of ECCO contact and crash proportions was consistent with that of the VSIS contact and crash proportions. The counties with the greatest differences were also similar, with the exception of Clarke and Story Counties for VSIS contacts, and Harrison and Monona for ECCO contacts. The overall rankings were slightly different as well.

In general, the number of counties with statistically significant differences of proportions between crashes in a given year and contacts the following year has decreased since 2009. In other words, law enforcement activities appear to be more closely following the previous year's crash experience. As mentioned previously, exposure, i.e. truck traffic, in these counties should also be taken into consideration when interpreting these data and before making any final determinations.

In the future, performing a county-level analysis comparing the proportion of contacts in a given year and crashes in the following year may provide additional insight into the possible impacts of law enforcement activities.

County-Level Assessment – Road Jurisdiction

In an effort to further disaggregate and refine the county-level analysis, crashes and citations were assigned to one of three road jurisdictions: primary (state), secondary (county), and municipal (city) roads. The 10 counties with the highest proportion of heavy-truck crashes statewide from 2009 through 2012, by road jurisdiction, are presented in Figure 36, Figure 37, and Figure 38.

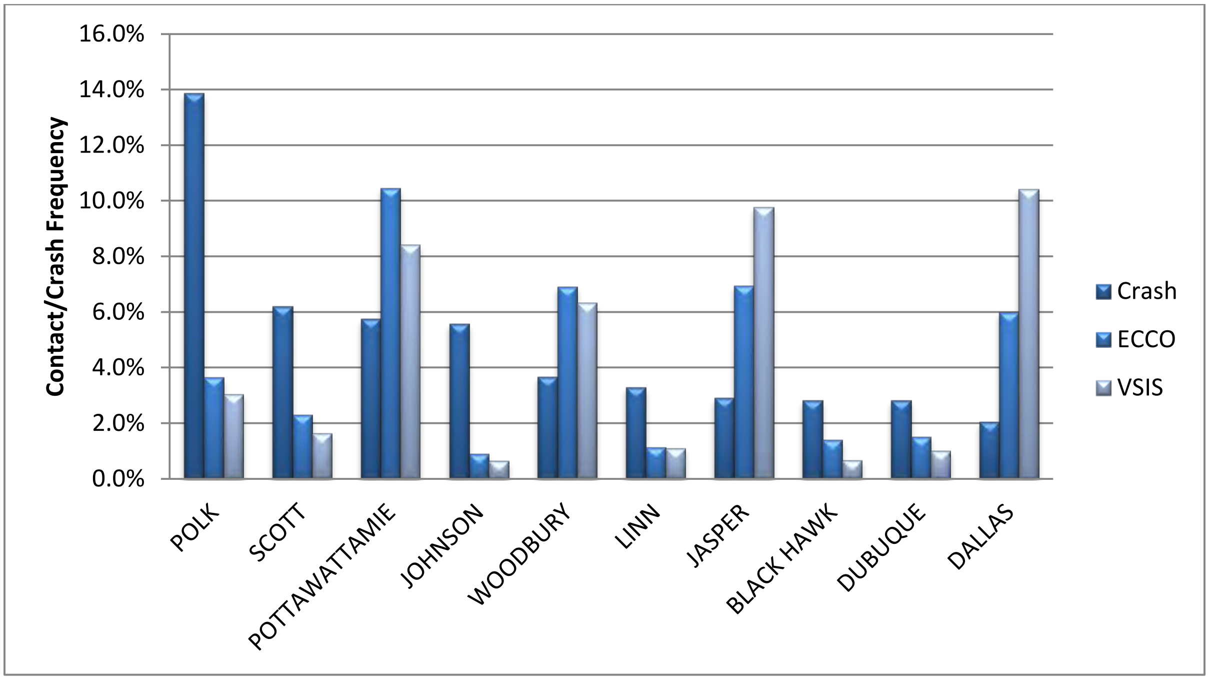


Figure 36. Counties with highest statewide proportion of crashes on primary roads 2009 through 2012

Figure 36 shows that Polk County had the highest proportion of crashes on the primary roads, with the proportion of contacts approximately 10 percent less. The county with the second highest proportion, Scott, was nearly eight percent less. Pottawattamie, Jasper, and Dallas Counties had the highest proportion of primary-road contacts, with a lesser proportion of crashes. Within the 10 counties, the proportion of crashes ranged from approximately 14 to 2 percent, and an equal number of counties had a higher proportion of crashes compared to contacts. The results of the ECCO contact-crash proportion comparison were generally consistent with the VSIS contact-crash proportion comparison.

Sioux County had the highest statewide proportion of crashes on secondary roads, with Polk County possessing the second highest proportion (Figure 37).

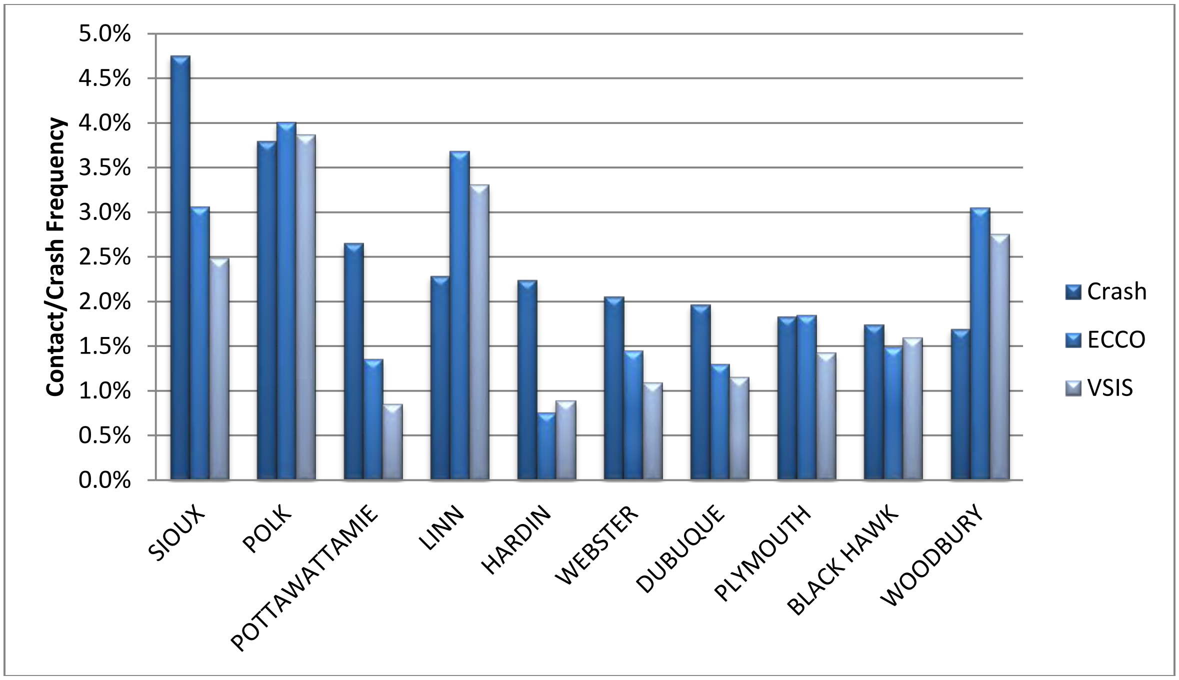


Figure 37. Counties with highest statewide proportion of crashes on secondary roads 2009 through 2012

The proportions of secondary-road contacts and crashes in Polk County was much closer than on the primary roads. Within the top 10, Dallas County had the highest proportion of contacts, and six counties had a higher proportion of crashes compared to contacts. Additionally, the range in the proportion of crashes was much smaller, from approximately five to two percent.

Figure 38 indicates that Polk County had the highest proportion of crashes statewide at nearly 18 percent, which is comparable to the percent of crashes on primary roads.

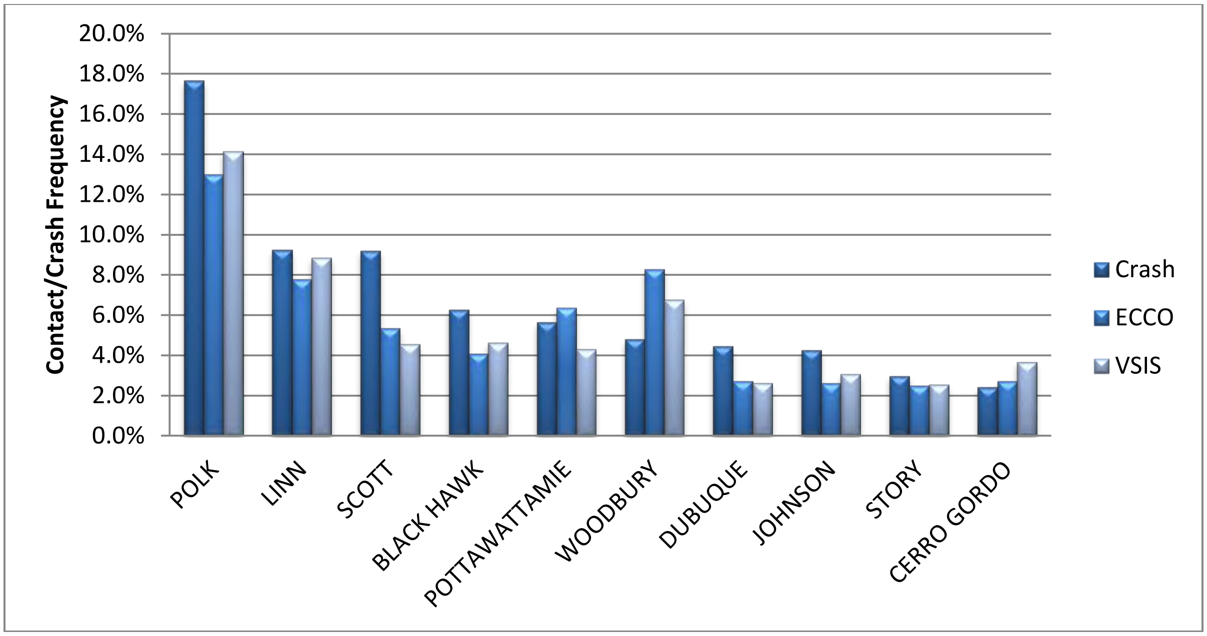


Figure 38. Counties with highest statewide proportion of crashes on municipal roads 2009 through 2012

Eight of the 10 counties with the highest proportion of municipal crashes had a lower proportion of both contact types. The exceptions were Woodbury and Cerro Gordo counties. As expected, all of the counties in the top 10 represent the counties with the largest cities or urban areas, in nearly the same order. The range in the proportion of crashes was similar to that of the primary roads, from approximately 18 to 2 percent.

Among all road jurisdictions, the results of the ECCO contact-crash proportion comparison were generally consistent with the VSIS contact-crash proportion comparison. The results of this analysis may potentially be used by law enforcement agencies to allocate resources to certain counties and, more specifically, types of roadways within those counties. This analysis could also be further refined by specific route(s) within a county. Additional considerations may include not only exposure (i.e. truck traffic) but crash frequency. For example, while a county may have the highest proportion of crashes on county roads, the crash experience may be distributed over a very large network and be relatively small compared to primary-road crashes in that, or another, county.

Visualization

As was noted previously, all reportable crashes on public roadways in Iowa are geospatially located using the Incident Location Tool (ILT). This tool is also used by Iowa DOT MVE and ISP to geospatially locate citations and inspections, known as ECCO and VSIS, respectively. Since these, as well as other, data sets exist in geographic information system (GIS) databases, flexibility exists in the manners in which they can be integrated, analyzed and presented. Specifically, crash and contact data may be integrated with other data sets, such as roadway and traffic, analyzed based on various metrics and visually presented at different levels of granularity.

For demonstration purposes, three general, example metrics were developed for the primary (state) roadways only: total heavy-truck crash or contact frequency, heavy-truck crash or contact frequency per mile of roadway, also known as density, and heavy crash or contact frequency per hundred million vehicle miles of heavy-truck travel, also known as rate. The latter two metrics were inspired by two of the four United States Road Assessment Program (usRAP) safety performance measures or risk mapping protocols. In usRAP, these performance measures are used to characterize the risk of crashes on specific road segments. Road segments are color coded to represent the level of risk categorized by proportions of the road network analyzed. (AAA 2014)

Several modifications were made to the standard usRAP protocols for this demonstration. For example, both crash and contact data were considered, independently, with contacts treated in a manner similar to crashes. Data are also presented both on a county-level and a road segment level. Additionally, while usRAP road segments are typically roadway characteristic dependent, e.g. roadway type, traffic volumes and speed limit, road segments for this demonstration were simplified, based only on unique county and route name combinations. This resulted in longer segments, potentially introducing more variability in crash and contact history along any given segment. Changes in road segmentation could potentially impact the complexion of the maps.

County-Level

Figure 39 presents the total number of heavy-truck crashes on primary roads within each county.

Crash frequency is mapped based on the statewide percentages, i.e. highest five percent, followed by the next 10, 20, 25, and 40 percent, respectively. On a county-level, the highest five percent represents the five counties with the highest crash frequency, because Iowa has 99 counties. The top counties all contain large metropolitan areas as well as interstate highways.

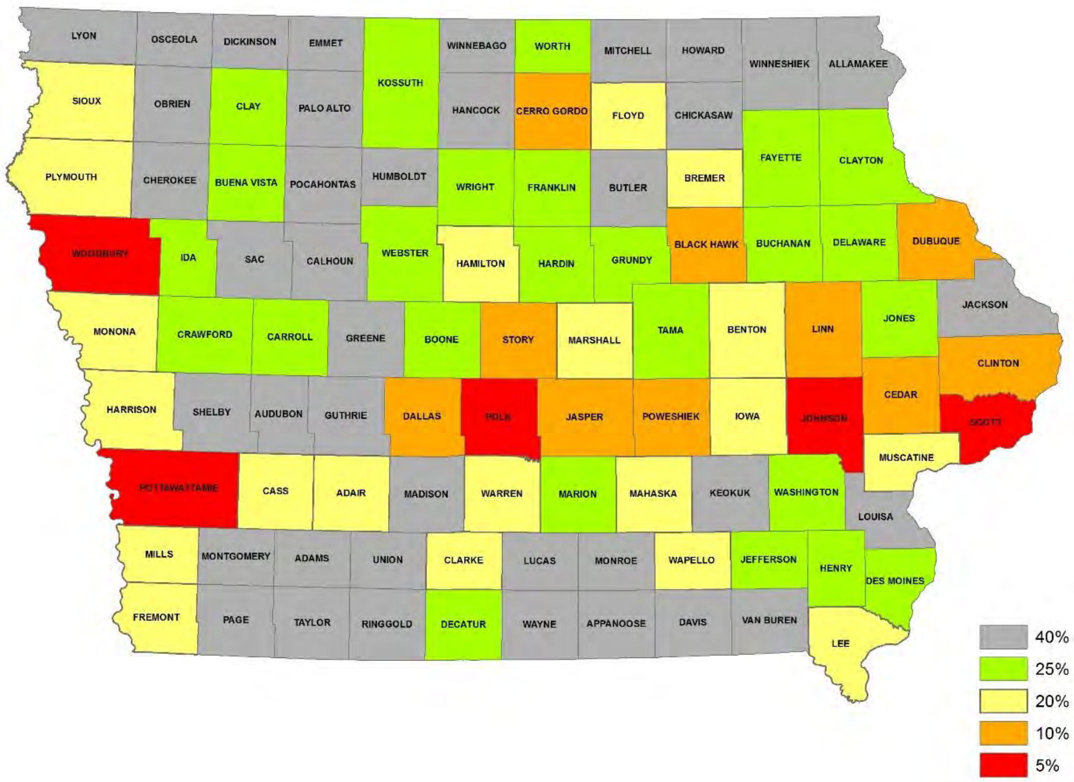


Figure 39. County-level heavy-truck primary-road crash frequency

Figure 40 (left) is similar to Figure 39, except that it presents crash density on primary roads within each county. In other words, the number of crashes were normalized by the mileage of primary roads within each county. Many of the rankings were similar, but it is apparent that there were changes among the resulting categories.

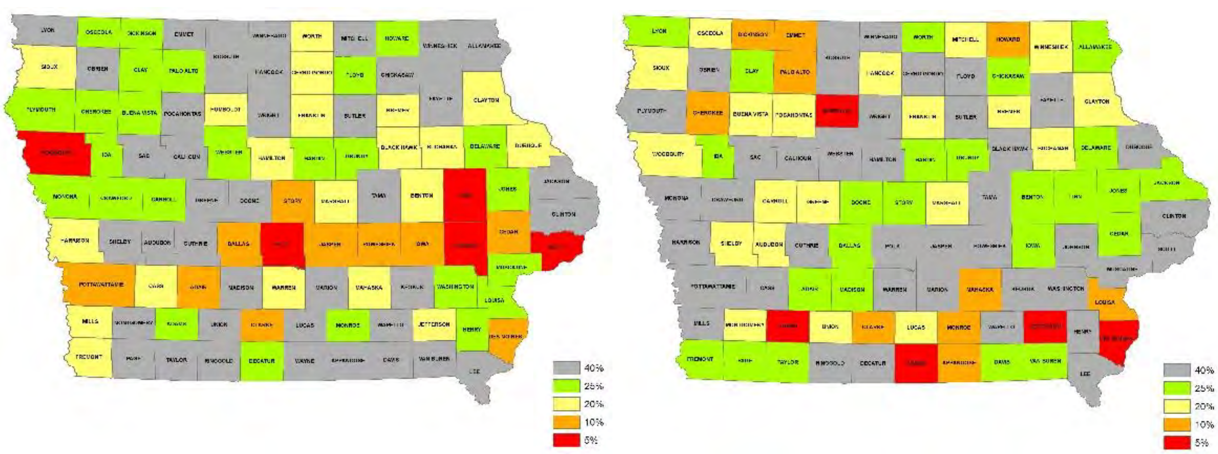


Figure 40. County-level primary-road heavy-truck crash history by density or crashes per mile (left) and crash rate or crashes per 100M VMT (right)

Of greater contrast is Figure 40 (right). It presents heavy-truck crash rate, or the number of crashes based on the heavy-truck traffic on primary roads within each county. Therefore, the rankings are exposure-based. Many of the highest 15 percent counties based on frequency or density are not in the highest 15 percent of crash rate. This may suggest that, while there are many heavy-truck crashes in these counties, the crash experience may not be high when considering the amount of truck traffic. For example, Polk County was in the top five counties for both crash frequency and rate but is in the lowest 40 percent for crash rate. Polk County is not only the largest county in the state but has two major interstates traversing it: I-35 and I-80. A combination of these maps, on a single or multiyear basis, may potentially be used to evaluate and plan resource allocation. These maps may also be refined by crash severity, times of day, manner of collision, or other crash characteristics.

Figure 41 presents total VSIS contact frequency on primary roads within each county.

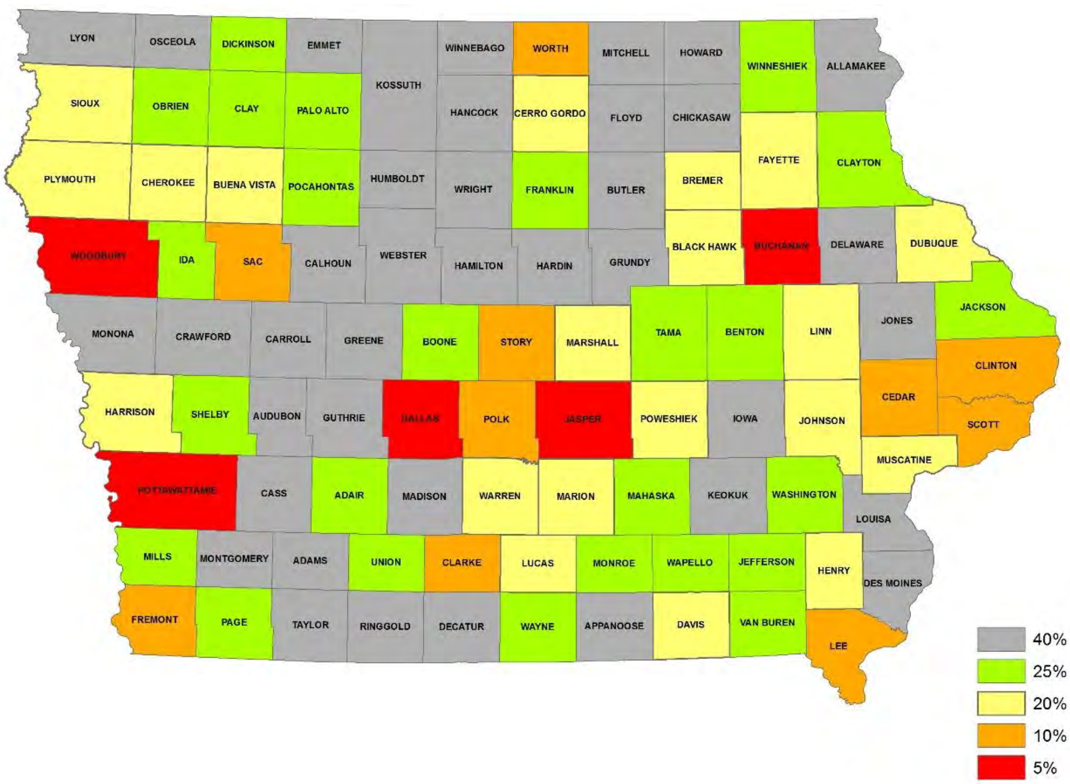


Figure 41. County-level primary-road VSIS contact frequency by county

A similar map may also be created for ECCO contacts. It, or the similar ECCO map, may be compared to the crash maps for resource allocation purposes. Figure 42 (left) and (right), respectively, presents the VSIS contact frequency based on primary-road mileage and primary-road heavy-truck traffic.

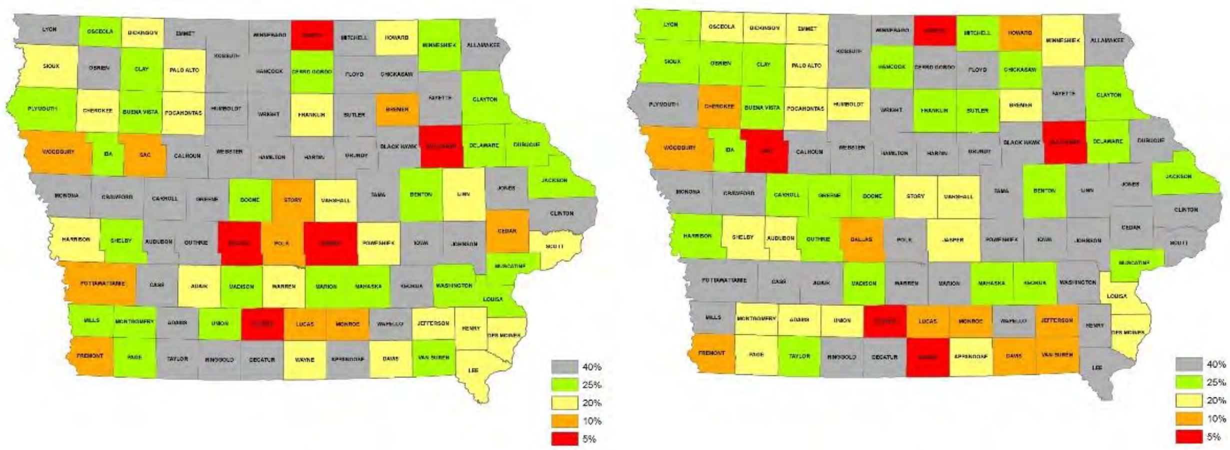


Figure 42. County-level primary-road VSIS contact history by density or contacts per mile (left) and contact rate or contacts per 100M VMT (right)

Route-Level

Figure 43 (top) and (bottom) is similar to Figure 40 (left) and (right), with the exception that heavy-truck crash density and rate are presented on a route-level instead of the county-level. This technique facilitates a less aggregate view of crash experience, although crash data are still presented on pre-determined roadway segments. On the route-level, the percentages are based on the cumulative primary-roadway mileage in the state. Therefore, the top five percent represents five percent of the state-maintained roadways. In Figure 43 (top), representing heavy-truck crashes per mile, the interstates are prominent in the top 15 percent, which is to be expected given the heavy-truck traffic. Conversely, these roads are often rated much lower with respect to heavy-truck crash rates, as can be seen in Figure 43 (bottom). This is likely because the crash experience is consistent with the heavy-truck traffic. The roads presented in Figure 43 (bottom) are more discontinuous than those in Figure 43 (top). Some of these road segments may simply have more crashes, relative to other roads. In other cases, road segments with lower truck traffic will be more sensitive to crash frequency.

Both of these maps can potentially be used, independently or in conjunction, to allocate resources depending on priorities. For example, if emphasis is on where the most crashes are occurring, Figure 43 (top) would be of more benefit. This emphasis would likely result in greater visibility and interaction of law enforcement with heavy trucks. On the other hand, if emphasis is where more crashes are occurring, relative to traffic (exposure), while Figure 43 (bottom) may be of more interest. It is possible that the visibility of law enforcement with heavy trucks could be lower, if traffic volumes are lower. An approach where highly rated on both maps are targeted may provide the most benefit. Additionally, all underlying crash data and the resulting discreet metric values, may also be evaluated in more detail within GIS or a spreadsheet.

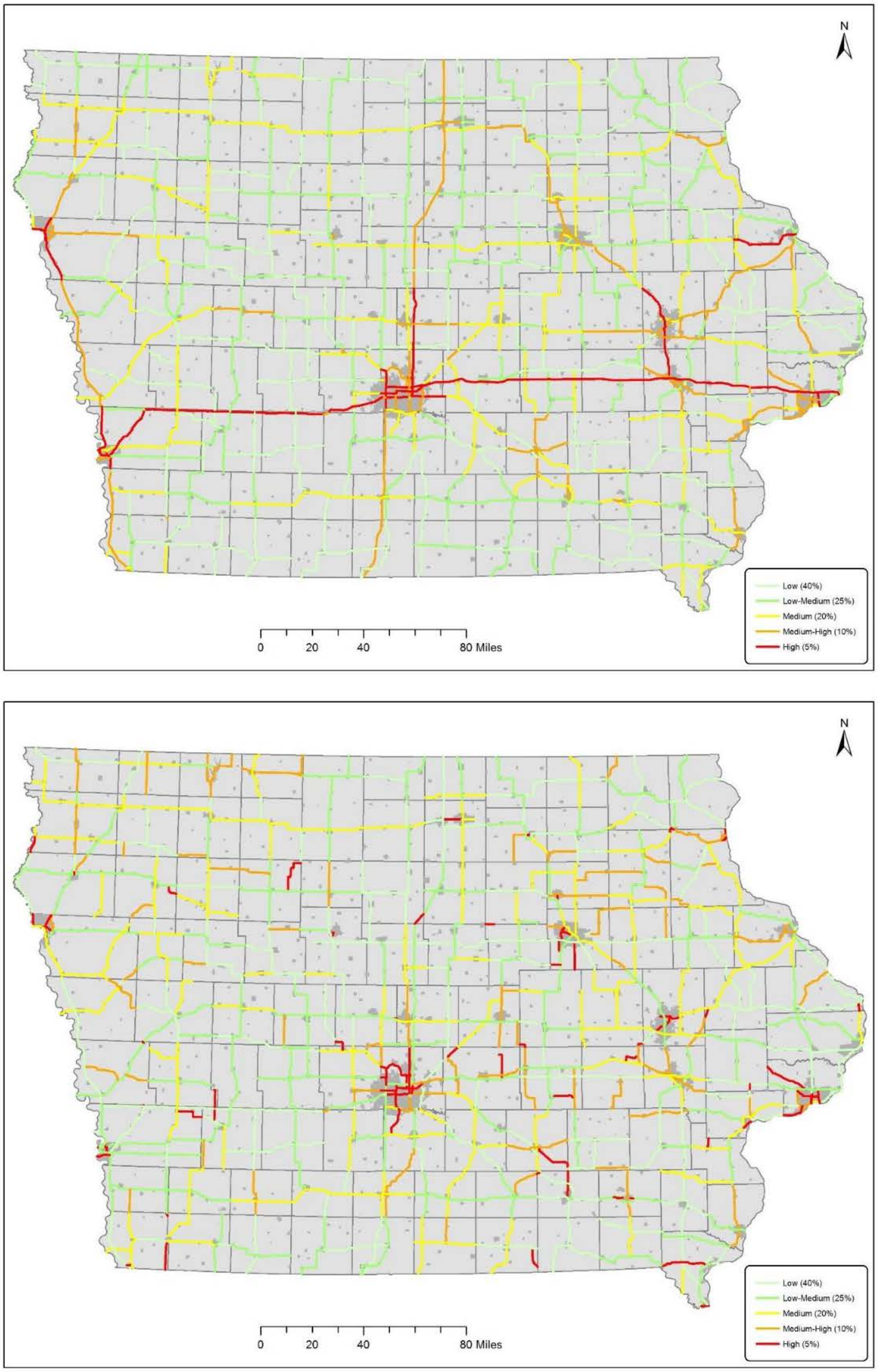
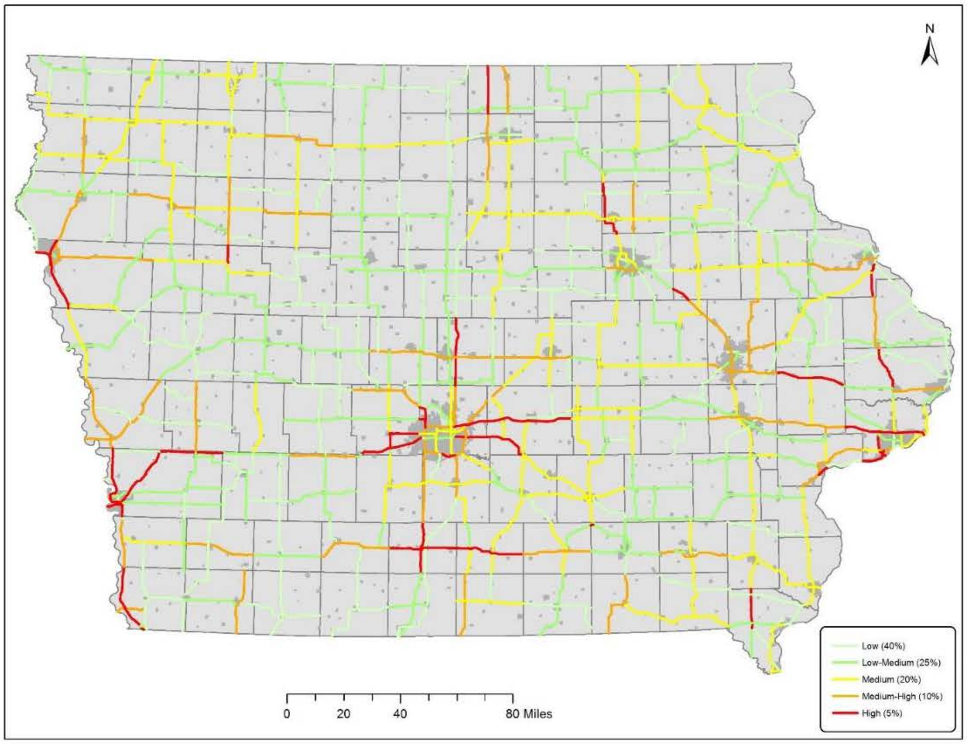


Figure 43. Route-level primary-road heavy-truck crash history by density or crashes per mile (top) and by rate or crashes per 100M VMT (bottom)

VSIS contact density (contacts per mile) and rate (contacts per 100 million vehicle miles of heavy-truck travel are presented in Figure 44 (top) and (bottom), respectively. All of the road segments with enforcement scales are represented in the top five percent of contacts per mile in Figure 44 (top). Other road segments are represented as well. Figure 44 (bottom) conveys the road segments with the highest number of inspections with respect to heavy-truck traffic. These maps may be used to assess the location and level of enforcement as well as be used in conjunction with the crash-based maps in Figure 43 (top) and (bottom) to investigate relationship between crash experience and inspection activity. Additionally, similar maps may also be created for ECCO contacts.



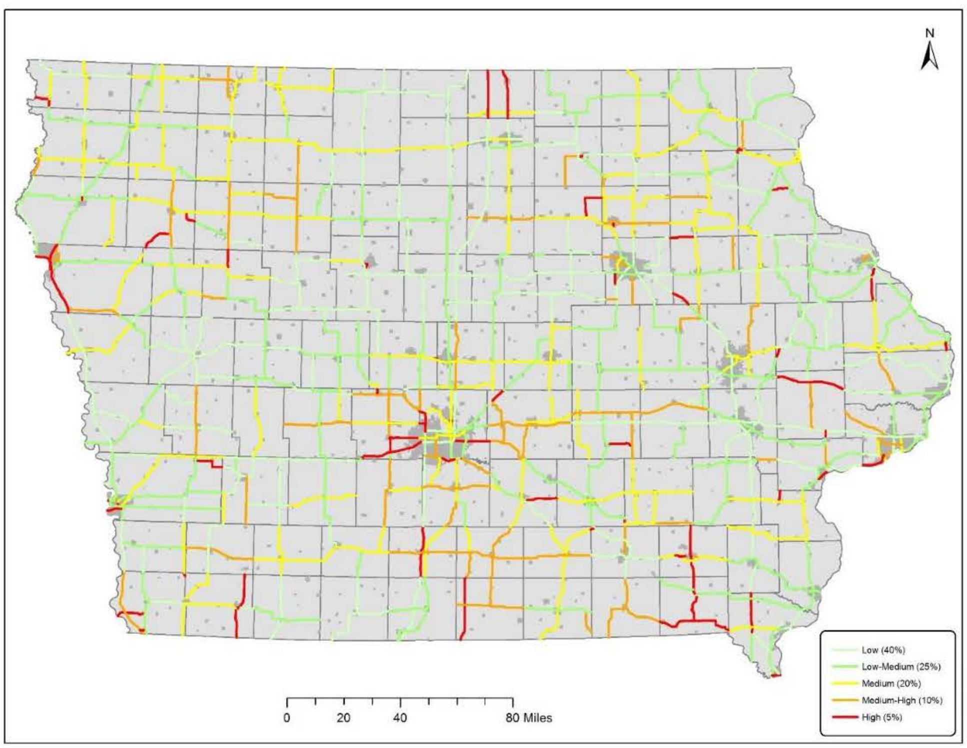


Figure 44. Route-level primary-road heavy-truck VSIS contact history by density or contacts per mile (top) and by rate or contacts per 100M VMT (bottom)

CONCLUSIONS

Findings from the single-vehicle crash (binary probit) model and multiple-vehicle crash (nested logit) model were both complimentary and contradictory. Both models found older drivers to be associated with more severe injuries. Both models also indicated crashes impacting and damaging the front of both heavy trucks and non-heavy trucks to play a significant role in the severity outcome of the crash. Model estimates also indicated rollovers to significantly influence the occurrence of severe crashes.

The main disparity of the two models relates to the effect single-unit and combination trucks have on crash severity, with combination trucks increasing the probability of a severe injury in the multiple-vehicle model and single-unit trucks increasing the probability of an injury in single-vehicle crashes. Other factors found to be significant in either of the two models relate to the manner of the collision, temporal factors (season, day of week, time of day), vehicle characteristics, roadway characteristics, and environmental factors.

Posted speed limits were also found to have potentially great influence on heavy-truck crash severity outcomes, with higher speeds increasing the probability of severe crash outcomes. The models also indicted certain times of the day to be significantly related to severe heavy-vehicle crashes. Model estimates indicate severe crashes are more likely during morning (5 a.m. to 8 a.m.) and midday (11 a.m. to 2 p.m.) hours of the day. Other temporal factors the model estimated to be significantly associated with severe crashes related to the day of the week the crash takes place. Model estimates found severe crashes to be more likely toward the beginning of the week (Monday or Tuesday) or over the weekend (Saturday or Sunday).

While the majority of crashes occurred in dry conditions, a higher proportion of single-vehicle crashes occurred on wet and icy surfaces while a higher proportion of multiple-vehicle crashes occurred under snowy and slushy conditions. Additionally, the majority of multiple-vehicle and single-vehicle crashes also occurred in daylight conditions, but a statistically significant greater proportion occurred in dark, unlighted road conditions.

Descriptive statistics, and a test of proportions, indicated proportionally more younger heavy-truck drivers (ages 20 to 34) involved in single-vehicle crashes compared to multiple-vehicle crashes. In addition, the proportion of heavy-truck drivers under the age of 30 involved in a crash was higher than Iowa CDL license holders, not considering vehicle miles of travel of these drivers. Heavy-truck driver age distribution is far more concentrated than non-heavy-truck driver age distribution, with a majority heavy-truck drivers being middle-aged.

Unfortunately, descriptive statistics of the most recent five years of licensure data revealed very little. No explanatory variables relating to driver age, license endorsements, license restrictions, license type, and gender were found to be significantly related to crash frequency.

Descriptive statistics and the results from test proportions indicated differences in proportions between law enforcement contacts and crashes both temporally and spatially for time of day, day of week, month, road classifications, and individual counties. No significant differences were found between VSIS and ECCO contacts, and their statewide proportions were generally consistent, which possibly suggests that either ECCO or VSIS contacts may be used as a proxy for law enforcement activity. Temporally, contact proportions were much lower during the early morning hours from 2:00 a.m. to 8:00 a.m. and late afternoon hours from 2:00 p.m. to 6:00 p.m. as well as on Saturday and Sunday. Enforcement contact proportions were generally lower for non-primary (state) roadways. Lower proportions of crashes were consistently observed with higher proportions of enforcement contacts. Such comparisons, as well as visual presentation of these data, may serve as useful tools in allocating enforcement resources and assessing possible enforcement impacts on traffic safety.

The findings of this research may potentially benefit the areas of heavy-truck design, driver education and licensing and law enforcement resource allocation. The findings are consistent with previous research identifying the importance of the heavy-truck frontal structure as well as other safety features, such as stability control, air bags, collision and lane departure warning systems and improved braking systems. In addition, the findings support education of heavy-truck drivers regarding the importance of being alert after extended off duty periods offers and susceptibility to fatigue in the morning. Lastly, the findings may be used, in part, by law enforcements agencies in developing schedules, establishing enforcement priorities and monitoring enforcement impacts.

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APPENDIX A: SUMMARY STATISTICS OF SELECT VARIABLES

Table A.1. Summary statics of select variables for multiple- and single-vehicle heavy-truck crashes 2007 through 2012

Variables	Multiple Vehicle Mean (Standard Deviation) or Percentage	Single Vehicle Mean (Standard Deviation) or Percentage
Crash Specific Characteristics		
Crash Severity		
Fatal and Major/Minor and Possible/PDO	5.54/22.2/72.3	3.86/20.3/75.8
Manner of Collision		
Non-Collision/Rear-end/Broadside/Head-on/Sideswipe(same direction)/Other/Not Reported/Unknown	2.33/30.0/18.4/3.31/33.1/11.0/1.62/0.23	93.6/0.00/0.05/0.37/0.00/0.26/2.36/3.36
Number of Vehicles per Crash		
Two Vehicles/Three or More Vehicles	91.2/8.82	-
Most Harmful Event		
Ran off Road/Crossed Centerline/Rollover/Jackknife/Collision with Pedestrian/Collision with Vehicle/Collision with Other non-Fixed Object/Animal/Collision With Fixed Object/Miscellaneous Event/Other/Not Reported/Unknown	0.35/0.82/0.62/0.28/0.03/88.8/0.79//0.08/0.83/0.45/2.5 6/4.17/0.22	3.92/0.16/29.9/9.78/0.00/0.60/1.87/8.82/33.8/0.66/6.48 /3.90/0.18
Vehicle in Collision With a Heavy Truck*		
Heavy Truck/Passenger Vehicle/Van/SUV/Light Truck/Other Vehicle Type	14.6/51.4/8.99/13.2/16.7/2.24	-
Time and Location Characteristics		
Month		
Jan/Feb/Mar/Apr/May/Jun/Jul/Aug/Sep/Oct/Nov/Dec	12.1/10.6/6.64/6.36/6.90/7.55/7.20/7.85/7.46/8.30/6.91 /12.2	9.83/10.1/6.52/6.76/7.32/7.78/7.41/7.05/6.99/9.34/9.94 /11.0
Day of Week		
Sun/Mon/Tue/Wed/Thu/Fri/Sat	4.88/17.3/18.6/16.9/17.3/17.5/7.55	
Time of Day		
1:00-1:59/2:00-3:59/4:00-5:59/6:00-7:59/8:00-9:59/10:00-11:59/12:00-13:59/ 14:00-15:59/16:00-17:59/18:00-19:59/20:00-21:59/22:00-23:59/Not Reported	1.64/1.22/2.18/8.95/15.2/15.5/15.3/16.2/11.8/5.91/3.61 /2.47/0.03	5.31/5.38/7.09/9.85/12.2/12.0/11.0/10.6/9.32/6.37/6.19 /4.69/0.04
Location		
Urban/Rural	59.9/40.1	34.9/65.1
Vehicle Characteristics		
Heavy Truck Age		
Continuous	7.59 (7.34)	7.28 (7.55)
Heavy Truck Type		
Single Unit/Combination	37.7/62.3	24.7/75.3
Heavy Truck Location of Initial Impact		
Front/Passenger Side/Rear/Driver Side/Other	26.5/25.0/17.0/23.8/7.70	22.5/30.9/4.32/20.0/22.3
Heavy Truck Location of Most Damage		
Front/Passenger Side/Rear/Driver Side/Other	25.5/23.5/15.5/22.5/13	18.9/29.4/4.60/20.5/22.3
Heavy Truck Occupancy		
Continuous	1.12 (0.51)	1.15 (0.50)
Vehicle other the a Heavy Truck - Vehicle Age *		
>5 years/>10 years	64.6/35.4	-
Vehicle Other than a Heavy Truck - Location of Most Damage*		
Front/Passenger Side/Rear/Driver Side	29.0/18.1/12.9/27.9	-
Vehicle Other than a Heavy Truck - Occupancy *		
Single Occupant/Multiple Occupants	74.0/26.0	-
Vehicle Other than a Heavy Truck - Vehicle Action *		
Turning/Slowing/Stopping or Slowing/Other	11.8/6.03/11.0/71.2	-

*Indicates indicator variables established by relating crash level information to the vehicle level. This relationship often results in a many-to-one relationship. Values may not add to 100 percent due to the possibility of a many-to-one relationship.

Table A.1. (continued) Summary statics of select variables for multiple- and single-vehicle heavy-truck crashes 2007 through 2012

Variables	Multiple Vehicle Mean (Standard Deviation) or Percentage	Single Vehicle Mean (Standard Deviation) or Percentage
Driver Characteristics		
Heavy Truck Driver's Age		
Continuous	45.5 (13.11)	44.6 (13.3)
Heavy Truck Driver's Gender		
Male/Female/Not Reported/Unknown	90.1/2.75/7.11/0.03	93.5/2.93/2.93/0.04
Heavy Truck Driver Contributing Circumstances		
No Improper Action/Ran Traffic Control Device/Traveling too Fast for Conditions/Crossed Centerline/ Lost Control/Swerved/Operating Recklessly/FTYROW/Distracted/Other/Not Reported/ Unknown	47.9/2.05/2.57/1.72/3.40/1.38/0.68/9.68/0.39/21.7/0.51 /8.03	23.3/0.57/9.96/0.53/31.34/3.13/0.90/1.15/1.56/20.2/0.0 7/7.25
Vehicle Other than a Heavy Truck - Driver's Age*		
<20/<25/<30/40 to 60/>60	12.1/22.8/31.1/27.2/24.5	-
Vehicle Other than a Heavy Truck - Driver's Gender*		
Male/Female/Not Reported/Unknown	51.3/39.8/8.78/0.04	-
Vehicle Other than a Heavy Truck - Driver Contributing Circumstances*		
Traveling too Fast for Conditions/Lost Control/FTYROW	5.83/6.61/9.39	-
Roadway and Environmental Characteristics		
Speed Limit		
5/10/15/20/25/30/35/40/45/50/55/60/65/Not Reported	0.17/0.32/0.39/1.08/17.2/6.51/13.0/1.54/6.89/1.84/23.9 /0.57/11.3/11.3/4.03	0.20/0.42/0.42/0.79/11.3/2.86/6.17/0.44/3.70/3.22/30.2 /0.27/12.9/19.3/8.17
Road Classification		
Interstate/US Route/IARoute/Secondary/Municipal/ Institutional/Unknown	25.9/24.0/12.5/10.0/26.7/0.14/0.73	32.6/21.4/10.8/20.9/12.9/0.05/1.34
Weather Conditions		
Clear/Partly Cloudy/Cloudy/Fog or Smoke/Mist/Rain/Sleet/Snow/Severe Wind/Blowing Debris/Other/Not Reported/Unknown	48.5/15.8/11.8/1.40/1.58/4.68/1.77/11.5/0.38/2.06/0.07 /0.34/0.24	42.3/12.6/10.3/1.24/1.81/6.92/3.24/10.8/1.67/2.54/0.11 /5.80/0.75
Surface Conditions		
Dry/Wet/Ice/Snow/Slush/Sand/Water/Other/Not Reported/Unknown	64.2/11.7/8.20/11.9/1.80/1.31/0.06/0.29/0.31/0.23	55.1/13.0/13.3/7.49/0.93/3.22/0.05/0.44/5.86/0.64
Light Conditions		
Daylight/Dark(road lighted)/Dark(road not lighted)/Other/Not Reported/Unknown	79.8/7.38/8.52/3.97/0.24/0.09	59.14/6.28/23.05/5.87/5.55/0.11

*Indicates indicator variables established by relating crash level information to the vehicle level. This relationship often results in a many-to-one relationship. Values may not add to 100 percent due to the possibility of a many-to-one relationship.

APPENDIX B: CRASH SEVERITY MODELS

Methodology

Transportation issues tend to be stochastic nature, which lends well to the use of statistical modeling in transportation analysis. One of the more frequently used methods of crash investigation in the literature was modeling crash severity using either unordered (multinomial logit or nested logit) or ordered (ordered logit or probit) discrete outcome models. Both ordered and unordered models have their own unique benefits and detriments and the choice of one method over the other involves taking tradeoffs into consideration. For this study, unordered models were utilized due to their flexibility and the associated superior fit over order models.

The preponderance of differences between single- and multiple-vehicle crashes was noticed during the descriptive analysis. These differences prompted the development of two separate models of heavy-truck crash severity, one for single-vehicle collisions and one for multiple-vehicle collisions. This splitting of the data was also verified using a transferability test.

Multiple-Vehicle Crash Severity Model

A nested logit model was developed where the outcomes fatal or major injury and minor or possible injury were nested to allow their shared unobserved effects to cancel out (see Figure B.1).

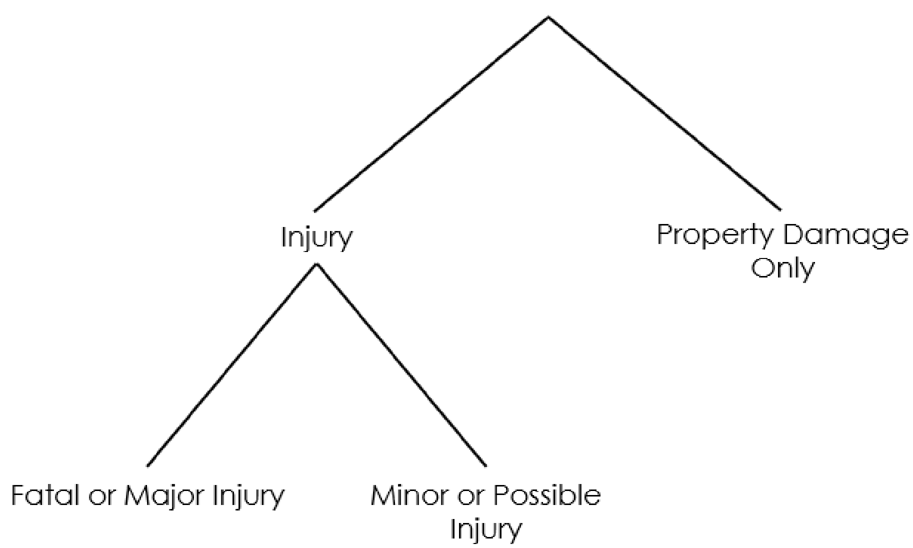

Figure B.1. Nested logit structure for multiple-vehicle crash severity model

Table B.1 presents the estimation results of the nested logit model. A total of 19,465 observations of multiple-vehicle heavy-truck crashes were used to estimate the model. From the table, one can observe the sign and magnitude of each of the 35 variable parameters and two constants included in the model. Parameters with positive signs indicate an increase in the likelihood of a severity outcome, while the opposite effect holds true for negative parameters. The statistical significance of each variable included in the model can also be seen in Table B.1. A one tailed *t*-test using α=0.05 ($t_{critical}$=1.645) was used to evaluate variable significance. The overall fit of the model is quite good (adjusted ρ^2 of 0.26) given the large amount of variance present in the data set as indicated by the large restricted log likelihood, *LL(0)* equal to -15,695.62. Additional tests of the appropriateness of the nested structure were conducted by verifying the estimated inclusive parameter φ was statistically greater than zero and less than one. This was accomplished using a two tailed *t*-test with α=0.05 ($t_{critical}$=1.96).

To better interpret the effect of the variables included in the model, elasticities and pseudo elasticities were computed and presented in Table B.2. Elasticities measure the percent change in the probability of a severity outcome given a one percent change in the value of a continuous variable. Pseudo elasticities, on the other hand, represent the percent change in the probability of a severity outcome given a change in an indicator variable from 0 to 1. All elasticities and pseudo elasticities shown in Table B.2 are direct elasticities.

Table B.1. Nested logit model estimation results for multiple-vehicle heavy-truck crashes

Variable	Injury (Upper Nest)		Fatal or Major Injury		Minor or Possible Injury		PDO	
	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic
Constant								
Minor/Possible Injury Crash	-	-	-	-	2.534	15.08	-	-
Property Damage Only (PDO) Crash	-	-	-	-	-	-	4.163	11.18
Crash Specific Characteristics								
(HDBRD) Head-on or Broadside Crash	0.740	15.08	-	-	-	-	-	-
(SDSWIPE) Sideswipe (same direction) Crash	-	-	-	-	-	-	0.709	13.60
(3PLUS) 3or More Vehicles in a Crash	0.654	10.37	-	-	-	-	-	-
(HTHT) Heavy Truck Crash with Heavy Truck	-	-	0.526	5.51	-	-	-	-
(VAN) Crash Involved a Van	-	-	0.596	5.19	-	-	-	-
(CAR) Crash Involved a Car	-	-	0.307	3.57	-	-	-	-
(SUV) Crash Involved a SUV	-	-	0.443	4.11	-	-	-	-
Time and Location Characteristics								
(LTSUMM) Late Summer (July, August, or September)	-	-	-	-	0.120	2.00	-	-
(FALL) Fall (October, November)	-	-	-	-	-	-	0.159	3.00
(BWEEK) Beginning of the Week (Monday or Tuesday)	-	-	0.282	3.69	-	-	-	-
(EWEEK) End of the Week (Thursday or Friday)	-	-	-	-	-	-	0.087	2.21
(WKND) Weekend (Saturday/Sunday)	-	-	0.289	2.63	-	-	-	-
(AM) Morning (5AM to 8AM)	-	-	0.211	1.95	-	-	-	-
(AFTRN) Afternoon (11AM to 2PM)	-	-	0.232	2.75	-	-	-	-
(PM) Evening Peak (3PM to 6PM)	-	-	-	-	-	-	0.161	3.46
Vehicle Attributes								
(COMB) Cargo Type Combination Truck	-	-	0.823	7.61	0.290	3.38	-	-
(HTFRNT) Heavy Truck Front Initial Impact	-	-	1.362	7.65	0.875	5.07	-	-
(HTSIDE) Heavy Truck Side (driver or passenger side) Initial Impact	-	-	-	-	0.209	2.87	-	-
(PVFRNT) Passenger Vehicle Front Most Damage	0.446	9.88	-	-	-	-	-	-
(PVSIDE) Passenger Vehicle Side Most Damage (driver or passenger side)	-	-	0.236	3.02	-	-	-	-
(PVREAR) Passenger Vehicle Rear Most Damage	-	-	-	-	0.418	4.28	-	-
(PVAGE10) Passenger Vehicle 10+ Years Old	0.302	7.92	-	-	-	-	-	-
(PVMULTIO) Passenger Vehicle had Multiple Occupants	0.140	3.39	-	-	-	-	-	-
Driver Characteristics								
(HTAGE) Heavy Truck Driver Age	-	-	0.006	2.41	-	-	-	-
(PVDRV60) Passenger Vehicle Driver 60+ Years Old	-	-	0.268	3.22	-	-	-	-
(PVFEMALE) Passenger Vehicle Driver is a Female	-	-	-	-	0.505	7.48	-	-
(PVFTYROW) Passenger Vehicle Driver FTYROW	-	-	-	-	-	-	0.248	3.97
Roadway and Environmental Characteristics								
(SPEED55) Speed Limit 55+ (fatal/major)	1.030	25.40	-	-	-	-	-	-
(WINTRD)Winter Road Surface (Ice, Snow, or Slush)	-	-	-	-	0.326	3.37	0.677	8.74
(Precip) Raining or Misting	-	-	-0.443	-2.81			-	-
(Dark) Dark Environment No Road Lighting	-	-	0.481	3.61	0.265	2.52	-	-
Log Likelihood at zero				**-15,695.62**				
Log Likelihood at convergence				**-11,542.43**				
Adjusted ρ^2				**0.26**				
Inclusive Parameter φ				**0.71**				
t-Statistic $\varphi \neq 0$				5.90				
t-Statistic $\varphi \neq 1$				-2.40				

Table B.2. Nested logit model estimated elasticities

Variable	Elasticity (%)			
	Injury (Upper Nest)	Fatal/Major Injury	Minor/Possible Injury	PDO
Crash Specific Characteristics				
(HDBRD) Head-on or Broadside Crash	67	-	-	-
(SDSWIPE) Sideswipe (same direction) Crash	-	-	-	21
(3PLUS) 3or More Vehicles in a Crash	56	-	-	-
(HTHT) Heavy Truck Crash with Heavy Truck	-	60	-	-
(VAN) Crash Involved a Van	-	70	-	-
(CAR) Crash Involved a Car	-	32	-	-
(SUV) Crash Involved a SUV	-	49	-	-
Time and Location Characteristics				
(LTSUMM) Late Summer (July, August, or September)	-	-	7	-
(FALL) Fall (October, November)	-	-	-	5
(BWEEK) Beginning of the Week (Monday or Tuesday)	-	29	-	-
(EWEEK) End of the Week (Thursday or Friday)	-	-	-	3
(WKND) Weekend (Saturday/Sunday)	-	30	-	-
(AM) Morning (5AM to 8AM)	-	21	-	-
(AFTRN) Afternoon (11AM to 2PM)	-	23	-	-
(PM) Evening Peak (3PM to 6PM)	-	-	-	5
Vehicle Attributes				
(COMB) Cargo Type Combination Truck	-	111	19	-
(HTFRNT) Heavy Truck Front Initial Impact	-	233	68	-
(HTSIDE) Heavy Truck Side (driver or passenger side) Initial Im	-	-	13	-
(PVFRNT) Passenger Vehicle Front Most Damage	37	-	-	-
(PVSIDE) Passenger Vehicle Side Most Damage	-	24	-	-
(PVREAR) Passenger Vehicle Rear Most Damage	-	-	28	-
(PVAGE10) Passenger Vehicle 10+ Years Old	24	-	-	-
(PVMULTIO) Passenger Vehicle had Multiple Occupants	10	-	-	-
Driver Characteristics				
(HTAGE) Heavy Truck Driver Age*	-	0.26	-	-
(PVDRV60) Passenger Vehicle Driver 60+ Years Old	-	27	-	-
(PVFEMALE) Passenger Vehicle Driver is a Female	-	-	35	-
(PVFTYROW) Passenger Vehicle Driver FTYROW	-	-	-	7
Roadway and Environmental Characteristics				
(SPEED55) Speed Limit 55+ (fatal/major)	112	-	-	-
(WINTRD)Winter Road Surface (Ice, Snow, or Slush)	-	-	21	20
(Precip) Raining or Misting	-	-33	-	-
(Dark) Dark Environment No Road Lighting	-	54	17	-

*Indicates continuous variable, all other variables are indicator varaibles taking the value of either 0 or 1

Single-Vehicle Crash Severity Model

Initial model outputs of the multinomial logit model indicated that all injury categories (fatal, major, minor, and possible injuries) should be grouped, and that a two-outcome binary model was more suitable for modeling single-vehicle heavy-truck crash severity. A total of 5,462 observations of single vehicle heavy-truck crashes were used for model estimation. Table shows the sign and magnitude of each of the 13 variable parameters and the constant included in the model. Positive coefficients indicate an increase in the likelihood of a crash with an injury sustained, while negative signs indicate the opposite effect. The statistical significance of each parameter included in the model was evaluated using a one tailed *t*-test and α=0.05 ($t_{critical}$ = 1.645). The overall fit of the single vehicle model (adjusted ρ^2 of 0.16) is not as good as the fit of the multiple-vehicle model. The single vehicle model's inferior fit, in comparison to the multiple-vehicle model, is likely due to the fewer number of variables that were introduced in the model (for example information on the non-heavy-truck driver and vehicle), and found to be significant in the multiple-vehicle model. Additionally, some of the most explanatory variables included in the multiple-vehicle model such as the manner of collision, were not applicable to the single vehicle model, leaving fewer variables available to explain the variance of the data.

To better interpret the results of the single vehicle binary probit model, it is common practice to estimate marginal effects for each variable included in the model instead of elasticities. Marginal effects represent the absolute change in probability for a unit change in an independent variable. Please refer again to Table B.3 for the results of this estimation.

Table B.3. Single vehicle binary probit model results

Variable	Coefficient	*t*- Statistic	Marginal Effect
Constant			
Injury Crash	-1.236	-12.70	-
Crash Specific Characteristics			
(X4) Heavy Truck Ran off the Road	0.130	2.85	0.04
(X6) Most Harmful Event was Rollover	0.802	16.45	0.25
(ANML) Most Harmful Event was Hitting an Animal	-0.769	-5.62	-0.16
Time and Location Characteristics			
(X88) Summer (June, July, or August)	0.110	2.10	0.03
(X96) End of Week (Thursday or Friday)	-0.100	-2.15	-0.03
Vehicle Attributes			
(X45) Vehicle was a Single Unit Truck	0.240	4.94	0.07
(X40) Front of Vehicle Most Damaged	0.264	3.87	0.08
(SDDMG) Side of Vehicle Most Damaged	-0.175	-3.29	-0.05
Driver Characteristics			
(X9) Heavy Truck Driver's Age*	0.004	2.83	0.0013
(X19) Heavy Truck Driver Lost Control	0.411	4.48	0.13
(X20) Heavy Truck Driver Traveling Too Fast	0.274	3.50	0.08
Roadway and Environmental Characteristics			
(X29) Speed Limit is less than 35mph	-0.472	-7.33	-0.12
(X86) Winter Surface Conditions	-0.423	-7.17	-0.11
Log Likelihood at zero		**-2726.43**	
Log Likelihood at convergence		**-2290.03**	
Adjusted ρ^2		**0.16**	

*Indicates continuous variable, all other variables are indicator variables taking the value of either 0 or 1

APPENDIX C: IOWA LICENSE RESTRICTIONS

Restrictions that Apply to Any Motor Vehicle License

C- Mechanical Aid (list aids in the Restriction Supplement Area, spinner knob, tri-pin, left foot accelerator, etc.)

D- Prosthetic Aid.

E- Automatic transmission.

F- Left outside mirror - If the customer has less than 20/100 acuity in left eye or wears a hearing aid.

G- No driving when headlights are required - If the customer has a visual acuity of 20/50 or less.

H- Temporary Restricted License (TRL - Work Permit)

I- Limited Other – Ignition Interlock Required

J- Restrictions on the back of the card.

P- Special Permit.

S- SR-22 or SR-23 insurance required.

T- Medical Report required at renewal.

U- Not valid for 2-wheel vehicles - For 3-wheel motorcycle or motorcycle with a side car.

V- Left and right outside mirrors - If the customer has a peripheral reading of less than 140 degrees.t apply to any motor vehicle license

Restrictions that Apply to Only Commercial Driver's License

H- Restricted CDL.

K- Intrastate Only (Not in use at this time)

L- Vehicles without Air brakes.

M- Class B Passenger Vehicle.

N- Class C Passenger Vehicle.

O- Except Tractor – Trailer (Not in use at this time)

W- Restricted CDL

APPENDIX D: CITATION AND INSPECTION ANALYSIS

Table D.1. Annual contact and crash frequency versus time of day 2009 through 2012

	2009			2010			2011			2012		
TOD	Crash 09	VSIS 09	ECCO 10	Crash 10	VSIS 10	ECCO 10	Crash 11	VSIS 11	ECCO 11	Crash 12	VSIS 12	ECCO 12
0:00-1:59	1.8%	2.4%	2.6%	2.5%	2.2%	2.3%	2.5%	1.2%	1.5%	2.9%	1.4%	1.7%
2:00-3:59	2.0%	1.8%	1.8%	2.1%	1.7%	1.6%	2.1%	0.6%	0.8%	2.7%	0.7%	0.8%
4:00-5:59	3.0%	0.8%	0.7%	3.4%	0.8%	0.8%	3.3%	0.4%	0.4%	3.7%	0.2%	0.3%
6:00-7:59	9.9%	5.7%	7.2%	8.3%	6.1%	8.1%	9.3%	3.3%	4.7%	9.4%	3.5%	5.6%
8:00-9:59	13.1%	22.9%	23.5%	14.6%	23.8%	24.1%	14.4%	19.8%	20.2%	14.2%	20.4%	20.5%
10:00-11:59	15.5%	23.7%	22.9%	15.8%	23.9%	23.7%	13.3%	22.9%	23.2%	13.7%	22.6%	22.2%
12:00-13:59	14.8%	19.7%	18.0%	14.2%	20.5%	18.2%	14.3%	23.8%	21.7%	14.0%	23.7%	21.7%
14:00-15:59	15.8%	7.8%	8.5%	15.1%	7.9%	8.5%	15.7%	12.3%	12.7%	15.0%	11.7%	12.1%
16:00-17:59	11.0%	5.7%	5.9%	10.5%	5.4%	5.7%	11.6%	7.3%	6.9%	11.9%	7.3%	7.3%
18:00-19:59	6.2%	4.9%	4.4%	6.0%	4.0%	3.5%	5.7%	4.2%	3.6%	6.0%	3.8%	3.4%
20:00-21:59	3.9%	2.7%	2.5%	4.3%	2.1%	1.8%	4.6%	2.8%	2.5%	3.8%	2.9%	2.6%
22:00-23:59	2.9%	1.7%	2.0%	3.2%	1.5%	1.8%	3.3%	1.4%	1.7%	2.7%	1.6%	1.8%

Table D.2. Total contact and crash frequency versus time of day 2009 through 2012

TOD	Crash	ECCO	VSIS
0:00-1:59	2.4%	2.0%	1.8%
2:00-3:59	2.2%	1.3%	1.2%
4:00-5:59	3.3%	0.6%	0.6%
6:00-7:59	9.2%	6.4%	4.6%
8:00-9:59	14.1%	22.1%	21.7%
10:00-11:59	14.7%	22.9%	23.3%
12:00-13:59	14.3%	19.8%	22.0%
14:00-15:59	15.4%	10.4%	10.0%
16:00-17:59	11.2%	6.5%	6.5%
18:00-19:59	6.0%	3.8%	4.2%
20:00-21:59	4.1%	2.4%	2.7%
22:00-23:59	3.0%	1.8%	1.6%

Table D.3. Percetange difference between contacts and crashes by time of day (same year)

Rank	Time of day (same year)	Difference
1	10:00-11:59	8.60%
2	12:00-13:59	7.64%
3	8:00-9:59	7.59%
4	14:00-15:59	-5.36%
5	16:00-17:59	-4.73%
6	6:00-7:59	-4.62%
7	4:00-5:59	-2.79%
8	18:00-19:59	-1.73%
9	20:00-21:59	-1.48%
10	22:00-23:59	-1.45%
11	2:00-3:59	-1.03%
12	0:00-1:59	-0.63%

Table D.4. Percetange difference between contacts and crashes by time of day (lagged year)

Rank	Time of day (laggedyear-Contacts09)	Difference
1	10:00-11:59	8.87%
2	8:00-9:59	7.24%
3	14:00-15:59	-5.98%
4	12:00-13:59	5.40%
5	16:00-17:59	-5.25%
6	6:00-7:59	-3.35%
7	4:00-5:59	-2.32%
8	20:00-21:59	-1.80%
9	18:00-19:59	-1.29%
10	22:00-23:59	-1.10%
11	2:00-3:59	-0.29%
12	0:00-1:59	-0.13%

Table D.5. Annual contact and crash frequency versus day of week 2009 through 2012

	2009			2010			2011			2012		
DOW	Crash 09	VSIS 09	ECCO 10	Crash 10	VSIS 10	ECCO 10	Crash 11	VSIS 11	ECCO 11	Crash 12	VSIS 12	ECCO 12
Sunday	5.4%	3.0%	3.5%	5.0%	2.8%	2.9%	5.2%	2.4%	2.4%	4.8%	2.8%	2.4%
Monday	17.7%	16.3%	16.2%	19.4%	16.6%	15.9%	17.7%	16.2%	16.1%	17.3%	16.3%	16.3%
Tuesday	18.6%	18.7%	18.4%	16.4%	19.3%	19.3%	18.5%	19.3%	19.3%	17.8%	18.9%	19.4%
Wednesd	15.5%	21.1%	20.6%	18.3%	21.1%	21.0%	16.7%	21.0%	20.3%	17.3%	21.7%	21.1%
Thursday	16.6%	20.2%	20.1%	16.9%	20.7%	20.3%	17.6%	21.4%	20.7%	16.9%	21.1%	20.6%
Friday	16.7%	17.4%	17.5%	15.9%	16.6%	17.1%	17.5%	16.7%	17.6%	18.5%	16.7%	17.4%
Saturday	9.4%	3.2%	3.8%	8.2%	2.9%	3.5%	6.8%	2.9%	3.6%	7.4%	2.6%	2.9%

Table D.6. Total contact and crash frequency versus day of week 2009 through 2012

DOW	Crash	ECCO	VSIS
Sunday	5.1%	2.8%	2.8%
Monday	18.1%	16.1%	16.4%
Tuesday	17.7%	19.0%	19.0%
Wednesd	17.0%	20.7%	21.2%
Thursday	17.0%	20.4%	20.9%
Friday	17.1%	17.4%	16.9%
Saturday	8.0%	3.4%	2.9%

Table D.7. Percetange difference between total contacts and crashes by day of week

Rank	Day of Week	Difference
1	Saturday	-5.11%
2	Wednesday	4.24%
3	Thursday	3.88%
4	Sunday	-2.37%
5	Monday	-1.74%
6	Tuesday	1.29%
7	Friday	-0.19%

Table D.8. Annual contact and crash frequency versus month 2009 through 2012

	2009			2010			2011			2012		
Month	Crash 09	VSIS 09	ECCO 10	Crash 10	VSIS 10	ECCO 10	Crash 11	VSIS 11	ECCO 11	Crash 12	VSIS 12	ECCO 12
Jan	12.7%	7.5%	7.3%	14.1%	6.1%	5.1%	11.4%	6.4%	6.0%	10.5%	8.6%	7.4%
Feb	6.4%	9.7%	9.9%	10.8%	8.2%	7.4%	9.2%	8.2%	7.9%	8.7%	9.1%	7.5%
Mar	6.0%	10.1%	11.5%	6.2%	10.0%	10.2%	6.3%	9.7%	10.4%	7.8%	9.4%	9.3%
Apr	6.9%	9.1%	10.0%	7.2%	8.8%	9.0%	6.4%	8.9%	9.7%	6.6%	9.8%	9.5%
May	7.3%	7.8%	8.5%	6.1%	7.9%	9.1%	7.7%	7.7%	8.7%	8.7%	9.1%	9.8%
Jun	7.5%	10.3%	10.0%	8.1%	8.4%	9.3%	7.7%	8.8%	9.3%	8.2%	9.3%	9.6%
Jul	7.4%	8.0%	8.1%	6.6%	7.7%	8.8%	8.1%	7.5%	8.2%	9.1%	7.7%	9.0%
Aug	7.3%	7.6%	7.9%	7.3%	7.8%	8.4%	8.9%	10.1%	12.0%	9.3%	9.4%	9.4%
Sep	7.2%	7.4%	7.0%	6.9%	8.6%	8.0%	7.9%	8.3%	8.5%	8.3%	4.3%	5.0%
Oct	8.2%	7.7%	6.8%	8.6%	8.6%	8.6%	9.5%	8.0%	8.3%	8.9%	8.7%	8.8%
Nov	7.9%	8.2%	7.7%	7.4%	8.8%	8.1%	8.4%	7.6%	8.0%	7.2%	7.3%	8.3%
Dec	15.1%	6.7%	5.3%	10.6%	9.0%	8.1%	8.5%	8.8%	3.0%	6.7%	7.2%	6.6%

Table D.9. Total contact and crash frequency versus month 2009 through 2012

Month	Crash	ECCO	VSIS
Jan	12.3%	6.5%	7.2%
Feb	8.9%	8.3%	8.8%
Mar	6.5%	10.4%	9.8%
Apr	6.8%	9.6%	9.2%
May	7.4%	9.0%	8.1%
Jun	7.8%	9.6%	9.2%
Jul	7.7%	8.5%	7.7%
Aug	8.1%	9.3%	8.8%
Sep	7.5%	7.1%	7.1%
Oct	8.8%	8.1%	8.3%
Nov	7.7%	8.0%	8.0%
Dec	10.4%	5.8%	7.9%

Table D.10. Percetange difference between total contacts and crashes by month

Rank	Month	Difference
1	Jan	-5.08%
2	Mar	3.22%
3	Dec	-2.53%
4	Apr	2.38%
5	Jun	1.40%
6	May	0.77%
7	Aug	0.61%
8	Oct	-0.53%
9	Sep	-0.45%
10	Nov	0.24%
11	Feb	-0.05%
12	Jul	0.00%

Table D.11. Contact frequency (2009) versus crash frequency (2008)

		Crash	VSIS	ECCO
No.	County	2008	2009	2009
77	POLK	13.7%	3.2%	3.3%
82	SCOTT	6.6%	1.7%	2.3%
57	LINN	5.0%	1.9%	1.5%
52	JOHNSON	4.9%	0.8%	0.6%
7	BLACK HAWK	4.6%	1.0%	1.6%
78	POTTAWATTAMIE	4.5%	5.8%	9.8%
97	WOODBURY	3.4%	6.4%	7.2%
31	DUBUQUE	2.7%	1.2%	1.5%
23	CLINTON	2.0%	1.5%	1.4%
48	IOWA	1.8%	0.2%	0.5%

Table D.12. Percetange difference between contacts and crashes by county (lagged year)

Rank	County (lagged year-Contacts09)	Difference
1	POLK	-10.51%
2	BUCHANAN	7.67%
3	DALLAS	7.62%
4	JASPER	7.35%
5	SCOTT	-4.85%
6	JOHNSON	-4.04%
7	BLACK HAWK	-3.62%
8	FREMONT	3.30%
9	LINN	-3.08%
10	WOODBURY	3.07%
11	SAC	2.64%
12	WORTH	2.37%
13	LEE	2.25%
14	CLARKE	1.96%
15	IOWA	-1.58%
16	DUBUQUE	-1.45%
17	STORY	1.42%
18	POTTAWATTAMIE	1.29%
19	HAMILTON	-1.20%
20	WEBSTER	-0.98%

Table D.13. Contact frequency (2010) versus crash frequency (2009)

		Crash	VSIS	ECCO
No.	County	2009	2010	2010
77	POLK	14.2%	4.0%	5.0%
82	SCOTT	5.8%	1.9%	2.7%
57	LINN	5.0%	1.8%	1.9%
78	POTTAWATTAMIE	5.0%	8.8%	9.5%
52	JOHNSON	4.5%	1.1%	1.3%
97	WOODBURY	4.2%	7.0%	7.5%
7	BLACK HAWK	3.8%	0.9%	1.6%
31	DUBUQUE	2.7%	1.2%	1.7%
85	STORY	2.1%	2.2%	2.1%
17	CERRO GORDO	1.9%	1.0%	1.2%

Table D.14. Contact frequency (2011) versus crash frequency (2010)

		Crash	VSIS	ECCO
No.	County	2010	2011	2011
77	POLK	13.1%	3.8%	5.0%
82	SCOTT	6.5%	2.0%	2.9%
78	POTTAWATTAMIE	4.9%	7.2%	8.3%
57	LINN	4.4%	1.8%	2.2%
97	WOODBURY	3.9%	4.2%	4.9%
52	JOHNSON	3.7%	0.7%	1.2%
7	BLACK HAWK	3.3%	1.1%	1.9%
31	DUBUQUE	2.8%	1.0%	1.6%
50	JASPER	2.3%	8.0%	5.2%
85	STORY	2.2%	2.0%	1.7%

Table D.15. Contact frequency (2012) versus crash frequency (2011)

		Crash	VSIS	ECCO
No.	County	2011	2012	2012
77	POLK	13.0%	4.4%	4.7%
82	SCOTT	6.3%	2.0%	2.8%
78	POTTAWATTAMIE	5.8%	8.4%	9.3%
57	LINN	5.3%	1.7%	2.1%
52	JOHNSON	5.0%	0.7%	1.1%
31	DUBUQUE	3.7%	1.1%	1.7%
7	BLACK HAWK	3.4%	1.0%	1.4%
97	WOODBURY	3.1%	6.7%	6.7%
85	STORY	2.3%	2.8%	2.1%
17	CERRO GORDO	1.8%	1.0%	1.0%

Table D.16. Annual and total contact versus crash frequency by county (top 10)

		2009			2010			2011			2012			Total		
No.	County	Crash	VSIS	ECCO	Crash	VSIS	ECCO	Crash	VSIS	ECCO	Crash	VSIS	ECCO	Crash	VSIS	ECCO
77	POLK	14.2%	3.2%	3.3%	13.1%	4.0%	5.0%	13.0%	3.8%	5.0%	13.6%	3.8%	4.7%	13.4%	3.8%	4.4%
82	SCOTT	5.8%	1.7%	2.3%	6.5%	1.9%	2.7%	6.3%	2.0%	2.9%	7.1%	2.0%	2.8%	6.4%	1.9%	2.6%
78	POTTAWATTAMIE	5.0%	5.8%	9.8%	4.9%	8.8%	9.5%	5.8%	7.2%	8.3%	5.3%	7.2%	9.3%	5.2%	7.5%	9.2%
57	LINN	5.0%	1.9%	1.5%	4.4%	1.8%	1.9%	5.3%	1.8%	2.2%	5.3%	1.8%	2.1%	5.0%	1.8%	1.9%
52	JOHNSON	4.5%	0.8%	0.6%	3.7%	1.1%	1.3%	5.0%	0.7%	1.2%	5.6%	0.7%	1.1%	4.6%	0.8%	1.0%
7	BLACK HAWK	3.8%	1.0%	1.6%	3.3%	0.9%	1.6%	3.4%	1.1%	1.9%	4.4%	1.1%	1.4%	3.7%	1.0%	1.6%
97	WOODBURY	4.2%	6.4%	7.2%	3.9%	7.0%	7.5%	3.1%	4.2%	4.9%	3.5%	4.2%	6.7%	3.7%	6.0%	6.6%
31	DUBUQUE	2.7%	1.2%	1.5%	2.8%	1.2%	1.7%	3.7%	1.0%	1.6%	3.5%	1.0%	1.7%	3.2%	1.1%	1.6%
85	STORY	2.1%	3.1%	2.0%	2.2%	2.2%	2.1%	2.3%	2.0%	1.7%	2.3%	2.0%	2.1%	2.2%	2.5%	2.0%
50	JASPER	1.8%	9.0%	6.6%	2.3%	8.5%	6.0%	1.5%	8.0%	5.2%	1.8%	8.0%	5.7%	1.9%	8.5%	5.9%

Table D.17. Percetange difference between total contacts and crashes by county (same year)

Rank	County (same year)	Difference
1	POLK	-9.59%
2	BUCHANAN	8.06%
3	DALLAS	7.73%
4	JASPER	6.65%
5	SCOTT	-4.50%
6	JOHNSON	-3.81%
7	LINN	-3.16%
8	SAC	2.73%
9	CLARKE	2.71%
10	BLACK HAWK	-2.67%
11	LEE	2.46%
12	WORTH	2.36%
13	WOODBURY	2.36%
14	POTTAWATTAMIE	2.29%
15	DUBUQUE	-2.02%
16	FREMONT	1.95%
17	WEBSTER	-0.97%
18	HAMILTON	-0.96%
19	CERRO GORDO	-0.89%
20	IOWA	-0.86%

Table D.18. Annual contact and crash frequency versus road classification 2009 through 2012

	2009			2010			2011			2012		
Road	Crash 09	VSIS 09	ECCO 10	Crash 10	VSIS 10	ECCO 10	Crash 11	VSIS 11	ECCO 11	Crash 12	VSIS 12	ECCO 12
Interstate	24.2%	49.0%	45.7%	26.2%	49.6%	45.8%	26.2%	48.6%	41.8%	27.3%	49.3%	42.3%
US Route	22.9%	25.3%	25.3%	23.7%	24.3%	24.4%	25.4%	23.9%	25.4%	23.8%	22.1%	22.2%
Iowa Route	12.8%	12.3%	13.6%	12.7%	11.2%	12.6%	11.7%	12.1%	13.6%	12.0%	12.1%	14.6%
Farm to Market Route	14.5%	7.1%	8.1%	15.5%	8.2%	8.8%	14.5%	8.8%	10.6%	15.1%	8.2%	10.5%
Local Road	25.6%	6.2%	7.3%	21.8%	6.7%	8.4%	22.3%	6.7%	8.5%	21.8%	8.3%	10.4%

Table D.19. Total contact and crash frequency versus road classification 2009 through 2012

	Crash	ECCO	VSIS
Interstate	25.9%	44.0%	49.1%
US Route	23.9%	24.3%	23.9%
Iowa Route	12.4%	13.6%	12.0%
Farm to Market Route	14.9%	9.5%	8.1%
Local Road	22.9%	8.6%	7.0%

Table D.20. Percetange difference between total contacts and crashes by road classification

Rank	Road System	Difference
1	Interstate	23.21%
2	Local Road	-15.90%
3	Farm to Market Route	-6.85%
4	Iowa Route	-0.41%
5	US Route	-0.05%

Table D.21. Top 10 counties total crashes on primary road versus contacts

Road Class	Primary Road														
Year	2009			2010			2011			2012			Grand Total		
County Na	Crash	ECCO	VSIS	Crash	ECCO	VSIS	Crash	ECCO	VSIS	Crash	ECCO	VSIS	Crash	ECCO	VSIS
POLK	13.9%	2.8%	2.7%	13.9%	3.9%	3.0%	13.3%	4.3%	3.0%	14.4%	3.8%	3.4%	13.9%	3.6%	3.0%
SCOTT	5.5%	2.0%	1.5%	6.1%	2.4%	1.6%	5.9%	2.5%	1.7%	7.4%	2.4%	1.7%	6.2%	2.3%	1.6%
POTTAWA	5.8%	10.9%	6.4%	5.0%	10.7%	9.8%	7.1%	9.5%	8.2%	5.3%	10.5%	9.5%	5.8%	10.5%	8.4%
JOHNSON	5.9%	0.5%	0.7%	3.9%	1.0%	0.8%	6.0%	1.0%	0.5%	6.9%	1.1%	0.6%	5.6%	0.9%	0.6%
WOODBU	4.2%	7.3%	6.5%	4.3%	7.8%	7.4%	2.7%	5.1%	4.3%	3.3%	7.2%	7.1%	3.7%	6.9%	6.3%
LINN	3.4%	1.0%	1.3%	2.5%	1.1%	1.1%	3.7%	1.2%	1.1%	3.7%	1.2%	0.9%	3.3%	1.1%	1.1%
JASPER	2.7%	7.5%	10.1%	3.7%	7.2%	9.8%	2.1%	6.2%	9.2%	2.9%	6.8%	10.0%	2.9%	7.0%	9.8%
BLACK HA	2.9%	1.3%	0.6%	2.4%	1.4%	0.6%	2.3%	1.8%	0.8%	3.8%	1.1%	0.7%	2.8%	1.4%	0.7%
DUBUQUE	2.2%	1.4%	1.1%	2.4%	1.7%	1.1%	3.5%	1.5%	0.9%	3.2%	1.5%	0.9%	2.8%	1.5%	1.0%
DALLAS	2.2%	6.2%	9.9%	2.4%	6.2%	10.8%	1.7%	5.9%	12.1%	1.8%	5.7%	8.9%	2.0%	6.0%	10.4%

Table D.22. Top 10 counties total crashes on secondary road versus contacts

Secondary Road															
	2009			2010			2011			2012			Grand Total		
	Crash	ECCO	VSIS	Crash	ECCO	VSIS	Crash	ECCO	VSIS	Crash	ECCO	VSIS	Crash	ECCO	VSIS
SIOUX	5.5%	4.0%	2.9%	3.8%	2.2%	1.6%	3.6%	3.3%	2.7%	6.5%	2.7%	2.5%	4.8%	3.1%	2.5%
POLK	4.6%	3.5%	3.3%	2.5%	4.9%	3.8%	4.4%	3.3%	3.8%	3.9%	4.3%	4.4%	3.8%	4.0%	3.9%
POTTAWA	2.9%	0.9%	0.6%	2.7%	1.1%	0.9%	2.3%	1.4%	0.9%	2.8%	1.8%	1.0%	2.7%	1.4%	0.9%
LINN	2.3%	3.5%	4.1%	1.6%	3.4%	2.6%	2.7%	3.9%	3.2%	2.8%	3.9%	3.3%	2.3%	3.7%	3.3%
HARDIN	2.0%	0.5%	0.4%	2.5%	0.3%	0.4%	2.1%	1.1%	1.1%	2.4%	1.0%	1.4%	2.2%	0.8%	0.9%
WEBSTER	2.3%	2.0%	1.0%	2.4%	1.7%	1.2%	1.9%	1.1%	1.0%	1.5%	1.1%	1.1%	2.1%	1.4%	1.1%
DUBUQUE	1.4%	1.2%	1.3%	2.5%	1.0%	1.3%	2.1%	1.2%	1.0%	1.7%	1.6%	1.1%	2.0%	1.3%	1.2%
PLYMOUT	2.5%	2.1%	1.3%	2.0%	1.6%	1.2%	1.7%	2.2%	1.8%	0.9%	1.6%	1.3%	1.8%	1.8%	1.4%
BLACK HA	1.1%	2.3%	2.3%	1.9%	0.9%	1.2%	1.9%	1.4%	1.5%	2.2%	1.3%	1.4%	1.7%	1.5%	1.6%
WOODBU	1.3%	3.8%	3.1%	1.4%	3.1%	2.4%	1.3%	2.1%	2.0%	3.0%	3.3%	3.4%	1.7%	3.1%	2.8%

Table D.23. Top 10 counties total crashes on municipal road versus contacts

Municipal Road															
	2009			2010			2011			2012			Grand Total		
	Crash	ECCO	VSIS	Crash	ECCO	VSIS	Crash	ECCO	VSIS	Crash	ECCO	VSIS	Crash	ECCO	VSIS
POLK	19.3%	9.3%	9.4%	17.3%	15.4%	16.2%	16.7%	13.5%	14.5%	17.0%	13.7%	15.9%	17.7%	13.0%	14.1%
LINN	8.4%	5.4%	8.5%	9.4%	7.6%	9.2%	9.8%	9.7%	9.9%	9.5%	8.5%	8.0%	9.2%	7.8%	8.9%
SCOTT	8.2%	5.2%	4.4%	9.9%	5.3%	4.7%	9.4%	5.2%	4.4%	9.3%	5.6%	4.8%	9.2%	5.3%	4.6%
BLACK HA	6.4%	4.8%	5.0%	6.0%	3.6%	4.0%	6.2%	4.1%	5.3%	6.5%	3.8%	4.3%	6.3%	4.1%	4.6%
POTTAWA	4.7%	6.3%	3.5%	6.1%	5.6%	4.5%	5.3%	5.0%	3.5%	6.6%	8.3%	5.5%	5.6%	6.4%	4.3%
WOODBU	5.6%	10.5%	9.2%	4.6%	8.4%	6.6%	4.8%	6.8%	5.7%	4.0%	7.4%	5.8%	4.8%	8.3%	6.8%
DUBUQUE	4.2%	2.6%	2.5%	3.8%	2.6%	2.4%	4.8%	2.4%	2.4%	5.2%	3.1%	3.0%	4.4%	2.7%	2.6%
JOHNSON	3.4%	2.0%	2.7%	4.2%	3.2%	4.1%	4.5%	3.1%	3.0%	5.2%	2.2%	2.5%	4.3%	2.6%	3.0%
STORY	2.5%	1.9%	2.0%	3.1%	2.6%	1.8%	3.2%	2.9%	3.2%	3.2%	2.6%	3.0%	3.0%	2.5%	2.5%
CERRO GO	2.7%	2.8%	3.8%	2.5%	3.1%	4.3%	2.5%	2.7%	3.4%	1.9%	2.3%	3.3%	2.4%	2.7%	3.7%

Table D.24. Contacts (2009) and crashes (2008) versus county

No.	County	Crash 2008	VSIS 2009	ECCO 2009
77	POLK	13.7%	3.2%	3.3%
82	SCOTT	6.6%	1.7%	2.3%
57	LINN	5.0%	1.9%	1.5%
52	JOHNSON	4.9%	0.8%	0.6%
7	BLACK HAWK	4.6%	1.0%	1.6%
78	POTTAWATTAMIE	4.5%	5.8%	9.8%
97	WOODBURY	3.4%	6.4%	7.2%
31	DUBUQUE	2.7%	1.2%	1.5%
23	CLINTON	2.0%	1.5%	1.4%
48	IOWA	1.8%	0.2%	0.5%
17	CERRO GORDO	1.7%	0.7%	0.8%
84	SIOUX	1.7%	1.1%	1.5%
85	STORY	1.7%	3.1%	2.0%
16	CEDAR	1.6%	2.2%	2.0%
50	JASPER	1.6%	9.0%	6.6%
25	DALLAS	1.3%	9.0%	5.7%
91	WARREN	1.3%	0.9%	0.7%
40	HAMILTON	1.2%	0.0%	0.1%
79	POWESHIEK	1.2%	0.9%	0.7%
94	WEBSTER	1.2%	0.3%	0.5%
70	MUSCATINE	1.1%	0.6%	0.5%
29	DES MOINES	1.0%	0.8%	0.6%
43	HARRISON	1.0%	1.4%	2.1%
90	WAPELLO	1.0%	0.5%	0.6%
62	MAHASKA	0.9%	0.6%	0.6%
64	MARSHALL	0.9%	0.7%	0.4%
75	PLYMOUTH	0.9%	0.7%	1.1%
92	WASHINGTON	0.9%	0.7%	0.6%
15	CASS	0.8%	0.2%	1.5%
35	FRANKLIN	0.8%	0.3%	0.4%
38	GRUNDY	0.8%	0.1%	0.1%
56	LEE	0.8%	3.1%	2.1%
1	ADAIR	0.7%	0.6%	1.6%
9	BREMER	0.7%	0.7%	0.6%
20	CLARKE	0.7%	2.7%	1.0%
33	FAYETTE	0.7%	0.5%	0.6%
42	HARDIN	0.7%	0.2%	0.2%
6	BENTON	0.6%	0.5%	0.6%
8	BOONE	0.6%	0.2%	0.2%
10	BUCHANAN	0.6%	8.2%	5.7%
14	CARROLL	0.6%	0.3%	0.9%

No.	County	Crash 2008	VSIS 2009	ECCO 2009
21	CLAY	0.6%	0.2%	0.3%
28	DELAWARE	0.6%	0.2%	0.3%
34	FLOYD	0.6%	0.2%	0.1%
53	JONES	0.6%	0.4%	0.2%
96	WINNESHIEK	0.6%	0.1%	0.1%
99	WRIGHT	0.6%	0.1%	0.1%
11	BUENA VISTA	0.5%	0.4%	0.4%
22	CLAYTON	0.5%	0.2%	0.3%
24	CRAWFORD	0.5%	0.1%	0.4%
36	FREMONT	0.5%	3.8%	4.8%
51	JEFFERSON	0.5%	0.5%	0.4%
55	KOSSUTH	0.5%	0.1%	0.1%
63	MARION	0.5%	0.6%	0.6%
67	MONONA	0.5%	0.3%	1.5%
81	SAC	0.5%	3.2%	2.9%
19	CHICKASAW	0.4%	0.2%	0.1%
27	DECATUR	0.4%	0.2%	0.1%
47	IDA	0.4%	0.1%	0.2%
49	JACKSON	0.4%	0.4%	0.4%
65	MILLS	0.4%	0.3%	0.5%
68	MONROE	0.4%	0.7%	0.5%
71	OBRIEN	0.4%	0.3%	0.4%
98	WORTH	0.4%	2.8%	2.3%
4	APPANOOSE	0.3%	0.1%	0.1%
12	BUTLER	0.3%	0.2%	0.1%
13	CALHOUN	0.3%	0.1%	0.4%
18	CHEROKEE	0.3%	0.3%	0.4%
26	DAVIS	0.3%	0.5%	0.4%
30	DICKINSON	0.3%	0.2%	0.3%
32	EMMET	0.3%	0.0%	0.0%
39	GUTHRIE	0.3%	0.2%	0.6%
44	HENRY	0.3%	1.1%	0.9%
45	HOWARD	0.3%	0.1%	0.2%
58	LOUISA	0.3%	0.3%	0.3%
59	LUCAS	0.3%	0.6%	0.3%
61	MADISON	0.3%	0.4%	0.3%
66	MITCHELL	0.3%	0.2%	0.2%
72	OSCEOLA	0.3%	0.2%	0.2%
74	PALO ALTO	0.3%	0.2%	0.2%
83	SHELBY	0.3%	0.2%	0.4%
86	TAMA	0.3%	0.6%	0.6%
88	UNION	0.3%	0.6%	0.3%
3	ALLAMAKEE	0.2%	0.0%	0.0%

No.	County	Crash 2008	VSIS 2009	ECCO 2009
5	AUDUBON	0.2%	0.1%	0.2%
46	HUMBOLDT	0.2%	0.0%	0.1%
60	LYON	0.2%	0.3%	0.4%
69	MONTGOMERY	0.2%	0.2%	0.3%
73	PAGE	0.2%	0.4%	0.6%
76	POCAHONTAS	0.2%	0.5%	0.5%
80	RINGGOLD	0.2%	0.1%	0.0%
95	WINNEBAGO	0.2%	0.0%	0.0%
2	ADAMS	0.1%	0.2%	0.3%
37	GREENE	0.1%	0.1%	0.5%
41	HANCOCK	0.1%	0.1%	0.1%
54	KEOKUK	0.1%	0.4%	0.5%
89	VAN BUREN	0.1%	0.5%	0.4%
93	WAYNE	0.1%	0.7%	0.4%
87	TAYLOR	0.0%	0.1%	0.2%

Table D.25. Contacts (2010) and crashes (2009) versus county

No.	County	Crash 2009	VSIS 2010	ECCO 2010
77	POLK	14.2%	4.0%	5.0%
82	SCOTT	5.8%	1.9%	2.7%
57	LINN	5.0%	1.8%	1.9%
78	POTTAWATTAMIE	5.0%	8.8%	9.5%
52	JOHNSON	4.5%	1.1%	1.3%
97	WOODBURY	4.2%	7.0%	7.5%
7	BLACK HAWK	3.8%	0.9%	1.6%
31	DUBUQUE	2.7%	1.2%	1.7%
85	STORY	2.1%	2.2%	2.1%
17	CERRO GORDO	1.9%	1.0%	1.2%
84	SIOUX	1.9%	0.7%	1.1%
50	JASPER	1.8%	8.5%	6.0%
23	CLINTON	1.6%	1.6%	1.6%
25	DALLAS	1.6%	9.8%	5.8%
91	WARREN	1.5%	0.9%	1.1%
94	WEBSTER	1.4%	0.3%	0.4%
40	HAMILTON	1.3%	0.2%	0.2%
29	DES MOINES	1.2%	0.5%	0.4%
16	CEDAR	1.1%	1.9%	1.7%
48	IOWA	1.1%	0.1%	0.6%
75	PLYMOUTH	1.1%	0.5%	0.8%
79	POWESHIEK	1.1%	0.6%	0.5%
6	BENTON	1.0%	0.3%	0.3%
33	FAYETTE	1.0%	0.4%	0.5%
64	MARSHALL	0.9%	0.5%	0.3%
70	MUSCATINE	0.9%	0.6%	0.5%
8	BOONE	0.8%	0.5%	0.4%
9	BREMER	0.8%	0.8%	0.7%
15	CASS	0.8%	0.2%	1.2%
21	CLAY	0.8%	0.4%	0.4%
43	HARRISON	0.8%	0.7%	1.2%
56	LEE	0.8%	4.1%	2.7%
62	MAHASKA	0.8%	0.3%	0.4%
90	WAPELLO	0.8%	0.3%	0.3%
24	CRAWFORD	0.7%	0.2%	0.3%
30	DICKINSON	0.7%	0.4%	0.5%
36	FREMONT	0.7%	2.9%	4.3%
53	JONES	0.7%	0.3%	0.4%
67	MONONA	0.7%	0.3%	1.5%
20	CLARKE	0.6%	2.2%	1.1%
34	FLOYD	0.6%	0.3%	0.3%

No.	County	Crash 2009	VSIS 2010	ECCO 2010
35	FRANKLIN	0.6%	0.4%	0.4%
42	HARDIN	0.6%	0.1%	0.1%
51	JEFFERSON	0.6%	0.5%	0.4%
86	TAMA	0.6%	0.2%	0.2%
92	WASHINGTON	0.6%	0.6%	0.5%
1	ADAIR	0.5%	0.3%	1.4%
11	BUENA VISTA	0.5%	0.4%	0.4%
13	CALHOUN	0.5%	0.3%	0.3%
14	CARROLL	0.5%	0.3%	0.5%
18	CHEROKEE	0.5%	0.5%	0.5%
22	CLAYTON	0.5%	0.2%	0.3%
32	EMMET	0.5%	0.1%	0.1%
55	KOSSUTH	0.5%	0.2%	0.2%
59	LUCAS	0.5%	0.7%	0.5%
63	MARION	0.5%	0.5%	0.5%
74	PALO ALTO	0.5%	0.3%	0.3%
96	WINNESHIEK	0.5%	0.1%	0.1%
10	BUCHANAN	0.4%	8.1%	6.2%
19	CHICKASAW	0.4%	0.2%	0.2%
28	DELAWARE	0.4%	0.3%	0.3%
38	GRUNDY	0.4%	0.1%	0.1%
44	HENRY	0.4%	0.7%	0.7%
65	MILLS	0.4%	0.4%	0.6%
66	MITCHELL	0.4%	0.1%	0.1%
98	WORTH	0.4%	2.0%	1.6%
99	WRIGHT	0.4%	0.1%	0.1%
3	ALLAMAKEE	0.3%	0.1%	0.1%
12	BUTLER	0.3%	0.2%	0.2%
27	DECATUR	0.3%	0.1%	0.1%
37	GREENE	0.3%	0.2%	0.4%
41	HANCOCK	0.3%	0.2%	0.1%
45	HOWARD	0.3%	0.1%	0.1%
47	IDA	0.3%	0.3%	0.4%
49	JACKSON	0.3%	0.5%	0.5%
68	MONROE	0.3%	0.3%	0.2%
71	OBRIEN	0.3%	0.3%	0.3%
88	UNION	0.3%	0.4%	0.3%
2	ADAMS	0.2%	0.0%	0.1%
4	APPANOOSE	0.2%	0.1%	0.1%
39	GUTHRIE	0.2%	0.2%	0.4%
46	HUMBOLDT	0.2%	0.0%	0.1%
58	LOUISA	0.2%	0.3%	0.3%
60	LYON	0.2%	0.2%	0.2%

No.	County	Crash 2009	VSIS 2010	ECCO 2010
61	MADISON	0.2%	0.3%	0.3%
69	MONTGOMERY	0.2%	0.3%	0.5%
72	OSCEOLA	0.2%	0.2%	0.2%
73	PAGE	0.2%	0.5%	0.7%
76	POCAHONTAS	0.2%	0.5%	0.5%
81	SAC	0.2%	3.6%	2.7%
83	SHELBY	0.2%	0.4%	0.6%
93	WAYNE	0.2%	0.4%	0.3%
95	WINNEBAGO	0.2%	0.1%	0.0%
5	AUDUBON	0.1%	0.3%	0.4%
26	DAVIS	0.1%	0.4%	0.5%
54	KEOKUK	0.1%	0.3%	0.3%
80	RINGGOLD	0.1%	0.1%	0.0%
87	TAYLOR	0.1%	0.0%	0.0%
89	VAN BUREN	0.1%	0.4%	0.4%

Table D.26. Contacts (2011) and crashes (2010) versus county

No.	County	Crash 2010	VSIS 2011	ECCO 2011
77	POLK	13.1%	3.8%	5.0%
82	SCOTT	6.5%	2.0%	2.9%
78	POTTAWATTAMIE	4.9%	7.2%	8.3%
57	LINN	4.4%	1.8%	2.2%
97	WOODBURY	3.9%	4.2%	4.9%
52	JOHNSON	3.7%	0.7%	1.2%
7	BLACK HAWK	3.3%	1.1%	1.9%
31	DUBUQUE	2.8%	1.0%	1.6%
50	JASPER	2.3%	8.0%	5.2%
85	STORY	2.2%	2.0%	1.7%
25	DALLAS	1.9%	10.8%	5.2%
17	CERRO GORDO	1.8%	1.0%	1.0%
23	CLINTON	1.8%	1.5%	1.6%
16	CEDAR	1.5%	0.5%	1.1%
84	SIOUX	1.5%	1.0%	1.3%
94	WEBSTER	1.4%	0.3%	0.4%
40	HAMILTON	1.3%	0.2%	0.2%
75	PLYMOUTH	1.1%	0.9%	1.2%
79	POWESHIEK	1.1%	0.4%	0.5%
91	WARREN	1.1%	1.0%	1.6%
29	DES MOINES	1.0%	0.3%	0.3%
42	HARDIN	1.0%	0.3%	0.3%
56	LEE	1.0%	3.0%	2.4%
70	MUSCATINE	1.0%	0.6%	0.7%
48	IOWA	0.9%	0.2%	0.9%
67	MONONA	0.9%	0.3%	1.3%
90	WAPELLO	0.9%	0.4%	0.6%
6	BENTON	0.8%	0.4%	0.5%
11	BUENA VISTA	0.8%	0.7%	0.8%
15	CASS	0.8%	0.2%	0.6%
20	CLARKE	0.8%	4.8%	2.5%
43	HARRISON	0.8%	0.2%	0.5%
64	MARSHALL	0.8%	0.5%	0.3%
1	ADAIR	0.7%	0.4%	0.9%
9	BREMER	0.7%	0.8%	0.8%
22	CLAYTON	0.7%	0.5%	0.5%
24	CRAWFORD	0.7%	0.2%	0.4%
44	HENRY	0.7%	0.4%	0.4%
62	MAHASKA	0.7%	0.3%	0.6%
65	MILLS	0.7%	0.4%	0.9%
33	FAYETTE	0.6%	0.7%	0.7%

No.	County	Crash 2010	VSIS 2011	ECCO 2011
34	FLOYD	0.6%	0.3%	0.3%
36	FREMONT	0.6%	1.9%	2.7%
38	GRUNDY	0.6%	0.1%	0.2%
63	MARION	0.6%	0.4%	0.4%
96	WINNESHIEK	0.6%	0.7%	0.6%
99	WRIGHT	0.6%	0.3%	0.3%
8	BOONE	0.5%	0.6%	0.5%
10	BUCHANAN	0.5%	8.9%	6.4%
14	CARROLL	0.5%	0.2%	0.2%
18	CHEROKEE	0.5%	0.8%	0.8%
21	CLAY	0.5%	0.5%	0.5%
35	FRANKLIN	0.5%	0.6%	0.6%
53	JONES	0.5%	0.3%	0.4%
55	KOSSUTH	0.5%	0.5%	0.4%
60	LYON	0.5%	0.2%	0.2%
71	OBRIEN	0.5%	0.5%	0.6%
81	SAC	0.5%	4.0%	3.2%
86	TAMA	0.5%	0.3%	0.4%
92	WASHINGTON	0.5%	0.3%	0.3%
13	CALHOUN	0.4%	0.2%	0.2%
27	DECATUR	0.4%	0.1%	0.1%
28	DELAWARE	0.4%	0.3%	0.4%
30	DICKINSON	0.4%	0.6%	0.6%
51	JEFFERSON	0.4%	0.3%	0.3%
59	LUCAS	0.4%	0.7%	0.5%
61	MADISON	0.4%	0.3%	0.2%
66	MITCHELL	0.4%	0.1%	0.1%
73	PAGE	0.4%	0.4%	0.7%
74	PALO ALTO	0.4%	0.5%	0.5%
88	UNION	0.4%	0.3%	0.4%
98	WORTH	0.4%	3.2%	3.0%
4	APPANOOSE	0.3%	0.1%	0.2%
5	AUDUBON	0.3%	0.0%	0.0%
19	CHICKASAW	0.3%	0.3%	0.3%
32	EMMET	0.3%	0.3%	0.2%
39	GUTHRIE	0.3%	0.3%	0.4%
41	HANCOCK	0.3%	0.3%	0.3%
45	HOWARD	0.3%	0.4%	0.3%
46	HUMBOLDT	0.3%	0.2%	0.3%
47	IDA	0.3%	0.6%	0.9%
49	JACKSON	0.3%	0.5%	0.5%
58	LOUISA	0.3%	0.1%	0.1%
68	MONROE	0.3%	0.2%	0.3%

No.	County	Crash 2010	VSIS 2011	ECCO 2011
83	SHELBY	0.3%	0.2%	0.3%
2	ADAMS	0.2%	0.1%	0.1%
3	ALLAMAKEE	0.2%	0.2%	0.2%
12	BUTLER	0.2%	0.3%	0.3%
37	GREENE	0.2%	0.1%	0.1%
69	MONTGOMERY	0.2%	0.4%	0.8%
72	OSCEOLA	0.2%	0.3%	0.4%
76	POCAHONTAS	0.2%	0.5%	0.7%
93	WAYNE	0.2%	0.2%	0.1%
26	DAVIS	0.1%	0.5%	0.8%
54	KEOKUK	0.1%	0.2%	0.4%
80	RINGGOLD	0.1%	0.1%	0.0%
87	TAYLOR	0.1%	0.0%	0.0%
89	VAN BUREN	0.1%	0.2%	0.3%
95	WINNEBAGO	0.1%	0.1%	0.0%

Table D.27. Contacts (2012) and crashes (2011) versus county

No.	County	Crash 2011	VSIS 2012	ECCO 2012
77	POLK	13.0%	4.4%	4.7%
82	SCOTT	6.3%	2.0%	2.8%
78	POTTAWATTAMIE	5.8%	8.4%	9.3%
57	LINN	5.3%	1.7%	2.1%
52	JOHNSON	5.0%	0.7%	1.1%
31	DUBUQUE	3.7%	1.1%	1.7%
7	BLACK HAWK	3.4%	1.0%	1.4%
97	WOODBURY	3.1%	6.7%	6.7%
85	STORY	2.3%	2.8%	2.1%
17	CERRO GORDO	1.8%	1.0%	1.0%
23	CLINTON	1.7%	1.2%	1.3%
50	JASPER	1.5%	8.6%	5.7%
84	SIOUX	1.5%	0.8%	1.0%
91	WARREN	1.3%	0.9%	1.5%
16	CEDAR	1.2%	0.3%	0.8%
25	DALLAS	1.2%	7.8%	4.9%
75	PLYMOUTH	1.2%	0.7%	0.9%
79	POWESHIEK	1.2%	0.9%	1.1%
40	HAMILTON	1.1%	0.3%	0.3%
48	IOWA	1.1%	0.2%	0.9%
64	MARSHALL	1.1%	0.7%	0.6%
65	MILLS	1.1%	0.5%	0.9%
94	WEBSTER	1.1%	0.3%	0.5%
1	ADAIR	1.0%	0.3%	0.9%
10	BUCHANAN	1.0%	9.1%	6.5%
20	CLARKE	1.0%	3.9%	2.3%
29	DES MOINES	1.0%	0.3%	0.2%
90	WAPELLO	1.0%	0.5%	0.5%
15	CASS	0.9%	0.2%	0.6%
43	HARRISON	0.9%	0.2%	0.6%
11	BUENA VISTA	0.8%	0.8%	0.9%
36	FREMONT	0.8%	2.1%	3.1%
56	LEE	0.8%	3.2%	1.7%
21	CLAY	0.7%	0.7%	0.7%
42	HARDIN	0.7%	0.6%	0.5%
55	KOSSUTH	0.7%	0.4%	0.4%
62	MAHASKA	0.7%	0.3%	0.5%
63	MARION	0.7%	0.6%	0.7%
70	MUSCATINE	0.7%	0.7%	0.7%
96	WINNESHIEK	0.7%	0.5%	0.4%
8	BOONE	0.6%	0.5%	0.4%

No.	County	Crash 2011	VSIS 2012	ECCO 2012
14	CARROLL	0.6%	0.1%	0.1%
18	CHEROKEE	0.6%	0.5%	0.6%
24	CRAWFORD	0.6%	0.2%	0.2%
33	FAYETTE	0.6%	0.5%	0.6%
46	HUMBOLDT	0.6%	0.2%	0.2%
49	JACKSON	0.6%	0.3%	0.4%
71	OBRIEN	0.6%	0.6%	0.7%
86	TAMA	0.6%	0.5%	0.7%
6	BENTON	0.5%	0.5%	0.7%
9	BREMER	0.5%	0.8%	0.8%
22	CLAYTON	0.5%	0.4%	0.4%
27	DECATUR	0.5%	0.1%	0.1%
28	DELAWARE	0.5%	0.3%	0.5%
35	FRANKLIN	0.5%	0.6%	0.6%
44	HENRY	0.5%	0.4%	0.4%
51	JEFFERSON	0.5%	0.4%	0.3%
67	MONONA	0.5%	0.3%	1.5%
13	CALHOUN	0.4%	0.2%	0.3%
30	DICKINSON	0.4%	0.6%	0.6%
34	FLOYD	0.4%	0.5%	0.3%
81	SAC	0.4%	1.5%	1.3%
88	UNION	0.4%	0.2%	0.2%
92	WASHINGTON	0.4%	0.3%	0.2%
99	WRIGHT	0.4%	0.2%	0.2%
3	ALLAMAKEE	0.3%	0.2%	0.1%
19	CHICKASAW	0.3%	0.4%	0.3%
32	EMMET	0.3%	0.2%	0.3%
41	HANCOCK	0.3%	0.3%	0.2%
47	IDA	0.3%	0.4%	0.5%
53	JONES	0.3%	0.2%	0.3%
59	LUCAS	0.3%	0.6%	0.8%
60	LYON	0.3%	0.3%	0.5%
61	MADISON	0.3%	0.2%	0.3%
66	MITCHELL	0.3%	0.4%	0.3%
72	OSCEOLA	0.3%	0.4%	0.4%
73	PAGE	0.3%	0.3%	0.5%
74	PALO ALTO	0.3%	0.7%	0.6%
93	WAYNE	0.3%	0.2%	0.2%
98	WORTH	0.3%	3.0%	2.3%
4	APPANOOSE	0.2%	0.1%	0.2%
12	BUTLER	0.2%	0.2%	0.3%
37	GREENE	0.2%	0.2%	0.2%
38	GRUNDY	0.2%	0.2%	0.2%

No.	County	Crash 2011	VSIS 2012	ECCO 2012
45	HOWARD	0.2%	0.4%	0.4%
54	KEOKUK	0.2%	0.2%	0.5%
68	MONROE	0.2%	0.4%	0.5%
69	MONTGOMERY	0.2%	0.3%	0.7%
83	SHELBY	0.2%	0.3%	0.6%
2	ADAMS	0.1%	0.1%	0.1%
5	AUDUBON	0.1%	0.1%	0.1%
26	DAVIS	0.1%	0.4%	0.7%
39	GUTHRIE	0.1%	0.2%	0.3%
58	LOUISA	0.1%	0.1%	0.1%
76	POCAHONTAS	0.1%	0.5%	0.5%
80	RINGGOLD	0.1%	0.0%	0.0%
89	VAN BUREN	0.1%	0.3%	0.3%
95	WINNEBAGO	0.1%	0.1%	0.0%
87	TAYLOR	0.0%	0.0%	0.0%

Table D.28. Annual contacts and crashes by county 2009 through 2012

		2009			2010			2011			2012		
No.	County	Crash	VSIS	ECCO	Crash	VSIS	ECCO	Crash	VSIS	ECCO	Crash	VSIS	ECCO
77	POLK	14.2%	3.2%	3.3%	13.1%	4.0%	5.0%	13.0%	3.8%	5.0%	13.6%	3.8%	4.7%
82	SCOTT	5.8%	1.7%	2.3%	6.5%	1.9%	2.7%	6.3%	2.0%	2.9%	7.1%	2.0%	2.8%
78	POTTAWATTAMIE	5.0%	5.8%	9.8%	4.9%	8.8%	9.5%	5.8%	7.2%	8.3%	5.3%	7.2%	9.3%
57	LINN	5.0%	1.9%	1.5%	4.4%	1.8%	1.9%	5.3%	1.8%	2.2%	5.3%	1.8%	2.1%
52	JOHNSON	4.5%	0.8%	0.6%	3.7%	1.1%	1.3%	5.0%	0.7%	1.2%	5.6%	0.7%	1.1%
7	BLACK HAWK	3.8%	1.0%	1.6%	3.3%	0.9%	1.6%	3.4%	1.1%	1.9%	4.4%	1.1%	1.4%
97	WOODBURY	4.2%	6.4%	7.2%	3.9%	7.0%	7.5%	3.1%	4.2%	4.9%	3.5%	4.2%	6.7%
31	DUBUQUE	2.7%	1.2%	1.5%	2.8%	1.2%	1.7%	3.7%	1.0%	1.6%	3.5%	1.0%	1.7%
85	STORY	2.1%	3.1%	2.0%	2.2%	2.2%	2.1%	2.3%	2.0%	1.7%	2.3%	2.0%	2.1%
50	JASPER	1.8%	9.0%	6.6%	2.3%	8.5%	6.0%	1.5%	8.0%	5.2%	1.8%	8.0%	5.7%
17	CERRO GORDO	1.9%	0.7%	0.8%	1.8%	1.0%	1.2%	1.8%	1.0%	1.0%	1.7%	1.0%	1.0%
23	CLINTON	1.6%	1.5%	1.4%	1.8%	1.6%	1.6%	1.7%	1.5%	1.6%	1.9%	1.5%	1.3%
84	SIOUX	1.9%	1.1%	1.5%	1.5%	0.7%	1.1%	1.5%	1.0%	1.3%	1.8%	1.0%	1.0%
25	DALLAS	1.6%	9.0%	5.7%	1.9%	9.8%	5.8%	1.2%	10.8%	5.2%	1.4%	10.8%	4.9%
16	CEDAR	1.1%	2.2%	2.0%	1.5%	1.9%	1.7%	1.2%	0.5%	1.1%	1.6%	0.5%	0.8%
94	WEBSTER	1.4%	0.3%	0.5%	1.4%	0.3%	0.4%	1.1%	0.3%	0.4%	1.1%	0.3%	0.5%
40	HAMILTON	1.3%	0.0%	0.1%	1.3%	0.2%	0.2%	1.1%	0.2%	0.2%	0.9%	0.2%	0.3%
79	POWESHIEK	1.1%	0.9%	0.7%	1.1%	0.6%	0.5%	1.2%	0.4%	0.5%	1.2%	0.4%	1.1%
91	WARREN	1.5%	0.9%	0.7%	1.1%	0.9%	1.1%	1.3%	1.0%	1.6%	0.8%	1.0%	1.5%
29	DES MOINES	1.2%	0.8%	0.6%	1.0%	0.5%	0.4%	1.0%	0.3%	0.3%	1.1%	0.3%	0.2%
48	IOWA	1.1%	0.2%	0.5%	0.9%	0.1%	0.6%	1.1%	0.2%	0.9%	1.1%	0.2%	0.9%
64	MARSHALL	0.9%	0.7%	0.4%	0.8%	0.5%	0.3%	1.1%	0.5%	0.3%	1.0%	0.5%	0.6%
75	PLYMOUTH	1.1%	0.7%	1.1%	1.1%	0.5%	0.8%	1.2%	0.9%	1.2%	0.6%	0.9%	0.9%
56	LEE	0.8%	3.1%	2.1%	1.0%	4.1%	2.7%	0.8%	3.0%	2.4%	0.7%	3.0%	1.7%
70	MUSCATINE	0.9%	0.6%	0.5%	1.0%	0.6%	0.5%	0.7%	0.6%	0.7%	0.9%	0.6%	0.7%
90	WAPELLO	0.8%	0.5%	0.6%	0.9%	0.3%	0.3%	1.0%	0.4%	0.6%	0.8%	0.4%	0.5%
15	CASS	0.8%	0.2%	1.5%	0.8%	0.2%	1.2%	0.9%	0.2%	0.6%	0.8%	0.2%	0.6%
20	CLARKE	0.6%	2.7%	1.0%	0.8%	2.2%	1.1%	1.0%	4.8%	2.5%	0.6%	4.8%	2.3%
43	HARRISON	0.8%	1.4%	2.1%	0.8%	0.7%	1.2%	0.9%	0.2%	0.5%	0.5%	0.2%	0.6%
1	ADAIR	0.5%	0.6%	1.6%	0.7%	0.3%	1.4%	1.0%	0.4%	0.9%	0.5%	0.4%	0.9%
6	BENTON	1.0%	0.5%	0.6%	0.8%	0.3%	0.3%	0.5%	0.4%	0.5%	0.5%	0.4%	0.7%
9	BREMER	0.8%	0.7%	0.6%	0.7%	0.8%	0.7%	0.5%	0.8%	0.8%	0.7%	0.8%	0.8%
11	BUENA VISTA	0.5%	0.4%	0.4%	0.8%	0.4%	0.4%	0.8%	0.7%	0.8%	0.5%	0.7%	0.9%
22	CLAYTON	0.5%	0.2%	0.3%	0.7%	0.2%	0.3%	0.5%	0.5%	0.5%	0.8%	0.5%	0.4%
24	CRAWFORD	0.7%	0.1%	0.4%	0.7%	0.2%	0.3%	0.6%	0.2%	0.4%	0.6%	0.2%	0.2%
33	FAYETTE	1.0%	0.5%	0.6%	0.6%	0.4%	0.5%	0.6%	0.7%	0.7%	0.7%	0.7%	0.6%
36	FREMONT	0.7%	3.8%	4.8%	0.6%	2.9%	4.3%	0.8%	1.9%	2.7%	0.8%	1.9%	3.1%
42	HARDIN	0.6%	0.2%	0.2%	1.0%	0.1%	0.1%	0.7%	0.3%	0.3%	0.5%	0.3%	0.5%
62	MAHASKA	0.8%	0.6%	0.6%	0.7%	0.3%	0.4%	0.7%	0.3%	0.6%	0.6%	0.3%	0.5%
65	MILLS	0.4%	0.3%	0.5%	0.7%	0.4%	0.6%	1.1%	0.4%	0.9%	0.5%	0.4%	0.9%
8	BOONE	0.8%	0.2%	0.2%	0.5%	0.5%	0.4%	0.6%	0.6%	0.5%	0.4%	0.6%	0.4%
10	BUCHANAN	0.4%	8.2%	5.7%	0.5%	8.1%	6.2%	1.0%	8.9%	6.4%	0.4%	8.9%	6.5%
21	CLAY	0.8%	0.2%	0.3%	0.5%	0.4%	0.4%	0.7%	0.5%	0.5%	0.6%	0.5%	0.7%
34	FLOYD	0.6%	0.2%	0.1%	0.6%	0.3%	0.3%	0.4%	0.3%	0.3%	0.8%	0.3%	0.3%
44	HENRY	0.4%	1.1%	0.9%	0.7%	0.7%	0.7%	0.5%	0.4%	0.4%	0.7%	0.4%	0.4%
55	KOSSUTH	0.5%	0.1%	0.1%	0.5%	0.2%	0.2%	0.7%	0.5%	0.4%	0.6%	0.5%	0.4%
63	MARION	0.5%	0.6%	0.6%	0.6%	0.5%	0.5%	0.7%	0.4%	0.4%	0.6%	0.4%	0.7%
67	MONONA	0.7%	0.3%	1.5%	0.9%	0.3%	1.5%	0.5%	0.3%	1.3%	0.4%	0.3%	1.5%
14	CARROLL	0.5%	0.3%	0.9%	0.5%	0.3%	0.5%	0.6%	0.2%	0.2%	0.6%	0.2%	0.1%
18	CHEROKEE	0.5%	0.3%	0.4%	0.5%	0.5%	0.5%	0.6%	0.8%	0.8%	0.4%	0.8%	0.6%
28	DELAWARE	0.4%	0.2%	0.3%	0.4%	0.3%	0.3%	0.5%	0.3%	0.4%	0.5%	0.3%	0.5%
30	DICKINSON	0.7%	0.2%	0.3%	0.4%	0.4%	0.5%	0.4%	0.6%	0.6%	0.4%	0.6%	0.6%
35	FRANKLIN	0.6%	0.3%	0.4%	0.5%	0.4%	0.4%	0.5%	0.6%	0.6%	0.6%	0.6%	0.6%
51	JEFFERSON	0.6%	0.5%	0.4%	0.4%	0.5%	0.4%	0.5%	0.3%	0.3%	0.4%	0.3%	0.3%
53	JONES	0.7%	0.4%	0.2%	0.5%	0.3%	0.4%	0.3%	0.3%	0.4%	0.6%	0.3%	0.3%
71	OBRIEN	0.3%	0.3%	0.4%	0.5%	0.3%	0.3%	0.6%	0.5%	0.6%	0.5%	0.5%	0.7%
86	TAMA	0.6%	0.6%	0.6%	0.5%	0.2%	0.2%	0.6%	0.3%	0.4%	0.4%	0.3%	0.7%
92	WASHINGTON	0.6%	0.7%	0.6%	0.5%	0.6%	0.5%	0.4%	0.3%	0.3%	0.4%	0.3%	0.2%
96	WINNESHIEK	0.5%	0.1%	0.1%	0.6%	0.1%	0.1%	0.7%	0.7%	0.6%	0.4%	0.7%	0.4%
99	WRIGHT	0.4%	0.1%	0.1%	0.6%	0.1%	0.1%	0.4%	0.3%	0.3%	0.3%	0.3%	0.2%
13	CALHOUN	0.5%	0.1%	0.4%	0.4%	0.3%	0.3%	0.4%	0.2%	0.2%	0.3%	0.2%	0.3%
38	GRUNDY	0.4%	0.1%	0.1%	0.6%	0.1%	0.1%	0.2%	0.1%	0.2%	0.4%	0.1%	0.2%

		2009			2010			2011			2012		
No.	**County**	**Crash**	**VSIS**	**ECCO**	**Crash**	**VSIS**	**ECCO**	**Crash**	**VSIS**	**ECCO**	**Crash**	**VSIS**	**ECCO**
59	LUCAS	0.5%	0.6%	0.3%	0.4%	0.7%	0.5%	0.3%	0.7%	0.5%	0.2%	0.7%	0.8%
60	LYON	0.2%	0.3%	0.4%	0.5%	0.2%	0.2%	0.3%	0.2%	0.2%	0.5%	0.2%	0.5%
74	PALO ALTO	0.5%	0.2%	0.2%	0.4%	0.3%	0.3%	0.3%	0.5%	0.5%	0.4%	0.5%	0.6%
98	WORTH	0.4%	2.8%	2.3%	0.4%	2.0%	1.6%	0.3%	3.2%	3.0%	0.6%	3.2%	2.3%
3	ALLAMAKEE	0.3%	0.0%	0.0%	0.2%	0.1%	0.1%	0.3%	0.2%	0.2%	0.2%	0.2%	0.1%
4	APPANOOSE	0.2%	0.1%	0.1%	0.3%	0.1%	0.1%	0.2%	0.1%	0.2%	0.4%	0.1%	0.2%
12	BUTLER	0.3%	0.2%	0.1%	0.2%	0.2%	0.2%	0.2%	0.3%	0.3%	0.3%	0.3%	0.3%
19	CHICKASAW	0.4%	0.2%	0.1%	0.3%	0.2%	0.2%	0.3%	0.3%	0.3%	0.2%	0.3%	0.3%
27	DECATUR	0.3%	0.2%	0.1%	0.4%	0.1%	0.1%	0.5%	0.1%	0.1%	0.2%	0.1%	0.1%
32	EMMET	0.5%	0.0%	0.0%	0.3%	0.1%	0.1%	0.3%	0.3%	0.2%	0.4%	0.3%	0.3%
39	GUTHRIE	0.2%	0.2%	0.6%	0.3%	0.2%	0.4%	0.1%	0.3%	0.4%	0.3%	0.3%	0.3%
41	HANCOCK	0.3%	0.1%	0.1%	0.3%	0.2%	0.1%	0.3%	0.3%	0.3%	0.3%	0.3%	0.2%
45	HOWARD	0.3%	0.1%	0.2%	0.3%	0.1%	0.1%	0.2%	0.4%	0.3%	0.3%	0.4%	0.4%
46	HUMBOLDT	0.2%	0.0%	0.1%	0.3%	0.0%	0.1%	0.6%	0.2%	0.3%	0.2%	0.2%	0.2%
47	IDA	0.3%	0.1%	0.2%	0.3%	0.3%	0.4%	0.3%	0.6%	0.9%	0.3%	0.6%	0.5%
49	JACKSON	0.3%	0.4%	0.4%	0.3%	0.5%	0.5%	0.6%	0.5%	0.5%	0.2%	0.5%	0.4%
58	LOUISA	0.2%	0.3%	0.3%	0.3%	0.3%	0.3%	0.1%	0.1%	0.1%	0.4%	0.1%	0.1%
61	MADISON	0.2%	0.4%	0.3%	0.4%	0.3%	0.3%	0.3%	0.3%	0.2%	0.4%	0.3%	0.3%
66	MITCHELL	0.4%	0.2%	0.2%	0.4%	0.1%	0.1%	0.3%	0.1%	0.1%	0.2%	0.1%	0.3%
73	PAGE	0.2%	0.4%	0.6%	0.4%	0.5%	0.7%	0.3%	0.4%	0.7%	0.3%	0.4%	0.5%
81	SAC	0.2%	3.2%	2.9%	0.5%	3.6%	2.7%	0.4%	4.0%	3.2%	0.2%	4.0%	1.3%
83	SHELBY	0.2%	0.2%	0.4%	0.3%	0.4%	0.6%	0.2%	0.2%	0.3%	0.3%	0.2%	0.6%
88	UNION	0.3%	0.6%	0.3%	0.4%	0.4%	0.3%	0.4%	0.3%	0.4%	0.1%	0.3%	0.2%
2	ADAMS	0.2%	0.2%	0.3%	0.2%	0.0%	0.1%	0.1%	0.1%	0.1%	0.2%	0.1%	0.1%
5	AUDUBON	0.1%	0.1%	0.2%	0.3%	0.3%	0.4%	0.1%	0.0%	0.0%	0.1%	0.0%	0.1%
37	GREENE	0.3%	0.1%	0.5%	0.2%	0.2%	0.4%	0.2%	0.1%	0.1%	0.2%	0.1%	0.2%
54	KEOKUK	0.1%	0.4%	0.5%	0.1%	0.3%	0.3%	0.2%	0.2%	0.4%	0.2%	0.2%	0.5%
68	MONROE	0.3%	0.7%	0.5%	0.3%	0.3%	0.2%	0.2%	0.2%	0.3%	0.2%	0.2%	0.5%
69	MONTGOMERY	0.2%	0.2%	0.3%	0.2%	0.3%	0.5%	0.2%	0.4%	0.8%	0.3%	0.4%	0.7%
72	OSCEOLA	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.3%	0.3%	0.4%	0.2%	0.3%	0.4%
76	POCAHONTAS	0.2%	0.5%	0.5%	0.2%	0.5%	0.5%	0.1%	0.5%	0.7%	0.2%	0.5%	0.5%
93	WAYNE	0.2%	0.7%	0.4%	0.2%	0.4%	0.3%	0.3%	0.2%	0.1%	0.0%	0.2%	0.2%
95	WINNEBAGO	0.2%	0.0%	0.0%	0.1%	0.1%	0.0%	0.1%	0.1%	0.0%	0.2%	0.1%	0.0%
26	DAVIS	0.1%	0.5%	0.4%	0.1%	0.4%	0.5%	0.1%	0.5%	0.8%	0.2%	0.5%	0.7%
80	RINGGOLD	0.1%	0.1%	0.0%	0.1%	0.1%	0.0%	0.1%	0.1%	0.0%	0.2%	0.1%	0.0%
87	TAYLOR	0.1%	0.1%	0.2%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%
89	VAN BUREN	0.1%	0.5%	0.4%	0.1%	0.4%	0.4%	0.1%	0.2%	0.3%	0.1%	0.2%	0.3%

Table D.29. Total contacts and crashes by county 2009 through 2012

No.	County	Total		
		Crash	VSIS	ECCO
77	POLK	13.4%	3.8%	4.4%
82	SCOTT	6.4%	1.9%	2.6%
78	POTTAWATTAMIE	5.2%	7.5%	9.2%
57	LINN	5.0%	1.8%	1.9%
52	JOHNSON	4.6%	0.8%	1.0%
7	BLACK HAWK	3.7%	1.0%	1.6%
97	WOODBURY	3.7%	6.0%	6.6%
31	DUBUQUE	3.2%	1.1%	1.6%
85	STORY	2.2%	2.5%	2.0%
50	JASPER	1.9%	8.5%	5.9%
17	CERRO GORDO	1.8%	0.9%	1.0%
23	CLINTON	1.8%	1.4%	1.5%
84	SIOUX	1.7%	0.9%	1.2%
25	DALLAS	1.6%	9.3%	5.4%
16	CEDAR	1.3%	1.2%	1.4%
94	WEBSTER	1.3%	0.3%	0.5%
40	HAMILTON	1.2%	0.2%	0.2%
79	POWESHIEK	1.2%	0.7%	0.7%
91	WARREN	1.2%	0.9%	1.2%
29	DES MOINES	1.1%	0.5%	0.4%
48	IOWA	1.0%	0.2%	0.7%
64	MARSHALL	1.0%	0.6%	0.4%
75	PLYMOUTH	1.0%	0.7%	1.0%
56	LEE	0.9%	3.3%	2.2%
70	MUSCATINE	0.9%	0.7%	0.6%
90	WAPELLO	0.9%	0.4%	0.5%
15	CASS	0.8%	0.2%	1.0%
20	CLARKE	0.8%	3.5%	1.7%
43	HARRISON	0.8%	0.6%	1.1%
1	ADAIR	0.7%	0.4%	1.2%
6	BENTON	0.7%	0.4%	0.5%
9	BREMER	0.7%	0.8%	0.7%
11	BUENA VISTA	0.7%	0.6%	0.6%
22	CLAYTON	0.7%	0.3%	0.4%
24	CRAWFORD	0.7%	0.2%	0.3%
33	FAYETTE	0.7%	0.5%	0.6%
36	FREMONT	0.7%	2.6%	3.8%
42	HARDIN	0.7%	0.3%	0.3%
62	MAHASKA	0.7%	0.4%	0.5%
65	MILLS	0.7%	0.4%	0.7%
8	BOONE	0.6%	0.4%	0.4%

No.	County	Total		
		Crash	VSIS	ECCO
10	BUCHANAN	0.6%	8.6%	6.2%
21	CLAY	0.6%	0.5%	0.5%
34	FLOYD	0.6%	0.3%	0.3%
44	HENRY	0.6%	0.6%	0.6%
55	KOSSUTH	0.6%	0.3%	0.3%
63	MARION	0.6%	0.5%	0.5%
67	MONONA	0.6%	0.3%	1.5%
14	CARROLL	0.5%	0.3%	0.5%
18	CHEROKEE	0.5%	0.5%	0.6%
28	DELAWARE	0.5%	0.3%	0.4%
30	DICKINSON	0.5%	0.5%	0.5%
35	FRANKLIN	0.5%	0.5%	0.5%
51	JEFFERSON	0.5%	0.4%	0.4%
53	JONES	0.5%	0.3%	0.3%
71	OBRIEN	0.5%	0.4%	0.5%
86	TAMA	0.5%	0.4%	0.5%
92	WASHINGTON	0.5%	0.5%	0.4%
96	WINNESHIEK	0.5%	0.4%	0.3%
99	WRIGHT	0.5%	0.2%	0.2%
13	CALHOUN	0.4%	0.2%	0.3%
38	GRUNDY	0.4%	0.1%	0.1%
59	LUCAS	0.4%	0.6%	0.5%
60	LYON	0.4%	0.2%	0.3%
74	PALO ALTO	0.4%	0.4%	0.4%
98	WORTH	0.4%	2.8%	2.3%
3	ALLAMAKEE	0.3%	0.1%	0.1%
4	APPANOOSE	0.3%	0.1%	0.1%
12	BUTLER	0.3%	0.2%	0.2%
19	CHICKASAW	0.3%	0.3%	0.2%
27	DECATUR	0.3%	0.2%	0.1%
32	EMMET	0.3%	0.2%	0.1%
39	GUTHRIE	0.3%	0.2%	0.4%
41	HANCOCK	0.3%	0.2%	0.2%
45	HOWARD	0.3%	0.3%	0.2%
46	HUMBOLDT	0.3%	0.1%	0.2%
47	IDA	0.3%	0.4%	0.5%
49	JACKSON	0.3%	0.4%	0.4%
58	LOUISA	0.3%	0.2%	0.2%
61	MADISON	0.3%	0.3%	0.3%
66	MITCHELL	0.3%	0.2%	0.2%
73	PAGE	0.3%	0.4%	0.6%
81	SAC	0.3%	3.1%	2.5%
83	SHELBY	0.3%	0.3%	0.5%

No.	County	Total		
		Crash	VSIS	ECCO
88	UNION	0.3%	0.4%	0.3%
2	ADAMS	0.2%	0.1%	0.1%
5	AUDUBON	0.2%	0.1%	0.2%
37	GREENE	0.2%	0.1%	0.3%
54	KEOKUK	0.2%	0.3%	0.4%
68	MONROE	0.2%	0.4%	0.4%
69	MONTGOMERY	0.2%	0.3%	0.6%
72	OSCEOLA	0.2%	0.3%	0.3%
76	POCAHONTAS	0.2%	0.5%	0.6%
93	WAYNE	0.2%	0.4%	0.2%
95	WINNEBAGO	0.2%	0.1%	0.0%
26	DAVIS	0.1%	0.4%	0.6%
80	RINGGOLD	0.1%	0.1%	0.0%
87	TAYLOR	0.1%	0.0%	0.1%
89	VAN BUREN	0.1%	0.3%	0.4%

Table D.30. Annual contacts and crashes on primary road by county

Year	2009			2010			2011			2012		
County	Crash	ECCO	VSIS	Crash	ECCO	VSIS	Crash	ECCO	VSIS	Crash	ECCO	VSIS
POLK	13.9%	2.8%	2.7%	13.9%	3.9%	3.0%	13.3%	4.3%	3.0%	14.4%	3.8%	3.4%
SCOTT	5.5%	2.0%	1.5%	6.1%	2.4%	1.6%	5.9%	2.5%	1.7%	7.4%	2.4%	1.7%
POTTAWATTAMIE	5.8%	10.9%	6.4%	5.0%	10.7%	9.8%	7.1%	9.5%	8.2%	5.3%	10.5%	9.5%
JOHNSON	5.9%	0.5%	0.7%	3.9%	1.0%	0.8%	6.0%	1.0%	0.5%	6.9%	1.1%	0.6%
WOODBURY	4.2%	7.3%	6.5%	4.3%	7.8%	7.4%	2.7%	5.1%	4.3%	3.3%	7.2%	7.1%
LINN	3.4%	1.0%	1.3%	2.5%	1.1%	1.1%	3.7%	1.2%	1.1%	3.7%	1.2%	0.9%
JASPER	2.7%	7.5%	10.1%	3.7%	7.2%	9.8%	2.1%	6.2%	9.2%	2.9%	6.8%	10.0%
BLACK HAWK	2.9%	1.3%	0.6%	2.4%	1.4%	0.6%	2.3%	1.8%	0.8%	3.8%	1.1%	0.7%
DUBUQUE	2.2%	1.4%	1.1%	2.4%	1.7%	1.1%	3.5%	1.5%	0.9%	3.2%	1.5%	0.9%
DALLAS	2.2%	6.2%	9.9%	2.4%	6.2%	10.8%	1.7%	5.9%	12.1%	1.8%	5.7%	8.9%
CEDAR	1.8%	2.2%	2.2%	2.3%	1.8%	2.0%	1.6%	1.2%	0.5%	2.0%	0.8%	0.3%
POWESHIEK	1.8%	0.6%	0.9%	1.4%	0.5%	0.5%	2.0%	0.6%	0.4%	2.1%	1.1%	0.8%
STORY	1.5%	2.1%	3.3%	1.9%	2.2%	2.3%	1.8%	1.6%	1.9%	1.9%	2.2%	2.9%
CLINTON	1.7%	1.2%	1.3%	1.6%	1.3%	1.3%	1.7%	1.2%	1.1%	1.8%	0.9%	0.8%
CERRO GORDO	1.7%	0.6%	0.4%	1.7%	0.6%	0.6%	1.6%	0.6%	0.6%	1.5%	0.7%	0.7%
WARREN	2.3%	0.8%	0.8%	1.3%	1.2%	0.9%	1.8%	1.7%	1.0%	1.1%	1.6%	0.9%
IOWA	1.6%	0.6%	0.2%	1.3%	0.7%	0.1%	1.5%	1.0%	0.2%	1.7%	1.0%	0.2%
HAMILTON	1.4%	0.1%	0.0%	2.0%	0.2%	0.2%	1.3%	0.2%	0.2%	0.8%	0.2%	0.3%
SIOUX	1.5%	1.2%	0.9%	1.4%	1.0%	0.6%	1.3%	1.0%	0.8%	1.2%	0.8%	0.6%
CASS	1.4%	1.6%	0.2%	1.3%	1.3%	0.2%	1.2%	0.7%	0.2%	1.4%	0.7%	0.3%
ADAIR	1.0%	1.5%	0.6%	1.1%	1.3%	0.3%	1.5%	0.9%	0.4%	0.7%	1.0%	0.3%
CLARKE	0.7%	1.1%	3.0%	1.2%	1.3%	2.5%	1.5%	3.0%	5.6%	0.9%	2.8%	4.7%
FREMONT	1.1%	5.5%	4.3%	0.7%	5.1%	3.3%	1.0%	3.3%	2.2%	1.0%	3.8%	2.4%
LEE	0.9%	1.6%	2.2%	1.0%	2.0%	2.8%	0.8%	1.4%	1.9%	0.9%	2.0%	3.6%
HARRISON	1.1%	2.3%	1.6%	1.0%	1.4%	0.8%	1.0%	0.6%	0.2%	0.5%	0.7%	0.2%
MUSCATINE	1.0%	0.4%	0.5%	1.0%	0.4%	0.6%	0.6%	0.6%	0.6%	0.8%	0.7%	0.7%
PLYMOUTH	0.8%	1.0%	0.6%	1.0%	0.7%	0.4%	1.1%	0.9%	0.8%	0.4%	0.7%	0.6%
MILLS	0.4%	0.6%	0.4%	1.0%	0.7%	0.4%	1.3%	1.1%	0.4%	0.5%	1.0%	0.5%
MONONA	1.2%	1.5%	0.3%	1.1%	1.6%	0.2%	0.6%	1.5%	0.3%	0.4%	1.7%	0.3%
WAPELLO	0.5%	0.5%	0.5%	1.0%	0.3%	0.3%	1.0%	0.5%	0.4%	0.8%	0.5%	0.5%
MAHASKA	1.1%	0.6%	0.6%	0.9%	0.4%	0.3%	0.8%	0.6%	0.3%	0.6%	0.4%	0.2%
FLOYD	0.6%	0.1%	0.1%	0.6%	0.2%	0.2%	0.6%	0.3%	0.3%	1.2%	0.2%	0.4%
BREMER	0.9%	0.5%	0.7%	0.6%	0.7%	0.8%	0.5%	0.8%	0.9%	0.8%	0.9%	0.9%
MARSHALL	0.5%	0.3%	0.6%	0.6%	0.2%	0.5%	0.7%	0.2%	0.4%	1.1%	0.5%	0.5%
BENTON	1.1%	0.6%	0.5%	0.8%	0.3%	0.3%	0.6%	0.5%	0.4%	0.3%	0.6%	0.4%
CLAYTON	0.5%	0.2%	0.2%	0.8%	0.2%	0.2%	0.6%	0.5%	0.4%	0.9%	0.4%	0.4%
FAYETTE	1.1%	0.5%	0.4%	0.7%	0.4%	0.4%	0.5%	0.7%	0.6%	0.5%	0.5%	0.4%
DES MOINES	0.9%	0.3%	0.4%	0.6%	0.2%	0.3%	0.6%	0.2%	0.2%	0.6%	0.1%	0.1%
FRANKLIN	0.7%	0.3%	0.2%	0.6%	0.3%	0.3%	0.7%	0.6%	0.6%	0.6%	0.6%	0.5%
CRAWFORD	0.6%	0.4%	0.1%	0.6%	0.3%	0.2%	0.5%	0.4%	0.2%	0.6%	0.3%	0.2%
JONES	0.7%	0.2%	0.4%	0.4%	0.3%	0.3%	0.4%	0.3%	0.2%	0.9%	0.2%	0.2%
BUCHANAN	0.3%	6.5%	9.4%	0.7%	7.2%	9.4%	0.8%	7.7%	10.3%	0.3%	7.7%	10.6%
HENRY	0.4%	0.8%	1.0%	0.8%	0.6%	0.7%	0.5%	0.4%	0.4%	0.4%	0.4%	0.4%
WEBSTER	0.6%	0.3%	0.2%	0.3%	0.2%	0.2%	0.7%	0.2%	0.2%	0.7%	0.3%	0.2%
DECATUR	0.4%	0.1%	0.3%	0.6%	0.1%	0.1%	0.7%	0.1%	0.1%	0.4%	0.1%	0.1%
BUENA VISTA	0.3%	0.3%	0.3%	0.6%	0.3%	0.3%	0.7%	0.6%	0.5%	0.4%	0.7%	0.6%
TAMA	0.5%	0.5%	0.4%	0.4%	0.2%	0.2%	0.7%	0.4%	0.3%	0.4%	0.7%	0.6%
WASHINGTON	0.5%	0.5%	0.5%	0.6%	0.5%	0.5%	0.5%	0.3%	0.3%	0.4%	0.2%	0.3%
CLAY	0.5%	0.2%	0.2%	0.3%	0.2%	0.2%	0.7%	0.3%	0.3%	0.4%	0.5%	0.6%
KOSSUTH	0.5%	0.1%	0.1%	0.4%	0.2%	0.2%	0.5%	0.3%	0.4%	0.6%	0.4%	0.3%
CARROLL	0.5%	0.9%	0.3%	0.4%	0.5%	0.3%	0.5%	0.2%	0.2%	0.5%	0.1%	0.1%
HARDIN	0.6%	0.2%	0.2%	0.6%	0.1%	0.1%	0.3%	0.2%	0.2%	0.3%	0.4%	0.5%
GRUNDY	0.5%	0.1%	0.1%	0.6%	0.1%	0.1%	0.2%	0.1%	0.1%	0.4%	0.2%	0.1%
IDA	0.4%	0.1%	0.1%	0.4%	0.4%	0.3%	0.5%	0.9%	0.6%	0.5%	0.5%	0.3%
WORTH	0.5%	2.5%	3.0%	0.3%	1.8%	2.2%	0.4%	3.5%	3.6%	0.6%	2.6%	3.4%
DELAWARE	0.4%	0.2%	0.2%	0.3%	0.3%	0.3%	0.4%	0.2%	0.2%	0.6%	0.4%	0.3%
JEFFERSON	0.4%	0.4%	0.5%	0.5%	0.3%	0.4%	0.5%	0.3%	0.3%	0.4%	0.3%	0.4%
MARION	0.5%	0.5%	0.5%	0.3%	0.4%	0.4%	0.6%	0.3%	0.3%	0.3%	0.6%	0.5%
BOONE	0.3%	0.2%	0.2%	0.5%	0.4%	0.4%	0.5%	0.5%	0.6%	0.3%	0.3%	0.4%
DICKINSON	0.5%	0.2%	0.2%	0.5%	0.3%	0.3%	0.4%	0.4%	0.4%	0.3%	0.3%	0.4%
WRIGHT	0.3%	0.1%	0.1%	0.6%	0.1%	0.1%	0.4%	0.3%	0.2%	0.3%	0.1%	0.2%
PALO ALTO	0.5%	0.2%	0.2%	0.3%	0.2%	0.2%	0.3%	0.4%	0.4%	0.4%	0.6%	0.6%

Year	2009			2010			2011			2012		
County	Crash	ECCO	VSIS	Crash	ECCO	VSIS	Crash	ECCO	VSIS	Crash	ECCO	VSIS
CHEROKEE	0.3%	0.4%	0.3%	0.4%	0.4%	0.4%	0.4%	0.6%	0.6%	0.3%	0.4%	0.4%
OBRIEN	0.3%	0.4%	0.3%	0.3%	0.3%	0.3%	0.5%	0.6%	0.5%	0.3%	0.5%	0.5%
WINNESHIEK	0.3%	0.1%	0.1%	0.4%	0.1%	0.1%	0.5%	0.6%	0.7%	0.3%	0.4%	0.5%
LUCAS	0.4%	0.3%	0.6%	0.2%	0.5%	0.7%	0.3%	0.5%	0.7%	0.3%	0.7%	0.6%
SHELBY	0.2%	0.4%	0.2%	0.3%	0.7%	0.4%	0.3%	0.4%	0.3%	0.4%	0.6%	0.3%
JACKSON	0.4%	0.4%	0.4%	0.2%	0.5%	0.4%	0.4%	0.5%	0.5%	0.1%	0.3%	0.3%
MONROE	0.3%	0.5%	0.7%	0.4%	0.2%	0.3%	0.2%	0.3%	0.3%	0.2%	0.4%	0.3%
SAC	0.1%	3.2%	3.5%	0.4%	3.1%	4.1%	0.6%	3.6%	4.5%	0.1%	1.4%	1.7%
CALHOUN	0.3%	0.2%	0.1%	0.2%	0.1%	0.1%	0.3%	0.1%	0.1%	0.3%	0.2%	0.1%
EMMET	0.3%	0.0%	0.0%	0.3%	0.1%	0.1%	0.2%	0.1%	0.2%	0.3%	0.2%	0.2%
HUMBOLDT	0.2%	0.1%	0.0%	0.3%	0.1%	0.1%	0.5%	0.2%	0.2%	0.1%	0.2%	0.1%
POCAHONTAS	0.3%	0.5%	0.5%	0.4%	0.5%	0.5%	0.1%	0.6%	0.5%	0.3%	0.5%	0.4%
CHICKASAW	0.4%	0.1%	0.1%	0.3%	0.2%	0.2%	0.2%	0.2%	0.3%	0.2%	0.2%	0.3%
HANCOCK	0.2%	0.1%	0.1%	0.3%	0.1%	0.2%	0.3%	0.2%	0.3%	0.3%	0.2%	0.2%
UNION	0.3%	0.3%	0.7%	0.2%	0.3%	0.4%	0.4%	0.3%	0.3%	0.1%	0.2%	0.1%
OSCEOLA	0.2%	0.2%	0.1%	0.3%	0.2%	0.2%	0.2%	0.3%	0.2%	0.3%	0.2%	0.2%
MADISON	0.1%	0.3%	0.3%	0.4%	0.2%	0.3%	0.1%	0.3%	0.3%	0.3%	0.3%	0.2%
ALLAMAKEE	0.3%	0.0%	0.0%	0.2%	0.1%	0.1%	0.3%	0.2%	0.2%	0.1%	0.1%	0.1%
GREENE	0.3%	0.5%	0.1%	0.3%	0.4%	0.1%	0.3%	0.1%	0.1%	0.1%	0.2%	0.2%
HOWARD	0.4%	0.1%	0.1%	0.3%	0.1%	0.1%	0.1%	0.3%	0.4%	0.2%	0.3%	0.3%
LOUISA	0.3%	0.3%	0.3%	0.2%	0.2%	0.2%	0.1%	0.1%	0.1%	0.3%	0.1%	0.0%
ADAMS	0.4%	0.3%	0.3%	0.3%	0.1%	0.1%	0.1%	0.1%	0.1%	0.2%	0.1%	0.0%
KEOKUK	0.2%	0.5%	0.4%	0.2%	0.3%	0.3%	0.3%	0.4%	0.1%	0.2%	0.5%	0.2%
MITCHELL	0.3%	0.2%	0.2%	0.3%	0.1%	0.1%	0.3%	0.1%	0.1%	0.0%	0.1%	0.2%
GUTHRIE	0.2%	0.4%	0.2%	0.2%	0.3%	0.2%	0.2%	0.2%	0.2%	0.3%	0.2%	0.2%
LYON	0.1%	0.4%	0.3%	0.1%	0.2%	0.2%	0.4%	0.2%	0.2%	0.2%	0.3%	0.2%
MONTGOMERY	0.1%	0.4%	0.2%	0.3%	0.6%	0.3%	0.1%	1.0%	0.5%	0.3%	0.9%	0.4%
WAYNE	0.3%	0.4%	0.7%	0.2%	0.2%	0.4%	0.2%	0.1%	0.2%	0.0%	0.2%	0.2%
APPANOOSE	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.3%	0.1%	0.1%
BUTLER	0.1%	0.1%	0.1%	0.1%	0.2%	0.2%	0.1%	0.2%	0.2%	0.3%	0.2%	0.2%
PAGE	0.1%	0.7%	0.4%	0.2%	0.8%	0.5%	0.2%	0.8%	0.4%	0.2%	0.6%	0.3%
DAVIS	0.1%	0.5%	0.5%	0.0%	0.5%	0.4%	0.2%	0.8%	0.5%	0.1%	0.7%	0.4%
VAN BUREN	0.1%	0.4%	0.5%	0.1%	0.5%	0.4%	0.1%	0.3%	0.2%	0.2%	0.3%	0.3%
AUDUBON	0.0%	0.3%	0.1%	0.2%	0.4%	0.3%	0.1%	0.0%	0.0%	0.1%	0.1%	0.1%
TAYLOR	0.1%	0.2%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%
RINGGOLD	0.1%	0.0%	0.1%	0.1%	0.0%	0.1%	0.1%	0.0%	0.1%	0.0%	0.1%	0.0%
WINNEBAGO	0.1%	0.0%	0.0%	0.1%	0.0%	0.1%	0.0%	0.1%	0.0%	0.1%	0.0%	0.0%

Table D.31. Total contacts and crashes on primary road by county 2009 through 2012

County	Crash	ECCO	VSIS
POLK	13.9%	3.6%	3.0%
SCOTT	6.2%	2.3%	1.6%
POTTAWATTAMIE	5.8%	10.5%	8.4%
JOHNSON	5.6%	0.9%	0.6%
WOODBURY	3.7%	6.9%	6.3%
LINN	3.3%	1.1%	1.1%
JASPER	2.9%	7.0%	9.8%
BLACK HAWK	2.8%	1.4%	0.7%
DUBUQUE	2.8%	1.5%	1.0%
DALLAS	2.0%	6.0%	10.4%
CEDAR	1.9%	1.6%	1.2%
POWESHIEK	1.8%	0.7%	0.7%
STORY	1.8%	2.0%	2.6%
CLINTON	1.7%	1.1%	1.1%
CERRO GORDO	1.6%	0.6%	0.6%
WARREN	1.6%	1.3%	0.9%
IOWA	1.5%	0.8%	0.2%
HAMILTON	1.4%	0.2%	0.2%
SIOUX	1.4%	1.0%	0.7%
CASS	1.3%	1.1%	0.2%
ADAIR	1.1%	1.2%	0.4%
CLARKE	1.1%	2.0%	4.0%
FREMONT	1.0%	4.5%	3.0%
LEE	0.9%	1.7%	2.6%
HARRISON	0.9%	1.3%	0.7%
MUSCATINE	0.9%	0.5%	0.6%
PLYMOUTH	0.9%	0.8%	0.6%
MILLS	0.8%	0.8%	0.4%
MONONA	0.8%	1.6%	0.3%
WAPELLO	0.8%	0.5%	0.4%
MAHASKA	0.8%	0.5%	0.4%
FLOYD	0.7%	0.2%	0.2%
BREMER	0.7%	0.7%	0.8%
MARSHALL	0.7%	0.3%	0.5%
BENTON	0.7%	0.5%	0.4%
CLAYTON	0.7%	0.3%	0.3%
FAYETTE	0.7%	0.5%	0.5%
DES MOINES	0.7%	0.2%	0.3%
FRANKLIN	0.7%	0.4%	0.4%
CRAWFORD	0.6%	0.3%	0.2%
JONES	0.6%	0.3%	0.3%
BUCHANAN	0.6%	7.2%	9.9%

County	Crash	ECCO	VSIS
HENRY	0.6%	0.6%	0.6%
WEBSTER	0.6%	0.3%	0.2%
DECATUR	0.5%	0.1%	0.2%
BUENA VISTA	0.5%	0.5%	0.4%
TAMA	0.5%	0.4%	0.4%
WASHINGTON	0.5%	0.4%	0.4%
CLAY	0.5%	0.3%	0.3%
KOSSUTH	0.5%	0.2%	0.3%
CARROLL	0.5%	0.4%	0.2%
HARDIN	0.5%	0.2%	0.2%
GRUNDY	0.5%	0.1%	0.1%
IDA	0.5%	0.4%	0.3%
WORTH	0.4%	2.6%	3.1%
DELAWARE	0.4%	0.3%	0.2%
JEFFERSON	0.4%	0.3%	0.4%
MARION	0.4%	0.4%	0.4%
BOONE	0.4%	0.3%	0.4%
DICKINSON	0.4%	0.3%	0.3%
WRIGHT	0.4%	0.1%	0.2%
PALO ALTO	0.4%	0.3%	0.4%
CHEROKEE	0.4%	0.4%	0.4%
OBRIEN	0.4%	0.4%	0.4%
WINNESHIEK	0.4%	0.3%	0.4%
LUCAS	0.3%	0.5%	0.6%
SHELBY	0.3%	0.5%	0.3%
JACKSON	0.3%	0.4%	0.4%
MONROE	0.3%	0.4%	0.4%
SAC	0.3%	2.8%	3.4%
CALHOUN	0.3%	0.2%	0.1%
EMMET	0.3%	0.1%	0.1%
HUMBOLDT	0.3%	0.2%	0.1%
POCAHONTAS	0.3%	0.5%	0.5%
CHICKASAW	0.3%	0.2%	0.2%
HANCOCK	0.3%	0.2%	0.2%
UNION	0.3%	0.3%	0.4%
OSCEOLA	0.3%	0.2%	0.2%
MADISON	0.2%	0.3%	0.3%
ALLAMAKEE	0.2%	0.1%	0.1%
GREENE	0.2%	0.3%	0.1%
HOWARD	0.2%	0.2%	0.2%
LOUISA	0.2%	0.2%	0.2%
ADAMS	0.2%	0.2%	0.1%
KEOKUK	0.2%	0.4%	0.3%
MITCHELL	0.2%	0.1%	0.1%

County	Crash	ECCO	VSIS
GUTHRIE	0.2%	0.3%	0.2%
LYON	0.2%	0.3%	0.2%
MONTGOMERY	0.2%	0.7%	0.3%
WAYNE	0.2%	0.3%	0.4%
APPANOOSE	0.2%	0.1%	0.1%
BUTLER	0.2%	0.2%	0.2%
PAGE	0.2%	0.7%	0.4%
DAVIS	0.1%	0.6%	0.5%
VAN BUREN	0.1%	0.4%	0.4%
AUDUBON	0.1%	0.2%	0.1%
TAYLOR	0.1%	0.1%	0.0%
RINGGOLD	0.1%	0.0%	0.1%
WINNEBAGO	0.1%	0.0%	0.0%

Table D.32. Annual contacts and crashes on secondary road by county

Year	2009			2010			2011			2012		
County	Crash	ECCO	VSIS	Crash	ECCO	VSIS	Crash	ECCO	VSIS	Crash	ECCO	VSIS
SIOUX	5.5%	4.0%	2.9%	3.8%	2.2%	1.6%	3.6%	3.3%	2.7%	6.5%	2.7%	2.5%
POLK	4.6%	3.5%	3.3%	2.5%	4.9%	3.8%	4.4%	3.3%	3.8%	3.9%	4.3%	4.4%
POTTAWATTAMIE	2.9%	0.9%	0.6%	2.7%	1.1%	0.9%	2.3%	1.4%	0.9%	2.8%	1.8%	1.0%
LINN	2.3%	3.5%	4.1%	1.6%	3.4%	2.6%	2.7%	3.9%	3.2%	2.8%	3.9%	3.3%
HARDIN	2.0%	0.5%	0.4%	2.5%	0.3%	0.4%	2.1%	1.1%	1.1%	2.4%	1.0%	1.4%
WEBSTER	2.3%	2.0%	1.0%	2.4%	1.7%	1.2%	1.9%	1.1%	1.0%	1.5%	1.1%	1.1%
DUBUQUE	1.4%	1.2%	1.3%	2.5%	1.0%	1.3%	2.1%	1.2%	1.0%	1.7%	1.6%	1.1%
PLYMOUTH	2.5%	2.1%	1.3%	2.0%	1.6%	1.2%	1.7%	2.2%	1.8%	0.9%	1.6%	1.3%
BLACK HAWK	1.1%	2.3%	2.3%	1.9%	0.9%	1.2%	1.9%	1.4%	1.5%	2.2%	1.3%	1.4%
WOODBURY	1.3%	3.8%	3.1%	1.4%	3.1%	2.4%	1.3%	2.1%	2.0%	3.0%	3.3%	3.4%
STORY	2.5%	0.8%	1.1%	0.9%	1.2%	0.9%	1.3%	1.3%	1.5%	1.7%	1.0%	1.1%
BUENA VISTA	1.6%	1.1%	1.1%	1.9%	0.9%	1.0%	1.5%	1.9%	1.8%	1.1%	2.1%	2.1%
CLAY	2.0%	0.7%	0.8%	1.6%	1.0%	1.0%	1.0%	1.8%	1.6%	1.7%	1.6%	2.1%
WINNESHIEK	1.8%	0.2%	0.1%	1.6%	0.1%	0.2%	1.5%	0.4%	0.7%	1.3%	0.3%	0.7%
JOHNSON	1.6%	1.0%	1.4%	1.6%	1.8%	1.9%	1.5%	0.7%	0.8%	1.3%	0.6%	0.7%
MARSHALL	2.0%	0.3%	0.5%	1.3%	0.3%	0.5%	1.9%	0.5%	0.7%	0.9%	1.2%	1.2%
LYON	0.7%	0.7%	0.6%	2.4%	0.4%	0.3%	0.6%	0.5%	0.3%	2.2%	1.5%	1.4%
BENTON	1.8%	0.8%	0.7%	1.6%	0.3%	0.3%	0.8%	0.5%	0.4%	1.5%	1.1%	1.0%
CLINTON	1.3%	1.3%	2.0%	2.4%	2.3%	2.3%	1.0%	2.7%	3.1%	0.9%	2.8%	2.9%
SCOTT	1.4%	2.5%	2.2%	1.1%	3.1%	2.2%	1.5%	3.8%	2.5%	1.7%	3.5%	3.2%
BUCHANAN	1.1%	1.3%	1.3%	0.6%	1.6%	1.7%	2.5%	1.7%	1.8%	1.5%	2.8%	2.6%
HAMILTON	2.0%	0.3%	0.1%	0.2%	0.4%	0.2%	1.3%	0.5%	0.5%	2.4%	0.9%	0.9%
HARRISON	1.1%	0.9%	0.4%	1.6%	0.5%	0.2%	1.7%	0.1%	0.1%	1.1%	0.2%	0.1%
KOSSUTH	1.1%	0.2%	0.2%	1.3%	0.2%	0.3%	1.7%	1.5%	1.5%	1.5%	1.1%	1.3%
CALHOUN	1.8%	2.1%	0.7%	1.6%	1.5%	1.3%	1.0%	1.0%	0.7%	0.9%	1.1%	0.8%
CLAYTON	1.1%	0.8%	0.7%	1.6%	0.5%	0.4%	1.5%	0.5%	0.7%	1.1%	0.9%	0.7%
FAYETTE	1.8%	0.9%	0.8%	0.9%	0.8%	0.6%	1.3%	0.9%	0.9%	1.3%	1.3%	1.5%
CHEROKEE	1.6%	0.6%	0.6%	1.1%	1.4%	1.3%	1.1%	2.2%	1.9%	1.3%	1.7%	1.3%
CEDAR	0.7%	1.5%	2.5%	0.9%	1.5%	2.2%	1.7%	0.8%	0.7%	1.7%	0.7%	0.7%
LEE	0.7%	8.2%	15.7%	2.0%	11.9%	21.9%	1.0%	10.6%	15.3%	1.1%	0.8%	1.6%
MARION	0.9%	1.5%	1.7%	1.3%	1.5%	1.3%	1.1%	0.9%	0.9%	1.7%	1.7%	1.7%
BOONE	1.6%	0.4%	0.7%	0.9%	0.5%	0.8%	1.1%	0.6%	1.0%	0.9%	0.9%	1.2%
CERRO GORDO	0.9%	1.7%	1.7%	0.9%	4.8%	2.2%	0.8%	2.4%	2.3%	2.2%	1.7%	2.1%
CRAWFORD	1.3%	0.3%	0.2%	1.3%	0.2%	0.1%	1.3%	0.2%	0.2%	0.6%	0.1%	0.1%
MILLS	0.5%	0.5%	0.4%	0.6%	0.9%	0.5%	2.1%	0.6%	0.5%	1.1%	0.8%	0.6%
BREMER	0.7%	0.7%	0.6%	1.6%	0.6%	0.5%	0.8%	0.6%	0.6%	0.9%	0.5%	0.7%
JASPER	1.1%	1.9%	2.3%	1.4%	0.9%	1.4%	1.0%	1.2%	2.0%	0.4%	1.9%	2.7%
MITCHELL	0.9%	0.4%	0.4%	0.9%	0.1%	0.2%	1.0%	0.5%	0.5%	1.3%	1.7%	2.1%
MUSCATINE	0.5%	0.5%	0.6%	1.3%	0.3%	0.3%	0.8%	0.3%	0.2%	1.5%	0.6%	0.5%
OBRIEN	0.9%	0.7%	0.5%	0.9%	0.7%	0.6%	1.3%	0.9%	0.9%	0.9%	1.8%	1.7%
CARROLL	0.4%	1.0%	0.6%	0.9%	0.9%	0.8%	1.5%	0.8%	0.7%	1.1%	0.2%	0.2%
DES MOINES	1.4%	2.0%	2.3%	1.1%	2.1%	1.7%	0.4%	0.7%	0.7%	0.9%	0.7%	1.1%
GRUNDY	0.9%	0.2%	0.2%	1.3%	0.1%	0.2%	0.6%	0.3%	0.4%	1.1%	0.5%	0.7%
IOWA	1.3%	0.3%	0.3%	0.9%	0.4%	0.2%	1.1%	0.4%	0.2%	0.4%	0.6%	0.2%
PALO ALTO	0.9%	0.4%	0.3%	1.1%	1.0%	1.1%	1.1%	1.3%	1.4%	0.6%	1.3%	1.4%
FREMONT	0.5%	1.1%	0.9%	0.6%	1.3%	0.6%	1.3%	0.2%	0.3%	1.3%	1.1%	0.9%
HOWARD	0.7%	0.3%	0.3%	0.9%	0.1%	0.1%	1.1%	0.5%	0.6%	0.9%	1.1%	1.3%
WARREN	0.7%	0.4%	1.6%	1.4%	0.8%	1.2%	1.1%	1.0%	1.3%	0.2%	0.8%	1.0%
DELAWARE	0.5%	0.9%	0.6%	0.6%	0.7%	0.9%	1.5%	1.3%	1.2%	0.9%	0.9%	0.9%
HENRY	0.5%	1.4%	1.6%	1.1%	1.2%	1.4%	0.6%	0.4%	0.3%	1.3%	0.3%	0.3%
WASHINGTON	0.7%	1.7%	2.1%	0.9%	0.9%	1.5%	0.8%	0.6%	0.5%	1.1%	0.5%	0.7%
BUTLER	1.3%	0.4%	0.6%	0.6%	0.6%	0.5%	0.8%	0.9%	0.9%	0.6%	0.4%	0.6%
DALLAS	0.9%	2.3%	2.3%	1.1%	2.1%	2.6%	1.0%	1.9%	2.8%	0.2%	1.7%	2.1%
FRANKLIN	1.1%	1.6%	1.6%	0.5%	1.3%	1.3%	0.6%	1.3%	1.2%	1.3%	1.4%	1.4%
LOUISA	0.4%	0.4%	0.4%	1.1%	1.0%	0.7%	0.2%	0.2%	0.3%	1.7%	0.2%	0.1%
APPANOOSE	0.2%	0.3%	0.3%	1.1%	0.0%	0.1%	0.8%	0.4%	0.3%	1.1%	0.2%	0.2%
CHICKASAW	0.7%	0.2%	0.4%	0.9%	0.5%	0.5%	1.1%	0.6%	0.7%	0.2%	1.1%	1.3%
HUMBOLDT	0.4%	0.2%	0.1%	0.6%	0.1%	0.0%	1.5%	0.3%	0.3%	0.6%	0.3%	0.2%
JEFFERSON	0.7%	0.7%	0.7%	0.6%	1.0%	1.0%	0.8%	0.2%	0.2%	1.1%	0.7%	0.8%
MADISON	0.7%	0.3%	0.3%	0.9%	0.2%	0.2%	0.6%	0.2%	0.3%	0.9%	0.5%	0.3%
TAMA	1.8%	1.2%	1.2%	0.5%	0.3%	0.3%	0.6%	0.8%	0.5%	0.2%	1.3%	0.6%
EMMET	1.3%	0.1%	0.1%	0.5%	0.8%	0.8%	0.8%	0.8%	1.2%	0.4%	0.7%	0.7%

Year	2009			2010			2011			2012		
County	**Crash**	**ECCO**	**VSIS**	**Crash**	**ECCO**	**VSIS**	**Crash**	**ECCO**	**VSIS**	**Crash**	**ECCO**	**VSIS**
GUTHRIE	0.5%	3.0%	0.7%	1.3%	1.8%	0.6%	0.4%	1.9%	1.0%	0.6%	0.6%	0.4%
SAC	0.7%	2.3%	1.9%	1.3%	1.5%	1.6%	0.4%	2.7%	2.1%	0.4%	1.3%	1.0%
WORTH	0.5%	1.7%	1.6%	0.6%	1.1%	1.1%	0.4%	1.5%	1.5%	1.5%	1.3%	1.4%
WRIGHT	0.9%	0.1%	0.1%	0.8%	0.2%	0.2%	0.8%	0.5%	0.5%	0.4%	0.5%	0.6%
FLOYD	0.4%	0.6%	0.8%	1.1%	0.7%	0.8%	0.6%	0.7%	0.7%	0.6%	1.3%	1.5%
HANCOCK	0.7%	0.2%	0.3%	0.6%	0.3%	0.5%	0.6%	0.4%	0.4%	0.9%	0.4%	0.4%
JONES	1.1%	0.4%	0.8%	0.8%	0.5%	0.4%	0.6%	0.7%	0.7%	0.2%	0.8%	0.8%
WAPELLO	0.2%	1.0%	0.8%	0.8%	0.4%	0.3%	0.8%	0.7%	0.5%	1.1%	0.7%	0.6%
ALLAMAKEE	0.9%	0.0%	0.1%	0.5%	0.1%	0.2%	0.6%	0.1%	0.2%	0.6%	0.2%	0.4%
PAGE	0.5%	0.3%	0.2%	0.2%	0.3%	0.2%	0.8%	0.1%	0.1%	1.3%	0.2%	0.1%
POWESHIEK	0.4%	0.8%	0.9%	1.1%	0.7%	1.0%	0.4%	0.6%	0.4%	0.4%	0.8%	0.9%
DICKINSON	0.9%	0.4%	0.5%	0.2%	1.3%	1.0%	1.0%	1.5%	1.8%	0.2%	1.7%	2.0%
MAHASKA	0.7%	0.7%	0.7%	0.3%	0.2%	0.5%	0.6%	0.8%	0.3%	0.6%	0.6%	0.3%
UNION	0.4%	0.3%	0.5%	0.8%	0.3%	0.4%	0.6%	0.5%	0.5%	0.4%	0.2%	0.2%
ADAIR	0.0%	3.5%	0.3%	0.3%	2.3%	0.1%	1.0%	1.3%	0.1%	0.9%	1.0%	0.3%
MONONA	0.5%	1.4%	0.8%	0.5%	0.9%	0.6%	0.8%	0.6%	0.3%	0.2%	0.6%	0.3%
WAYNE	0.5%	0.2%	0.4%	0.5%	0.6%	0.8%	0.8%	0.2%	0.3%	0.2%	0.3%	0.6%
WINNEBAGO	0.4%	0.1%	0.1%	0.5%	0.0%	0.0%	0.8%	0.1%	0.1%	0.4%	0.1%	0.1%
JACKSON	0.0%	0.4%	0.4%	0.5%	0.5%	0.9%	1.0%	0.4%	0.4%	0.4%	0.5%	0.4%
AUDUBON	0.2%	0.1%	0.1%	0.9%	0.1%	0.1%	0.4%	0.1%	0.0%	0.0%	0.0%	0.1%
CLARKE	0.7%	0.6%	0.9%	0.5%	0.1%	0.5%	0.4%	0.1%	0.3%	0.0%	0.2%	0.2%
IDA	0.4%	0.9%	0.6%	0.8%	0.7%	0.7%	0.4%	1.3%	0.8%	0.0%	1.0%	0.7%
LUCAS	0.7%	0.2%	0.5%	0.6%	0.7%	1.3%	0.2%	0.7%	1.0%	0.0%	1.0%	0.9%
OSCEOLA	0.4%	0.4%	0.5%	0.5%	0.7%	0.4%	0.8%	1.0%	1.1%	0.0%	1.8%	1.7%
SHELBY	0.7%	0.3%	0.1%	0.5%	0.0%	0.0%	0.2%	0.0%	0.2%	0.2%	0.9%	0.4%
DAVIS	0.2%	0.2%	0.3%	0.3%	0.2%	0.3%	0.2%	0.4%	0.3%	0.9%	0.7%	0.7%
MONTGOMERY	0.5%	0.2%	0.1%	0.3%	0.0%	0.0%	0.2%	0.0%	0.0%	0.4%	0.1%	0.1%
RINGGOLD	0.5%	0.0%	0.1%	0.2%	0.0%	0.1%	0.0%	0.1%	0.1%	0.6%	0.0%	0.0%
CASS	0.7%	1.1%	0.3%	0.0%	0.3%	0.2%	0.2%	0.2%	0.1%	0.2%	0.2%	0.1%
DECATUR	0.5%	0.2%	0.3%	0.3%	0.2%	0.2%	0.2%	0.1%	0.2%	0.0%	0.2%	0.2%
MONROE	0.4%	0.4%	0.5%	0.3%	0.6%	0.3%	0.4%	0.2%	0.1%	0.0%	1.0%	1.0%
VAN BUREN	0.4%	0.8%	0.6%	0.3%	0.3%	0.4%	0.4%	0.4%	0.3%	0.0%	0.6%	0.6%
POCAHONTAS	0.2%	0.6%	0.7%	0.2%	0.9%	0.8%	0.4%	1.2%	0.8%	0.2%	0.9%	0.9%
ADAMS	0.2%	0.2%	0.1%	0.2%	0.0%	0.0%	0.2%	0.3%	0.1%	0.2%	0.1%	0.1%
GREENE	0.2%	0.4%	0.2%	0.0%	0.5%	0.5%	0.4%	0.2%	0.1%	0.2%	0.2%	0.2%
KEOKUK	0.4%	0.5%	0.4%	0.0%	0.5%	0.3%	0.0%	0.4%	0.2%	0.4%	0.5%	0.3%
TAYLOR	0.2%	0.0%	0.0%	0.2%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Table D.33. Total contacts and crashes on secondary road by county 2009 through 2012

County	Crash	ECCO	VSIS
SIOUX	4.8%	3.1%	2.5%
POLK	3.8%	4.0%	3.9%
POTTAWATTAMIE	2.7%	1.4%	0.9%
LINN	2.3%	3.7%	3.3%
HARDIN	2.2%	0.8%	0.9%
WEBSTER	2.1%	1.4%	1.1%
DUBUQUE	2.0%	1.3%	1.2%
PLYMOUTH	1.8%	1.8%	1.4%
BLACK HAWK	1.7%	1.5%	1.6%
WOODBURY	1.7%	3.1%	2.8%
STORY	1.6%	1.1%	1.2%
BUENA VISTA	1.6%	1.6%	1.6%
CLAY	1.6%	1.3%	1.5%
WINNESHIEK	1.6%	0.3%	0.5%
JOHNSON	1.5%	0.9%	1.1%
MARSHALL	1.5%	0.6%	0.8%
LYON	1.5%	0.8%	0.7%
BENTON	1.4%	0.7%	0.6%
CLINTON	1.4%	2.3%	2.6%
SCOTT	1.4%	3.2%	2.6%
BUCHANAN	1.4%	1.9%	1.9%
HAMILTON	1.4%	0.6%	0.5%
HARRISON	1.4%	0.4%	0.2%
KOSSUT*H	1.4%	0.8%	0.9%
CALHOUN	1.3%	1.4%	0.9%
CLAYTON	1.3%	0.7%	0.6%
FAYETTE	1.3%	1.0%	1.0%
CHEROKEE	1.3%	1.5%	1.3%
CEDAR	1.2%	1.1%	1.4%
LEE	1.2%	7.2%	12.7%
MARION	1.2%	1.4%	1.4%
BOONE	1.1%	0.6%	0.9%
CERRO GORDO	1.1%	2.5%	2.1%
CRAWFORD	1.1%	0.2%	0.2%
MILLS	1.1%	0.7%	0.5%
BREMER	1.0%	0.6%	0.6%
JASPER	1.0%	1.5%	2.1%
MITCHELL	1.0%	0.8%	0.9%
MUSCATINE	1.0%	0.4%	0.4%
OBRIEN	1.0%	1.1%	1.0%
CARROLL	1.0%	0.7%	0.6%
DES MOINES	1.0%	1.3%	1.4%

County	Crash	ECCO	VSIS
GRUNDY	1.0%	0.3%	0.4%
IOWA	1.0%	0.5%	0.2%
PALO ALTO	1.0%	1.0%	1.1%
FREMONT	0.9%	0.9%	0.7%
HOWARD	0.9%	0.6%	0.6%
WARREN	0.9%	0.8%	1.3%
DELAWARE	0.9%	1.0%	0.9%
HENRY	0.9%	0.8%	0.8%
WASHINGTON	0.9%	0.9%	1.1%
BUTLER	0.8%	0.5%	0.7%
DALLAS	0.8%	1.9%	2.5%
FRANKLIN	0.8%	1.4%	1.4%
LOUISA	0.8%	0.4%	0.3%
APPANOOSE	0.8%	0.2%	0.2%
CHICKASAW	0.8%	0.6%	0.8%
HUMBOLDT	0.8%	0.2%	0.2%
JEFFERSON	0.8%	0.7%	0.7%
MADISON	0.8%	0.3%	0.2%
TAMA	0.8%	1.0%	0.6%
EMMET	0.7%	0.6%	0.7%
GUTHRIE	0.7%	1.7%	0.7%
SAC	0.7%	1.9%	1.6%
WORTH	0.7%	1.4%	1.4%
WRIGHT	0.7%	0.4%	0.4%
FLOYD	0.7%	0.9%	1.0%
HANCOCK	0.7%	0.3%	0.4%
JONES	0.7%	0.6%	0.7%
WAPELLO	0.7%	0.7%	0.5%
ALLAMAKEE	0.6%	0.1%	0.2%
PAGE	0.6%	0.2%	0.2%
POWESHIEK	0.6%	0.7%	0.8%
DICKINSON	0.5%	1.3%	1.4%
MAHASKA	0.5%	0.6%	0.4%
UNION	0.5%	0.3%	0.4%
ADAIR	0.5%	1.9%	0.2%
MONONA	0.5%	0.8%	0.5%
WAYNE	0.5%	0.3%	0.5%
WINNEBAGO	0.5%	0.1%	0.1%
JACKSON	0.5%	0.4%	0.5%
AUDUBON	0.4%	0.1%	0.1%
CLARKE	0.4%	0.2%	0.4%
IDA	0.4%	1.0%	0.7%
LUCAS	0.4%	0.7%	0.9%
OSCEOLA	0.4%	1.1%	1.0%

County	Crash	ECCO	VSIS
SHELBY	0.4%	0.4%	0.2%
DAVIS	0.4%	0.4%	0.4%
MONTGOMERY	0.4%	0.1%	0.1%
RINGGOLD	0.3%	0.0%	0.1%
CASS	0.3%	0.4%	0.1%
DECATUR	0.3%	0.2%	0.2%
MONROE	0.3%	0.6%	0.5%
VAN BUREN	0.3%	0.6%	0.5%
POCAHONTAS	0.2%	0.9%	0.8%
ADAMS	0.2%	0.2%	0.1%
GREENE	0.2%	0.3%	0.2%
KEOKUK	0.2%	0.5%	0.3%
TAYLOR	0.1%	0.0%	0.0%

Table D.34. Annual contacts and crashes on municipal road by county

Year	2009			2010			2011			2012		
County	**Crash**	**ECCO**	**VSIS**	**Crash**	**ECCO**	**VSIS**	**Crash**	**ECCO**	**VSIS**	**Crash**	**ECCO**	**VSIS**
POLK	19.3%	9.3%	9.4%	17.3%	15.4%	16.2%	16.7%	13.5%	14.5%	17.0%	13.7%	15.9%
LINN	8.4%	5.4%	8.5%	9.4%	7.6%	9.2%	9.8%	9.7%	9.9%	9.5%	8.5%	8.0%
SCOTT	8.2%	5.2%	4.4%	9.9%	5.3%	4.7%	9.4%	5.2%	4.4%	9.3%	5.6%	4.8%
BLACK HAWK	6.4%	4.8%	5.0%	6.0%	3.6%	4.0%	6.2%	4.1%	5.3%	6.5%	3.8%	4.3%
POTTAWATTAMIE	4.7%	6.3%	3.5%	6.1%	5.6%	4.5%	5.3%	5.0%	3.5%	6.6%	8.3%	5.5%
WOODBURY	5.6%	10.5%	9.2%	4.6%	8.4%	6.6%	4.8%	6.8%	5.7%	4.0%	7.4%	5.8%
DUBUQUE	4.2%	2.6%	2.5%	3.8%	2.6%	2.4%	4.8%	2.4%	2.4%	5.2%	3.1%	3.0%
JOHNSON	3.4%	2.0%	2.7%	4.2%	3.2%	4.1%	4.5%	3.1%	3.0%	5.2%	2.2%	2.5%
STORY	2.5%	1.9%	2.0%	3.1%	2.6%	1.8%	3.2%	2.9%	3.2%	3.2%	2.6%	3.0%
CERRO GORDO	2.7%	2.8%	3.8%	2.5%	3.1%	4.3%	2.5%	2.7%	3.4%	1.9%	2.3%	3.3%
WEBSTER	2.2%	1.4%	0.8%	3.1%	1.0%	0.6%	1.6%	1.6%	1.2%	1.6%	1.0%	0.8%
CLINTON	1.7%	3.5%	4.3%	2.0%	3.8%	4.0%	2.2%	4.0%	3.8%	2.5%	3.3%	3.6%
DES MOINES	1.5%	3.3%	4.1%	1.7%	1.3%	2.1%	2.3%	1.2%	0.9%	2.1%	0.7%	0.9%
MARSHALL	1.2%	0.6%	1.4%	1.0%	0.5%	1.1%	1.7%	1.2%	1.4%	0.9%	1.4%	1.8%
DALLAS	1.2%	3.9%	3.5%	1.5%	5.9%	4.6%	0.3%	3.0%	3.9%	1.4%	2.9%	2.8%
WAPELLO	1.6%	0.9%	1.0%	0.8%	0.3%	0.3%	1.2%	0.6%	0.7%	0.8%	0.5%	0.5%
PLYMOUTH	1.0%	1.7%	1.4%	0.8%	0.9%	0.7%	1.2%	1.9%	2.1%	0.9%	1.6%	1.5%
MUSCATINE	0.8%	1.7%	2.5%	0.9%	1.7%	1.6%	0.9%	1.4%	1.7%	0.9%	1.3%	1.8%
SIOUX	0.7%	1.8%	1.5%	0.2%	1.0%	0.6%	0.9%	1.8%	1.4%	0.7%	1.2%	0.9%
BOONE	1.2%	0.1%	0.1%	0.2%	0.8%	0.7%	0.5%	0.6%	0.7%	0.4%	0.6%	0.6%
MARION	0.4%	0.4%	0.8%	0.9%	0.4%	0.3%	0.4%	0.6%	0.4%	0.7%	0.8%	0.7%
HAMILTON	0.9%	0.0%	0.0%	0.6%	0.0%	0.1%	0.5%	0.1%	0.1%	0.2%	0.3%	0.3%
LEE	0.7%	1.0%	0.9%	0.5%	0.6%	0.6%	0.8%	0.6%	0.5%	0.2%	0.6%	0.5%
WARREN	0.7%	0.6%	0.6%	0.4%	0.5%	0.8%	0.6%	0.9%	1.1%	0.7%	1.0%	1.1%
CRAWFORD	0.5%	0.1%	0.1%	0.6%	0.2%	0.3%	0.5%	0.6%	0.4%	0.5%	0.1%	0.1%
BUENA VISTA	0.4%	1.3%	1.4%	0.7%	0.8%	1.0%	0.6%	1.5%	1.6%	0.3%	1.0%	1.4%
FAYETTE	0.6%	1.3%	1.0%	0.2%	0.7%	0.6%	0.5%	0.8%	0.9%	0.9%	1.0%	0.9%
MAHASKA	0.4%	0.7%	0.5%	0.5%	0.3%	0.2%	0.5%	0.3%	0.3%	0.7%	0.5%	0.4%
CHEROKEE	0.4%	0.3%	0.3%	0.5%	0.4%	0.4%	0.7%	1.1%	1.2%	0.3%	0.5%	0.5%
DICKINSON	0.9%	0.9%	0.9%	0.2%	1.1%	1.1%	0.2%	1.4%	1.3%	0.7%	1.2%	1.2%
CLAY	0.6%	0.5%	0.5%	0.3%	1.2%	1.2%	0.7%	1.2%	1.3%	0.2%	0.8%	0.8%
HARDIN	0.2%	0.1%	0.2%	1.0%	0.0%	0.0%	0.6%	0.6%	0.9%	0.0%	0.8%	1.1%
JASPER	0.5%	0.8%	1.1%	0.3%	0.4%	0.5%	0.6%	0.6%	0.8%	0.4%	1.2%	1.0%
HENRY	0.2%	1.0%	1.1%	0.2%	0.6%	1.0%	0.5%	0.2%	0.3%	0.9%	0.3%	0.3%
OBRIEN	0.2%	0.4%	0.4%	0.6%	0.3%	0.4%	0.5%	0.8%	0.8%	0.5%	0.5%	0.4%
JEFFERSON	1.0%	0.4%	0.5%	0.2%	0.4%	0.5%	0.3%	0.3%	0.3%	0.0%	0.3%	0.3%
BREMER	0.6%	0.6%	0.8%	0.3%	0.5%	0.5%	0.3%	0.4%	0.4%	0.3%	0.2%	0.2%
PAGE	0.2%	0.2%	0.1%	0.8%	0.1%	0.1%	0.4%	0.1%	0.3%	0.0%	0.0%	0.1%
WINNESHIEK	0.2%	0.3%	0.1%	0.5%	0.2%	0.2%	0.6%	0.5%	0.6%	0.2%	0.3%	0.5%
WRIGHT	0.4%	0.1%	0.2%	0.4%	0.1%	0.1%	0.3%	0.1%	0.2%	0.4%	0.2%	0.2%
BENTON	0.5%	0.3%	0.5%	0.4%	0.2%	0.2%	0.1%	0.3%	0.2%	0.4%	0.6%	0.5%
CARROLL	0.5%	0.6%	0.4%	0.2%	0.3%	0.5%	0.3%	0.5%	0.5%	0.4%	0.2%	0.1%
JONES	0.4%	0.3%	0.4%	0.5%	0.6%	0.6%	0.2%	0.6%	0.5%	0.3%	0.5%	0.3%
LUCAS	0.3%	0.3%	0.3%	0.6%	0.2%	0.2%	0.2%	0.4%	0.5%	0.3%	0.7%	0.5%
TAMA	0.3%	1.6%	1.7%	0.5%	0.2%	0.3%	0.3%	0.3%	0.1%	0.3%	0.3%	0.2%
FLOYD	0.5%	0.1%	0.2%	0.5%	0.4%	0.3%	0.1%	0.3%	0.3%	0.2%	0.2%	0.4%
JACKSON	0.2%	0.5%	0.5%	0.4%	0.4%	0.4%	0.7%	0.3%	0.5%	0.1%	0.5%	0.5%
WASHINGTON	0.8%	1.0%	1.0%	0.2%	0.6%	0.8%	0.2%	0.2%	0.2%	0.1%	0.1%	0.1%
CEDAR	0.2%	0.6%	0.9%	0.3%	0.4%	0.4%	0.3%	0.5%	0.4%	0.5%	0.2%	0.3%
DELAWARE	0.3%	0.4%	0.2%	0.5%	0.4%	0.3%	0.3%	0.6%	0.5%	0.1%	0.6%	0.6%
MONONA	0.0%	1.6%	0.7%	0.6%	1.0%	0.8%	0.3%	0.1%	0.3%	0.4%	0.8%	0.4%
KOSSUTH	0.1%	0.0%	0.1%	0.2%	0.1%	0.1%	0.6%	0.2%	0.3%	0.3%	0.1%	0.2%
MADISON	0.2%	0.6%	0.5%	0.2%	0.8%	1.0%	0.5%	0.1%	0.1%	0.4%	0.1%	0.2%
UNION	0.2%	0.1%	0.4%	0.6%	0.1%	0.3%	0.3%	0.5%	0.4%	0.0%	0.2%	0.4%
CLARKE	0.3%	0.2%	0.3%	0.2%	0.6%	0.9%	0.3%	0.6%	0.9%	0.2%	0.4%	0.5%
MONTGOMERY	0.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.4%	0.0%	0.0%	0.4%	0.1%	0.0%
POWESHIEK	0.3%	0.8%	0.9%	0.4%	0.7%	0.7%	0.3%	0.2%	0.4%	0.0%	1.1%	1.2%
APPANOOSE	0.4%	0.1%	0.0%	0.2%	0.3%	0.2%	0.2%	0.0%	0.1%	0.2%	0.4%	0.2%
EMMET	0.3%	0.0%	0.0%	0.1%	0.1%	0.0%	0.1%	0.2%	0.4%	0.5%	0.2%	0.4%
HARRISON	0.2%	0.5%	0.3%	0.1%	0.4%	0.3%	0.4%	0.0%	0.0%	0.3%	0.1%	0.1%
BUCHANAN	0.2%	0.7%	0.5%	0.2%	0.6%	0.3%	0.5%	0.6%	0.5%	0.1%	0.9%	0.8%
CLAYTON	0.3%	0.2%	0.1%	0.2%	0.5%	0.4%	0.0%	0.3%	0.6%	0.4%	0.3%	0.4%

Year	2009			2010			2011			2012		
County	**Crash**	**ECCO**	**VSIS**	**Crash**	**ECCO**	**VSIS**	**Crash**	**ECCO**	**VSIS**	**Crash**	**ECCO**	**VSIS**
MITCHELL	0.3%	0.3%	0.2%	0.3%	0.0%	0.0%	0.1%	0.0%	0.0%	0.1%	0.2%	0.2%
CASS	0.1%	0.7%	0.4%	0.2%	0.5%	0.4%	0.5%	0.2%	0.0%	0.1%	0.4%	0.1%
IOWA	0.2%	0.2%	0.3%	0.2%	0.3%	0.3%	0.2%	0.3%	0.1%	0.2%	0.4%	0.3%
GREENE	0.3%	0.6%	0.1%	0.2%	0.4%	0.2%	0.0%	0.1%	0.1%	0.2%	0.2%	0.2%
BUTLER	0.1%	0.4%	0.4%	0.2%	0.1%	0.1%	0.1%	0.4%	0.4%	0.3%	0.5%	0.4%
CALHOUN	0.2%	0.7%	0.4%	0.1%	0.3%	0.6%	0.2%	0.3%	0.3%	0.1%	0.3%	0.2%
CHICKASAW	0.2%	0.1%	0.2%	0.0%	0.3%	0.3%	0.2%	0.0%	0.1%	0.2%	0.2%	0.1%
FRANKLIN	0.2%	0.3%	0.3%	0.2%	0.2%	0.2%	0.1%	0.0%	0.1%	0.2%	0.2%	0.2%
HUMBOLDT	0.2%	0.1%	0.1%	0.0%	0.0%	0.0%	0.3%	0.5%	0.4%	0.2%	0.5%	0.4%
LYON	0.1%	0.2%	0.1%	0.2%	0.0%	0.0%	0.1%	0.0%	0.0%	0.2%	0.1%	0.1%
MILLS	0.2%	0.0%	0.0%	0.2%	0.0%	0.0%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%
SAC	0.2%	0.3%	0.4%	0.1%	0.7%	0.7%	0.1%	0.2%	0.4%	0.3%	0.3%	0.2%
ALLAMAKEE	0.0%	0.0%	0.0%	0.1%	0.0%	0.1%	0.3%	0.0%	0.1%	0.2%	0.1%	0.2%
AUDUBON	0.1%	0.0%	0.0%	0.2%	0.0%	0.0%	0.1%	0.0%	0.0%	0.1%	0.0%	0.0%
MONROE	0.2%	0.2%	0.3%	0.2%	0.0%	0.2%	0.0%	0.1%	0.1%	0.1%	0.6%	0.7%
OSCEOLA	0.2%	0.1%	0.1%	0.1%	0.0%	0.0%	0.1%	0.3%	0.1%	0.1%	0.1%	0.1%
PALO ALTO	0.2%	0.4%	0.3%	0.1%	0.3%	0.2%	0.1%	0.5%	0.5%	0.1%	0.3%	0.4%
SHELBY	0.1%	0.1%	0.1%	0.1%	0.2%	0.1%	0.1%	0.0%	0.0%	0.3%	0.2%	0.1%
WORTH	0.2%	0.2%	0.3%	0.2%	0.4%	0.6%	0.0%	0.5%	0.5%	0.2%	0.7%	1.3%
ADAIR	0.1%	1.6%	0.2%	0.3%	1.6%	0.6%	0.0%	0.6%	0.1%	0.0%	0.3%	0.1%
FREMONT	0.1%	0.2%	0.1%	0.2%	0.2%	0.1%	0.0%	0.0%	0.1%	0.1%	0.1%	0.1%
GUTHRIE	0.1%	0.6%	0.1%	0.2%	0.2%	0.1%	0.0%	0.1%	0.1%	0.2%	0.2%	0.1%
HANCOCK	0.2%	0.1%	0.2%	0.1%	0.2%	0.1%	0.2%	0.3%	0.3%	0.0%	0.2%	0.2%
WINNEBAGO	0.2%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.1%	0.2%	0.2%	0.2%
HOWARD	0.1%	0.0%	0.1%	0.1%	0.0%	0.0%	0.1%	0.0%	0.1%	0.1%	0.0%	0.2%
RINGGOLD	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	0.2%	0.0%	0.0%
ADAMS	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.1%	0.0%	0.0%
IDA	0.0%	0.0%	0.1%	0.0%	0.4%	0.3%	0.0%	0.7%	0.5%	0.2%	0.5%	0.4%
WAYNE	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.2%	0.0%	0.1%	0.0%	0.1%	0.1%
DAVIS	0.0%	0.2%	0.3%	0.1%	0.0%	0.0%	0.0%	0.5%	0.3%	0.0%	0.2%	0.1%
DECATUR	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.1%
GRUNDY	0.0%	0.1%	0.2%	0.0%	0.0%	0.1%	0.0%	0.0%	0.1%	0.1%	0.1%	0.1%
KEOKUK	0.0%	0.3%	0.4%	0.1%	0.2%	0.2%	0.0%	0.0%	0.1%	0.0%	0.3%	0.2%
LOUISA	0.0%	0.1%	0.2%	0.0%	0.0%	0.2%	0.1%	0.1%	0.1%	0.0%	0.1%	0.1%
VAN BUREN	0.0%	0.1%	0.2%	0.0%	0.0%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.1%
POCAHONTAS	0.0%	0.4%	0.5%	0.0%	0.5%	0.5%	0.0%	0.6%	0.5%	0.0%	0.5%	0.6%
TAYLOR	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Table D.35. Total contacts and crashes on municipal road by county 2009 through 2012

County	Crash	ECCO	VSIS
POLK	17.7%	13.0%	14.1%
LINN	9.2%	7.8%	8.9%
SCOTT	9.2%	5.3%	4.6%
BLACK HAWK	6.3%	4.1%	4.6%
POTTAWATTAMIE	5.6%	6.4%	4.3%
WOODBURY	4.8%	8.3%	6.8%
DUBUQUE	4.4%	2.7%	2.6%
JOHNSON	4.3%	2.6%	3.0%
STORY	3.0%	2.5%	2.5%
CERRO GORDO	2.4%	2.7%	3.7%
WEBSTER	2.2%	1.2%	0.9%
CLINTON	2.1%	3.6%	3.9%
DES MOINES	1.8%	1.6%	1.9%
MARSHALL	1.2%	0.9%	1.4%
DALLAS	1.1%	3.9%	3.7%
WAPELLO	1.1%	0.6%	0.6%
PLYMOUTH	1.0%	1.6%	1.4%
MUSCATINE	0.9%	1.5%	1.9%
SIOUX	0.6%	1.5%	1.1%
BOONE	0.6%	0.5%	0.6%
MARION	0.6%	0.5%	0.6%
HAMILTON	0.6%	0.1%	0.1%
LEE	0.6%	0.7%	0.6%
WARREN	0.6%	0.7%	0.9%
CRAWFORD	0.5%	0.2%	0.2%
BUENA VISTA	0.5%	1.1%	1.4%
FAYETTE	0.5%	0.9%	0.9%
MAHASKA	0.5%	0.4%	0.3%
CHEROKEE	0.5%	0.6%	0.6%
DICKINSON	0.5%	1.2%	1.1%
CLAY	0.5%	0.9%	1.0%
HARDIN	0.5%	0.4%	0.6%
JASPER	0.5%	0.8%	0.8%
HENRY	0.4%	0.5%	0.6%
OBRIEN	0.4%	0.5%	0.5%
JEFFERSON	0.4%	0.4%	0.4%
BREMER	0.4%	0.4%	0.5%
PAGE	0.4%	0.1%	0.1%
WINNESHIEK	0.4%	0.3%	0.4%
WRIGHT	0.4%	0.1%	0.2%
BENTON	0.4%	0.4%	0.3%
CARROLL	0.4%	0.4%	0.4%

County	Crash	ECCO	VSIS
JONES	0.4%	0.5%	0.4%
LUCAS	0.4%	0.4%	0.4%
TAMA	0.4%	0.6%	0.6%
FLOYD	0.3%	0.3%	0.3%
JACKSON	0.3%	0.4%	0.5%
WASHINGTON	0.3%	0.5%	0.5%
CEDAR	0.3%	0.4%	0.5%
DELAWARE	0.3%	0.5%	0.4%
MONONA	0.3%	0.9%	0.5%
KOSSUTH	0.3%	0.1%	0.2%
MADISON	0.3%	0.4%	0.4%
UNION	0.3%	0.2%	0.4%
CLARKE	0.3%	0.4%	0.6%
MONTGOMERY	0.3%	0.0%	0.0%
POWESHIEK	0.3%	0.7%	0.8%
APPANOOSE	0.3%	0.2%	0.1%
EMMET	0.3%	0.1%	0.2%
HARRISON	0.3%	0.3%	0.2%
BUCHANAN	0.2%	0.7%	0.6%
CLAYTON	0.2%	0.3%	0.4%
MITCHELL	0.2%	0.1%	0.1%
CASS	0.2%	0.4%	0.2%
IOWA	0.2%	0.3%	0.3%
GREENE	0.2%	0.3%	0.1%
BUTLER	0.2%	0.3%	0.3%
CALHOUN	0.2%	0.4%	0.4%
CHICKASAW	0.2%	0.1%	0.2%
FRANKLIN	0.2%	0.2%	0.2%
HUMBOLDT	0.2%	0.3%	0.2%
LYON	0.2%	0.1%	0.1%
MILLS	0.2%	0.0%	0.0%
SAC	0.2%	0.4%	0.4%
ALLAMAKEE	0.1%	0.1%	0.1%
AUDUBON	0.1%	0.0%	0.0%
MONROE	0.1%	0.3%	0.3%
OSCEOLA	0.1%	0.1%	0.1%
PALO ALTO	0.1%	0.4%	0.3%
SHELBY	0.1%	0.1%	0.1%
WORTH	0.1%	0.4%	0.7%
ADAIR	0.1%	1.0%	0.2%
FREMONT	0.1%	0.1%	0.1%
GUTHRIE	0.1%	0.3%	0.1%
HANCOCK	0.1%	0.2%	0.2%
WINNEBAGO	0.1%	0.1%	0.1%

County	Crash	ECCO	VSIS
HOWARD	0.1%	0.0%	0.1%
RINGGOLD	0.1%	0.0%	0.0%
ADAMS	0.1%	0.0%	0.0%
IDA	0.0%	0.4%	0.3%
WAYNE	0.0%	0.0%	0.1%
DAVIS	0.0%	0.2%	0.2%
DECATUR	0.0%	0.0%	0.0%
GRUNDY	0.0%	0.1%	0.1%
KEOKUK	0.0%	0.2%	0.2%
LOUISA	0.0%	0.1%	0.1%
VAN BUREN	0.0%	0.1%	0.1%
POCAHONTAS	0.0%	0.5%	0.5%
TAYLOR	0.0%	0.0%	0.0%

Table D.36. Percentage differences between total VSIS contacts and crashes by county 2009 through 2012

Rank	County (same year)	Difference
1	POLK	-9.59%
2	BUCHANAN	8.06%
3	DALLAS	7.73%
4	JASPER	6.65%
5	SCOTT	-4.50%
6	JOHNSON	-3.81%
7	LINN	-3.16%
8	SAC	2.73%
9	CLARKE	2.71%
10	BLACK HAWK	-2.67%
11	LEE	2.46%
12	WORTH	2.36%
13	WOODBURY	2.36%
14	POTTAWATTAMIE	2.29%
15	DUBUQUE	-2.02%
16	FREMONT	1.95%
17	WEBSTER	-0.97%
18	HAMILTON	-0.96%
19	CERRO GORDO	-0.89%
20	IOWA	-0.86%
21	SIOUX	-0.78%
22	CASS	-0.60%
23	DES MOINES	-0.59%
24	POWESHIEK	-0.47%
25	CRAWFORD	-0.47%
26	WAPELLO	-0.46%
27	HARDIN	-0.40%
28	MARSHALL	-0.37%
29	MONONA	-0.34%
30	PLYMOUTH	-0.32%
31	CLINTON	-0.31%
32	ADAIR	-0.31%
33	MAHASKA	-0.31%
34	POCAHONTAS	0.31%
35	DAVIS	0.31%
36	FLOYD	-0.31%
37	STORY	0.30%
38	CLAYTON	-0.30%
39	BENTON	-0.28%
40	KOSSUTH	-0.28%
41	LUCAS	0.28%

Rank	County (same year)	Difference
42	WRIGHT	-0.27%
43	GRUNDY	-0.27%
44	MILLS	-0.27%
45	WARREN	-0.26%
46	CARROLL	-0.26%
47	VAN BUREN	0.24%
48	JONES	-0.24%
49	MUSCATINE	-0.23%
50	HUMBOLDT	-0.22%
51	CALHOUN	-0.21%
52	FAYETTE	-0.21%
53	DECATUR	-0.19%
54	WAYNE	0.18%
55	WINNESHIEK	-0.18%
56	EMMET	-0.18%
57	HARRISON	-0.17%
58	CLAY	-0.17%
59	MONROE	0.17%
60	CEDAR	-0.16%
61	APPANOOSE	-0.15%
62	DELAWARE	-0.14%
63	ALLAMAKEE	-0.14%
64	MITCHELL	-0.13%
65	KEOKUK	0.13%
66	LYON	-0.13%
67	BOONE	-0.13%
68	BREMER	0.12%
69	JACKSON	0.11%
70	WINNEBAGO	-0.10%
71	TAMA	-0.10%
72	LOUISA	-0.09%
73	PAGE	0.08%
74	MARION	-0.07%
75	HENRY	0.07%
76	GREENE	-0.07%
77	BUENA VISTA	-0.07%
78	MONTGOMERY	0.07%
79	HANCOCK	-0.06%
80	JEFFERSON	-0.06%
81	RINGGOLD	-0.06%
82	WASHINGTON	-0.06%
83	CHICKASAW	0.05%
84	ADAMS	-0.05%
85	UNION	-0.05%

Rank	County (same year)	Difference
86	FRANKLIN	-0.04%
87	OBRIEN	-0.04%
88	MADISON	-0.04%
89	AUDUBON	-0.04%
90	BUTLER	-0.03%
91	HOWARD	-0.03%
92	IDA	0.03%
93	GUTHRIE	-0.03%
94	PALO ALTO	0.02%
95	OSCEOLA	0.02%
96	SHELBY	0.02%
97	TAYLOR	-0.02%
98	CHEROKEE	-0.01%
99	DICKINSON	0.00%

Table D.37. Percentage differences between VSIS contacts (2009) and crashes (2008) by county

Rank	County	Difference
1	POLK	-10.51%
2	BUCHANAN	7.67%
3	DALLAS	7.62%
4	JASPER	7.35%
5	SCOTT	-4.85%
6	JOHNSON	-4.04%
7	BLACK HAWK	-3.62%
8	FREMONT	3.30%
9	LINN	-3.08%
10	WOODBURY	3.07%
11	SAC	2.64%
12	WORTH	2.37%
13	LEE	2.25%
14	CLARKE	1.96%
15	IOWA	-1.58%
16	DUBUQUE	-1.45%
17	STORY	1.42%
18	POTTAWATTAMIE	1.29%
19	HAMILTON	-1.20%
20	WEBSTER	-0.98%
21	CERRO GORDO	-0.94%
22	HENRY	0.75%
23	GRUNDY	-0.73%
24	SIOUX	-0.70%
25	WAYNE	0.54%
26	CASS	-0.54%
27	WRIGHT	-0.53%
28	CEDAR	0.53%
29	WINNESHIEK	-0.52%
30	FRANKLIN	-0.50%
31	HARDIN	-0.49%
32	CLINTON	-0.47%
33	KOSSUTH	-0.43%
34	WAPELLO	-0.43%
35	MUSCATINE	-0.42%
36	FLOYD	-0.41%
37	DELAWARE	-0.41%
38	WARREN	-0.39%
39	CRAWFORD	-0.37%
40	VAN BUREN	0.36%
41	HARRISON	0.35%

Rank	County	Difference
42	BOONE	-0.33%
43	CLAY	-0.33%
44	UNION	0.33%
45	CARROLL	-0.32%
46	MAHASKA	-0.32%
47	MONROE	0.31%
48	LUCAS	0.30%
49	POWESHIEK	-0.29%
50	POCAHONTAS	0.29%
51	KEOKUK	0.29%
52	CLAYTON	-0.27%
53	IDA	-0.27%
54	DES MOINES	-0.26%
55	TAMA	0.26%
56	MARSHALL	-0.25%
57	EMMET	-0.24%
58	FAYETTE	-0.23%
59	PLYMOUTH	-0.21%
60	MONONA	-0.21%
61	DAVIS	0.21%
62	CHICKASAW	-0.21%
63	APPANOOSE	-0.20%
64	ALLAMAKEE	-0.19%
65	JONES	-0.19%
66	HUMBOLDT	-0.18%
67	ADAMS	0.18%
68	OSCEOLA	-0.18%
69	HOWARD	-0.18%
70	WASHINGTON	-0.18%
71	CALHOUN	-0.17%
72	WINNEBAGO	-0.17%
73	PAGE	0.15%
74	SHELBY	-0.15%
75	OBRIEN	-0.14%
76	MARION	0.13%
77	ADAIR	-0.12%
78	DECATUR	-0.12%
79	BUTLER	-0.10%
80	RINGGOLD	-0.10%
81	LYON	0.07%
82	TAYLOR	0.07%
83	BENTON	-0.07%
84	BUENA VISTA	-0.06%
85	GUTHRIE	-0.05%

Rank	County	Difference
86	MADISON	0.05%
87	DICKINSON	-0.05%
88	AUDUBON	-0.05%
89	PALO ALTO	-0.04%
90	MITCHELL	-0.04%
91	BREMER	-0.03%
92	MILLS	-0.02%
93	HANCOCK	-0.02%
94	JEFFERSON	-0.01%
95	MONTGOMERY	0.01%
96	GREENE	0.01%
97	LOUISA	0.01%
98	CHEROKEE	0.00%
99	JACKSON	0.00%

Table D.38. Percentage differences between total ECCO contacts and crashes by county 2009 through 2012

Rank	County (same year)	Difference
1	POLK	-9.00%
2	BUCHANAN	5.60%
3	JASPER	4.03%
4	POTTAWATTAMIE	4.00%
5	DALLAS	3.85%
6	SCOTT	-3.77%
7	JOHNSON	-3.61%
8	FREMONT	3.08%
9	LINN	-3.03%
10	WOODBURY	2.95%
11	SAC	2.20%
12	BLACK HAWK	-2.06%
13	WORTH	1.89%
14	DUBUQUE	-1.56%
15	LEE	1.33%
16	HAMILTON	-0.95%
17	CLARKE	0.93%
18	MONONA	0.83%
19	CERRO GORDO	-0.81%
20	WEBSTER	-0.81%
21	DES MOINES	-0.64%
22	MARSHALL	-0.57%
23	ADAIR	0.51%
24	POWESHIEK	-0.45%
25	DAVIS	0.45%
26	HARDIN	-0.43%
27	SIOUX	-0.43%
28	WAPELLO	-0.39%
29	POCAHONTAS	0.37%
30	FLOYD	-0.35%
31	HARRISON	0.35%
32	MONTGOMERY	0.35%
33	CRAWFORD	-0.34%
34	IOWA	-0.33%
35	PAGE	0.31%
36	KOSSUTH	-0.31%
37	CLAYTON	-0.30%
38	CLINTON	-0.29%
39	WRIGHT	-0.29%
40	MUSCATINE	-0.28%
41	KEOKUK	0.28%

Rank	County (same year)	Difference
42	GRUNDY	-0.27%
43	WINNESHIEK	-0.27%
44	VAN BUREN	0.26%
45	JONES	-0.24%
46	STORY	-0.24%
47	DECATUR	-0.22%
48	SHELBY	0.20%
49	BOONE	-0.20%
50	EMMET	-0.20%
51	BENTON	-0.19%
52	CLAY	-0.18%
53	MAHASKA	-0.18%
54	CASS	0.17%
55	LUCAS	0.17%
56	GUTHRIE	0.17%
57	IDA	0.17%
58	ALLAMAKEE	-0.16%
59	HUMBOLDT	-0.15%
60	MITCHELL	-0.15%
61	APPANOOSE	-0.14%
62	MONROE	0.14%
63	FAYETTE	-0.13%
64	JEFFERSON	-0.12%
65	WINNEBAGO	-0.11%
66	HANCOCK	-0.10%
67	CALHOUN	-0.10%
68	JACKSON	0.09%
69	GREENE	0.09%
70	DELAWARE	-0.09%
71	HOWARD	-0.08%
72	RINGGOLD	-0.07%
73	CHICKASAW	-0.07%
74	WASHINGTON	-0.07%
75	CEDAR	0.07%
76	MARION	-0.06%
77	LOUISA	-0.06%
78	OSCEOLA	0.06%
79	WAYNE	0.06%
80	LYON	-0.06%
81	MILLS	0.05%
82	PLYMOUTH	-0.05%
83	CARROLL	-0.05%
84	UNION	-0.05%
85	BREMER	0.04%

Rank	County (same year)	Difference
86	MADISON	-0.04%
87	BUENA VISTA	-0.03%
88	FRANKLIN	-0.03%
89	CHEROKEE	0.03%
90	AUDUBON	0.03%
91	OBRIEN	0.03%
92	DICKINSON	0.03%
93	ADAMS	-0.02%
94	HENRY	0.02%
95	BUTLER	-0.02%
96	PALO ALTO	0.02%
97	TAMA	-0.01%
98	WARREN	0.01%
99	TAYLOR	0.01%

Table D.39. Percentage differences between ECCO contacts (2009) and crashes (2008) by county

Rank	County	Difference
1	POLK	-10.35%
2	POTTAWATTAMIE	5.28%
3	BUCHANAN	5.09%
4	JASPER	4.94%
5	FREMONT	4.33%
6	DALLAS	4.33%
7	SCOTT	-4.31%
8	JOHNSON	-4.22%
9	WOODBURY	3.87%
10	LINN	-3.46%
11	BLACK HAWK	-2.97%
12	SAC	2.39%
13	WORTH	1.91%
14	IOWA	-1.27%
15	LEE	1.23%
16	DUBUQUE	-1.19%
17	HAMILTON	-1.13%
18	HARRISON	1.03%
19	MONONA	0.97%
20	ADAIR	0.96%
21	CERRO GORDO	-0.83%
22	GRUNDY	-0.75%
23	CASS	0.73%
24	WEBSTER	-0.72%
25	CLINTON	-0.63%
26	MARSHALL	-0.56%
27	MUSCATINE	-0.55%
28	WARREN	-0.55%
29	POWESHIEK	-0.54%
30	WRIGHT	-0.53%
31	HENRY	0.53%
32	WINNESHIEK	-0.52%
33	HARDIN	-0.50%
34	FRANKLIN	-0.46%
35	FLOYD	-0.45%
36	KOSSUTH	-0.42%
37	GREENE	0.42%
38	GUTHRIE	0.38%
39	BOONE	-0.38%
40	DES MOINES	-0.38%
41	PAGE	0.37%

Rank	County	Difference
42	DELAWARE	-0.37%
43	CEDAR	0.36%
44	WAPELLO	-0.35%
45	JONES	-0.34%
46	KEOKUK	0.34%
47	CLAY	-0.32%
48	VAN BUREN	0.32%
49	MAHASKA	-0.30%
50	TAMA	0.29%
51	STORY	0.29%
52	POCAHONTAS	0.28%
53	WAYNE	0.25%
54	CLAYTON	-0.25%
55	EMMET	-0.24%
56	SIOUX	-0.24%
57	CARROLL	0.23%
58	DECATUR	-0.23%
59	PLYMOUTH	0.22%
60	IDA	-0.22%
61	APPANOOSE	-0.22%
62	WASHINGTON	-0.22%
63	CHICKASAW	-0.21%
64	CLARKE	0.21%
65	ADAMS	0.19%
66	ALLAMAKEE	-0.19%
67	DAVIS	0.18%
68	MONTGOMERY	0.18%
69	WINNEBAGO	-0.17%
70	MILLS	0.17%
71	BREMER	-0.17%
72	HOWARD	-0.17%
73	LYON	0.16%
74	CRAWFORD	-0.15%
75	OSCEOLA	-0.14%
76	RINGGOLD	-0.14%
77	MONROE	0.13%
78	TAYLOR	0.13%
79	BUTLER	-0.11%
80	JEFFERSON	-0.10%
81	HUMBOLDT	-0.10%
82	FAYETTE	-0.09%
83	MITCHELL	-0.09%
84	CALHOUN	0.08%
85	BUENA VISTA	-0.07%

Rank	County	Difference
86	AUDUBON	0.07%
87	LUCAS	0.06%
88	OBRIEN	-0.05%
89	MARION	0.05%
90	SHELBY	0.05%
91	BENTON	-0.04%
92	HANCOCK	-0.04%
93	UNION	-0.04%
94	CHEROKEE	0.04%
95	MADISON	0.03%
96	LOUISA	0.03%
97	DICKINSON	-0.02%
98	JACKSON	-0.02%
99	PALO ALTO	-0.02%