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Overtime Traffic Enforcement Evaluation: A Methodology for Selecting Agencies and Enforcement Periods

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OVERTIME TRAFFIC ENFORCEMENT EVALUATION: A METHODOLOGY FOR SELECTING AGENCIES AND ENFORCEMENT PERIODS

by

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Multiple studies have stated the advantages of police traffic enforcement on crash reduction (Zaidel, February 2002). It is very important to identify locations and time periods where police enforcement produces the greatest crash reductions. The objectives of this study were to: (1) determine the impact of overtime traffic enforcement on crash occurrence; (2) develop procedures to identify police agencies with potential to reduce targeted crashes; and (3) develop procedures to identify additional time periods in which enforcement activities should be conducted. In order to accomplish these objectives, many methodologies were explored. The study used crash and enforcement data collected by the Michigan Office of Highway Safety Planning (OHSP). The first objective was accomplished by applying trend analysis combined with simple regression analysis. The results indicated a positive impact of police enforcement on crash occurrence. The remaining objectives were accomplished by using a modified Critical Rate (CR) method. The results from these analyses indicated that both modified Critical Rate methods, objectively establish means for the selection of agencies and time periods. Despite these results, further efforts should be made in identifying statistical approaches to determine the impact of enforcement on crash occurrence, and enhancing the current analysis including more quality data.

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INTRODUCTION

Overview

Police traffic enforcement is one of the most applied means of reducing crashes involving impaired driving and safety belt misuse. Multiple studies conducted in multiple countries have shown the impact of police traffic enforcement on crash reduction. Some of these studies reported accident reduction of around 25% due to police traffic enforcement (Zaidel, February 2002). More specific studies have shown the impact of police enforcement on alcohol and drug related crashes as well as compliance with safety belt regulations. According to many studies conducted in countries such as the United States, Canada, Australia and many European countries, police enforcement significantly reduces the number of crashes involving driving under the influence of alcohol or drugs. Also, studies suggest an increase in the use of safety belts in presence of police enforcement. Considering the impact police enforcement makes on accidents, it is of great importance to create the scenarios where police enforcement activities promise the greatest crash reduction rates.

Problem Statement

The Michigan Office of Highway Safety Planning (OHSP) manages federal funds provided by the National Highway Traffic Safety Administration (NHTSA) to implement behavioral-based traffic safety programs. One of the requirements for the programs is to include periodic traffic enforcement campaigns to reduce motor vehicle related fatalities and injuries. The main focus of these enforcement activities is to reduce incidents involving impaired driving and safety belt misuse. The current methodology used by

OHSP to determine which police agencies should be entitled to perform traffic enforcement activities is based on two criteria: (1) countywide crash data and (2) available funding level on an annual basis. OHSP focuses on fatal and serious crashes involving impaired driving and safety belt misuse. OHSP determines the average annual number of fatal and serious injury crashes for each county, ranking counties accordingly. Police agencies within the top counties are identified and selected to perform traffic enforcement activities.

Although ranking counties based on annual average number of fatal and serious injury crashes provides insight into which locations have serious safety problems resulting from impaired driving and safety belt misuse, the methodology does not consider variability in characteristics of agencies and counties. For example, the size of a county (by area and population) is directly related to the number of crashes observed, which may lead to a biased ranking and ultimately selection of counties to receive funding. Also, there is variability of impaired and unrestrained driving related fatal and serious injury crashes among different agencies within a given county. For instance, if a county presents a high number of fatal and serious injury crashes, and consequently results to be one of the top counties of the computed rank, this does not indicate all police agencies within this county need to be selected to conduct overtime traffic enforcement activities. For similar reasons, it can also be stated that not all agencies within low-ranked counties are not to be selected. A county with many agencies with low crash counts but few agencies with considerably high crash counts will most likely be ranked low, resulting in exclusion of these high-crash agencies from funding considerations. The metric used to determine the agencies to be selected to conduct overtime traffic enforcement is another important factor requiring consideration. OHSP uses impaired and unrestrained driving related fatal and serious injury crash counts as a measure of safety. However, as stated above, each county and agency has different characteristics, thus the amount of crashes in each county is always going to be different. For instance, most populated counties are expected to have more crashes than those with low population. Also, counties with the greatest highway mileage and vehicle miles traveled (VMT) are more likely to have higher crash counts. Thus, only considering crash counts may be biased toward counties with bigger areas, higher population, and higher traffic. It is therefore imperative to consider such factors in analysis of crashes for selecting agencies to be funded.

OHSP is required by the NHTSA to conduct traffic enforcement campaigns during St. Patrick's Day (late March to early April), Memorial Day (late May to early June), Independence Day (early July), and Labor Day (late August to early September). In addition to these periods, OHSP establishes time periods in which traffic enforcement campaigns are optionally conducted by selected police agencies. By performing enforcement activities at the right time, police agencies can increase the probability of reducing crashes. Thus, it becomes imperative to identify the proper time periods when overtime traffic enforcement should be conducted.

Study Objective

Based on what has been stated above, the main objectives of this study were: (1) determining the impact of overtime traffic enforcement activities on fatal (K), incapacitating (A), and non-incapacitating (B) impaired and unrestrained driving related crash occurrence in Michigan, (2) determining the appropriate means to identify police agencies to conduct overtime traffic enforcement, and (3) identifying the right procedures to select time periods when overtime traffic enforcement activities should be conducted in order to increase the probability of reducing crash occurrences.

LITERATURE REVIEW

Introduction

This section presents a review of previous studies in which police enforcement and its impact on crash occurrence has been evaluated. This review is intended to provide insight on what has been done in the past to resolve problems similar to the one engaged in this study and to identify the weaknesses and limitations that affected the studies in question. Also, theoretical information regarding procedures and/or methodologies that can be used to accomplish the study objectives is briefly described.

Related Studies

A study conducted in Greece (Yannis, Papadimitriou, & Antoniou, 2008) focused on determining the impact of intensified police enforcement on fatal accidents and casualties involving drunk driving and speeding in different regions of Greece. Different levels of enforcement were registered for each region. To determine the impact of an intensified enforcement program on accidents in different regions, (Yannis, Papadimitriou, & Antoniou, 2008) applied a multivariate multilevel analysis technique. The results of this study indicated an overall reduction of crashes due to the implementation of intensified police enforcement. Although different levels of enforcement were registered for each region, no significant regional variation of the results was identified, leading the researchers to conclude that intensified police enforcement directly impacts drivers' behaviors.

An experimental investigation was conducted by the Institute of Transport Economics (VAA, 1997) in Norway to determine the impact of police enforcement on speeding. In this study, police enforcement performance was tested by conducting normal enforcement activities in a 35-km road segment. For the purpose of this study, police officers participating in the enforcement activities accordingly planned how the enforcement would be conducted based on their experience. Two speed limit zones were used (60km/h and 80km/h) in this study. The results indicated that police enforcement reduced the average speed during and after the implementation of enforcement for the enforced road segment when compared to a similar road segment. According to what the field experiment results state, the reduction of the average speed ranges between 0.9-4.8km/h for both speed limits zones. Also, the results indicated a time-halo effect which for some sections of the road lasted up to eight weeks.

One of the most critical weaknesses of experimental evaluation of police enforcement is the time of exposure limitations. Police enforcement does not necessarily have the same impact for all periods. Another limitation of this approach is that it requires multiple resources, and thus, a limited amount of sites are selected to perform experimental studies. Utilizing a limited amount of sites does not fully explain the real impact of enforcement on drivers' behaviors.

When police enforcement is not perceived by drivers, no impact of enforcement in drivers' behaviors is to be expected. A study in which a survey of speed choice on Norwegian rural roads with 80 km/h speed limits was conducted by Eirin Olaussen Ryeng (Ryeng, 2012). The main focus of this study was to determine the speed choice of drivers. The aim was to study deliberate speeding to identify any correlations between speed choice and (1) the drivers' perceptions of the level of police enforcement, (2) penalties for speeding and (3) the speed choice of the other drivers on the road.

According to the information collected in the survey, in general, drivers do not have an accurate perception of the level of enforcement on the roads. Also, the survey results stated that the speed of other drivers considerably influences the speed choice of other drivers. Another finding given by the survey stated that penalties are well known by drivers. However, the results suggested high penalties only affect the speed choice of drivers marginally.

Conducting surveys roadside can be considered an advantage; however, two main weaknesses can be mentioned regarding this method: (1) drivers stopped roadside may answer with little accuracy because people may want to leave the place and continue their journey; (2) these types of surveys can result in bias because drivers may not answer the questions with correct information to avoid giving information that can result in traffic violation incrimination.

Random Road Watch (RRW) is a traffic-policing program in operation in Queensland, Australia. This enforcement type differs from usual police enforcement in that activities are randomly scheduled in low levels by an explicit resource management technique (Newstead, Cameron, & Leggett, 2001). A study was conducted in which the Random Road Watch program was evaluated. For the purpose of this study, a quasi-experimental study design was used incorporating Poisson regression statistical analysis techniques. According to the analysis made, the program shows an overall effectiveness. Also, greater impact is registered for crashes involving fatalities, with reductions of 31%. The results also indicate that crash reduction is less as severity level decreases; however, crash reduction increases when time of implementation of program increases. Overall, 11% crash reduction was observed in the presence of RRW.

A study at the University of Kentucky (Pigman & Agent, September 1984) evaluated the effectiveness of increased police enforcement, targeting alcohol and drug related accidents at selected locations. For this analysis, four types of data were used: accident data, arrest and adjudication data, cost-effectiveness data and personal opinion data. A before-and-after study along with time series analysis was conducted in order to determine the impact of enforcement on alcohol and drug related crashes. The analysis results indicated that increased police enforcement significantly reduces the number of accidents involving alcohol in all evaluated locations. The analysis showed a correlation between number of arrests and crash reduction. Cost-benefits ratios were estimated and found to be greater than one for all locations. Along with statistical and mathematical analyses, a survey was performed in which drivers' opinions about alcohol and drug related enforcement programs was obtained. From this survey, the general perception drivers have on police enforcement was evaluated.

A review of multiple studies was performed by Enhanced Safety Coming from Appropriate Police Enforcement (ESCAPE) (Zaidel, February 2002). By the utilization of meta-analysis, this review was intended to summarize the evidence indicating the effectiveness of police enforcement on road safety. The evidence stating the effectiveness of enforcement comes from increased enforcement efforts in projects and experiments oriented to selected roads, a few behaviors and/or specific time periods. This indicated that for most projects, temporary increases in local resources or shifting of resources are required to concentrate policing efforts in a selected area. For assessing drunk driving only, thirty-six studies conducted in countries such as Australia, Canada, England, New Zealand, the United States, etc. were evaluated using meta-analysis.

The results for alcohol and drug related crashes enforcement meta-analysis indicates an overall reduction of accidents by 3.7%. When considered separately, an overall 9% reduction was shown for alcohol and drug related crashes involving fatalities; on the other hand, for alcohol and drug related crashes involving injury, a 7% reduction was shown. Surprisingly, the effect on daytime accidents seems to be larger than at nighttime as the daytime reduction is 12% compared to 7% at nighttime.

As presented above, many studies have assessed the effectiveness of police enforcement on road safety. Many different approaches have been used to identify the benefits of police enforcement. However, each approach has weaknesses and strengths, and is suited to specific situations. Choosing the right approach is crucial to confidently evaluate police enforcement, and it is of great importance to keep in mind that the best approach to be used is the one that better fits the situation in which the study is being conducted.

Review of Literature on Approaches for Analyzing Crash Data

In order to identify locations (police agencies) with the highest potential for reducing fatal and serious injury crashes, it is important to quantify the impact of grant-funded overtime police enforcement on these crash types using historical enforcement data. Potential approaches for conducting such analyses include simple trend analysis, spatial analysis, cross-sectional analysis, and before-after analysis. In this study, these methods were explored for applicability to the data at hand. In order to conduct a before-after study, it is critical that the two periods (before and after) be clearly distinguishable. Since it was not possible to identify these periods for the data at hand, the before-after analysis was not appropriate for this study. This study focused on trend analysis, spatial analysis and cross-sectional analysis as described in the data analysis section. The following sections describe these methods as documented in existing literature. In addition to simple trend analysis, spatial analysis and cross-sectional analysis, this section also describes methods used to identify hazardous locations.

Trend Analysis

Trend analysis can be used to identify the presence of any trend in historically impaired and unrestrained crashes at the county or agency level. This can be accomplished by creating plots to identify the trend of crashes. These trends can be compared between funded and non-funded counties, or funded and non-funded agencies. Trend analysis can also be used to compare observed trends between consecutive enforcement weeks as compared to the trend exhibited by weeks without enforcement. However, this approach has several limitations, such as not accounting for county or agency characteristics, as well as not accounting for the impact of overtime enforcement. Nevertheless, when supplemented with other approaches such as regression analysis and data normalization (e.g., Critical Rate method), trend analysis can lead to statistically significant conclusions.

Spatial Analysis

Under spatial analysis, advanced techniques such as Geographical Information Systems (GIS) are used to map crashes by pre-defined geographic entities (such as county, city, township, etc.). The common approach is to use density maps, in which point data, such as crashes, are distributed over a geographic entity using scaling measures such as area, roadway network, population, etc., to create continuous raster (Hashimoto, 2005). This allows for relating crash occurrences to characteristics of the geographic entities under consideration. In this study, the characteristics of the geographic entities can include not only demographics and traffic characteristics, but also information about whether the geographic entity had received overtime funding or not. The geographical maps can show the locations experiencing the highest number of fatal and serious injury crashes. This can be correlated with the locations that have received funding in the past. It can also help determine which locations have not been funded but have a potential for reducing fatal and severe injury crashes. Spatial analysis can also show the relative trend (geographically) of fatal and serious injury crash occurrences when multiple years of data are analyzed. Graettinger et al (2005) utilized GIS to map crashes and correlate them with existing roadway features like bridges, crossroads, railroad grade crossings, etc. Spatial analyses were performed on crash data that were mapped using the GIS application to identify "hot spots" at intersections, road segments, and mileposts.

Cross-Sectional Analysis

Cross-sectional studies compare the safety performance of a location or group of locations with the treatment of interest to similar sites without the treatment at a single point in time. In this case, the treatment of interest is funding provided by OHSP to agencies to conduct overtime traffic enforcement. With similar locations, a crash modification factor (CMF) for overtime traffic enforcement can be estimated as the ratio of the average fatal and serious injury crash frequency for locations with and without the funding. Cross-sectional analyses are often accomplished through multiple variable regression models. However, the models need to account for all variables that affect safety. The models can then be used to estimate the change in crashes that results from a unit change in a specific variable (in this case, availability of overtime funding). The CMF is derived from the model parameters. For multivariate regression models, the number of locations required depends on a number of factors including:

- Average crash frequencies
- The number of variables desired in the model
- The level of statistical significance desired in the model
- The amount of variation in each variable of interest between locations.

Common approaches for cross-sectional crash data analyses include estimation of ordinary least square (OLS) models and count data models such as Poisson and Negative Binomial. Standard textbooks (Washington, Karlaftis, & Mannering, 2011), (Greene, 2012), (Gujarati & Porter, 2009) present detailed derivation of OLS models such as linear regression models. In the linear regression model, the number of fatal and serious injury crashes (dependent variable) is assumed to be a linear function of one or more independent variables (such as agency characteristics and status of overtime funding) plus an error to account for all other unmeasured factors. This linear function is usually written as:

$$Y_i = \beta_1 + \beta_2 X_{2i} + \beta_3 X_{3i} + \cdots + \beta_k X_{ki} + \varepsilon_i$$

where Y_i represents the number of fatal and serious injury crashes, X_i denotes factors affecting the number of crashes, and ε_i is a random error term. Dara (2012) applied a linear regression model to analyze the impact of traffic tickets on accidents. The model relating the accidents and tickets was specified as follows:

$$Accidents_{it} = \alpha_i + \delta_t + \beta_1 Tickets_{it} + X_{it}\beta_2 + \varepsilon_{it}$$

where α_i represents the municipality, δ_t represents the calendar of constant impacts including days, months, and open holidays, and X_{it} represents a vector of regulation influencing accidents and traffic volume including weather conditions, populations, proportion of unemployment and such. In this situation β_1 would be a negative value since the expected result is that tickets reduce the number of accidents and non-compliance behavior.

Although linear regression models can be used to model crash occurrence (Srinivasan & Carter, 2011), these models incorrectly assume that the distribution defining the crash frequencies is a normal distribution—an assumption which many studies have found to be incorrect. In contrast, with the fact that count data (such as fatal and serious injury crashes) is never negative, these linear regression models sometimes resulted in or predicted negative crashes. For this reason the most common methods used in modeling crashes are Poisson regression modeling or Negative Binomial regression modeling (Tegge, Jo, & Ouyang, 2010), (Lord, 2006), (Zlatoper, 1989). These methods are best suited for count data to which crash data belong.

The main challenges associated with the cross-sectional studies include the difficulty of including the unmeasured factors (known or unknown) in the model, and in some cases, the sample size may affect the inferences as well as the number of variables to be included in the model. Also, correlation of the variables may make it difficult to derive significant and meaningful inferences from cross-sectional analysis. For example, while overtime enforcement activities are expected to reduce the number of targeted crashes in funded locations, the results may show the opposite because only agencies with high numbers of crashes were funded. In other words, agencies with many hours of enforcement are characterized with high numbers of impaired and unrestrained crashes. As a result, there is a positive correlation between enforcement activities and number of crashes.

Site Prioritization

Prioritization of sites consists of determining which sites (road segments and/or intersections) are considered hazardous. In the field of road safety, identifying sites in which proportionally high numbers of crashes are recorded is of great importance. This information allows traffic safety professionals and road safety agencies to make more accurate decisions on where efforts to improve road safety should be made. In this section, the advantages and limitations of different prioritization methodologies are exposed.

Average Crash Frequency

Average crash frequency is the simplest methodology for prioritization of sites (Garber & Hoel, 2009). This method consists of taking the average number of crashes observed for a specific period of time. However, this methodology is biased to sites with high traffic volumes. This type of analysis may therefore lead to erroneous conclusions. Despite its simplicity and ease of application, it is not usually recommended for use.

Crash Rate

In this methodology rates are determined by accounting for exposure data, such as traffic volume and the length of road section being considered. Commonly used rates are rate per million of entering vehicles (RMEVs) usually used for intersections, and rate per 100 million vehicle-miles (RMVM) usually used for road segments (Garber & Hoel, 2009).

The RMEV is the number of crashes per million vehicles entering the study site, and it is expressed as:

$$RMEV = \frac{A * 1{,}000{,}000}{V}$$

where:

RMEV = crash rate per million entering vehicles

A = number of crashes, total or by type occurring in a single year at the location

V = average daily traffic (ADT) 365

The RMVM is the number of crashes per 100 million vehicle miles at the study site, and it is expressed as:

$$RMEV = \frac{A * 100{,}000{,}000}{VMT}$$

where:

A = Number of crashes, total or by type at the study location, during a given period

VMT = Vehicle miles of travel during the given period

= ADT (number of days in study period) x (length of road)

The crash rates method, which is stronger than average crash frequency methodologies, consider the effect of an exposure. However, it does not take into account other factors, such as confounding factors, which may affect the occurrence of crashes. Also, the use of crash rate tends to be biased toward sites with low traffic volumes.

The Equivalent Property-Damage-Only (EPDO)

The equivalent property-damage-only method assigns weights to a crash based on its severity. The weights are estimated based on societal costs of crashes by severity. These weights are usually estimated based on the lower level of injury, thus, crashes are expressed as equivalent number of crashes of the lower severity. Number of crashes (Bham, & Manepalli , 2009). For example, crashes resulting in a fatality are weighted much higher than a crash that only resulted in vehicle damage only. The weights are calculated with the following expression:

$$weight_i = \frac{Cost\ for\ crash\ severity_i}{Cost\ for\ PDO\ crash\ severity}$$

Then, after all weights are estimated, the score for each site is estimated as follows:

$$EPDO_s = A * f_1 + B * f_2 + \cdots pdo$$

The main advantages of EPDO methods are: (1) simplicity of conduction and (2) accounting for crash severity. Despite these advantages, the equivalent property-damage-only method does not account for many other factors such as regression to the mean, traffic volume, and threshold of identifying when experimented crashes are more than predicted.

Critical Rate

The Critical Rate (CR) method is used to identify possible hazardous locations (Garber & Hoel, 2009). Taking into account the fact that traffic crashes are random occurrences, it is impractical to classify locations as hazardous by simply considering the number of crashes. Instead, the Critical Rate method uses traffic volume to determine crash rates at a specific location and then determines if this rate is significantly higher than the average for a predefined group of sites equivalent to the one being evaluated. The Critical Rate method was originally developed in the field of quality control (STOKES & MUTABAZI, 1983) and was used to determine when a piece of work was statistically significant under quality standards requirements based on the quality of other pieces of work. Similarly, the Critical Rate method statistically determines if a site is experiencing crash rates greater than for similar sites. The Critical Rate method is express as follows:

$$CR = AVR + \frac{0.5}{TB} + TF\sqrt{\frac{AVR}{TB}}$$

where:

CR = Critical crash rate (per 100 million vehicle-miles or per million entering vehicles)

AVR = Average crash rate for the facility type

TF = Test factor (the number of standard deviations at a given confidence level)

TB = Traffic base (per 100 million vehicle-miles or million entering vehicles)

In the Critical Rate method, all sites' crash rates are compared to an overall average by computing the expected crash rate for each site based on this average, then the actual crash rate is divided into the estimated crash rate, if the results of this ratio are greater than 1, then the site is registering more crashes than the average and is thus identified as hazardous. The TF factor included in the equation shown above, accounts for statistical significance.

Selection of an Approach for Analyzing Crashes in this Study

For this study applicability of each of the above methods in analyzing fatal and serious injury crashes was evaluated. While it is practical to conduct spatial analysis and/or cross-sectional analysis on the enforcement data available, it is impractical to conduct the before-after analyses due to lack of appropriate data. Enforcement data was available from fiscal year 2009, 2010, 2011 and 2012. However, only 2012 and part of the 2011 fiscal year enforcement data were reliable for conducting analysis due to inconsistencies in the way police agencies reported the results of performed activities in previous periods. Prior to May 2011, data were reported on an aggregated basis. Without sufficient data in the after period, it is impractical to conduct the before-after analyses. Therefore, this study focused on conducting detailed trend analyses, spatial analyses and cross-sectional analyses only. The following chapter discusses the methodology of this study.

METHODOLOGY

Introduction

In order to accomplish the objectives of this study, the first step was to conduct preliminary crash data analysis. The aim of this analysis was to acquire insight of geographical and time crash patterns. By identifying these patterns, useful information that can help identify the right methodologies and procedures to be used in the subsequent analyses was obtained. Geographical patterns were identified and presented with the use of Geographic Information System (GIS) software. Timely crash patterns were identified with the use of Microsoft Excel and other statistical software.

Impact of Overtime enforcement

In order to determine the impact of overtime police traffic enforcement on crash occurrence, two approaches are going to be explored: (1) statistical analysis and (2) trend analysis. For the statistical analysis approach, cross-sectional analysis techniques were used. To apply this approach, two groups were formed; one group was composed of all police agencies which have been funded to conduct overtime traffic enforcement in the study period, and the other group constituted of all police agencies which have not been funded to conduct overtime traffic enforcement in the past. Two types of statistical modeling methodologies were explored: Count Models (Poisson models, Negative Binomial models) and linear models (Linear Regression models). Poisson models and Negative Binomial models were estimated and tested in order to determine which model is more appropriate for the data being used. Linear regression models on the other hand were estimated and the results were compared to the results of count models.

For the trend analysis approach, two groups were formed. One group composed of all counties in which police agencies have received funds to conduct overtime traffic enforcement, and the second groups composed of all counties in which no police agency has received funds to conduct overtime traffic enforcement. Then, weekly crash data were obtained for both groups and comparison between them will be made. Considering that the groups to be compared are different in size and attributes, it would be impractical to make a comparison taking into account the number of crashes only; thus, to fairly compare crash occurrence for each group, comparison between these groups will be made based on crash percentages. By comparing the safety performance of both groups, and relating these results with the level of enforcement conducted, the impact of enforcement on crash occurrence can be visualized.

The results of these two approaches will be carefully studied and compared in order to reach the most accurate and meaningful conclusions regarding the effectiveness of overtime traffic enforcement campaigns.

Agency Selection

After carefully reviewing multiple approaches for identifying police agencies with the greatest potential to reduce the occurrence of fatal and serious injury, and alcohol and safety belt related crashes, and considering the limitations faced by this study, the concept of the Critical Rate (CR) method was considered the best option to identify agencies to receive funds to conduct overtime traffic enforcement.

As stated earlier in the literature review, the CR method is commonly used to identify hazardous locations by comparing the safety performance of a site with the average performance of sites with similar characteristics. Considering the characteristics of the sites being evaluated, data availability issues and the objective of this analysis, a variation of the CR method was developed.

The Critical Rate (CR) method uses the following expression:

$$CR = AVR + \frac{0.5}{TB} + TF\sqrt{\frac{AVR}{TB}}$$

Where:

CR = Critical crash rate (per selected normalization unit)

AVR = Average crash rate for the facility type

TF = Test factor (the number of standard deviations at a given confidence level)

TB = Traffic base (per selected normalization unit)

The Critical Rate method is usually applied to identify if road segments and/or intersections are hazardous. Due to lack of VMT data at the agency level, modifications of the Critical Rate method were necessary. The following modifications were made to suite the method to the data available:

- The TB, which is the traffic base (usually per 100 million VMT for road segments or million entering vehicles for intersections), was modified by using total road length for each geographic. The resulting TB unit was “per 10,000 road miles.”
- The AVR was then calculated to estimate the crash rate for each agency based on total road length.
- Finally, the unit for the final critical rate was “per 10,000 road miles.”

The Critical Rate method accounts for injury severity levels by utilizing equivalent crashes. This is important because a location with more severe crashes receives more weight. Typically, when evaluations are made utilizing the Critical Rate method, sites are ranked based on the resulting values of the ratios. In this analysis, however, it was important to also look at the number of crashes experienced by a given agency. However, once the ranking was determined using the Critical Rate method, some top agencies, as expected, had observed very few crashes. To avoid overestimating agencies where high critical ratios are observed but had low potential to reduce crashes due to the amount of crashes, ranking was based on the amount of crashes a location needed to reduce to have the expected crash rate. Therefore, the Critical Rate method allowed consideration of both agency characteristics as well as the overall number of crashes that need to be reduced for an agency to be below the average.

In the process of identifying agencies with the highest potential to reduce fatal and serious injury, and alcohol and safety belt related crashes, the analysis was conducted at two different geographical levels: county level and local police agency level. In addition, in order to highlight the differences between the new approach and the current approach used by the OHSP (average crash frequency), the analyses were conducted using both methods, and then comparison between the results will be made.

Police departments serve different purposes and areas. For instance, universities, airports, and tribes are patrolled by their own police departments. However, these police agencies usually serve within the jurisdiction of other police agencies, and thus police agencies serving within other police agencies' areas were considered for funding only if the police agency in which they fall, was selected.

On the other hand, Michigan State Police (MSP) posts serve larger areas (two or more counties). In regards to traffic enforcement, MSP mainly serve state roads. Considering this fact, the need of evaluating MSP separate from other agencies became necessary.

In order to identify MSP agencies with the greatest potential to reduce fatal and serious injury crashes involving impaired and unrestrained driving, fatal and serious injury crashes involving impaired and unrestrained driving which occurred only on state roads were identified. Then, the same approach used for selecting regular police agencies was also used for selection of MSP posts.

Taking into account that this study deals with large numbers of analysis units, the results for agency selection analysis were presented in the form of maps. Maps allow for a more comprehensive way of presenting results at both aggregate and disaggregate levels. Presenting the results of maps also allows for identifying and visualizing geographical patterns. For instance, identifying problematic regions in which multiple agencies or counties with high crash rates are clustered.

Time Period Selection

Additional time periods in which overtime traffic enforcement should be conducted were determined by applying the CR method. As already mentioned, the CR method was used to identify hazardous locations; however, for this analysis the CR method was modified for assessing time units such as weeks.

By identifying such time periods, enforcement activities would have more impact on targeted crash occurrence. In order to identify weeks with highest potential to reduce crashes through enforcement, a modified critical rate method was used. This method enabled classification of weeks as hazardous and non-hazardous by establishing an average week. In order to capture variations in the number of crashes observed per week as shown in Figure 14, analysis was based on the proportion of fatal and serious injury, alcohol and drug related crashes of all alcohol crashes and the proportion of fatal and serious injury, safety belt related crashes of all safety belt crashes. For week analysis, the modified critical rate method uses the sum of alcohol/drug or unrestrained driving related crashes divided by 100 as the TB (100 alcohol/drug or unrestrained driving related crashes).

Specifically, the total number of fatal and serious injury, alcohol/drug and unrestrained driving related crashes was determined for each week in the period from 2008 to 2012. All alcohol/drug and unrestrained driving related crashes for each week were also determined. Then the crash rate was calculated by dividing the total equivalent crashes for each week by 100 alcohol and drug or unrestrained driving related crashes previously obtained per each week. Comparing the proportion of fatal and serious injury alcohol/drug and unrestrained driving related crashes of all alcohol/drug and all unrestrained driving related crashes, respectively, among all weeks; reflects weeks having an overall severity level greater than it should be based on an average. It is logical to expect similar crash proportion regarding severity level, for instance, if a week presents an outstanding proportion of fatal crashes, there might be factors influencing higher proportion of fatal crash occurrence. For selection of time periods, week ranks were estimated based on the number of crashes a week would need to reduce the number of crashes to be below the average. This helps to identify weeks with the highest potential to reduce fatal and serious injury crashes involving impaired and unrestrained driving.

DATA

Crash Data

The five-year (2008-2012) crash data was obtained from the Michigan State Police (MSP). The data was processed to identify impaired and unrestrained driving-related crashes. Fatal and serious injury crashes (KAB) were identified at both county level and agency level. Also, crashes were summarized by time periods: yearly, monthly and weekly.

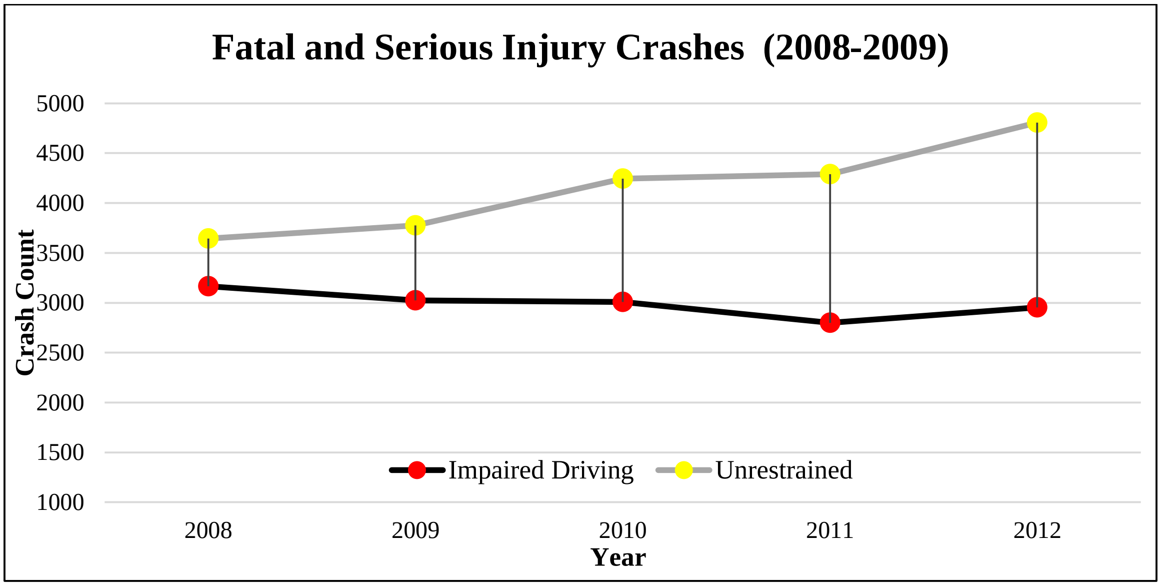


Figure 1 *Fatal and serious injury impaired driving-related crashes and fatal and serious injury unrestrained driving-related crashes*

A crash data sample is shown in Figure 1 and Figure 2. Figure 1 shows the total number of fatal and serious injury, impaired driving related crashes and the total number of fatal and serious injury safety belt related crashes for each year in the time period from 2008-2012. On the other hand, Figure 2 shows the fatal and serious injury, impaired driving related crashes as a percentage of all crashes, as well as the fatal and serious injury, safety belt related crashes as a percentage of all crashes.

From these figures, the yearly amount of impaired driving related crashes and unrestrained driving related crashes can be seen (Figure 1). Also, the proportion of each crash type when compared to total crashes is illustrated (Figure 2).

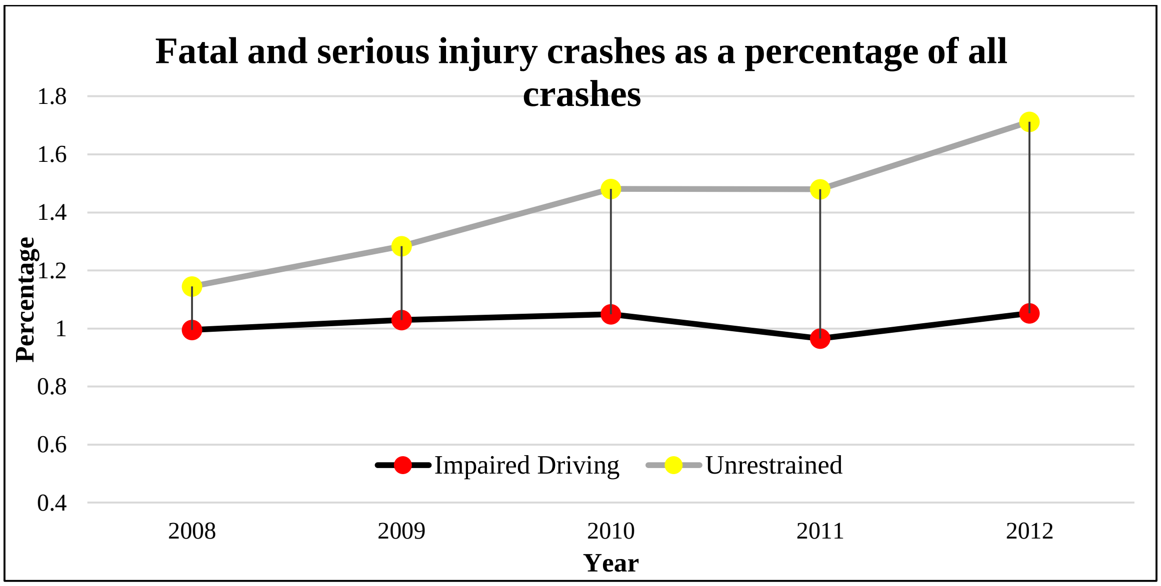


Figure 2. *Fatal and serious injury impaired driving-related crashes and fatal and serious injury unrestrained driving-related crashes*

Enforcement and Agency Data

Historical enforcement data reported by agencies since fiscal years 2009 to 2013 were provided by the Office of Highway Safety Planning. As mentioned earlier, these enforcement data were inconsistent due to changes in reporting requirements. Prior to May 2011, data were reported by the lead agency on an aggregated basis while after that data was reported at agency level. Other agency data included type of agency (i.e., local, county, or state), location of agency, as well as number of police officers.

Table 1. *Enforcement data summary (2009-2013). Number of hours per year and type*

Year	Funded Counties	Granted hours for impaired enforcement	Granted Hours for seatbelt enforcement
2009	52	35,088	24,368
2010	28	24,444	12,815
2011	36	13,613	9,586
2012	28	29,105	16,926
2013	26	34,129	17,090

Table 1 presents a summary of the enforcement data used in this study. Along with number of hours granted to an agency, enforcement data reported by county and/or agencies, information such as arrest, vehicles stopped, number of citations etc.

Other Data

In addition to crash and enforcement data, demographics and traffic and road data were collected as well. Demographic data, including population, were collected from the Michigan Department of Technology, Management and Budget (DTMB) website (Michigan, 2001). Traffic and roadway data, including vehicle miles traveled (VMT), road length, and Average Annual Daily Traffic (AADT), were collected from the Michigan Department of Transportation (MDOT). All collected data was processed at different geographic levels (depending on data availability) using ArcGIS, a Geographic Information Systems (GIS) software. For example, while it was possible to process road length data at city and township level, the VMT was only available at county level, hence limiting its usage in agency-level analyses.

ANALYSIS AND RESULTS

Preliminary Crash Data Analysis

This section presents preliminary crash data as well as detailed crash data analysis relating enforcement activities with targeted crashes. Analyses were accomplished utilizing Geographic Information Systems (GIS) software, Microsoft Excel and other analysis software. To identify potential time periods to be considered for conducting enforcement, five years (2008-2012) of crash data were utilized.

Spatial Analysis

This section presents spatial analysis conducted at county level, and trend analysis conducted at both month and week level. For better explanation, analysis results are presented in maps and graphs.

Figures 3 and 4 show the areas of the state with the highest number of fatal and serious injury related crashes with alcohol and drugs and unrestrained driving. From these figures, it can be clearly seen that counties in the southeast area of the state had the highest amount of crashes. It can also be observed that the density maps show a concentration of crashes in Bay, Saginaw and Genesee counties. In the southwest area of the state, counties such as Kent and Kalamazoo have a high concentration of fatal and serious injury, alcohol and drug and safety belt related crashes. Also, both maps show the concentration of crashes in Ingham and Eaton Counties. Although these two figures help in visualizing counties with high numbers of crashes, they do not fully explain why such observation is made because they do not account for size and other characteristics of these counties.

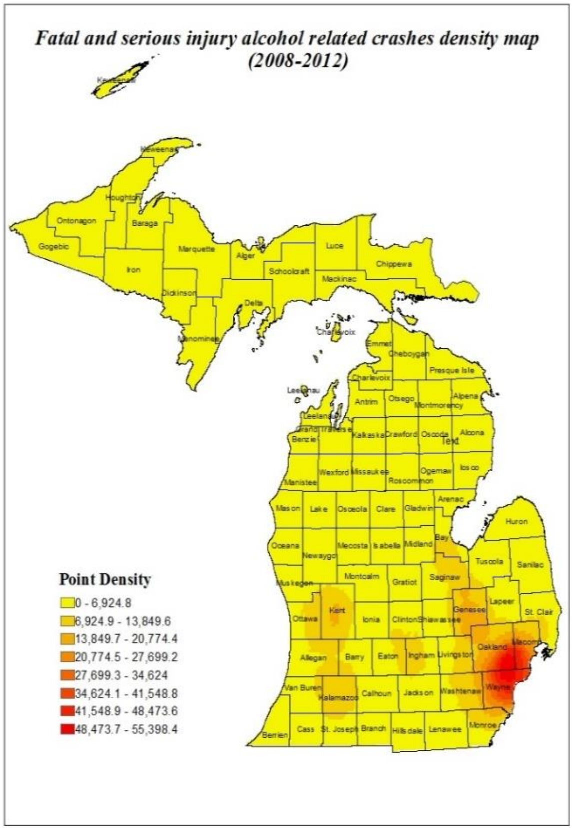


Figure 3. Fatal and serious injury alcohol and drug related crashes. Point density Map

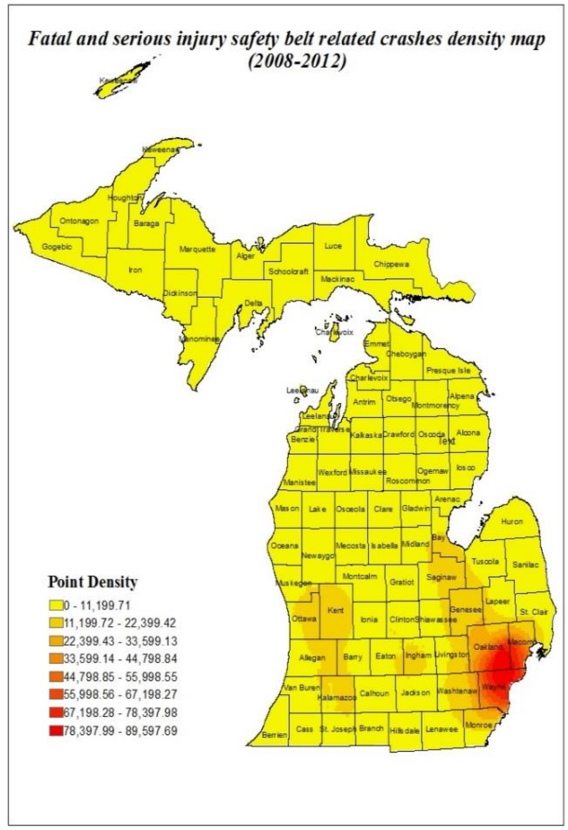


Figure 4. Fatal and serious injury safety belt related crashes. Point density Map

Figure 5 presents the average of fatal and serious injury, alcohol and drug related crashes in each county from 2008 to 2012 while Figure 6 shows the average of fatal and serious injury, alcohol and drug related crashes in each county from 2008 to 2012 normalized by population. As reflected in Figure 1 and Figure 5, the southeast area of the state presents the highest amount of crashes. Also a large concentration of alcohol and drug related crashes can be observed in various counties in the southwest area of the state. Counties such as Kent, Kalamazoo, Allegan and Berrien are worth mentioning as having a considerably high amount of crashes. It can also be visualized that counties located in the northern area of the Lower Peninsula and those in the Upper Peninsula seem to experience relatively less fatal and serious injury, alcohol and drug related crashes. In contrast to Figure 5, Figure 6 indicates that counties located in the northern area of the state (northern area of the Lower Peninsula and those in the Upper Peninsula), appear to be the most critical area. This is because the number of crashes observed with relation to their population is relatively higher than those observed in highly populated counties in the south part of the state.

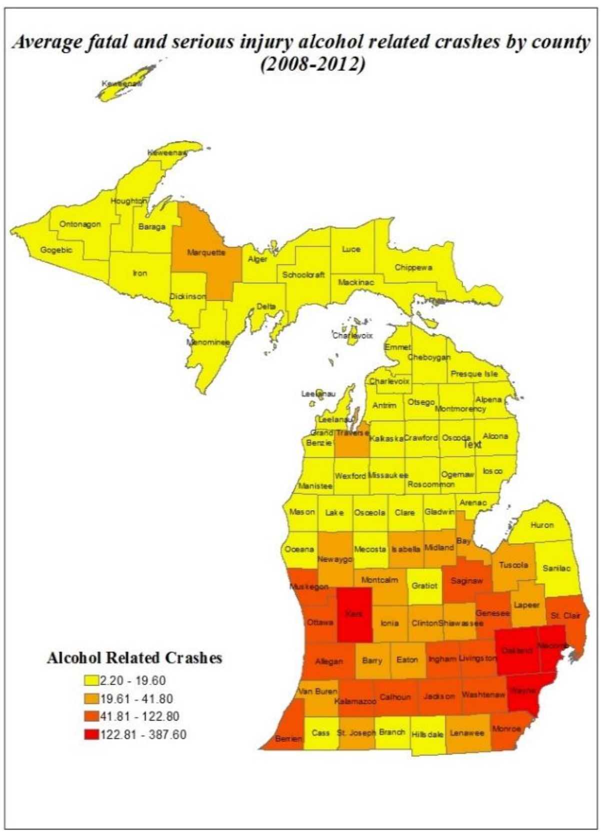


__Figure 5.__ Average fatal and serious injury alcohol-drug related crashes by county (2008-2012)

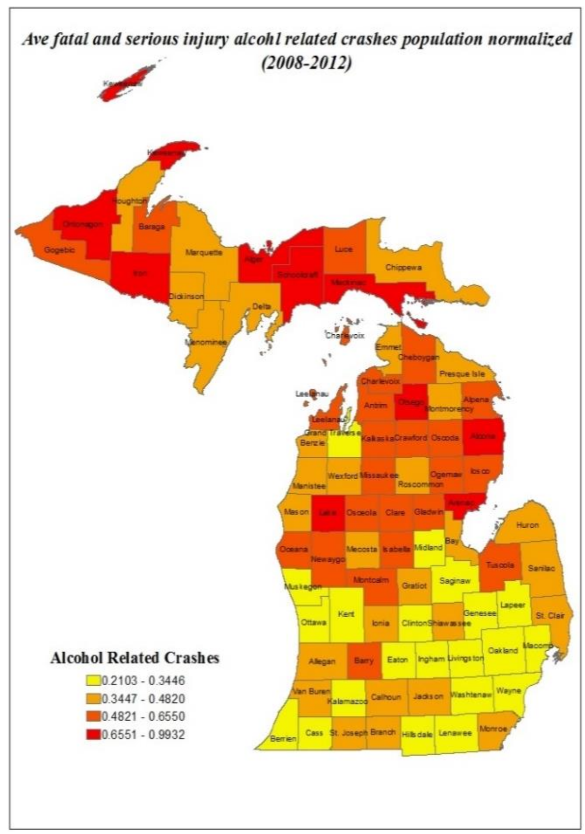


__Figure 6.__ Average fatal and serious injury alcohol-drug related crashes by county (2008-2012) Normalized by population

Figure 7 shows the average of fatal and serious injury, alcohol and drug related crashes in each county from 2008 to 2012 normalized by Vehicle Miles Traveled (VMT) while Figure 8 shows the average of fatal and serious injury, alcohol and drug related crashes in each county from 2008 to 2012 normalized by roadway length. Similar to what is seen in Figure 6, Figure 7 shows counties located in the Upper Peninsula and northern area of the Lower Peninsula as the most critical. Figure 8, on the other hand, presents patterns more consistent with patterns shown in Figures 3 and 5. Even though variation between counties' values can be observed between Figure 8, Figure 5 and Figure 3, the general trend seems to be the same.

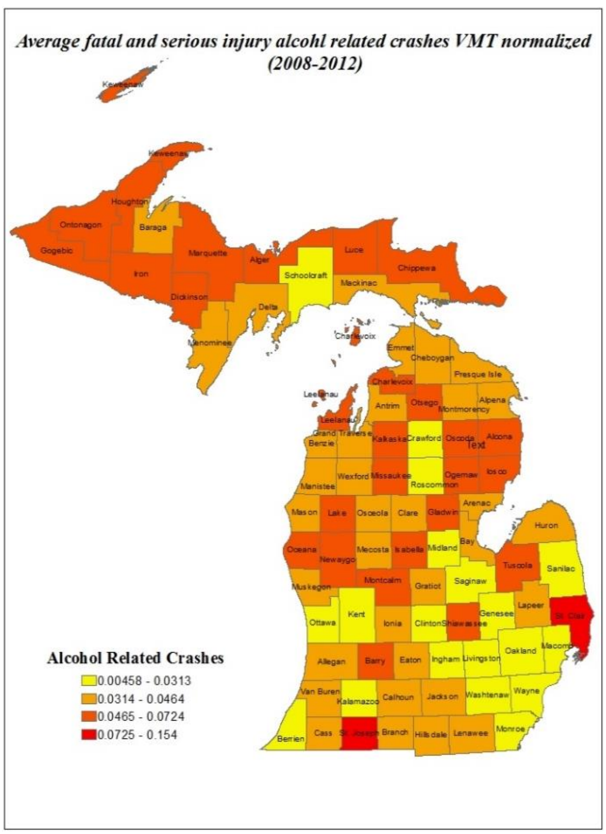


Figure 7. Average fatal and serious injury alcohol-drug related crashes by county (2008-2012) Normalized by Vehicle Miles Traveled

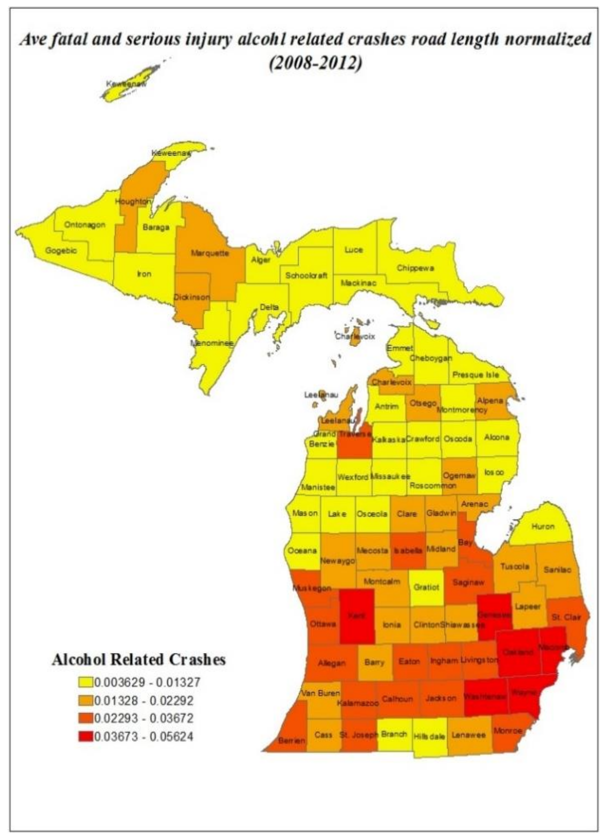


Figure 8. Average fatal and serious injury alcohol-drug related crashes by county (2008-2012) Normalized by Road length

These comparisons clearly indicate the need to consider county characteristics when assessing the number of fatal and serious injury crashes related with impaired and unrestrained driving. Point density analysis (Figures 3 and 4) and polygon analysis (Figures 5, 6, 7 and 8) provide important information at the aggregate level. However, in order to get more detail and meaningful results, disaggregate and more geographically specific assessment need to be conducted. To that end, density maps in which reasonably small geographic units are used were created.

A 2 km by 2 km grid system was created using Geographic Information System (GIS) software. This grid was used to spatially relate crashes falling within each square of the grid. The creation of this map helped identify specific areas where considerably high numbers of crashes have occurred by carefully examining patterns resulting from this analysis.

After carefully reviewing these results, many areas with scattered squares where crashes occurred were identified. This made it difficult to confidently identify areas where crashes were significantly concentrated. To address this issue, "hot spot" analysis was performed utilizing Geographic Information Systems (GIS) software. Hot spot analysis refers to the determination of spatial relationships between events (Esri, 1995). In other words, hot spot analysis is used to determine if events are statistically significantly clustered. This analysis allowed confident identification of places with high rates of fatal and serious injury crash occurrence.

The average number of fatal and serious injury alcohol and drug related crashes from 2008 to 2012 is shown in Figure 9. This map offers great opportunities for identifying specific areas where crashes occur with higher frequency. Figure 8, on the other hand, presents an improved distribution of crashes, showing areas where crashes are statistically clustered.

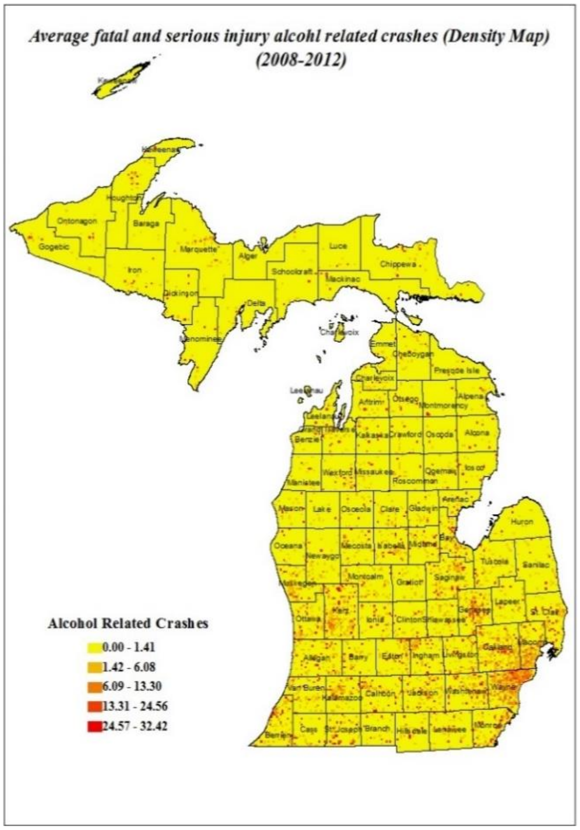


Figure 9. Average fatal and serious injury alcohol-drug related crashes, Square density map

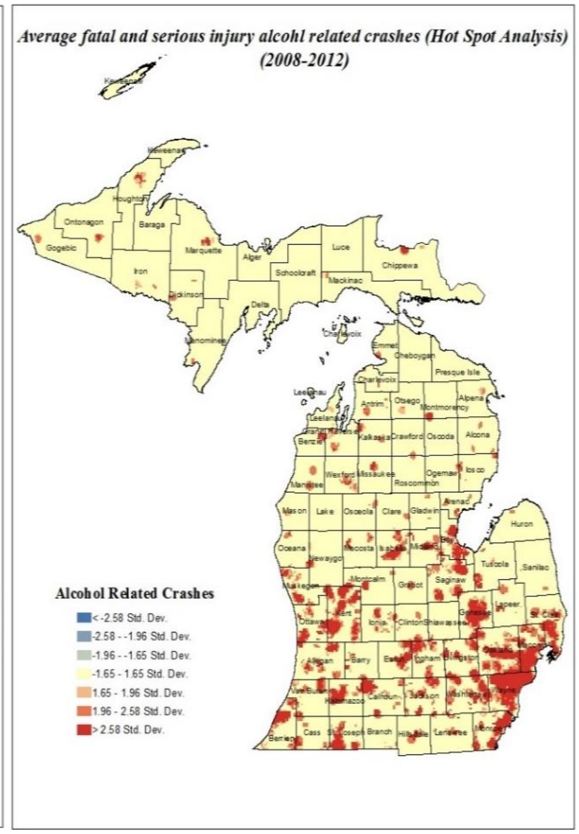


Figure 10. Average fatal and serious injury alcohol/drug-related crashes, Hot Spot Analysis

As expected, Figure 10 shows areas with high crash clustering in the southeast area of the state. The same is observed in counties such as Bay, Saginaw, Genesee, Kent, Kalamazoo, Eaton and others. The most important information that can be obtained from this analysis is that some counties that were shown as problematic based on their overall number of crashes possess areas where no clustering is observed and just a few areas have significant crash concentration. On the other hand, counties that normally result to be less critical, now show areas where special considerations may be warranted. For instance, counties such as Hillsdale and Oceana do not show significance when analyzed at the county level (see Figure 5); however, the hotspot analysis results show areas where crashes are clustered.

Similar analyses were conducted for unrestrained fatal and serious injury crashes. A hot spot analysis is shown in Figure 11.0. These results are interpreted as for impaired driving related crashes analysis. More detailed safety belt analysis is presented in appendix D.

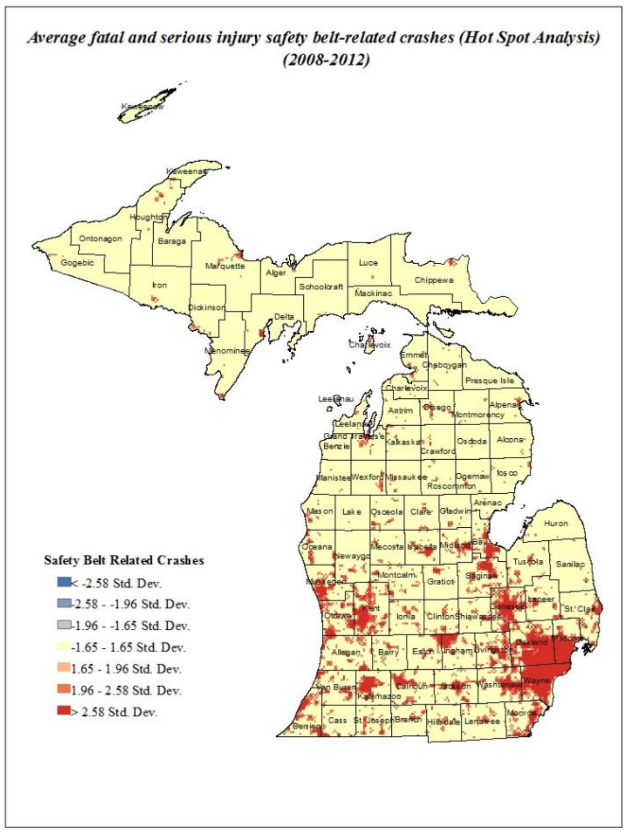


Figure 11. *Average fatal and serious injury safety belt-related crashes, Hot Spot Analysis*

Time of the Year Analysis

In order to identify variation by time of fatal and serious injury crashes, five years (2008-2012) of crash data was used. Fatal and serious injury, alcohol and drug related crashes and fatal and serious injury, safety belt related crashes were analyzed separately. Yearly pattern analysis was conducted in order to determine general crash trends overtime. The general trend shown by alcohol analysis shows a decrease of alcohol and drug related crashes over the period. On the other hand, alcohol and drug related crashes and safety belt crashes analysis shows an increase trend on a yearly basis. In addition to yearly trend analysis, average monthly crash data were analyzed. Figure 12 shows the monthly average amount of total crashes from 2008 to 2012. From this figure it can be seen that warmer months have fewer crashes than colder months.

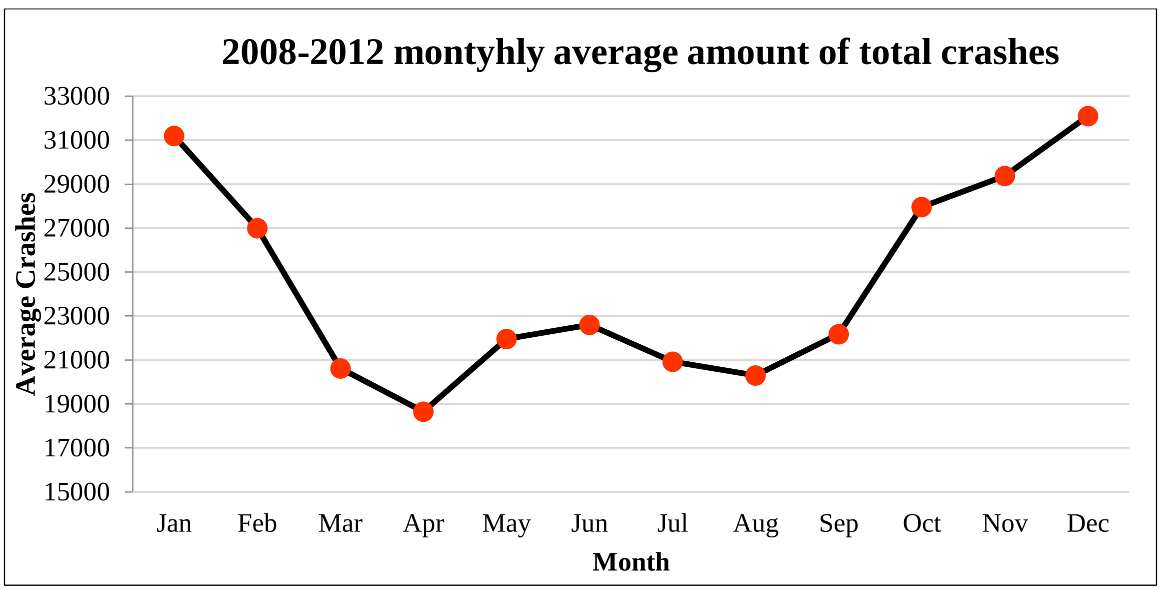


Figure 12. *2008-2012 monthly average amount of total crashes*

Monthly analysis was performed using alcohol and drug related crashes and safety belt related crashes. A comparison between alcohol and drug and safety belt crashes was performed as shown in Figure 13. In contrast to the trend of the monthly average total crashes shown in figure 12, in colder months the amount of fatal and serious injury, alcohol and drug related crashes and fatal and serious injury, safety belt related crashes is lower, while for warmer months the opposite is observed.

The pattern observed for fatal and serious injury, alcohol and drug related crashes and safety belt related crashes in Figure 13 was also observed when fatal and serious injury alcohol and drug related crashes and fatal and serious injury, safety belt related crashes as a percentage of fatal and serious injury crashes were used. This suggests that warmer months are not only associated with a higher amount of fatal and serious injury alcohol and drug related crashes and safety belt related crashes, they also experience a proportionally higher level of severe crashes.

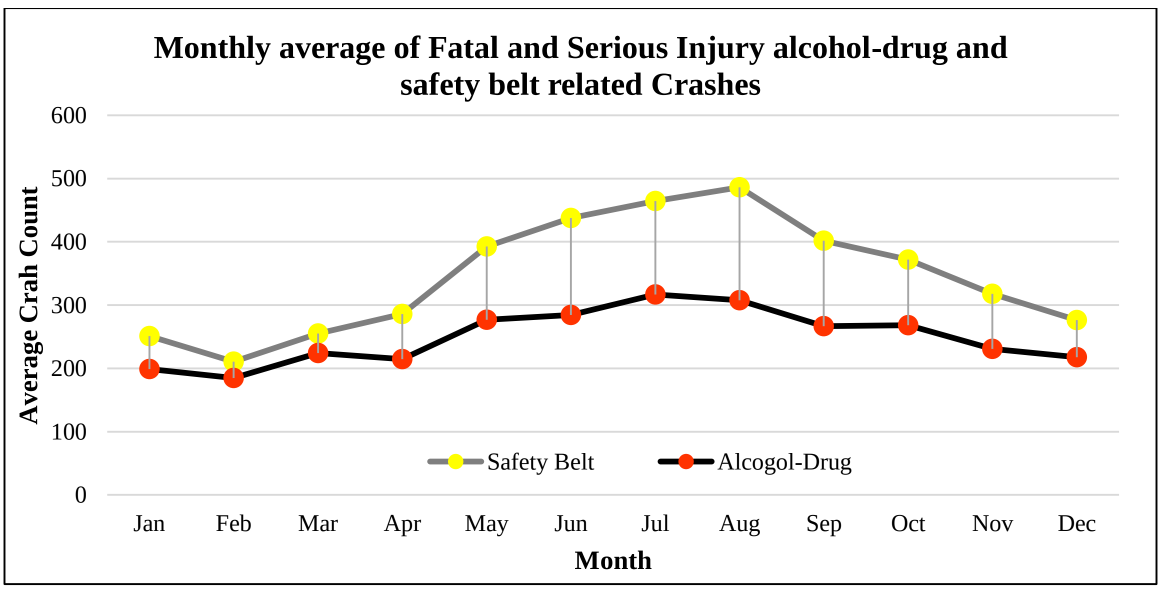


Figure 13. *Monthly average of fatal and serious injury alcohol-drug related crashes and safety belt related crashes*

In order to get more detailed information on crash occurrence overtime, analysis based on week of the year was performed. Figure 14 presents the weekly average of fatal and serious injury, alcohol and drug related crashes and safety belt related crashes. The pattern shown in this analysis is similar to the pattern shown for monthly analysis. However, with this analysis, specific weeks within a month are identified and differences between them can be seen. This is even more important when considering that enforcement activities are conducted closer to a weekly basis rather than a monthly basis.

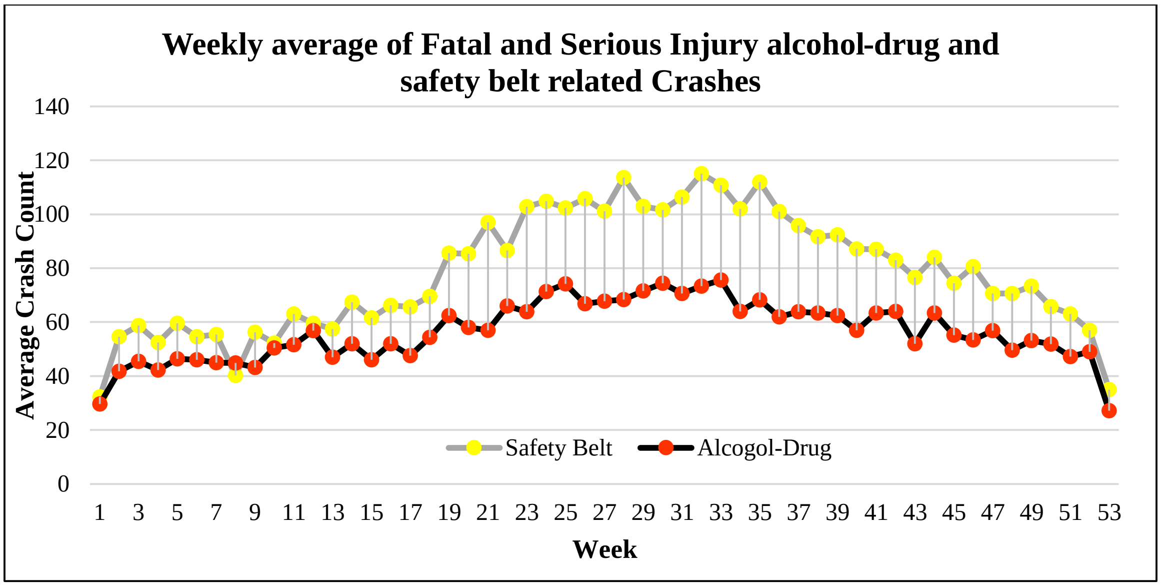


Figure 14. *Weekly average of fatal and serious injury alcohol-drug and safety belt related crashes*

In order to get further insight regarding trends and temporal patterns of crash occurrence, time series analysis was conducted using fatal and serious injury crashes related to impaired and unrestrained driving

Time series analysis, unlike conventional trend analysis, considers three types of behaviors also known as movements: long term movements, cyclical movement and seasonal movement (Hamilton, 1994). Long term movements describe the general trend shown by a complete set of data while cyclical movement aims to describe the trends regarding multiple periods. Seasonal movement, on the other hand, is intended to describe patterns that occurred seasonally within the period being studied. In addition to these three movements, irregular or random movement is considered. Assuming interaction among these movements, time series analysis models the behavior of the data and allows for forecasting future outcomes (Washington, Karlaftis, & Mannering, 2011).

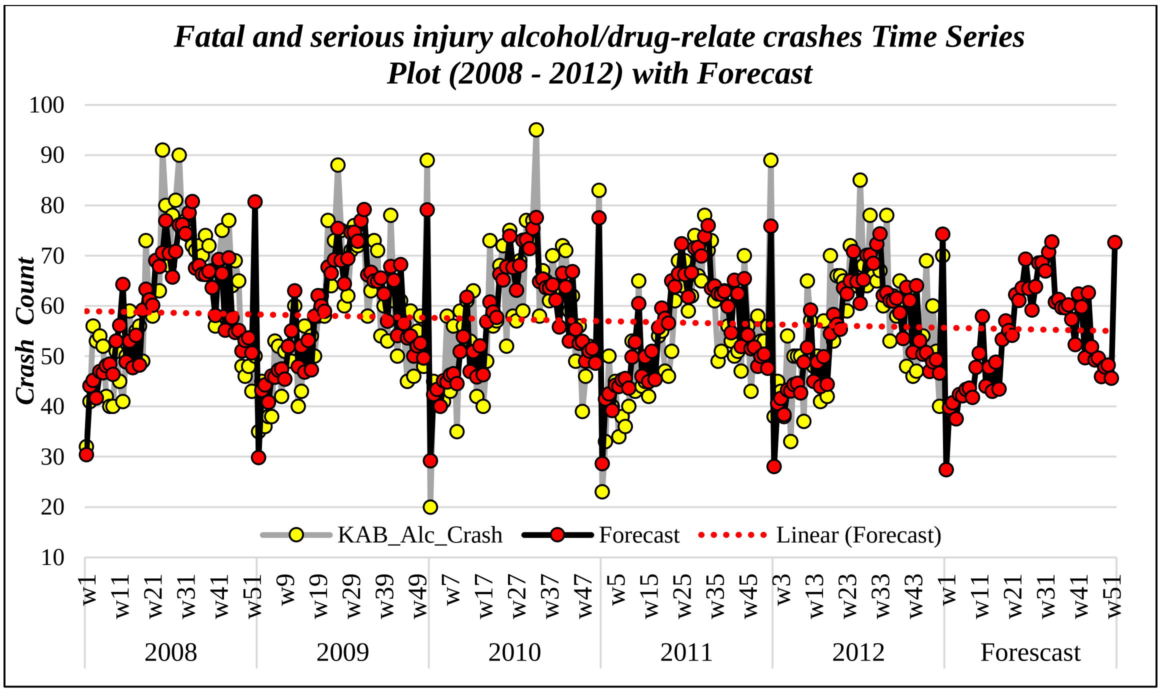


Figure 15. *Fatal and Serious injury alcohol/drug related crashes, time series analysis*

Figure 15.0 presents the result of time series analysis (moving average) applied to fatal and serious injury crashes involving impaired driving. In Figure 15.0, three different lines are shown: the actual crash count, the modeled crash count and forecast, and a (linear) trend line estimated for the modeled crash count and forecast line. In the first place, this figure helps in visualizing the similitude of the actual crash count and modeled crash count. As can be seen, the line representing the actual crash count and the modeled crash count are similar, indicating the model is appropriately simulating the patterns described by the data. From Figure 15.0, cyclical and seasonal movement can be identified. For instance, cyclical movement can be observed by yearly patterns; in other words, similar patterns are observed from year to year. Also, a long term movement trend is identified. As suggested by the trend line displayed in Figure 15.0, the long term is suggesting a general decrease on the number of crashes.

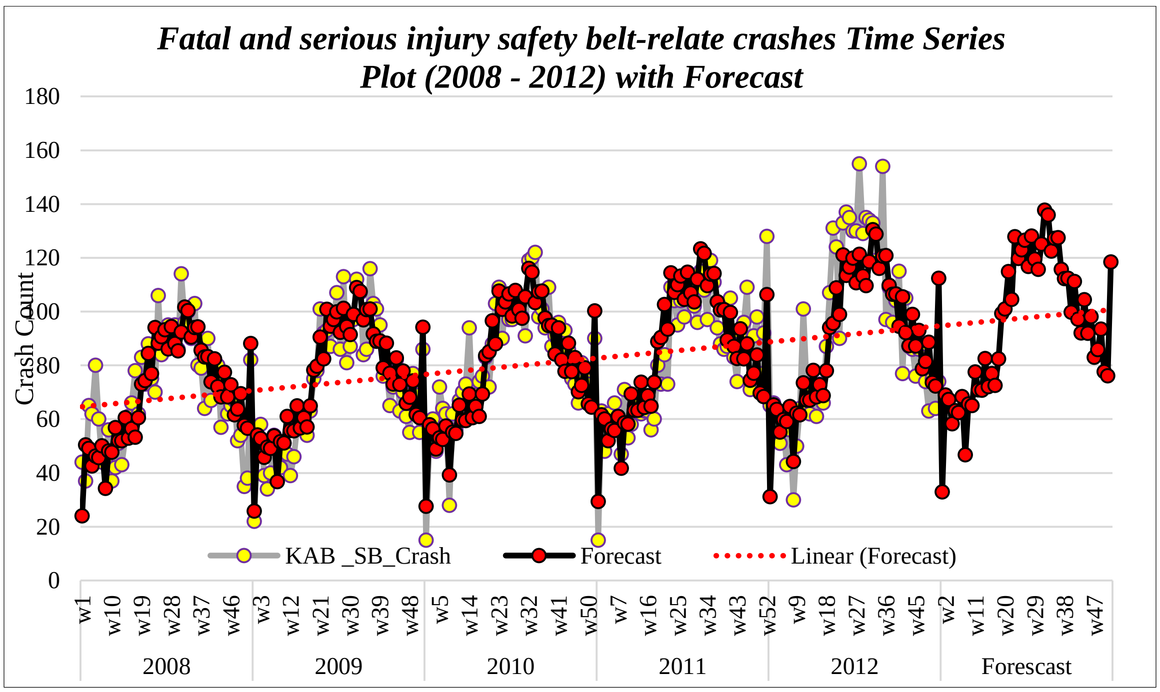


Figure 16. *Fatal and Serious injury unrestrained related crashes, time series analysis*

Figure 16.0 presents the results of time series analysis (moving average) applied to fatal and serious injury unrestrained crashes. In Figure 16.0, three different lines are shown: the actual crash count, the modeled crash count and forecast, and a (linear) trend line estimated for the modeled crash count and forecast line. In the first place, this figure helps in visualizing the similitude of the actual crash count and modeled crash count. As can be seen, the line representing the actual crash count and the modeled crash count are similar, indicating the model is appropriately simulating the patterns described by the data. From Figure 16.0, cyclical and seasonal movement can be identified. For instance, cyclical movement can be observed by yearly patterns, in other words, similar patterns are observed from year to year. Also, the long term movement trend is identified. As suggested by the trend line displayed in Figure 16.0, the long term is suggesting a general increase in the number of crashes.

Determining the Impact of Enforcement Activities on Crash Occurrence

This section presents statistical analyses and trend analyses in which the impact of overtime traffic enforcement campaigns on crash occurrence is evaluated. The results for each analysis is discussed in detail.

Statistical Analysis

As stated in the literature review section, the cross-sectional analysis approach is used to statistically determine the impact of countermeasures, such as overtime traffic enforcement campaigns, by comparing safety performance of two groups, which in this case will be enforced agencies and non-enforced agencies. Two modeling approaches are used for the purpose of applying cross-sectional analysis: count models (Poisson models and Negative Binomial Models) and linear models (Linear Regression models). For statistical analysis purposes, 553 police agencies were identified and their jurisdiction areas properly delimited. Individual characteristics for each police agency area were then obtained. Characteristics such as population, road length, number of bars, hours of enforcement, presence of media campaign, etc. are considered as variables that may influence crash occurrence. Along with variables that could be positive or negatively influencing crash occurrence within police agencies' areas, variables (crashes) being influenced by the characteristics already mentioned, such as impaired driving related crashes and safety belt related crashes, were identified for each police agency. In table 1.0, a description of these characteristics (variables) identified for each police agency area is displayed.

Table 2. *Statistical modeling variables. Individual police agency characteristics*

Code	***Name***	***Description***
county_name	County Name	Name of the county in which the police agency is located
agency_id	Agency ID	Unique Identification number applied to each police agency
alc_crash	Impaired driving related crashes	Number of crashes involving impaired driving in each agency area
sb_crash	Safety belt related crashes	Number of crashes involving unrestrained in each agency area
alc_kab	KAB impaired driving related crashes	Number of fatal and serious injury crashes Involving impaired driving in each police agency area
sb_kab	KAB unrestrained related crashes	Number of fatal and serious injury crashes Involving impaired driving in each police agency area
population	Agency Population	Total population for each agency
road_length	Agency Road Length	Total road length for each police agency in miles
area	Agency Area	Total area for each police agency in square miles
population_density	Agency Population Density	Population density for each police agency in people per square miles
no_bars	Number of bars	Number of bars located in each police agency area
impaired_mandatory	Mandatory Impaired Enforcement	Number of hours Granted to an agency to conduct required impaired overtime traffic enforcement activities
impaired_optional	Optional Impaired Enforcement	Number of hours Granted to an agency to conduct optional impaired overtime traffic enforcement activities

Table 2. – Continued

impaired_total	Combined Impaired Enforcement	Number of hours Granted to an agency to conduct impaired overtime traffic enforcement activities
seatbelt_mandatory	Mandatory safety belt Enforcement	Number of hours Granted to an agency to conduct required safety belt overtime traffic enforcement activities
seatbelt_optional	Optional safety belt Enforcement	Number of hours Granted to an agency to conduct optional safety belt overtime traffic enforcement activities
seatbelt_total	Combined safety belt Enforcement	Number of hours Granted to an agency to conduct unrestrained overtime traffic enforcement activities
paid_media	Paid media campaign	A binary variable (1,0) indicating whether or not a police agency area was cover by paid media campaign
police_officers	Number of police officers	Number of police officers serving in an agency
msp	Michigan State Police	A binary variable (1,0) indicating whether or not the Michigan State police department in which an agency is located received funds to conduct over time traffic enforcement
male_per	Male percentage	The percentage of male population in each police area
famale_per	Female percentage	The percentage of female population in each police area
age_median_ave	Age Median	The median age of the population in each police agency y area
age 15_19_per	Age 15-19 percentage	The percentage of population with ages 15-19 in each police agency area
age_20_34_per	Age 20-34 percentage	The percentage of population with ages 20-34 in each police agency area
age_35_59_per	Age 35-59 percentage	The percentage of population with ages 35-59 in each police agency area
age_60+_per	Age 60+ percentage	The percentage of population with ages 60+ in each police agency area
white_per	White percentage	Percentage of white population in each police agency area
black_per	Black percentage	Percentage of black population in each police agency area
native_american_per	Native American percentage	Percentage of Native American population in each police agency area
asian_per	Asian percentage	Percentage of Asian population in each police agency area
pacific_islander_per	Pacific islander percentage	Percentage of Pacific Islander population in each police agency area

Table 2. – Continued

hispanic_per	Hispanic percentage	Percentage of Hispanic population in each police agency area
other_race_per	Other race percentage	Percentage of Other races population in each police agency area

Proper enforcement data at the agency level was only available from part of fiscal year 2011 (from May 2011), fiscal year 2012 and part of the fiscal year 2013 (October, November, and December 2012). Thus, crash data to conduct the analysis was obtained for the same time period (from May 2011 to December 2012).

Count Models

Count data serve to model non-negative integers, and it is constantly used in the field of transportation. In order to identify which count model is the most appropriate for the available data, a preliminary analysis was conducted. This analysis was intended to test the hypothesis under which Poisson models and Negative Binomial models work. Poisson models assume that the mean equals the variance while the Negative Binomial model assumes that the mean is not equal to the variance (Washington, Karlaftis, & Mannering, 2011). To test this hypothesis, the over-dispersion parameter was estimated. The over-dispersion parameter indicates whether a data set is over-dispersed or under-dispersed. When a data set is over-dispersed, it indicates that the mean is statistically different than the variance. On the other hand, when a data set is said to be under-dispersed, it indicates that the mean is not statistically different than the variance (Washington, Karlaftis, & Mannering, 2011). The results of this test indicate that the data set is over-dispersed, indicating that the modeling approach which best fit the current data set is the Negative Binomial model.

The 2011 and 2012 data sets for impaired driving related crashes were separately modeled by using Negative Binomial models with the help of STATA 12 software. The results for both data sets consistently indicated that enforcement activities were negatively influencing crash occurrence. Also, in order to get a more detailed analysis, mandatory impaired enforcement, optional impaired enforcement and combined impaired enforcement were modeled separately. A data set including the whole period (May 2011 to December 2011) was also modeled. For this data set, all crashes involving impaired driving and fatal and serious injury crashes were separately modeled in order to determine the impact of enforcement on impaired driving crashes and the severity level of these types of crashes.

Table 3. *Result Sample. Negative Binomial model results for fatal and serious injury crashes involving impaired driving.*

KAB involving Impaired driving	***Coefficient***	***Standard Error***	***z***	***P>|z|***
Agency population	1.5E-05	3.92E-06	3.81	0
Agency road Length	0.00147	0.0001099	13.42	0
Agency number of bars	0.08061	0.0149472	5.39	0
Combined Impaired Enforcement	0.00121	0.0004685	2.58	0.01
Number of police officers	-0.0064	0.0008898	-7.17	0
Black percentage	0.01895	0.0041992	4.51	0
Asian percentage	0.07307	0.0225186	3.24	0.001
Model constant	-0.0161	0.1067003	-0.15	0.88
Number of observations = 553				
LR chi2 (8) = 538.87				
Prob > chi2 = 0				
Pseudo R^2 = 0.1658				
Alpha (over-dispersion) = 0.7497947				

Table 2. presents a results sample from a Negative Binomial model in which the combined impaired enforcement impact on fatal and serious injury crashes involving impaired driving is being evaluated. According to the results, variables, such as agency road length, agency population and agency number of bars, appear to be significantly increasing the number of fatal and serious injury crashes involving impaired driving. On the other hand, only the number of police officers appears to be significantly reducing the number of fatal and serious injury crashes involving impaired driving. More importantly, the results also indicate that combined impaired enforcement is promoting the increase of fatal and serious injury crashes involving impaired driving.

Similar results to the ones displayed in Figure 2 were obtained from all analysis conducted with Negative Binomial models for aggregated and disaggregated data sets models.

As was done for impaired driving crashes, the 2011 and 2012 data sets for unrestrained driving crashes were separately modeled by using Negative Binomial models with the help of STATA 12 software. The results for both data sets consistently indicated that enforcement activities were negatively influencing crash occurrence. Detailed analysis in which different levels of enforcement and different unrestrained severity levels are evaluated was also conducted for unrestrained crashes data sets.

Table 4. *Result Sample. Negative Binomial model results for fatal and serious injury crashes involving unrestrained driving.*

KAB involving Impaired driving	***Coefficient***	***Standard Error***	***z***	***P>|z|***
Agency population	2.75E-05	4.05E-06	6.77	0
Agency road Length	0.000928	0.000104	8.92	0
Agency number of bars	0.085994	0.014491	5.93	0
Combined Impaired Enforcement	0.001531	0.000563	2.72	0.007
Number of police officers	-0.0082	0.001149	-7.13	0
Age 20-34 percentage	0.02862	0.009551	3	0.003
Model constant	0.404104	0.177741	2.27	0.023
Number of observations	= 553			
LR chi2(6)	= 513.38			
Prob > chi2	= 0			
Pseudo R2	= 0.1401			
alpha (Over Dispersion)	= 0.868276			

Table 3.0 presents a results sample from a Negative Binomial model in which the combined unrestrained enforcement impact on fatal and serious injury crashes involving unrestrained is being evaluated. According to the results, as it was observed for impaired driving related crashes (Table 2.0), variables such as agency road length, agency population and agency number of bars, appear to be significantly increasing the number of fatal and serious injury unrestrained crashes. On the other hand, only the number of police officers appears to be significantly reducing the number of fatal and serious injury unrestrained crashes. However, what is even more important is the fact that the results also indicate that combined unrestrained enforcement is promoting the increase of fatal and serious injury crashes involving unrestrained driving.

The results obtained from the Negative Binomial models indicate that when police traffic enforcement increases, the number of fatal and serious injury crashes involving impaired and unrestrained driving also increase. This opposes a considerable amount of studies that have stated the advantages of police enforcement in reducing crashes (Zaidel, February 2002). Considering these facts, further analysis was conducted in order to identify the causes influencing the results obtained.

Crash data analysis was conducted at the agency level, in which the amount of crashes for police agencies that have participated in the enforcement programs and the amount of crashes of police agencies that have not participated in the enforcement programs was separately obtained.

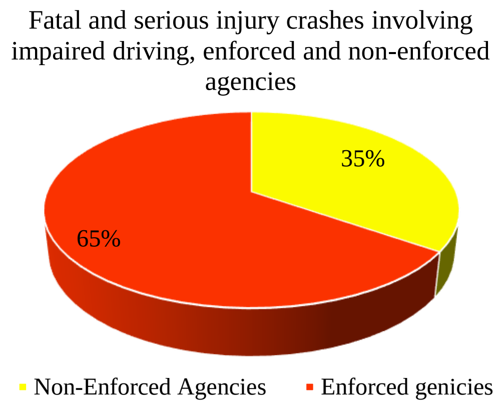


Figure 17. *Fatal and serious injury crashes involving impaired driving, enforced and non-enforced agencies*

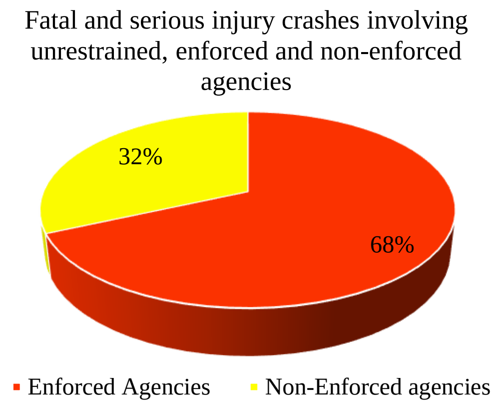


Figure 18. *Fatal and serious injury crashes involving unrestrained, enforced and non-enforced agencies*

The amount of fatal and serious injury crashes involving impaired and unrestrained driving, separated by enforced and non-enforced agencies are shown in Figure 17 and 18 respectively. These figures clearly show that the crash counts registered for agencies that received funds to conduct overtime traffic enforcement are higher than for police agencies which did not. This fact alone does not necessarily suggest anything important; however, the amount of agencies participating in the enforcement programs are just 29% of the police agencies considered in this study, meaning that the majority of crashes occurring in the state occurred within the boundaries of participating agencies.

For a more meaningful analysis, the correlation between KAB impaired driving related crashes and granted hours of enforcement was estimated with the help of STATA 12 statistical software. In the same fashion, the correlation between KAB unrestrained related crashes and granted hours of enforcement was also determined. Tables 4.0 and 5.0 show the results for both correlation analyses. According to the results presented in Table 4.0 and Table 5.0, there is a strong positive correlation between crash counts and granted hours of enforcement for both impaired driving related crashes and unrestrained driving related crashes. A positive linear correlation between enforcement hours and crashes indicates that when the number of enforcement hours is increased the number of crashes is going to increase.

Table 5. *Linear correlation between fatal and serious injury crashes involving impaired driving and impaired enforcement granted hours*

Correlation	KAB impaired driving related crashes	Combined impaired enforcement
KAB impaired driving related crashes	1.0000	**--**
Combined Impaired Enforcement	**0.7204**	1.0000

Table 6. *Linear correlation between fatal and serious injury crashes involving unrestrained driving and unrestrained driving enforcement granted hours*

Correlation	KAB unrestrained related crashes	Combined safety belt Enforcement
KAB unrestrained related crashes	1.0000	--
Combined safety belt Enforcement	**0.8185**	1.0000

These results are consistent with the results of the Negative binomial models previously presented in this section, which state that enforcement hours increases the number of crashes. On the other hand, it would be incorrect to take these results as valid. All agencies selected to receive funds for overtime traffic enforcement during the study period were selected under the means of crash counts. Selected police agencies received funds based on crash counts and available funds; therefore, agencies with higher numbers of crashes received a higher amount of hours. Considering these facts, it is logical to expect results indicating that enforcement hours are negatively influencing the number of crashes.

Linear Regression Models

Linear regression models were estimated in this study with the purpose of accounting for correlation between enforcement hours and crashes. Unlike count models, linear regression models deal with non-integer numbers, allowing for normalization of crashes. Some characteristics of police agency areas are strong indicators of crash occurrence. For instance, traffic counts are strongly related to crash occurrence; thus, normalizing the crash count of agencies with one of their characteristics (crash rate) is going to allow for a fair mean of comparison between non-enforced agencies and enforced agencies.

In order to determine the best normalization parameter (agency characteristic) to be used in this analysis, a correlation analysis was conducted with the help of STATA 12 statistical software. Due to their presence in each of the police areas studied, agency population, agency road length, and agency area were the only characteristics considered in this analysis. Table 6 and Table 7 show the results of the correlation analysis for impaired driving related crashes and unrestrained related crashes respectively. As indicated by the results, agency populations seem to be the characteristic with the highest correlation for both impaired driving and unrestrained related crashes. Agency road length, on the other hand, is moderately correlated with crashes involving impaired driving and strongly correlated with unrestrained crashes. Lastly, agency area does not present any correlation for crashes involving impaired driving or unrestrained.

Table 7. *Linear correlation between fatal and serious injury crashes involving unrestrained, agency population, and agency road length and agency area.*

Correlation	KAB unrestrained related crashes	Agency population	Agency road length	Agency Area
KAB unrestrained related crashes	1.0000	--	--	--
Agency population	**0.9484**	1.0000	--	--
Agency road length	0.5763	0.5889	1.0000	--
Agency Area	0.2486	0.2245	0.8396	1.0000

Table 8.0 *Linear correlation between fatal and serious injury crashes involving impaired driving, agency population, and agency road length and agency area*

Correlation	KAB unrestrained related crashes	Agency population	Agency road length	Agency Area
KAB impaired related crashes	1.0000	--	--	--
Agency population	**0.9295**	1.0000	--	--
Agency road length	0.8330	0.6539	1.0000	--
Agency Area	0.4639	0.2423	0.8203	1.0000

Linear regression models were estimated using *agency population* and *road length* normalization parameters for both impaired driving related crashes and unrestrained driving related crashes. As with count models (Negative Binomial models), detailed and general data sets were modeled using linear regression.

Table 9. *Sample results. Linear regression model results for fatal and serious injuring crashes involving impaired driving*

KAB Impaired driving/agency Population	***Coefficient***	***Standard Error***	***t***	***P>|t|***
Agency road length	0.000231	4.55E-05	5.09	0
<u>*Combined Impaired Enforcement*</u>	<u>***-0.0002***</u>	<u>*0.000102*</u>	<u>***-1.96***</u>	<u>*0.05*</u>
Number of police officer/Agency area	-0.02311	0.006194	-3.73	0
Model constant	0.482303	0.037246	12.95	0
Number of observations = 553				
Prob > F = 0				
R-squared = 0.101				
Adj R-squared = 0.0961				

Table 8.0 shows a sample of results obtained by using linear regression applied to fatal and serious injury crashes involving impaired driving. According to these results, agency road length significantly increases the number of fatal and serious injury crashes involving impaired driving, while combined impaired enforcement and number of police officers significantly reduced the number of fatal and serious injury crashes involving impaired driving.

Table 10. *Sample results. Linear regression model results for fatal and serious injuring crashes involving unrestrained driving*

KAB unrestrained/agency Population	***Coefficient***	***Standard Error***	***t***	***P>|t|***
Agency area	5.89E-07	9.36E-08	6.29	0
Combined unrestrained enforcement	**-3.90E-07**	2.15E-07	***-1.81***	0.071
Agency number of bars	2.07E-05	6.55E-06	3.16	0.002
Model Constant	0.000522	2.74E-05	19.07	0
Number of observations = 553				
Prob > F = 0				
R-squared = 0.0858				
Adj R-squared = 0.0808				

On the other hand, table 9.0 shows a sample of results obtained by using linear regression applied to fatal and serious injury crashes involving unrestrained driving. These results state that agency area and agency number of bars significantly increases the number of fatal and serious injury crashes involving unrestrained driving, while combined unrestrained enforcement significantly (80% confidence) reduces the number of fatal and serious injury crashes involving unrestrained.

In order to account for the issues aforementioned, further analysis was conducted. These analyses indicate that there is strong imbalance in the data set. The characteristics of agencies participating in the enforcement programs are too far apart to be comparable to the characteristics of those agencies that have not participated in the enforcement programs. For instance, agencies located in the southeast regions of the state and agencies located at the northern region of the state present characteristics that are too difficult to compare. Thus, it would be impractical to evaluate the impact of overtime traffic enforcement on crash occurrence applying linear regression model.

Trend Analysis

After considering and exploring multiple options, it was decided to evaluate the impact of enforcement activities utilizing trend analysis supplemented with simple regression analyses. In essence, a comparison between the weekly performances of two groups (non-enforced counties and enforced counties) was made. Counties where enforcement activities have been performed are the counties with the highest amount of crashes; thus, if comparison between enforced and non-enforced counties is made considering only crash counts, the results are going to be meaningless. To account for this issue, fatal and serious injury, alcohol and drug related crashes as well as fatal and serious injury safety belt related crashes were expressed in percentages. Three metrics were used to estimate these percentages: total crashes, total alcohol and drug related crashes and total safety belt related crashes. These percentages were estimated for each group in each week. Then the differences between them were calculated by subtracting the percentage of the enforced counties from that of the non-enforced counties. A positive (+) difference indicated that the percentage of non-enforced counties is greater while a negative (-) result indicated that the percentage of enforced counties is greater. Then the time when traffic enforcement activities were conducted were identified and compared to the results of the two groups. There are two main reasons for using county level data instead of agency level data to conduct trend analysis: (1) Characteristics at the county level are more comparable among enforced and non-enforced groups than at the agency level, and (2) enforcement data is available at the county level for a greater period (October 2009 – December 2012) allowing for a more meaningful analysis.

Although results shows most enforced weeks having lower percentages for enforced counties, it could not confidently be established if enforcement activities make an impact on crash occurrence. To confidently establish if enforcement makes an impact on crash occurrence, a linear regression model was developed. The objective of a linear regression model was to determine the relationship between enforcement activities and the difference in percentages observed. This relationship can be translated as an indicator of the impact of enforcement activities on the difference in percentages observed. Figure 19 shows the comparison between enforced and non-enforced counties' fatal and serious injury, alcohol and drug related crashes as a percentage of all crashes. It can be seen that the percentage corresponding to non-enforced counties is generally greater than the percentage for enforced counties. The observed trend is suggesting enforced counties have proportionally less fatal and serious injury alcohol and drug related crashes as a percentage of all crashes.

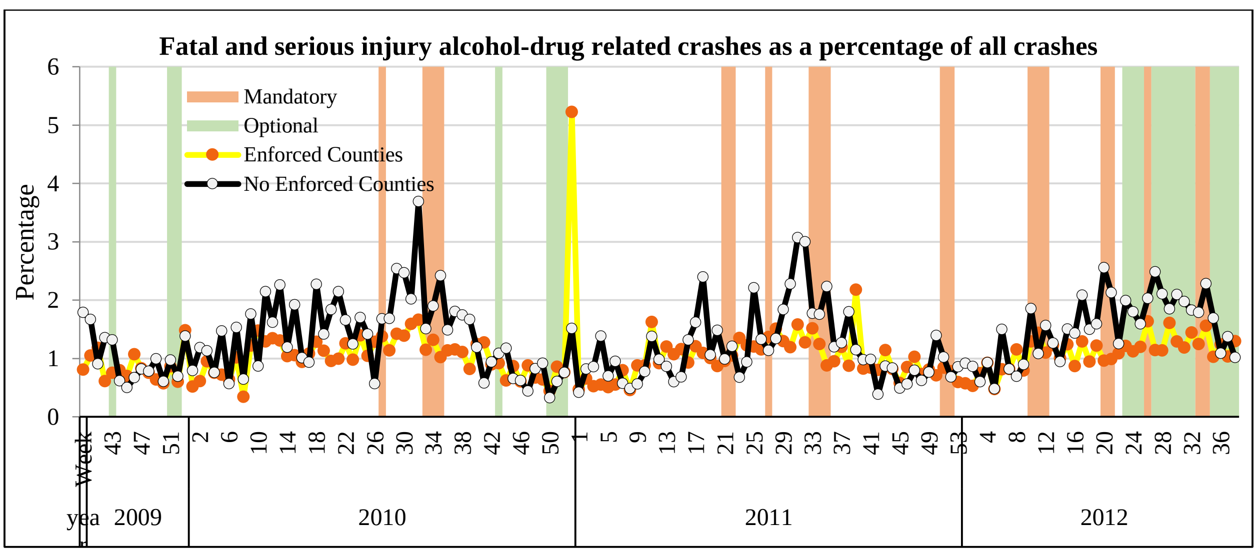


Figure 19. *Fatal and serious injury alcohol-drug related crashes as a percentage of all crashes*

Figure 19 also identifies weeks that were enforced during the study period. The vertical orange bars identify weeks with mandatory enforcement activities while the green vertical bars correspond to the weeks when optional enforcement activities were performed. By looking at the difference between enforced and non-enforced counties in enforced weeks, the trend indicates greater percentage for non-enforced weeks. Even though this pattern is suggesting that enforcement activities have an impact on crash occurrence, further analysis was performed to verify this.

In order to statistically determine if traffic enforcement activities have an impact on crash occurrence, a linear regression model was estimated. Two variables were used in this model; the dependent variable was the difference between non-enforced counties and enforced counties (non-enforced counties – enforced counties), and the independent variable was a binary variable (1, 0) indicating whether or not optional or mandatory traffic enforcement activities were conducted for a specific week. The model was estimated using STATA 12 statistical software.

Table 11. *Linear regression model results for fatal and serious injury crashes involving impaired driving as a percentage of all crashes*

% difference in KAB crashes	***Coefficient***	***Standard Error***	***t***	***P>|t|***
Presence of enforcement	***0.219***	0.109	***2.00***	0.047
Model constant	0.216	0.055	3.94	0.00

Number of observations = 169
F(1, 157) = 4
Prob > F = 0.0472
R-squared = 0.0248
Adj R-squared = 0.0186

The results given by the software (Table 10.0) indicate that the presence of enforcement positively increased the difference between percentages of enforced counties and non-enforced counties at the 95% confidence level. This means that for weeks where traffic enforcement activities are conducted, enforced counties exhibited a lower percentage of fatal and serious injury, alcohol and drug-related crashes of all crashes.

In order to obtain a more specific assessment of overtime traffic enforcement activities, an analysis aiming to determine the impact of a single hour of enforcement was also conducted using trend analysis. This analysis was conducted by taking the difference between non-enforced counties' and enforced counties' crash percentages for only weeks in which overtime traffic enforcement was conducted. Then, the average difference between non-enforced and enforced counties percentages for these weeks was estimated for the whole period (October 2009 – December 2012). For the same period, the average number of granted hours of enforcement was estimated. Finally, the average difference was divided into the average granted hours of enforcement, obtaining the percentage difference improvement made by one single hour of enforcement. The average hours of enforcement and the average difference of percentage was also determined by fiscal year to gain insight into the relationship between the amount of hours of enforcement and crashes.

The results of this analysis indicate that for each hour of enforcement granted to agencies in a county, the difference of non-enforced counties and enforced counties in fatal and serious injury crashes involving impaired driving as a percentage of all crashes is going to increase by 0.00051%. This result suggests that each hour of enforcement reduces the amount of expected crashes for a county.

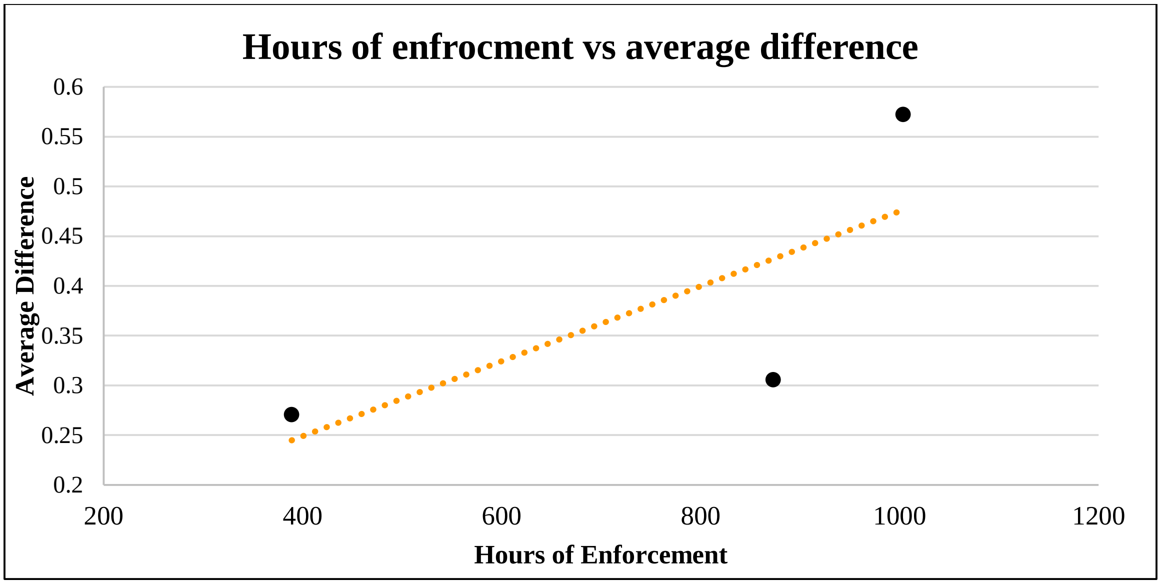


Figure 20. *Hours of enforced vs with the difference of percentage of fatal and serious injury crashes involving impaired*

On the other hand, Figure 20 presents the relationship between hours of enforcement and the difference between non-enforced counties' and enforced counties' percentages of fatal and serious injury crashes involving impaired driving of all crashes. Data for fiscal year 2009, fiscal year 2010 and fiscal year 2011 were used to build this plot. The analysis shown in Figure 20 clearly states that there is a positive relationship between hours of enforcement and difference of crash percentages. The trend line shown in Figure 20 indicates that if the amount of granted hours is increased, the differences in percentage also increases, meaning that the expected number of crashes for enforced counties decreases when the amount of hours is increased.

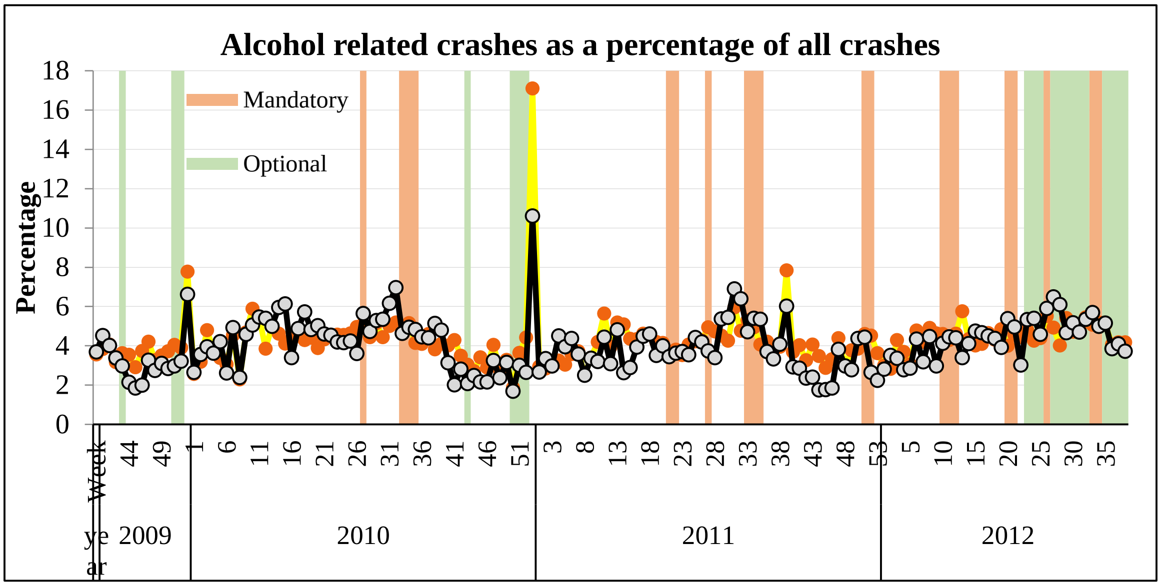


Figure 21.0 *non-enforced and enforced counties comparison, impaired driving crashes as a percentage of all crashes*

In Figure 21, an analysis showing a comparison between non-enforced counties and enforced counties is shown. The percentage of all alcohol and drug related crashes of all crashes (as opposed to those used in Figure 19, which utilized fatal and serious injury crashes as a percentage of all crashes) was used to compare the performance of these two groups. In this analysis the pattern shows an overall higher percentage for enforced counties. As for the previous analysis, a linear regression model was formulated.

The formulation for this model followed the same format used to formulate the previous model; however, the results (Table 11.0) indicate that the presence of enforcement positively increases the difference between percentages of enforced counties and non-enforced counties at the 80% confidence level. These results are not as strong as for the previous analysis, which focused on fatal and serious injury crashes as a percentage of all crashes. Thus, it can be concluded that enforcement activities results are associated with a greater impact on fatal and serious injury, alcohol and drug related crashes than for all alcohol and drug related crashes. In practical terms, this can be associated with less aggressive driving after drinking during the enforcement weeks, or drinking less during the enforcement weeks.

Table 12. *Linear regression model results, alcohol and drug related crashes as a percentage of all crashes*

% difference in KAB crashes	***Coefficient***	***Standard Error.***	***t***	***P>|t|***
Presence of enforcement	**0.269**	0.185	**1.45**	0.149
Model constant	-0.301	0.093	-3.24	0.001

Number of observations = 159
F(1, 157) = 2.10
Prob > F = 0.149
R-squared = 0.0132
Adj R-squared = 0.0069

Trend analysis was also used to visualize potential reduction of fatal and serious injury crashes as a result of enforcement activities. To that end, the trends observed during and after traffic enforcement activities periods for enforced and non-enforced counties were compared. In Figure 14, a comparison between the performance of enforced and non-enforced counties for a specific period is shown. This comparison was made by computing the fatal and serious injury alcohol and drug related crashes as a percentage of all crashes for successive weeks. It is expected that enforcement activities not only impact the week they are performed but also the succeeding week.

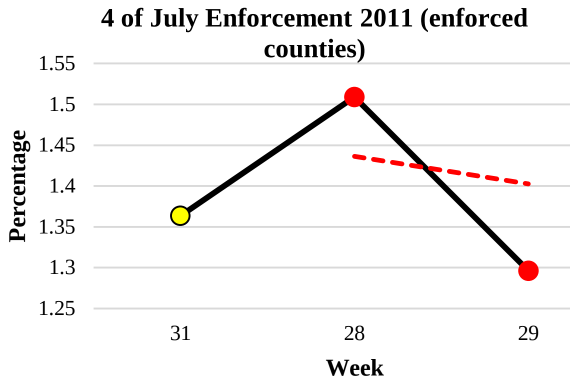


Figure 22. *2011 4th of July enforcement evaluation based on fatal and serious injury alcohol-drug related crashes as a percentage of all crashes, enforced counties*

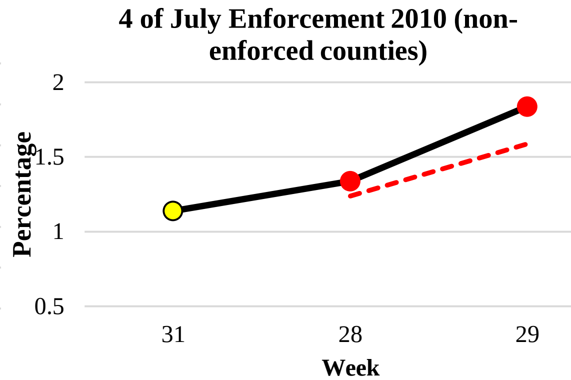


Figure 23. *2011 4th of July enforcement evaluation based on fatal and serious injury alcohol-drug related crashes as a percentage of all crashes, non-enforced counties*

The enforcement period shown in Figure 22.0 and Figure 23.0 corresponds to the 4th of July of 2011 impaired traffic enforcement activities. Although this enforcement was only a few days over a week, a 3 week period was chosen. The trend line shown for enforced counties indicates there was decrease in the fatal and serious injury alcohol and drug related crashes as a percentage of all crashes. In contrast, the trend line shown for non-enforced counties presents an increased trend line, which indicates that the percentage of fatal and serious injury, alcohol and drug related crashes of all crashes in that period is higher than for enforced counties.

For more reliable results, an analysis using the average percentage change from 2010 to 2012 of the 4th of July traffic enforcement activities was made, as shown in Figure 18. For this analysis, the trend line shown by enforced counties presents a decreasing trend, indicating a decrease on the average percentage of fatal and serious injury, alcohol and drug related crashes of all crashes. However, the trend line shown for non-enforced counties presents an increasing trend. Again, enforcement activities have proven to be positively influencing fatal and serious injury, alcohol and drug related crashes.

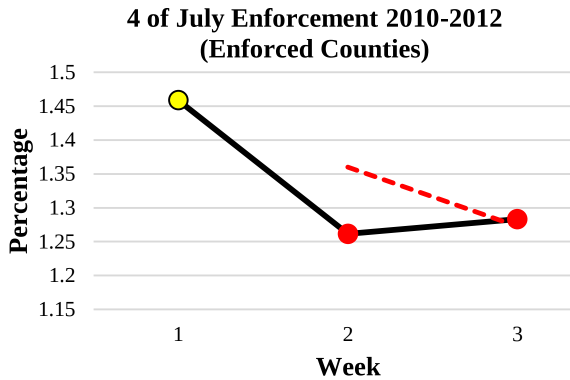


Figure 24. *2010-2012 4th of July enforcement evaluation based on fatal and serious injury alcohol/drug-related crashes as a percentage of all crashes, enforced counties*

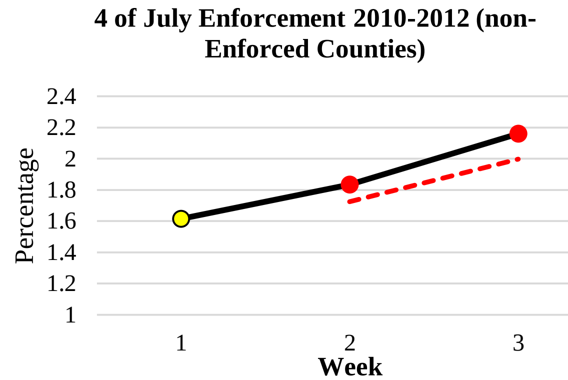


Figure 25. *2010-2012 4th of July enforcement evaluation based on fatal and serious injury alcohol/drug-related crashes as a percentage of all crashes, non-enforced counties*

Figure 19 shows the comparison between enforced and non-enforced counties' fatal and serious injury, safety belt related crashes as a percentage of all crashes. The figure shows that enforced counties generally present higher percentages for weeks when enforcement was not performed. On the other hand, enforced counties generally present lower percentages for weeks when enforcement was performed.

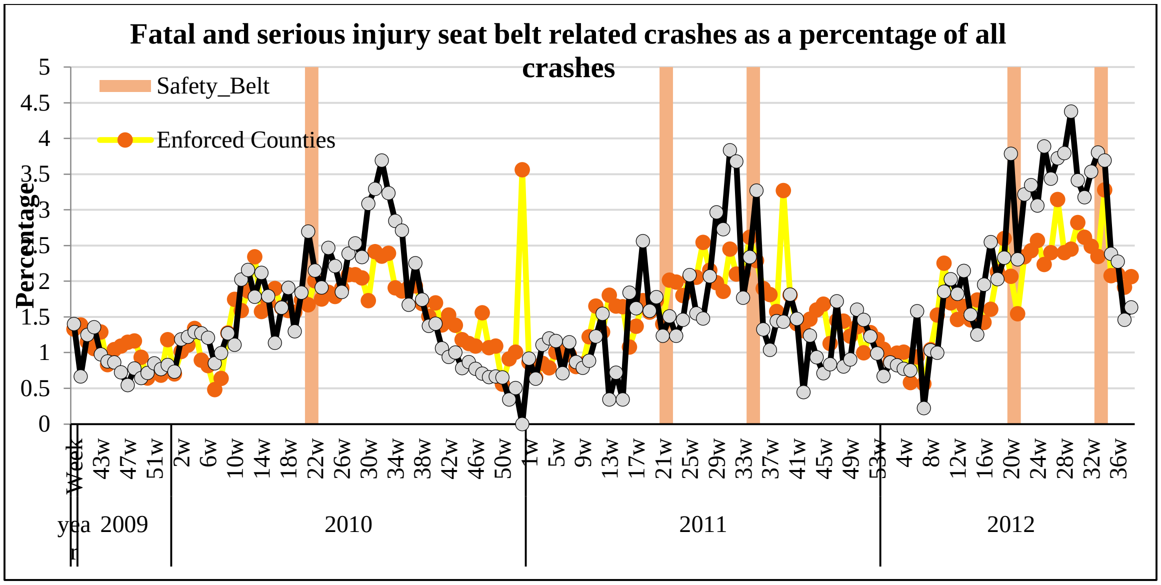


Figure 26.0 *non-enforced and enforced counties comparison, fatal and serious injury crashes involving unrestrained as a percentage of all crashes*

In order to confidently determine if the presence of enforcement positively impacts the occurrence of fatal and serious injury, safety belt related crashes, a lineal regression model was formulated. This model was formulated as it was formulated for the alcohol and drug related crashes analysis explained earlier in this section, with the only difference that the independent variable is the combination of enforcement activities and paid media campaign. This variable is a binary variable, and it takes a value of one when both enforcement activities and paid media campaigns are performed in the same week.

The results obtained from this model indicate that the presence of enforcement and media campaigns concurrently increases the difference between percentages for the enforced counties and those for the non-enforced counties at the 95% confidence level. This means that for weeks where traffic enforcement activities are conducted enforced counties are expected to have lower fatal and serious injury, safety belt related crashes as a percentage of all crashes.

Table 13. *Linear regression model results, fatal and serious injury safety belt-related crashes as a percentage of all crashes*

% difference in KAB crashes	Coefficient	Standard Error	t	P>|t|
Presence of enforcement	**0.717**	0.309	**2.33**	0.021
Model constant	0.034	0.055	0.62	0.534

Number of observations = 159

F(1, 157) = 5.41

Prob > F = 0.0213

R-squared = 0.0333

Adj R-squared = 0.0271

As performed for impaired driving related crashes, an analysis of the impact a single hour of enforcement has on crashes was also conducted for unrestrained driving related crashes. In this analysis, the average difference between non-enforced and enforced counties' percentages for these weeks was estimated for the whole period (October 2009 – December 2012). For the same period, the average number of granted hours of enforcement was estimated. Finally, the average difference was divided into the average granted hours of enforcement, obtaining the percentage difference improvement made by one single hour of enforcement. The average hours of enforcement and the average difference of percentage was also determined by fiscal year to gain insight into the relationship between the amount of hours of enforcement and crashes.

The results of this analysis indicate that for each hour of enforcement granted to agencies in a county, the difference of non-enforced counties and enforced counties in fatal and serious injury crashes involving unrestrained driving as a percentage of all crashes is going to increase by 0.0013967%. This result suggests that each hour of enforcement reduces the amount of expected crashes for a county.

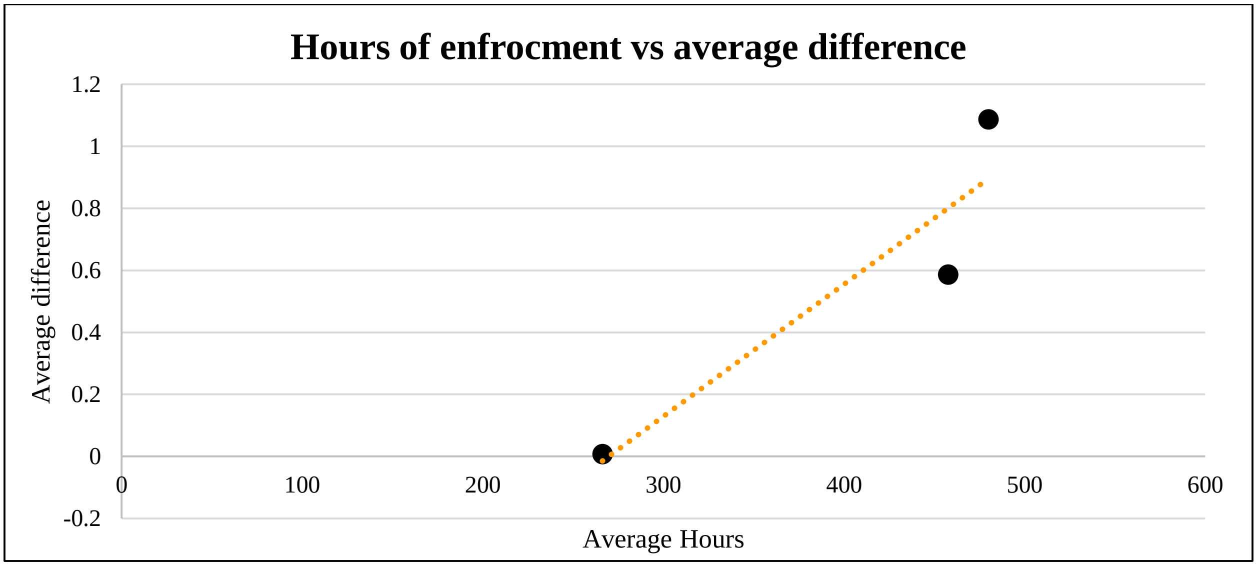


Figure 27. *Hours of enforced vs with the difference of percentage of fatal and serious injury crashes involving impaired*

On the other hand, Figure 27 presents the relationship between hours of enforcement and the difference between non-enforced counties' and enforced counties' percentages of fatal and serious injury crashed involving unrestrained driving of all crashes. In order to build this plot, data for fiscal year 2009, fiscal year 2010 and fiscal year 2011 was used.

The analysis shown in Figure 27 clearly states that there is a positive relationship between hours of enforcement and difference of crash percentages. The trend line shown in Figure 27 indicates that if the amount of granted hours is increased, the differences in percentage also increases, meaning that the expected number of crashes for enforced counties decreases when the amount of hours is increased.

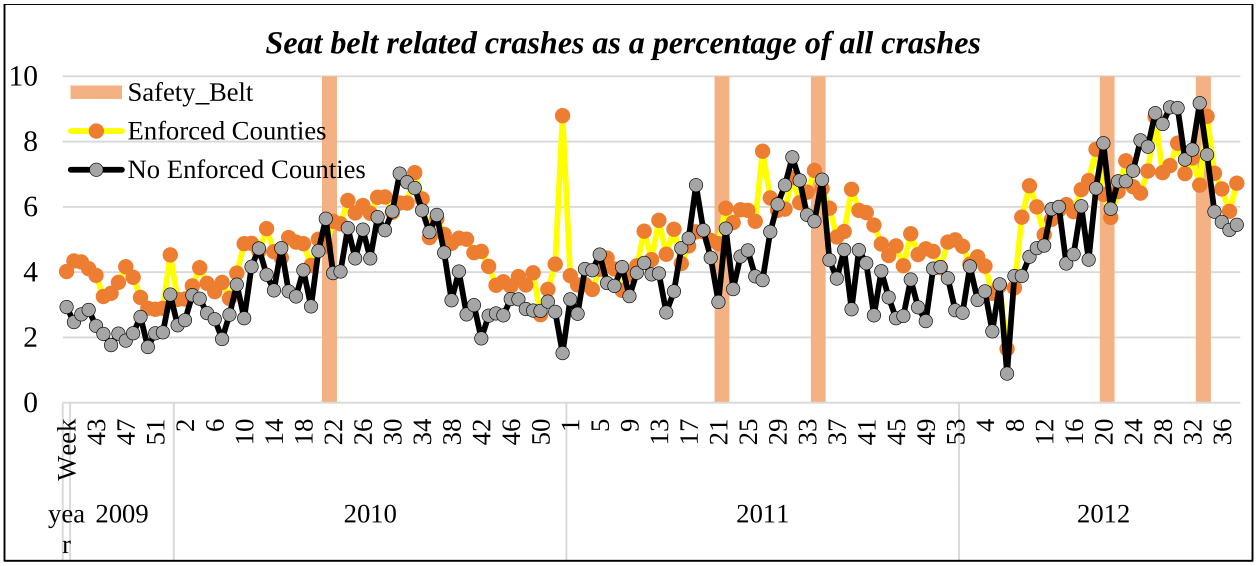


Figure 28. *non-enforced and enforced counties comparison, unrestrained crashes as a percentage of all crashes*

A comparison between non-enforced counties and enforced counties considering the percentage of all safety belt related crashes of all crashes was made. In Figure 28.0, it can be seen that, for most weeks, the percentage corresponding to enforced counties is higher. On the other hand, for weeks where enforcement was performed, the percentage of enforced counties is generally lower.

Table 14. *Linear regression model results, safety belt- related crashes as a percentage of all crashes*

% difference in KAB crashes	*Coefficient*	*Standard error*	*t*	*P>|t|*
Presence of enforcement and media campaign	**1.165**	0.513	**2.27**	0.024
Model constant	-0.851	0.091	-9.36	0.000

Number of observations = 159
F(1, 157) = 5.16
Prob > F = 0.0244
R-squared = 0.0318
Adj R-squared = 0.0257

As for previous analyses, a linear regression model was formulated. The results of this model indicated that traffic enforcement activities combined with paid media campaigns increases the difference between percentages of enforced counties and non-enforced counties at the 95% confidence level. This means that for weeks where traffic enforcement activities are conducted, enforced counties are expected to have a lower percentage of safety belt related crashes of all crashes. It also signifies the importance of coupling paid media campaigns with enforcement activities for a greater impact on seat belt use.

An assessment of the impact traffic enforcement activities have on crash occurrence during and after weeks when enforcement was conducted by comparing the trends observed during and after traffic enforcement activities periods.

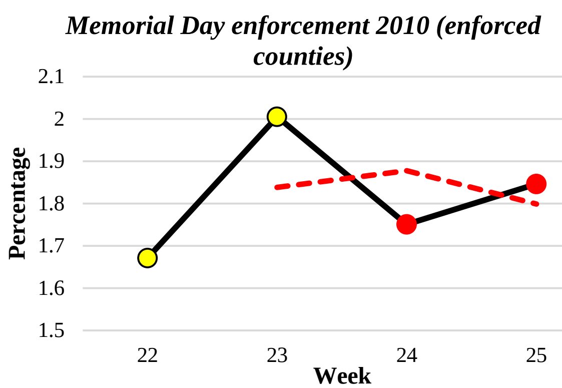


Figure 29. *2010 memorial day enforcement evaluation based on weekly percentage change, enforced counties*

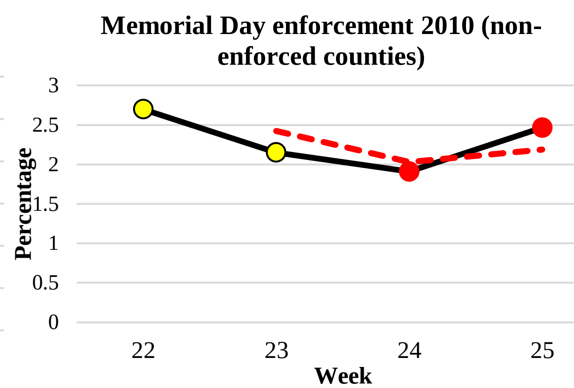


Figure 30. *2010 memorial day enforcement evaluation based on weekly percentage change, non-enforced counties*

In Figure 29 and Figure 30, a comparison between the performance of enforced and non-enforced counties for specific periods is shown. This comparison was made by computing the percentage of fatal and serious injury, safety belt related crashes of all crashes for consecutive weeks. The enforcement period shown in this figure corresponds to the Memorial Day 2011 safety belt and child restraint enforcement activities. Although this enforcement lasted for 2 weeks, a 4-week period was chosen. The trend line for enforced counties indicates that there is a decrease in the percentage of fatal and serious injury, safety belt related crashes of all crashes. In contrast, the trend line shown for non-enforced counties presents an increased trend, which indicates that there is an overall increase in the percentage of fatal and serious injury, safety belt related crashes of all crashes.

For more reliable results, an analysis using the average percentage from 2010 to 2012 Memorial Day traffic enforcement activities was made. For this analysis the trend line shown by enforced counties in Figure 31 presents a decreasing trend, indicating a decrease on the average percentage change. However, the trend line shown for non-enforced counties in Figure 32 presents an increasing trend. Again, enforcement activities coupled with media campaigns have proved to be positively influencing fatal and serious injury safety belt related crashes.

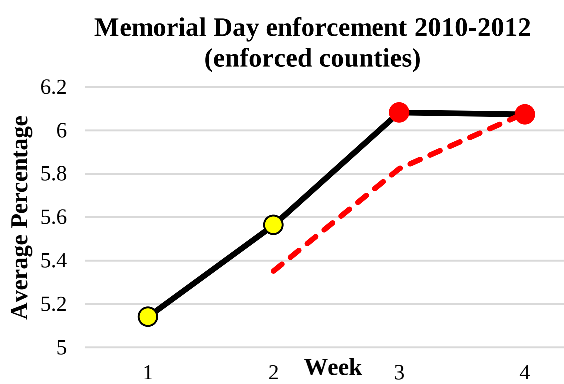


Figure 31. *2010-2012 Memorial Day enforcement evaluation based on average weekly percentage, enforced counties*

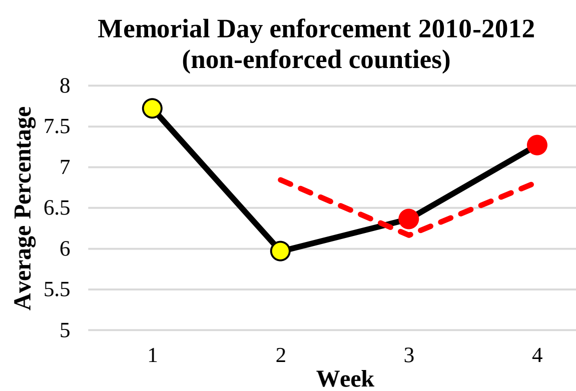


Figure 32. *2010-2012 Memorial Day enforcement evaluation based on average weekly percentage, non-enforced counties*

Police Agency Selection

Selection of Agencies

Agencies for conducting traffic enforcement activities were identified based on the Critical Rate (CR) method (Garber, 2009). Contrary to average crash count only (the current method used by OHSP), the Critical Rate method integrates site characteristics (such as traffic volume, road length and population) to identify sites with crash rates significantly higher than the average crash rate for similar sites. The method classifies sites as dangerous if the average crash rate for a specific site is greater than the expected crash rate for this specific site. Basically, the observed crash rate for the site is divided into the expected crash rate, and if this ratio is greater than one, the site is classified as hazardous. In this analysis, sites were defined as local law enforcement agencies as well as Michigan State Police (MSP) posts. However, the local agencies and the MSP posts were handled separately due to their differences in coverage area.

Selection of Agencies for Alcohol/Drug Related Enforcement

For comparison purposes, ranking was performed using both the modified Critical Rate method and the average of historical crashes (as used in previous analyses by OHSP). Figure 33 and Figure 34 present the ranking results for counties based on the two methodologies. Figure 33 shows the results of OHSP's current methodology of determining agencies to conduct overtime traffic enforcement activities.

Figure 34 presents the results of the rank resulting from the modified Critical Rate method explained earlier in this section. These maps in Figure 33 and Figure 34 show the 28 top counties in the state resulting from both ranking methodologies. Only 28 counties were selected at the top because, according to the result of the modified Critical Rate method, only 28 counties are considered more hazardous than the state average. From Figure 33 and Figure 34, it can be seen that counties, such as Wayne, Oakland, Kalamazoo, Kent, Van Buren and others, are in both ranking results. However, multiple counties are also present in only one methodology, signifying the difference between the methods. Counties such as St. Joseph and Midland are shown to be at the top for the modified Critical Rate method, while counties such as Tuscola and Lenawee are just at the top of the rank for the crash count (current methodology) method.

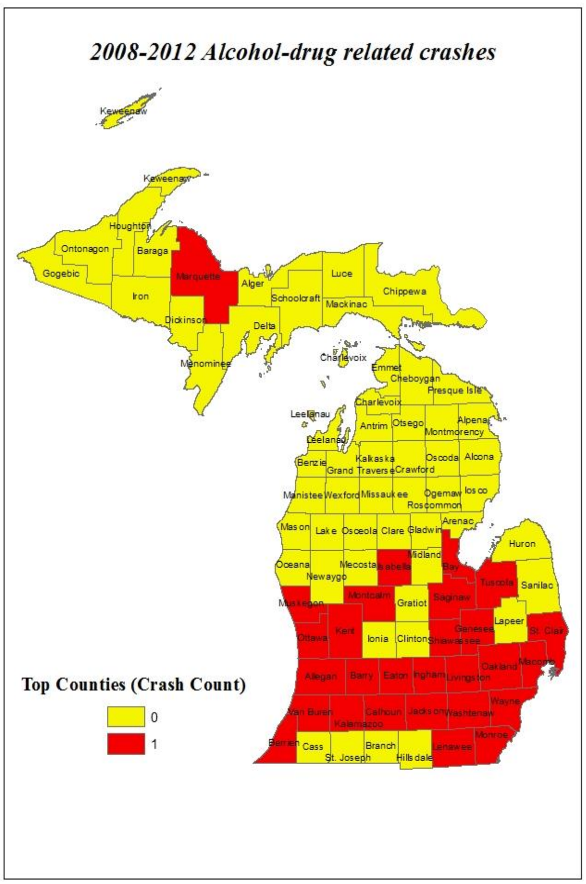


Figure 33. *Average crash rate methods for county ranking, fatal and serious injury crash involving Impaired driving (2008-2012)*

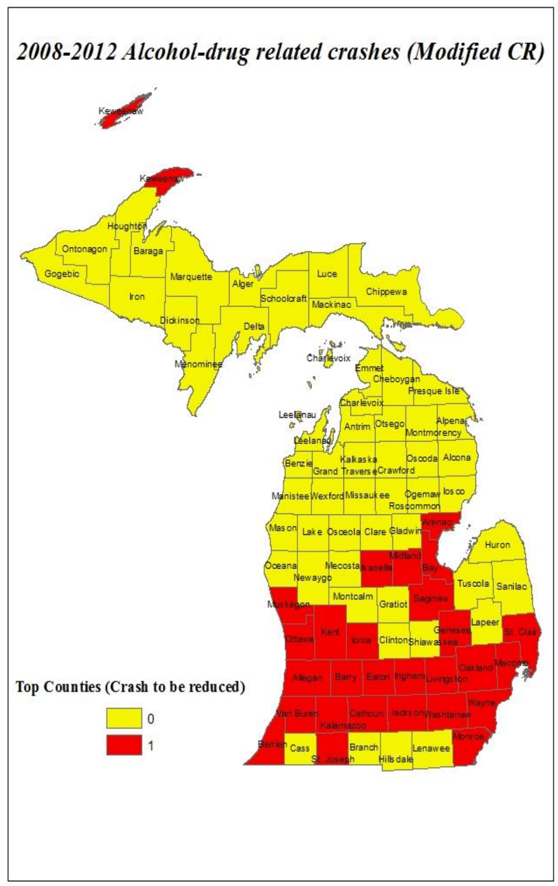


Figure 34. *Modified Critical Rate methods for county ranking, fatal and serious injury crash involving Impaired driving (2008-2012)*

Considering the limitations of county-level evaluation for selecting police agencies to conduct overtime traffic enforcement activities, it was considered to explore the possibility of evaluating agencies individually. To that end, all police agencies throughout the state were identified. Crash data for each police agency was then identified by using location information provided in each crash record. Also, road length for each police agency area was obtained using Geographic Information Systems (GIS) software. Similar to the county level, ranking of agencies was based on both the modified Critical Rate method and the current method implemented by OHSP.

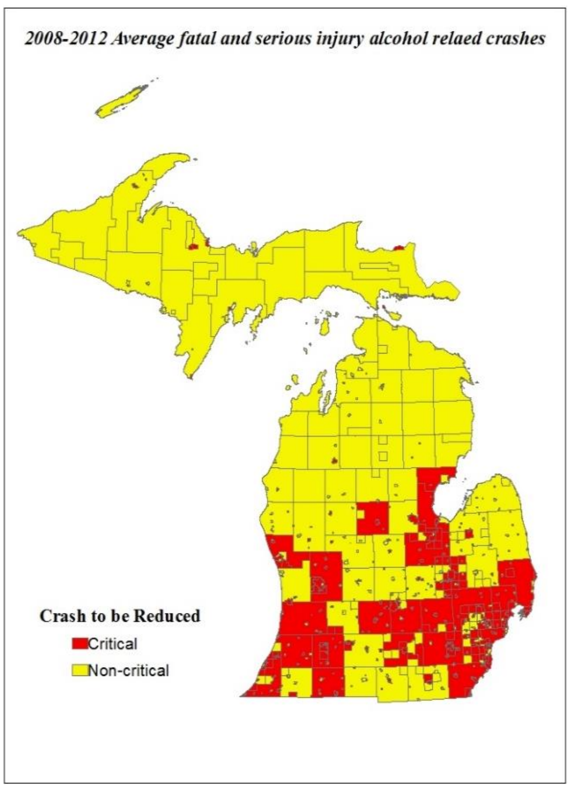


Figure 35. *Average crash rate methods for agency ranking, fatal and serious injury crash involving Impaired driving (2008-2012)*

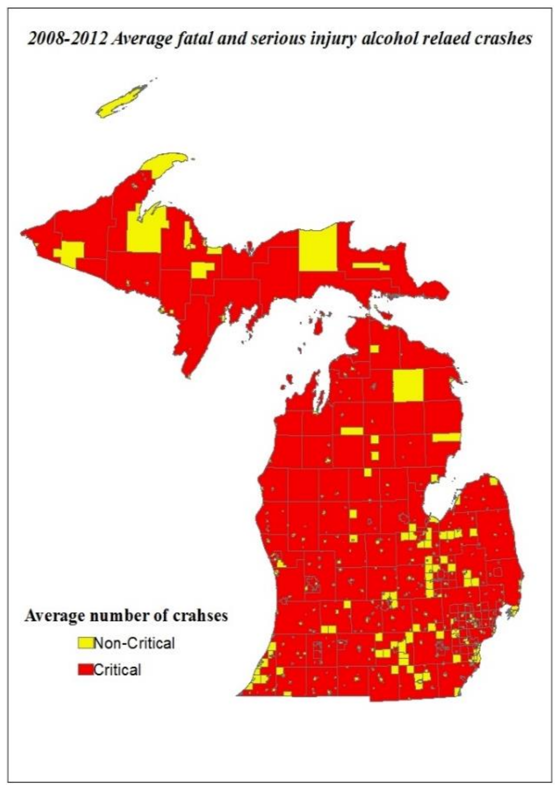


Figure 36. *Modified Critical Rate methods for agency ranking, fatal and serious injury crash involving Impaired driving (2008-2012)*

Figure 35 and 36 show agencies selected based on the crash count ranking methodology and the modified Critical Rate methodology, respectively. For these rankings, the first 150 agencies were considered to be at the top of the rankings. Although 168 agencies were found to exceed the state average, only the first 150 agencies with the greatest potential to reduce a considerable amount of crashes in order to be at the average were selected. For instance, for one of the agencies with a higher crash rate than the average, the amount it would need to reduce in order to be at average, is just 0.23 equivalent B crashes. From the maps shown in Figure 35 and Figure 36, it can be observed that police agencies at the top of the crash count rank are mainly influenced by the size of the area for those agencies. This pattern illustrates one of the weaknesses of the crash count method. Larger areas are expected to have a higher number of crashes although it does not necessarily mean that this amount of crashes is proportionally higher than for other smaller areas. In contrast, police agencies at the top of the modified Critical Rate ranking are not necessarily affected by their area; the relevance of a police agency area is related to the number of crashes and the police agency area's characteristics. Appendix A presents the list of all 150 agencies selected based on each methodology.

State police departments (MSP) have jurisdiction over large areas, composed of 2 or more counties. These areas are also known as posts and are considered when selecting agencies to conduct overtime traffic enforcement activities. The evaluation for these police agencies needs to be made separately from other police agencies. State police agencies conduct traffic enforcement mainly at state roads; thus, evaluation of these agencies was made considering crashes occurring only at state roads.

With the help of Geographic Information Systems (GIS) software, crashes spatially related to state roads were identified. Then, these crashes were geographically related to state police individual jurisdiction areas.

In Figure 37 and Figure 38, the results for crash count rank and the modified critical rate method rank are presented respectively. As can be seen, the results are the same for both ranks. This pattern is probably exists because the higher amount of crashes of some state police areas greatly increases the overall, average crash rate.

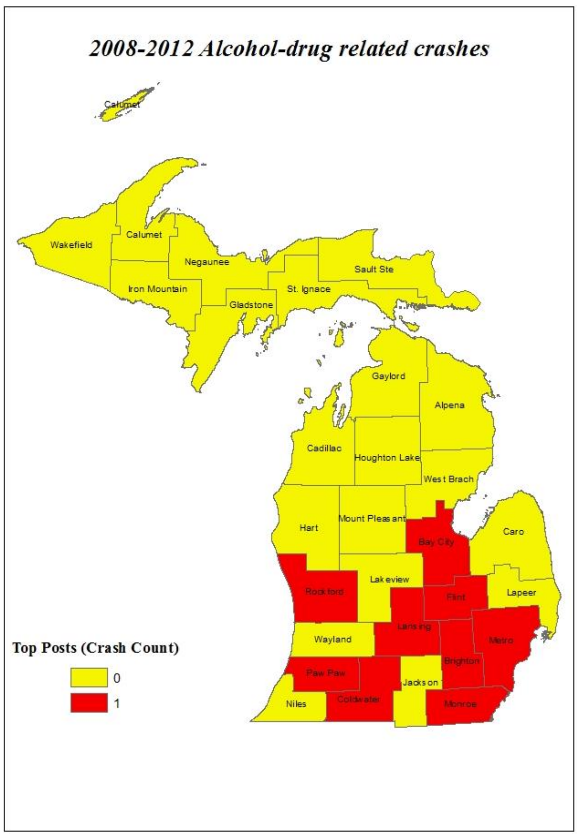


Figure 37. Average crash rate methods for post ranking, fatal and serious injury crash involving Impaired driving (2008-2012)

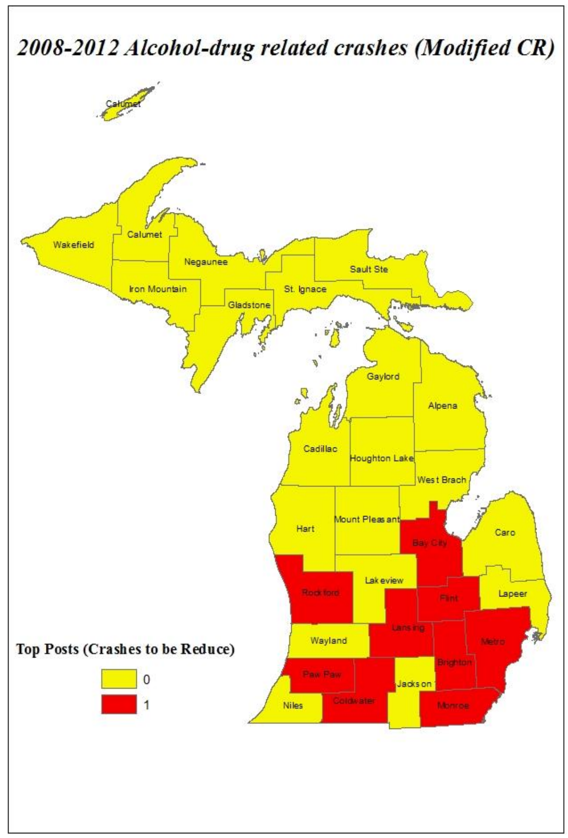


Figure 38. *Modified critical rate methods for post ranking, fatal and serious injury crash involving Impaired driving (2008-2012)*

The Lower Peninsula and the Upper Peninsula of the state of Michigan present different characteristics due to their geographical position; thus, comparing agencies located at the Upper Peninsula and the Lower Peninsula together could lead to biased results. Taking this into account, analyses were performed in which the Upper Peninsula and the Lower Peninsula were evaluated separately.

Figure 39 and Figure 40 present the results of the police agency ranks estimated with the average crash rate method and the modified Critical Rate method respectively. For these analyses, the agencies located at the Upper Peninsula and Lower Peninsula were separately evaluated because of the reasons already stated.

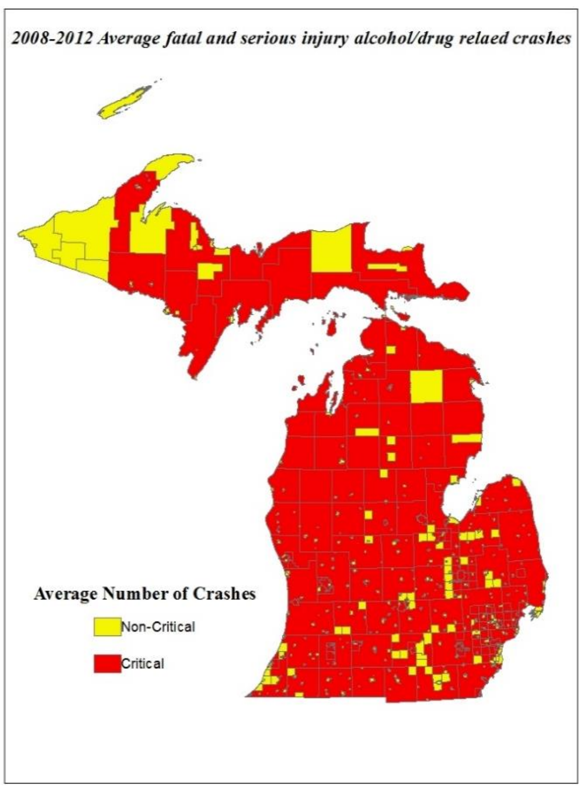


Figure 39. *Average crash rate methods for agency ranking, LP and UP separated, fatal and serious injury crash involving Impaired driving (2008-2012)*

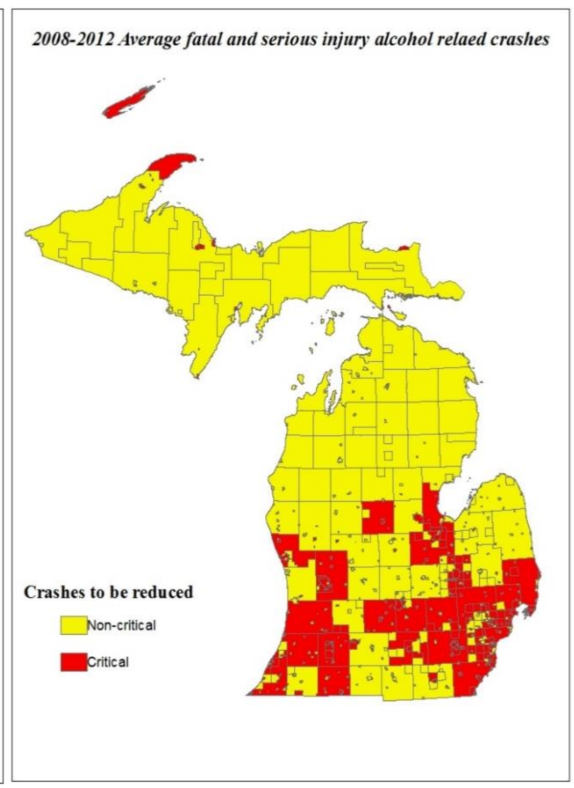
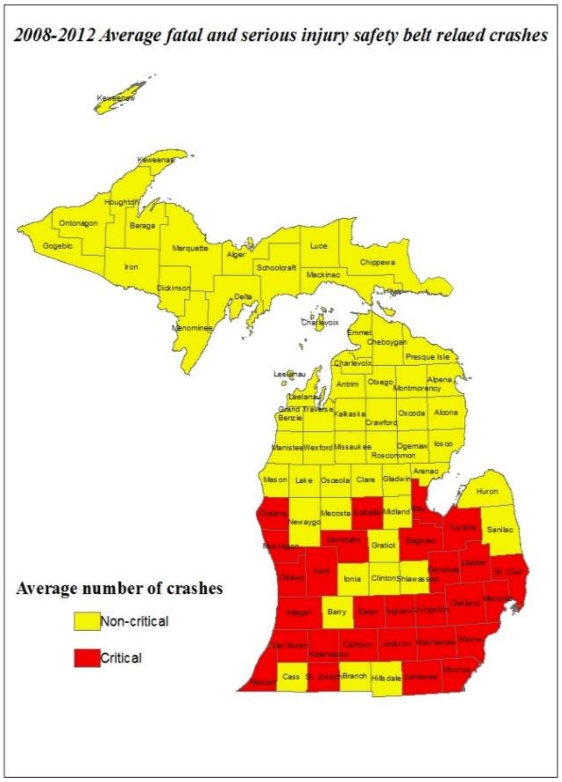


Figure 40. *Modified critical rate methods for agency ranking, LP and UP separated, fatal and serious injury crash involving Impaired driving (2008-2012)*

Figure 39 and Figure 40 show 149 agencies for the Lower Peninsula and 10 agencies for the Upper Peninsula, which were found to be above the average. The results for these analyses are pretty similar to the results shown for the analysis performed including all agencies (Figure 37 and 38). The results are displayed with more detail in Appendix B.

Selection of Agencies for Safety Belt Enforcement

Similar to alcohol and drug enforcement analysis, the two ranking methodologies were used to select agencies for seat belt enforcement. Figure 41 and Figure 42 present the county-level ranking results for two different ranks methodologies. In these maps a similar trend to what was found for alcohol and drug related crashes is observed. Many counties are found in both ranks but some of them are specifically present in just one of them. Counties such as Tuscola and Lapeer are just at the top in the crash count methodology while counties such as Grand Traverse and Montcalm form part of the top counties for the modified critical rate method.



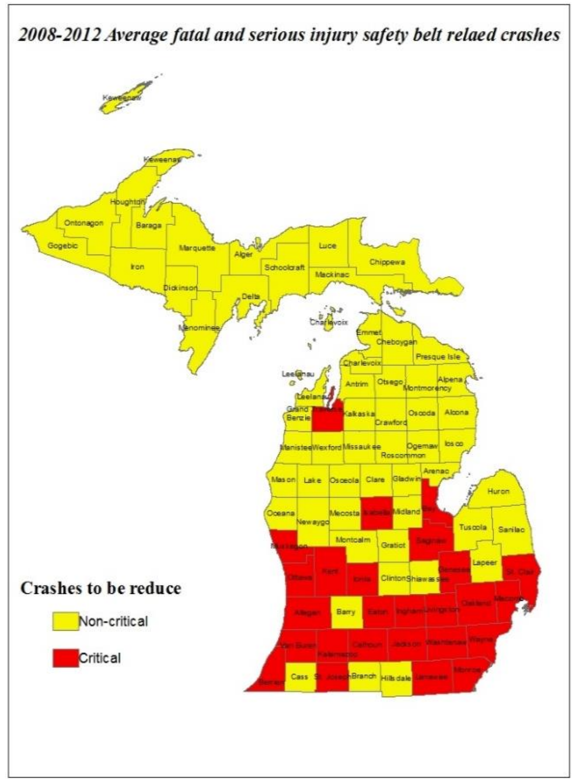


Figure 41. *Average crash rate methods for county ranking, fatal and serious injury crashes involving unrestrained (2008-2012)*

Figure 42. *Modified critical rate methods for county ranking, fatal and serious injury crashes involving unrestrained (2008-2012)*

As mentioned before, there are limitations regarding the selection of police agencies to conduct overtime traffic enforcement activities based on county-level analysis. To that end, ranking was also performed at the agency level. A comparison between selection results for safety belt related enforcement at the agency level is presented in Figures 41.0 and figure 42.0. Similar to selection of agencies for alcohol and drug related enforcement, 150 agencies were considered to be at the top of the ranks. As can be seen, selection based on crash count is mostly biased to the geographically larger agencies. In contrast, for the modified critical rate selection results, it can be seen that only a few of the geographically larger areas were selected. Patterns shown for each map are particularly different. When looking at the county level analysis, the similarities between results are noticeable; however, when agency level ranking results are carefully examined, substantial differences are seen. The complete list for the ranks are shown in Appendix A.

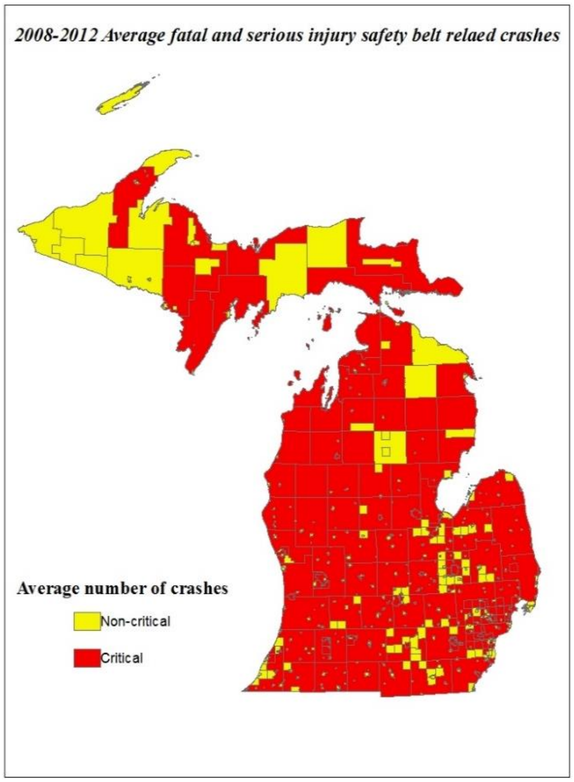


Figure 43. *Average crash rate methods for agency ranking, fatal and serious injury crashes involving unrestrained (2008-2012)*

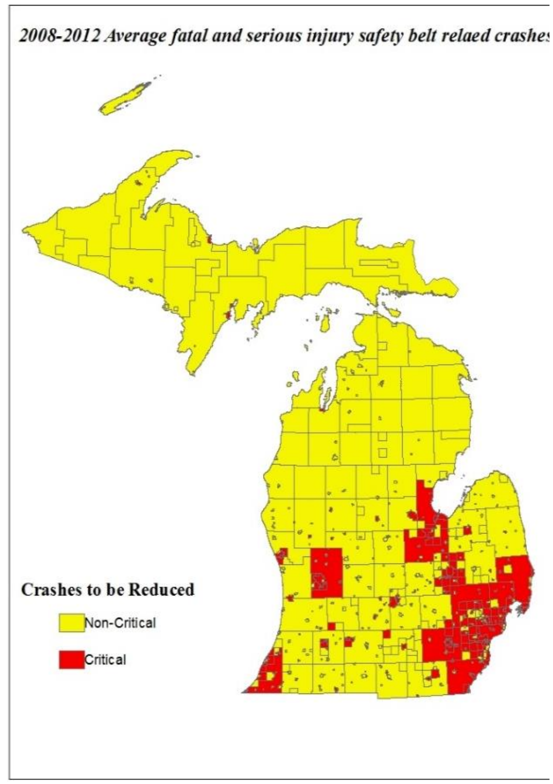


Figure 44. *Modified critical rate methods for agency ranking, fatal and serious injury crashes involving unrestrained (2008-2012)*

Figures 45 and 46 show the results for the crash count rank and the modified critical rate method rank respectively. Different to what is observed for alcohol and drug related crashes analysis (Figures 37 and 38), the results for these ranks present some differences; for instance, Monroe post did not rank critical for the average crash rate method, while ranking critical for the modified critical rate method.

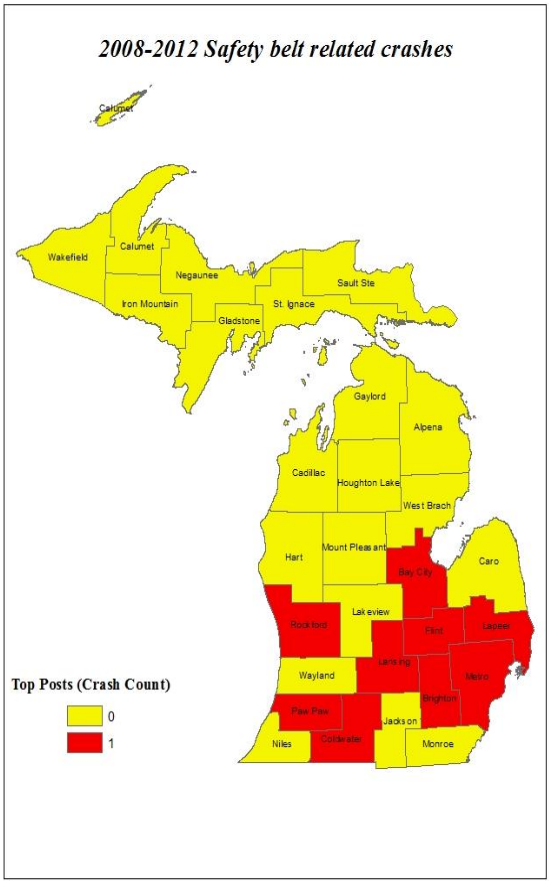


Figure 45. Average crash rate methods for post ranking, fatal and serious injury crashes involving unrestrained (2008-2012)

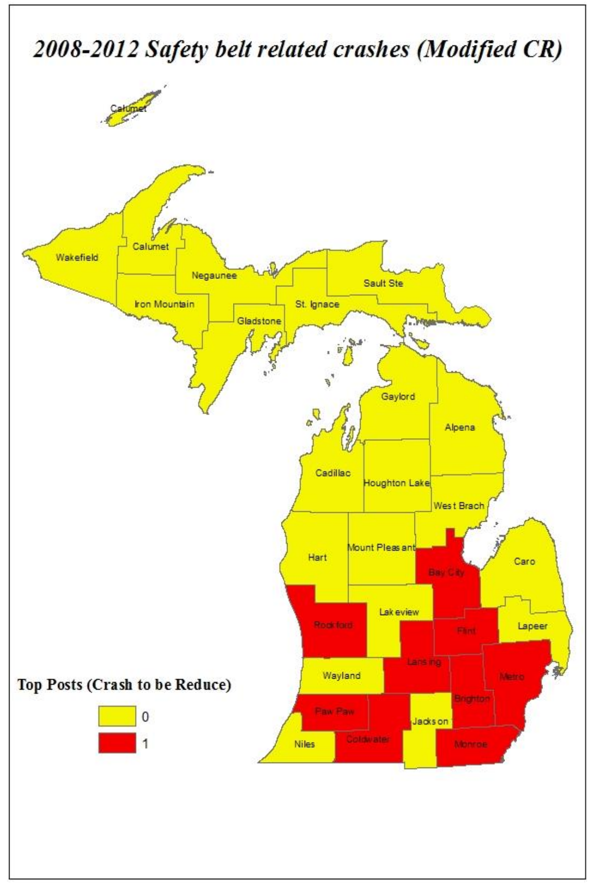


Figure 46. Modified critical rate methods for post ranking, fatal and serious injury crashes involving unrestrained (2008-2012)

Figure 47 and Figure 48 present the results of the police agency ranks estimated with the average crash rate method and the modified critical rate method respectively. For these analyses, the agencies located at the Upper Peninsula and Lower Peninsula were separately evaluated because of the reasons already stated in the previous section.

Figure 47 and Figure 48 show 153 agencies for the Lower Peninsula and 8 agencies for the Upper Peninsula, which were found to be above the average. The results for these analyses are pretty similar to the results shown for the analysis performed including all agencies (Figure 43 and 44). The results are displayed with more detail in Appendix B.

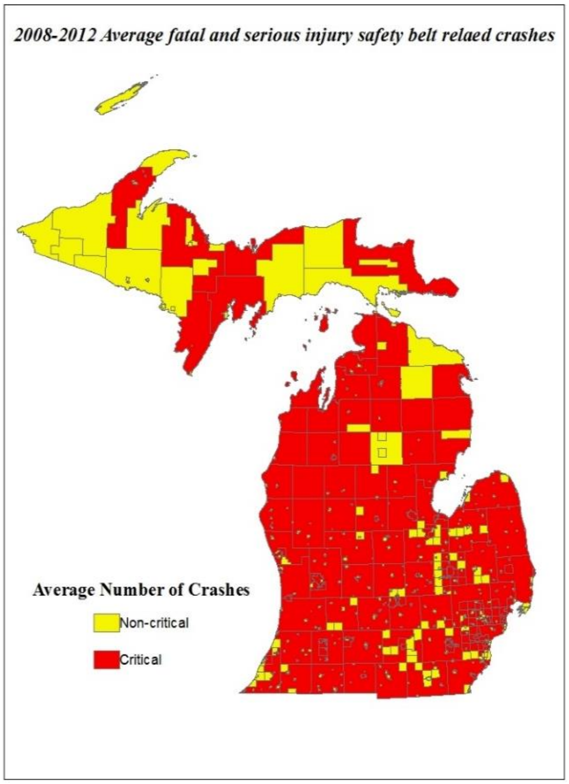


__Figure 47.__ Average crash rate methods for agency ranking, LP and UP separated, fatal and serious injury crash involving unrestrained (2008-2012)

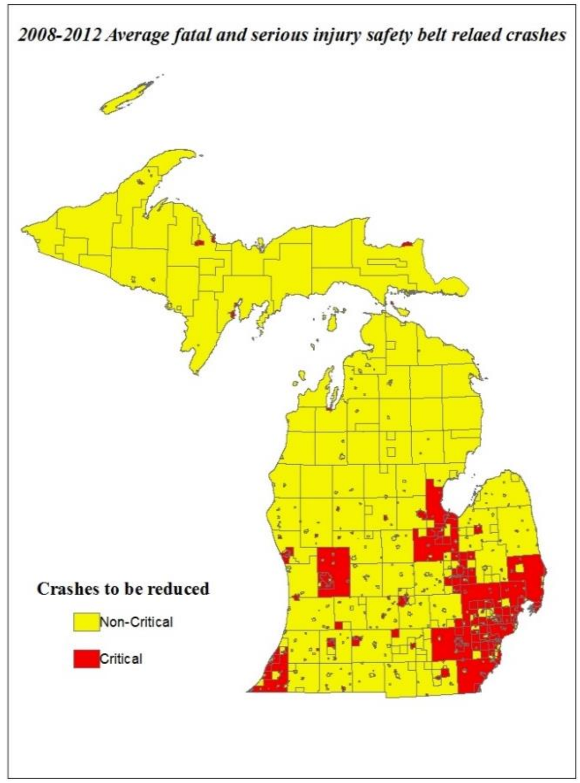


__Figure 48.__ Modified critical rate methods for agency ranking, LP and UP separated, fatal and serious injury crash involving unrestrained (2008-2012)

Selection of Time of the Year

Selecting Time Period for Conducting Impaired Driving Enforcement

Figure 49 presents the results based on the modified critical rate method. As can be seen, there are some negative values and some positive values. Positive values indicate the weeks that are above the average and, thus, are classified as hazardous weeks. On the other hand, weeks with negative values are below the average and thus are classified as non-hazardous. From figure 49 it can be also observed that, in general, weeks in warmer months are above the average. The figure also shows weeks with mandatory enforcement for FY 2013. The weeks with the highest spikes have a greater potential to reducing targeted crashes through enforcement.

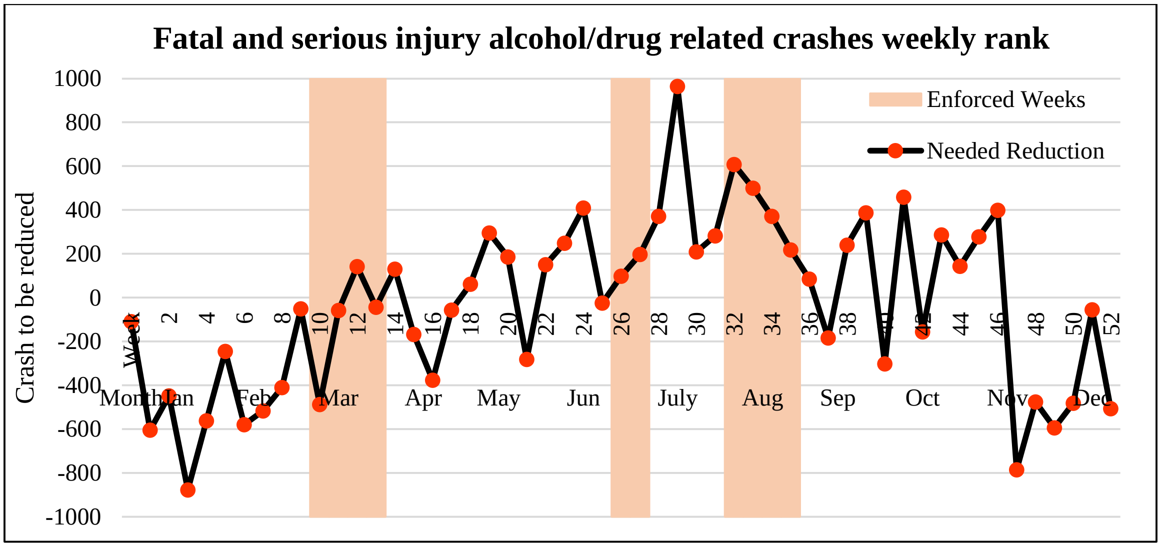


Figure 49. *Fatal and serious injury alcohol-drug related crashes weekly rank, modified critical rate method*

Selecting Time Periods for Conducting Safety Belt Enforcement

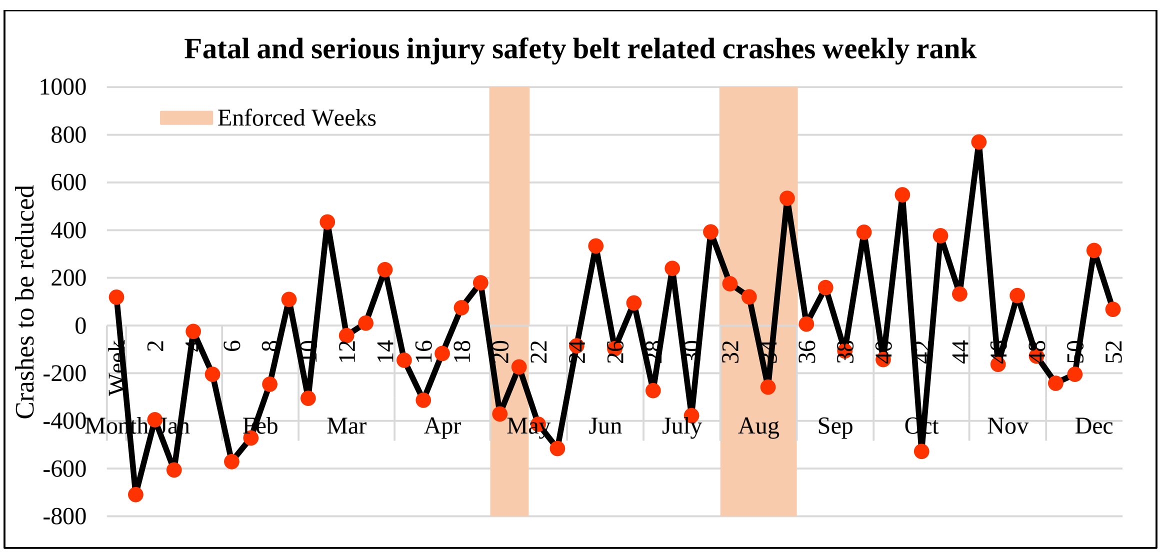


Figure 50. *Fatal and serious injury safety belt related crashes weekly rank, modified critical rate method*

Figure 50 presents the results for the modified critical rate by week. As can be seen there are some negative values and some positive values. Similar to the results of the alcohol and drug related crash analysis above, the positive values indicate weeks which are above the average while the weeks with negative values represent weeks with values below the average and thus are classified as non-hazardous. Also, the mandatory periods specified by OHSP in 2013 are shown. While the results do not show specific patterns, it can be seen that there are some weeks that deserve consideration. Weeks such as those in between 36 and 44 show a high amount of equivalent crashes to be reduced in order for them to be at the average level.

CONCLUSIONS

Conclusions

The objectives of this study were: (1) determining the impact of overtime traffic enforcement activities on crash occurrence; (2) identifying areas with potential to reduce crashes; and (3) identifying time periods when overtime traffic enforcement activities should be conducted in order to increase the potential for reducing impaired and unrestrained driving related KAB crashes in Michigan. To accomplish the objectives, a variety of analyses including trend analysis, spatial analysis, and statistical analysis were performed. The modified Critical Rate (CR) method was used to identify locations with impaired and unrestrained driving related KAB crashes exceeding the state average. Results obtained from this method were compared to those obtained from the current method used by OHSP. The modified Critical Rate method was also used to identify time periods with the greatest potential for reducing targeted crashes.

Statistical analyses results demonstrate that overtime traffic enforcement activities positively impact fatal and serious injury, alcohol and drug related crashes as well as fatal and serious injury, safety belt related crashes. Specifically, the following conclusions were made:

- Mandatory and optional impaired overtime traffic enforcement activities positively impact the occurrence of fatal and serious injury, alcohol and drug related crashes.
- Mandatory and Optional impaired overtime traffic enforcement activities positively impact the occurrence alcohol and drug related crashes (80% confidence level).

- Safety belt traffic enforcement activities, when combined with paid media campaigns, positively influence both, fatal and serious injury, alcohol and drug related crashes and safety belt related crashes.

To select agencies with the greatest potential for reducing the targeted crashes, agency-level analyses were performed. The agency-level analyses helped to account for limitations associated with using county level analysis. The modified Critical Rate method enabled analyses using equivalent crashes, which account for crash severity level. The approach included normalization of crash data among different agencies, which helped compare geographically and demographically diverse agencies. It also allowed for establishing state averages used as thresholds for comparison and performance evaluation. With normalization, this method eliminated the impact of the size and other characteristics of agencies in the selection process. Analyses in which agencies in the Lower Peninsula and agencies in the Upper Peninsula were independently evaluated were also performed.

To select time periods with the greatest potential to reduce targeted crashes, the modified Critical Rate method was also used. This method allowed for identification of critical weeks – weeks with the number of targeted crashes exceeding the average week in a year.

Recommendations

Taking into consideration that maximizing the probability of reducing crashes by implementation of police enforcement programs is going to serve the dual purpose of saving lives and avoiding significant economic losses, the following recommendations for future studies are made:

- Inclusion of actual hours of enforcement worked by participating agencies in the analysis. By collecting and maintaining data on actual hours worked, more meaningful results are going be obtained.
- Include future historical data in which more quality enforcement data is available.
- Integration of level of funds available for overtime traffic enforcement into the conduction to allow more specific agencies and time periods selection.
- Explore statistical analysis approaches that can help identify the impact of enforcement on crash occurrence more accurately.

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APPENDICES

A. Appendix Selection of Agencies for Funding

Results from the modified Critical Rate method and the crash count ranking method for fatal and serious injury, alcohol and drug related crashes as well as for fatal and serious injury, safety belt related crashes are presented in the following summary tables. The modified Critical Rate method results indicated that 150 agencies above the state average have potential to reduce the number of equivalent crashes. Considering this, the top 150 agencies were selected for both ranking methods to fairly compare the results shown for both of the methodologies. In the modified Critical Rate method, the first step is to determine whether an agency is above a previously computed average for the population. After identifying agencies that are above the average, the number of equivalent non-incapacitating injury (B) crashes each agency needs to reduce to be at the average is determined. The agency with the highest number of crashes that need to be reduced is ranked at the top. On the other hand, for the crash count methodology, only crash counts are considered. Based on average fatal and serious injury (KAB) crashes, agencies are ranked in ascending order. Agencies at the top of the rank for both methodologies have been identified and presented in the tables below. Highlighted rows correspond to those agencies that can be found in both rankings. Non-highlighted rows correspond to those agencies found in only one of the methodologies. Table A-1 and Table A-2 present the top 150 agencies for ranks evaluated based on alcohol and drug related crashes for both crash count methodology and the modified Critical Rate methodology, respectively. Table A-3 and Table A-4 present the 150 agencies identified based on safety belt related crashes for both crash count methodology and the modified Critical Rate methodology, respectively. When comparing results from the crash count methodology to those from the modified Critical Rate method, applied to fatal and serious injury, alcohol and drug related crashes, it can be seen that only 80 agencies are ranked by both methods. This indicates that 47 percent of agencies in the crash count methodology are not considered to be among the most critical agencies. Also, when comparing the results for fatal and serious injury, safety belt related crashes, it was found that just 78 agencies repeat for both rank results, which indicates 48 percent of the agencies resulting at the top of the crash count methodology are not considered to be among the most critical agencies based on the results from the modified Critical Rate method.

Table A-15. *Fatal and serious injury alcohol related crashes top 150 agencies using the crash count ranking methodology*

Crash Count Methodology			
County	**Agency ID**	**KAB Alcohol Crash Count**	**Rank**
Wayne	131	160.80	1
Oakland	385	92.60	2
Kent	268	75.40	3
Kent	201	57.20	4
Washtenaw	528	54.80	5
Allegan	8	48.00	6
Ottawa	400	47.40	7
St. Clair	455	41.20	8
Monroe	347	40.60	9
Livingston	301	38.60	10
Genesee	166	38.20	11
Kalamazoo	262	34.80	12
Macomb	310	34.60	13
Eaton	144	33.80	14
Bay	36	31.60	15
Macomb	527	30.80	16
Van Buren	519	30.80	17
Jackson	258	30.40	18
Berrien	46	30.00	19
Ingham	283	29.80	20
Isabella	254	28.40	21
Tuscola	513	28.20	22
Calhoun	73	26.80	23
Montcalm	350	25.40	24
Ingham	245	25.00	25
Grand Traverse	202	24.80	26
Muskegon	361	23.80	27
Shiawassee	477	23.80	28
Ionia	247	23.40	29
Newaygo	373	22.80	30
Macomb	494	22.60	31
Saginaw	450	22.40	32
Wayne	302	21.60	33
Barry	30	20.60	34
Macomb	109	20.60	35

Lapeer	285	20.60	36
Kalamazoo	263	20.40	37
Wayne	502	20.40	38
Wayne	125	19.80	39
Marquette	322	19.00	40
St. Joseph	460	18.80	41
Oakland	529	18.60	42
Washtenaw	15	18.20	43
Sanilac	466	18.00	44
Jackson	292	17.60	45
Mecosta	330	17.40	46
Midland	340	17.40	47
Calhoun	34	17.20	48
Wayne	537	17.00	49
Oakland	511	16.80	50
Oakland	483	16.40	51
Kent	549	16.40	52
Oakland	449	16.20	53
Clinton	107	15.60	54
Otsego	398	14.80	55
Cass	86	14.60	56
Clare	102	14.20	57
Gladwin	193	14.00	58
Gratiot	205	14.00	59
Oceana	387	13.80	60
Macomb	474	13.80	61
Ogemaw	388	13.40	62
Branch	59	13.20	63
Wayne	76	13.20	64
Macomb	456	13.20	65
Macomb	98	13.00	66
Muskegon	363	13.00	67
Macomb	447	12.80	68
Chippewa	100	12.60	69
Oakland	162	12.40	70
Antrim	16	12.40	71
Houghton	235	12.40	72
Cheboygan	94	12.00	73
Leelanau	291	11.60	74
Mason	326	11.40	75

Oakland	21	11.40	76
Hillsdale	228	11.40	77
Kent	524	11.40	78
Emmet	153	11.20	79
Osceola	394	11.20	80
Arenac	17	11.20	81
Huron	241	11.20	82
Charlevoix	91	11.00	83
Wexford	538	11.00	84
Oakland	540	10.80	85
Alpena	13	10.80	86
Saginaw	451	10.80	87
Genesee	167	10.60	88
St. Clair	420	10.60	89
Wayne	520	10.60	90
Genesee	188	10.40	91
Genesee	70	10.20	92
Iosco	249	10.20	93
Jackson	259	9.60	94
Manistee	314	9.60	95
Kalkaska	265	9.60	96
Wayne	297	9.60	97
Kalamazoo	422	9.60	98
Wayne	429	9.60	99
Oakland	311	9.40	100
Alcona	5	9.20	101
Oakland	225	9.00	102
Missaukee	346	9.00	103
Monroe	348	8.40	104
Oakland	55	8.40	105
Wayne	443	8.40	106
Wayne	66	8.20	107
Delta	128	8.20	108
Lake	277	8.20	109
Genesee	198	8.00	110
Oakland	383	8.00	111
Crawford	120	8.00	112
Mackinac	307	7.80	113
Washtenaw	414	7.80	114
Kent	269	7.60	115

Benzie	44	7.40	116
Bay	35	7.40	117
Isabella	358	7.40	118
Iron	250	7.40	119
Ottawa	230	7.20	120
Wayne	124	7.00	121
Roscommon	445	7.00	122
Dickinson	134	7.00	123
Ingham	142	6.80	124
Wayne	534	6.80	125
Menominee	334	6.60	126
Oakland	535	6.60	127
Livingston	207	6.60	128
Schoolcraft	469	6.40	129
Saginaw	452	6.40	130
Gogebic	195	6.20	131
Calhoun	154	6.20	132
Kalamazoo	264	6.20	133
Alger	6	6.20	134
Ontonagon	391	6.00	135
Wayne	533	6.00	136
Washtenaw	551	6.00	137
Macomb	143	5.80	138
Oakland	164	5.80	139
Wayne	10	5.80	140
Genesee	189	5.80	141
Midland	341	5.60	142
Muskegon	381	5.60	143
Genesee	123	5.40	144
Oscoda	395	5.20	145
Presque Isle	426	5.20	146
Muskegon	364	5.00	147
Chippewa	468	5.00	148
Wayne	221	4.80	149
Genesee	359	4.80	150

Table A-2. *Fatal and serious injury alcohol related crashes top 150 agencies using the modified critical rate ranking methodology*

Modified Critical Rate Methodology Rank			
County	**Agency ID**	**Crash to be reduced**	**Rank**
Wayne	131	5,519.03	1
Genesee	166	1,158.24	2
Kent	268	773.44	3
Monroe	347	695.86	4
Kent	201	669.81	5
Washtenaw	528	641.42	6
Bay	36	578.71	7
Macomb	527	548.63	8
Oakland	385	526.72	9
St. Clair	455	436.61	10
Macomb	310	418.96	11
Kent	549	414.83	12
Wayne	502	392.69	13
Allegan	8	378.61	14
Macomb	494	376.83	15
Ingham	283	350.08	16
St. Joseph	460	293.55	17
Jackson	258	282.36	18
Wayne	537	261.35	19
Wayne	443	257.24	20
Calhoun	34	247.10	21
Macomb	98	244.91	22
Oakland	529	237.65	23
Isabella	254	230.19	24
Wayne	429	227.22	25
Genesee	167	217.91	26
Wayne	302	215.68	27
Kalamazoo	262	213.36	28
Macomb	109	211.55	29
Berrien	46	195.01	30
Oakland	540	192.18	31
Kalamazoo	263	187.24	32
Saginaw	450	182.75	33
Oakland	511	177.28	34
Muskegon	363	168.30	35

Wayne	297	162.13	36
Monroe	155	160.33	37
Eaton	144	158.05	38
Macomb	447	151.39	39
Berrien	461	150.87	40
Kent	524	144.32	41
Oakland	225	139.15	42
Kalamazoo	422	125.41	43
Monroe	348	123.14	44
Muskegon	361	122.58	45
Genesee	188	122.48	46
St. Clair	420	117.71	47
Livingston	207	117.20	48
Kalamazoo	264	115.45	49
Oakland	483	113.82	50
Saginaw	68	108.83	51
Wayne	125	108.08	52
St. Joseph	496	105.33	53
Genesee	70	105.07	54
Genesee	359	101.78	55
Genesee	123	85.89	56
St. Clair	105	85.34	57
Wayne	66	85.11	58
Houghton	218	78.92	59
Genesee	198	77.76	60
Oakland	21	73.13	61
Wayne	510	72.70	62
Wayne	520	71.73	63
Genesee	189	70.29	64
Livingston	301	69.13	65
Wayne	534	68.51	66
Saginaw	451	68.15	67
Berrien	43	67.64	68
Van Buren	519	66.93	69
Marquette	323	64.07	70
Kent	269	63.73	71
Wayne	533	63.32	72
Wayne	418	62.22	73
Ingham	245	62.15	74
Berrien	298	61.79	75

Oakland	384	60.58	76
Wayne	484	60.23	77
Oakland	311	57.44	78
Jackson	259	56.33	79
Wayne	10	55.26	80
Macomb	456	53.93	81
Jackson	365	52.40	82
Wayne	546	51.51	83
Midland	341	51.02	84
St. Joseph	117	50.76	85
Jackson	52	50.11	86
Macomb	89	48.53	87
Montcalm	237	46.90	88
Livingston	515	44.70	89
Kent	88	44.38	90
Saginaw	452	40.27	91
Eaton	93	39.24	92
Calhoun	489	37.42	93
Berrien	42	36.81	94
Monroe	138	33.66	95
Ingham	142	31.98	96
Washtenaw	551	29.77	97
Delta	192	29.53	98
Oakland	280	29.02	99
Lenawee	1	28.04	100
Washtenaw	414	27.68	101
Wayne	227	27.33	102
Washtenaw	15	27.17	103
Genesee	504	26.03	104
Wayne	440	25.54	105
Macomb	518	23.40	106
Wayne	191	22.00	107
Oakland	449	21.75	108
Calhoun	154	21.71	109
Macomb	371	20.96	110
Wayne	436	19.56	111
Cass	392	18.60	112
Lapeer	243	18.11	113
Oakland	404	17.48	114
Allegan	415	17.34	115

Oakland	544	17.33	116
Muskegon	381	17.09	117
Newaygo	539	17.05	118
Monroe	482	16.84	119
Calhoun	233	16.46	120
Barry	425	16.26	121
Saginaw	97	15.59	122
Iosco	501	15.15	123
Barry	339	15.10	124
Wayne	147	14.29	125
Berrien	62	13.61	126
Oakland	231	13.47	127
Newaygo	374	13.23	128
Arenac	17	12.94	129
Saginaw	61	12.90	130
Genesee	163	11.81	131
Isabella	358	11.37	132
Oakland	45	11.09	133
Oakland	343	10.28	134
Barry	31	9.64	135
Saginaw	434	9.42	136
Washtenaw	378	9.38	137
Washtenaw	463	9.36	138
Ingham	284	9.22	139
Livingston	63	9.12	140
Saginaw	508	8.82	141
Ottawa	552	8.79	142
Gratiot	257	8.67	143
Oakland	54	8.26	144
Wayne	212	8.21	145
Marquette	255	8.08	146
Wayne	379	7.89	147
Macomb	143	7.82	148
Marquette	367	7.77	149
Muskegon	542	7.76	150

Table A-3. *Fatal and serious injury safety belt related crashes top 150 agencies using the crash count ranking methodology*

Crash Count Methodology			
County	**Agency ID**	**KAB Safety Belt Crash Count**	**Rank**
Wayne	131	321.2	1
Oakland	385	103.6	2
Kent	201	90	3
Kent	268	73.8	4
Washtenaw	528	57.6	5
Ottawa	400	57.6	6
Monroe	347	56.2	7
Ingham	283	48.8	8
Macomb	527	48.2	9
Kalamazoo	263	48	10
Macomb	310	45.6	11
Allegan	8	45.2	12
St. Clair	455	44.2	13
Genesee	166	42.8	14
Bay	36	42.4	15
Wayne	125	42.2	16
Livingston	301	41.8	17
Saginaw	451	41.2	18
Oceana	387	40.6	19
Ottawa	230	38.6	20
Washtenaw	15	37.6	21
Macomb	109	37.2	22
Bay	35	35.8	23
Kalamazoo	262	35.8	24
Van Buren	519	33.6	25
Calhoun	73	33.6	26
Berrien	46	33	27
Wayne	302	32.6	28
Kent	549	32.4	29
Macomb	447	31.6	30
Muskegon	363	31.6	31
Saginaw	452	31.6	32
Montcalm	350	31	33
Oakland	483	30.4	34
Isabella	254	29.6	35

Wayne	502	29.4	36
Oakland	449	28.8	37
Eaton	144	28.8	38
Wayne	537	28.6	39
Macomb	494	27.8	40
Ionia	247	27.8	41
Newaygo	373	27.4	42
Saginaw	450	27	43
Tuscola	513	26.8	44
Ingham	142	26.6	45
Jackson	258	26.2	46
Muskegon	361	25.4	47
Oakland	511	24.8	48
Calhoun	34	24.4	49
St. Clair	420	24.4	50
Lapeer	285	23.6	51
Ingham	245	23.4	52
St. Joseph	460	23.2	53
Macomb	456	22.2	54
Grand Traverse	202	21	55
Jackson	292	20.8	56
Osceola	394	20.8	57
Sanilac	466	20.6	58
Shiawassee	477	20.6	59
Mecosta	330	20.4	60
Oakland	529	19.6	61
Clare	102	19.2	62
Oakland	162	19.2	63
Jackson	259	19	64
Midland	340	18.8	65
Wayne	76	18.6	66
Emmet	153	18.6	67
Hillsdale	228	18.6	68
Otsego	398	17.6	69
Wayne	429	17	70
Mason	326	16.8	71
Cass	86	16.2	72
Cheboygan	94	16.2	73
Clinton	107	16.2	74
Marquette	322	16.2	75

Barry	30	15.4	76
Chippewa	100	15.4	77
Macomb	474	15.2	78
Wayne	124	14.6	79
Alcona	5	14.4	80
Oakland	311	14.4	81
Branch	59	14.2	82
Charlevoix	91	14.2	83
Ogemaw	388	14.2	84
Kalamazoo	422	13.4	85
Wayne	484	13.2	86
Genesee	188	13.2	87
Gratiot	205	13.2	88
Alpena	13	13	89
Wayne	443	13	90
Huron	241	12.8	91
Houghton	235	12.8	92
Oakland	21	12.6	93
Wayne	217	12.6	94
Gladwin	193	12.4	95
Antrim	16	12.2	96
Genesee	70	12.2	97
Wexford	538	12	98
Delta	128	11.8	99
Midland	341	11.8	100
Oakland	164	11.6	101
Arenac	17	11.6	102
Kalamazoo	264	11.6	103
Oakland	225	11.4	104
Wayne	297	11.4	105
Macomb	98	11.2	106
Wayne	418	11.2	107
Wayne	520	11.2	108
Iosco	249	11	109
Kent	524	10.8	110
Genesee	167	10.8	111
Berrien	43	10.6	112
Missaukee	346	10.6	113
Oakland	383	10.4	114
Washtenaw	414	10.4	115

Crawford	120	10.4	116
Wayne	66	10.2	117
Menominee	334	10.2	118
Grand Traverse	509	10.2	119
Muskegon	364	9.8	120
Oakland	55	9.6	121
Manistee	314	9.6	122
Muskegon	381	9.6	123
Kalkaska	265	9.4	124
Oakland	540	9.4	125
Leelanau	291	9.4	126
Isabella	358	9.2	127
Alger	6	9	128
Wayne	246	8.8	129
Monroe	348	8.8	130
Chippewa	468	8.8	131
Calhoun	154	8.8	132
Kent	269	8.4	133
Marquette	323	8.4	134
Oakland	384	8.4	135
Washtenaw	551	8.4	136
Macomb	143	8.2	137
Livingston	207	8.2	138
Mackinac	307	8.2	139
Wayne	534	8	140
Wayne	185	7.8	141
Dickinson	134	7.6	142
Genesee	357	7.6	143
Genesee	189	7.6	144
Wexford	72	7.4	145
Lake	277	7.4	146
Oscoda	395	7.2	147
Wayne	548	7.2	148
Benzie	44	7.2	149
Shiawassee	403	7.2	150

Table A-4. *Fatal and serious injury safety belt related crashes top 150 agencies using the modified critical rate ranking methodology*

Modified Critical Rate Methodology Rank			
County	**Agency ID**	**Crash to be reduced**	**Rank**
Wayne	131	10,053.39	1
Kent	201	1,160.99	2
Genesee	166	1,140.03	3
Monroe	347	1,053.60	4
Wayne	429	772.70	5
Macomb	447	692.27	6
Ingham	283	602.54	7
Macomb	527	598.80	8
Kent	549	585.16	9
Wayne	302	545.44	10
Wayne	502	516.34	11
Wayne	537	495.68	12
Muskegon	363	471.40	13
Macomb	109	423.85	14
Macomb	310	418.02	15
Oakland	511	395.74	16
Kalamazoo	263	375.68	17
Oakland	483	374.14	18
Macomb	494	346.39	19
Saginaw	451	339.73	20
Washtenaw	528	334.86	21
Oakland	225	333.56	22
Wayne	443	332.85	23
St. Clair	420	310.13	24
Macomb	98	298.59	25
Saginaw	452	291.58	26
Bay	36	290.00	27
Genesee	189	285.88	28
Wayne	125	285.30	29
Kent	268	280.91	30
Oakland	385	248.86	31
Bay	35	248.61	32
Genesee	70	247.48	33
Calhoun	34	234.28	34
Washtenaw	414	191.12	35

Wayne	418	189.23	36
Ingham	142	187.06	37
Monroe	155	182.84	38
Ottawa	230	178.40	39
Washtenaw	15	177.60	40
Wayne	246	173.02	41
Saginaw	450	163.91	42
St. Clair	455	163.58	43
Marquette	323	160.46	44
Wayne	484	155.75	45
Oakland	311	149.25	46
Genesee	359	147.97	47
Kalamazoo	264	144.48	48
Wayne	217	141.27	49
Genesee	123	137.66	50
Berrien	43	135.44	51
St. Joseph	496	134.58	52
Berrien	29	131.44	53
Oakland	449	127.58	54
Genesee	504	127.56	55
Oakland	21	126.88	56
Berrien	461	125.62	57
Monroe	348	121.85	58
Wayne	10	116.82	59
Oakland	384	116.66	60
Wayne	534	114.80	61
Washtenaw	551	114.07	62
Macomb	89	111.65	63
Jackson	259	108.38	64
Wayne	436	106.57	65
Wayne	66	106.10	66
Lenawee	427	102.01	67
Macomb	456	101.33	68
Kent	524	95.63	69
Wayne	147	94.02	70
Oakland	540	90.06	71
Genesee	167	89.75	72
Houghton	236	86.34	73
Muskegon	362	85.48	74
Berrien	46	85.47	75

Wayne	297	82.10	76
Oakland	164	82.03	77
Oakland	162	78.99	78
Macomb	518	77.35	79
Wayne	76	75.47	80
Ingham	284	70.76	81
Wayne	520	68.95	82
Muskegon	381	68.48	83
Oakland	416	67.71	84
Barry	425	66.59	85
Wayne	221	64.78	86
Macomb	371	61.00	87
Kalamazoo	470	60.91	88
Midland	341	59.60	89
Oakland	529	59.59	90
Livingston	207	57.76	91
Saginaw	61	55.58	92
Muskegon	364	53.35	93
Gratiot	462	53.30	94
Wayne	546	50.08	95
Genesee	188	50.06	96
Lenawee	1	48.41	97
Wayne	533	48.28	98
St. Clair	105	46.90	99
Monroe	342	43.73	100
Grand Traverse	509	41.11	101
Macomb	143	40.92	102
Kent	269	40.90	103
Calhoun	489	40.60	104
Mecosta	49	40.00	105
Genesee	182	38.45	106
Jackson	490	37.48	107
Eaton	93	37.11	108
Saginaw	553	37.04	109
Wayne	331	33.97	110
Saginaw	486	33.12	111
Bay	216	30.82	112
Delta	156	30.69	113
Genesee	198	29.47	114
St. Clair	320	29.45	115

Shiawassee	522	28.81	116
Berrien	298	27.76	117
Washtenaw	378	27.64	118
Wayne	124	25.46	119
Tuscola	329	25.25	120
Oakland	404	24.81	121
Oakland	280	24.36	122
Oceana	226	23.22	123
Montcalm	281	21.53	124
Delta	192	21.47	125
St. Joseph	117	20.88	126
Genesee	356	20.82	127
Oakland	383	19.32	128
Oakland	393	18.92	129
Montcalm	237	18.58	130
St. Clair	77	18.53	131
Sanilac	465	17.80	132
Lenawee	353	16.94	133
Wayne	227	16.70	134
Newaygo	539	16.50	135
Iosco	501	16.32	136
Lapeer	243	15.83	137
Newaygo	374	15.76	138
Genesee	122	15.63	139
Cass	87	15.35	140
Allegan	415	15.33	141
Hillsdale	260	15.32	142
Isabella	358	14.85	143
Shiawassee	409	13.96	144
Saginaw	505	13.81	145
Eaton	200	13.62	146
Wayne	209	13.25	147
Kent	303	12.82	148
Genesee	163	12.40	149
Tuscola	244	11.33	150

B. Appendix; *Selection of Agencies for Funding (Separated Peninsula Analysis)*

Table B-1. *Fatal and serious injury alcohol-drug related crashes top 149 agencies using the crash count ranking methodology for agencies in the Lower Peninsula.*

Crash Count Methodology			
County	**Agency ID**	**KAB alcohol crash count**	**Rank**
Wayne	131	160.8	1
Oakland	385	92.6	2
Kent	268	75.4	3
Kent	201	57.2	4
Washtenaw	528	54.8	5
Allegan	8	48	6
Ottawa	400	47.4	7
St. Clair	455	41.2	8
Monroe	347	40.6	9
Livingston	301	38.6	10
Genesee	166	38.2	11
Kalamazoo	262	34.8	12
Macomb	310	34.6	13
Eaton	144	33.8	14
Bay	36	31.6	15
Van Buren	519	30.8	16
Macomb	527	30.8	17
Jackson	258	30.4	18
Berrien	46	30	19
Ingham	283	29.8	20
Isabella	254	28.4	21
Tuscola	513	28.2	22
Calhoun	73	26.8	23
Montcalm	350	25.4	24
Ingham	245	25	25
Grand Traverse	202	24.8	26
Muskegon	361	23.8	27
Shiawassee	477	23.8	28
Ionia	247	23.4	29
Newaygo	373	22.8	30
Macomb	494	22.6	31
Saginaw	450	22.4	32

Wayne	302	21.6	33
Barry	30	20.6	34
Macomb	109	20.6	35
Lapeer	285	20.6	36
Kalamazoo	263	20.4	37
Wayne	502	20.4	38
Wayne	125	19.8	39
St. Joseph	460	18.8	40
Oakland	529	18.6	41
Washtenaw	15	18.2	42
Sanilac	466	18	43
Jackson	292	17.6	44
Mecosta	330	17.4	45
Midland	340	17.4	46
Calhoun	34	17.2	47
Wayne	537	17	48
Oakland	511	16.8	49
Oakland	483	16.4	50
Kent	549	16.4	51
Oakland	449	16.2	52
Clinton	107	15.6	53
Otsego	398	14.8	54
Cass	86	14.6	55
Clare	102	14.2	56
Gladwin	193	14	57
Gratiot	205	14	58
Oceana	387	13.8	59
Macomb	474	13.8	60
Ogemaw	388	13.4	61
Branch	59	13.2	62
Wayne	76	13.2	63
Macomb	456	13.2	64
Macomb	98	13	65
Muskegon	363	13	66
Macomb	447	12.8	67
Antrim	16	12.4	68
Oakland	162	12.4	69
Cheboygan	94	12	70
Leelanau	291	11.6	71
Oakland	21	11.4	72

Hillsdale	228	11.4	73
Mason	326	11.4	74
Kent	524	11.4	75
Arenac	17	11.2	76
Emmet	153	11.2	77
Huron	241	11.2	78
Osceola	394	11.2	79
Charlevoix	91	11	80
Wexford	538	11	81
Alpena	13	10.8	82
Saginaw	451	10.8	83
Oakland	540	10.8	84
Genesee	167	10.6	85
St. Clair	420	10.6	86
Wayne	520	10.6	87
Genesee	188	10.4	88
Genesee	70	10.2	89
Iosco	249	10.2	90
Jackson	259	9.6	91
Kalkaska	265	9.6	92
Wayne	297	9.6	93
Manistee	314	9.6	94
Kalamazoo	422	9.6	95
Wayne	429	9.6	96
Oakland	311	9.4	97
Alcona	5	9.2	98
Oakland	225	9	99
Missaukee	346	9	100
Oakland	55	8.4	101
Monroe	348	8.4	102
Wayne	443	8.4	103
Wayne	66	8.2	104
Lake	277	8.2	105
Crawford	120	8	106
Genesee	198	8	107
Oakland	383	8	108
Washtenaw	414	7.8	109
Kent	269	7.6	110
Bay	35	7.4	111
Benzie	44	7.4	112

Isabella	358	7.4	113
Ottawa	230	7.2	114
Wayne	124	7	115
Roscommon	445	7	116
Ingham	142	6.8	117
Wayne	534	6.8	118
Livingston	207	6.6	119
Oakland	535	6.6	120
Saginaw	452	6.4	121
Calhoun	154	6.2	122
Kalamazoo	264	6.2	123
Wayne	533	6	124
Washtenaw	551	6	125
Wayne	10	5.8	126
Macomb	143	5.8	127
Oakland	164	5.8	128
Genesee	189	5.8	129
Midland	341	5.6	130
Muskegon	381	5.6	131
Genesee	123	5.4	132
Oscoda	395	5.2	133
Presque Isle	426	5.2	134
Muskegon	364	5	135
Jackson	52	4.8	136
Wayne	221	4.8	137
Wayne	246	4.8	138
Genesee	359	4.8	139
Wayne	418	4.8	140
Genesee	432	4.8	141
Wayne	484	4.8	142
Saginaw	61	4.6	143
Genesee	357	4.6	144
Berrien	43	4.2	145
Saginaw	68	4.2	146
Washtenaw	378	4.2	147
Monroe	155	4	148
Muskegon	179	4	149

Table B-2. *Fatal and serious injury alcohol-drug related crashes top 149 agencies using the modified critical rate ranking methodology for agencies in the Lower Peninsula.*

Modified Critical Rate Methodology			
County	**Agency ID**	**Crashes to be Reduced**	**Rank**
Wayne	131	5484.295	1
Genesee	166	1151.157	2
Kent	268	741.7458	3
Monroe	347	676.7139	4
Kent	201	661.237	5
Washtenaw	528	617.6241	6
Bay	36	564.5758	7
Macomb	527	542.2682	8
Oakland	385	491.0615	9
St. Clair	455	416.2888	10
Kent	549	411.1845	11
Macomb	310	404.4688	12
Wayne	502	389.2309	13
Macomb	494	370.9824	14
Allegan	8	352.3662	15
Ingham	283	343.9721	16
St. Joseph	460	279.475	17
Jackson	258	269.1235	18
Wayne	537	257.5265	19
Wayne	443	256.6192	20
Calhoun	34	242.4521	21
Macomb	98	241.9225	22
Oakland	529	233.3455	23
Wayne	429	224.4448	24
Genesee	167	214.9548	25
Isabella	254	214.8147	26
Wayne	302	209.9006	27
Macomb	109	206.8082	28
Kalamazoo	262	196.0272	29
Oakland	540	189.3737	30
Kalamazoo	263	183.0581	31
Berrien	46	180.8154	32
Oakland	511	171.8982	33
Saginaw	450	167.2992	34
Muskegon	363	165.5159	35
Wayne	297	160.3437	36
Monroe	155	158.9818	37

Berrien	461	149.8242	38
Macomb	447	149.0579	39
Kent	524	142.0232	40
Eaton	144	140.4457	41
Oakland	225	138.122	42
Monroe	348	121.7766	43
Kalamazoo	422	121.757	44
Genesee	188	116.4222	45
St. Clair	420	115.7503	46
Livingston	207	114.6359	47
Kalamazoo	264	113.5977	48
Oakland	483	109.3704	49
Muskegon	361	108.7282	50
Saginaw	68	106.8272	51
St. Joseph	496	104.3813	52
Wayne	125	102.925	53
Genesee	70	102.4049	54
Genesee	359	99.83248	55
St. Clair	105	84.03977	56
Genesee	123	84.03716	57
Wayne	66	82.68728	58
Genesee	198	74.62987	59
Wayne	510	71.49434	60
Oakland	21	70.87711	61
Wayne	520	68.73833	62
Genesee	189	68.08166	63
Wayne	534	67.42161	64
Berrien	43	64.98588	65
Saginaw	451	64.296	66
Kent	269	61.08532	67
Wayne	533	60.9834	68
Berrien	298	60.10271	69
Wayne	418	59.47303	70
Oakland	384	59.24326	71
Wayne	484	58.66629	72
Oakland	311	55.725	73
Jackson	259	54.14627	74
Wayne	10	53.51209	75
Macomb	456	51.19542	76
Jackson	365	51.17355	77
Wayne	546	50.59791	78
St. Joseph	117	50.42118	79

Livingston	301	49.81474	80
Van Buren	519	48.70671	81
Macomb	89	48.01647	82
Ingham	245	47.91152	83
Jackson	52	47.75184	84
Midland	341	47.17126	85
Montcalm	237	46.47791	86
Kent	88	43.97593	87
Livingston	515	43.48767	88
Eaton	93	38.3959	89
Saginaw	452	37.40949	90
Calhoun	489	36.73015	91
Berrien	42	35.9132	92
Monroe	138	32.97461	93
Ingham	142	29.93393	94
Oakland	280	28.77205	95
Washtenaw	551	28.73756	96
Lenawee	1	26.69974	97
Wayne	227	26.51063	98
Wayne	440	25.22607	99
Washtenaw	414	24.90461	100
Genesee	504	24.71124	101
Macomb	518	22.89463	102
Washtenaw	15	22.31517	103
Wayne	191	21.59171	104
Macomb	371	20.50498	105
Calhoun	154	19.73492	106
Wayne	436	19.11683	107
Oakland	449	18.60991	108
Lapeer	243	17.70039	109
Cass	392	17.34305	110
Oakland	404	17.18516	111
Allegan	415	16.91787	112
Newaygo	539	16.76455	113
Monroe	482	16.4872	114
Oakland	544	16.38434	115
Calhoun	233	16.16863	116
Saginaw	97	15.21778	117
Barry	425	14.97218	118
Iosco	501	14.80945	119
Barry	339	14.69125	120
Muskegon	381	14.50691	121

Wayne	147	13.7397	122
Berrien	62	13.21064	123
Oakland	231	12.98336	124
Newaygo	374	12.78229	125
Saginaw	61	11.04069	126
Genesee	163	10.82434	127
Oakland	45	10.31825	128
Isabella	358	10.06381	129
Oakland	343	9.76802	130
Washtenaw	463	8.742487	131
Livingston	63	8.455356	132
Ottawa	552	8.244113	133
Barry	31	8.187418	134
Ingham	284	8.182473	135
Gratiot	257	8.147033	136
Saginaw	434	7.89454	137
Wayne	212	7.587878	138
Washtenaw	378	7.540524	139
Oakland	54	7.488013	140
Wayne	379	7.370241	141
Muskegon	542	7.262033	142
Saginaw	508	7.17302	143
Kent	439	6.697359	144
Macomb	143	6.326452	145
Eaton	200	6.023571	146
Lenawee	2	6.020373	147
Tuscola	79	5.539764	148
Wayne	209	5.240565	149

Table B-3. *Fatal and serious injury alcohol-drug related crashes top 10 agencies using the crash count ranking methodology for agencies in the Upper Peninsula.*

Crash Count Methodology			
County	**Agency ID**	**KAB alcohol crash count**	**Rank**
Marquette	322	19	1
Chippewa	100	12.6	2
Houghton	235	12.4	3
Delta	128	8.2	4
Mackinac	307	7.8	5
Iron	250	7.4	6
Dickinson	134	7	7
Menominee	334	6.6	8
Schoolcraft	469	6.4	9
Alger	6	6.2	10

Table B-4. *Fatal and serious injury alcohol-drug related crashes top 10 agencies using the modified critical rate ranking methodology for agencies in the Lower Peninsula.*

Modified Critical Rate Methodology			
County	**Agency ID**	**Crashes to be Reduced**	**Rank**
Houghton	218	85.40	1
Marquette	323	79.31	2
Delta	192	39.11	3
Keweenaw	270	24.35	4
Chippewa	468	20.38	5
Marquette	367	16.25	6
Marquette	255	16.25	7
Houghton	236	11.55	8
Mackinac	308	10.06	9
Menominee	335	8.97	10

Table B-5. *Fatal and serious injury safety-belt related crashes top 153 agencies using the crash count ranking methodology for agencies in the Lower Peninsula.*

Crash Count Methodology			
County	**Agency ID**	**KAB safety belt crash count**	**Rank**
Wayne	131	321.2	1
Oakland	385	103.6	2
Kent	201	90	3
Kent	268	73.8	4
Ottawa	400	57.6	5
Washtenaw	528	57.6	6
Monroe	347	56.2	7
Ingham	283	48.8	8
Macomb	527	48.2	9
Kalamazoo	263	48	10
Macomb	310	45.6	11
Allegan	8	45.2	12
St. Clair	455	44.2	13
Genesee	166	42.8	14
Bay	36	42.4	15
Wayne	125	42.2	16
Livingston	301	41.8	17
Saginaw	451	41.2	18
Oceana	387	40.6	19
Ottawa	230	38.6	20
Washtenaw	15	37.6	21
Macomb	109	37.2	22
Bay	35	35.8	23
Kalamazoo	262	35.8	24
Calhoun	73	33.6	25
Van Buren	519	33.6	26
Berrien	46	33	27
Wayne	302	32.6	28
Kent	549	32.4	29
Muskegon	363	31.6	30
Macomb	447	31.6	31
Saginaw	452	31.6	32
Montcalm	350	31	33
Oakland	483	30.4	34
Isabella	254	29.6	35
Wayne	502	29.4	36
Eaton	144	28.8	37

Oakland	449	28.8	38
Wayne	537	28.6	39
Ionia	247	27.8	40
Macomb	494	27.8	41
Newaygo	373	27.4	42
Saginaw	450	27	43
Tuscola	513	26.8	44
Ingham	142	26.6	45
Jackson	258	26.2	46
Muskegon	361	25.4	47
Oakland	511	24.8	48
Calhoun	34	24.4	49
St. Clair	420	24.4	50
Lapeer	285	23.6	51
Ingham	245	23.4	52
St. Joseph	460	23.2	53
Macomb	456	22.2	54
Grand Traverse	202	21	55
Jackson	292	20.8	56
Osceola	394	20.8	57
Sanilac	466	20.6	58
Shiawassee	477	20.6	59
Mecosta	330	20.4	60
Oakland	529	19.6	61
Clare	102	19.2	62
Oakland	162	19.2	63
Jackson	259	19	64
Midland	340	18.8	65
Wayne	76	18.6	66
Emmet	153	18.6	67
Hillsdale	228	18.6	68
Otsego	398	17.6	69
Wayne	429	17	70
Mason	326	16.8	71
Cass	86	16.2	72
Cheboygan	94	16.2	73
Clinton	107	16.2	74
Barry	30	15.4	75
Macomb	474	15.2	76
Wayne	124	14.6	77
Alcona	5	14.4	78
Oakland	311	14.4	79

Branch	59	14.2	80
Charlevoix	91	14.2	81
Ogemaw	388	14.2	82
Kalamazoo	422	13.4	83
Genesee	188	13.2	84
Gratiot	205	13.2	85
Wayne	484	13.2	86
Alpena	13	13	87
Wayne	443	13	88
Huron	241	12.8	89
Oakland	21	12.6	90
Wayne	217	12.6	91
Gladwin	193	12.4	92
Antrim	16	12.2	93
Genesee	70	12.2	94
Wexford	538	12	95
Midland	341	11.8	96
Arenac	17	11.6	97
Oakland	164	11.6	98
Kalamazoo	264	11.6	99
Oakland	225	11.4	100
Wayne	297	11.4	101
Macomb	98	11.2	102
Wayne	418	11.2	103
Wayne	520	11.2	104
Iosco	249	11	105
Genesee	167	10.8	106
Kent	524	10.8	107
Berrien	43	10.6	108
Missaukee	346	10.6	109
Crawford	120	10.4	110
Oakland	383	10.4	111
Washtenaw	414	10.4	112
Wayne	66	10.2	113
Grand Traverse	509	10.2	114
Muskegon	364	9.8	115
Oakland	55	9.6	116
Manistee	314	9.6	117
Muskegon	381	9.6	118
Kalkaska	265	9.4	119
Leelanau	291	9.4	120
Oakland	540	9.4	121

Isabella	358	9.2	122
Calhoun	154	8.8	123
Wayne	246	8.8	124
Monroe	348	8.8	125
Kent	269	8.4	126
Oakland	384	8.4	127
Washtenaw	551	8.4	128
Macomb	143	8.2	129
Livingston	207	8.2	130
Wayne	534	8	131
Wayne	185	7.8	132
Genesee	189	7.6	133
Genesee	357	7.6	134
Wexford	72	7.4	135
Lake	277	7.4	136
Benzie	44	7.2	137
Oscoda	395	7.2	138
Shiawassee	403	7.2	139
Wayne	548	7.2	140
Wayne	10	7	141
Oakland	535	7	142
Bay	216	6.8	143
Genesee	359	6.8	144
Branch	111	6.6	145
Macomb	175	6.6	146
Ingham	336	6.6	147
Alpena	14	6.4	148
Genesee	198	6.4	149
Jackson	52	6	150
Genesee	123	5.8	151
Ottawa	199	5.8	152
Wayne	221	5.8	153

Table B-6 *Fatal and serious injury safety belt related crashes top 153 agencies using the modified critical rate ranking methodology for agencies in the Lower Peninsula.*

Modified Critical Rate Methodology			
County	**Agency ID**	**Crashes to be Reduced**	**Rank**
Wayne	131	9943.50	1
Kent	201	1134.06	2
Genesee	166	1117.80	3
Monroe	347	993.18	4
Wayne	429	764.07	5
Macomb	447	685.02	6
Ingham	283	583.39	7
Macomb	527	578.86	8
Kent	549	573.79	9
Wayne	302	527.35	10
Wayne	502	505.57	11
Wayne	537	483.76	12
Muskegon	363	462.76	13
Macomb	109	409.02	14
Oakland	511	378.88	15
Macomb	310	372.34	16
Kalamazoo	263	362.62	17
Oakland	483	360.24	18
Wayne	443	330.96	19
Oakland	225	330.42	20
Macomb	494	328.09	21
Saginaw	451	327.70	22
St. Clair	420	304.07	23
Macomb	98	289.28	24
Saginaw	452	282.69	25
Genesee	189	279.05	26
Wayne	125	269.17	27
Washtenaw	528	259.70	28
Bay	36	245.47	29
Bay	35	240.84	30
Genesee	70	239.18	31
Calhoun	34	219.75	32
Washtenaw	414	182.49	33
Ingham	142	180.73	34
Wayne	418	180.68	35
Kent	268	180.67	36
Monroe	155	178.68	37

Ottawa	230	171.30	38
Wayne	246	168.40	39
Washtenaw	15	162.41	40
Wayne	484	150.91	41
Oakland	311	143.94	42
Genesee	359	141.93	43
Wayne	217	139.28	44
Kalamazoo	264	138.76	45
Oakland	385	136.04	46
Genesee	123	131.92	47
St. Joseph	496	131.66	48
Berrien	29	127.40	49
Berrien	43	127.20	50
Genesee	504	123.51	51
Berrien	461	122.43	52
Oakland	21	119.91	53
Oakland	449	117.81	54
Monroe	348	117.66	55
Saginaw	450	115.20	56
Oakland	384	112.56	57
Wayne	534	111.45	58
Wayne	10	111.43	59
Washtenaw	551	110.92	60
Macomb	89	110.10	61
Wayne	436	105.25	62
Jackson	259	101.62	63
St. Clair	455	99.44	64
Wayne	66	98.59	65
Lenawee	427	97.36	66
Macomb	456	92.84	67
Wayne	147	92.35	68
Kent	524	88.52	69
Muskegon	362	82.59	70
Oakland	540	81.33	71
Genesee	167	80.55	72
Oakland	164	78.63	73
Wayne	297	76.59	74
Macomb	518	75.81	75
Ingham	284	67.58	76
Oakland	416	67.06	77
Barry	425	62.64	78
Wayne	221	62.31	79

Oakland	162	62.12	80
Muskegon	381	60.47	81
Wayne	76	60.36	82
Kalamazoo	470	60.05	83
Wayne	520	59.65	84
Macomb	371	59.63	85
Gratiot	462	51.70	86
Saginaw	61	49.85	87
Livingston	207	49.81	88
Midland	341	47.58	89
Muskegon	364	47.35	90
Wayne	546	47.30	91
Oakland	529	46.13	92
Lenawee	1	44.29	93
St. Clair	105	42.89	94
Monroe	342	42.08	95
Wayne	533	41.03	96
Berrien	46	40.74	97
Calhoun	489	38.51	98
Mecosta	49	37.67	99
Saginaw	553	36.91	100
Grand Traverse	509	36.44	101
Macomb	143	36.31	102
Genesee	182	34.67	103
Eaton	93	34.52	104
Jackson	490	34.00	105
Kent	269	32.67	106
Wayne	331	32.16	107
Genesee	188	31.07	108
Saginaw	486	30.84	109
Shiawassee	522	28.37	110
St. Clair	320	28.23	111
Bay	216	26.60	112
Tuscola	329	24.69	113
Oakland	404	23.94	114
Oakland	280	23.64	115
Oceana	226	22.59	116
Berrien	298	22.53	117
Washtenaw	378	21.94	118
Montcalm	281	20.74	119
Genesee	356	20.04	120
St. Joseph	117	19.86	121

Genesee	198	19.72	122
Oakland	393	17.81	123
St. Clair	77	17.74	124
Montcalm	237	17.32	125
Sanilac	465	16.65	126
Lenawee	353	16.12	127
Wayne	124	15.73	128
Newaygo	539	15.67	129
Iosco	501	15.30	130
Genesee	122	14.62	131
Lapeer	243	14.62	132
Newaygo	374	14.42	133
Cass	87	14.35	134
Hillsdale	260	14.34	135
Wayne	227	14.20	136
Allegan	415	14.06	137
Shiawassee	409	12.99	138
Eaton	200	11.84	139
Kent	303	11.52	140
Isabella	358	10.83	141
Wayne	209	10.27	142
Genesee	163	9.40	143
Oakland	231	9.35	144
Saginaw	505	8.99	145
Tuscola	244	7.89	146
Oakland	383	7.31	147
Wayne	379	7.14	148
Kalamazoo	523	6.46	149
Van Buren	328	6.11	150
Muskegon	542	5.79	151
Oakland	104	5.61	152
Barry	339	5.60	153

Table B-7. *Fatal and serious injury safety belt related crashes top 8 agencies using the crash count ranking methodology for agencies in the Upper Peninsula.*

Crash Count Methodology			
County	**Agency ID**	**KAB safety belt crash count**	**Rank**
Marquette	322	16.2	1
Chippewa	100	15.4	2
Houghton	235	12.8	3
Delta	128	11.8	4
Menominee	334	10.2	5
Alger	6	9	6
Chippewa	468	8.8	7
Marquette	323	8.4	8

Table B-8. *Fatal and serious injury safety belt related crashes top 8 agencies using the modified critical rate methodology for agencies in the Upper Peninsula.*

Modified Critical Rate Methodology			
County	**Agency ID**	**Crashes to be Reduced**	**Rank**
Marquette	323	207.56	1
Houghton	236	109.92	2
Delta	156	72.51	3
Delta	192	50.87	4
Chippewa	468	43.22	5
Marquette	255	22.79	6
Mackinac	308	19.76	7
Marquette	367	11.06	8

C. Appendix: Selection of Weeks for Funding

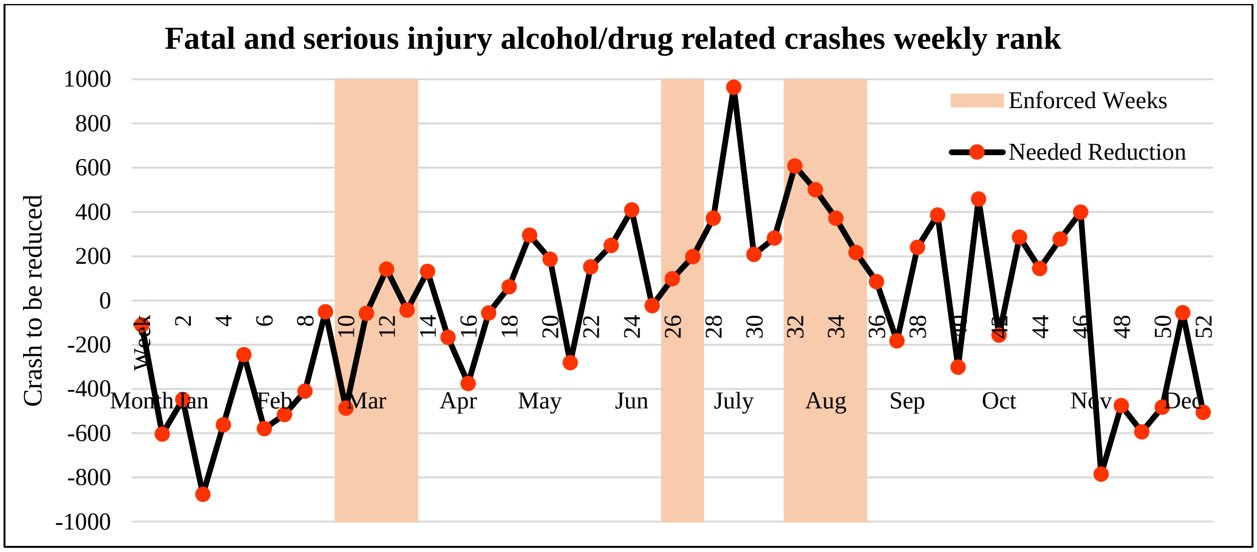


Figure C-1. *Fatal and serious injury alcohol-drug related crashes weekly rank*

Figure C-1 shows the five-year (2008-2012) number of *fatal and serious injury, alcohol and drug related crashes* that need to be reduced in each week in order to be at average. Therefore, weeks with values above the zero line are considered above the average, and their corresponding number of equivalent crashes (B level) that need to be reduced is shown. Table C-1 presents the weeks with crashes exceeding the average week in descending order. The highlighted rows indicate mandatory weeks. Therefore, optional enforcement should be considered during the non-highlighted weeks.

Table C-1. *Fatal and serious injury alcohol/drug-related crashes top critical weeks*

Modified Critical Rate Method		
Month	***Week #***	***Needed Reduction***
July	30	964.1
August	33	607.7
August	34	500.1
October	42	458.9
June	25	409.1
November	47	398.6
October	40	386.7
August	35	371.5
July	29	371.4
May	20	295.2
October	44	286.6
August	32	282.4
November	46	277.8
June	24	247.9
September	39	240.0
Sep	36	217.2
July	31	208.5
July	28	197.7
May	21	186.2
June	23	150.9
November	45	143.7
March	13	141.3
April	15	130.8
July	27	98.3
September	37	85.5
May	19	61.5

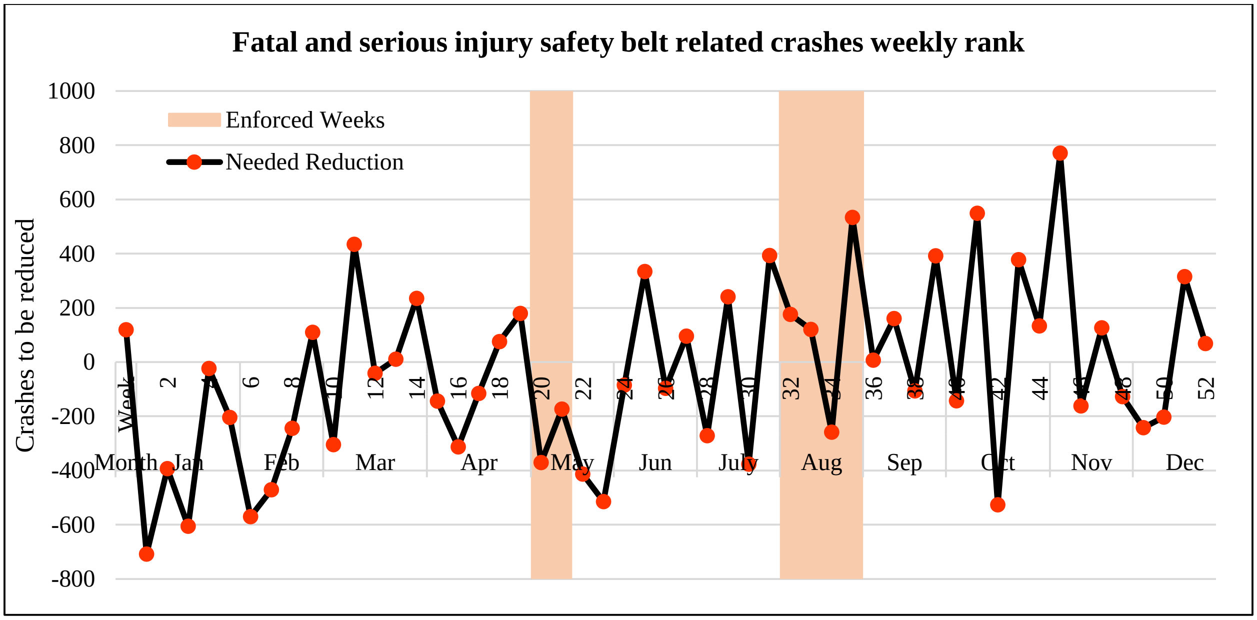


Figure C-2. *Fatal and Serious injury safety belt related crashes weekly rank*

Similar to Figure C-1, Figure C-2 shows the five-year (2008-2012) number of *fatal and serious injury, safety belt related crashes* that need to be reduced in each week in order to be at average. A rank of the weeks is presented in Table B-2. The highlighted rows indicate mandatory weeks. Therefore, optional enforcement should be considered during the non-highlighted weeks.

Table C2. *Fatal and serious injury safety belt-related crashes, top critical weeks*

Modified Critical Rate Method		
Month	***Week***	***Needed Reduction***
Nov	46	770.59
Oct	42	548.57
Sep	36	534.04
March	12	434.99
Aug	32	392.70
Oct	40	391.63
Oct	44	377.45
Jun	26	333.68
Dec	52	314.98
July	30	240.72
April	15	234.52
May	20	179.89
Aug	33	176.09
Sep	38	160.48
Nov	45	133.60
Nov	48	126.76
Aug	34	120.34
January	1	119.10
March	10	110.30
July	28	95.77
April	19	75.07
Dec	53	68.70
March	14	11.17
Sep	37	6.80

D. Appendix: Safety belt Spatial Analysis

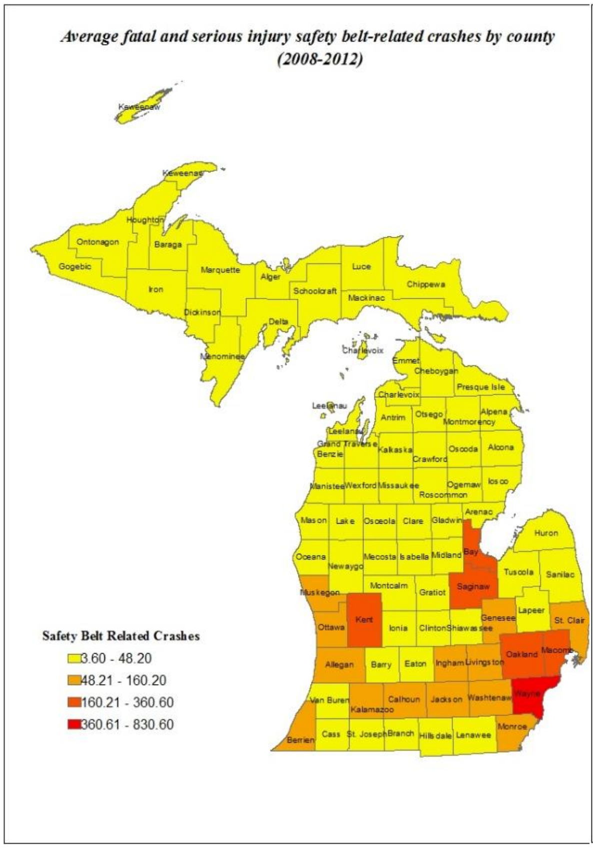


Figure D-1 *Average fatal and serious injury safety belt-related crashes by county (2008-2012)*

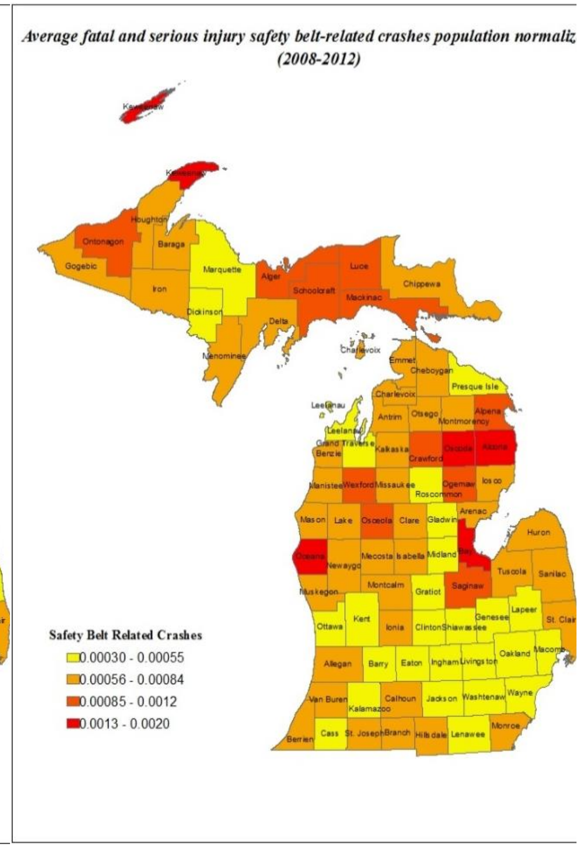
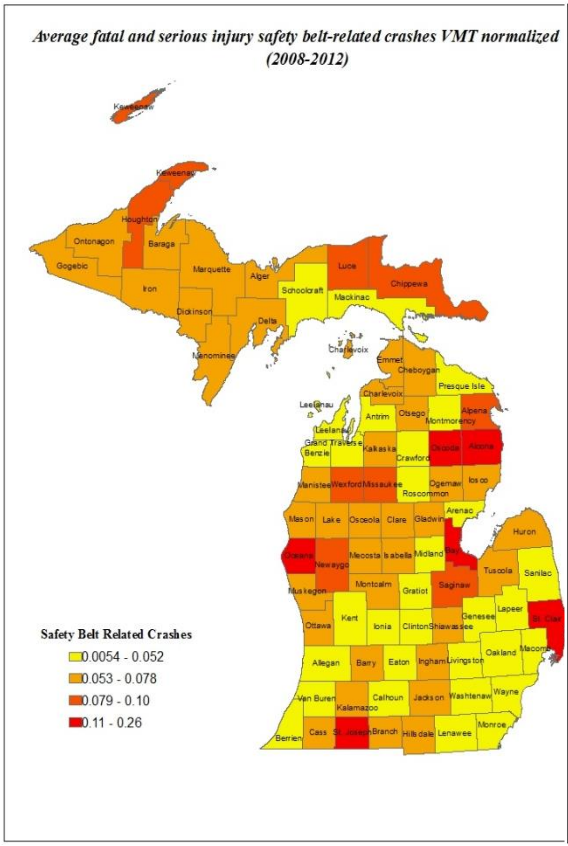


Figure D-2 *Average fatal and serious injury safety belt-related crashes by county (2008-2012) Normalized by population*



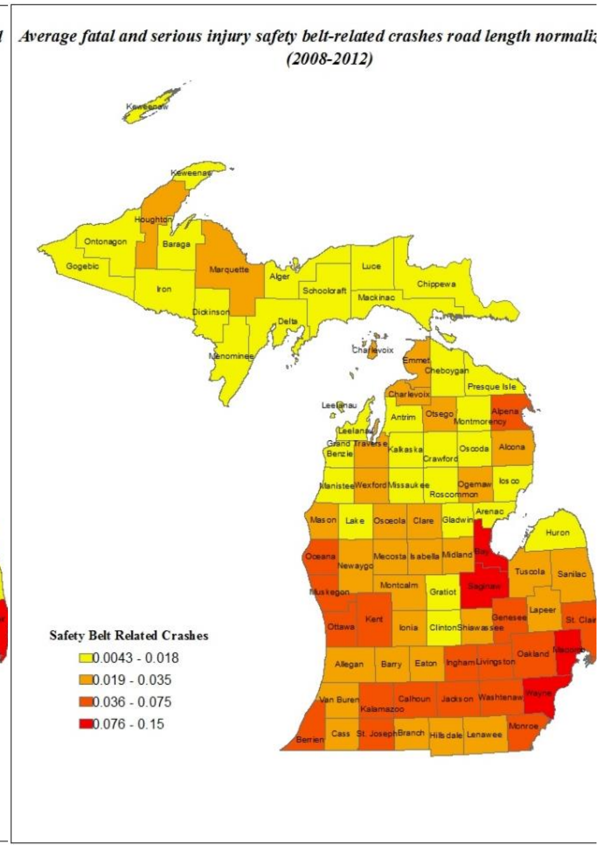


Figure D-3 *Average fatal and serious injury safety belt-related crashes by county (2008-2012) Normalized by Vehicle Miles Traveled*

Figure D-4 *Average fatal and serious injury safety belt-related crashes by county (2008-2012) Normalized by Road length*

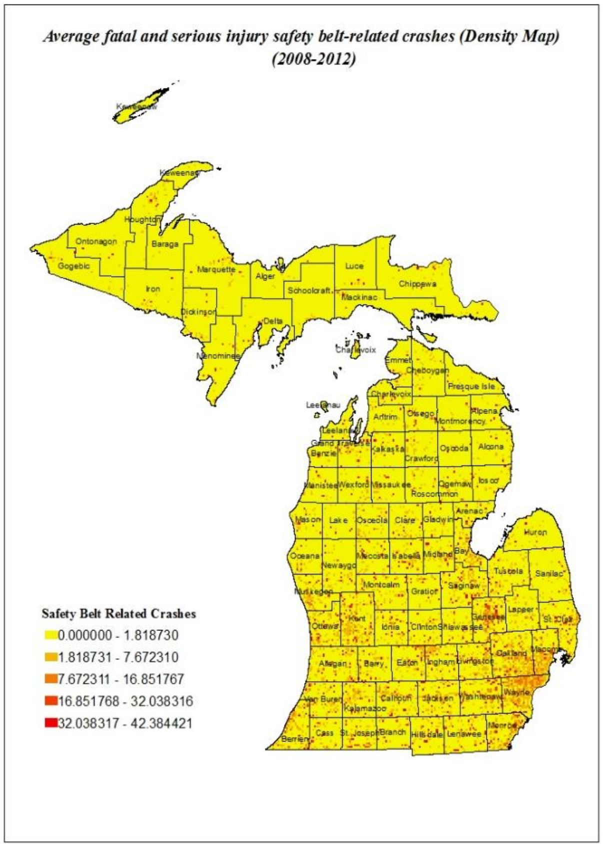


Figure D-5 *Average fatal and serious injury safety belt-related crashes, square density map*

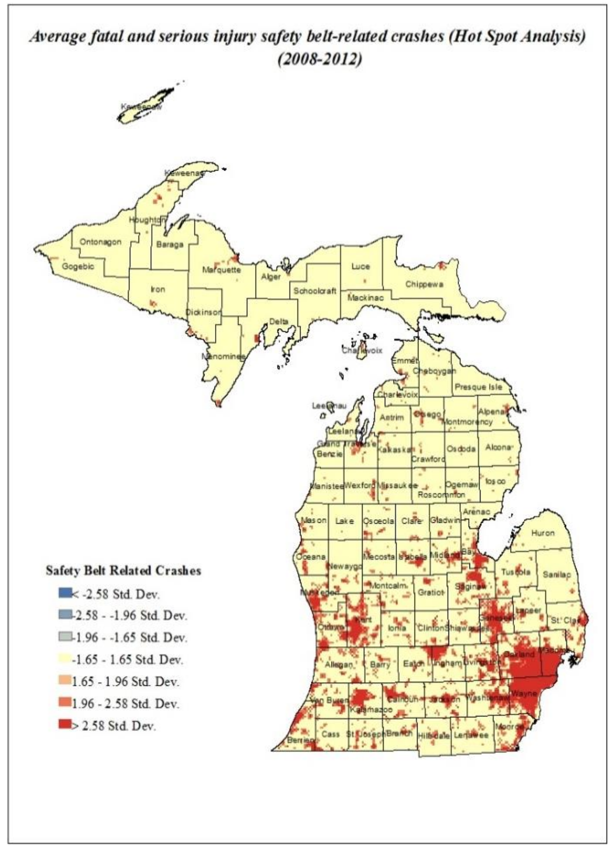


Figure D-6 *Average fatal and serious injury safety belt-related crashes, hot spot analysis*