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Evaluation of crash modification factors and functions including time trends at intersections

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EVALUATION OF CRASH MODIFICATION FACTORS AND FUNCTIONS INCLUDING TIME TRENDS AT INTERSECTIONS

by

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ABSTRACT

Traffic demand has increased as population increased. The US population reached 313,914,040 in 2012 (US Census Bureau, 2015). Increased travel demand may have potential impact on roadway safety and the operational characteristics of roadways. Total crashes and injury crashes at intersections accounted for 40% and 44% of traffic crashes, respectively, on US roadways in 2007 according to the Intersection Safety Issue Brief (FHWA, 2009). Traffic researchers and engineers have developed a quantitative measure of the safety effectiveness of treatments in the form of crash modification factors (CMF). Based on CMFs from multiple studies, the Highway Safety Manual (HSM) Part D (AASHTO, 2010) provides CMFs which can be used to determine the expected number of crash reduction or increase after treatments were installed.

Even though CMFs have been introduced in the HSM, there are still limitations that require to be investigated. One important potential limitation is that the HSM provides various CMFs as fixed values, rather than CMFs under different configurations. In this dissertation, the CMFs were estimated using the observational before-after study to show that the CMFs vary across different traffic volume levels when signalizing intersections. Besides screening the effect of traffic volume, previous studies showed that CMFs could vary over time after the treatment was implemented. Thus, in this dissertation, the trends of CMFs for the signalization and adding red light running cameras (RLCs) were evaluated. CMFs for these treatments were measured in each month and 90-day moving windows using the time series ARMA model. The results of the signalization show that the CMFs for rear-end crashes were lower at the early phase after the signalization but gradually increased from the 9th month. Besides, it was also found that the safety effectiveness is significantly worse 18 months after installing RLCs.

Although efforts have been made to seek reliable CMFs, the best estimate of CMFs is still widely debated. Since CMFs are non-zero estimates, the population of all CMFs does not follow normal distributions and even if it did, the true mean of CMFs at some intersections may be different than that at others. Therefore, a bootstrap method was proposed to estimate CMFs that makes no distributional assumptions. Through examining the distribution of CMFs estimated by bootstrapped resamples, a CMF precision rating method is suggested to evaluate the reliability of the estimated CMFs. The result shows that the estimated CMF for angle+left-turn crashes after signalization has the highest precision, while estimates of the CMF for rear-end crashes are extremely unreliable. The CMFs for KABCO, KABC, and KAB crashes proved to be reliable for the majority of intersections, but the estimated effect of signalization may not be accurate at some sites.

In addition, the bootstrap method provides a quantitative measure to identify the reliability of CMFs, however, the CMF transferability is questionable. Since the development of CMFs requires safety performance functions (SPFs), could CMFs be developed using the SPFs from other states in the United States? This research applies the empirical Bayes method to develop CMFs using several SPFs from different jurisdictions and adjusted by calibration factors. After examination, it is found that applying SPFs from other jurisdictions is not desired when developing CMFs.

The process of estimating CMFs using before-after studies requires the understanding of multiple statistical principles. In order to simplify the process of CMF estimation and make the CMFs research reproducible. This dissertation includes an open source statistics package built in R (R, 2013) to make the estimation accessible and reproducible. With this package, authorities are able

to estimate reliable CMFs following the procedure suggested by FHWA. In addition, this software package equips a graphical interface which integrates the algorithm of calculating CMFs so that users can perform CMF calculation with minimum programming prerequisite.

Expected contributions of this study are to 1) propose methodologies for CMFs to assess the variation of CMFs with different characteristics among treated sites, 2) suggest new objective criteria to judge the reliability of safety estimation, 3) examine the transferability of SPFs when developing CMF using before-after studies, and 4) develop a statistics software to calculate CMFs. Finally, potential relevant applications beyond the scope of this research, but worth investigation in the future are discussed in this dissertation.

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LIST OF ACRONYMS/ABBREVIATIONS

AADT	Annual Average Daily Traffic
AASHTO	American Association of State Highway & Transportation Officials
ADT	Average Daily Traffic
AIC	Akaike Information Criterion
AMF	Accident Modification Factor
AR	Autoregressive
ARMA	Autoregressive–moving-average Model
BC	Bootstrap Confidence Interval
BIC	Bayesian Information Criterion
CARS	Crash Analysis Reporting System
CG	Comparison Group
CMF	Crash Modification Factor
CMFunction	Crash Modification Function
CRF	Crash Reduction Factor
CSV	Comma-separated Values
DOT	Department of Transportation
EACF	Expected Average Crash Frequency
EB	Empirical Bayesian
EEACF	Excess Expected Average Crash Frequency
FARS	Fatality Analysis Reporting System
FB	Full Bayesian

FDOT	Florida Department of Transportation
FHWA	Federal Highway Administration
FI	Fatal and Injury
GIS	Geographic Information System
GLM	Generalized Linear Model
GUI	Graphical User Interface
HCM	Highway Capacity Manual
HSM	Highway Safety Manual
INAR	Integer-valued Autoregressive
INMA	Integer-valued Moving-average
KABCO	Crash with All Severity Types
KABC	Crash with Fatality, Disabling Injury, Evident Injury, and Possible Injury
KAB	Crash with Fatality, Disabling Injury, and Evident Injury
KA	Crash with Fatality and Disabling Injury
K	Crash with Fatality
MA	Moving-average
MVM	Million Vehicle Miles
NB	Negative Binomial
NCHRP	National Cooperative Highway Research Program
PDO	Property Damage Only
RCI	Roadway Inventory Characteristics
RLC	Red Light Camera

ROR	Run-off Roadway
RTM	Regression-to-the-mean
SBC	Schwarz's Bayesian Criterion
SE	Standard Error
SPF	Safety Performance Function
SVROR	Single Vehicle Run-off Roadway
TRB	Transportation Research Board
TWLTL	Two-way Left-turn Lane
USCB	United States Census Bureau
VEWF	Vehicle Entering when Flashing
VMT	Vehicle-Miles-Traveled

CHAPTER 1 : INTRODUCTION

1.1 Overview

Traffic demand has increased as population increased. The US population reached 313,914,040 in 2012 according to United State Census Bureau (USCB, 2012). Increased travel demand may have potential impact on roadway safety and the operational characteristics of roadways. Total crashes and injury crashes at intersections account for 40% and 44% of traffic crashes, respectively, on the US roadways in 2007 according to the Intersection Safety Issue Brief (FHWA, 2009). The Highway Safety Manual (HSM) (AASHTO, 2010) is a result of extensive work spearheaded by the Transportation Research Board's (TRB) Committee on Highway Safety Performance. HSM will enable officials to benefit from the extensive research in safety of highways as it bridges the gap between research and practice. The HSM's analytical tools and techniques provide quantitative information on crash analysis and evaluation for decision making in planning, design, operation, and maintenance. Thus, an assessment of the applicability of this manual in Florida is essential. Part D of the HSM provides a comprehensive list of crash modification factors (CMFs), which were compiled from past studies of the effects of various safety treatments (i.e., countermeasures).

The HSM Part D introduces a methodology to evaluate the effects of safety treatments (countermeasures). These can be quantified by CMFs. The HSM Part D identifies CMFs based on literature review and experts or at least trends (or unknown effects) for each treatment. CMFs are expressed as numerical values to identify the percent increase or decrease in crash frequency together with the standard error. To further explain, CMFs are multiplicative factors that are used to estimate the expected changes in crash frequencies as a result of improvements with specific treatments. The CMFs have been estimated using observational before-after studies that account

for the regression-to-the-mean bias. Although various CMFs have been calculated and introduced in the HSM, still there are critical limitations that are required to be investigated.

This study particularly focuses on the relationship between CMFs and annual average daily traffic volume (AADT) for different crash severities and crash types. To fulfill this objective, CMFs are calculated for different ranges of AADT. CMFs are calculated for these AADT ranges to understand the influence of AADT on CMFs for more accurate estimation of CMFs.

There is potential lag of drivers' awareness of roadway treatments suggested by Sacchi et al. (2014). Variations in the CMFs for the signalization and adding RLCs over time are examined using a time series model. This information would be helpful for traffic engineers to understand trends of safety performance of the treatments in the long term. This dissertation evaluates the effectiveness of the signalization in reducing rear-end and angle + left-turn crashes and the effectiveness of adding RLCs in reducing total and fatal+injury crashes.

Previous research efforts have focused on separating the treatment effects into crash modification functions based on temporal (Park et al., 2015; Sacchi et al., 2014; Wang et al., 2015b), traffic volume (Sacchi and Sayed, 2014; Wang and Abdel-Aty, 2014), area type (Wang and Abdel-Aty, 2014), and speed limit (Lee et al., 2015). The CMFs can be conceptualized as a nested structure as shown in Figure 1-1. The CMFs for increasingly specific groups have smaller sample sizes, but also lower variation, due to greater homogeneity among the samples. The data (crash, geometry, target location) needed to conduct a before-after study is expensive to collect. Therefore, if the CMF is stable at a higher, more aggregate level, it is not necessary to collect more data and

investigate at a more specific, less aggregate levels. By calculating the CMFs using bootstrapped resamples (bootstrapped CMFs), the stability of the estimate can be examined by calculating the bootstrap confidence interval (BC). If the BC is higher/lower than one, the CMF can be considered trustworthy and further split-up is not required. As suggested by the CMF Clearinghouse (FHWA, 2016), randomly selected sites will increase the reliability of CMFs. The resampling procedure adds randomization to identify unstable results and compensates for small sample sizes. Based on the distribution of bootstrap CMFs, a precision rating is suggested in the result section of this chapter to help with decision making.

Figure 1-1 Nested CMF Structure

In addition, it is also important to validate the transferability of SPFs using different states/sources because data collection requires significant cost. Using the target intersections, before-after study is conducted using empirical Bayes (EB) method. In order to perform EB analysis, it is needed to develop SPFs and calculate the predicted crashes based on the SPFs to serve as priors. This research compares the CMFs values among multiple SPFs from Ohio, Florida, and the SPFs in the HSM. If the CMFs calculated by the SPFs in the HSM are close to the CMFs when using the SPFs

in Florida, it would be a substantial benefit because it is not necessary to re-estimate SPFs based on local conditions for signalization.

In this dissertation, crash severities were categorized according to the KABCO scale as follows: fatal (K), incapacitating injury (A), non-incapacitating injury (B), possible injury (C) and property damage only (O).

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1.2   <u>Research Objectives</u>

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The dissertation focuses on the development and evaluation of CMFs and the functions of CMFs. The main objectives are:

1. Evaluate CMFs at different traffic volume with different roadway characteristics among treated sites over time

2. Construct a reliable way to evaluate the quality of CMFs

3. Identify the transferability of SPFs in the calculation of CMFs using EB method

The detailed objectives will be realized by the following tasks;

The first objective is analyzing CMFs at different characteristics and was achieved by following tasks:

a) Estimating CMFs at different traffic volume for each crash type (Chapter 3)

b) Estimating CMFs at different time period and using ARMA time series model to model the time trend of CMFs. (Chapter 4)

The second objective can be achieved by the following tasks:

c) Developing an algorithm to automate the calculation of CMFs to be used to fulfilling the computation of bootstrapped data(Chapter 5)

d) Selecting the ideal SPFs formulation using traffic exposure parameter (all possibility combination set of AADT) and other independent variables (Chapter 6)

e) Analyzing the density plot of bootstrapped CMF using the bootstrapped resamples (Chapter 6)

f) Suggesting improved CMF quality rating method using objective quantitative method to replace the qualitative rating method suggested by CMF clearinghouse (FHWA, 2016) (Chapter 6)

The following tasks were implemented to achieve the third objective:

g) Developing SPFs using data from different states (Chapter 5)

h) Comparing the CMF values using the SPFs developed based on different states (Chapter 5)

1.3   Organization of the Dissertation

The dissertation is organized as follows: Chapter 2, following this chapter, summarizes the literature on previous CMF and related studies. Current CMF calculation methods (various observational before-after studies and cross-sectional method) are presented. Moreover, current issues of CMF related researches and their limitations are discussed. The review of literature used bootstrap resampling technique to ensure the reliability of CMFs. In addition, it will also be explained how to address limitations in these studies.

Chapter 3 estimates the CMFs under different traffic volume and discovers that the safety impact varied at different range of traffic volume. Chapter 4 suggests a comprehensive analysis about the development of function of CMFs to assess the variation over time using ARMA time series modeling techniques. Chapter 5 presents a statistical software to calculate CMFs. This tool is used to support further analysis performed in chapter 6 and is an easy to use statistical tool for public to develop CMFs following the procedure suggested by Gross et al. (2010). Chapter 6 gives a comprehensive analysis about the reliability of CMFs by estimating the nonparametric bootstrap approach without any distribution assumption. By analyzing the bootstrapped CMFs, a CMF rating criterion is suggested to evaluate the quality of the CMFs. Chapter 7 examined the transferability of SPFs when developing CMFs through comparing the values of CMF develop using SPFs developed from different states. Finally, Chapter 8 summarizes the dissertation and presents potential improvement for future applications of estimation of CMFs.

CHAPTER 2 : LITERATURE REVIEW

2.1   Crash Modification Factors

There have been many research papers on the calibration and validation of the crash prediction models used in the HSM. For instance, Sacchi et al. (2012) studied the transferability of the HSM crash prediction algorithms on two-lane rural roads in Italy. The authors firstly estimated a local baseline model as well as evaluated each CMF based on the Italian data. Homogeneous segmentation for the chosen study roads has been performed just to be consistent with the HSM algorithms. In order to quantify the transferability, a calibration factor has been evaluated to represent the difference between the observed number of crashes and the predicted number of crashes by applying HSM algorithm.

With four-year crash data, the calibration factor came out to be 0.44 which indicates the HSM model has over-predicted the collisions. After investigating the predicted values with the observed values by different AADT levels, the authors concluded that the predicted ability of the HSM model for higher AADT is poor and a constant value of "calibration factor" is not appropriate. This effect was also proved from the comparison between the HSM baseline model and the local calculated baseline model. Furthermore, the authors evaluated CMFs for three main road features (Horizontal Curve, Driveway Density and Roadside Design). The calculation of CMFs has been grouped according to Original CMFs, and results of comparing the calculated CMFs to baseline CMFs indicated that the CMFs are not unsuitable for local Italian roadway characteristics since most of them are not consistent.

Finally, several well-known goodness-of-fit measures have been used to assess the recalibrated HSM algorithms as a whole, and the results are consistent as the results mentioned in the split investigation of HSM base model and CMFs. With these facts the authors concluded that the HSM is not suitable to transferable to Italy roads and Europe should orient towards developing local SPFs/CMFs.

Sun et al. (2011) calibrated the SPF for rural multilane highways in the Louisiana State roadway system. The authors investigated how to apply the HSM network screening methods and identified the potential application issues. Firstly the rural multilane highways were divided into sections based on geometric design features and traffic volumes, all the features are distinct within each segment. Then by computing the calibration factor, the authors found out that the average calibration parameter is 0.98 for undivided and 1.25 for divided rural multilane highways. These results turned out that HSM has underestimated the expected crash numbers.

Besides the calibration factor evaluation, the authors investigated the network screening methods provided by HSM. 13 methods are promoted in the HSM, each of these methods required different data and data availability issue is the key part of HSM network screening methods application. In the paper, four methods have been adopted: crash frequency, crash rates, and excess expected average crash frequency using SPFs (EEACF) and expected average crash frequency with EB Adjustment (EACF). Comparisons between these methods have been done by ranking the most hazardous segments and findings indicate that the easily used crash frequency method produced similar results to the results of the sophisticated models; however, crash rate method could not provide the same thing.

Xie et al. (2011) investigated the calibration of the HSM prediction models for Oregon State Highways. The authors followed the suggested procedures by HSM to calibrate the total crashes in Oregon. In order to calculate the HSM predictive model, the author identified the needed data and came up with difficulties in collecting the pedestrian volumes, the minor road AADT values and the under-represented crash locations. For the pedestrian volume issue, the authors assumed to have "medium" pedestrian when calculate the urban signalized intersections. While for the minor road AADT issue, the authors developed estimation models for the specific roadway types. Then the calibration factors have been defined for the variety types of highways and most of these values are below than 1. These findings indicate an overestimation for the crash numbers by the HSM. However, the authors attribute these results to the current Oregon crash reporting procedures which take a relative high threshold for the Property Damage Only (PDO) crashes. Then for the purpose of proving the crash reporting issue, the authors compared the HSM proportions of different crash severity levels and the Oregon oriented values. Furthermore, calibration factors for fatal and injury crashes have been proved to be higher than the total crash ones, which also demonstrated that Oregon crash reporting system introduce a bias towards the fatal and injury conditions. So the authors concluded that the usages of severity-based calibration factors are more suitable for the Oregon State highways.

Lubliner and Schrock (2012) investigated different aspects of calibrate the predictive method for rural two-lane highways in Kansas State. Two data sets were collected in this study; one data set was used to develop the different model calibration methods and the other one was adopted for evaluating the models accuracy for predicting crashes.

At first, the authors developed the baseline HSM crash predictive models and calculated the Observed-Prediction (OP) ratios. Results showed a large range of OP ratios which indicate the baseline method is not very promising in predicting crash numbers. Later on, the author tried alternative ways to improve the model accuracy. Since crashes on Kansas rural highways have a high proportion of animal collision crashes which is nearly five times the default percentage presented in the HSM. The authors tried to come up with a (1) statewide calibration factor, (2) calibration factors by crash types, (3) calibration using animal crash frequency by county and (4) calibration utilizing animal crash frequency by section. The empirical Bayes (EB) method was introduced to see whether it would improve the accuracy and also a variety of statistical measures were performed to evaluate the performance. Finally, the authors concluded that the applications of EB method showed consistent improvements in the model prediction accuracy. Moreover, it was suggested that a single statewide calibration of total crashes would be useful for the aggregate analyses while for the project-level analysis, the calibration using animal crash frequency by county is very promising.

Banihashemi (2011) performed a heuristic procedure to develop SPFs and CMFs for rural two-lane highway segments of Washington State and compared the developed models to the HSM model. The author utilized more than 5000 miles of rural two-lane highway data in Washington State and crash data for 2002-2004. Firstly the author proposed an innovative way to develop SPFs and CMFs, incorporating the segment length and AADT. Then CMFs for lane width, shoulder width, curve radius and grade have been developed. After all these procedures, the author came up with two self-developed SPFs and then compared them with the HSM model. The comparison was done at three aggregation levels: (1) consider each data as single observation (no aggregation), (2)

segments level with a minimum 10 miles length and (3) aggregated based on geometric and traffic characteristics of highway segments. A variety of statistical measures were introduced to evaluate the performances and the author concluded that mostly the results are comparable, and there is no need to calibrate new models. Finally a sensitivity analysis was conducted to see the influence of data size issue on the calibration factor for the HSM model, and the conclusions indicated that a dataset with at least 150 crashes per year are most preferred for Washington State.

Later on, Banihashemi (2012) conducted a sensitivity analysis for the data size issue for calculating the calibration factors. Mainly five types of highway segment and intersection crash prediction models were investigated; Rural two-lane undivided segments, rural two-lane intersections, rural multilane segments, rural multilane intersections and urban/suburban arterials. Specifically, eight highway segment types were studied. Calibration factors were calculated with different subsets with variety percentages of the entire dataset. Furthermore, the probability that the calibrated factors fall within 5% and 10% range of the ideal calibration factor values were counted. Based on these probabilities, recommendations for the data size issue to calibrate reliable calibration factors for the eight types of highways have been proposed. With the help of these recommendations, the HSM predictive methods can be effectively applied to the local roadway system.

Brimley et al. (2012) evaluated the calibration factor for the HSM SPF for rural two-lane two-way roads in Utah. Firstly, the authors used the SPF model stated in the HSM and found out the calibration factor to be 1.16 which indicate a under estimate of crash frequency by the base model. Later on, under the guidance of the HSM, the authors developed jurisdiction-specific negative binomial models for the Utah State. More variables like driveway density, passing condition, speed

limit and etc. were entered into the models with the p-values threshold of 0.25. Bayesian information criterion (BIC) was selected to evaluate the models and the finally chosen best promising model show that the relationships between crashes and roadway characteristics in Utah may be different from those presented in the HSM.

Zegeer et al. (2012) worked on the validation and application issues of the HSM to analysis of horizontal curves. Three different data sets were employed in this study: all segments, random selection segments and non-random selection segments. Besides, based on the three data sets, calibration factors for curve, tangent and the composite were calculated. Results showed that the curve segments have a relative higher standard deviation than the tangent and composite segments. However, since the development of a calibration factor requires a large amount of data collecting work, a sensitivity analysis of each parameter's influence for the output results for curve segments have been performed. HSM predicted collisions were compared as using the minimum value and the maximum value for each parameter. The most effective variables were AADT, curve radius and length of the curve. Other variables like grade, driveway density won't affect the result much if the mean value were utilized when developing the models. Finally, validation of the calibration factor was performed with an extra data set. Results indicated that the calibrated HSM prediction have no statistical significant difference with the reported collisions.

Elvik (2009) examined whether accident modification functions could be transferred globally based on the data from Canada, Denmark, and Germany etc. Srinivasan et al. (2013) examined the safety effect of converting the signals to composite LED bulbs. The empirical Bayes before-after method was used for the evaluation and CMFs were estimated for 3 and 4 leg intersections

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for 8 different crash types. Persaud et al. (2013) evaluated SPFs of passing relief lanes using the empirical Bayes before-after method and cross-sectional method. Based on their results, state-specific CMFs were established for passing lanes. Simpson and Troy (2013) tried to evaluate safety effectiveness of intersection conflict warning system named "Vehicle Entering When Flashing" (VEWF) at stop-controlled intersection. CMFs were provided for all sites of study and each category using the empirical Bayes before-after evaluation.

Bauer and Harwood (2013) evaluated the safety effect of the combination of horizontal curvature and longitudinal grade on rural two-lane highways. Safety prediction models for fatal-and-injury and PDO crashes were evaluated, and CMFs representing safety performance relative to level tangents were developed from these models. Zeng and Schrock (2013) tried to address 10 shoulder design types' safety effectiveness between the winter and non-winter periods. For this, a cross-sectional approach was applied to develop SPFs of the winter and non-winter periods.

Lu et al. (2013) compared the results of two methods, the empirical Bayes (EB) approach adopted in the HSM and the Safety Analyst application for evaluating safety performance functions (SPFs). Models were estimated for both total crashes and fatal and injury (F+I) crashes, and the two models yielded very similar performance of crash prediction.

Kim et al. (2013) developed a four-step procedure for SPFs using categorical impact and clustering analysis. They claimed that their procedure can easily predict crash frequency more accurately. Mehta and Lou (2013) evaluated the applicability of the HSM predictive methods to develop state-specific statistical models for two facility types, two-lane two-way rural roads and four-lane

divided highways. Nordback et al. (2014) presented for the first time specific SPFs for bicycle in Colorado. The developed SPFs demonstrated that intersections with more cyclists have fewer collisions per cyclist, illustrating that cyclists are safer at intersections with larger number of cyclists.

Cafiso et al. (2013) compared the effect of choosing different segmentation methods; they examined using short and long roadway segments to calibrate the SPF. In addition to the segment selection criteria, new treatment types have also been identified beside those which included in the HSM. Lan and Srinivasan (2013) focused on the safety performance on discontinuing late night flash operation at signalized intersections. The study also compared between empirical Bayes and full Bayes.

2.2 Intersection Safety Analysis

From an operational point of view, each state in the US has its own regulation in defining intersection-related crashes. Intersection-related crashes are typically defined as the crashes that occur within the "intersection influence area". Wang and Abdel-Aty (2007, Wang et al. (2008) suggested that the intersection influence area is determined based on the intersection type and configuration. However, two hundred and fifty feet from the intersection point has been commonly designated as the boundary of the intersection-influence area (Harwood et al., 2007; Hughes et al., 2004; Wang et al., 2008). Researches also put attention on develop crash models accounting spatial and temporal effect (Quddus, 2008; Song et al., 2006; Wang and Abdel-Aty, 2006; Wang et al., 2006)

The development and use of CMFs have recently been more common with the publication of the HSM and National Cooperative Highway Research Program (NCHRP) Crash Experience Warrant for Traffic Signals (McGee et al., 2003). Researchers have developed the best ways to collect data and evaluate CMFs in order to predict the potential crash reduction once treatments are implemented. According to the HSM, rear-end crashes are expected to increase whereas angle and left-turn crashes are expected to decrease after signalization. Angle and left-turn crashes usually have higher severity levels than rear-end crashes. Therefore, examining reduction in KABC crashes is also crucial when estimating the safety effect of signalization. However, some researchers debated that possible injury crashes (C) are not considered as injury crashes. Therefore, CMFs were developed for KABC and KAB crashes separately.

HSM provides CMFs for signalization in two categories of intersections. One is urban four legged intersections and the other is rural three and four legged intersections (AASHTO, 2010). In the HSM, AADT was not addressed in urban areas and only one range of AADT was specified in rural areas. Thus, the HSM does not clearly show the relationship between AADT and CMF. CMFs for signalization in urban areas for fatal and injury crashes were addressed in the crash experience in signal warrant studies (McGee et al., 2003). The CMFs in the warrant study are not significant for both urban three and four legged intersections. The CMFs will be compared among the HSM, the warrant study, and Florida specific in this proposal in the later chapter. Aul and Davis (2006) applied propensity score method and using EB and FB method to estimate the safety effeteness of signalization.

In particular, crashes at signal-controlled intersections are closely related to driver's violation of traffic signals. For instance, Hill and Lindly (2002) found that the violation rate was 3.2 per

intersection per hour. Retting et al. (1999) also found that an average violation rate was 3 per intersection per hour in Virginia. Brittany et al. (2004) found that 20 percent of the drivers failed to obey the traffic signal. In general, higher rates of driver violation of traffic signals will result in higher frequency of intersection-related crashes. For instance, 6,396 people who failed to follow the traffic light were involved in fatal and injury (F+I) crashes in Florida (Yan et al., 2005).

Researcher dedicated in the field of red light running related crashes (Campbell et al., 2004; Council et al., 2005a, 2005b; Hillier et al., 1993; IIHS, 2013; McGee and Eccles, 2003; Rocchi and Hemsing, 1999; Shin and Washington, 2007; South et al., 1988; Washington and Shin, 2005). According to the HSM (AASHTO, 2010), rear-end crashes are expected to increase whereas angle and left-turn crashes are expected to decrease after the signalization. Persaud et al. (2005) evaluated the safety effect of RLCs and concluded that RLCs decreased right-angle crashes and increased rear-end crashes. Erke (2009) also showed that RLC reduced angle crashes by 10 percent and increased rear-end crashes by 40 percent using meta-analysis. Similarly, Abdel-Aty et al. (2014) found that adding RLCs increased rear-end crashes by 17% to 41% and reduced angle and left-turn crashes by 13% to 26%. However, a research conducted by Florida Highway Patrol (FDOT) claimed that RLCs even reduced rear-end crashes based on the result provided by 73 Florida law enforcement agencies. Approximately sixty percent of the agencies reported reductions in total crashes, side impact crashes and rear-end crashes. This result is not consistent with previous research (Abdel-Aty et al., 2014; Erke, 2009) which found an increment in rear-end crashes. These opposite effects of RLCs on rear-end crashes are potentially due to a lag of driver's awareness of RLCs in the short term after RLCs were installed and the variation in safety effects of RLCs over time which will be explained in chapter 4.

2.3   Before and After Studies

Crash modification factors are known also as collision modification factors or accident modification factors (CMFs or AMFs), all of which have exactly the same function. Crash reduction factors (CRFs) function in a very similar way as they represent the expected reduction in number of crashes for a specific treatment. The proper calibration and validation of crash modification factors will provide an important tool to practitioners to adopt the most suitable cost effective countermeasure to reduce crashes at hazardous locations. It is expected that the implementation of CMFs will gain more attention after the recent release of the HSM and the 2009 launch of the CMF Clearinghouse (FHWA, 2011). There are different methods to estimate CMFs, these methods vary from a simple before and after study and before and after study with comparison group to a relatively more complicated methods such as empirical Bayes and full Bayes methods.

2.3.1   The Simple (Naïve) Before-After Study

This method compares numbers of crashes before and after the treatment is applied. The main assumption of this method is that the number of crashes before the treatment would be expected without the treatment. This method tends to overestimate the effect of the treatment because of the regression to the mean problem (Hauer, 1997).

The naïve before-after approach is the simplest approach. Crash counts in the before period are used to predict the expected crash rate and, consequently, expected crashes had the treatment not been implemented. This basic naïve approach assumes that there was no change from the 'before' to the 'after' period that affected the safety of the entity under scrutiny; hence, this approach is unable to account for the passage of time and its effect on other factors such as exposure,

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maturation, trend and regression-to-the-mean bias. Despite the many drawbacks of the basic naïve before-after study, it is still quite frequently used in the professional literature because; 1) it is considered as a natural starting point for evaluation, and 2) its easiness of collecting the required data, and 3) its simplicity of calculation. The basic formula for deriving the safety effect of a treatment based on this method is shown in Equation 2-1:

$$CMF = \frac{N_a}{N_b} \tag{2-1}$$

where N_a and N_b are the number of crashes at a treated site in the after and before the treatment, respectively. It should be noted that with a simple calculation, the exposure can be taken into account in the naïve before-after study. The crash rates for both before and after the implementation of a project should be used to estimate the CMFs which can be calculated as:

$$Crash\ Rate = \frac{Total\ Number\ of\ Crashes}{Exposure} \tag{2-2}$$

where the 'Exposure' is usually calculated in million vehicle miles (MVM) of travel, as indicated in Equation 2-3:

$$Exposure = \frac{Project\ Section\ Length\ in\ Miles \times Mean\ ADT \times Number\ of\ Years \times 365\ Days}{1,000,000} \tag{2-3}$$

Each crash record would typically include the corresponding average daily traffic (ADT). For each site, the mean ADT can be computed by Equation 2-4:

$$Mean\ ADT = \frac{Summation\ of\ Individual\ ADTs\ Associated\ with\ each\ Crash}{Total\ Number\ of\ Crashes} \tag{2-4}$$

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2.3.2   The Before-After Study with Comparison Group

This method is similar to the simple before and after study, however, it uses a comparison group of untreated sites to compensate for the external causal factors that could affect the change in the number of crashes. This method also does not account for the regression to the mean as it does not account for the naturally expected reduction in crashes in the after period for sites with high crash rates.

To account for the influence of a variety of external causal factors that change with time, the before-after with comparison group study can be adopted. A comparison group is a group of control sites that remained untreated and that are similar to the treated sites in trend of crash history, traffic, geometric, and geographic characteristics. The crash data at the comparison group are used to estimate the crashes that would have occurred at the treated entities in the 'after' period had treatment not been applied. This method can provide more accurate estimates of the safety effect than a naïve before-after study, particularly, if the similarity between treated and comparison sites is high. The before-after with comparison group method is based on two main assumptions (Hauer, 1997):

1. The factors that affect safety have changed in the same manner from the 'before' period to 'after' period in both treatment and comparison groups, and

2. These changes in the various factors affect the safety of treatment and comparison groups in the same way.

Based on these assumptions, it can be assumed that the change in the number of crashes from the 'before' period to 'after' period at the treated sites, in case of no countermeasures had been

implemented, would have been in the same proportion as that for the comparison group. Accordingly, the expected number of crashes for the treated sites that would have occurred in the 'after' period had no improvement applied ($N_{expected, T,A}$) follows (Hauer, 1997):

$$N_{expectedT,A} = N_{observedT,B} \times \frac{N_{observedC,A}}{N_{observedC,B}} \qquad (2\text{-}5)$$

If the similarity between the comparison and the treated sites in the yearly crash trends is ideal, the variance of $N_{expected, T,A}$ can be estimated from Equation 2-6:

$$Var(N_{expectedT,A}) = N_{expectedT,B}^{2}(1/N_{observedT,B} + 1/N_{observedC,B} + 1/N_{observedC,A}) \qquad (2\text{-}6)$$

It should be noted that a more precise estimate can be obtained in case of using non-ideal comparison group as explained in (Hauer, 1997), Equation 2-7:

$$Var(N_{expectedT,A}) = N_{expectedT,B}^{2}(1/N_{observedT,B} + 1/N_{observedC,B} + 1/N_{observedC,A} + Var(\omega)) \qquad (2\text{-}7)$$

$$\omega = \frac{r_c}{r_t} \qquad (2\text{-}8)$$

where

$$r_c \cong \frac{N_{expectedc,A}}{N_{expectedc,B}} \qquad (2\text{-}9)$$

and

$$r_t \cong \frac{N_{expected,t,A}}{N_{expected,t,B}} \qquad (2\text{-}10)$$

The CMF and its variance can be estimated from Equations 2-11 and 2-12.

$$CMF = (N_{observedT,A}/N_{expectedT,A})/(1+(Var(N_{expectedT,A})/N_{expectedT,A}^2)) \qquad (2\text{-}11)$$

$$Var(CMF) = \frac{CMF^2[(1/N_{observedT,A})+((Var(N_{expectedT,A})/N_{expectedT,A}^2)]}{[1+(Var(N_{expectedT,A})/N_{expectedT,A}^2]^2} \qquad (2\text{-}12)$$

where,

$N_{observed,T,B}$= the observed number of crashes in the before period for the treatment group;

$N_{observed,T,A}$= the observed number of crashes in the after period for the treatment group;

$N_{observed,C,B}$= the observed number of crashes in the before period in the comparison group;

$N_{observed,C,A}$= the observed number of crashes in the after period in the comparison group;

ω = the ratio of the expected number of crashes in the 'before' and 'after' for the treatment and the

  comparison group;

r_c = the ratio of the expected crash count for the comparison group;

r_t = the ratio of the expected crash count for the treatment group.

There are two types of comparison groups with respect to the matching ratio; 1) the before-after study with yoked comparison which involves a one-to-one matching between a treatment site and a comparison site, and 2) a group of matching sites that are few times larger than treatment sites. The size of a comparison group in the second type should be at least five times larger than the treatment sites as suggested by Pendleton (1991). Selecting matching comparison group with similar yearly trend of crash frequencies in the 'before' period could be a daunting task. In this study a matching of at least 4:1 comparison group to treatment sites was conducted. Identical length of three years of the before and after periods for the treatment and the comparison group was selected.

2.3.3 The Empirical Bayes Before-After Study

The empirical Bays (EB) method can account for the regression to the mean issue by introducing an estimated for the mean crash frequency of similar untreated sites using SPFs. Since the SPFs use AADT and sometimes other characteristics of the site, these SPFs also account for traffic volume changes which provides a true safety effect of the treatment (Hauer, 1997).

In the before-after with empirical Bayes method, the expected crash frequencies at the treatment sites in the 'after' period had the countermeasures not been implemented is estimated more precisely using data from the crash history of a treated site, as well as the information of what is known about the safety of reference sites with similar yearly traffic trend, physical characteristics, and land use. The method is based on three fundamental assumptions (Hauer, 1997):

1. The number of crashes at any site follows a Poisson distribution.

2. The means for a population of systems can be approximated by a Gamma distribution.

3. Changes from year to year from sundry factors are similar for all reference sites.

Figure 2-1 illustrates the conceptual approach used in the EB method (Harwood et al., 2002).
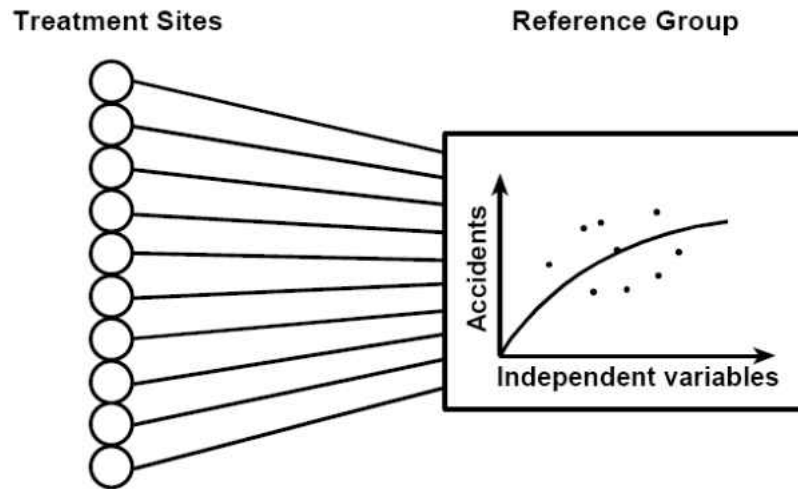
Figure 2-1 Conceptual Approach of the Empirical Bayesian Method

(Source: Harwood et al., 2003)

One of the main advantages of the before-after study with empirical Bayes is that it accurately accounts for changes in crash frequencies in the 'before' and in the 'after' periods at the treatment sites that may be due to regression-to-the-mean bias. It is also a better approach than the comparison group for accounting for influences of traffic volumes and time trends on safety. The estimate of the expected crashes at treatment sites is based on a weighted average of information from treatment and reference sites as given in (Hauer, 1997; Persaud and Lyon, 2007):

$$\hat{E}_i = (\gamma_i \times y_i \times n) + (1 - \gamma_i)\eta_i$$

(2-13)

where γ_i is a weight factor estimated from the over-dispersion parameter of the negative binomial regression relationship and the expected 'before' period crash frequency for the treatment site as shown in Equation 2-14:

$$\gamma_i = \frac{1}{1 + k \times y_i \times n}$$

(2-14)

where,

y_i= Number of average expected crashes of given type per year estimated from the SPF (represents the 'evidence' from the reference sites).

η_i = Observed number of crashes at the treatment site during the 'before' period

n = Number of years in the before period,

k = Over-dispersion parameter

The 'evidence' from the reference sites is obtained as output from the SPF. SPF is a regression model which provides an estimate of crash occurrences on a given roadway section. Crash frequency on a roadway section may be estimated using negative binomial regression models (Abdel-Aty and Radwan, 2000; Persaud, 1990; Washington et al., 2011), and therefore it is the form of the SPFs for negative binomial model is used to fit the before period crash data of the reference sites with their geometric and traffic parameters. A typical SPF will be of the following form:

$$y_i = e^{(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n)}$$

(2-15)

where,

β_i's = Regression Parameters;

x_1, x_2= logarithmic values of AADT and section length, respectively;

x_i's($i > 2$) = Other traffic and geometric parameters of interest.

Over-dispersion parameter, denoted by k is the parameter which determines how widely the crash frequencies are dispersed around the mean. The standard deviation (σ_i) for the estimate in Equation 2-16 is given by:

$$\hat{\sigma}_i = \sqrt{(1-\gamma_i) \times \hat{E}_i}$$

(2-16)

It should be noted that the estimates obtained from Equation 2-16 are the estimates for number of crashes in the before period. Since, it is required to get the estimated number of crashes at the treatment site in the after period; the estimates obtained from Equation 2-16 are adjusted for traffic volume changes and different before and after periods (Hauer, 1997; Noyce et al., 2006). The adjustment factors are given as below:

$$\rho_{AADT} = \frac{AADT_{after}^{\alpha_1}}{AADT_{before}^{\alpha_1}}$$

(2-17)

where,

ρ_{AADT} = adjustment factor for AADT;

$AADT_{after}$ = AADT in the after period at the treatment site;

$AADT_{before}$ = AADT in the before period at the treatment site;

α_I = regression coefficient of AADT from the SPF.

$$\rho_{time} = \frac{m}{n}$$ (2-18)

where,

ρ_{time} = Adjustment factor for different before-after periods;

m = Number of years in the after period;

n = Number of years in the before period.

Final estimated number of crashes at the treatment location in the after period ($\hat{\pi}_i$) after adjusting

for traffic volume changes and different time periods is given by:

$$\hat{\pi}_i = \hat{E}_i \times \rho_{AADT} \times \rho_{time}$$ (2-19)

The index of effectiveness (θ_i) of the treatment is given by:

$$\hat{\theta}_i = \frac{\hat{\lambda}_i / \hat{\pi}_i}{1 + \left(\hat{\sigma}_i^2 \Big/ \hat{\pi}_i^2 \right)}$$ (2-20)

where,

$\hat{\lambda}_i$ = Observed number of crashes at the treatment site during the after period.

The percentage reduction (τ_i) in crashes of particular type at each site i is given by:

$$\hat{\tau}_i = (1 - \hat{\theta}_i) \times 100\%$$

(2-21)

The Crash Reduction Factor or the safety effectiveness ($\hat{\theta}$) of the treatment averaged over all sites would be given by (Persaud et al., 2004):

$$\hat{\theta} = \frac{\sum_{i=1}^{m} \hat{\lambda}_i \left/ \sum_{i=1}^{m} \hat{\pi}_i \right.}{1 + \left(\text{var}(\sum_{i=1}^{m} \hat{\pi}_i) \left/ (\sum_{i=1}^{m} \hat{\pi}_i)^2 \right. \right)}$$

(2-22)

where,

m = total number of treated sites;

$$\text{var}(\sum_{i=1}^{k} \hat{\pi}_i) = \sum_{i=1}^{k} \rho_{AADT}^2 \times \rho_{time}^2 \times \text{var}(\hat{E}_i) \text{ (Hauer, 1997)}$$

(2-23)

The standard deviation ($\hat{\sigma}$) of the overall effectiveness can be estimated using information on the variance of the estimated and observed crashes, which is given by Equation 2-24.

$$\hat{\sigma} = \sqrt{\frac{\theta^2 \left[\left(\mathrm{var}(\sum_{i=1}^{k} \hat{\pi}_i) \Big/ (\sum_{i=1}^{k} \hat{\pi}_i)^2 \right) + \left(\mathrm{var}(\sum_{i=1}^{k} \hat{\lambda}_i) \Big/ (\sum_{i=1}^{k} \hat{\lambda}_i)^2 \right) \right]}{\left[1 + \left(\mathrm{var}(\sum_{i=1}^{k} \hat{\pi}_i) \Big/ (\sum_{i=1}^{k} \hat{\pi}_i)^2 \right) \right]^2}} \tag{2-24}$$

where,

$$\mathrm{var}(\sum_{i=1}^{k} \hat{\lambda}_i) = \sum_{i=1}^{k} \lambda_i \qquad \text{(Hauer, 1997)} \tag{2-25}$$

Equation 2-25 is used in the analysis to estimate the expected number of crashes in the after period at the treatment sites, and then the values are compared with the observed number of crashes at the treatment sites in the after period to get the percentage reduction in number of crashes resulting from the treatment.

Many researches dedicated estimating before and after study based on FB methods (Carriquiry and Pawlovich, 2004; El-Basyouny and Sayed, 2010; Persaud et al., 2010; Yanmaz-Tuzel and Ozbay, 2010).

2.4 Negative Binomial Models

Crash data have a gamma-distributed mean for a population of systems, allowing the variance of the crash data to be more than its mean (Shen, 2007). Suppose that the count of crashes on a roadway section is Poisson distributed with a mean λ, which itself is a random variable and is gamma distributed, then the distribution of frequency of crashes in a population of roadway sections follows a negative binomial probability distribution (Hauer, 1997).

$y_i|\lambda_i \approx$ Poisson (λ_i)

$\lambda \approx$ Gamma (a,b)

Then,

$$P(y_i) \approx \text{Negbin }(\lambda_i, k) = \frac{\Gamma(1/k + y_i)}{y_i!\Gamma(1/k)} \left(\frac{k\lambda_i}{1 + k\lambda_i}\right)^{y_i} \left(\frac{1}{1 + k\lambda_i}\right)^{1/k} \tag{2-26}$$

Where y = number of crashes on a roadway section per period;

λ = expected number of crashes per period on the roadway section;

k= over-dispersion parameter.

The expected number of crashes on a given roadway section per period can be estimated by Equation 2-27.

$$\lambda = \exp(\beta^T X + \varepsilon) \tag{2-27}$$

where,

β = a vector of regression of parameter estimates;

X= a vector of explanatory variables;

$\exp(\varepsilon)$ = a gamma distributed error term with mean one and variance k.

Because of the error term the variance is not equal to the mean, and is given by Equation 2-28.

$$\text{var}(y) = \lambda + k\lambda^2 \tag{2-28}$$

As $k \to 0$, the negative binomial distribution approaches Poisson distribution with mean λ. The parameter estimates of the binomial regression model and the dispersion parameter are estimated by maximizing the likelihood function given in Equation 2-29.

$$l(\beta, k) = \prod_i \frac{\Gamma(1/k + y_i)}{y_i! \Gamma(1/k)} \left(\frac{k\lambda_i}{1 + k\lambda_i} \right)^{y_i} \left(\frac{1}{1 + k\lambda_i} \right)^{1/k}$$ (2-29)

Using the above methodology negative binomial regression models were developed and were used to estimate the number of crashes at the treated sites. Many researchers have applied fixed effect negative binomial models to estimate crash count model (Lord et al., 2008) and some researcher applied random effect negative binomial model (Chin and Quddus, 2003). Lord and Persaud (2000) develop accident prediction models using generalized estimating equations procedure to consider the models with and without trend.

2.5   Cross-Sectional Studies

It should be noted that the CMF for certain treatments (e.g., median width) can only be estimated using the cross-sectional method, but not before-after method. This is because it is difficult to isolate the effect of the treatment from the effects of the other treatments applied at the same time using the before-after method (Harkey, 2008).

The method is used in the following conditions (AASHTO, 2010): 1) the date of the treatment installation is unknown, 2) the data for the period before treatment installation are not available, and 3) the effects of other factors on crash frequency must be controlled for creating a crash modification function (CMFunction).

The cross-sectional method requires the development of crash prediction models (i.e., SPFs) for calculation of CMFs. The models are developed using the crash data for both treated and untreated sites for the same time period (3-5 years). According to the HSM, 10~20 treated and 10~20 untreated sites are recommended. However, the cross-sectional method requires much more samples than the before-after study, say 100~1000 sites (Carter et al., 2012). Sufficient sample size is particularly important when many variables are included in the SPF. This ensures large variations in crash frequency and variables, and helps better understand their inter-relationships. The treated and untreated sites must have comparable geometric characteristics and traffic volume (AASHTO, 2010).

The research developed a generalized linear model (GLM) with a negative binomial distribution (NB) using these crash data as it is the most common type of function which accounts over-

dispersion. The model describes crash frequency in a function of explanatory variables including geometric characteristics, AADT and length of roadway segments as follows:

$$F_i = \exp(\alpha + \beta_1 * \ln AADT_i + \beta_2 * Length_i + \cdots + \beta_k * x_{ki}) \qquad (2\text{-}30)$$

where,

F_i = crash frequency on a road segment i;

$Length_i$ = length of roadway segment i (mi);

$AADT_i$ = average annual daily traffic on a road segment i (veh/day);

x_{ki} = geometric characteristic k (i.e., treatment) of a road segment i ($k > 2$);

α = constant;

$\beta_1, \beta_2, \dots, \beta_k$ = coefficient for the variable k.

In the above equation, length and AADT are control variables to identify the isolated effect of the treatment(s) on crash frequency. Since the above model form is log-linear, the CMFs can be calculated as the exponent of the coefficient associated with the treatment variable as follows (Carter et al., 2012; Lord and Bonneson, 2007; Stamatiadis, 2009):

$$CMF = \exp(\beta_k * (x_{kt} - x_{kb})) = \exp(\beta_k) \qquad (2\text{-}31)$$

where,

x_{kt} = geometric characteristic k of treated sites;

x_{kb} = geometric characteristic k of untreated sites (baseline condition).

The above model can be applied to prediction of total crash frequency or frequency of specific crash type or crash severity. The standard error (SE) of the CMF is calculated as follows (Bahar, 2010):

$$SE = \frac{\exp(\beta_k * (x_{kt} - x_{kb}) + SE_{\beta_k}) - \exp(\beta_k * (x_{kt} - x_{kb}) - SE_{\beta_k})}{2} \qquad (2\text{-}32)$$

where,

SE = standard error of the CMF;

$SE_{\beta k}$ = standard error of the coefficient β_k.

Instead of applying NB model, researchers tried to estimate crash counts using poisson, poisson-gamma and zero-inflated regression models (Lord et al., 2005). Researchers also model crash performance under Bayesian framework (Li et al., 2008).

2.6   Crash Modification Function

In order to estimate CMFs under different circumstances, crash modification function (CMFunction) is a preferred way to measure CMF variation if the sample size is sufficient. Elvik (2009) developed a CMFunction to account for the variation in CMFs for both adding bypass roads and installing roundabouts using Power functions. The author also applied linear, logarithmic, inverse, quadratic, power, and exponential models to identify the relationship between CMF and police speed enforcement. Among these models, the inverse model was found to be the best model. The result also shows that more frequent enforcement reduced the CMF (Elvik, 2011). Sacchi et al. (2014) found that CMFs for updating signal arms varied over time using log-linear and log-non-linear models. Therefore, it is important to understand how CMFs vary over time to consider lag effects of the treatment.

2.7   Time Series Modeling

The ARMA (AutoRegressive Moving Average) model consists of the autoregressive (AR) and moving average (MA) models. The model is usually referred to as ARMA (p,q) where p and q represent the possible lags that affect the ARMA model. For instance, the AR (2) model represents that the first and second lags are used to predict the autoregressive relationship for the target time period. The MA (3) model represents the first, second and third lags are used to predict the moving average for the target time period. When these two AR (2) and MA (3) models are combined, the model is referred to as ARMA (2,3). According to the previous studies (Box et al., 2013; Woodward et al., 2011), the ARMA model can be specified as follows:

$$\hat{X}(t) \;=\; \phi_1 X(t-1) \;+\ldots+\phi_p\, X(t-p) \;+\; Z(t) \;+\; \theta_1 Z(t-1) \;+\; \ldots+\; \theta_q\, Z(t-q) \qquad \text{(2-33)}$$

where X= General Time Series

$\hat{X}(t)$= Forecast of the time series Y for time t

X(t-1)~X(t-p)= Previous P values of time Series X

ϕ_i, …, ϕ_p = Coefficient estimated for autoregressive model

θ_i, …, θ_q = Coefficient estimated for moving average model

Models are selected on the basis of the Akaike Information Criterion (AIC) and Schwarz's Bayesian Criterion (SBC). Once ideal time series models are identified, we apply the models to predict $\hat{X}$ (t) for future time periods. Statistics Analysis Software, SAS is used to develop the ARMA model.

Holder and Wagenaar (1994) conducted research using time series model related to DUI crash in Oregon. Hu et al., (2013) estimating safety performance related to time effect using temporal modeling of highway crash counts for senior and non-senior drivers. Liu and Chen (2004); Wagenaar, 1982To account for the temporal variation in safety performance, time series models such as the ARMA model (Box et al., 2013; Noland and Quddus, 2004) have been applied by traffic safety researchers. (Liu and Chen, 2004) applied the ARMA model and the Holt-Winter exponential smoothing (Winters, 1960) to forecast traffic fatalities in the United States. Time series intervention study was also applied to account countermeasure other than before and after study (Box and Tiao, 1975; El-Basyouny and Sayed, 2012; Noland et al., 2008; Sharma and Khare, 1999)

Quddus, (2008) applied the integer-valued autoregressive (INAR) to forecast crashes in the UK and compared the model with the ARMA model. The time series model under poisson distribution is discussed by (McKenzie, 1988; Zeger and Qaqish, 1988; Zeger, 1988). INAR and INMA process are discussed by statisticians (Al-Osh and Alzaid, 1988; Al-Osh and Alzaid, 1987). Brijs et al. (2008) also applied the INAR model along with weather information including temperature, sunshine hours, precipitation, air pressure and visibility. However, these studies focused on modeling crash counts but not estimating the CMF using the ARMA model.

2.8   Bootstrap Resampling Method

Bootstrap resampling is based on the idea that samples are independent and identically distributed (i.i.d.) random variables. The method involves drawing samples from samples, with replacement, to build a new subsample as shown in Figure 2-2 (James et al., 2013). This figure explains that the resamples $Z^{*1}, Z^{*2}, ...$ to Z^{*B} are generated from the original sample Z (left side of the figure).

Assuming the original sample has 3 observations with ID (shown as Obs in the column name) 1,2, and 3. The first resample Z^{*1} draws "Obs=1" one time, and "Obs=3" two times and constructs a new resampled dataset. Similarly, the second resample Z^{*2} draws "Obs=1" one time, "Obs=2", one time, and "Obs=3", 1 time and constructs an identical dataset as the original sample. To further explain, bootstrapping is a non-parametric method as it requires no distributional assumptions about the original dataset. Bootstrap is a common technique used in the field of statistics, with applications such as improving the selection of model parameters. In the transportation safety field, Ogilvie (2014) used bootstrap to verify the stability of standardized direct effect. Voigt et al. (2008) used bootstrap method to examine the effect consistency at different time periods. Abay (2015) and Li et al. (2014) developed the distribution of the estimated parameter in the safety performance functions (SPFs) using the bootstrap method. Jun et al. (2014) compared the difference between a crash-involved and a crash-not-involved driver using logistic regression with bootstrap. Although bootstrap is widely used in the transportation field, there is limited precedence of its application in estimating the CMF. Ye and Lord (2009) used bootstrap in a simulation test to estimate the variance in a before-after study using the naïve method, and compare the bootstrapped result with the naïve method and empirical Bayes method, respectively, and found the crash count is not Poisson distributed.

In practice, the bootstrap technique can be implemented using most statistical software. In this dissertation, R (R Core Team, 2013) is used for the bootstrap resampling. To extract a resample, using the *sample()* function in R *base* package (R, 2013):

$$sample(data, \ replace=T)$$

where   *data*: original dataset

        replace=T: resampling based on the original dataset with replacement

The resamples generator is developed based on this function to create the resamples for treated data and reference data. This procedure is further explained in the methodology section, below.
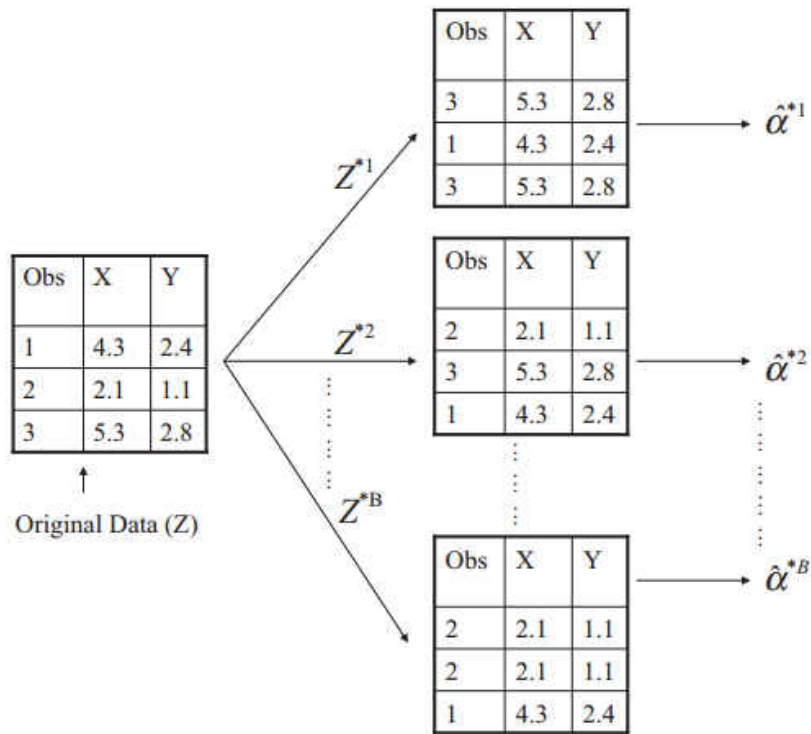
Figure 2-2 The bootstrap approach based on James et al. (2013)

CHAPTER 3 : SAFETY EVALUATION OF SIGNALIZATION FOR DIFFERENT LEVELS OF TRAFIC VOLUME

3.1 Introduction

Highway Safety Manual part D (AASHTO, 2010) provides CMFs which can be used to determine the expected number of crash reduction or increase after converting stop-controlled to signal-controlled intersections. These CMFs in HSM help engineers easily measure the safety and cost effectiveness of signalizing intersections. However, due to the differences in area type, road geometry, and traffic volume, CMFs could vary among different intersections. For instance, the HSM suggests that the CMF for all crash types after signalization is significant below 1 (0.56) in rural areas but it is not statistically different from 1 (0.95) in urban areas. Therefore, it is important to understand how CMFs vary with different roadway characteristics and ensure that signalization would have a positive effect on crash reduction for more specific conditions of an intersection, for example the traffic volume level.

This chapter evaluates the safety effects of converting urban four-legged stop-controlled intersections to urban four-legged signal-controlled intersections using crash records and roadway inventory data in Florida. CMFs are calculated using observational before-and-after study with the EB method. For the prediction of expected crash frequency, SPFs are developed for three severity categories (KABCO, KABC, and KAB) and two crash types (rear-end, angle+left-turn), separately. The models are developed using the NB model formulation.

This study particularly focuses on the relationship between CMFs and AADT for different crash severities and crash types. To fulfill this objective, CMFs were calculated for five different ranges

of AADTs. CMFs for these five AADT ranges are calculated and compared to understand the influence of AADT on CMFs for more accurate estimation of CMFs.

3.2 Data Preparation

Data were collected and combined from the following five database sources: Roadway Characteristic Inventory (RCI) in Florida, Crash Analysis Report (CAR), Florida Financial Management Search System, Transtat I-View, and Google Earth. The Financial Management Search System provides the information on projects constructed for FDOT. The CAR system provides information on all the reported crashes in Florida including severity, crash type, and other crash-related characteristics. This system allows us to locate crashes from 2003 to current. Crashes are divided into 30 different crash types including angle, rear-end, head-on and sideswipe, etc. However, left-turn crashes were sometimes misclassified as angle crashes and vice versa. Therefore, in order to compensate for this misclassification, the CMFs were developed for the combined angle+left-turn crashes.

Target intersections have been chosen from the Financial Project Search System from FDOT. Signalization of stop-controlled intersections was identified as the major treatment. In the Financial Project Search System, one district was chosen at a time with status "Construction Complete". For the phasing selection, "Construction Contract" was selected for the years between 2005 and 2010 because the RCI data are only available from 2004 to current. Therefore, in order to obtain a reliable sample size, projects which were completed in the years 2005-2010 are preferred.

However, Financial Search System does not provide some essential variables such as AADT. Thus, other sources such as Google Earth and the RCI needed to be used to acquire the micro-level properties of the chosen sites. Also, through the TranStat I-View (a Geographical Database System provided by FDOT TranStat Department), we could precisely match the milepost of the constructed intersections; however, TranStat I-View does not provide historical satellite maps. Thus, the precise location was matched from TranStat I-View to historical satellite maps from Google Earth, RCI Database, and FDOT Video Log.

A total of 142 intersections (treated sites) which were converted from an urban four-legged stop control to an urban four-legged signal control intersection were identified from the Financial Project Search System. The CMFs were estimated based on these signalized intersections. Urban three-legged intersections were not considered in this study due to a lack of samples. Due to the limitation of Florida Roadway Characteristic data, the minor road ID could not be identified for some of the intersections. Also, 79.6% of the minor road AADTs were missing among the treated intersections used in this study. Thus, SPFs were developed only for the intersections with known major and minor AADTs but the minor AADT was not significant in the SPFs. Although it is suggested by HSM to include the minor road AADT in the SPFs even if it is not significant, the number of observations for developing the SPFs will be reduced by 79.6%. To develop more robust SPFs with more samples, only the major road AADTs was used in SPFs. Previous research (Wang et al., 2015b) found inconsistency of CMFs between the first year and the years after intersections were signalized, the data within one year was removed after the treatment had been implemented. Crash data were collected for the two-year before period from 2003 to 2004 and the two-year after period from 2011 to 2012.

Reference sites were also collected to address regression-to-the-mean (RTM) bias. A total of 126 urban four-legged stop controlled intersections (reference sites) were identified to develop SPFs using Florida Roadway Characteristic Inventory along with GIS database Transtat I-View. A total of 1,512 crashes occurred at these intersections over 10 years from 2003 to 2012. The AADT of the major road were included in SPFs.

Table 3-1 shows mean, standard deviation and range of crash frequencies for the reference sites by severity and crash type. In terms of severity, angle and left-turn crashes usually have higher severity levels than rear-end crashes. Therefore, examining the reduction in KABC crashes is also crucial when estimating the safety effect of signalization. However, some researchers debated that possible injury crashes (C) are not considered as injury crashes. Due to this uncertainty, CMFs were developed for KABC and KAB crashes separately. In the table, "KABCO Crashes", "KABC Crashes", and "KAB Crashes" represent total crashes, fatal and injury crashes including possible injury, and fatal and injury crash excluding possible injury, respectively. Two categories of crash types are rear-end and angle + left-turn crashes. Table 3-1 also shows the range of the AADT on the major road with variable name "Major AADT".

Table 3-1 Data Used to Develop the Safety Performance Function

	No. of Observation	Mean	Standard Deviation	Minimum	Maximum
KABCO Crashes	126	12	21.9	0	134
KABC Crashes	126	6.13	11.3	0	52
KAB Crashes	126	3.45	6.63	0	38
Rear-End Crashes	126	2.91	7.37	0	50
Angle+Left Crashes	126	5.02	10.6	0	57
Major AADT	126	9791	8590	850	42500

3.3   Methodology

3.3.1   Negative Binomial Model

To evaluate the relationship between CMFs and AADT, SPFs were developed for KABCO, KABC, KAB, rear-ends, angle, left-turn and angle + left-turn crashes. The SPF is a negative binomial model for crash counts (Washington et al., 2011). In the model, the crash count is a target variable while AADT, the number of through lanes on the major road, number of legs, operation class (rural or urban), etc. are covariates. The advantage of using negative binomial (NB) distribution to model the distribution of crash frequencies is that the Poisson distribution requires that the mean and variance be equal ($E[y_i] = VAR[y_i]$) (Washington et al., 2011) where y_i = predicted crash frequency. When this equality does not hold (statistically), the data are said to be underdispersed ($E[y_i] >$ $VAR[y_i]$) or overdispersed ($E[y_i] < VAR[y_i]$). The negative binomial model allows for

overdispersion in that the mean of Poisson counts over sites i is itself gamma distributed and is described by the following equation:

$$\lambda_i = EXP(\beta x_i + \varepsilon_i) = EXP(\beta x_i) EXP(\varepsilon_i)$$

(3-1)

where x is the covariate, β is the associated coefficient, λ is the expected crash count, and $EXP(\varepsilon_i)$ is a gamma-distributed error term with mean = 1 and variance α^2. The addition of this term allows the variance to differ from the mean as below:

$$VAR[y_i] = E[y_i][1 + \alpha \cdot E[y_i]] = E[y_i] + \alpha \cdot E[y_i]^2$$

(3-2)

For detail, please refer chapter 2.4.

3.3.2 Empirical Bayes Method

The EB method combines the strengths of a before-and-after study that uses specific case-control techniques with regression methods for estimating safety. Unlike other methods, it increases the precision of estimation and it also corrects for the regression-to-mean bias. According to (Hauer, 1997), the safety performance can be estimated through the following steps:

$$\hat{\pi} = \gamma * E\{k\} + (1 - \gamma) K$$

(3-3)

where $\hat{\pi}$ =Expected crash count if there had been no treatment

E{k}=predicted crash counts based on Safety Performance Function

K= observed crash counts before treatment

γ, $(1 - \gamma)$ =Weight for predicted crash counts and observed crash counts, respectively.

The method of calculating the assigned weight is shown below as suggested by Hauer (1997):

$$\gamma = \frac{1}{1+\frac{\mu*Y}{\varphi}} \qquad (3\text{-}4)$$

where μ = predicted crashes before treatment (per year)

   Y = number of year(s)

   φ =overdispersion parameter

After $\hat{\pi}$ is calculated, Gross et al. (2010) adjusted the value of $\hat{\pi}$ as follows:

$$\hat{\pi}^* = \hat{\pi} * (E\{l\}/E\{k\}) \qquad (3\text{-}5)$$

where $\hat{\pi}^*$= Expected crash counts if there had been no treatment after adjustment

   $\hat{\pi}$ = Expected crash counts if there had been no treatment before adjustment

   $E\{l\}$= predicted crash counts after treatment

   $E\{k\}$= predicted crash counts before treatment.

The CMF can be written in the form as follow:

$$\hat{\theta} = \frac{[\hat{\lambda}/\hat{\pi}^*]}{[1+\text{Var}\{\hat{\pi}^*\}/\hat{\pi}^{*2}]} \qquad (3\text{-}6)$$

where $\hat{\theta}$ = crash modification factor

   λ = Observed crash counts after treatment.

If $\hat{\theta} < 1$, the treatment has a positive effect. If $\hat{\theta} > 1$, it is expected to have a negative effect on safety performance. Variance of the CMF is shown in the following equation:

$$\widehat{Var(\hat{\theta})} = \frac{\widehat{\theta^2}[\frac{\widehat{var(\hat{\lambda})}}{\hat{\lambda}^2} + \frac{\widehat{var(\hat{\pi})}}{\hat{\pi}^{*2}}]}{[1 + \frac{\widehat{var(\hat{\pi})}}{\hat{\pi}^{*2}}]^2} \qquad (3\text{-}7)$$

3.4   Results

Five SPFs were developed for KABCO, KABC, KAB, rear-end, and angle+left-turn crashes at urban four-legged intersections using the NB model.   To accurately identify the relationships between crashes and variables, we eliminated the insignificant variables.   After SPFs were specified, CMFs were estimated for different AADT ranges using its respective SPF.

3.4.1   Safety Performance Functions

In the final models "ln(Major.AADT)" are significant at a 95% as shown in Table 3-2. The SPF is described in the following equation:

$$N = \exp[\beta_0 + \beta_1 * \ln(Major.AADT)] \qquad (3\text{-}8)$$

where

N = Predicted crash Frequency, Major. AADT = AADT on major road,

β_0 = Intercept, β_1 = Coefficient for $\ln(Major.AADT)$,

Since the crash data was collected from 2003 to 2012, we assumed that the AADT in the median year, i.e. 2007, represents AADT in the 10-years period.   SPFs were developed for different

severity levels including KABCO, KABC, and KAB crashes as shown in Table 3-2. The log of

AADT on the major road [ln(Major.AADT)] is significant at a 99% confidence level with all

coefficient to be positive. SPFs were also developed for the 5 crash settings as shown in Table

3-2. Each SPFs predict annual crash count using numbers of year as offset in the NB models. In

this table, the Theta value is the over-dispersion parameter as shown in equation 4. Besides, AIC

represents the Akaike Information Criterion which is a robust measure of model fitness.

Table 3-2 SPF for different crash severity levels (urban four-legged intersections)

	Severity level or crash type				
	KABCO	KABC	KAB	Rear-End	Angle+Left-Turn
	(1)	(2)	(3)	(4)	(5)
ln(Major.AADT)	1.826***	2.113***	1.976***	2.035***	1.940***
(Standard Error)	(0.252)	(0.248)	(0.247)	(0.265)	(0.263)
Constant	-16.764***	-20.042***	-19.334***	-20.330***	-18.570***
(Standard Error)	(2.254)	(2.247)	(2.255)	(2.445)	(2.381)
Observations	126	126	126	126	126
Log Likelihood	-312.211	-263.994	-223.334	-190.906	-244.687
Theta	0.201	0.266	0.305	0.316	0.218
AIC	628.422	531.987	450.667	385.812	493.374

Note: $^{*}p<0.1;\ ^{**}p<0.05;\ ^{***}p<0.01$

3.4.2 Observational Before-and-After Study

The CMFs were calculated using an observational before-and-after study with the EB method. The results of the EB method shown in Table 3-3 illustrate that signalization increased the number of KABCO crashes by 14% and this increase is statistically significant at a 95% confidence level. On the other hand, signalization reduced KABC and KAB crashes by 8% and 24%, respectively. Table 3-3 shows that the standard errors were lower for the Florida-based CMFs than the CMFs

provided in the HSM and the NCHRP Report 491 except for rural intersections in the HSM. In addition, based on the standard errors shown in Table 3-3, the Florida-based CMF for KABC crashes is not statistically significant at a 90% confidence level, but the CMF for KAB crashes is statistically significant at a 95% confidence level. Comparing the Florida-based CMFs with the CMFs from the HSM and the NCHRP Report 491, the results from these two references show higher standard error for KABCO and KABC crashes, respectively. For KABCO crashes, the Florida-based CMF is not significantly different from the CMF from the HSM. For KABC crashes, both Florida-based CMF and the CMF from the NCHRP Report 491 are not statistically significant. However, the Florida-based results point out that signalization is more effective in reducing injury crashes (KABC and KAB crashes) compared to KABCO crashes. In addition, the Florida-based result for KABC crashes has lower standard comparing to the NCHRP Report 491. For rear-end crashes, the Florida-based result shows similar result comparing to the HSM but with lower standard error. On the other hand, the Florida-based crash data has problem with mixing right-angle and left-turn crashes. Therefore, it is not possible to estimate the impact of right-angle and left-turn crashes separately to be compared with the CMF of the angle crashes in the HSM. Based on the available information, it can be concluded that both the Florida-based CMF of angle+left-turn crashes and the CMF of angle crashes in the HSM are significantly lower than one.

Table 3-3 Comparison of Crash Modification Factors for Signalization

Area Type	Number of Legs	Crash Severity	CMF	Standard Error	Reference
Urban	4	KABCO	0.95	0.09	AASHTO (2010)
Urban	4	Rear-End	**2.43**	**0.4**	AASHTO (2010)
Urban	4	Angle	**0.33**	**0.06**	AASHTO (2010)
Urban	4	KABC	0.77	0.27	McGee et al. (2003)
Urban	4	KABCO	**1.14**	**0.05**	This Florida-based research
Urban	4	KABC	0.92	0.05	This Florida-based research
Urban	4	KAB	**0.76**	**0.05**	This Florida-based research
Urban	4	Rear-End	**2.19**	**0.19**	This Florida-based research
Urban	4	Angle+ Left-Turn	**0.57**	**0.04**	This Florida-based research

The values in bold are statistically significant at a 95 % confidence level.

3.4.3   Variability of Crash Modification Factors

In order to investigate the relationship between CMFs and AADT, the sites were classified into five groups based on AADT. These five AADT groups are 1) ≤ 10,000 vpd, 2) 10,001-20,000 vpd, 3) 20,001-25,000 vpd, 4) 25,001-35,000 vpd, and 5) > 35,000 vpd. The numbers of sites and 10-year crashes for each AADT group are shown in Table 3-4.

Table 3-4 Numbers of Sites and 10-year Crashes in Each AADT Group

	AADT Group (vpd)				
	Less than 10,000	10,001- 20,000	20,001- 25,000	25,001- 35,000	Greater than 35,000
# of Sites	11	36	17	33	45
KABCO_Before	29	172	105	282	475
KABCO_After	46	215	116	278	581
KABC_Before	17	105	70	157	293
KABC_After	16	106	66	135	280
KAB_Before	12	61	45	84	158
KAB_After	4	47	42	78	114
Rear_End_Before	5	44	21	57	134
Rear_End_After	16	100	46	116	322
Angle_Left_Before	16	75	47	129	182
Angle_Left_After	17	56	33	63	94

The CMFs for each severity level are shown in Table 3-5 and Figure 3-1 Comparison of CMFs for different AADT ranges by crash severity. The 90% confidence interval for each AADT group is plotted in Figure 3-1 Comparison of CMFs for different AADT ranges by crash severity. The center of each vertical line is the expected value of CMF. The top and bottom ends of the vertical lines represent the upper and lower bounds of a 90% confidence interval, respectively.

Table 3-5 Crash Modification Factors for Signalization by Crash Severity and AADT range

AADT	CMF (Standard Error) KAB Crashes	CMF (Standard Error) KABC Crashes	CMF (Standard Error) KABCO Crashes
≤ 10,000 (Group1)	0.146** 0.047	0.376** 0.102	0.735** 0.159
10,001 – 20000 (Group2)	0.500** 0.081	0.630** 0.078	0.851 0.084
20,001-25,000 (Group3)	0.947 0.197	0.964 0.162	1.139* 0.157
25,001-35,000 (Group4)	0.909 0.138	0.844 0.094	0.978 0.082
>35000 (Group5)	0.683** 0.075	0.887 0.072	1.188** 0.076

* significant at a 90% confidence level.

** significant at a 95% confidence level
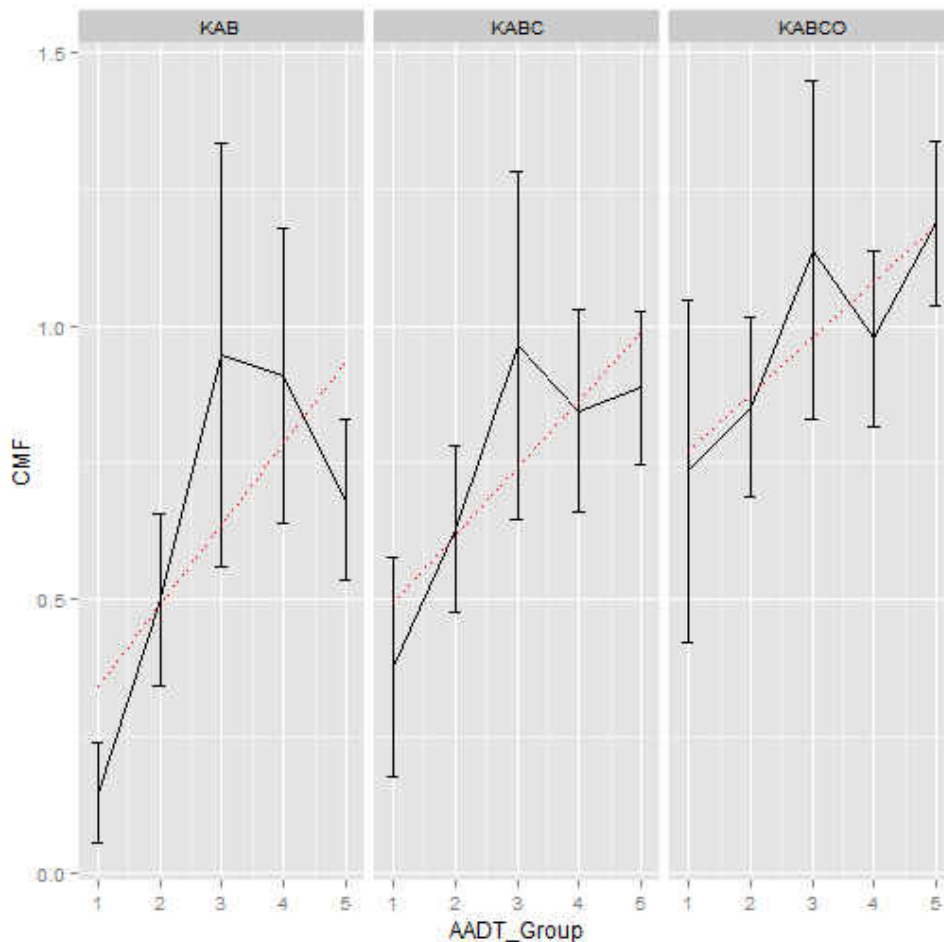
Figure 3-1 Comparison of CMFs for different AADT ranges by crash severity

Figure 3-1 shows that the values of CMFs for signalization have an upward trend for different AADT ranges in general. Figure 3-1 also shows that signalization can significantly reduce KABC and KAB crashes at lower AADT ranges ($\leq$ 20,000 vpd) and KAB crashes at AADT greater than 35,000 vpd. CMFs among three severity categories (KABCO, KABC, and KAB) were also compared. In AADT group 5 (> 35,000 vpd), the expected CMFs for KABC and KAB crashes are significantly lower than the CMF for KABCO crashes. Another important finding is that in AADT group 5, the CMF for KAB crashes is significantly lower than 1 unlike the CMFs for KABCO and KABC crashes.

Overall signalization has positive safety effect for all severity levels for lower AADT (Groups 1 and 2) at a 95% confidence level except KABCO crashes which is only significant at an 80% confidence level. However, signalization does not have significant safety effects on reduction in KABCO, KABC and KAB crashes for the two AADT groups 3 and 4. It can be noticed that signalization may increase the number of crashes for these two AADT groups although its safety effects are not statistically significant (i.e. CMFs are not statistically different from 1). This indicates that signalization is more effective in reducing fatal and injury crashes at the intersections with lower traffic volume than the intersections with higher traffic volume.

Another finding is that CMFs for KAB and KABC crashes were consistently lower than CMFs for KABCO crashes for all AADT groups. Furthermore, CMFs for KAB crashes are also lower than CMFs for KABC crashes except AADT group 4. This result indicates that signalization is more effective in reducing fatal and injury crashes than property damage only crashes. It is worth mentioning that signalization is more effective in reducing all severities of crashes at the intersections with AADT lower than 20,000 vpd than the intersections with AADT higher than 20,000 vpd. This result is consistent with the HSM which has lower CMF at 0.56 at rural area for KABCO crashes which have lower AADT than the urban area. In addition, the expected CMFs for KAB crashes are lower than CMFs for KABC crashes within the same AADT group except 25,001-35,000 vpd. Therefore, based on the dotted red trend line shown in Figure 3-1, the observed order of CMFs is expressed as follows:

Expected CMF value: KABCO > KABC > KAB

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CMFs were also calculated for 2 major crash types (rear-end and angle+left-turn). As shown in Table 3-6 and Figure 3-2, CMFs for rear-end crashes were significantly higher than one at a 90% confidence interval for all AADT groups except for AADT group 1. For angle+left-turn crashes, CMFs are significantly lower than one at a 90% confidence interval for all AADT groups.

Table 3-6 Crash Modification Factors for Signalization by Crash Type

	CMF	CMF
	(Standard Error)	(Standard Error)
AADT	Angle+Left-Turn	Rear End Crashes
≤ 10,000	**0.466	1.336
(Group1)	0.131	0.590
10,001 – 20000	**0.490	*1.447
(Group2)	0.072	0.273
20,001-25,000	*0.713	**2.153
(Group3)	0.145	0.638
25,001-35,000	**0.481	**1.975
(Group4)	0.059	0.362
>35000	**0.492	**2.25
(Group5)	0.051	0.269

* significant at a 90% confidence level.

** significant at a 95% confidence level
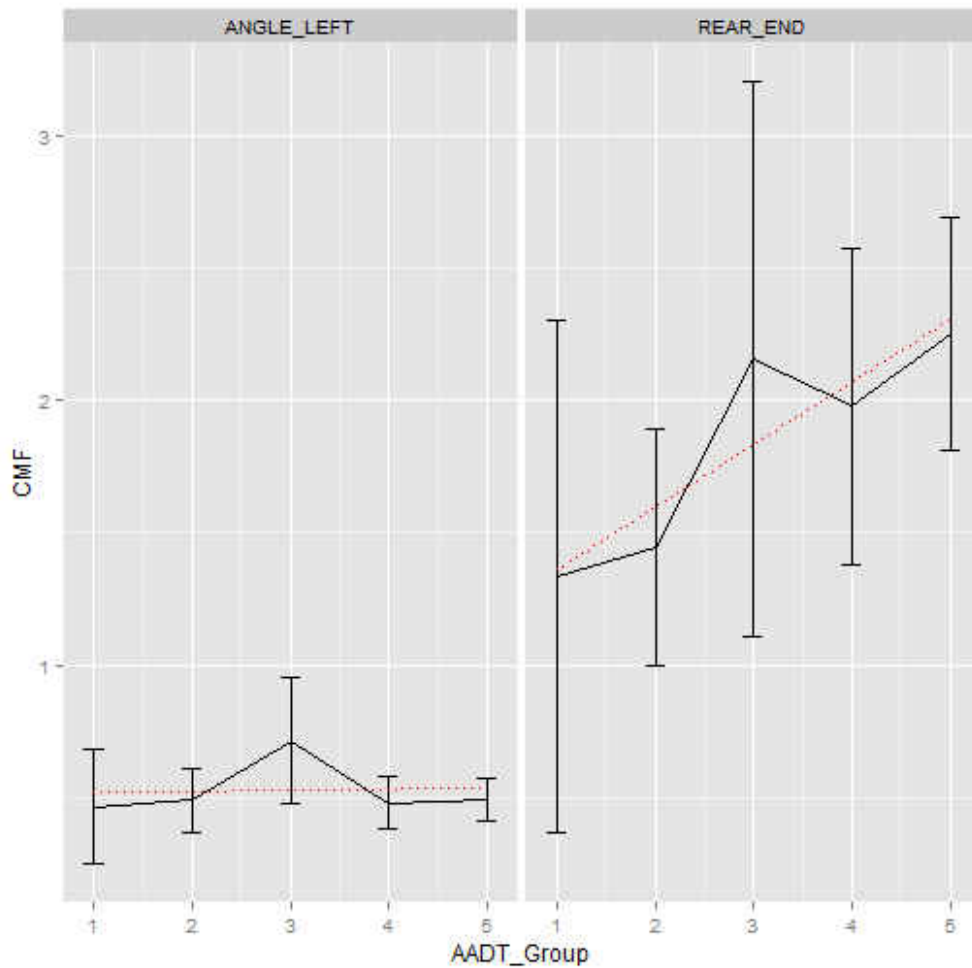
Figure 3-2 Comparison of CMFs for Different AADT Ranges by Crash Type

The trend of CMFs for rear-end crashes in Figure 3-2 has an increasing trend. For the AADT group

1, the large standard error in rear-end crashes is due to the low crash count for intersections with

low AADT. On the other hand, the expected CMFs increased with AADT and reached its peaks at

AADT groups 3 and 5. It is worth noting that the confidence interval for group 3 is large.

Therefore, it lacks evidence to conclude that group 3 and 5 are the worst cases. However, one

would infer from Figure 3-2 that the aggregated CMF for AADT groups 3, 4 and 5 is 2.17, which

is higher than the aggregated CMF for AADT groups 1 and 2 which has the value of 1.45. This

indicates that signalization could increase the number of rear-end crashes at the intersections with higher AADT.

For angle+left-turn crashes, the CMFs were lower than the CMFs for rear-end crashes at all AADT ranges as shown in Figure 3-2. The figure also shows that all CMFs for angle+left-turn crashes are consistently lower than 1 with less fluctuation across different AADT groups unlike CMFs for rear-end crashes. Based on the variance of CMFs as shown in Table 6, signalization reduces angle+left-turn crashes by 28-53%. This range of variation is relatively smaller compared to the ranges of variation for rear-end, KABCO, KABC, and KAB crashes. Therefore, it can be concluded that signalization can significantly reduce angle+left-turn crashes regardless of AADT.

Figure 3-2 visually compares CMFs between rear-end and angle+left-turn crashes. The red dotted lines represent the simple linear trends of CMFs for angle+left-turn and rear-end crashes. The trends show that the CMFs for angle+left-turn crashes are generally similar among different AADT groups whereas the CMFs for rear-end crashes increase with AADT.

3.5   Conclusion

In this chapter, safety effects of converting urban four-legged stop-controlled intersections to urban four-legged signal-controlled intersections were evaluated based on crash modification factors (CMFs). Since traffic volumes at intersections are likely to affect the safety of signalization, this study investigates the variations in CMFs for signalization at five ranges of Average Annual Daily Traffic volumes (AADT).

CMFs were calculated using the observational before-after study with the EB method. CMFs for signalization were separately determined for three crash severity categories (KABCO, KABC, and KAB) and two crash types (rear-end and angle + left-turn). Five safety performance functions (SPFs) were developed using the negative binomial (NB) model formulation to predict crash frequency. The variable in the SPFs is the log of the AADT on the major road. Based on the results of the NB models, an intersection with higher AADT has a higher crash frequency for all severities and crash types.

Based on the comparison of CMFs by crash severity, it was found that signalization reduced fatal and injury crashes (KABC and KAB) more than total crashes (KABCO). In particular, signalization is more likely to reduce fatal and injury crashes when AADT is lower at intersections. Also, CMFs for KAB crashes were consistently lower than CMFs for KABCO crashes at all AADT ranges. It is also identified that the general relationship between CMF and AADT. When comparing CMFs among the five AADT ranges, installing traffic signals at the stop-controlled intersections with AADT greater than 35,000 vpd significantly increases the number of total crashes as indicated by CMFs greater than one. In addition, safety effect of signalization is not significant for KABC and KAB crashes at the intersections with AADT of 20,001– 35,000 vpd. Based on this finding, the target intersections at this AADT range must be carefully considered to ensure safety effectiveness of signalization before implementation of signalization.

From the result of CMFs for rear-end crashes, it was found that the signalization significantly increased rear-end crashes for AADT greater than 20,000 vpd at a 90% confidence level. In particular, the increase in rear-end crashes was generally higher at the intersections with higher

AADT. This is potentially because as AADT increases, the number of conflicts among vehicles entering the intersection also increases. Thus, signalization generally has a negative effect on the reduction of rear-end crashes.

In contrast, the signalization significantly reduced angle+left-turn crashes for all AADT groups at a 90% confidence level. However, the reduction in angle+left-turn crashes was similar for different AADT groups. This is potentially because signals can better control the movements of left-turn vehicles than stop signs and reduce their conflicts with vehicles in other approaches at intersections. Therefore, it can be concluded that the signalization can consistently reduce angle+left-turn crashes regardless of AADT, but it rather increases rear-end crashes, particularly at the intersections with higher AADT. Thus, it is recommended to assess the trade-off between reductions in angle+left-turn crashes and increase in rear-end crashes for different levels of traffic volume.

The results of this study can be improved if more detailed geometric and traffic signal phase features of intersections are available. With this additional information, it is possible to develop CMFs for more specific types of intersections such as CMFs for intersections with exclusive turning lanes and protected left-turn phases. More samples of intersections would help observe more general relationship between the CMF and AADT since CMFs can be calculated for smaller ranges of AADT. For example, intersections could be spitted in the range of 25,001-35,000 vpd into two ranges of 25,001-30,000 vpd and 30,001-35,000 vpd, and measure the respective CMFs for smaller intervals of AADT. It's also possible to develop a crash modification function to account for the effects of difference in AADT and other roadway characteristics. If the CMF is

significantly higher than one for a target AADT range, it is suggested to use more specific

modification or improvement of the signalization warrant for that particular AADT range.

CHAPTER 4 : ESTIMATING SAFETY PERFORMANCE TRENDS OVER TIME FOR TREATMENTS AT INTERSECTIONS IN FLORIDA

4.1   Introduction

Traffic researchers and engineers have developed a quantitative measure for safety effectiveness of signalization in the form of the Crash Modification Factor (CMF). Based on CMFs from multiple studies, the Highway Safety Manual (HSM) Part D (AASHTO, 2010) provides CMFs which can be used to predict the expected number of crash reduction or increase after converting stop-controlled to signal-controlled intersections (defined as "the signalization") and installing RLCs.

There is potential lag of drivers' awareness of roadway treatments suggested by Sacchi et al. (2014). Thus, the objectives of this study are to analyze the variations in the CMFs for the signalization and adding RLCs over time and to predict the CMFs for the treatments using a time series model. This information would be helpful for traffic engineers to understand trends of safety performance of the treatments in the long term. This chapter evaluates the effectiveness of the signalization in reducing rear-end and angle + left-turn crashes and the effectiveness of adding RLCs in reducing total and fatal+injury crashes.

To better reflect the short term variations in CMFs, CMFs are calculated using the observational before-after study with the comparison group method in each month and 90-day moving windows. Then ARMA time series model was applied to predict trends of CMFs over time for each treatment.

4.2   Data Preparation

The data for the signalization were collected and combined from the following six database sources: Roadway Characteristic Inventory (RCI) in Florida, Crash Analysis Report (CAR), Florida Financial Management Search System, Transtat I-View, Orange County Traffic Engineering Department and Google Earth.   The Financial Management Search System provides the information on projects constructed for the Florida Department of Transportation (FDOT).   For the crash report, the CAR system provided the information on all the reported crashes in Florida including severity, crash type, and other crash-related characteristics.   This system allowed us to locate crashes from 2003 to 2013.   Crashes were divided into 30 different crash types including angle, rear-end, head-on and sideswipe, etc.   However, it was verified that left-turn crashes were sometimes misclassified as angle crashes and vice versa.   Therefore, angle crashes and left-turn crashes were combined into angle + left-turn crashes.

Target intersections for signalization have been chosen from the Financial Project Search System from the FDOT.   Signalization of stop-controlled intersections was identified as a major treatment. Through the TranStat iView, it is possible to precisely match the mile post of the constructed intersections. However, the TranStat iView did not provide historical satellite maps.   Thus, the precise location was matched from TranStat iView to historical satellite maps from Google Earth, RCI Database, and FDOT Video Log.   A total of 32 intersections (treated sites) which were converted from a stop-controlled to a signal-controlled intersection were identified from the Financial Project Search System.   The CMFs were estimated based on these 32 signalized intersections. A total of 190 stop-controlled intersections without the signalization treatment were identified as the comparison sites.

The locations of RLCs and their construction dates were retrieved from the Orange County Engineering Department in the City of Orlando. A total of 19 intersections were identified as the sites with RLCs in Orange County. To examine the effects of each treated site, 185 untreated intersections were located in southwest Florida where no RLC were installed over the study period. However, due to a lack of samples for each crash type, this study focused on crash severity instead of crash type.

Table 4-1 and Table 4-2 show the numbers of sites and observed 30-day study periods, average crash frequencies per 30 days and their standard deviation, and the range of crash frequencies among the treated sites. In Table 4-1, "Angle + Left-turn Crashes" indicates the crash count for angle crashes plus left turn crashes, "KABCO Crashes" and "KABC Crashes" represent total crashes and fatal and injury crashes including possible injury, respectively.

Table 4-1 Descriptive Statistics for Treated Sites

Variable	Numbers of Treated Sites	Numbers of 30-day Intervals *	Average Crashes per 30 Days	Standard Deviation	Minimum # of Crashes	Maximum # of Crashes
Signalization						
Rear-end Crash	32	28	6.4138	2.1132	2	10
Angle + Left-Turn Crash	32	28	3.1034	1.3976	1	6
Adding RLCs						
KABCO Crash	19	36	8.1667	4.0249	2	21
KABC Crash	19	36	4.3889	2.7597	1	13

*Time length after treatment was implemented in 30 days unit.

Table 4-2 Descriptive Statistics for Comparison Sites

Variable	Numbers of Comparison Sites	Numbers of 30-day Intervals *	Average Crashes per 30 Days	Standard Deviation	Minimum # of Crashes	Maximum # of Crashes
Signalization						
Rear-end Crash	190	28	3.7241	1.6881	1	8
Angle + Left-Turn Crash	190	28	4.3103	2.1062	1	9
Adding RLCs						
KABCO Crash	95	36	100.1111	17.9073	58	138
KABC Crash	95	36	37.9167	9.5300	23	64

*Time length after treatment was implemented in 30 days unit.

4.3   Methodology

4.3.1   Before-After Study with Comparison Group Method

Comparison group before-after study estimates safety effects of the treatment not only using crash data for the treatment sites, but also crash data for the untreated sites which are chosen as comparison group. The method compensates for the external causal factors that could affect the change in the number of crashes. Previous research (AASHTO, 2010; Abdel-Aty et al., 2014) applied the empirical Bayes and full Bayes methods in order to capture the regression-to-the-mean (RTM) bias. Although these two methods account for the RTM bias, they require ADT data along with other geometry information to develop safety performance function. Notwithstanding, traffic volume data is retrieved as Annual Average Daily Traffic (AADT). Therefore, it is not feasible in many cases to estimate the safety effect within a year using the empirical Bayes and full Bayes methods.

Thus, to capture the safety effect in time periods shorter than a year, this study estimated monthly CMFs using the before-after study with comparison group method. First, it can be observed that the CMFs in each month (30 days) but found that CMFs significantly fluctuated over time. This RTM bias makes it difficult to observe the general trends. Therefore, the CMFs were also calculated in 3-month (90 days) moving windows. In this case, instead of calculating the CMF for each month (i = 1 to n), the monthly moving averages of CMF in three months (i.e. the current month and the following two months) was calculated. For instance, the CMF for p = 1 (the first moving window) reflects a moving average of the CMFs for i = 1, 2 and 3 months. This way, the CMFs would indicate the safety effect for 3 consecutive months.

According to Hauer (1997), before estimating the CMF using the comparison group method, sample odds ratio need to be checked to make sure the comparison sites are comparable with the treated sites. For both target treatments, the odds ratio (Equation 4-1) between the comparison group and the treated group are close to 1. Thus, it is proper to use the comparison groups for analyzing the effects for signalization and RLC at intersections.

$$S= \frac{[(Tb*Ca)/(Ta*Cb)]}{[1+\frac{1}{Ta}+\frac{1}{Cb}]} \qquad (4-1)$$

Where

S = Sample odds ratio;

Tb = Crash for treatment group at before period;

Ta = Crash for treatment group at after period;

Cb = Crash for comparison group at before period;

Ca = Crash for comparison group at after period.

There are two main assumptions in the before-after study with comparison group method Hauer (1997):

1. The factor Ta/Tb= Ca/Cb

2. Changes in the various factors affect the safety of both treatment and comparison groups in same scale.

Based on these assumptions, it can be assumed that the change in the number of crashes from the 'before' period to 'after' period at the treated sites, in case of no countermeasures had been implemented, would have been in the same proportion as that for the comparison group. Accordingly, the expected number of crashes for the treated sites that would have occurred in the

'after' period had no improvement applied ($N_{expected, T,A}$) can be calculated using Equation 4-2 Hauer (1997):

$$N_{expectedT,A} = N_{observedT,B} \times \frac{N_{observedC,A}}{N_{observedC,B}}$$ (4-2)

If the similarity between the comparison and treated sites in the yearly crash trends is ideal, the variance of $N_{expected, T,A}$ can be estimated from Equation 4-3:

$$Var(N_{expectedT,A}) = N_{expectedT,B}^{2}(1/N_{observedT,B} + 1/N_{observedC,B} + 1/N_{observedC,A})$$ (4-3)

It should be noted that a more precise estimate can be obtained in case of using non-ideal comparison group as explained in Hauer (1997), Equation 4-4:

$$Var(N_{expectedT,A}) = N_{expectedT,B}^{2}(1/N_{observedT,B} + 1/N_{observedC,B} + 1/N_{observedC,A} + Var(\omega))$$ (4-4)

where

$$\omega = \frac{r_{c}}{r_{t}} \quad \text{and} \quad r_{c} \cong \frac{N_{expectedc,A}}{N_{expectedc,B}} \quad \text{and} \quad r_{t} \cong \frac{N_{expected,t,A}}{N_{expected,t,B}}$$

The CMF and its variance can be estimated using Equation 4-5 and 4-6 as follows:

$$CMF = (N_{observedT,A}/N_{expectedT,A})/(1 + (Var(N_{expectedT,A})/N_{expectedT,A}^{2}))$$ (4-5)

$$Var(CMF) = \frac{CMF^{2}[(1/N_{observedT,A}) + ((Var(N_{expectedT,A})/N_{expectedT,A}^{2})]}{[1 + (Var(N_{expectedT,A})/N_{expectedT,A}^{2}]^{2}}$$ (4-6)

4.3.2   ARMA Time Series Model

The ARMA (Auto Regressive Moving Average) model consists of the autoregressive (AR) and moving average (MA) models. The model is usually referred to as ARMA (p,q) where p and q represent the possible lags that affect the ARMA model. For instance, the AR (2) model represents that the first and second lags are used to predict the autoregressive relationship for the target time period. The MA (3) model represents the first, second and third lags are used to predict the moving average for the target time period. When these two AR (2) and MA (3) models are combined, the model is referred to as ARMA (2,3). According to the previous studies (Box et al., 2013; Woodward et al., 2011), the ARMA model can be specified as follows:

$$\hat{X}(t) \; = \; \phi_1 X(t-1) \; +...+ \phi_p \, X(t-p) \; + \, Z(t) \; + \; \theta_1 Z(t-1) \; + \; ...+ \; \theta_q \, Z(t-q) \qquad (4\text{-}7)$$

where   X= General Time Series

$\hat{X}(t)=$ Forecast of the time series Y for time t

X(t-1)~X(t-p)= Previous P values of time Series X

f_i, …, f_p = Coefficient estimated for autoregressive model

θ_i, …, θ_q = Coefficient estimated for moving average model

Models are selected on the basis of the Akaike Information Criterion (AIC) and Schwarz's Bayesian Criterion (SBC). Once ideal time series models are identified, the optimized model was used to predict $\hat{X}$ (t) for future time periods. Statistics Analysis Software, SAS (SAS) was used to develop the ARMA model.

4.4   Results

4.4.1   Trends of CMF for Signalization

CMFs were calculated based on the crash counts for each month by referencing the comparison group. The monthly CMF trend for rear-end crashes is shown in the upper part of Figure 4-1. The figure shows that CMFs for the ninth and the fifteenth month after the treatment are peak points.   According to previous research (Wang and Abdel-Aty, 2014), the CMF for the signalization indicates that the CMF for rear-end crashes is 1.7- 2.7 at a 95 percent confidence interval. Therefore, it appears that these high CMFs were observed due to the regression to the mean (RTM) bias. In order to account for the RTM bias, the CMFs in 90-day moving windows were also observed. As shown in Figure 4-1, the variations in the CMF were lower for 90-day moving windows. The bottom part of Figure 4-1 shows the variations in CMF for angle and left-turn crashes.

It should be noted that the CMF for rear end crashes was lower at the beginning and started increasing 9 months after the signalization. On the other hand, the CMFs for angle + left turn crashes showed the opposite trend - is the CMF was higher at the beginning and started decreasing 9 months after the signalization.
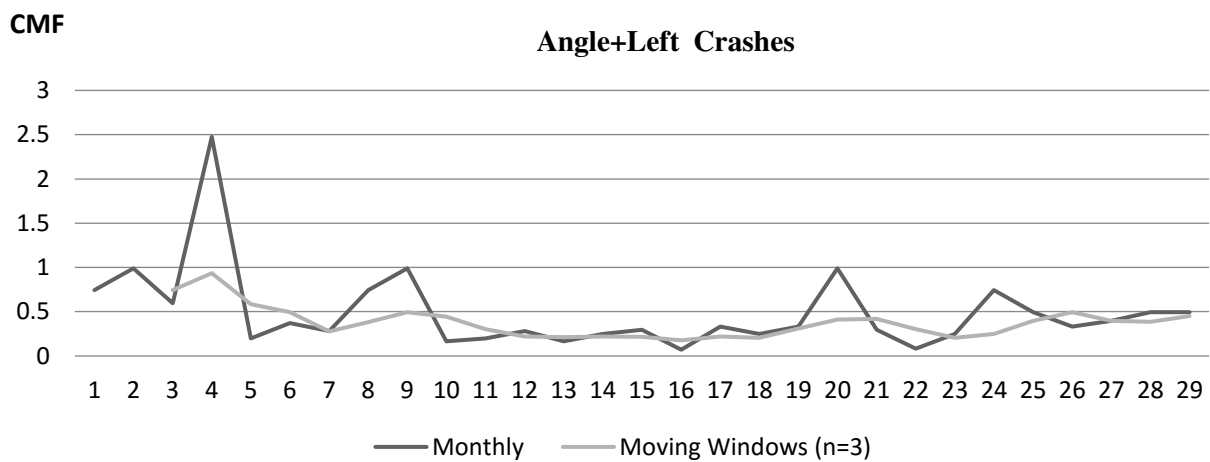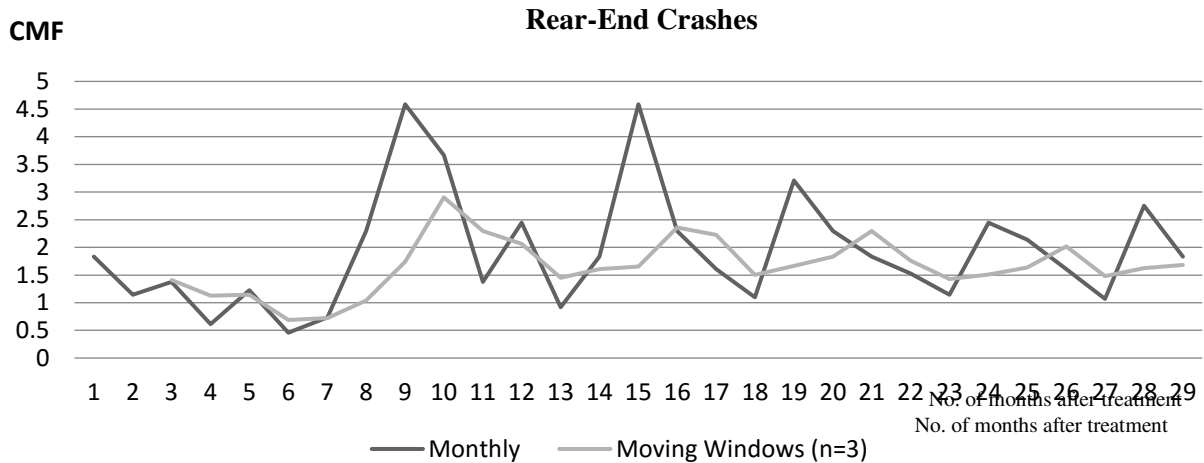
Figure 4-1 Monthly variations in CMF for the signalization (Rear-end and Angle + Left-turn crashes)

For rear-end crashes, Table 4-3 shows that the CMF for the first 9 months is lower than the CMF for the 1st-29th month whereas the CMF for the 10th-29th month is higher than the CMF for the 1st-29th month. At an 85% confidence interval, the CMFs for rear-end crashes for the first 9 month and the 10th-29th month are 0.996~1.520 and 1.521~1.947, respectively. Since these two intervals do not overlap, the CMF for the 10th-29th month is significantly higher than the CMF for the 1st-9th month at a 85% confidence level. On the other hand, Table 4-3 shows that angle + left-turn crashes have opposite effect compared to rear-end crashes. The CMF for the first nine months is

0.575 with standard error at 0.039. This CMF is significantly less than the CMF for the $10^{th} \sim 29^{th}$ month at a 95% confidence level. The results indicate that the crash reduction rate is higher for angle + left-turn crashes at later period (the 10th-29th month). On the other side, the crashes performance is worse at later period (the 10th-29th month) for rear-end crashes.

These results are potentially due to changes in driver behavior over time after the intersection control changes from stop control to signal control. In general, it takes a certain amount of time for drivers to be adapted to any change in intersection control. It is possible that drivers are more cautious immediately after the intersections are signalized but their behavior gradually changes (e.g. more risk-taking) as they are more familiar with the new signal design. Thus, a significant increase in CMFs after the 9th month indicates that it took approximately 9 months for drivers to be adapted to the new signalized intersections. This demonstrates that true safety effects of the signalization can be observed several months after (rather than immediately after) the completion date of the treatment.

CMFs for signalization were calculated using the full time period to consider severities for both crashes types. According to Table 4-3, signalization effectively reduce F+I crashes for angle+left turn crashes by 63.8% but slightly increase in F+I crashes for rear-end crashes by 14.7%. This indicates that angle+left-turn crashes are more likely to be severe than rear-end crashes. Thus, it can be concluded that the benefit of a larger reduction in F+I angle+left-turn crashes outweighs the cost of a smaller increase in F+I rear-end crashes by signalization after comparing these two factors.

Table 4-3 CMFs for Signalization at Different Time Periods

Crash Type (Number of months after signalization)	Method	
	Comparison Group Before-After	
	CMF (Safety Effectiveness)	S.E
Rear-End Crashes (1-29)	1.580 -58.0%	0.116
Rear-End Crashes (1-9)	1.258 -25.8%	0.182
Rear-End Crashes (10-29)	1.734 -73.4%	0.148
Rear-End F+I Crashes (1-29)	1.147 -14.7%	0.132
Angle+Left-turn Crashes (1-29)	0.356 64.4%	0.04
Angle+Left-turn Crashes (1-9)	0.575 42.5%	0.039
Angle+Left-turn Crashes (10-29)	0.284 71.6%	0.052
Angle+Left-turn F+I Crashes (1-29)	0.362 -63.8%	0.05

4.4.2 Estimating CMF Trends for Signalization Using ARMA Model

This study also predicted the trend of CMF over time using the ARMA (Box et al., 2013) model after checking the autocorrelation function (ACF) and partial autocorrelation (PACF). The optimized model for rear end crashes are shown in Table 4-4. Table 4-4(a) shows the model for CMFs in each month and Table 4-4(b) shows the model for CMFs in 90-day moving window. Based on the fit of each model, (1,1) and (0,3) were found to be the optimized model to represent CMFs for each month and 90-day moving windows, respectively. The coefficients for the MA and AR parameters represent the relationship of the observed data between the current month and n previous months. Higher coefficient reflects that the data for the previous month(s) have stronger influence on data for the current month. For instance, if the coefficient for AR(1) is small or AR(1) is not statistically significant, there is no strong influence of the data for the previous month(s) on the data for the current month.

The ARMA model with CMFs in 90-day moving windows has lower values of AIC and SBC than the model with CMFs in each month. This indicates that the prediction capability is better for the model with CMFs in 90-day moving windows than the model with CMFs in each month.

Table 4-4 Estimated Parameters in ARMA Model for Signalization (Rear-end Crashes)

CMF in each month (a)					
Parameter	Estimate	Standard Error	t Value	Pr > |t|	Lag
MU	1.93506	0.22824	8.48	<.0001	0
MA1,1	-0.83199	0.20568	-4.05	0.0004	1
AR1,1	-0.52604	0.31657	-1.66	0.1086	1
				AIC=86.83	SBC=90.93
CMF in 90-day moving windows (b)					
Parameter	Estimate	Standard Error	t Value	Pr > |t|	Lag
MU	1.62658	0.16142	10.08	<.0001	0
MA1,1	-0.80688	0.16762	-4.81	<.0001	1
MA1,2	-0.59535	0.16969	-3.51	0.0018	2
				AIC=26.90765	SBC=30.79516

Figure 4-2 shows the observed and predicted CMFs for rear end crashes in each month and 90-day moving windows. The dotted line is the end of the observation period and the shaded area is a 95% confidence interval. As shown in Figure 4-2, the ARMA model fits better for the CMFs in 90-day moving windows than the CMFs in each month for 29 months after the signalization.

However, the predicted CMFs for the time period after the 29th month (i.e. beyond the observation time period) were nearly constant. This is because the ARMA model does not have an obvious autoregressive value. Therefore the constant value is the predicted mean CMF. In fact, it is not ideal to apply this model to predict the CMF values after the 29th month since the CMF is not statistically different from 1 due to very high standard errors.
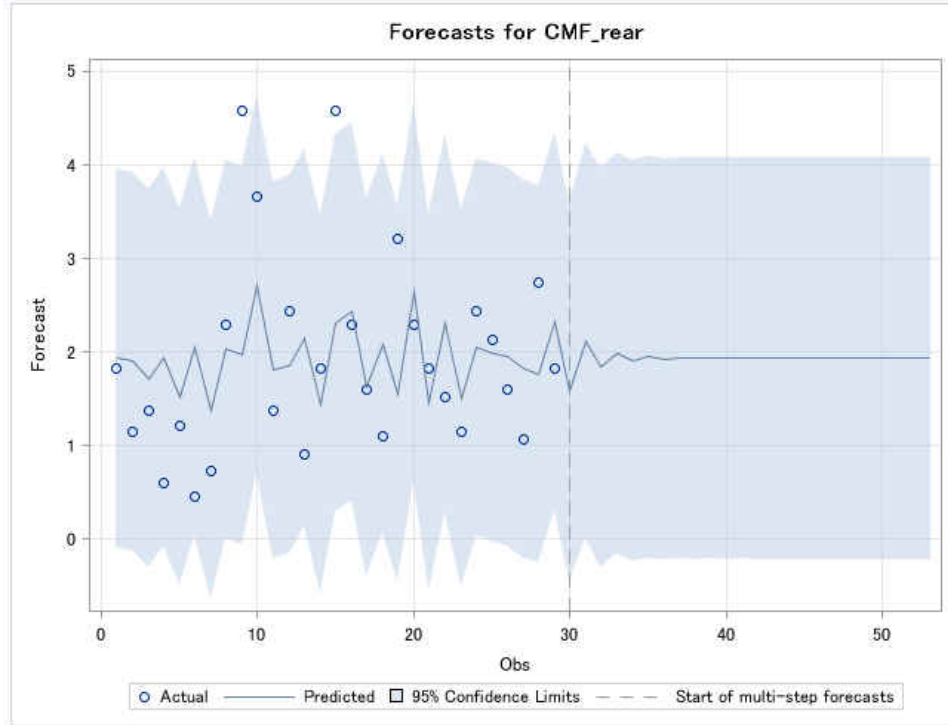
(a) CMF in each month
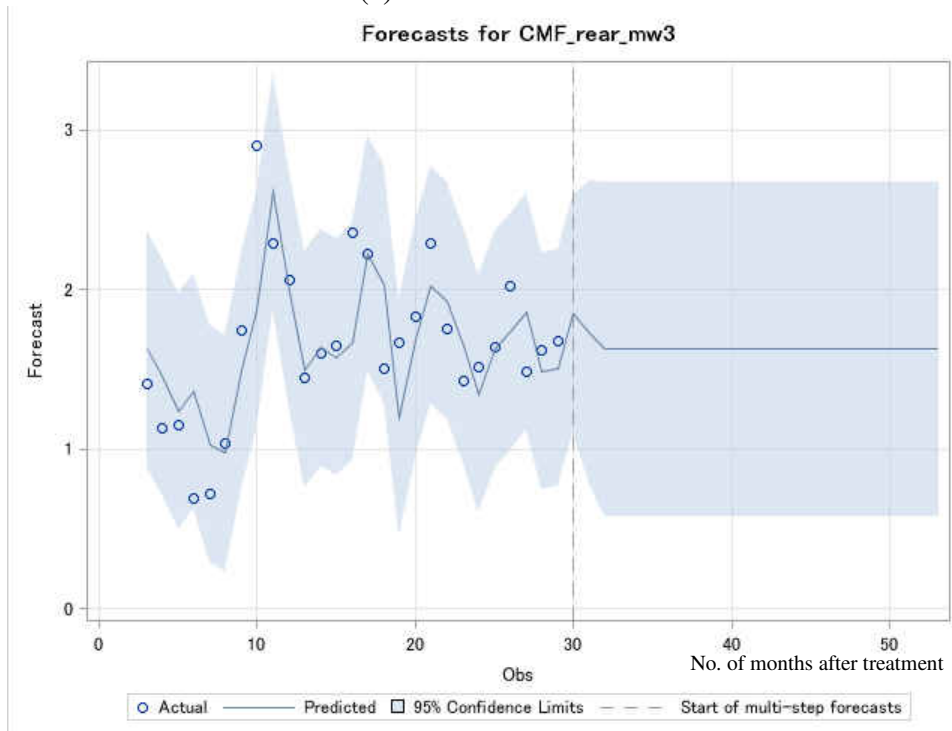
(b) CMF in 90-day moving windows

Figure 4-2 Prediction of monthly variations in CMFs for the signalization using ARMA models (Rear-end crashes)

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The AR(1) and MA(3) models were used to explain the CMFs in each month and 90-day moving windows, respectively. Similar to rear-end crashes, using the CMFs for angle + left-turn crashes in 9-month moving windows also increased model fit as indicated by lower AIC and SBC values.

Table 4-5 Estimated Parameters in ARMA Model for Signalization (Angle + Left-Turn Crashes)

CMF in each month (a)					
Parameter	Estimate	Standard Error	t Value	Pr > |t|	Lag
MU	0.49333	0.09231	5.34	<.0001	0
AR1,1	0.05041	0.19221	0.26	0.7951	1
				AIC=40.80	SBC=43.53
CMF in 90-day moving windows (b)					
Parameter	Estimate	Standard Error	t Value	Pr > |t|	Lag
MU	0.43488	0.0685	6.35	<.0001	0
MA1,1	-1.10728	0.19582	-5.65	<.0001	1
MA1,2	-0.82782	0.26027	-3.18	0.0042	2
MA1,3	-0.42102	0.19746	-2.13	0.0439	3
				AIC=-33.91	SBC=-28.7254

Figure 4-3 shows the CMFs for angle + left-turn crashes in each month and 90-day moving windows. The ARMA model could not predict a clear trend of CMFs since the noise level was too high to predict the CMF values as shown in Figure 4-3 (a). On the other hand, the predicted CMFs in 90-day moving windows is consistently below 1 as shown in Figure 4-3 (b). Similar to rear-end crashes, the ARMA model fits better for the CMFs in 90-day moving windows than the CMFs in each month. However, the predicted CMFs after the 29th month were statistically significant (i.e. the CMF is significantly lower than 1). This indicates that the signalization would have significant safety effects on reducing angle + left-turn crashes in the long term.
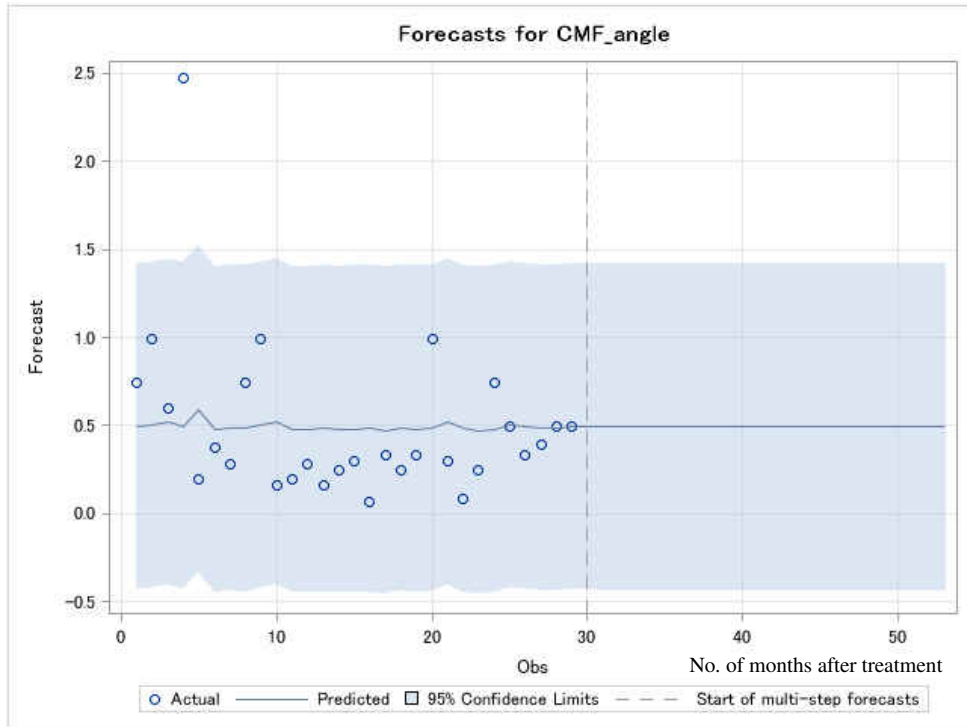
(a) CMF in each month
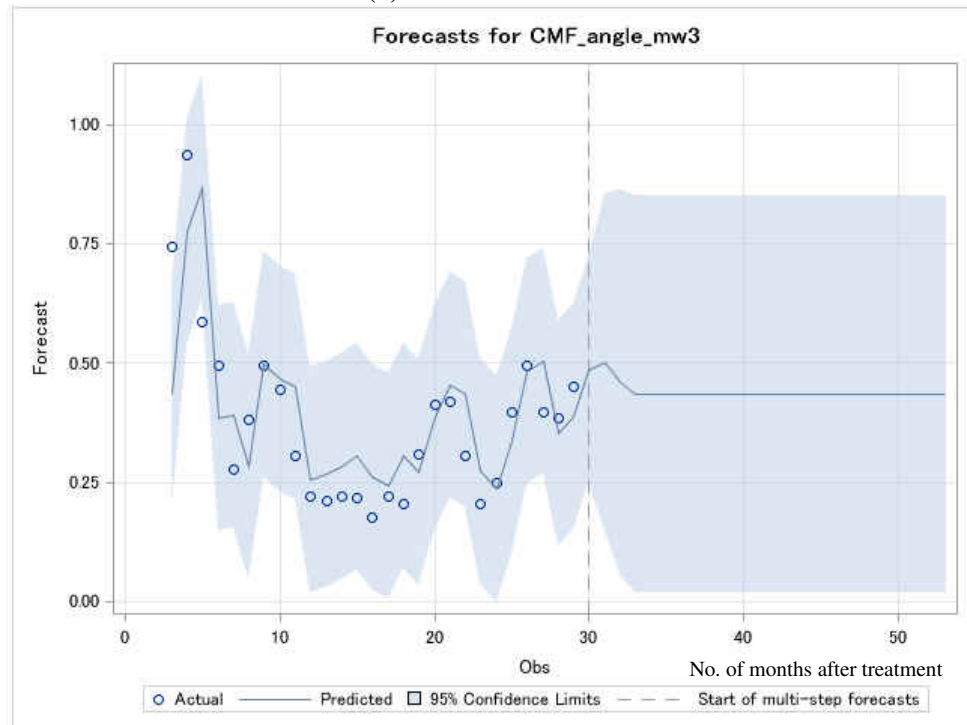
(b) CMF in 90-day moving windows

Figure 4-3 Prediction of monthly variations in CMFs for the signalization using ARMA models
(Angle + Left-turn crashes)

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4.4.3 CMF Trends for Adding RLCs

The trends of CMFs for adding RLCs for total and F+I crashes are shown in Figure 4-4. The crash data for adding RLCs were available for a longer time period (36 months) than the crash data for the signalization. Previous studies (Abdel-Aty et al., 2014; Erke, 2009) found that the CMFs for adding RLCs were higher than 1 for rear-end crashes and lower than 1 for angle crashes. However, due to a lack of samples for each crash type, this study focused on crash severity instead of crash type. As shown in the upper part of Figure 4-4, the CMF for total crashes generally decreased in the first 9 months after adding RLCs and then started increasing. The CMF for F+I crashes showed a similar trend – it decreased in the first 13 months and then started increasing as shown in the bottom part of Figure 4-4.
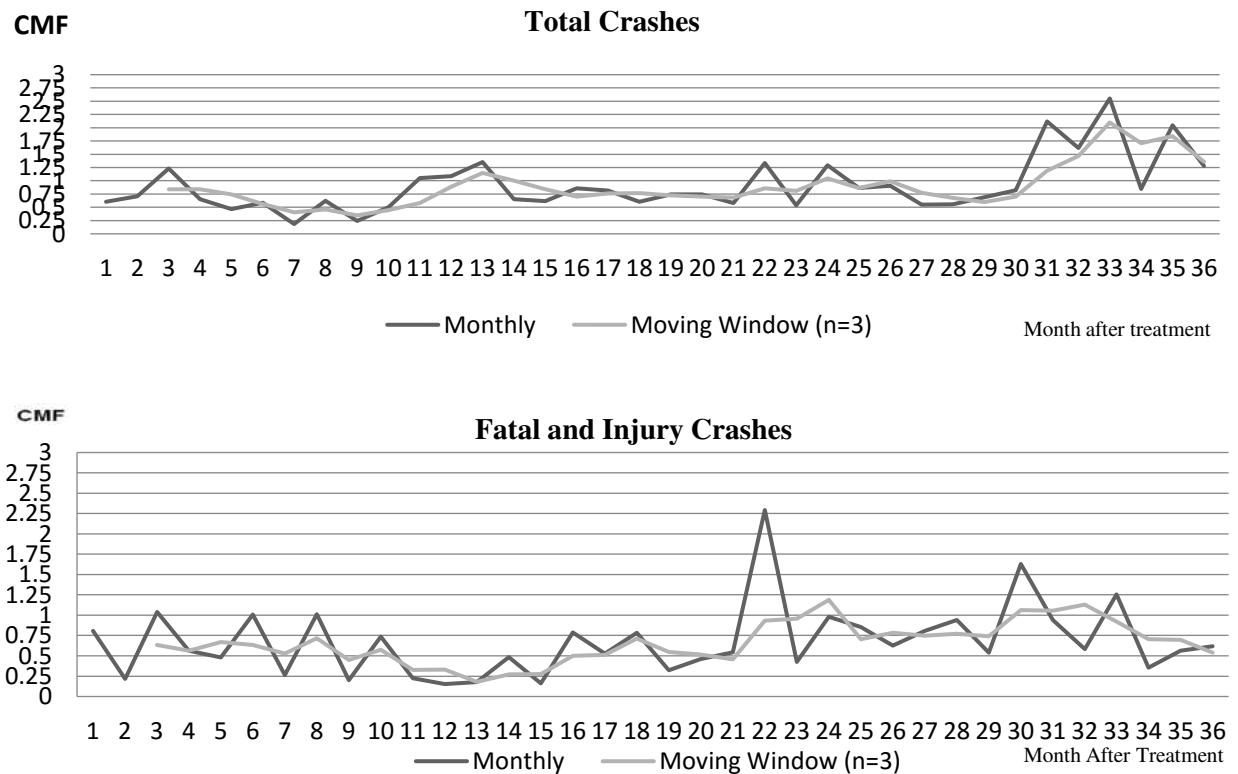
Figure 4-4 Monthly variations in CMFs for adding RLCs (Total Crashes and F+I Crashes)

The CMFs were calculated for total crashes and F+I crashes for adding RLCs as shown in Table 4-6. For the total crashes, the CMF for the first 18 months was lower than the CMF for the 1st-36th month whereas the CMF for the 19th-36th month was higher than the CMF for the 1st-36th month. Also, the CMF for the first 18 months is significantly lower than the CMF for the 19th-36th month at a 95 confidence level.

A similar trend of CMFs was observed for F+I crashes as shown in the bottom part of Table 4-6. The CMF for the first 18 months was significantly lower than the CMF for the following 18 months at a 90% confidence level.

Table 4-6 CMFs for Adding RLCs at Different Time Period

Severity Type (Number of months after adding RLCs)	Method	
	Comparison Group Before-After	
	CMF (Safety Effectiveness)	S.E
Total Crashes (1-36)	**0.872** 12.80%	**0.056**
Total Crashes (1-18)	**0.695** 30.50%	**0.063**
Total Crashes (19-36)	1.089 -8.90%	**0.087**
F+I Crashes (1-36)	**0.652** 34.80%	**0.057**
F+I Crashes (1-18)	**0.518** 48.20%	**0.067**
F+I Crashes (19-36)	**0.789** 21.10%	**0.083**

4.4.4 Estimating CMF Trends of Adding RLCs Using ARMA Model

The AR(2) and AR(1) models were used for total crashes to explain the CMFs in each month and 90-day moving windows as shown in Table 4-7. The ARMA model with the CMFs in each month did not have a good fit compared to the model with the CMFs in 9-month moving windows as indicated by higher AIC and SBC values. Also, the AR(1) estimator is not statistically significant at a 95% confidence level.

Table 4-7 Estimated Parameters in ARMA Model for RLCs (Total Crashes)

CMF for each month					
Parameter	**Estimate**	**Standard Error**	**t Value**	**Approx Pr > |t|**	**Lag**
MU	0.90417	0.20563	4.4	0.0001	0
AR1,1	0.19211	0.15298	1.26	0.218	1
AR1,2	0.51495	0.16529	3.12	0.0038	2
				AIC=45.78 SBC=50.55	
CMF for 90-day moving windows					
Parameter	**Estimate**	**Standard Error**	**t Value**	**Approx Pr > |t|**	**Lag**
MU	0.90077	0.17081	5.27	<.0001	0
AR1,1	0.85561	0.09832	8.7	<.0001	1
				AIC=-3.99 SBC=-0.93	

Figure 4-5 shows the CMFs for total crashes in each month and 90-day moving windows. The confidence interval for the CMFs in each month is much wider than the interval for the CMFs in 90-day moving windows. However, the predicted CMF after the 40th month is approximately 1. This suggests that the installation of RLCs would not have significant safety effects on reducing total crashes in the long term.
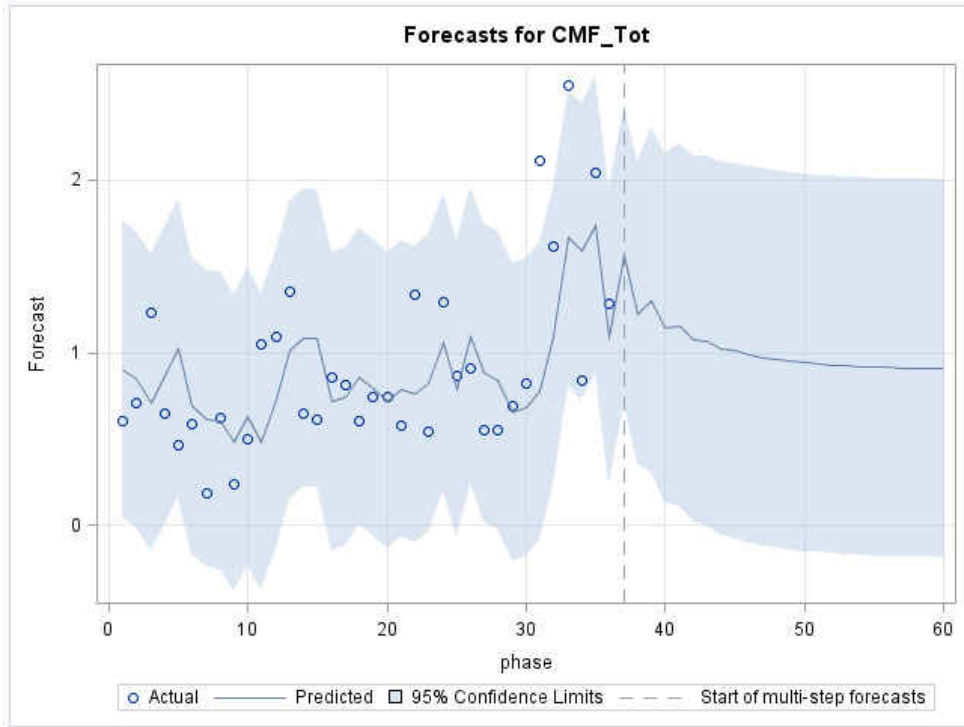
(a) CMFs in each month
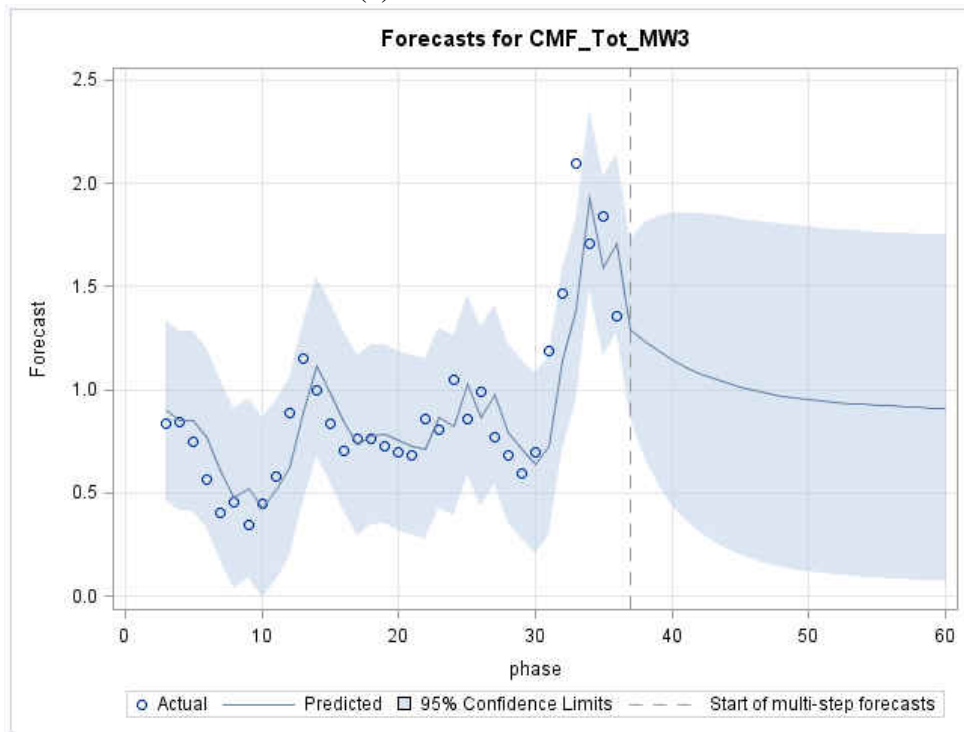
(b) CMFs in 90-day moving windows

Figure 4-5 Monthly variations in CMFs for adding RLCs using ARMA model (Total crashes).

The AR (1) + MA (2) and AR (1) models were used for F+I crashes to explain the CMFs in each month and 90-day moving windows, respectively as shown in Table 4-8. Similar to total crashes, the model with the CMFs in each month did not have good fit compared to the model with the CMFs in moving windows. Also, MA(1) and AR (1) estimators are not statistically significant at a 95% confidence level.

Table 4-8 Estimated Parameters in ARMA Model for Adding RLCs (F+I Crashes)

F+I Crashes per Month					
Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.66898	0.08948	7.48	<.0001	0
MA1,1	0.42097	0.50157	0.84	0.4075	1
MA1,2	-0.33345	0.16925	-1.97	0.0575	2
AR1,1	0.2812	0.52927	0.53	0.5989	1
				AIC=45.45 SBC=51.78	
F+I Crashes MW3					
Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.64434	0.09467	6.81	<.0001	0
AR1,1	0.73171	0.12139	6.03	<.0001	1
				AIC=-20.56 SBC=-17.51	

Figure 4-6(a) shows the CMFs for total crashes in each month and 90-day moving windows. The confidence interval for the CMFs in each month was much wider than the confidence interval for the CMFs in 90-day moving windows. In fact, when focusing on the mean value using the monthly

model, the predicted CMF after the 40th month is at 0.7. This suggests that the installation of RLCs would reduce total crashes in the long term but not significant at 95 level.

The CMFs for F+I crashes are shown in Figure 4-6(b). The confidence interval for the CMFs in each month was also much wider than the CMFs in 90-month windows. The figure shows a downward trend of the predicted CMF for the first 13 months followed by an upward trend for the 13th-25th month and a downward trend after the 25th month. To take a closer look at its predicted CMF, the CMF at 40th month is lower than one. In this case, it indicates that there is higher probability that CMF will be lower than 1 for F+I crashes using moving windows however not statistically significant at 95% level.
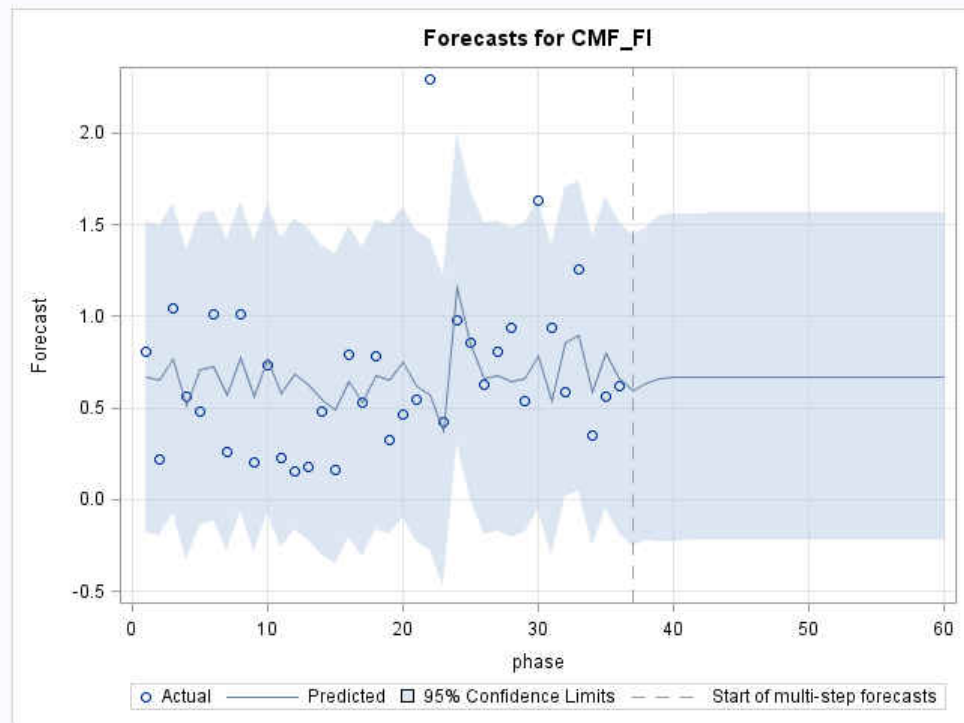
(a) CMFs in each month
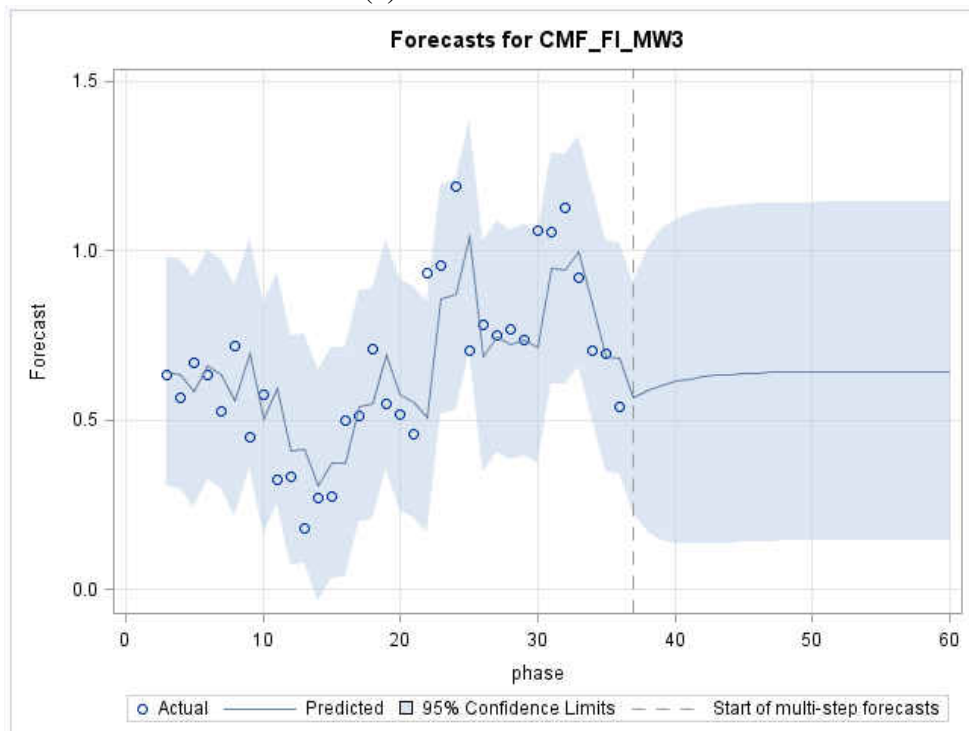
(b) CMFs in 90-day moving windows

Figure 4-6 Prediction of monthly variations in CMFs for adding RLCs using ARMA models (F+I crashes)

4.5   Conclusion

This study analyzes the trends of CMFs for the signalization of stop-controlled intersections and adding RLCs over time after these treatments are implemented. The CMFs were estimated using the Before-After study with comparison group method since Bayesian framework (empirical Bayes or full Bayes) requires detailed traffic volume data that are not readily available. The data used in this study are the records of intersection-related crashes in Florida during the time period between the treatment completion date and the end of 2013.   Monthly CMFs were calculated in each month and 90-day (three months) moving windows. The CMFs for total observation periods (28 months for the signalization and 36 months for adding RLCs), and early phase and later phase in the total period were also calculated.   The study also developed the ARMA time series model (Box et al., 2013) to predict the trends of CMFs over time on a monthly basis.

The results of the signalization show that the CMFs for rear-end crashes were initially low during the early phase after the signalization but started increasing from the 9th month. On the other hand, the CMFs for angle + left-turn crashes were initially higher during the early phase after the signalization but started decreasing from the 9th month then became stable. This indicates a lag in safety effects of the signalization as it takes time for road users to be adapted to the new intersection control. The results of adding RLCs show that the CMFs for both total and F+I crashes were higher during the first 18 months than the following 18 months. Thus, the CMFs for the early phase after adding RLCs did not reflect the safety performance in the later phase.

The results of the ARMA model show that the model can better predict trends of the CMFs for the signalization and adding RLCs when the CMFs are calculated in 90-day moving windows

compared to the CMFs calculated in each month. Moving windows is used to compensate the noise due to short sample size. If sample size is good enough to develop time series model using single month, it is suggested not using moving windows because this allows us to see the pure monthly effect. The study also demonstrates that the ARMA time series model can be applied to the prediction of the CMFs in the long term based on historical trend of CMFs over time. Although the predicted CMFs generally had large standard errors (i.e. not statistically significant safety effect), the CMF was significantly lower than 1 at a 95% confidence level for angle + left-turn crashes after the signalization. Thus, it is expected that the signalization has significant positive safety effects in reducing angle + left-turn crashes in the long term.

Based on the results in this study, it is concluded that trends of CMF over time need to be observed after the treatment is installed. If there is any significant change in CMFs between the first several months and the following several months, using the data from the early period after the treatment will result in bias of estimating CMFs. Thus, to avoid making erroneous decisions in selecting the treatments based on biased CMFs, the CMF should capture the long-term safety effects of the treatment based on their observed and predicted trends over time.

When estimating CMFs based on time, there is a trade-off between selecting longer time interval and shorter time interval as an observation unit. When using longer time interval, the variations in CMFs among different intervals will be smaller. Thus, noise can be reduced by using longer time interval. However, the short-term effect cannot be captured when using longer interval. To select more appropriate CMFs, it is recommended to develop CMF functions using time series model with shorter time intervals as long as the sample size in each interval is sufficient.

Afterwards, one could calculate CMFs based on the function. If the sample is too restricted to develop time series models, it is recommended to estimate CMFs for the first year and the period afterwards separately.

CHAPTER 5 : AN R PACKAGE FOR CALCULTION OF THE CRASH MODIFICATION FACTORS WITH GRAPHICAL USER INTERFACE

5.1   Introduction

The HSM Part D provides a comprehensive list of the effects of safety treatments (countermeasures). These effects are quantified by crash modification factors (CMFs), which are based on the compilation from past studies of the effects of various safety treatments. The HSM Part D provides CMFs for treatments applied to roadway segments (e.g., roadside elements, alignment, signs, rumble strips, etc.), intersections (e.g., control), interchanges, special facilities (e.g., highway-rail crossings), and road networks. The objective of this chapter is to develop an R package for engineers to develop CMF.

Before-after study is widely used to develop CMFs comparing to cross-sectional analysis. In detail, the before-after method includes naïve before-after study, before-after study with comparison group (CG), before-after study with empirical Bayesian (EB) methods, and before-after study with full Bayesian. In this package, three methods are provided which are naïve, comparison group, and EB method. For calculating CMFs using the EB method, one need to develop safety performance functions (SPFs), which predict crash frequency as a function of explanatory variables. This package was built based on the methodology by previous publications (Gross et al., 2010; Hauer, 1997). In fact, before-after study has been used in HSM (AASHTO, 2010) Part D, (Abdel-Aty et al., 2014), and many others. Therefore, this package improves the efficiency and correctness of implementing before and after studies.

In R (R, 2013) environment, it requires installation before using this package. This package can be downloaded from the author's Github site (Wang and Norberg, 2015). Besides, this package was built using *devtools* by Wickham and Chang (2015). Before using this package, users should install R package *devtools* first in order to install the package from Github. After installing *devtools*, users can input *install_github* to install this package *bastudy* using the code as follows:

```
install.packages(devtools)
library(devtools)
devtools::install_github("doubleck/bastudy")
```

In addition, the graphical user interface was also developed using *shiny* (Chang et al., 2016). Before using the graphical interface, *shiny* needed to be installed in advance. The installation of the *shiny* can be achieved by using the code as follows:

```
install.packages(shiny)
library(shiny)
```

5.2   Methodology and Package Usage

In this package, there are four main methods.

1. Naïve

2. Comparison Group

3. Empirical Bayes

4. Graphical Interface

The introduction of each function will be introduced in this section.

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5.2.1 Naïve Method

According to Hauer (1997), naïve before-after study is the simplest form that it compares the crash count of the before period with the crash count of the after period. In this case, it assumes the passage of time from before to after is not associated with changes that affected the traffic safety.

Since the duration of the before and after can be different, r_d is used to represent the ratio of the durations as shown in Equation 5-1.

$$r_d = \frac{\text{Duration of after period}}{\text{Duration of before period}} \tag{5-1}$$

The expected crashes for the after period if there were no treatment is shown in Equation 5-2:

$$N_{expected,T,A} = r_d * N_{observed,T,B} \tag{5-2}$$

where,

$N_{expected,T,A}$= The expected crashes for the after period if there were no treatment

r_d= The ratio of the durations

$N_{observed,T,B}$= The observed crashes for the before period

The variance of the expected crashes for the after period if they were no treatment can be written as shown in Equation 5-3:

$$Var(N_{expected,T,A}) = r_d^2 * N_{observed,T,B} \tag{5-3}$$

Afterward, crash modification factor using naïve method can be calculated using the equation as indicated in Equation 5-4:

$$CMF = (N_{observed,T,A}/N_{expected,T,A})/(1 + (Var(N_{expected,T,A})/N_{expected,T,A}^2)) \tag{5-4}$$

The variance of the crash modification factor using the naïve method is shown in Equation 5-5:

$$\mathrm{Var(CMF)} = \frac{\mathrm{CMF}^2[(1/N_{observedT,A}) + ((\mathrm{Var}(N_{expectedT,A})/N_{expectedT,A}^{2})]}{[1 + (\mathrm{Var}(N_{expectedT,A})/N_{expectedT,A}^{2}]^2} \qquad (5\text{-}5)$$

The detailed usage of can be found in the documentation file along with the software. The detail usage to calculate CMF using the naïve before-after study is explained using the following code:

```
naive(before, after, depVar, db = 1, da = 1, alpha = 0.95)
```

Where,

before   Treatment data, before treatment was made

after   Treatment data, after treatment was made

depVar   The dependent variable (the number of crashes - should always be of class integer or

numeric).

db   duration of before period (typically years)

da   duration of after period (typically years)

alpha   Level of confidence

Example code:

```
naive(treat_before,treat_after,depVar="KABCO_Crashes",db=3,da=3,alpha=0.95)
```

5.2.2 Comparison Group

Comparison group before-after study estimates safety effects of the treatment not only using crash data for the treatment sites, but also crash data for the untreated sites, which are chosen as the comparison group. The method compensates for the external causal factors that could affect the change in the number of crashes.

The expected number of fatalities for the treated sites that would have occurred in the 'after' period had no improvement applied ($N_{expected, T,A}$) can be calculated using Equation 5-6 (Hauer, 1997):

$$N_{expectedT,A} = N_{observedT,B} \times \frac{N_{observedC,A}}{N_{observedC,B}}$$

(5-6)

If the similarity between the comparison and treated sites in the yearly crash trends is ideal, the variance of $N_{expected, T,A}$ can be estimated from Equation 5-7:

$$Var(N_{expectedT,A}) = N_{expectedT,B}{}^2 (1/N_{observedT,B} + 1/N_{observedC,B} + 1/N_{observedC,A})$$

(5-7)

It should be noted that a more precise estimate can be obtained in case of using ideal comparison group as explained by Hauer (1997), Equation 5-8:

$$Var(N_{expectedT,A}) = N_{expectedT,B}{}^2 (1/N_{observedT,B} + 1/N_{observedC,B} + 1/N_{observedC,A} + Var(\omega))$$

(5-8)

where

$$\omega = \frac{r_c}{r_t} \quad \text{and} \quad r_c \cong \frac{N_{expectedc,A}}{N_{expectedc,B}} \quad \text{and} \quad r_t \cong \frac{N_{expected,t,A}}{N_{expected,t,B}}$$

The CMF (Crash Modification Factor) and its variance can be estimated using Equations 5-9 and 5-10 as follows:

$$CMF = (N_{observed,T,A}/N_{expected,T,A})/(1+(Var(N_{expected,T,A})/N_{expected,T,A}^2)) \qquad (5\text{-}9)$$

$$Var(CMF) = \frac{CMF^2[(1/N_{observed,T,A})+((Var(N_{expected,T,A})/N_{expected,T,A}^2)]}{[1+(Var(N_{expected,T,A})/N_{expected,T,A}^2]^2} \qquad (5\text{-}10)$$

The syntax used to perform a comparison group before-after study can be found in the help document as:

```
CompGroup(compBefore, compAfter, before, after, depVar, alpha = 0.95)
```

where,

compBefore	Comparison data in before period
compAfter	Comparison data in after period
before	Treatment data, before some change was made
after	Treatment data, after some change was made
depVar	The dependent variable (the number of crashes - should always be of class integer or numeric).
alpha	Level of confidence

Example code:

```
CompGroup(compBefore=comparison_before,compAfter=comparison_after,before=trea
        t_before,after=treat_after,depVar="KABCO_Crashes",db=3,da=3,alpha=0
        .95)
```

For further example code, please refer to the documentation file after installing "bastudy" package from Github (Wang and Norberg, 2015).

5.2.3   Empirical Bayes Method

The empirical Bayes (EB) method combines the strengths of a before and after study that uses specific case-control techniques with regression methods for estimating safety. Unlike other methods, it increases the precision of estimation and it also corrects for the regression to the mean bias.

According to Hauer (Hauer, 1997), the safety performance can be estimated using Equation 5-11:

$$N_{expected,T,A} = \gamma * N_{predicted,B} + (1 - \gamma)N_{observed,T,B} \qquad (5\text{-}11)$$

Where $N_{expected,T,A}$=Expected crash count if there had been no treatment

$N_{predicted,B}$=predicted crash counts based on SPF multiply by the calibration factor

$N_{observed,T,B}$= observed crash counts before treatment

γ =Weight between observed crash counts and predicted crash counts

Afterward, $N_{predicted,B}$ was re-estimated based on SPFs and Calibration factors from different states and calculated the predicted crash counts accordingly. Then the updated $N_{expected,T,A}$ after substitution was retrieved.

The method of the assigned weight is shown below as suggested by Hauer (1997). The weight is inversely proportional to the variances of the corresponding random variables as shown in Equation 5-12. When two estimates of unequal precision are joined, the weights γ and $1 - \gamma$ that minimize the expected squared error of estimation are inversely proportional to the variance φ of the estimate.

$$\gamma = \frac{1}{1+\frac{\mu*Y}{\varphi}} \qquad (5\text{-}12)$$

Where μ = predicted crashes before treatment (per year)

Y = number of year(s)

φ = overdispersion parameter

In this term, the overdispersion parameter γ is different for each SPFs.

After $N_{expected,T,A}$= is calculated, Gross et al. (2010) suggest to use $N_{expected,T,A}$= to adjust the value of $\hat{\pi}$ which can be shown in Equation 5-13:

$$N^*_{expected,T,A} = N_{expected,T,A} * \frac{N_{predicted,T,A}}{N_{predicted,T,B}} \qquad (5\text{-}13)$$

Where $N^*_{expected,T,A}$= Expected crash count if there had been no treatment after adjustment

$N_{expected,T,A}$= Expected crash count if there had been no treatment before adjustment

$N_{predicted,T,A}$= Predicted crashes after treatment

$N_{predicted,T,B}$= Predicted crashes before treatment

The CMF can be written in the form as shown in Equation5-14:

$$CMF = (N_{observedT,A}/N_{expectedT,A})/(1+(Var(N_{expectedT,A})/N_{expectedT,A}^2))$$ (5-14)

Where CMF = crash modification factor

$N_{observed,T,A}$ = Observed after crash

When $\hat{\theta}$ <1, the treatment has a positive effect; when $\hat{\theta}$ >1 it is expected to have a negative effect on safety performance.

The variance of CMF is shown in Equation 5-15:

$$Var(CMF) = \frac{CMF^2[(1/N_{observedT,A}) + ((Var(N_{expectedT,A})/N_{expectedT,A}^2)]}{[1+(Var(N_{expectedT,A})/N_{expectedT,A}^2]^2}$$ (5-15)

The syntax used to perform an empirical Bayes before-after study can be achieved by:

```
empBayes(reference, before, after, depVar, offsetVar = NULL, indepVars =
        setdiff(names(reference), c(depVar, offsetVar)), forceKeep = NULL,
        alpha = 0.95)
```

reference   Reference data

before   Treatment data, before some change was made

after   Treatment data, after some change was made

depVar   The dependent variable (the number of crashes - should always be of class integer
                or numeric).

offsetVar   An offset variable (eg years)

indepVars   Variables used to model the outcome variable depVar

forceKeep   A character vector of variable names. These variables will not be considered for

removal during the variable selection process.

alpha   Level of confidence

Example code:

```
empBayes(reference=reference_group, before=treat_before, after=treat_after,
         depVar="KABCO_Crashes", offsetVar = NULL, indepVars=
         c("Major_AADT", "Speed_Limit"), forceKeep = "Major_AADT" alpha =
         0.95)
```

It is worth mentioning that the negative binomial model is estimated using *MASS* package with

function "glm.nb" (Venables and Ripley, 2002). Besides, if the forceKeep does not specify, the

algorithm will select optimized variables using stepwise selection based on Akaike Information

Criterion (AIC).

5.3   Graphical User Interface, GUI

Three methods, naïve, comparison group, and empirical Bayes calculation are all prepared with

graphical user interface. After installing *bastudy*, the user input *bagui()* to use the user interface.

Besides, in the recent update (03/10/2016), this GUI was ported to the server and can be accessed

using the link: "https://junghanwang.shinyapps.io/bastudy/"

In the GUI, there are 3 tabs in the GUI, each tab deal with one type of before-after study. The first

tab, naïve before-after study is shown in Figure 5-1. The user has to select "Naïve" under "Select

Analysis Type". Then upload data to be analyzed. The before data and the after data need to be uploaded separately with the same variable name. In detail, the data uploaded was set to be comma-separated values (CSV). Once the system detects the CSV files for the before and the after with identical variable names, the user can select the target variable. Afterward, the duration for before and after period can be input with numeric value based on the data. Then, the next input is a bar scale for the confidence level. The default value of the confidence interval was set to be 95 percent level. The user can drag it up and down as needed.
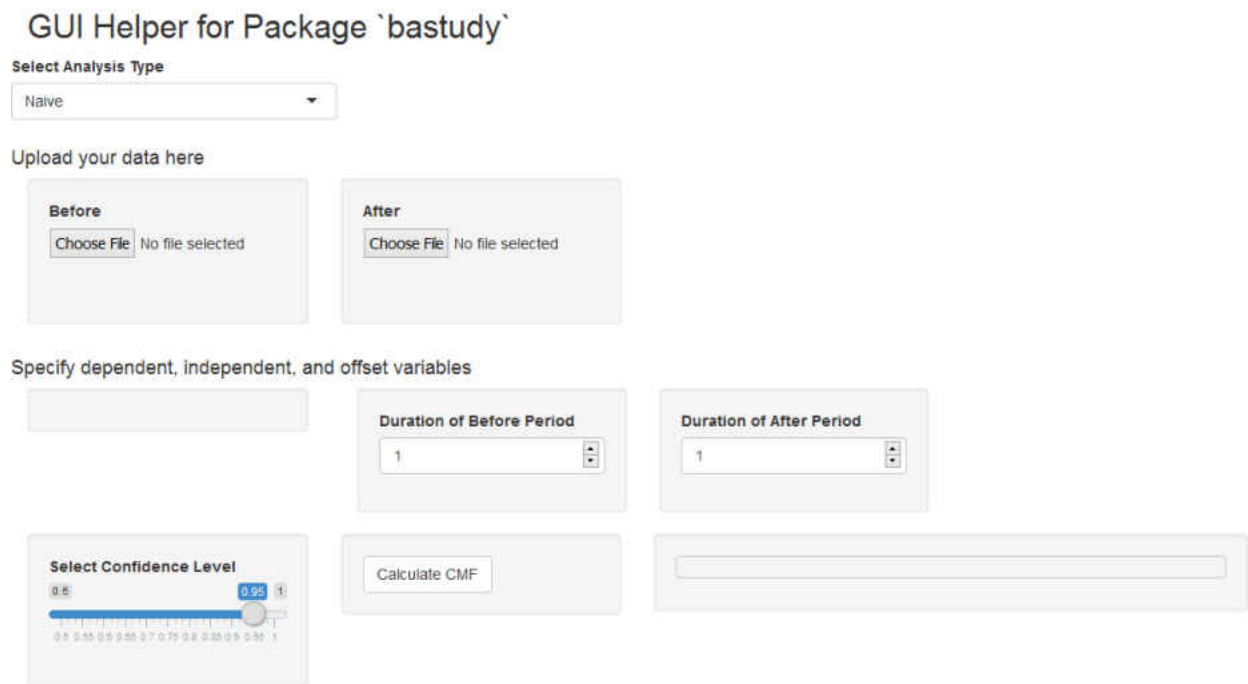
Figure 5-1 Graphical User Interface for Naive Before-after Study

The second tab is comparison group before-after study as shown in Figure 5-2. The user has to select four CSV files to be analyzed. These four files are the before data and the after data for treated sites and the before and after data for comparison sites. Similar to naïve, these variables have to share the same variable name. Once the system detects the CSV files for the before and

the after with identical variable names, user can select the target variable and set the confidence level and press the "Calculate CMF" button.
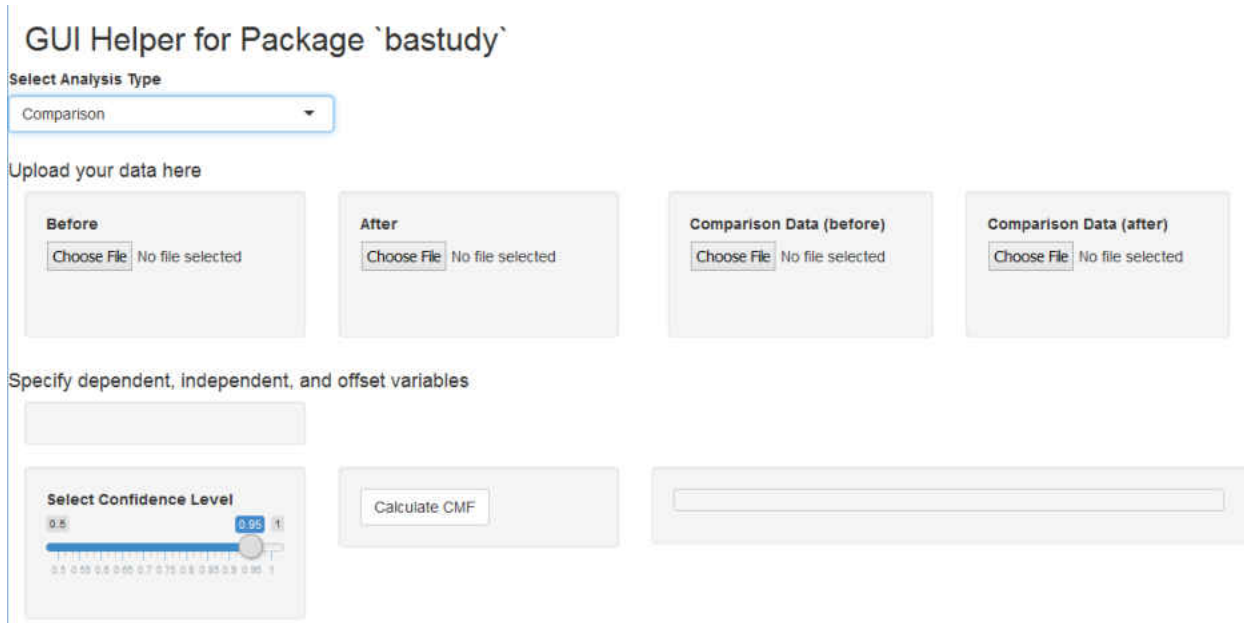
Figure 5-2 Graphical User Interface for Comparison Group Before-after Study

The last tab is the GUI for empirical Bayes method as shown in Figure 5-3. The user has to select three CSV files to be analyzed. The first two files are the before and after data for treated sites. The third file is the reference sites used to develop safety performance function using the negative binomial model. After the files are loaded, the user needs to select the target variable, offset variable (year in the sample file), and independent variables. Once these factors set up, users can select the confidence interval and press the "Calculate CMF" button to get the CMF value.

GUI Helper for Package `bastudy`

Select Analysis Type

Empirical Bayes ▾

Upload your data here

Before
Choose File No file selected

After
Choose File No file selected

Reference Data
Choose File No file selected

Specify dependent, independent, and offset variables

Select Confidence Level
0.5   0.95 1

0.5 0.55 0.6 0.65 0.7 0.75 0.8 0.85 0.9 0.95 1

Calculate CMF
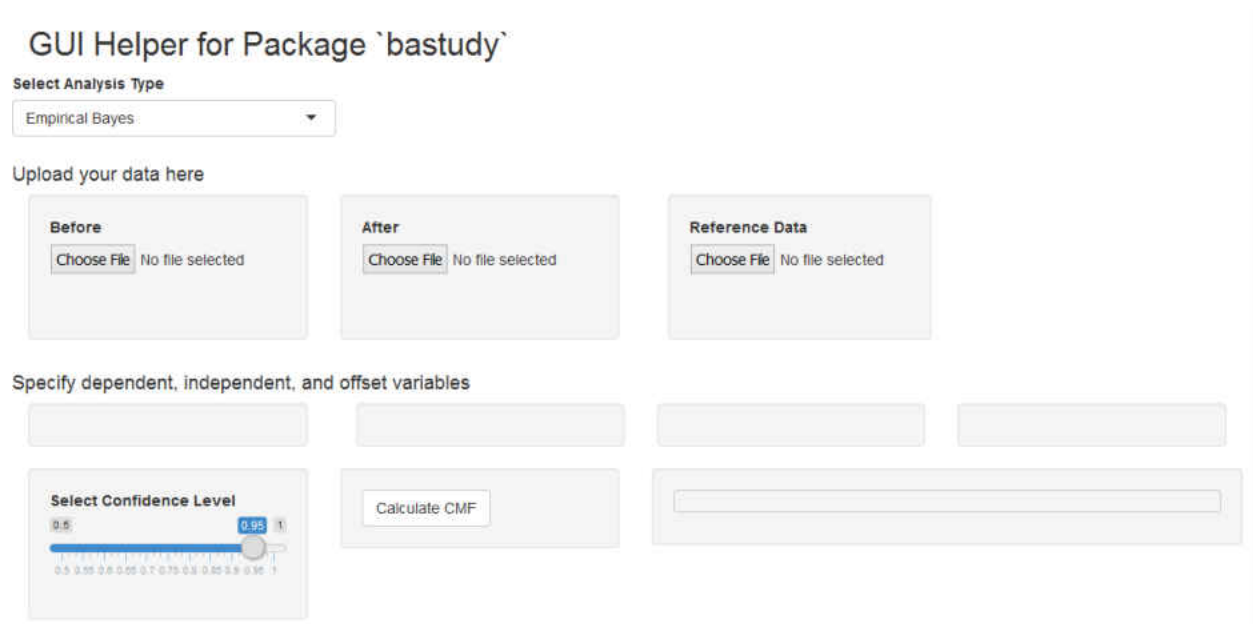
Figure 5-3 Graphical User Interface for Empirical Bayesian Before-after Study

5.4   Future Improvement

This package provides a way for traffic safety engineers to estimate crash modification factor. It was released to simplify the estimation of CMFs. Since all codes are open-sourced, users can feel free to improve this package without notifying the author or contact the author to improve this tool.

In the future, for the empirical Bayes analysis, HSM(AASHTO, 2010) suggests incorporating overdispersion function instead of fixed overdispersion parameter for roadway segment. However, adjusting overdispersion cannot be achieved using *bastudy* package and may be improved in the future.

Besides, Sacchi and Sayed (2015) claim that the full Bayesian method is the most accurate method for calculating CMFs. Therefore, it will be beneficial to include the full Bayesian method in this

package in the future. Again, since this package is an open-source software under the license specified in the package license document. By writing this package, I hope it can benefit the society and improve traffic safety by providing straightforward and trustworthy CMFs calculations.

CHAPTER 6 : MODIFICATION FACTORS USING EMPIRICAL BAYES METHOD WITH RESAMPLING TECHNIQUE

6.1 Introduction

Traffic researchers and engineers have developed the crash modification factor (CMF) as a quantitative measure of safety and effectiveness of signalization. Based on multiple studies, the Highway Safety Manual (HSM) Part D (AASHTO, 2010) provides CMFs which can be used to determine the expected crash reduction or increase after converting stop-controlled to signal-controlled intersections. These CMFs in HSM help engineers easily measure the safety and cost-effectiveness of treatments. After the HSM was introduced, many states in the United States, including Florida (Abdel-Aty et al., 2014; Park et al., 2015; Wang et al., 2015a), Utah (Brimley et al., 2012), Kansas (Lubliner and Schrock, 2012), Oregon (Xie et al., 2011), and others, have investigated the suitability of applying the values in the HSM to local intersections. In addition, the CMF Clearinghouse (FHWA, 2016) gathered 5378 CMFs, some of the which have different values for the same target treatment. When estimating CMFs using empirical data, there exist differences between samples such as geographic location, traffic volume, lane configuration, surrounding facilities, etc. It is not feasible to treat each combination of conditions separately due to the small sample sizes that would result. As such, many CMF values in the HSM assume all sites share the same true CMF value. This approach ignores site-specific features as well as potential interaction effects between site characteristics. Previous research efforts have focused on separating the treatment effects into crash modification functions based on temporal (Park et al., 2015; Sacchi et al., 2014; Wang et al., 2015b), traffic volume (Sacchi and Sayed, 2014; Wang and Abdel-Aty, 2014), area type (Wang and Abdel-Aty, 2014), and speed limit (Lee et al., 2015). The CMFs can be conceptualized as a nested structure as shown in Figure 6-1. The CMFs for

increasingly specific groups have smaller sample sizes, but also lower variation, due to greater homogeneity among the samples.
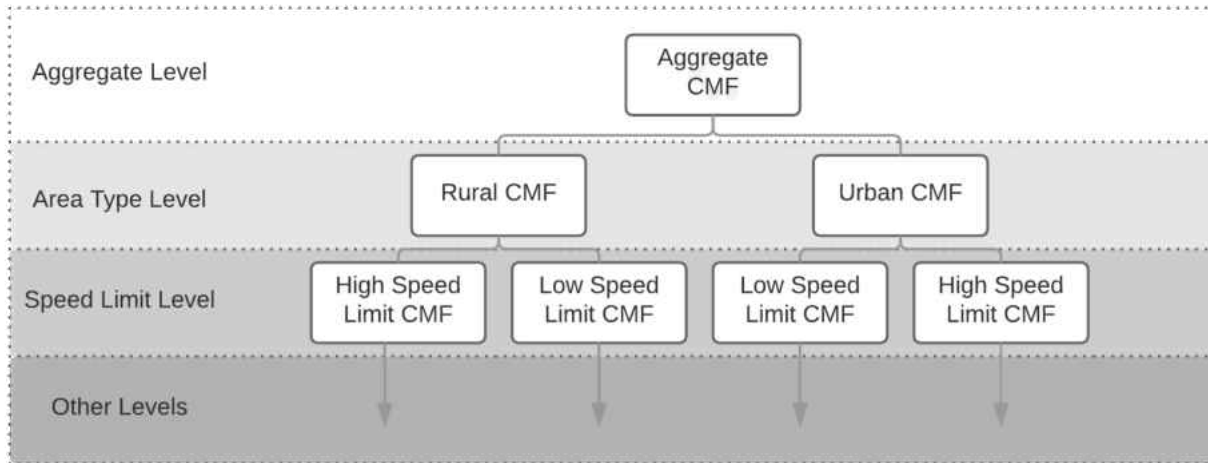
Figure 6-1 Nested CMF Structure

The data (crash, geometry, target location) needed to conduct a before-after study is expensive to collect. Therefore, if the CMF is stable at a higher, more aggregate level, it is not necessary to collect more data and investigate at a more specific, less aggregate levels. By calculating the CMFs using bootstrapped resamples (bootstrapped CMFs), the stability of the estimate can be examined by calculating the bootstrap confidence interval (BC). If the BC is higher/lower than one, the CMF can be considered trustworthy and further split-up is not required. As suggested by the CMF Clearinghouse (FHWA, 2016), randomly selected sites will increase the reliability of CMFs. The resampling procedure adds randomization to identify unstable results and compensates for small sample sizes. Based on the distribution of bootstrap CMFs, a precision rating is suggested in the result section of this chapter to help with decision making.

Applying this method, this study evaluates the safety effects of converting urban four-legged stop-controlled intersections to urban four-legged signal-controlled intersections using Florida's crash

records and roadway characteristics inventory data. The study develops CMFs for different crash types and severities. Crash severities are classified into the following 5 levels, according to the KABCO scale developed by the National Safety Council (1989): fatal (K), incapacitating injury (A), non-incapacitating (B), possible injury (C), and property damage only (O). CMFs are calculated using observational before-and-after study with the empirical Bayes method. The CMFs were developed for three severities (KABCO, KABC, and KAB) and two crash types (rear-end, angle+left-turn). For each crash category, the CMFs were developed using the original and resampled datasets. In this chapter, 100 resamples were generated based on the original dataset. After calculating all 100 bootstrapped CMFs for each crash category, the precision rating was identified for each crash category.

6.2   Methodology

6.2.1   Workflow

The workflow used to calculate the bootstrapped CMFs is shown in Figure 6-2. The first step in the workflow is to obtain the original dataset. The second step in the workflow is the bootstrap resampling of the original data. This was done via a program making use of R's *sample()* function, described previously. In the third step, each resampling of the data was passed, along with the optimized SPF (introduced later in the following section), to the R package *bastudy* mentioned in Chapter 5. Next, the bootstrapped CMFs were calculated using the *empBayes()* function in the *bastudy* package. Finally, analysis was performed based on the distribution of the bootstrapped CMFs and the suggested precision ratings were formulated.
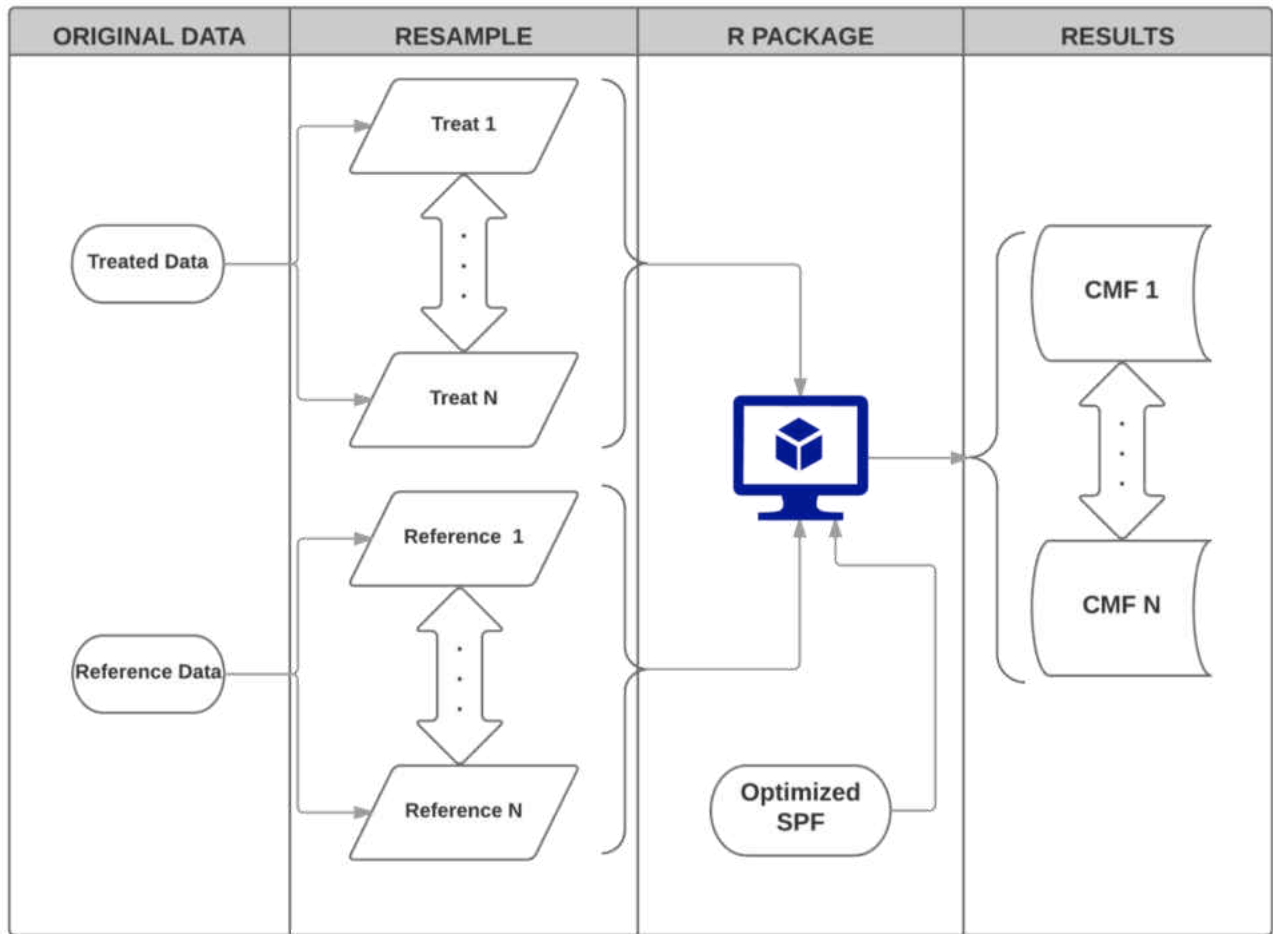
Figure 6-2 Workflow for calculating bootstrapped CMF

6.2.2   Safety Performance Functions

In order to apply the empirical Bayes method, it is necessary to estimate SPFs based on the reference sites in order to estimate the expected crash count if the sites were not treated. The most common type of SPFs has been a generalized linear model (GLM) with negative binomial distribution as the model accounts for over-dispersion. In this chapter, the negative binomial models were developed based on the function *glm.nb()* in R's MASS package (Venables and Ripley, 2002) with the equation explicated below:

$$N = EXP^{(\beta_0 + \Sigma \beta_{pi} * Volume_{pi} + \beta_q * Ratio_q + \beta_r * Spd\_maj + \beta_s * Spd\_min)} \qquad (6\text{-}1)$$

Where,

β_0 = Intercept

β_{pi} = Summation of all coefficients for volume p_i [1] [2]

β_q = Coefficient for ratio of the AADT on the major road and minor road,

β_r = Coefficient for major road speed limit

β_s = Coefficient for minor road speed limit

In the equation, there are eight volume sets and two ratio sets which are explained in the following paragraphs. The crash frequency models assume a Poisson distribution with a gamma distributed error term. The coefficient associated with each covariate represents the relationship between the covariate and crash frequency. HSM defines the base condition SPFs using only the natural log of the annual average daily traffic (AADT) on the major and the minor roads when developing the negative binomial model. HSM does not suggest covariates for developing full SPFs. Abdel-Aty et al. (2014) conclude that using full SPFs achieves better model fitness than the SPFs found in the HSM. Dixon et al. (2015), suggested the critical variables for developing SPFs for urban signalized intersections:

---

[1] If the volume is the logarithmic of the traffic volume on major road and minor road, then the β_{p1} is the coefficient for ln(major traffic) and β_{p2} is the coefficient for ln(minor traffic)

[2] All 8 exposure variable set are explained in the next session

- The natural log of the AADT on the major road; ln(AADT_{Major})

- The natural log of the AADT on the minor road; ln(AADT_{Minor})

- Speed limit on the major road; Speed_{Major}

- Speed limit on the minor road; Speed_{Minor}

In fact, Dixon et al.'s (2015) results show that the natural log of the AADT on the major and the minor roads alone do not always achieve good model fit. Following the suggestions of Dixon et al. (2015), the authors of this chapter considered several combinations of covariates for estimating SPFs. However, the SPF for KABCO crashes was best modeled using ln(AADT_{Major}) and ln(AADT_{Minor}), which is consistent with the HSM's recommendation. Akaike Information Criterion (AIC) was used to compare models. The optimal model formulation for KAB crash counts used ln(AADT_{Major}), the speed limit on the major road, and a latent variable developed by the authors called "modular AADT". "Modular AADT" is calculated using the AADT on the major and minor roads as shown in Equation 6-2. The fit of SPF improves by substituting the exposure measures from the AADT on the major and minor road with the latent variable.

$$modAADT = \sqrt{(maj\_aadt^2 + min\_aadt^2)} \qquad (6\text{-}2)$$

Based on these findings, it can be concluded that different exposure methods should be tested for different crash categories. Therefore, in order to determine the best combination of exposure variables and speed limit, a full-factorial experiment (Montgomery, 2008) was constructed using each of the eight exposure metrics with other variables as shown in Table 6-1. These eight exposures are listed below:

- **Exposure 1** *ln(Maj):* The log of the AADT on the major road

- **Exposure 2** *ln(Maj), ln(Min):* The log of the AADT on the major and the minor road

- **Exposure 3** *ln(total):* The log of the summed AADT on the major and minor road

- **Exposure 4** *ln(mod):* The log of the modular AADT on the major and minor roads

- **Exposure 5** *ln(Maj),(Maj):* The log of the AADT on the major road and the non-log form

- **Exposure 6** *ln(Maj), ln(Maj), (Maj), (Min):*The log of the AADT on the major and the minor road and the non-log form

- **Exposure 7** *ln(Total), (Total):* The log of the summed AADT on the major and minor road and the non-log form

- **Exposure 8** *ln(Mod), (Mod):* The log of the modular AADT on the major and minor road and the non-log form

Each exposure variable was paired with no ratio, a ratio of the AADT in Equations 6-3 and 6-4, and the speed limit on the major and minor road. Besides, the experimental design excluded the ratio if minor AADT was missing. For example, the experiment was removed when *ln(Maj)* is the only exposure with the ratio1 or ratio2.

$$\textbf{ratio1} = \textbf{ln}\frac{\textbf{min}}{\textbf{maj}} \tag{6-3}$$

$$\textbf{ratio2} = \frac{\textbf{ln(min)}}{\textbf{ln(maj)}} \tag{6-4}$$

With the full-factorial design, 64 SPFs were developed for each crash category (KABCO, KABC, KAB, rear-end, angle+left-turn) for a total of 320 SPFs. To compute these efficiently, an R program was developed to fit each SPF and return the resulting AIC. For each crash category, an

AIC comparison chart was used to compare the 64 SPFs and the simplest optimal model was chosen from these as show in Table 6-2.

Table 6-1 Factorial Experiment of Safety Performance Functions

	ln(Maj)	ln(Min)	ln(Total)	ln(Mod)	Maj	Min	Total	Mod	Ratio1	Ratio2	Spd Maj	Spd Min
1	+											
2	+										+	
3	+											+
4	+										+	+
5	+	+										
6	+	+									+	
7	+	+										+
8	+	+									+	+
9			+									
10			+								+	
11			+									+
12			+								+	+
13			+						+			
14			+						+		+	
15			+						+			+
16			+						+		+	+
17			+							+		
18			+							+	+	
19			+							+		+
20			+							+	+	+
21				+								
22				+							+	
23				+								+
24				+							+	+
25				+					+			
26				+					+		+	
27				+					+			+
28				+					+		+	+
29				+						+		
30				+						+	+	
31				+						+		+
32				+						+	+	+
33	+				+							
34	+				+						+	
35	+				+							+
36	+				+						+	+
37	+	+			+	+						
38	+	+			+	+					+	
39	+	+			+	+						+
40	+	+			+	+					+	+
41			+				+					
42			+				+				+	
43			+				+					+
44			+				+				+	+
45			+				+		+			
46			+				+		+		+	
47			+				+		+			+
48			+				+		+		+	+
49			+				+			+		
50			+				+			+	+	
51			+				+			+		+
52			+				+			+	+	+
53				+				+				
54				+				+			+	
55				+				+				+
56				+				+			+	+
57				+				+	+			
58				+				+	+		+	
59				+				+	+			+
60				+				+	+		+	+
61				+				+		+		
62				+				+		+	+	
63				+				+		+		+
64				+				+		+	+	+

Table 6-2 Optimal Safety Performance Functions

	KABCO (1)	KABC (2)	KAB (3)	Rear-End (4)	Angle+Left-Turn (5)
			Dependent variable:		
log_maj_aadt	1.606***			2.171***	
	(0.252)			(0.275)	
log_mod_aadt		3.688***	3.873***		2.990***
		(0.701)	(0.748)		(0.695)
mod_aadt		-0.0001**	-0.0001***		-0.0001**
		(0.0001)	(0.0001)		(0.0001)
speed_maj	0.078***	0.066**	0.072**		0.113***
	(0.027)	(0.030)	(0.029)		(0.024)
speed_min		0.056*	0.065**	0.061**	
		(0.033)	(0.032)	(0.028)	
Constant	-15.489***	-35.365***	-37.996***	-21.277***	-29.183***
	(2.222)	(5.931)	(6.421)	(2.852)	(5.754)
Observations	124	124	124	124	124
Log Likelihood	-303.571	-245.190	-200.676	-186.123	-230.428
Overdis. Param.	0.231***	0.471***	0.612***	0.355***	0.370***
AIC	613.142	500.379	411.351	378.247	468.855
Note:					*p<0.1;** p<0.05;*** p<0.01

6.2.3　Optimize Safety Performance Functions

SPFs were developed for KABCO, KABC, KAB, rear-end, and angle+left-turn crashes at urban four-legged intersections using maximum likelihood estimation to fit the negative binomial models. According to Figure 6-3, there is a trend that the AADT exposure 1-4 outperform AADT exposure 5-8, which indicates that using only the natural log of AADT perform better when I fit the SPFs for KABCO crashes. After screening, the optimized model is the second design which is the log of the major AADT with the major speed limit.
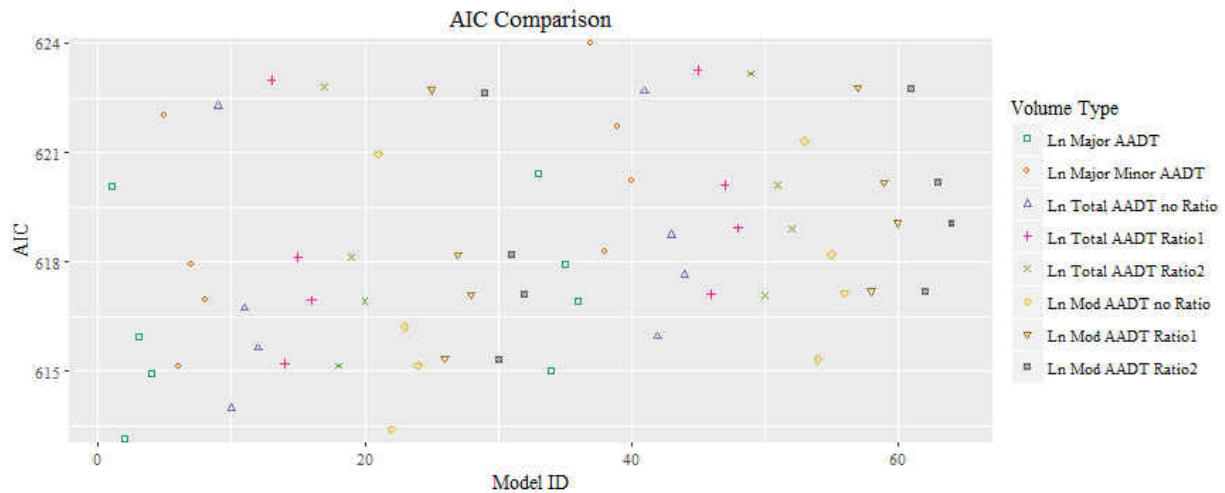
Figure 6-3 AICs for each SPF in KABCO crashes

In Figure 6-4, the AIC result is opposite, the AADT exposure 5-8 outperform AADT exposure 1-4. This suggests adding the non-log form of AADT provides a better fit when developing the SPFs for KABC crashes at urban four-legged intersections. Based on the figure, the optimized model is the 56th design which is the log of the modular AADT, modular AADT, speed limit on the major road, and speed limit on the minor road.
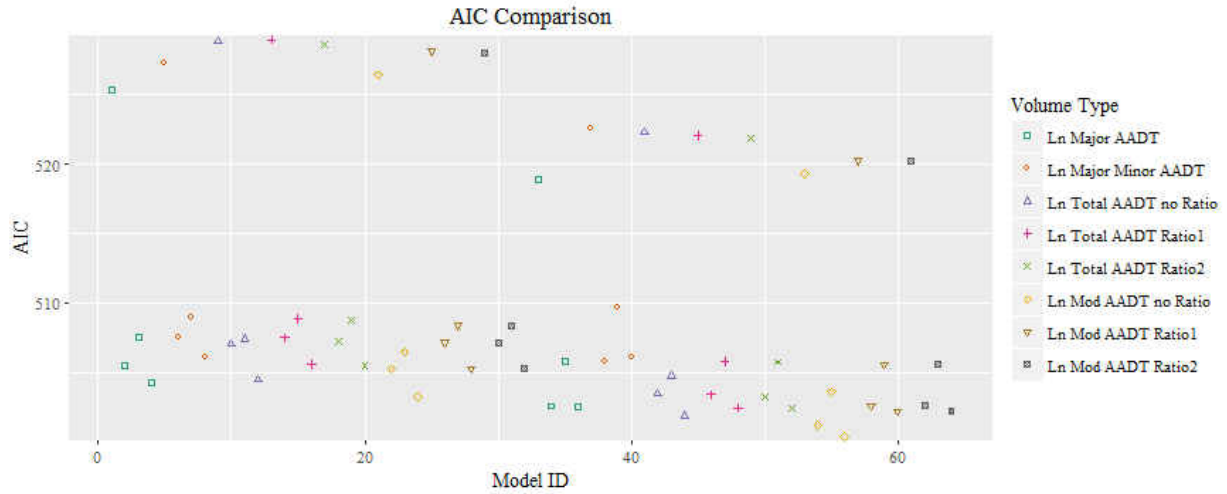
Figure 6-4 AICs for each SPF in KABC crashes

For KAB crashes, the AIC shown in Figure 6-5 share similar trend compared to Figure 6-4. SPFs with the log and the non-log form of AADT provide a better fit when developing the SPFs. Besides, the optimized model is the same as the SPF in KABC crashes which is the 56th design.
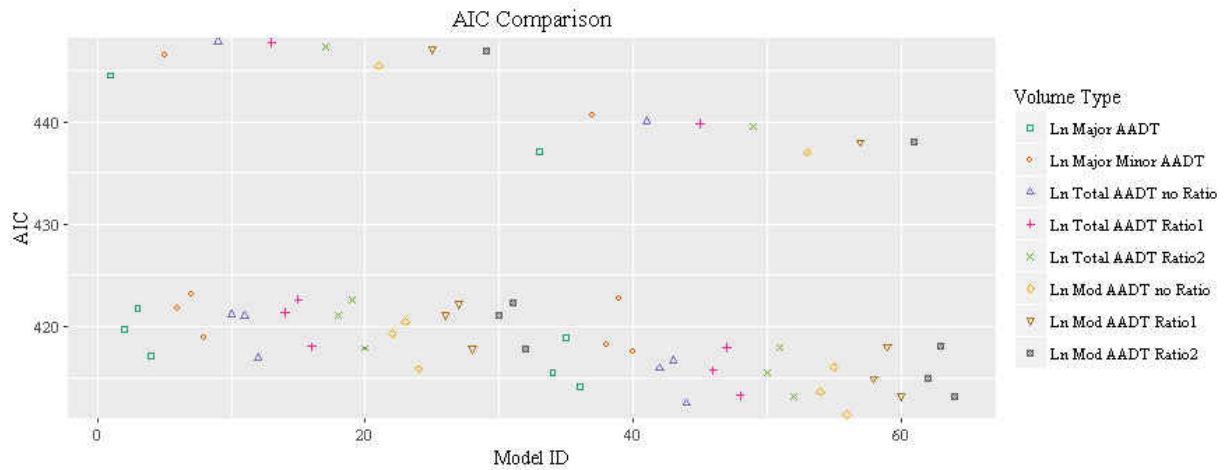
Figure 6-5 AICs for each SPF in KAB crashes

For rear-end crashes, Figure 6-6 indicates there is a trend that the AADT exposure 1-4 outperform AADT exposure 5-8, which indicates that using only the natural log of AADT perform better when I fit the SPFs for rear-end crashes. In this screening, the optimized model is the third design which is the log of the major AADT with the minor speed limit.
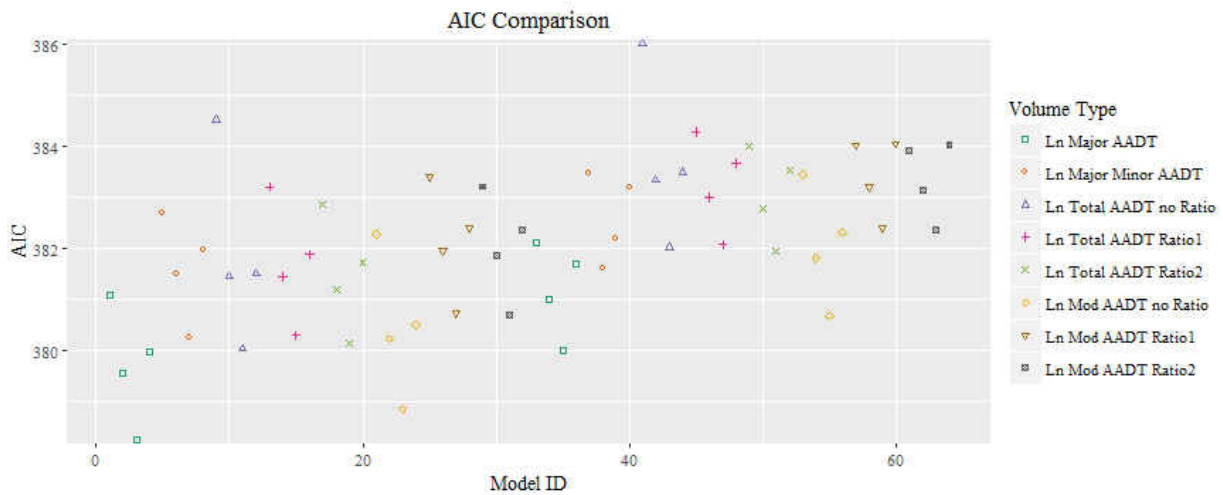
Figure 6-6 AICs for each SPF in rear-end crashes

For angle+left-turn crashes, Figure 6-7 shows AADT exposure 1-4 have higher AIC comparing to AADT exposure 5-8. In this screening, the optimized model is the 54th design which is the log of the modular AADT, modular AADT, and the major speed limit.
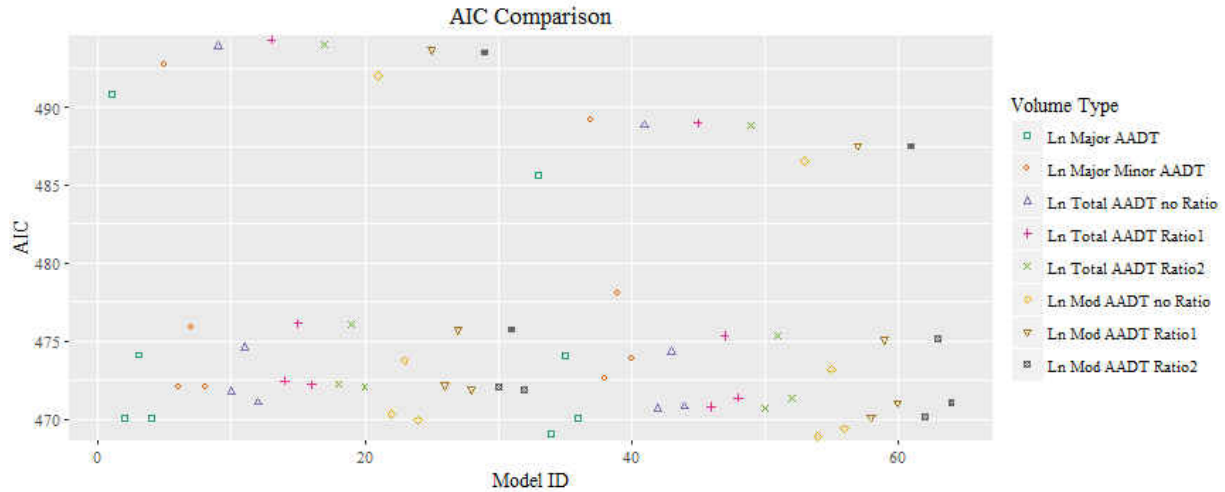
Figure 6-7 AICs for each SPF in angle+left-turn crashes

For all developed SPFs, the AIC differences among top 5 SPFs are small and do not show improvement from one to the other. Another finding is that adding the AADT ratio between the major road and the minor road does not improve the model fit for any crash category when estimating crash frequency on urban four-legged stop controlled intersections. Other than the AADT ratio, the speed limit was included in all optimized SPFs. This infers that the speed limit is an important factor when developing SPFs which is also suggested by Dixon et al. (2015). In addition, the AADT exposure in the optimized SPFs for KABC, KAB, and angle+left-turn include the log of the modular AADT and modular AADT. This explains that the AADT on the minor road needs to be considered when developing SPFs for severe crashes such as KABC, KAB, and angle+left-turn. On the other hand, only the log of the AADT on the major road is selected for the KABCO, and rear-end crashes. This indicates the log of the AADT on the major road is sufficient when developing SPFs for non-severe crashes such as KABCO and rear-end.

6.3   Data Preparation

Data were collected and combined from the following five database sources: Roadway Characteristics Inventory in Florida, Crash Analysis Report, Florida Financial Management Search System, TranStat iView, and Google Earth.

- Roadway Characteristics Inventory in Florida - provides detailed information of each roadway such as AADT and speed limit

- The Crash Analysis Report System provides information on all the reported crashes in Florida, including severity, crash type, and other crash-related characteristics

- The Financial Management Search System - provides the information on projects constructed for FDOT

- TranStat iView - a geographical database system provided by FDOT TranStat Department, which provides satellite images of street view to with lat-long and roadway mileage point

- Google Earth - provides historical street view to validate the existence of the construction

Using these data sources, crashes from 2003 to 2015 were collected. These crashes are divided into 30 different crash types including angle, rear-end, head-on and sideswipe, etc. Left-turn crashes were sometimes misclassified as angle crashes and vice versa. To compensate for this misclassification, I developed CMFs for the combined angle+left-turn crashes.

The treated intersections in this study are chosen from the FDOT's Financial Project Search System. Signalization of stop-controlled intersections was identified as the major treatment. In the Financial Project Search System, I chose the signalization project from 2005 to 2010. The Financial Search System does not provide some essential variables such as AADT. Thus, I had to

refer to other sources such as Google Earth and the RCI to acquire the roadway features of the chosen sites. Through the TranStat iView, I could also precisely match the milepost of the constructed intersections; however, TranStat iView does not provide historical satellite maps, so I matched the precise location from TranStat I-View to historical satellite maps from Google Earth, RCI Database, and FDOT Video Log.

A total of 29 intersections (treated sites) which were converted from an urban four-legged stop control to an urban four-legged signal control intersection were identified using the Financial Project Search System. The CMFs were estimated based on these signalized intersections. The authors' previous research (Wang et al., 2015b) found an inconsistency in CMFs between the first year after signalization and following years, so I removed data within one year of signalization. After removing these periods, crash data were prepared for conducting before-after analysis. The two-year crash data before signalization was queried from 2003 to 2004 and another two-year crash data after signalization were queried from 2011 to 2012.

Reference sites were also collected to address regression-to-the-mean bias. A total of 124 urban four-legged stop-controlled intersections (reference sites) were identified to develop SPFs using Florida Roadway Characteristics Inventory along with GIS database TranStat iView. A total of 1,512 crashes occurred at these intersections over 10 years from 2003 to 2012. The AADT of the major road was included in the SPF.

Table 6-3 and Table 6-4 show the mean, standard deviation, and range of crash frequencies for the reference sites and treated sites by severity and crash type. In terms of severity, angle and left-

turn crashes usually have higher severity levels than rear-end crashes. Therefore, examining the reduction in KABC crashes is crucial when estimating the safety effect of signalization. Srinivasan et al. (2010) debate whether possible injury crashes (C) should be considered injury crashes. To satisfy both perspectives, CMFs were developed for KABC and KAB crashes separately. Rear-end and angle + left-turn crashes are also evaluated separately. Table 6-3 Table 6-3 Reference Data Used to Develop the Safety Performance Functionand Table 6-4 also include the range of the AADT on the major road (rows titled "Major AADT").

Table 6-3 Reference Data Used to Develop the Safety Performance Function

	No. of Observation	Mean	Standard Deviation	Minimum	Maximum
KABCO Crashes	124	12.15	22.00	0	134
KABC Crashes	124	6.13	11.35	0	52
KAB Crashes	124	3.45	6.68	0	38
Rear-End Crashes	124	2.91	7.43	0	50
Angle+Left Crashes	124	5.02	10.64	0	57
Major AADT	124	9802	8648	850	42,500
Minor AADT	124	1783	1684	100	15,000
Major Speed Limit	124	35.6	7.59	20	55
Minor Speed Limit	124	30.81	6.79	15	55

Table 6-4 Crash Data for Treated Intersections

	No. of Observation	Mean	Standard Deviation	Minimum	Maximum
KABCO Crashes Before	29	11.66	9.89	0	40
KABC Crashes Before	29	6.48	5.17	0	22
KAB Crashes Before	29	3.35	2.55	0	8
Rear-End Crashes Before	29	3.41	3.71	0	13
Ang+Left Crashes Before	29	4.79	4.87	0	18
KABCO Crashes After	29	11.66	12.67	0	55
KABC Crashes After	29	5.24	4.67	0	19
KAB Crashes After	29	2.35	2.48	0	11
Rear-End Crashes After	29	6.17	9.31	0	42
Ang+Left Crashes After	29	2.03	2.11	0	9
Major AADT Before	29	35,954	24820	6,800	110,500
Major AADT After	29	38,275	30862	6,700	149,000
Minor AADT Before	29	10,513	13024	1,416	63,500
Minor AADT After	29	7,728	8683	700	37,000
Major Speed Limit	29	43.79	6.64	35	55
Minor Speed Limit	29	34.14	6.95	25	45

6.4　Result and Discussion

6.4.1　Observational Before-and-After Study on the Original Data

After identifying the SPFs with the lowest AIC, five CMFs were calculated using the optimized SPFs to perform an observational before-and-after study via the empirical Bayes method. The results are shown in Table 6-5. It is found that the signalization decreased the number of KABCO crashes by 17%, KABC crashes by 19%, and KAB crashes by 29%. Note that the standard errors are lower for the Florida-based CMFs than those provided in the HSM (KABCO and rear-end) and the NCHRP Report 491 (KABC). In addition, based on the standard errors shown in Table 6-5, the Florida-based CMF for KABC and KAB crashes are significantly lower than one at a 90% confidence level, leading us to conclude that signalization reduces these type of crashes. These findings differ from those of NCHRP Report 491, which does not find the CMF for KABC crashes to be significantly less than one. This may be a consequence of the fact that my estimated CMF for KABC crashes has a lower standard error than that in the NCHRP Report 491. For rear-end crashes, the Florida-based result shows a lower CMF, with a smaller standard error, than that in the HSM.

On the other hand, the Florida-based crash data have a problem with mixing right-angle and left-turn crashes. Therefore, I could not estimate the impact of right-angle and left-turn crashes separately to be compared with the CMF of the angle crashes in the HSM. Based on the available information, I can conclude that both the Florida-based CMF of angle+left-turn crashes and the CMF of angle crashes in the HSM are significantly lower than one.

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Table 6-5 Comparison of Crash Modification Factors for Signalization

Reference	Number of Legs	Crash Severity	CMF	Standard Error
HSM (2010)	4	KABCO	0.95	0.09
HSM (2010)	4	Rear-End	**2.43**	**0.4**
HSM (2010)	4	Angle	**0.33**	**0.06**
NCHRP Report 491 (2003)	4	KABC	0.77	0.27
This Florida-based research	4	KABCO	**0.83**	**0.06**
This Florida-based research	4	KABC	**0.81**	**0.08**
This Florida-based research	4	KAB	**0.71**	**0.10**
This Florida-based research	4	Rear-End	1.28	0.17
This Florida-based research	4	Angle+Left-Turn	**0.43**	**0.05**

The values in bold are statistically significant at a 95 % confidence level.

6.4.2   Observational Before-and-After Study on the Resampled Data

The number of observations for each resampled data are the same as the original dataset which is 29 for the treated sites and 124 for the referenced sites. Using the resampled data, the CMFs for crash severity and crash type are shown in Figure 6-8 and Figure 6-9, respectively. All bootstrap CMFs were aligned with the horizontal axis, which were calculated based on each resample. In the figures, the expected CMF values are plotted in blue. The 90 percent upper bound confidence intervals were plotted in green while the lower confidence intervals were in red.

The CMFs estimated using the original datasets are 0.83, 0.81, and 0.71 for KABCO, KABC, and KAB crashes. Although these three CMFs are significantly lower than one, the crash counts used for the estimation were aggregated from all samples which ignores the heterogeneity of each site. To solve this, the bootstrap technique was used to examine the stability of the CMFs. Figure 6-8(a) shows the result of the bootstrapped CMFs for KABCO crashes which 74 percent of the

bootstrapped CMFs are significantly lower than one with 1 percent significantly higher than 1.

For KABC crashes, the result is shown in Figure 6-8(b) with 66 percent of the bootstrapped CMFs

significantly lower than one and 1 percent higher than 1. For KAB crash as shown in Figure 6-8(c),

78 percent of the bootstrapped CMFs are lower than 1 and none of the bootstrapped CMF is higher

than one.

a. CMF Values for KABCO Crashes
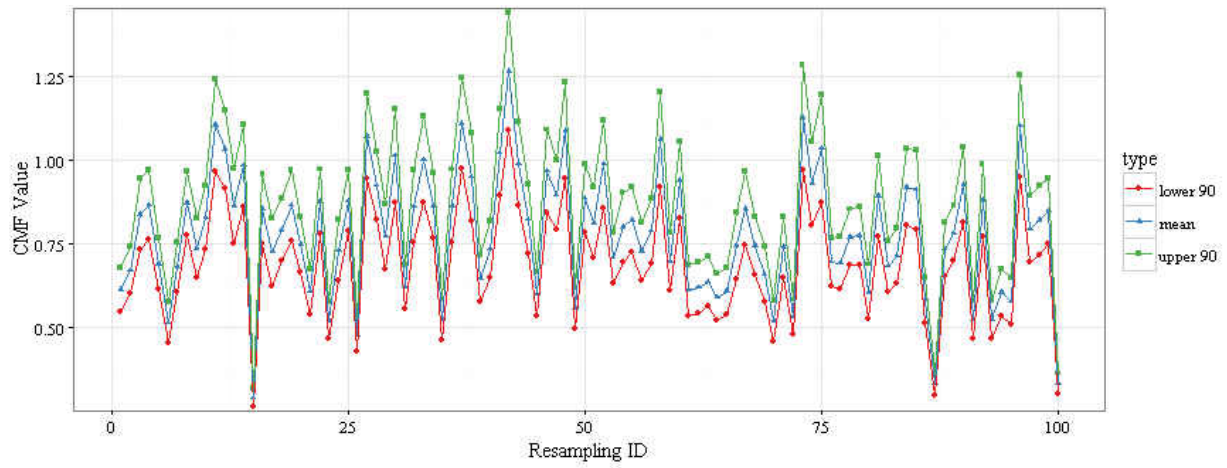
b. CMF Values for KABC Crashes
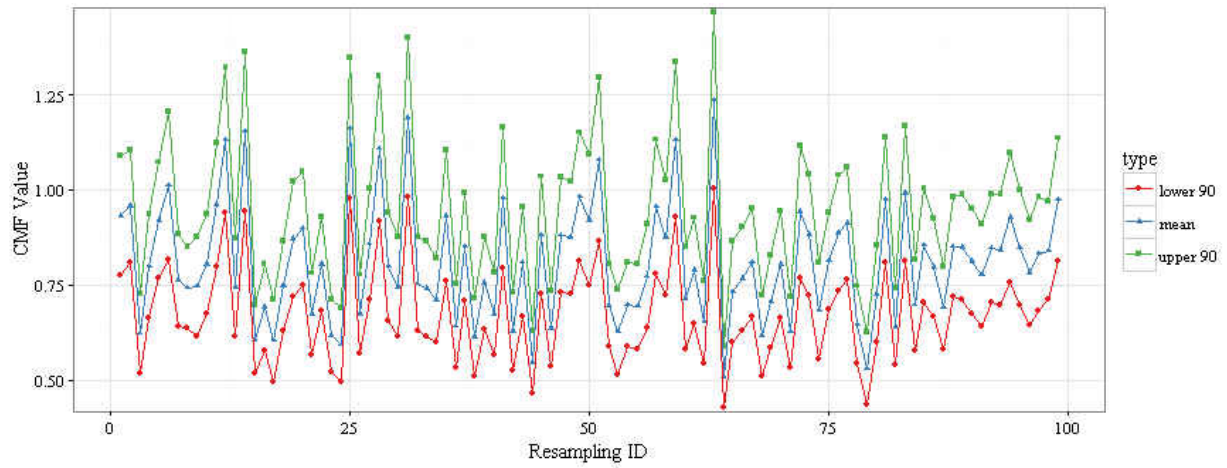
c. CMF Values for KAB Crashes
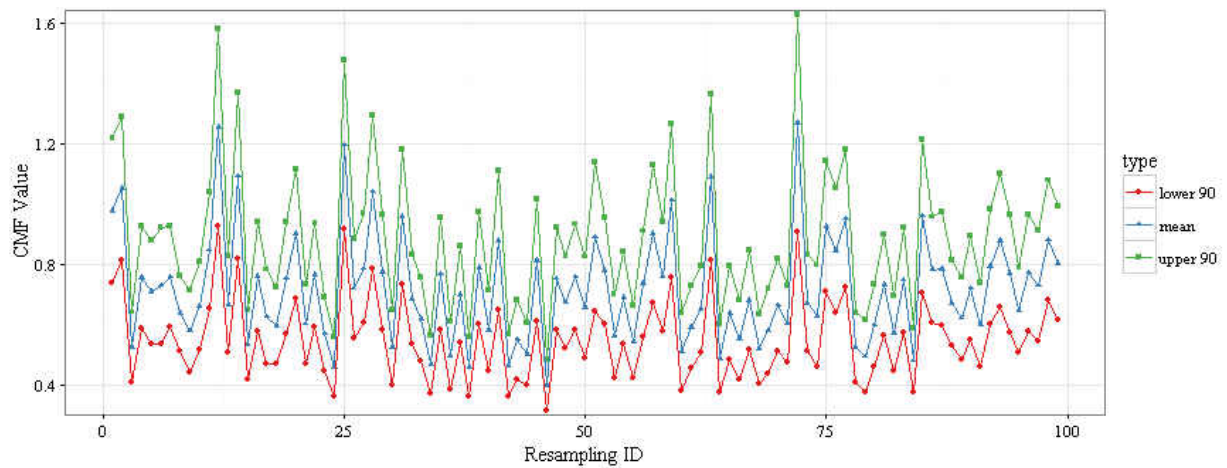
Figure 6-8 CMF Values for each Resamples for KABCO KABC KAB Crashes

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The bootstrapped CMFs for rear-end crashes are displayed in Figure 6-9(a), and the bootstrapped CMFs for angle-left turn crashes are shown in Figure 6-9(b). For rear-end crashes, the range of the bootstrapped CMFs is wider than the other crash categories which suggests the effect is not stable. In detail, as shown in Figure 6-9(a), the CMF values can differ from 0 to 3. Such differences can lead to erroneous judgement if the stability is not considered. On the other hand, the bootstrapped CMFs for angle+left-turn crash in Figure 6-9(b) is stable with 98 percent of the CMF values significantly below 1 and none of the CMF value significantly higher than 1. This proves signalization stably decreases angle+left-turn crashes at the current aggregation level.

a. CMF Values for Rear-End Crashes
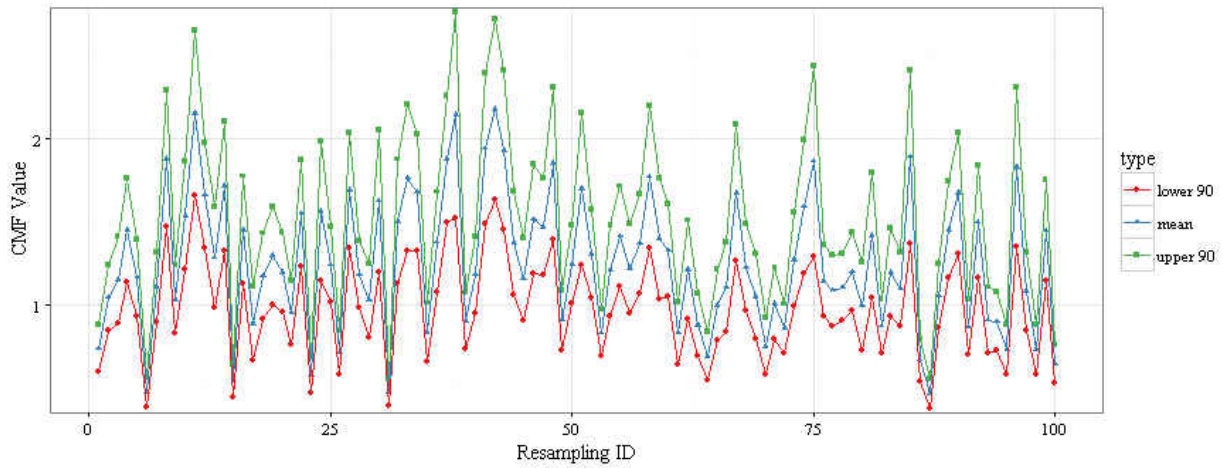
b. CMF Values for Angle+Left-Turn Crashes
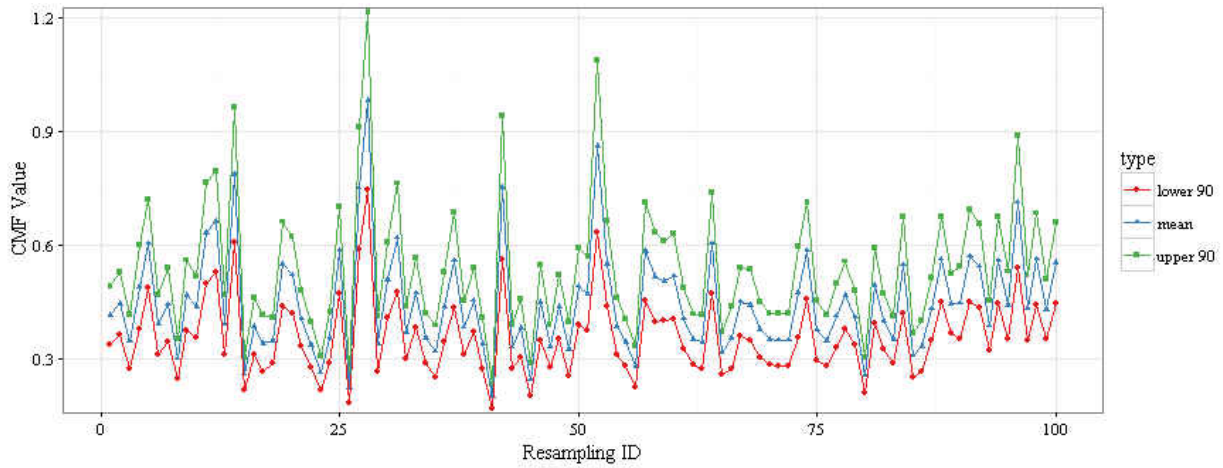
Figure 6-9 CMF Values for each Resamples for Rear- End and Angle+Left-Turn Crashes

The descriptive statistics of bootstrapped CMFs are shown in Table 6-6. In the table, the bootstrap standard deviation, 5th percentile, and 95th percentile of bootstrap CMFs are shown. The bootstrapped CMFs for angle+left-turn crashes are the only crash category that has 95 percent fallen under 1. Besides, the bootstrapped standard deviation is the smallest for angle+left-turn crashes. Based on these criteria, it is concluded that the CMF for angle+left-turn crashes is very reliable.

Table 6-6 Bootstrapped Confidence Interval under Normal Distribution

	KABCO	KABC	KAB	Rear-End	Angle+Left
Standard Deviation	0.19	0.15	0.18	0.40	0.14
5th Percentile	0.52	0.61	0.48	0.64	**0.26**
95th Percentile	1.09	1.13	1.05	1.89	**0.71**

Bold: 95% of the CMFs are lower than one

The resampling results shown in Figure 6-8 and Figure 6-9 were summarized using box plots (box and whisker diagram, McGill et al., 1978) and histograms as shown in Figure 6-10. It is worth mentioning that these diagrams were plotted Figure 6-10 using the R package *ggplot2* (Wickham, 2009). Each dot in the box plots represents a bootstrapped CMF calculated from a resample. In order to clearly observe the data points, all dots are displayed randomly (horizontal wise) instead of mapping the dots in the center line. At the bottom of Figure 6-10, the histograms and density plots (using Gaussian kernel) show the distributions of the bootstrapped CMFs. It was found that all five histograms are unimodal distributions which has only one peak. If the distribution is a multimodal distribution which has multiple peaks, the CMF is less reliable and requires further screening to yield a stable CMF.
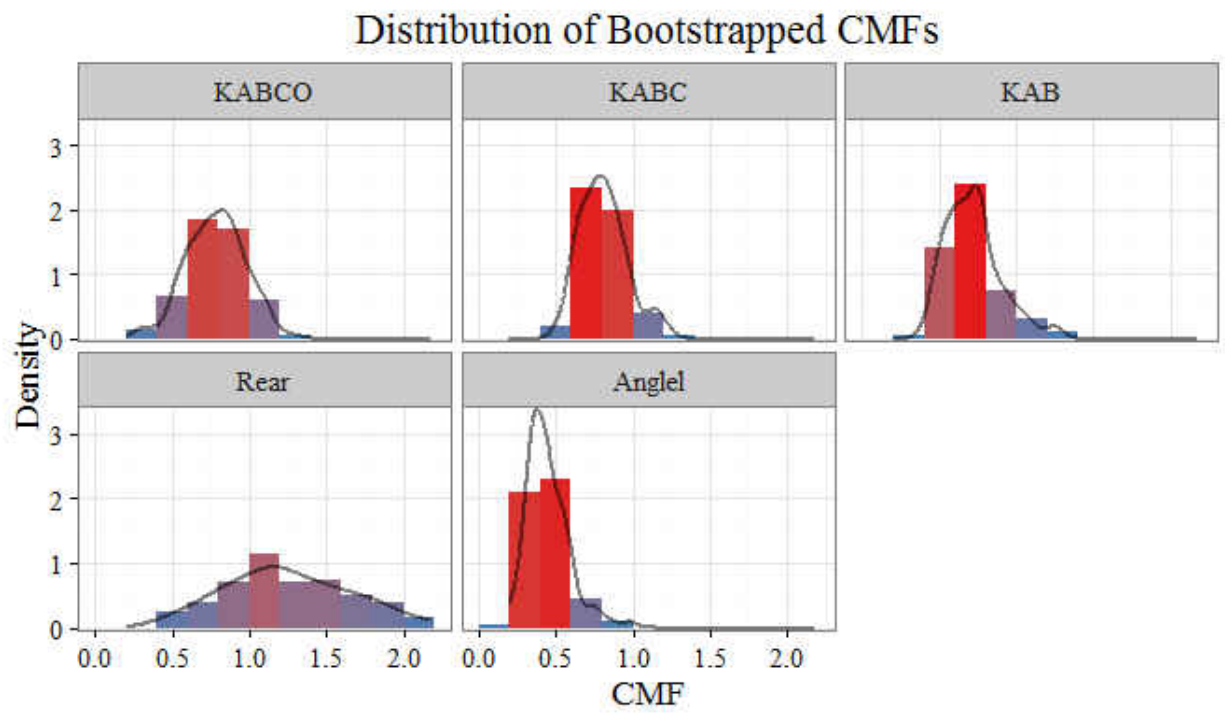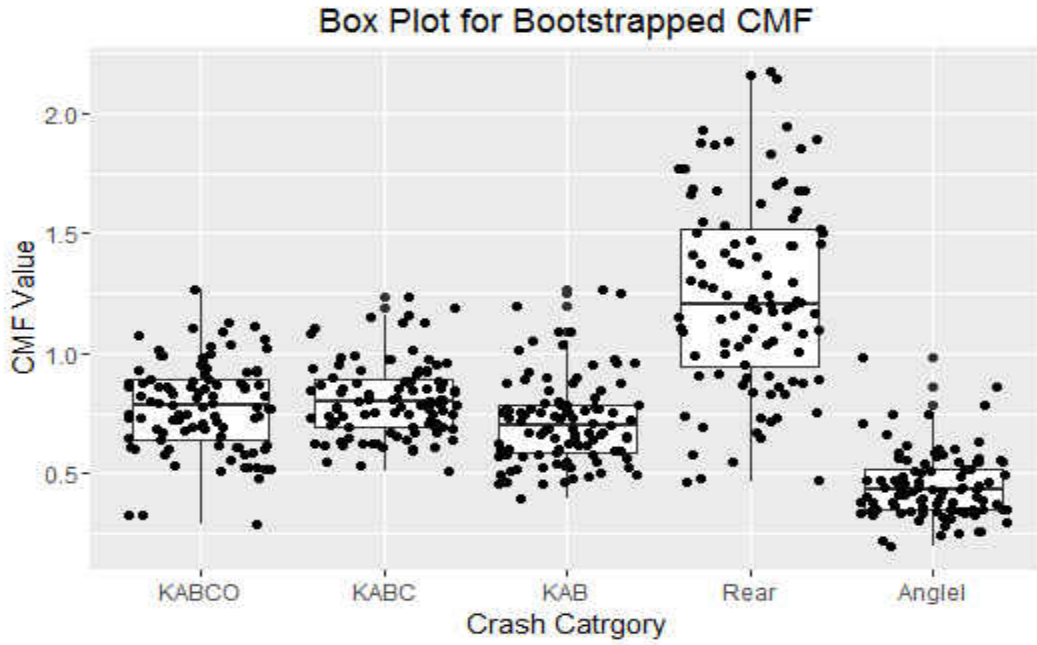
Figure 6-10 Box-Plot and Histograms of the Bootstrapped CMF

6.4.3 CMF Precision Rating

As suggested by the current CMF Clearinghouse (FHWA, 2016), the quality of the CMFs was determined using the "star quality rating". One rating criterion is "controlling the potential bias" which suggests controlling all sources of known potential bias. Agreeing that controlling potential bias is important, this criterion can be strengthened using the summary statistics of bootstrapped CMFs as mentioned in the previous chapter as a quantitative measurement towards bias. Previous research focused on screening the bias such as traffic volume and time using CMF function, however, the reliability of the CMF after screening is still not quantified. Due to the fact that there are countless factors to control, it is important to analyze whether the developed CMFs can be applied to the candidate site in different situations. In this case, a precision rating is suggested in this chapter in Table 6-7. Three criteria are introduced which are "CMF using the original dataset is significantly above or below 1", "90% of the bootstrapped CMFs are above or below 1 at 90% level", and "the bootstrapped CMFs follow a unimodal distribution".

Table 6-7 Rating for the Reliability of the CMFs

	Original CMF >1 Original CMF <1	Bootstrap CMF >1 Bootstrap CMF <1	Unimodal	Precision Rating
Condition 1	+	+	Yes	*****
Condition 2	+	-	Yes	***
Condition 3	+	+	No	****
Condition 4	-	+	Yes	****
Condition 5	+	-	No	**
Condition 6	-	-	Yes	**
Condition 7	-	-	No	*

Therefore, this table answers the question that, whether the CMF need additional screening or the CMF is already stable at the current aggregation level as previously introduced in Figure 6-1. In addition, using this precision rating, it is found that only the CMF for angle+left-turn crashes, falls within condition 1 which is the most stable CMF with the highest precision rating. The CMFs for KABCO, KABC, KAB crashes, falls within condition 2 which the results are informative but may need further screening. Besides, the CMF for rear-end crashes is condition 6 with precision rating equals 2. This CMF provides potential trend for engineering consideration, but cannot be used to calculate the cost after signalization. In summary, it is concluded that the precision rank of the CMFs is:

Precision of CMF: Angle+Left> KABC>KAB> KABCO> Rear-End

6.5   Conclusion and Recommendations

In this chapter, safety effects of converting urban four-legged stop-controlled intersections to urban four-legged signal-controlled intersections were evaluated based on CMFs. In addition, the bootstrap resampling technique was used to analyze the stability of each crash category. The CMFs were calculated using the observational before-after study using the empirical Bayes method. CMFs were determined for three crash severity categories (KABCO, KABC, and KAB) and two crash types (rear-end and angle + left-turn). In order to develop the CMFs using the empirical Bayes method, the optimized SPFs were identified based on the result of the factorial experiment. In summary, adding non-log exposure (AADT) in the negative binomial formulation improves the model fit for KABC, KAB, and Angle+Left-Turn. Another finding is that using the modular AADT as the exposure parameter improves the model fits in KABC, KAB, and Angle+Left-Turn crashes. In addition, using only AADT of the major road achieve the best model fit for KABCO

and rear-end crashes. In addition to the exposure parameter, the speed limit on the major road was found to be an important factor which is significant in KABCO, KABC, KAB, and Angle+Left-Turn. On the other hand, the speed limit on the minor road was found to be significant for KABC, KAB, and rear-end crashes. Therefore, when developing SPFs for stop-controlled intersections, it is suggested to collect the information of the speed limit on the major and the minor roads.

The CMF estimates using the original dataset are consistent with previous studies in HSM, NCHRP Report 491 and FDOT Part D Project. The signalization lowers total, severe crashes and angle crashes, but increase rear-end crashes. After evaluating the bootstrapped CMFs, it is found that the CMF for angle+left-turn crashes is stable, whereas, the CMFs for KABCO, KABC, KAB, and rear-end are not stable. Furthermore, the standard deviation of bootstrapped CMFs for rear-end crashes is the largest. Accordingly, the angle+left-turn crashes after signalization is categorized as "condition 1" with the highest precision using the precision rating suggested in this chapter. The CMFs for KABCO, KABC, KAB crashes were categorized as "condition 2" which can be used to predict the future crashes at average condition but not to a specific site. In addition, the CMF for rear-end crashes is "condition 6" which only provide clues for the future prediction, but cannot be applied to calculate the expected crashes. Therefore, the CMFs for KABCO, KABC, KAB, and rear-end crashes require further screening to yield a stable CMF. These CMFs may have interaction with skew angle, turning lanes, land use (commercial/residential), and/or factors other than geometry design such as country, climate, and/or driver composition.

Further improvement can be performed regarding the ratio of the observation between each bootstrap trial and the original sample. In this chapter, the number of the observations in each

bootstrapped resample is the same as the original dataset. Larger observation in each resample will yield a smaller bootstrap CI but harder to identify the heterogeneity of the CMF. This ratio should be situational and requires further investigation to suggest an appropriate value. Therefore, it requires further study to find an optimal ratio between the bootstrapped resamples and original dataset.

CHAPTER 7 : SAFETY PERFORMANCE FUNCTIONS FOR DEVELOPING CRASH MODIFICATION FACTORS USING EMPIRICAL BAYES METHOD

7.1 Introduction

The purpose of this chapter is to validate the transferability of SPFs using different states/sources (i.e., Ohio and HSM which developed based on data from Minnesota and North Carolina) and apply SPFs from these sources to compare the CMF values for signalization in Florida. I located the treated intersections which control type changed from two-way stop controlled to signal controlled. Using these target intersections, before-after study is conducted using empirical Bayes (EB) method. In order to perform EB analysis, it is needed to develop SPFs and calculate the predicted crashes based on the SPFs to serve as priors. Since these treatments are located in the state of Florida, the SPFs in Florida are likely to have the highest accuracy. Under this assumption, this chapter compares the CMFs values among multiple SPFs from these 3 sources. If the CMFs calculated by the SPFs in HSM are close to the CMFs when using the SPFs in Florida, it would be a substantial benefit because it is not necessary to re-estimate SPFs based on local conditions for signalization.

The issue of transferability of SPFs and calibrating SPFs is an important topic. Developing SPFs requires a tremendous effort of data collection and data analysis. If SPFs are transferable, researchers and engineers could skip the model development stage which is the most challenging part when developing new SPFs. Many states in the US have already developed their own calibration factors based on the SPFs provided in HSM (AASHTO, 2010). Nowadays, several studies investigate the impact of the calibration of the SPFs in HSM for local roadway networks

(Cafiso et al., 2013; Mehta and Lou, 2013; Persaud et al., 2002; Sun et al., 2006; Tegge et al., 2010; Xie et al., 2011; Young et al., 2012). Besides, the calibration factors based on the SPFs in HSM are examined for places outside America such as Saudi Arabia (Al Kaaf and Abdel-Aty, 2015) and Italy (Dell'Acqua et al., 2014). These studies all pointed out that calibrated HSM models perform better (measured by model fit) than non-calibrated one.

7.2 Data Preparation

7.2.1 Data Description

Data in Florida were collected and combined from the following five database sources; Roadway Characteristic Inventory (RCI), Crash Analysis Report (CAR), Florida Financial Management Search System, Transtat iView, and Google Earth. The Financial Management Search System provides projects constructed for FDOT. The CAR system has all the reported crashes. Crash reports included in CAR have information such as severity, crash type, and other crash related characteristics. This system allows us to locate crashes from 2003 to date. Crashes are divided into 30 different crash types including rear end, head on, side swipe, angle, etc. Crashes are also divided into five crash severities: fatal, incapacitating injury, non-incapacitating, possible injury and PDO.

In order to compare the transferability of applying SPFs from HSM, I specifically target four-legged intersections in urban/suburban areas. Since crash reports in Florida sometimes misclassify left-turn crashes as angle crashes, I could only estimate angle and left turn crashes together. In HSM, the expected crash count for different crash types such as rear-end crashes and angle crashes are calculated based on proportion to KABC crashes and PDO crashes. However, there is no

proportion of left turn crashes provided by HSM. Therefore, it is not possible to calculate the predicted crash count for left-turn crashes using the ratio suggested in HSM. In this case, I cannot compare the CMFs value for angle crashes nor left turn crashes.

The treatment locations were chosen from two sources, one is from the Financial Project Search System and another part is from RCI, both maintained by FDOT. I have selected the signal installation date from 2005 to 2010. After retrieving these data, we combined traffic volume on the major road and the minor road with the target intersections using GIS. On the other hand, the Ohio data is collected from the Highway Safety Information System (HSIS). Crash data was combined from 2003 to 2011.

7.2.2 Summary of Data Collection

Twenty-nine intersections that were signalized were identified in Florida. The CMFs were estimated based on these 29 signalized intersections. For reference intersections in Florida, data for 126 intersections were located with major and minor AADT. On the other hand, I have more than 1000 reference locations in the state of Ohio. In order to compare the Florida SPFs with Ohio SPFs, I also control the sample size by randomly selecting 126 intersections from Ohio. The descriptive statistics for the treatment group, Florida reference group, and Ohio reference group are shown in Table 7-1. In the first part of the table, descriptive statistics for the treated sites are shown, if the variable is in before condition I inserted "*Before*", if it is after condition I inserted "*After*".

The roadway variables include:

(1) Annual average daily traffic on major road (Maj_AADT)

(2) Annual average daily traffic on minor road (Min_AADT)

(3) Total Average annual daily traffic entering the intersection (Tot_AADT)

For each variable, simple statistics is provided with mean, standard deviation and minimum and maximum value also shown in Table 7-1. In addition, descriptive statistics of three crash types are also shown. On top of the crash count, the crash rate for each crash types is calculated. The unit of rate is "million vehicles entering the intersection per year per site". The detailed explanations for these crash types are:

(1) *Total crashes* (KABCO) - /per site per yr

(2) *Fatality and injury crashes* (KABC) - /per site per yr

(3) *Rear-end crashes* (Rear) - /per site per yr

(4) *Total crash Rate* (KABCO_Rate) - / per mvmt per yr per site

(5) *Fatality and injury crash Rate* (KABC_Rate) - / per mvmt per yr per site

(6) *Rear-end crash Rate* (Rear_Rate) - per mvmt per yr per site

Overall, 29 treatment sites are located with 126 reference sites from Florida and 126 reference sites from Ohio. To insure the quality of the SPFs, I checked the reference group to verify that there is no major geometry change in the research period. For the data in Florida, I have checked street images from multiple years using Google Earth. On the other hand, for the data in Ohio, I made sure that the selected sites do not overlap with the treatment list in the research period.

The crash rate for KABCO is much higher in Ohio compared to Florida. Ohio has KABCO crash rate at 276 per million vehicles per year, and there are only 78.981 crashes per million vehicles per year in Florida. A similar situation was found for rear-end crashes. The rear-end crash rate in Ohio is more than 5 times than in Florida which is a significant different. On the other hand, crash rate for KABC in Ohio is 60 percent more than in Florida. Due to the differences in crash rate, it is expected that the predicted crash count for each state based on its own SPFs are different. Therefore, the calibration factor is needed to bridge this gap across regions.

Table 7-1 Descriptive Statistics

Descriptive Statistics for Treatment Sites   N=29

Statistic	Mean	St. Dev.	Min	Max
Maj_AADT_Before	35,954	24,820	6,800	110,500
Min_AADT_Before	10,513	13,024	1,416	63,500
Tot_AADT_Before	46,467	35,156	10,281	162,500
Maj_AADT_After	38,275	30,862	6,700	149,000
Min_AADT_After	7,728	8,684	700	37,000
Tot_AADT_After	46,002	33,906	8,100	169,000
KABCO_Before	11.655	9.893	0	40
KABCO_After	11.655	12.670	0	55
KABC_Before	6.483	5.166	0	22
KABC _After	5.241	4.673	0	19
Rear_Before	3.414	3.708	0	13
Rear_After	6.172	9.312	0	42

Descriptive Statistics for Reference Sites in Florida   N=126

Statistic	Mean	St. Dev.	Min	Max
Maj_AADT	9,791	8,590	850	42,500
Min_AADT	1,864	1,902	100	15,000
Total_AADT	11,655	9,145	1,500	48,500
KABCO	1.198	2.186	0	13.4
KABC	0.613	1.128	0	5.2
Rear	0.291	0.737	0	5
KABCO_Rate (per mvmt/yr)	78.981	151.491	0	839.080
KABC_Rate (per mvmt/yr)	40.812	85.410	0	586.207
Rear_Rate (per mvmt/yr)	16.542	36.981	0	245.989

Descriptive Statistics for Reference Sites in Ohio   N=126

Statistic	Mean	St. Dev.	Min	Max
Maj_AADT	13,031	8,625	530	46,090
Min_AADT	4,401	3,593	259	19,400
Total_AADT	17,432	10,708	980	54,249
KABCO	5.6226	7.073	0	38.889
KABC	1.324	1.158	0	7.556
Rear	2.336	3.692	0	23.667
KABCO_Rate (per mvmt/yr)	276.309	240.000	0	1158.701
KABC_Rate (per mvmt/yr)	66.968	58.946	0	249.373
Rear_Rate (per mvmt/yr)	104.122	119.719	0	606.938

7.3   Results

Safety performance functions were developed using the NB Model formulation.   SPFs were developed based on total crashes, KABC (fatal and injury) crashes, and rear-end crashes respectively.   In this study, I targeted on four-legged intersections as my locations. In this section, SPFs for Florida, Ohio and HSM will be developed.   Calibration factors are also shown in the following paragraph.   The predicted crash counts were calculated from the SPFs then adjusted by calibration factors.   Using the different predicted crash counts from each source (Florida, OH, HSM), I estimated CMF accordingly.

7.3.1   Safety Performance Function

HSM and other research suggest that it is ideal to use the log of major AADT and the log of minor AADT to develop SPFs.   However, after developing SPFs using major and minor AADT as separate variables, I found that the model fitness is worse than using the total AADT in Florida and Ohio. In addition, the log of minor AADT is not significant in Florida.   Therefore, I estimated the models using the log of the total AADT.   On the other hand, I applied the base condition model of the urban and suburban arterials in HSM.   The model form in HSM is provided with the coefficient of the log of major AADT and the log of minor AADT.   In this case, Equation 7-1 represents the model form for developing SPFs for Florida and Ohio and Equation 7-2 demonstrates the equation for HSM.

The variables included in the model form can be explained as follows:

    i.   Log AADT on Both Major and Minor Road   (Log Total_AADT)

    ii.   Log AADT on Major Road   (Log Major_AADT)

    iii.   Log AADT on Minor Road   (Log Minor_AADT)

The equations can be written in this form.

$$N = \exp(\beta_0 * (\text{Total\_AADT})^{\wedge} \beta_1) \tag{7-1}$$

$$N = \exp(\beta_0 * (\text{Major\_AADT})^{\wedge} \beta_2 * (\text{Minor\_AADT})^{\wedge} \beta_3) \tag{7-2}$$

where   N=Crash Frequency $\beta_0 = $ Intercept $\beta_1 = $ Coefficient for log(Total_aadt)

$\beta_2 = $ Coefficient for log(Major_AADT) $\beta_3 = $ Coefficient for log(Minor_AADT)

The relationship between total AADT and each crash types is shown in Figure 7-1. The y-axis is the predicted crash count per year and x-axis is AADT entering the intersections. Due to the limitation that I do not have the data for developing the SPFs in HSM, I cannot include the fitted line for HSM. In the figure, the dark gray lines represent fitted values for Florida and the lighter gray lines represent fitted values for Ohio. For crash types "KABCO" and "rear-end" crashes, Ohio's predicted crashes is higher than Florida's for our study AADT group. However, for KABC crashes, Ohio's predicted crashes is higher only at low AADT intersections. Florida's predicted crash count becomes higher when total AADT is higher than 15,955 (vehicles entering intersection).
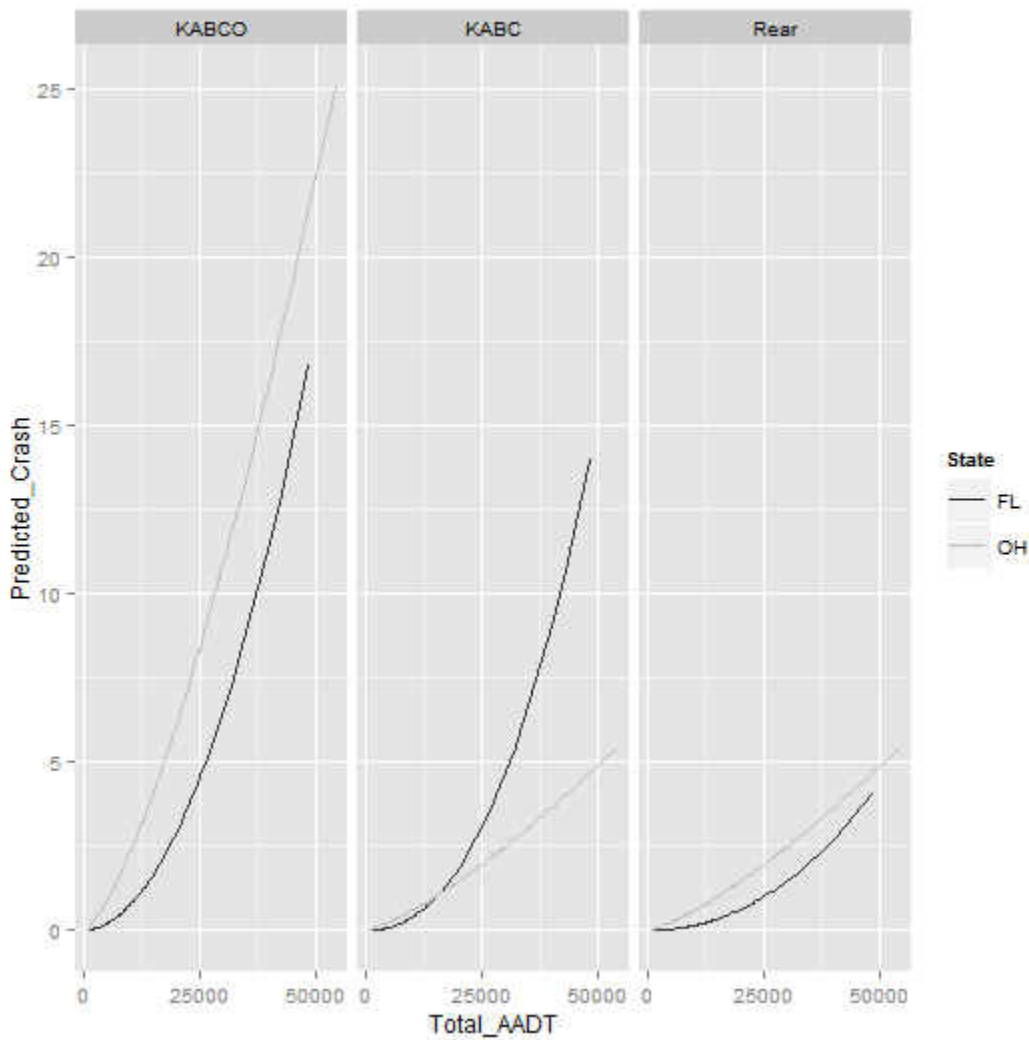
Figure 7-1 Scatter Plot for Crash Count and Total AADT

The results in Table 7-2, show that three variables were selected to be included in the final SPF. According to the result, I could see that the coefficient is much different from each source. For the models developed for Florida and Ohio, all listed coefficient is significant at 99 percent level. When comparing the SPFs from Florida with Ohio, the coefficient of the log of total AADT is very different from the coefficient in Ohio. Besides, the SPFs from HSM consist of the major and minor AADT separately, which is different from Florida and Ohio condition as well. It is worth

noting that there are no SPFs for rear-end nor left turn crashes in the SPFs from HSM. Instead, a proportion was suggested based on FI and PDO crashes respectively in HSM. Therefore, as shown in Table 7-2, the SPF for rear-end is stated as the pound sign.

It is worth noting that in HSM, the suggested way to calculate rear-end crashes is to estimate KABC and PDO crashes first, and then multiply the predicted crashes by a certain ratio to get the predicted count. In fact, the SPFs are developed based on the data from Minnesota and North Carolina. However, the proportion factors are developed based on the data collected in California. This inconsistency may cause potential bias when applying the SPFs to estimate rear-end crashes.

Table 7-2 SPFs for each Crashes Types (The Urban 4-Leg Intersections)

Negative Binomial Model using Data in Florida N=126

	Dependent variable:		
	KABCO	KABC	Rear
Constant	-18.601	-22.222	-21.754
log(Total_AADT)	1.985	2.304	2.147
Overdispersion Parameter	0.193	0.250	0.294

Negative Binomial Model using Data in Ohio N=126

	Dependent variable:		
	KABCO	KABC	Rear
Constant	-12.212	-12.709	-16.864
log(Total_AADT)	1.416	1.321	1.791
Overdispersion Parameter	1.487	1.534	1.140

Negative Binomial Model using Data in HSM N=96

	Dependent variable:		
	KABCO	KABC	Rear
Constant	-8.97	-11.20	#
log(Major_AADT)	0.82	0.93	#
log(Minor_AADT)	0.25	0.28	#
Overdispersion Parameter	2.50	2.08	#

Note: #Use proportion in HSM
    All coefficients are significant at 99% level

The CMFs were calculated as shown in Table 7-3, After calculating the predicted crash count from SPFs, the empirical Bayes method was utilized to estimate the crash modification factors (CMFs) for each category. The comprehensive CMFs result is shown in Table 7-3. Similar to previous research findings, signalization will result in more rear-end crashes. However, the CMFs for KABCO are different from HSM. According to HSM, the CMF is at 0.95 when signalizing an intersection in an urban area. But the CMF calculated in Florida is at 0.785 which is 0.165 lower than HSM. In fact, if I apply the SPFs and its corresponding calibration factors, the CMF values will become 1.062 and 1.072 which is significantly higher than using the SPF in Florida.

Table 7-3 Crash Modification Factors using SPFs of Different States w/o Calibration Factors

	FLORIDA		OHIO		HSM	
	CMF	Standard Error	CMF	Standard Error	CMF	Standard Error
KABCO	0.785	0.057	1.060	0.083	1.072	0.084
KABC_CMF	0.599	0.057	0.856	0.089	0.855	0.089
REAR_CMF	1.283	0.167	1.829	0.258	1.814	0.255

The calibration factors were estimated in this chapter as shown in Table 7-4. In Ohio, the calibration factors show the crash count is higher than that in Florida. Therefore, the calibration factors for all crash severities and types are below 1. For rear-end crashes, the calibration factor is as low as 0.23. This means that the rear-end crash count in Ohio is much higher than in Florida. On the other hand, the SPFs suggested in HSM were developed using data from Minnesota and North Carolina. It is worth noting that the number of KABC crashes depicted in HSM is much less than in Florida.

Table 7-4 Calibration Factors for OH and HSM SPFs Based on FL

	KABCO	KABC	REAR
OH	0.3835	0.8171	0.2342
HSM	0.785	2.067	0.5229

After applying calibration factors along with the predicted crash count based on the SPFs, the adjusted CMFs are shown in Table 7-5. Comparing the results without applying calibration factors as shown in Table 7-3 with the calibrated ones shown in Table 7-5, there is only minor difference. This is due to the weight for predicted value E{k} is small as shown in Equation 3-3. Therefore, after adjustment by Equation 3-5 which is the ratio suggested by Gross et al., 2010, the differences are marginal.

Table 7-5 Crash Modification Factors using SPFs of Different States with Calibration Factors

	FLORIDA		OHIO		HSM	
	CMF	Standard Error	CMF	Standard Error	CMF	Standard Error
KABCO	0.785	0.057	1.062	0.083	1.072	0.084
KABC_CMF	0.599	0.057	0.857	0.089	0.852	0.088
REAR_CMF	1.283	0.167	1.837	0.260	1.818	0.256

By plotting the CMF values in Table 7-5Table 7-5 to line chart as shown in Figure 7-2, I can observe the difference more closely. The CMFs using HSM and Ohio SPFs are significantly higher for KABCO and KABC crashes when using the locally developed Florida SPFs (after adjustment by the calibration factor). This is an important finding since the CMFs become insignificant in KABCO crashes when applying SPF from different sources. If I apply the SPF using Florida data, I would expect to get 21.5% crash reduction and it is statistically significant. However, substituting the Florida SPFs with the SPFs from HSM or Ohio, I would get CMF values slightly higher than

1 and not significant. In addition, the rear-end crashes have a similar pattern which CMFs from

HSM and Ohio are also higher than Florida but not significant.
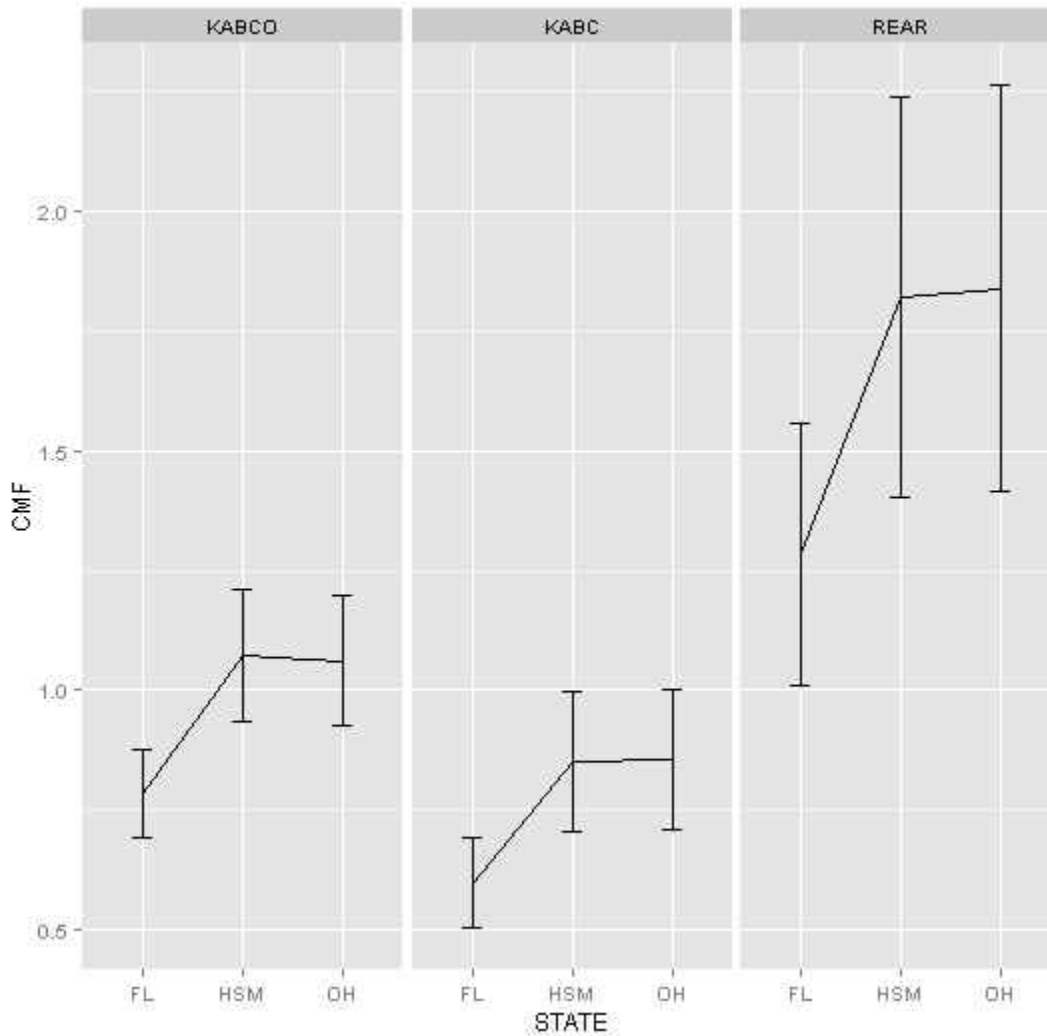

Figure 7-2 Comparison of CMF using SPFs from the Different States (90% Confidence Interval)

The estimated CMFs were compared from this chapter with others. According to the results shown

in Table 7-6Table 7-6, the CMFs for KABCO and KABC crashes in this chapter is not significantly

different from previous research (HSM (AASHTO, 2010) and NCHRP Vol. 491(McGee et al.,

2003)). In fact, the results specified in this chapter have a lower standard error which indicates that the CMFs are more precise. However, there is one issue worth noting which is that the CMFs were developed for all types of crashes in HSM and NCHRP Vol.491. However, the CMFs in this chapter are specifically for multi-vehicle crashes. The reason I did not use all types of crashes (including single vehicle crashes) is due to the SPFs in HSM separate the urban/suburban into multi-vehicle crashes and single vehicle crashes. In order to compare CMFs using SPFs provided in the HSM, I chose multi-vehicle crashes since the majority of crashes at intersections are multi-vehicle crashes. Therefore, the CMF values stated in Table 7-6 can still be compared with the sources from HSM and NCHRP Vol. 491.

Table 7-6 Signalization Crash Modification Factors in HSM and NCHRP Report

Crash Severity	Crash Type	CMF	Standard Error	Reference
KABCO	All Crash	0.95	0.09	HSM (AASHTO, 2010)
KABCO	Multi	**0.785**	**0.06**	This chapter (FL SPF)
KABCO	Multi	1.06	0.08	This chapter (OH SPF)
KABCO	Multi	1.07	0.08	This chapter (HSM SPF)
KABC	All Crash	0.77	0.27	NCHRP Volume 491 (McGee et al., 2003)
KABC	Multi	**0.60**	**0.06**	This chapter (FL SPF)
KABC	Multi	0.86	0.09	This chapter (OH SPF)
KABC	Multi	0.85	0.09	This chapter (HSM SPF)

Bold text significant at 90% confidence interval
*Multi represents multi-vehicle crashes

7.4   Conclusion

In this chapter, I estimated CMFs for the safety effect of signalization implemented in Florida. This chapter applied the empirical Bayes method to develop CMFs for KABCO, KABC, and rear-end crashes using SPFs and calibration factors developed based on Florida, HSM (North Carolina

and Minnesota), and Ohio. The results showed the significant difference between the CMFs using Florida, Ohio, and HSM SPFs. Therefore, I concluded that it is not suitable to apply data to SPFs developed from other jurisdictions without further investigation.

The CMFs were estimated for three crash types (i.e., KABCO, KABC, rear-end). For each crash type, the Florida, Ohio, and HSM SPFs were used to estimate CMFs. It was observed that the coefficients of SPFs from the three sources are not comparable. In addition, the calibration factors comparing the observed crash counts in Florida to the predicted crash counts from Ohio and HSM SPFs were also calculated. According to the results, the calibration factor for Ohio KABCO crashes is 0.38. On the other hand, the calibration factor for KABC crashes in HSM is 2.07. In fact, the different reporting threshold among states may be the key factor to explain why the calibration factor is needed. In Ohio, the reporting threshold is $1000+ of property damage. However, in Florida, the threshold is based on specific crash conditions. These crash types are, involve any injury, leaving the scene, commercial motor vehicles involved, require a wrecker to remove it from the scene, and driving under influence. The different reporting threshold has to be considered when using SPFs from non-local ones. That is to say, the calibration factors not only adjusting the different crash behavior among states but also adjusting the different reporting threshold. It is challenging to separate the effect of reporting differences from behavioral differences. Therefore, in this paper, I used the calibration factors to consider the combination effect as suggested by HSM and found the calibration factors are really different for each crash type and state. Moreover, it is desirable that the next edition of HSM address the issue of reporting threshold because its SPFs are intended for nationwide use.

Comparing the CMFs calculated based on the calibrated SPFs with the non-calibrated SPFs, it was found that differences are minimal. In detail, I found that when observed before and observed after crashes at 150 (crash count for KABC) or more, there is no significant difference between whether using the calibrated SPFs or not. Another important finding in this chapter is that some CMF values are statistically significantly different when using SPFs developed from other states. In fact, the CMFs for KABCO and KABC crashes are 0.785 and 0.60 for Florida, 1.06 and 0.86 for Ohio, and 1.07 and 0.85 for HSM, respectively. The CMFs using the data in Florida are significantly lower than Ohio and HSM. This indicates that SPFs may not be transferrable and it results in the biased estimation of CMFs. An erroneous judgment would be made if I borrow SPFs from other states. The CMF is 0.785 for KABCO using the SPF in Florida which is a closer estimate since the treatment targets are located in Florida. However, when applying the SPFs from Ohio or HSM, I would get a higher CMF value at 1.06 and 1.07, respectively. In this case, if Florida does not have its own SPFs and borrows the SPFs from HSM or Ohio, the judgment will be different from using the Florida SPF. Therefore, according to these results, it is suggested to apply SPFs from other jurisdictions after thorough examination and validation when developing CMFs. It would be most desirable to use locally developed SPFs if sufficient traffic and crash data are available.

CHAPTER 8 : CONCLUSION

8.1 Summary

The dissertation focuses on exploration and development of CMFs. The main objective of this study are to 1) develop CMFs at different situations with different roadway characteristics among treated sites over time, 2) construct a reliable way to evaluate the quality of CMFs, 3) identify the transferability of SPFs in the calculation of CMFs using EB method. Based on the evaluation results, corresponding improvement suggestions have been made.

In chapter 3, the CMFs were estimated using the observational before-after study to show that the CMFs vary across different traffic volume levels when signalizing intersections. Besides screening the effect of traffic volume, the trends of CMFs for the signalization and adding red light running cameras (RLCs) were evaluated in chapter 4. CMFs for these treatments were measured in each month and 90- day moving windows using the time series ARMA model. The results of the signalization show that the CMFs for rear-end crashes were lower at the early phase after signalization but gradually increased from the 9th month onward. Besides, it was also found that the safety effectiveness is significantly worse 18 months after installing RLCs.

In chapter 5, four major CMFs calculating methods are introduced for helping users developing CMFs using naïve, comparison group, and empirical Bayes methods. In addition, graphical user interfaces (GUIs) are provided to help users to use this tool. By inputting the data in CSV format using the GUI, this package is capable to calculate the expected value of CMF, variance of CMF, standard error of CMF, upper bound confidence interval, and lower bound confidence interval.

In chapter 6, efforts have been made to seek reliable CMFs, the best estimate of CMFs is still widely debated. Since CMFs are non-zero estimates, the population of all CMFs does not follow normal distributions and even if it did, the true mean of CMFs at some intersections may be different than that at others. Therefore, a bootstrap method was proposed to estimate CMFs that makes no distributional assumptions. Through examining the distribution of CMFs estimated by bootstrapped resamples, a CMF precision rating method is suggested to evaluate the reliability of the estimated CMFs. The result shows that the estimated CMF for angle+left-turn crashes after signalization has the highest precision, while estimates of the CMF for rear-end crashes are extremely unreliable. The CMFs for KABCO, KABC, and KAB crashes proved to be reliable for the majority of intersections, but the estimated effect of signalization may not be accurate at some sites.

In chapter 7, the empirical Bayes method was applied to develop CMFs using several SPFs from different jurisdictions and adjusted by calibration factors. After examination, it is found that applying SPFs from other jurisdictions is not desired when developing CMFs.

8.2   Research Implication

The implications from Chapter 3 are as follow: signalization reduced fatal and injury crashes (KABC and KAB) more than total crashes (KABCO). In particular, signalization is more likely to reduce fatal and injury crashes when AADT is lower at intersections. Also, CMFs for KAB crashes were consistently lower than CMFs for KABCO crashes at all AADT ranges. When comparing CMFs among the five AADT ranges, installing traffic signals at the stop-controlled intersections with AADT greater than 35,000 vpd significantly increases the number of total crashes as indicated

by CMFs greater than one. In addition, safety effect of signalization is not significant for KABC and KAB crashes at the intersections with AADT of 20,001– 35,000 vpd. For rear-end crashes, it was found that the signalization significantly increased rear-end crashes for AADT greater than 20,000 vpd. In particular, the increase in rear-end crashes was generally higher at the intersections with higher AADT. Signalization generally has a negative effect on the reduction of rear-end crashes. In contrast, the signalization significantly reduced angle+left-turn crashes for all AADT groups.

The findings in chapter 4 show the following implication: CMFs for signalizing an intersection and adding RLCs were measured in each month and 90- day moving windows respectively. The ARMA time series model was applied to predict trends of CMFs over time based on monthly variations in CMFs. The results of the signalization show that the CMFs for rear-end crashes were lower at the early phase after the signalization but gradually increased from the 9th month. On the other hand, the CMFs for angle crashes were higher at the early phase after adding RLCs but decreased after the 9th month and then became stable. It was also found that the CMFs for total and fatal/injury crashes after adding RLCs in the first 18 months were significantly greater than the CMFs in the following 18 months. This indicates that there was a lag effect of the treatments on safety performance. The results of the ARMA model show that the model can better predict trends of the CMFs for the signalization and adding RLCs when the CMFs are calculated in 90- day moving windows compared to the CMFs calculated in each month. In particular, the ARMA model predicted a significant safety effect of the signalization on reducing angle and left-turn crashes in the long term. Thus, it is recommended that the safety effects of the treatment be

assessed using the ARMA model based on trends of CMFs in the long term after the implementation of the treatment.

Chapter 5 is dedicated to developing an R package to develop CMFs. This package is named "bastudy". In this package, three major CMFs calculating methods were introduced to develop CMFs using naïve, comparison group, and empirical Bayes methods. More importantly, this package was used to support the examination of the reliability of CMFs addressed in chapter 6.

In chapter 6, the effort was done to identify the quality of CMFs. Through examining the distribution of CMFs for five crash categories, estimated by bootstrapped resamples of this data, a CMF precision rating method is suggested to evaluate the reliability of the estimated CMFs. The analysis shows that the estimated CMF for angle+left-turn crashes after signalization has the highest precision, while estimates of the CMF for rear-end crashes are extremely unreliable. The CMFs for KABCO, KABC, and KAB crashes proved to be reliable for the majority of intersections, but the estimated effect of signalization may not be accurate at some sites.

Several important implications were found from Chapter 7. CMFs for the effect of signalization at intersections in Florida were estimated. The empirical Bayes method was used to develop CMFs for KABCO, KABC, and rear-end crashes using several safety performance functions (SPFs) from different jurisdictions and adjusted by calibration factors. These SPFs were developed using Florida's and Ohio's data. Also, the SPFs suggested in the HSM were used to calculate CMFs. By developing and comparing the SPFs from different states, it can be concluded that it might not be suitable to apply SPFs from other states without thorough examinations. The CMF is 0.785 for

KABCO using the SPF in Florida and it was significantly smaller than 1, which indicates that the signalization at intersections results in more total crashes. However, when applying the SPFs from Ohio and HSM, higher CMFs of 1.06 and 1.07 were obtained, respectively. Also they were both significantly larger than 1. It shows that the signalization brings about less total crashes. The major finding of this chapter is that the CMF values may be significantly different when applying SPFs developed from other states. Therefore, one would have biased CMFs if borrowing SPFs from other states without proper adjustments.

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