White Paper: Enhancing Statistical Methodologies for Highway Safety Research—Impetus from FHWA
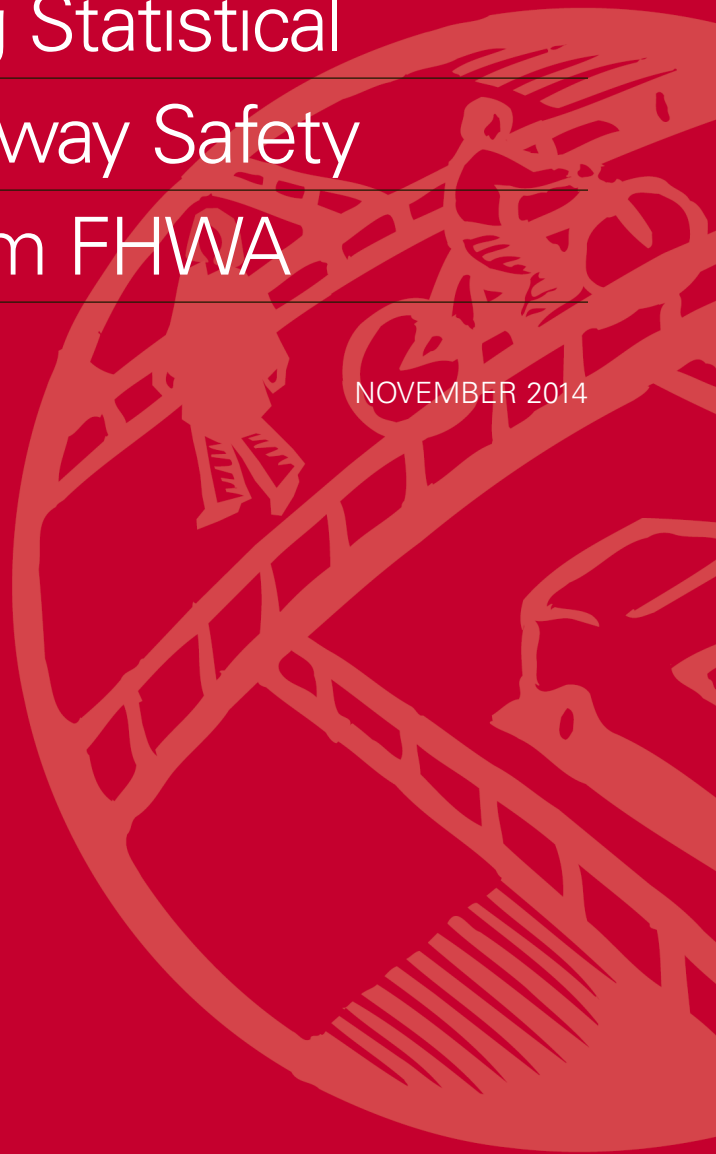
U.S. Department of Transportation
Federal Highway Administration

FOREWORD

The Federal Highway Administration's ultimate goal for the Development of Crash Modification Factors (DCMF) program is to save lives by identifying new safety strategies that effectively reduce crashes and promoting them for nationwide installation by providing measures of their safety effectiveness. State transportation departments and other transportation agencies need to have objective measures for safety effectiveness before investing in new safety improvements strategies.

Statistical methodologies are heavily used for all studies performed under the DCMF, but these methodologies have been borrowed from other fields and, therefore, have limitations in capability and applicability when used for highway safety research. Accordingly, a secondary goal of the DCMF program is to advance highway safety and related research by establishing sound statistical methodologies, specifically for highway transportation, in cooperation with the American Statistical Association and other statistical communities. This white paper identifies and discusses opportunities for advancing methodologies to estimate crash modification factors (CMFs) and safety performance functions (SPFs) and outlines considerations and future steps that should be taken to encourage researchers to explore these techniques in their research to develop CMFs and SPFs.

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TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No. FHWA-HRT-14-081	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle Enhancing Statistical Methodologies for Highway Safety Research – Impetus from FHWA		5. Report Date November 2014
		6. Performing Organization Code
7. Author(s) David Banks, Bhagwant Persaud, Craig Lyon, Kimberly Eccles, and Scott Himes		8. Performing Organization Report No.
9. Performing Organization Name and Address VHB 4000 WestChase Boulevard, Suite 530 Raleigh, NC 27607		10. Work Unit No. (TRAIS)
		11. Contract or Grant No.
12. Sponsoring Agency Name and Address Office of Safety R&D Federal Highway Administration 6300 Georgetown Pike McLean, VA 22101-2296		13. Type of Report and Period Covered
		14. Sponsoring Agency Code
15. Supplementary Notes FHWA Contracting Officer Technical Manager: Roya Amjadi		

16. Abstract
The Federal Highway Administration Development of Crash Modification Factors (DCMF) Program was established in 2012 to address highway safety research needs for evaluating new and innovative safety strategies (improvements) by developing reliable quantitative estimates of their effectiveness in reducing crashes. A goal of the DCMF is to advance highway safety and related research by establishing a sound foundation for the development of highway transportation specific statistical methodologies in cooperation with the American Statistical Association and other statistician communities. In pursuit of that goal, a two-day Technical Experts meeting brought together researchers from the road safety, statistics, and other statistics-related fields such as epidemiology, biostatistics, and agent based modeling that have methodologies relevant to highway safety research applications. The meeting resulted in guidance and materials that supported the development of this white paper, which identifies and discusses opportunities for advancing methodologies to estimate crash modification factors and safety performance functions. The paper outlines considerations and future steps to encourage researchers to explore these techniques in their research.

17. Key Words Crash Modification Factors, Safety Performance Functions, Crash Analysis, Statistical Methodologies, Safety Evaluation	18. Distribution Statement No restrictions. This document is available to the public through NTIS: National Technical Information Service Springfield, VA 22161 http://www.ntis.gov		
19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages 41	22. Price

Form DOT F 1700.7 (8-72)   **Reproduction of completed page authorized**

SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
LENGTH				
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
AREA				
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
VOLUME				
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
NOTE: volumes greater than 1000 L shall be shown in m^3				
MASS				
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
TEMPERATURE (exact degrees)				
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
ILLUMINATION				
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
FORCE and PRESSURE or STRESS				
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
LENGTH				
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
AREA				
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
VOLUME				
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
MASS				
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
TEMPERATURE (exact degrees)				
°C	Celsius	1.8C+32	Fahrenheit	°F
ILLUMINATION				
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
FORCE and PRESSURE or STRESS				
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380.
(Revised March 2003)

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INTRODUCTION

BACKGROUND ON THE DEVELOPMENT OF CRASH MODIFICATION FACTORS (DCMF) PROGRAM

The Federal Highway Administration (FHWA) DCMF program was established in 2012 to address highway safety research needs for evaluating new and innovative safety strategies (improvements) by developing reliable quantitative estimates of their effectiveness in reducing crashes.

The ultimate goal of the DCMF program is to save lives by identifying new safety strategies that effectively reduce crashes and promote them for nationwide installation by providing measures of their safety effectiveness and benefit to cost ratios (B/C) through research. State transportation departments and other transportation agencies need to have objective measures for safety effectiveness and B/C ratios before investing in new strategies for statewide safety improvements. There are 38 State transportation departments that provide technical feedback on safety improvements to the DCMF program and implement new safety improvements to facilitate evaluations. These States are members of the Evaluation of Low Cost Safety Improvements Pooled Fund Study, which functions under the DCMF program.

Statistical methodologies are heavily used for all studies performed under the DCMF program, but these methodologies have been borrowed from various statistical fields and have limitations in capability and applicability when used for highway safety research. Accordingly, a secondary goal of DCMF program is to advance highway safety and related research by establishing a sound foundation for the development of highway transportation specific statistical methodologies in cooperation with the American Statistical Association (ASA) and other statistician communities.

This white paper may be considered as the first brick for laying the foundation for future highway transportation specific statistical methodologies and/or a future statistical field customized for research and application in various highway transportation areas.

PROJECT BACKGROUND

The goals of the project on which this white paper is based were as follows:

- Identify new statistical methodologies.
- Improve and advance the current methodologies used in the development of Safety Performance Functions (SPFs) and Crash Modification Factors (CMFs).
- Suggest an initial set of reliable and time/labor efficient methodologies that can be used by the FHWA and State transportation departments and other transportation agencies for SPF and CMF development.

Working toward these goals, the project team, in consultation with FHWA, planned a two-day technical experts meeting to bring together researchers from the road safety, statistics, and other statistics-related fields such as epidemiology, biostatistics, and agent based modeling that have methodologies relevant to highway safety research applications. The meeting was arranged to

work with attendees in identifying applicable advanced methodologies and/or improve existing methodologies for the development of SPFs and CMFs.

Prior to the meeting, introductory/educational material for highway safety improvement evaluations and sample data were provided to the invited statisticians and other experts. This advance information was intended to prepare the experts to share their assessments of the current practice in highway safety improvement evaluations, identify opportunities and issues, and make initial suggestions at the end of the meeting on ways to improve the existing methodologies.

This white paper is the final product of this project and has been developed based on the outcome of the meeting to record the expert assessments of current practices for highway safety improvement evaluations, opportunities and issues, the suggestions that were made, and possible future steps for advancing the safety evaluation methodologies. Since the paper is specific to what was presented and discussed at the meeting, it is of necessity not an exhaustive assessment of needs related to the estimation of SPFs and CMFs. Rather, the scope is limited to an initial set of suggestions for improving estimation methodologies. In some cases the suggestions pertain to methodologies that have been investigated by highway safety researchers. Reporting on these methodologies as an outcome of a meeting of statistical experts provides support for continued and expanded research in those areas.

It is expected that a key benefit of the project will be the initiation of dialog, and collaboration between, highway safety researchers, statisticians, and other experts to work together to continue to find new, and/or improve current methodologies for the development of SPFs and CMFs.

Selection and Preparation of Technical Experts

The project team, in coordination with FHWA, identified and invited statistical and other technical experts with expertise in methodologies that may be applicable to highway safety improvement evaluations or the development of prediction models. Selections were based on suggestions from both the FHWA and project team (most notably, Dr. David Banks in his capacity as chair of the ASA Transportation Interest Group, who also served as one of the experts). The selection of technical experts was guided by several considerations, including the following:

- They should have extensive experience in statistics, including a preference for a Ph.D. in statistics.
- They will not have been directly involved in the evaluation of road safety engineering treatments related to infrastructure.
- They should have expertise/experience in some sort of treatment/program evaluation that requires the statistical analysis/modeling of time series and/or cross-sectional data.
- They should have an established track record that qualifies them as experts in their field.

The project team also sought to have the sample of technical experts drawn from the following categories:

- **Category 1:** Experts with no experience in road safety data analysis who have related expertise in some sort of treatment/program evaluation that requires the statistical analysis/modeling of time series and/or cross-sectional data.
- **Category 2:** Experts in transportation engineering and/or statistics with extensive seminal research in statistical analysis of crash data but who have not been involved directly in CMF or SPF development.
- **Category 3:** Experts who have worked in road safety evaluations related to driver and enforcement programs.

The chosen experts included five from category 1, two from category 2, and one from category 3. Appendix A lists the invited technical experts, along with their affiliations and areas of expertise.

Experts in the development of SPFs and CMFs were intentionally excluded, given the objectives of the project to generate ideas from statisticians in other areas. However, several members of the project team with considerable experience in SPF and CMF estimation were present at the meeting and ensured that the discussion focused on the task at hand.

The project team communicated with the selected experts to share material and data for highway safety improvement evaluations in advance of the technical experts meeting for the purpose of preparing them for the meeting. In the preparation period, the project team provided further information and assistance, and answered questions on the provided material and data. The materials provided included the following:

- A document providing an overview of SPFs and CMFs and issues in their development.
- *A Guide to Developing Quality Crash Modification Factors*, FHWA-SA-10-032.
- *How to Choose Between Calibrating SPFs from the HSM and Developing Jurisdiction-Specific SPFs*, a report from Project TPF-5(255) of the Transportation Pooled Fund Program.
- *Safety Evaluation of Improved Curve Delineation*, FHWA-HRT-09-045, a report for a completed Empirical Bayes (EB) before-after evaluation.
- *Safety Evaluation of Lane and Shoulder Width Combinations on Rural, Two-Lane, Undivided Roads*, FHWA-HRT-09-031, a report for a completed case-control evaluation.

Technical Experts Meeting and Follow Up

The technical experts meeting was held for two days in December 2013 in Raleigh, NC, at the National Institute of Statistical Sciences. Following a review of the background material shared, each invited expert presented on his or her work and how it could relate to similar problems in the development of SPFs and CMFs. This was followed by extensive discussion and brainstorming. The products produced from the meeting included the following:

- Meeting notes.
- A list of concerns and issues.
- A list of opportunities for improving transportation safety research.
- Initial suggestions for new methodologies or methodology improvements.
- Possible follow ups and next steps.
- A draft marketing and communications plan.

The final project task is the development of the white paper and a final marketing and communication plan. This document constitutes the white paper, which is organized as follows:

- Chapter 1 provides background information on crash modification factors and safety performance functions, mainly for the benefit of statisticians who have not worked in the area of road safety analysis.
- This section provides the backdrop for chapter 2, in which opportunities for advancing methodologies for estimating CMFs and SPFs are identified and discussed.
- Finally, chapter 3 provides considerations and future steps, with a view to ensuring that the opportunities identified for enhancing the SPF and CMF estimation methodologies will be seized by researchers.
- Appendices A–C provide details on the technical experts, an overview of commonly applied methods in estimating CMFs, and an assessment of issues in current highway safety improvement evaluations, respectively.
- Appendix D provides summaries for a small sample of recent road safety research that applied some of the innovative statistical techniques identified at the technical experts meeting. The intent of this appendix is to illustrate that the application of these advanced techniques is topical and is not beyond the capabilities of road safety researchers and, in so doing, to stimulate others to pursue these techniques in their research to develop CMFs and SPFs.
- Appendix E provides a summary of additional ideas for discussion generated by FHWA reviewers of a draft of this paper.

CHAPTER 1. BACKGROUND ON CMFs AND SPFs

The intent of this introductory section is to provide basic background material for the benefit of uninitiated statisticians who have not worked on these topics. Following a brief overview, some content is provided on the main issues encountered, and the statistical tools applied, by researchers currently working in these areas. This section provides context for the main section that follows on opportunities for advancing the methodologies for CMF and SPF estimation.

OVERVIEW OF CMFs, CMFUNCTIONS AND SPFs

A CMF is a multiplicative factor used to compute the number of crashes that would be expected after implementing a given countermeasure at an existing roadway site or after making a change to a roadway being designed. The CMF is multiplied by the expected crash frequency without the countermeasure. A CMF greater than 1.0 indicates an expected increase in crashes, while a value less than 1.0 indicates an expected reduction in crashes. For example, a CMF of 0.8 indicates a 20 percent expected reduction in crashes.

A CMFunction is a formula used to compute the CMF for a specific site based on its characteristics. It is not always reasonable to assume a uniform safety effect for all sites with different characteristics (e.g., safety benefits may be greater for high traffic volumes). A countermeasure may also have several levels or potential values (e.g., improving intersection skew angle, or widening a shoulder). A crash modification function allows the CMF to change over the range of a variable or combination of variables. Where possible, it is preferable to develop CMFunctions as opposed to a single CMF value since safety effectiveness most likely varies based on site characteristics. In practice, however, this is often difficult since more data are required to detect such differences.

Example

The CMFunction for improving intersection skew angle at a rural, four-legged, stop-controlled intersection is a function of the absolute value of intersection angle minus 90 degrees, where the intersection angle is in degrees, as shown in the equation in figure 1.

$$CMF(Intersection\ Skew) = \exp(0.0054 * |Intersection\ Angle - 90°|)$$

Figure 1. Equation. CMFunction for intersection skew angle.

The CMFunction allows the user to calculate the CMF for a specific intersection skew angle compared to a baseline of 90 degrees. For example, if the intersection angle is 120 degrees, the CMF is exp(0.0054*|120º - 90º|) = 1.18. Note that the CMF is the same if the other angle of the intersection is used: exp(0.0054*|60º - 90º|) = 1.18.

As the intersection angle approaches 90 degrees, the CMF approaches 1.0. For instance, if the intersection angle is 100 degrees, the CMF is computed as exp(0.0054*|100º - 90º|) = 1.06.

SPFs are essentially mathematical equations that relate the expected number of crashes of different types to site characteristics. These models always include traffic volume as a form of exposure but may also include site characteristics such as lane width, shoulder width,

radius/degree of horizontal curves, presence of turn lanes (at intersections), and traffic control (at intersections).

The following is an example of an SPF for a segment of road:

$$Crashes/mile/year = (\alpha)(AADT)^{b1}\exp(b_2 \times \text{ Lane Width})$$

Figure 2. Equation. Example SPF.

Where α, b_1, and b_2 are parameters estimated in the modeling process, *AADT* is the estimated average annual daily traffic volume on the roadway, and lane width is the width of the travel lanes measured in feet.

Safety performance functions are used in the development of CMFs through before-after studies and in this context are crash prediction models. With caution, they can be used to develop CMFs through cross-sectional studies; in this context they are explanatory models since the variable coefficients are used to estimate the CMFs that reflect the effect on safety of changing the value of a variable.

KEY ISSUES IN THE ESTIMATION OF SPFs AND CMFs

In road safety research, experimental studies are extremely rare. There is a reliance on observational data, meaning that data are collected retrospectively by observing the performance of an existing road system, where the treatment has already been implemented at some sites, usually not on the basis of a planned experiment, but on engineering considerations, including safety. There are several important issues that are typically considered in the estimation of SPFs and CMFs.

Regression to the Mean in CMF Estimation From Before-After Studies

Regression to the mean (RTM) is the natural tendency of observed crashes to regress (return) to the mean in the year following an unusually high or low crash count. RTM effects arise when sites with randomly high short-term crash counts are selected for treatment and experience a subsequent reduction in crashes when these counts regress toward their true long-term mean. Not accounting for this will exaggerate any safety benefits estimated for sites with randomly high counts and underestimate the benefit for sites with randomly low counts.

Changes in Exposure in CMF Estimation From Before-After Studies

The greatest predictor of crashes is the amount of exposure, measured by the amount of traffic. If exposure changes at a site over time it is important to account for the impact of these changes on the expected number of crashes. This is particularly important for treatments that may impact exposure. For example, if a stop-controlled intersection is converted to a roundabout and vehicle delays are reduced then traffic volumes may increase as traffic is attracted from nearby routes.

Time Trends in CMF Estimation From Before-After Studies

Another confounding factor is general time trends in expected crashes. Time trends may occur due to several unmeasured changes that can occur including: demographic changes, weather, crash reporting practices, levels of enforcement, etc.

Endogeneity Between Variables in Estimating CMFs from SPFs

Road safety situations often exist when some of the explanatory variables may depend on the dependent variable (frequency of crashes) themselves. Bias due to endogeneity can lead to incorrect conclusions from a model, e.g., a model may show that a treatment is associated with an increased number of crashes, when in reality the treatment may actually reduce crashes. This becomes a critical issue if the SPF is used to estimate the CMF associated with a particular treatment. For example, left-turn lanes at intersections are likely to be implemented at sites with large numbers of left-turn related crashes. Therefore a prediction model that includes the presence of left turn lanes as an independent variable is likely to suffer due to endogeneity bias. This has been found where conventional cross-sectional models have indicated a higher expected crash frequency at sites with left-turn lanes than those without.

Correlation Between Predictor Variables in Estimating CMFs from SPFs

A high degree of correlation among explanatory variables in the model makes it very difficult to determine a reliable estimate of the effects of particular variables. For example, if horizontal curvature is correlated with clear zone/roadside hazards, then it is difficult to isolate the safety effect of horizontal curvature. It may be tempting to remove one of the correlated variables, but this can lead to omitted variable bias.

STATISTICAL TOOLS COMMONLY APPLIED IN THE DEVELOPMENT OF SPFs AND CMFs

This section presents an overview of commonly applied statistical tools in the development of SPFs and CMFs at present.

Generalized Linear Modeling

The most common approach in road safety research for the development of SPFs is to apply generalized linear modeling with a negative binomial error distribution and log link function. The negative binomial distribution has been adopted because it is appropriate for non-negative count data (crash frequencies) and reflects the observed overdispersion found in crash data.

Recent advances have seen some researchers apply alternate model specifications including the following:

- Poisson log-normal.
- Conway-Maxwell-Poisson.
- Random parameter negative binomial.
- Full Bayes Markov Chain Monte Carlo (MCMC) methods.

The Full Bayes MCMC methods are particularly appealing in that they have the capability of allowing complex model forms, accounting for spatial correlation and the use of prior information about estimated parameters.

Determining Functional Form of Models

There are few available tools applied in road safety research for determining the appropriate model form. Typical measures of goodness of fit include the t-statistic of estimated parameters, chi-square statistics, Akaike's information criterion and the Bayesian Information Criterion.

Testing of variables for inclusion is sometimes done through a forward or backward stepwise regression. Some methods for determining the functional form are described below.

Integrate-Differentiate Method

The method is based on the Empirical Integral Function. To illustrate we will use the traffic volume variable *AADT* for road segments of equal length. The data are divided into groups, for example, 0–1,000, 1,001–2,000, etc. For each group the average crash rate is determined and the area of the bin is equal to this average crash rate multiplied by the bin width (1,000 in this case). The value of the Empirical Integral Function is then the sum of bin areas from the lowest *AADT* group up to that boundary. In such a plot some order can be seen whereas in a simple scatterplot of crashes versus a variable of interest it is very difficult to perceive any pattern.

The essence here is that there exists some function linking crashes to *AADT*. There then exists an Integral Function as well. We can use the Empirical Integral Function to make an informed judgment about what the true Integral Function is. If this is successful then the function linking crashes to the variable of interest is the derivative of the Integral Function.

Analysis of Over Versus Under Prediction

In this method a model without the variable of interest is applied to the data. Then using the variable of interest, the data are divided into groups (e.g., 10-ft lanes, 11-ft lanes etc.). The ratio of observed/predicted for each group is then determined and plotted versus the value of the variable defining the group. The plot is used to infer an appropriate relationship between the dependent variable and the variable of interest.

Cumulative Residual (CURE) Plots

In the CURE method the cumulative residuals (the difference between the observed and predicted values for each observation) are plotted in increasing order for each covariate separately. Also plotted are graphs of the 95-percent confidence limits. If there is no bias in the model, the plot of cumulative residuals should oscillate around the x-axis without systematic over or under-prediction, and stay inside of these confidence limits. In the context of CURE plots, it is important to recognize that the plot is not only a reflection of the functional form of the particular explanatory variable, but also whether other relevant explanatory factors have been included in the model in an appropriate form (i.e., the extent to which there is omitted variable bias).

CHAPTER 2. OPPORTUNITIES FOR NEW OR ENHANCED METHODOLOGIES EMERGING FROM THE TECHNICAL EXPERTS MEETING

This section provides summary information on the most promising and relevant tools and methodologies that emerged from the technical experts meeting presentations and discussions. Eight such items were identified. Some of these items entail relatively technical methodology, and it is beyond the scope of this document to describe those in full detail. However, interested readers can easily learn more by examining standard texts in statistics, or by searching on keywords to find pertinent research papers.

THE COX PROPORTIONAL HAZARDS MODEL

The advantage of the Cox proportional hazards model is that it has been extensively studied and elaborated upon in the statistical research community, usually in the context of medical applications (e.g., How does weight, alcohol consumption and smoking affect the risk of heart attack at age 60?). In particular, there are methods for handling time-varying covariates, assessing goodness of fit, and setting confidence intervals, as well as addressing much more complex interactions. For example, in highway studies, illumination and traffic volume both vary by time of day. Below is an outline on how the model might be applied in highway safety analysis.

Suppose Y is a random variable denoting the time until the next automobile crash on a given short stretch of roadway, where the roadway has various characteristics X_1, …, X_p, where those characteristics are explanatory variables such as speed limit, illumination, number of lanes, and so forth. If Y has the density function $f(y)$, then its hazard function is defined as $f(y)/[1 - F(y)]$, where $F(y)$ is the cumulative distribution function of Y. The hazard function can be interpreted as the probability of a crash in the next instant, given that there have been no crashes in the previous y time units.

The Cox proportional hazards model is a key tool for studying hazard functions. The model form is as follows:

$$\frac{f(y)}{[1 - F(y)]} = \lambda_0(y) \exp(\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p)$$

Figure 3. Equation. Cox proportional hazards model.

Where $\lambda_0(y)$ is a baseline hazard function and the exponential term shows how roadway characteristics elevate or reduce the risk of a crash.

Specifically, if there are two factors, where X_1 is road curvature and X_2 is shoulder width, then the CMF for X_1 is $exp(\beta_1 X_1)$, since this is the multiplier that shows how a specific value for curvature increases or decreases the crash risk compared to the baseline risk.

This model, which has had some application in other areas of safety research, is clearly relevant for CMF estimation. As a caution in using it for this purpose, goodness of fit concerns arise if the

form of the model does not correctly describe the data, perhaps because some key variable or interaction has not been included, or because some transformation is required. And principled confidence intervals on the β_j terms allow one to decide whether or not a specific characteristic is significantly relevant to the hazard function.

NON-PARAMETRIC REGRESSIONS

Classical regression assumes there is an additive linear relationship between the mean response and the predictor variables, as follows:

$$Y = b_0 + b_1 x_1 + b_2 x_2 + \cdots b_p x_p + \text{error}$$

Figure 4. Equation. Classic linear regression model.

(In developing SPFs, a log-linear model form is typically used, as noted in the Statistical Tools Commonly Applied in the Development of SPFs and CMFs section.)

In contrast, nonparametric regression assumes that the mean of Y is an unknown smooth function of the predictor variables. This allows the data to determine form of the relationship, as follows:

$$Y = f(X_1, \cdots, X_p) + \text{error}$$

Figure 5. Equation. Nonparametric regression model.

where, as usual, the error is assumed to be approximately normally distributed with mean 0 and unknown but constant variance (this assumption can be relaxed).

Nonparametric regression is similar to nonlinear regression, except that nonlinear regression requires one to specify the form of the relationship (e.g., logistic, sinusoidal, etc.) in advance.

In the context of traffic safety, nonparametric regression greatly extends the flexibility of the modeling; nearly all multiple regression models in highway safety analysis could be improved by the use of this tool. And nonparametric regression can extend the scope of application in unexpected ways. For example, the Cox proportional hazards model assumes that the roadway characteristics in the exponential function act as a linear regression, but nonparametric regression allows the generalization of the hazard function to the following:

$$\frac{f(y)}{[1 - F(y)]} = \lambda_0(y) \exp\left[h(X_1, \cdots, X_p)\right]$$

Figure 6. Equation. Nonparametric regression model with a generalization of the hazard function.

where the $h(.)$ function is a nonparametric regression. There are a number of nonparametric regression techniques that are available; a paper summarized in appendix D describes the use of Multivariate Adaptive Regression Splines to study red-light running, but one can also use Random Forests, Support Vector Machines, and other methods.

Appendix D also provides two recent and relevant examples on the use of non-parametric regression in traffic safety research.

PRINCIPAL COMPONENT REGRESSION

Principal components analysis is used in multivariate analysis. For example, suppose one measured many things about someone's driving, such as average highway speed, maximum speed, the average highway following distance, average gap acceptance, and so forth. With a large sample of people, one might use principal components analysis to understand the correlation structure in the data. For example, it might be that the first principal axis is associated with speed, so that maximum speed and average speed load heavily on that axis. This first axis is the direction in the data space that explains the largest amount of the observed variation in the data. The next axis is perpendicular to the first, and might correspond to use of turn signals. It is the direction which is orthogonal to the first axis and which explains the largest proportion of the remaining variation. One can continue in this way, until one accounts for all the variation.

One could use the scores on each of these axes as explanatory variables for regression analysis, but the principal components that describe the data may not be the best ones for predicting the outcome of interest. In this example, the components that are listed might be good for predicting the probability that the driver will have an accident (after logit transformation to handle the fact that probabilities lie between 0 and 1), but the components listed would do a poor job of predicting how many miles the person drives in a day.

Principal components regression generalizes principal components analysis by finding the set of mutually perpendicular (orthogonal) axes such that the scores on those axes provide the strongest linear relationship (i.e., correlation) with the response variable of interest. In general, changing the response variable will lead to a different set of principal components. Since traffic safety studies often examine different responses, principal components regression could be helpful. It is closely related to partial least squares methods, and there are nonparametric generalizations, too.

HIERARCHICAL BAYESIAN MODELING

Hierarchical Bayes methods, which have been used in safety research, allow analysts to borrow information across similar but not identical situations, and to shrink estimates within a natural mathematical framework, which provably improves predictive accuracy. Borrowing can occur across outcome measures or predictor variables.

A hierarchical Bayesian model places distributions on the parameters used at lower levels in the model. For example, in a recent analysis of National Highway Transportation Safety Administration Fatality Analysis Reporting System data, a Poisson model was used for the number of accidents in a State, where the Poisson parameter was a linear combination of various predictors: unemployment rate, graduated license programs, age and state indicator variables, and so forth.[2] The regression coefficient on each of these was a hyperparameter, and thus had its own distribution. For example, the State effect was modeled as a random variable that was 1 of 50 draws from a normal distribution with unknown mean and large variance.

One result of this kind of model is that information from all 50 States can inform the estimates for each other. If Idaho has an unlucky year in terms of fatalities, the Idaho effect is still modeled

as a draw from a normal distribution common to all States; thus, although the traditional estimate for unlucky Idaho would be very high, the other States are lower and this will pull the estimate from Idaho down from its unrepresentative high value. We say that the estimate for Idaho has "borrowed strength" from the data on the other States, and this has "shrunk" the estimate towards the common mean of all 50 States.

Appendix D summarizes one recent example from road safety research in which CMFs were developed from SPFs estimated with hierarchical Bayesian modeling.

SPATIAL KERNEL AVERAGED PREDICTORS

Traditional spatial regression uses the measurements at a specific location to predict the response at that location. Spatial kernel averaging extends this by also using measurements from nearby locations.

For example, suppose one wanted to predict the number of accidents at a given intersection. One could use traffic volume, average speed, road type and signage at that location as predictors. But spatial kernel averaging would also include traffic volume data from nearby roads, average speed from nearby roads, and so forth. The weight on those other predictors would diminish as the distance from the location of interest increases. In some cases this may improve predictive accuracy by taking better account of large-scale factors such as shopping mall locations and local driving temperament. It is notable that the analyst does not have to specify these large-scale factors; the kernel averaging handles those effects automatically.

One advantage of this approach is that distance does not have to be geographic. It may be decided that intersections with similar features are "close" even if they are thousands of miles away from each other. Expert judgment may be used to determine the distance metric.

Appendix D provides a recent example from road safety research in which kernel averaging was used for developing safety performance functions for traffic analysis zones.

CHANGEPOINT DETECTION

There are frequentist and Bayesian methods for doing changepoint detection, and it would make sense to use these methods to routinely monitor local crash rates to see if there are emerging problems. Such methods could help understand the impact of changes such as graduated licensure programs and drunk driving crackdowns, as well as flagging unexpected changes, which upon further examination, may be traced to changing populations or lax enforcement. For example, a changepoint that reflects improved safety appears in 2005, when the number of fatal crashes dropped precipitously, and the causal mechanisms should be studied to ensure that the improvement continues.

Changepoint methodology can also be helpful in identifying break points when creating "buckets," e.g., ranges of traffic volume for which an outcome measure, such as crashes, is fairly constant. Creating buckets is not always advisable, but it is often done in transportation science so as to increase the available sample size when studying rare events. The "cutpoints" that are relevant to traffic safety may be very different from the cutpoints that relate to fuel efficiency, and changepoint analysis offers a principled way to determine appropriate brackets. As such, it would be very useful for the disaggregate analysis that is usually undertaken in evaluations

conducted for FHWA's Evaluation of Low Cost Countermeasures (ELCS) project. In particular, the methodology would be useful in establishing categorical variables that would be necessary for the development of CMFunctions that are seen as key to improving the transferability of future CMFs. For example, the methodology may be considered in National Cooperative Highway Research Program (NCHRP) Project 17-63, which is developing guidance for future researchers for the estimation of such CMFunctions.[3]

Changepoint methods can be used to find regions (buckets) in which the CMFunctions are locally linear or locally constant. That enables easier modeling and probably more accurate uncertainty statements when estimating the impact of specific safety measures.

Changepoint analysis is usually used to discover when a process has shifted or drifted away from its historical mean. In traffic safety, there was a huge drift down in fatalities that started in 2005. The usual approach for discovering when a shift/drift starts is to build a model for the historical process, a model for the change, and treat the changepoint time as a parameter to be estimated. Changepoint methodology is mature, and there are many sophisticated implementations that can be chosen to fit the specific application.

TIME SERIES MODELS AND DISTRIBUTED LAGS

Distributed lag models are used in time series, where a future value is predicted as a linear regression upon previous values at different times. If, for example, one is trying to predict the number of vehicles on the road tomorrow, one might use a regression function that includes the amount of traffic today, the amount of traffic a week earlier than tomorrow, and the amount of traffic one year ago. This enables one to capture current effects (e.g., snowfall), weekend or weekday effects, and seasonal effects, respectively.

In transportation applications, there is the potential for more sophisticated applications than standard univariate time series. First, one can use dynamic factor models, in which latent factors determine the behavior. For example, it may be that the time series of hourly average traffic speed depends upon the mix of the drivers, so that the proportion of commuters, shoppers, and professional drivers on the road is an unobserved latent factor that affects the time series. Second, one could study multivariate time series, where one tracks over time two or more variables, say traffic speed and traffic volume, and these are correlated. Third, one could develop a new methodology for time series analysis when the unit of observation is network-valued, say the flows between specific points.

These models can become sophisticated and difficult. They should be considered carefully before adoption, since if the chosen model is not a good approximation to the process that generates the data, one can be misled. These models generally make strong assumptions and can be sensitive to small violations of those assumptions.

MULTIVARIATE NONPARAMETRIC TESTS

Rosenbaum proposed a nonparametric test for whether two multivariate populations are the same.[4] For example, suppose one wanted to decide whether there are differences in driving styles between people from Canada and the United States. One would then collect a random sample of 100 Canadian and 100 U.S. drivers and measure many features of their driving, such

as following distance, maximum speed on highway, average speed on residential roads, etc. The next step is to build a metric: the distance between two people in the combined samples might be the Euclidean distance between their vectors of measurements, or it could be a more complicated distance that weights some features more heavily than others. Then one goes through all 200 people and finds the driver who is closest to each person in terms of this metric.

Under the null hypothesis that there is no difference between U.S. and Canadian drivers, it is equally likely that the nearest neighbor will be a U.S. or Canadian driver. Under the alternative hypothesis, U.S. drivers will tend to be neighbors of other U.S. drivers, and Canadian drivers will be neighbors of other Canadians. And the probabilities of a given number of same-same links are easy to calculate.

A good feature of this test is that one can try many different metrics, to explore which factors most distinctively separate U.S. and Canadian drivers. And, because of the combinatorial explosion in the number of possible links, the alpha level of the test is not as quickly eroded under multiple testing as usually happens.

OTHER METHODS

Statistics is rich in methodology, and some of it will apply to transportation safety. Currently, transportation scientists make heavy use of statistics, but their toolkit is based upon historical practice and may not be as current or as broad as is possible. Stronger collaborations with research statisticians will surely update the methodologies and promote better outcomes.

CHAPTER 3. FUTURE STEPS AND OTHER CONSIDERATIONS

A number of institutional suggestions, technical approach suggestions, and other considerations were identified during and following the technical experts meeting. On the basis of these suggestions, some future steps are outlined that might foster the effective implementation of the suggestions. The suggestions are categorized below as institutional or technical.

INSTITUTIONAL SUGGESTIONS

The following is a set of considerations for institutional initiatives to advance the development of new statistical methodologies that might improve how SPFs and CMFs are developed, by engaging researchers highly qualified in statistical methods, and by fostering high-level research in general:

- FHWA may consider hiring statisticians to work alongside transportation engineers. This may require special funding and longer-term commitment to such a program.
- FHWA may consider an active role and more regular participation in the annual meetings of the ASA and other statistical communities, and in conducting workshops, developing sessions, and making presentations.
- FHWA may consider creating opportunities for sabbatical and internship programs in areas of statistics at the Turner-Fairbank Highway Research Center. This could be an extension of similar programs in other fields.
- FHWA may consider promoting the enhancement of statistics course requirements for civil engineering students to increase the comprehension of statistics by graduates working in road safety analysis. At present, a graduate course in statistics is typically not compulsory.
- Transportation safety data might be made available by facilitating free download to interested statisticians and advertising the availability of these data. Specifically, these data would pertain to the information required to develop SPFs and CMFs. The databases used for the FHWA ELCS project might be tapped for this purpose. Highway Safety Information System data are already readily available and might be used for SPF development research. *Machine Learning* and *Chance* magazines were suggested as means to advertise the availability of these data to graduate students and other researchers in statistics.
- Short courses and workshops might be arranged at the ASA and other related annual meetings on current highway safety research practices/products in order to introduce these topics, to discuss the needs for new methodologies, and to introduce data resources and capabilities in sparking creativity and innovation in both researchers and decision makers.
- FHWA may conduct a workshop with the Transportation Research Board (TRB) committees ABJ80 (Statistical Methods) and ANB20 (Safety Data, Analysis and Evaluation) for effectively marketing the need for statistical innovation in highway safety analysis applications. There have been sporadic attempts at putting on such workshops, the most recent being a hands-on workshop before the January 2014 annual meeting conducted by Ezra Hauer on developing SPFs. Consideration may be given to developing a workshop that would be led by statisticians or by both statisticians and transportation engineers highly skilled in statistics.

- FHWA may consider sponsoring a graduate student competition for working with transportation safety data to solve a set of problems related to highway safety methodology development. Graduate students in statistics should be encouraged to participate.
- FHWA may publish articles in *Public Roads* magazine to communicate the increasing need for statistical expertise in highway safety application to practitioners.
- FHWA, in coordination with ASA, might make presentations and hold workshops for new highway safety research products in selected schools of statistics nationwide. This is to communicate to/with faculty and students and introduce highway safety research methodology needs and sources of data to spark statistical research inspiration.
- Consideration may be given to future and alternative sources of data, e.g., Strategic Highway Research Program data, and data available from mobile devices, in developing new statistical methods.

TECHNICAL APPROACH SUGGESTIONS

Below is a summary of specific technical approaches that could be pursued in high-level research aimed at improving CMF and SPF estimation. Specifically, it is suggested that future researchers engage in the following:

- The application of a multivariate hierarchical Bayes modeling approach for estimating SPFs. Among other strengths, this approach allows for borrowing of information across outcome and predictor variables to make stronger inferences.
- The modeling of spatial correlation and the analyzing of locations as a network in estimating SPFs.
- The use of prior information in the estimation of CMFs/SPFs through the hierarchical Full Bayes approach. For example, the prior estimation may pertain to previously estimated SPFs and CMFs of relevance.
- The exploration of meta-regression for developing CMFunctions. It is expected that this approach will be pursued in NCHRP Project 17-63.
- The use of multilevel modeling where treatment effects are heterogeneous and nested. For example, results from individual sites may be nested by county of origin.
- The continued pursuit of the use of surrogate measures estimated from simulation by seeking better simulation models and better models to relate crashes to surrogate measures.
- The exploration of data imputation methods to address missing data instead of discarding those observations. This would pertain both to data for treatment and non-treatment reference/comparison sites.
- The use of propensity scores for comparison or reference sites matching to reduce bias between treated and non-treated groups.

OTHER CONSIDERATIONS

A number of items for potential DCMF program next steps were identified during and after the technical experts meeting. These are as follows:

- Experts might be convened on a regular (perhaps annual) basis for follow-up and discussion of fresh ideas. A desirable format would be to utilize a combination of "new" experts and some from the most recent meeting.
- Research needs statements for guiding future research in new statistical methodologies might be created and disseminated through appropriate channels, e.g., TRB. Since TRB committees are charged with creating these statements, appropriate committees such as ABJ80 (Statistical Methods) and ANB20 (Safety Data, Analysis and Evaluation) and ANB25 (Highway Safety Performance) could be instrumental in leading this effort.
- Projects might be funded through the DCMF contract to pursue the application and demonstration of identified methodologies using existing databases. Some projects could involve statisticians only and some could be joint with the DCMF project team, other prominent road safety researchers, and statisticians.
- Results of research using new methods resulting from this white paper might be disseminated through conferences such as the TRB and ASA annual meetings. Research in progress could be presented at appropriate TRB committee meetings and the ASA transportation interest group.
- The ASA transportation interest group might be engaged to foster the encouragement of research using the new methods, the presentation of not only the results of this research but also the details of research in progress.

APPENDIX A. TECHINAL EXPERTS INFORMATION

Table 1. Technical experts information.

Name/Education	Affiliation	Area of Expertise	Category[1]
Amy Herring Sc.D. Biostatistics	Associate Chair and Professor, Biostatistics University of North Carolina Gillings School of Global Public Health	• Biostatistics • Epidemiology • Longitudinal and multivariate data • Hierarchical models • Latent variables • Bayesian methods	1
Eric Laber Ph.D. Statistics	Assistant Professor, Statistics North Carolina State University	• Optimization of treatment regimes • Bootstrap methods • Empirical processes	1
Fan Li Ph.D. Statistics	Assistant Professor, Statistical Science Duke University	• Causal inference • Missing data imputation • Model selection	1
Matt Heaton Ph.D. Statistics	Assistant Professor, Statistics Brigham Young University	• Spatial processes • Surveillance models • Monte Carlo methods	1
Bailey Fosdick Ph.D. Statistics	Postdoctoral Fellow Statistical and Applied Mathematical Sciences Institute, Research Triangle Park, NC Statistical Science, Duke University	• Network models	1
Bani Mallick Ph.D. Statistics	Distinguished Professor, Statistics Texas A&M University	• Bayesian hierarchical modeling • Nonparametric regression and classification • Bioinformatics • Spatio-temporal modeling • Machine learning • Functional data analysis • Bayesian nonparametrics	2

Name/Education	Affiliation	Area of Expertise	Category[1]
Alan Karr Ph.D. Applied Mathematics	Professor, Statistics University of North Carolina Director of the National Institute of Statistical Sciences	• Statistical inference for stochastic processes • Agent-based models	2
David Banks Ph.D. Statistics	Professor, Statistics Duke University	• Data mining and statistical modeling • Risk analysis	2
Ward Vanlaar Ph.D. Transportation Science	Vice President of Research Traffic Injury Research Foundation, Ottawa	• Multilevel modeling • Meta-analysis • Time series analysis • Survival analysis • Logistic regression • Multidimensional scaling	3

[1] Category 1 includes experts with no experience in road safety data analysis who have related expertise in some sort of treatment/program evaluation that requires the statistical analysis/modeling of time series and/or cross-sectional data. Category 2 includes experts in Transportation Engineering and/or Statistics with extensive seminal research in statistical analysis of crash data but who have not been involved directly in CMF or SPF development. Category 3 includes experts who have worked in road safety evaluations related to driver and enforcement programs.

APPENDIX B. OVERVIEW OF COMMONLY APPLIED METHODS IN ESTIMATING CMFS

The aim of this section is not to go in depth into the most commonly applied methodologies but rather to illustrate how they are applied in road safety research. Selected references are also provided where further information may be found.

EB BEFORE-AFTER STUDIES

The EB methodology for observational before-after studies is considered rigorous in that it accounts for regression-to-the-mean. In the process, SPFs are used and the use of these addresses the following:

- It overcomes the difficulties of using crash rates in normalizing for volume differences between the before and after periods.
- It accounts for time trends through the reference group SPFs.
- It reduces the level of uncertainty in the estimates of safety effect through the estimation of robust SPFs.

In the EB approach, the change in safety for a given crash type at a site is given by the following:

$$\Delta \, \text{Safety} = \lambda - \pi$$

Figure 7. Equation. Change in safety using the EB approach.

Where:
λ = expected number of crashes that would have occurred in the after period without the strategy.
π = number of reported crashes in the after period.

In estimating λ, the effects of RTM and changes in traffic volume are explicitly accounted for using SPFs, relating crashes of different types to traffic flow and other relevant factors for each jurisdiction based on untreated sites (reference sites). Annual SPF multipliers are calibrated to account for temporal effects on safety (e.g., variation in weather, demography, and crash reporting).

In the EB procedure, the SPF is used to first estimate the number of crashes that would be expected in each year of the before period at locations with traffic volumes and other characteristics similar to the one being analyzed (i.e., reference sites). The sum of these annual SPF estimates (P) is then combined with the count of crashes (x) in the before period at a strategy site to obtain an estimate of the expected number of crashes (m) before strategy. This estimate of m is computed as follows:

$$m = w(P) + (1 - w)(x)$$

Figure 8. Equation. Expected number of crashes before strategy implementation using the EB approach.

Where w is estimated from the mean and variance of the SPF estimate as follows:

$$w = \frac{1}{1+kP}$$

Figure 9. Equation. Estimated weight using the EB approach.

Where k = constant for a given model and is estimated from the SPF calibration process with the use of a maximum likelihood procedure. In that process, a negative binomial distributed error structure is assumed with k being the overdispersion parameter of this distribution.

A factor is then applied to m to account for the length of the after period and differences in traffic volumes between the before and after periods. This factor is the sum of the annual SPF predictions for the after period divided by P, the sum of these predictions for the before period. The result, after applying this factor, is an estimate of λ. The procedure also produces an estimate of the variance of λ.

The estimate of λ is then summed over all sites in a strategy group of interest (to obtain λ_{sum}) and compared with the count of crashes observed during the after period in that group (π_{sum}). The variance of λ is also summed over all sites in the strategy group.

The CMF (θ) is estimated as follows:

$$\theta = \frac{\pi_{sum}/\lambda_{sum}}{1 + \left(Var(\lambda_{sum})/\lambda_{sum}^2\right)}$$

Figure 10. Equation. CMF estimate using the EB approach.

The standard deviation of θ is given by the following:

$$StDev(\theta) = \sqrt{\frac{\theta^2 \left(\frac{Var(\pi_{sum})}{\pi_{sum}^2} + \frac{Var(\lambda_{sum})}{\lambda_{sum}^2}\right)}{\left(1 + \frac{Var(\lambda_{sum})}{\lambda_{sum}^2}\right)^2}}$$

Figure 11. Equation. Standard deviation of the CMF estimate using the EB approach.

The percent change in crashes is calculated as $100(1-\theta)$; thus a value of $\theta = 0.7$ with a standard deviation of 0.12 indicates a 30 percent reduction in crashes with a standard deviation of 12 percent.

CROSS-SECTIONAL STUDIES

Cross-sectional studies are particularly useful for estimating CMFs where there are insufficient instances where the treatment was applied to conduct a before-after study. For example, there

may be few or no projects where the shoulder is widened, for example, from 4 to 6 ft. However, there would be many road segments with 4-ft shoulders and many with 6-ft shoulders. The reason that before-after studies are impractical in such cases is that there are often not enough before-after situations to allow for credible results.

In practice, it is difficult to collect data for enough locations that are alike in all factors affecting crash risk. Hence, cross-sectional analyses are often accomplished through multiple variable regression models. In these models an attempt is made to account for all variables that affect safety. If such attempts are successful, the models can be used to estimate the change in crashes that results from a unit change in a specific variable. The CMF is derived from the model parameters. The regression approach for estimating a CMF is consistent with the belief that the CMF is a function of the traits of the treated unit. A cross-sectional approach can be used to develop a CMFunction, and is preferable if the cause-effect relationship with crashes can be determined with confidence.

CMFs estimated from cross-section studies could be inaccurate for a number of reasons, including inappropriate functional form, omitted variable bias, or correlation of variables. It is common practice to use generalized linear modeling techniques, assuming a negative binomial error structure, to estimate multivariate crash prediction models. However, it is difficult to account for all factors that affect safety using such modeling techniques. For example, intersections with left-turn lanes also tend to have illumination. If a crash prediction model is used to estimate a CMF for left-turn lanes, and the presence of illumination is not accounted for in the model, the difference in model predictions with and without left-turn lanes could be partly due to illumination differences. Ironically, it is precisely because a variable is found to be correlated with another variable that it may be omitted during the model fitting exercise. Including correlated variables could in fact lead to effects that are counterintuitive (e.g., illumination increases night time crashes).

OVERVIEW OF CASE-CONTROL STUDIES

Case-control methods have been used in certain areas of highway safety, but few have focused on the effects of geometric design elements. For example, case-control studies have been applied to investigate the effectiveness of motorcycle-helmet use and the crash risk of hours of service for truck drivers. More recently, the case-control method was employed to estimate CMFs for geometric design elements, including lane and shoulder width. Case-control studies assess whether exposure to a potential risk factor is disproportionately distributed between the cases and controls, thereby indicating the likelihood of an actual risk factor.

The likelihood of an actual risk factor is expressed as the odds ratio between two levels of a variable. For example, it may be found that the odds of a crash occurring on horizontal curves with a degree of curvature greater than 15 degrees is 1.5 times the odds of a crash occurring on curves less than 15 degrees. The odds ratio is a direct estimate of the CMF. Risk factors may take the form of binary variables (e.g., median barrier, roadway lighting, or guiderail) or multi-level variables such as lane width (e.g., 9-, 10-, 11-, and 12-ft lanes). The sample is summarized by risk factor and case-control status to calculate the odds ratio. To illustrate the concept of the odds ratio, consider the data in table 2.

Table 2. Tabulation for simple case-control analysis.

Risk Factor	Number of Cases	Number of Controls
With	A	B
Without	C	D

The odds ratio (CMF) is expressed as the expected increase or decrease in the outcome in question due to the presence of the risk factor. An odds ratio greater than 1.0 suggests that the presence of the risk factor increases risk, while a value less than 1.0 would suggest a decrease in risk. Using the notation in the table the odds ratio (OR) is calculated as:

$$OR = CMF = \frac{A/C}{B/D}$$

Figure 12. Equation. Odds ratio calculation.

Case-control studies cannot be used to measure the probability of an event (e.g., crash, severe injury, etc.) in terms of expected frequency. They are more often used to show the relative effects of risk factors. Statistical analyses, such as multiple logistic regression techniques, are commonly used to clarify these relationships because they are able to examine the risk associated with one factor while controlling for other factors.

Finally, the case-control method cannot demonstrate causality because there is no time sequence of events in the analysis. Instead, the odds ratio indicates the increased likelihood of a crash occurring when a risk factor (e.g., roadway characteristic is present. It does not, however, recognize differences between locations with many crashes or a single crash. This is a loss of potentially important information and thus, the true increase in risk could be underestimated.

APPENDIX C. ASSESSMENT OF ISSUES IN CURRENT HIGHWAY SAFETY IMPROVEMENT EVALUATIONS

This appendix outlines concerns and issues in developing CMFs and SPFs. This list was provided to the technical experts prior to the meeting and any further insights directly gained from the meeting into these issues has been added as underlined text. Opportunities for potentially addressing many of these issues in the process of improving SPF and CMF estimation are also summarized.

Based on the presentations and discussions on the first day of the technical experts meeting, the research team prioritized these issues according to perceived potential for being addressed with statistical tools and processes presented. (Note that this does not imply priority of these issues but instead priority for the second day's discussion based on the tools and processes presented in the first day.) Three priority levels were assigned with level 1 being the highest. A brief summary of each issue is presented next, organized by priority level.

Priority 1

- Low sample means and sample size in SPF development.
- CMFs for rare crash types (e.g., pedestrians, motorcycle-involved).
- Reliability of CMFs inferred from cross-sectional regression models.
- Developing CMFunctions, including the estimation of the variance of a CMF estimated from a CMFunction.
- Use of prior knowledge in SPF or CMF estimations.
- Application of multiple CMFs.

Priority 2

- Isolating effects of individual treatments when treatment combinations are applied.
- Calculate variance of SPF*CMFs.

Priority 3

- CMFs for rare treatments.
- Defining Reference/Comparison group when treatment is universal.
- Assessing potential reference groups for before-after studies.
- Estimating required sample size for EB studies and cross-section studies.

PRIORITY 1 ISSUE SUMMARY

Low Sample Means and Small Sample Sizes in SPF Development

Data used for road safety research often have low sample means of crashes and/or a small sample size of locations. Research has shown that a low sample mean combined with a small sample size can seriously affect the goodness of fit statistics and the estimation of the overdispersion parameter, no matter which estimator is used within the estimation process. The probability the dispersion parameter becomes unreliably estimated increases significantly as the sample mean

and sample size decrease. Are there more appropriate distributions than negative binomial, which may overcome these problems?

CMFs for Rare Crash Types

Some treatments target crash types that are rare in occurrence. For example, crashes between vehicles and pedestrians are typically severe but occur infrequently and spread out over many locations. Current evaluation methods are challenged to find reliable results with low numbers of crashes.

Reliability of CMFs Inferred From Cross-Sectional Regression Models

For some types of treatments there are few instances where a variable of interest is changed, for example, the radius of a horizontal curve. In these cases we rely on cross-sectional regression models to derive a CMF. The reliability of such CMFs is questionable due to omitted variable bias, correlated predictor variables and endogeneity. Tools are needed to deal with these issues.

Developing CMFunctions, Including the Estimation of the Variance of a CMF Estimated from a CMFunction

Techniques for developing CMFunctions are required. CMFunctions are equations relating the expected CMF for a specific site to its characteristics. The variances of the estimated CMFs also need to be estimated.

Use of Prior Knowledge in SPF or CMF Estimations

The development of SPFs and CMFs typically ignores prior knowledge. While full Bayes MCMC modeling has been used to some extent in road safety, prior knowledge is still typically ignored and uninformative priors is the norm. Methods for making use of prior knowledge are required.

The technical experts questioned why uninformative priors are used when previous information does exist.

Application of Multiple CMFs

When multiple CMFs are to be applied, common practice is to multiply the CMFs to estimate the combined effect when multiple countermeasures are implemented at one location. Currently, there is limited research to support the combination of CMFs for this purpose. Although implementing several countermeasures is likely more effective than implementing a single countermeasure, it is unlikely that the full effect of each countermeasure would be realized when implemented concurrently. This is particularly true if the countermeasures target the same crash type (e.g., installing lighting and enhancing pavement markings to address nighttime crashes). Therefore, unless the countermeasures act completely independently and target unique crash types, multiplying several CMFs is likely to overestimate the combined effect. The likelihood of overestimation increases with the number of CMFs that are multiplied.

PRIORITY 2 ISSUE SUMMARY

Isolating Effects of Individual Treatments When Treatment Combinations Are Applied

Often several treatments are applied simultaneously. For example, widening a shoulder and applying shoulder rumble strips at the same time. Methods for separating the effects of each individual treatment are needed.

Calculate Variance of SPF*CMFs

The current procedure for applying SPFs and CMFs together is to multiply the crash prediction of the SPF by all CMFs to be applied, which may come from various studies. Guidance is needed on how to estimate the variance of this estimate. The variance of the SPF prediction and variance of each CMF estimate should be known.

The technical experts suggested that the SPF*CMF approach is similar to a Cox Proportional Hazards Model and emphasized the statistical inaccuracies of multiplying multiple CMFs together and assuming independence. (See next issue.) The experts identified that the main effects in the HSM method are well established, but the interactions are unknown, which will derail the process. They reaffirmed the fact that the error in the prediction cannot be estimated within the current HSM model.

PRIORITY 3 ISSUE SUMMARY

CMFs for Rare Treatments

Some treatments are rarely implemented, particularly new and emerging treatments. Current evaluation methods are challenged to find reliable results with low numbers of sites.

Defining Reference/Comparison Group When Treatment Is Universal

Some treatments are universally implemented. For example, a city may implement pedestrian countdown signals at all signalized intersections in the course of a year. When this is the case there is no natural reference/comparison group.

Assessing Potential Reference Groups for EB Before-After Studies

The reference groups selected for EB before-after studies are selected so that they match the treatment sites as close as possible in all factors that may influence crashes. Aside from considering summary statistics of these variables and comparing the crash trends over time there are no tools for assessing and comparing the appropriateness of potential groups.

Estimating Required Sample Size for EB Studies and Cross-Section Studies

Methods for determining the required sample sizes for estimating CMFs from EB before-after studies and cross-sectional regression studies are lacking. For before-after studies we typically assume a comparison-group study for estimating required sample size.

APPENDIX D. EXAMPLES OF APPLICATION OF ADVANCED METHODS IN TRANSPORTATION SAFETY RESEARCH

This section provides summaries for a small, and mostly recent sample of road safety research that applied some of the advanced, innovative statistical techniques identified at the technical experts meeting. Some of this research culminated in papers presented at the very recent TRB Annual Meeting held in January 2014 in Washington, DC. The abstracts are reproduced from the papers.

The intent of this appendix is to illustrate that the application of these advanced techniques is topical and is not beyond the capabilities of road safety researchers and, in so doing, to stimulate others to pursue these techniques in their research to develop CMFs and SPFs.

NON-PARAMETRIC REGRESSION

Elmitiny, N., Harb, R., Radwan, E. and Ahmed, M. "Traffic Operation Factors Related to Red-light Running: An Empirical Analysis." Presented at the Transportation Research Board Annual Meeting, Washington, DC, January 2014.

Abstract: This paper investigates the relationship between the red light running phenomena and traffic parameters in the vicinity of intersections. Data was collected on two intersections in Central Florida for a period of 9 months using traffic monitoring cameras acquired from ITERIS. Collected data included traffic characteristics; signal timing data, as well as the frequency of red light running 7 days a week, 24 h a day. Using Augmented Multivariate Adaptive Regression Splines (MARS), a recursive non-parametric regression technique, it was determined that traffic volume, average speed, percentage time green, and percentage large vehicles in the traffic composition were strongly associated with red-light running. It was also observed that vehicular volume and percentage large vehicles have an interactive relationship with red-light running. Increase in percentage in traffic volume is associated with an increase in the red-light running.

Thakali, L., Fu, L., and Chen, T. "Comparison Between Parametric and Nonparametric Approaches for Road Safety Analysis: Case Study of Winter Road Safety." Presented at the Transportation Research Board Annual Meeting, Washington, DC, January 2014.

Abstract: In road safety research, a parametric approach is commonly applied in modeling road collisions, which have resulted in many different types of models such as Poisson, Negative Binomial and Poisson lognormal. While easy to apply and interpret, a parametric approach has several critical limitations due to the modeling requirement of assuming a specific probability distribution form for each model variable (e.g., collision frequency) and a pre-specified functional relationship between each model parameter and the predictors. These assumptions, if violated, could lead to biased and/or erroneous inferences on the effect of these predictors on the dependent variable. This paper introduces a data-driven, nonparametric alternative called Kernel regression, which circumvents the need for the aforementioned assumptions. This paper compares the parametric and nonparametric approaches through an empirical study using a large dataset consisting of hourly observations of collisions, road weather and surface conditions, and traffic counts from highways in Ontario, Canada, over six winter seasons. It is shown that the nonparametric approach has the advantage of being able to capture the significant nonlinear and

interacting effects of some condition factors. The paper also illustrate the practical implications of the differences between the two approaches, including evaluation of the risk levels of road surface conditions for the road users and quantification of safety benefits of maintenance operations for transportation authorities.

BAYESIAN HIERARCHICAL MODELS

Chen, Y. and Persaud, B. "Methodology to Develop Crash Modification Functions for Road Safety Treatments with Fully Specified and Hierarchical Models." Presented at the Transportation Research Board Annual Meeting, Washington, DC, January 2014.

Abstract: CMFs for road safety treatments are developed as multiplicative factors that are used to reflect the expected changes in safety performance associated with changes in highway design and/or traffic control features. However, current CMFs have methodological drawbacks. For example, variability with application circumstance is not well understood, and, as important, correlation is not addressed when several CMFs are applied multiplicatively. These issues can be addressed by developing SPFs with components of CMFunctions, an approach that includes all CMF related variables, along with others, while capturing quantitative and other effects of factors and accounting for cross-factor correlations. CMFunctions can capture the safety impact of factors through a continuous and quantitative approach, avoiding the problematic categorical analysis that is often used to capture CMF variability. There are two formulations to develop such SPFs with CM-Function components—fully specified models and hierarchical models. Based on sample datasets from two Canadian cities, both approaches are investigated in this paper. While both model formulations yielded promising results and reasonable CMFunctions, the hierarchical model was found to be more suitable in retaining homogeneity of first-level SPFs, while addressing CM-Functions in sublevel modeling.

El-Basyouny, K., Barua, S., Islam, M. and Li, R. "Assessing the Effect of Weather States on Crash Severity and Type using Fully Bayesian Multivariate Safety Models." Presented at the Transportation Research Board Annual Meeting, Washington, DC, January 2014.

Abstract: Rather than investigate the isolated effects of individual weather elements on crash occurrence, this study investigates the aggregated effect of weather states, which are defined as a combination of various weather elements (i.e., temperature, snow, rain, and wind speed), on crash occurrence. The main argument is that a combination of weather elements might better represent a particular weather condition and subsequent safety outcome. Therefore, to explore the effect of various weather states on crash severity and type, this study defined 12 weather states, based on temperature, snow, rain and wind speed, and developed multivariate safety models using 11 years of daily weather and crash data for the entire City of Edmonton. The proposed models were estimated in a Full Bayesian context via a Markov Chain Monte Carlo simulation, while a posterior predictive approach was used to assess the models' goodness of fit. Results suggested that Property-Damage-Only (PDO) crashes increased by 4.5–45 percent due to adverse weather states. It was also shown that PDO crashes were more affected by adverse weather states compared to severe (injury and fatal) crashes. With regard to crash type, adverse weather states were associated with an increased occurrence of 9–73.7 percent for all crash types, with the highest increase recorded for Ran-Off-Road (ROR) crashes. The duration of daylight hours was found to be significant and negatively related to all crash types and PDO crashes. In

addition, sudden weather changes of major snow or rain were statistically significant and positively related to all crash types. Days-of-the-week (i.e., weekdays and weekend) and seasons-of-the-year (winter, spring, summer, and fall) were used as dummy variables and were statistically significant in relation to crash occurrence.

PRINCIPAL COMPONENTS ANALYSIS

Papadimitriou E. and Yannis, G. "Is Road Safety Management Linked to Road Safety Performance?" *Accident Analysis and Prevention,* Volume 59, October 2013, pp. 593–603.

Abstract: This research aims to explore the relationship between road safety management and road safety performance at country level. For that purpose, an appropriate theoretical framework is selected, namely the "SUNflower" pyramid, which describes road safety management systems in terms of a five-level hierarchy: (i) structure and culture, (ii) programmes and measures, (iii) "intermediate" outcomes—safety performance indicators (SPIs), (iv) final outcomes—fatalities and injuries, and (v) social costs. For each layer of the pyramid, a composite indicator is implemented, on the basis of data for 30 European countries. Especially as regards road safety management indicators, these are estimated on the basis of Categorical Principal Component Analysis upon the responses of a dedicated road safety management questionnaire, jointly created and dispatched by the ETSC/PIN group and the "DaCoTA" research project. Then, quasi-Poisson models and Beta regression models are developed for linking road safety management indicators and other indicators (i.e. background characteristics, SPIs) with road safety performance. In this context, different indicators of road safety performance are explored: mortality and fatality rates, percentage reduction in fatalities over a given period, a composite indicator of road safety final outcomes, and a composite indicator of "intermediate" outcomes (SPIs). The results of the analyses suggest that road safety management can be described on the basis of three composite indicators: "vision and strategy," "budget, evaluation and reporting," and "measurement of road user attitudes and behaviours." Moreover, no direct statistical relationship could be established between road safety management indicators and final outcomes. However, a statistical relationship was found between road safety management and "intermediate" outcomes, which were in turn found to affect "final" outcomes, confirming the SUNflower approach on the consecutive effect of each layer.

SPATIAL KERNEL AVERAGING

Hadayeghi A., Shalaby A. and Persaud, B. "Development of Planning Level Transportation Safety tools using Geographically Weighted Poisson Regression." *Accident Analysis and Prevention,* Volume 42, Issue 2, March 2010, pp. 676–688.

Abstract: A common technique used for the calibration of collision prediction models is the Generalized Linear Modeling (GLM) procedure with the assumption of Negative Binomial or Poisson error distribution. In this technique, fixed coefficients that represent the average relationship between the dependent variable and each explanatory variable are estimated. However, the stationary relationship assumed may hide some important spatial factors of the number of collisions at a particular traffic analysis zone. Consequently, the accuracy of such models for explaining the relationship between the dependent variable and the explanatory variables may be suspected since collision frequency is likely influenced by many spatially

defined factors such as land use, demographic characteristics, and traffic volume patterns. The primary objective of this study is to investigate the spatial variations in the relationship between the number of zonal collisions and potential transportation planning predictors, using the Geographically Weighted Poisson Regression modeling technique. The secondary objective is to build on knowledge comparing the accuracy of Geographically Weighted Poisson Regression models to that of Generalized Linear Models. The results show that the Geographically Weighted Poisson Regression models are useful for capturing spatially dependent relationships and generally perform better than the conventional Generalized Linear Models.

COX PROPORTIONAL HAZARDS MODEL

Abstract: The analysis of discrete accident data and aggregate exposure data frequently necessitates compromises that can obscure the relationship between accident occurrence and potential causal risk components. One way to overcome these difficulties is to develop a model of accident occurrence that includes accident and exposure data at a mathematically consistent disaggregate level. This paper describes the conceptual and mathematical development of such a model using principals of survival theory. The model predicts the probability of being involved in an accident at time t given that a vehicle has survived until that time. Several alternative functional forms are discussed including additive, proportional hazards and accelerated failure time models. Model estimation is discussed for the case in which both accident and non-accident trips are included and for the case with only accident data. As formulated, the model has the distinct advantage of being able to consider accident and exposure data at a disaggregate level in an entirely consistent analytic framework. A conditional accident analysis is undertaken using truck accident data obtained from a major national carrier in the United States. Model results are interpretable and generally reasonable. Of particular interest is that segmenting accidents in several categories yields very different sets of significant parameters. Driver service hours seemed to most strongly effect accident risk: regularly scheduled drivers who take frequent trips are likely to have a reduced risk of an accident, particularly if they have a longer (greater than eight) number of hours off-duty just prior to a trip.

APPENDIX E. ADDITIONAL IDEAS GENERATED BY FHWA REVIEWERS FOR DISCUSSION

Several notable experts with a combination of statistical and transportation safety research were asked to review the draft white paper and provide comments. These valuable reviews provided additional ideas. The scope of the body of the white paper is necessarily limited to ideas presented and discussed at the technical experts meeting, but the additional ideas generated by the reviewers are documented in this appendix in keeping with the objectives of the white paper. To maintain the anonymity of the peer review process these ideas are not attributed to any specific reviewer, although their contribution is acknowledged and appreciated.

INSTITUTIONAL SUGGESTIONS

Several comments were received with respect to the Institutional Suggestions section of this white paper and include the following:

- To conduct a study that classifies currently available data sources, and their limitations, in the context of estimating CMFs and SPFs.
- To conduct a study that reviewed research designs and their limitations, in the context of estimating CMFs and SPFs.
- To develop a framework that located the roles that CMFs and SPFs can, and should, play in safety research and how methods based on these functions relate to alternative methodologies.

TECHNICAL APPROACH SUGGESTIONS

A number of comments were received with respect to the Technical Approach Suggestions section of this white paper. These relate to other methodologies not discussed and issues not addressed.

Application of Interrupted Time Series Design and Generalized Linear Segmented Regression Analysis

An interrupted time series design is a quasi-experimental method used to determine the impact of an intervention. A generalized linear segmented regression analysis with time as a variable to control for overall trend and intervention as a variable to estimate the effect of the countermeasure is a statistical method for analyzing the data from the interrupted time series design.[15] Although this method has not yet been widely used in estimating CMFs and SPFs, it has a great potential to overcome some of the long-lasting problems in estimation of CMFs and SPFs in that it can account for time trends from before-after studies as well as can cope with a problem of defining reference/comparison group when treatment is universal. This method needs to be promoted and disseminated along with other new or enhanced methodologies.

Meta-Analysis

Given that individual studies relating to transportation safety issues are often conducted with modest sample sizes, especially when they address countermeasure evaluations, meta-analysis

based summary assessment of functional forms, parameter estimates, and results would be of great interest.

ADDITIONAL METHODS

Additional methods not mentioned but which may have relevance include the following:

- Semiparametric methods.
- Survey sampling and sampling at large.
- Stochastic processes in both discrete and continuous time.

ADDITIONAL ISSUES

- How to deal with data quality problems caused by missing and/or imputed data in the context of estimating CMFs and/or SPFs.
- How to handle measurement and/or reporting errors.
- What to do about lack of between-site data comparability when estimating CMFs and SPFs (e.g., jurisdictions may use different crash reporting thresholds).
- For each of models explained, their logical/preferred assumption of crash distribution needs to be clarified.

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