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Collision modification functions: Incorporating changes over time

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ABSTRACT

Collision modification factors (CMFs) are considered the primary tools for estimating the effectiveness of safety treatments at road sites. Three main techniques are commonly used to estimate CMFs: the empirical Bayes (EB) method, the comparison-group (CG) method, and a combination of the EB and CG methods. CMF estimates from these techniques are usually provided with a measure of uncertainty of the estimate, in the form of standard error and confidence interval.

However, representing CMFs as point estimates may not be adequate to explain how a safety countermeasure affects collision frequency over time and to evaluate the presence of novelty effects associated with the treatment. Therefore, the main goal of this study is to show how to overcome this drawback through the development of collision modification functions (CMFunctions) which incorporate changes over time for the treatment effectiveness, rather than using a single value.

Within a fully Bayesian (FB) context, linear and non-linear intervention models, which acknowledge that the safety treatment effects do not always occur instantaneously but are spread over future time periods, provide a promising methodological framework for estimating CMFunctions with time trend.

A case study is presented where the linear and non-linear intervention models were applied to estimate the effectiveness of the "Signal Head Upgrade Program" recently implemented in the city of Surrey (British Columbia, Canada). The results of the case study highlight the advantages of estimating CMFunctions with time trend and impact on the economic evaluation of safety countermeasures. Given the way future benefits are discounted to present values, the results of using a CMFunction can affect the cost effectiveness of safety countermeasures significantly. The results also showed the non-linear intervention models provide a more realistic trend where the treatment effect in the long-run converges to an everlasting treatment impact.

1. Introduction

An important component of any transportation project is the explicit evaluation of the safety performance. An explicit safety evaluation facilitates the quantification of the project safety impacts resulting from changes in the design and operation parameters. Quantifying these safety impacts can support the planning and design process by allowing decision makers the opportunity to analyse the safety benefits in relation to the cost of the project. This "trade-off" analysis allows for the justification and rationalization of highway infrastructure investment. The ability to accurately quantify safety impacts is commonly achieved by utilizing safety evaluation tools such as collision prediction models (CPMs) and collision modification factors (CMFs) (Highway Safety Manual, 2010). CMFs are multiplicative factors, generally based on empirical evidence from time series (i.e., observational before-after studies) or cross-sectional analysis of the safety impacts of individual geometric design and/or traffic control features (Gross et al., 2010). A CMF is intended to reflect the safety impact associated with site characteristics as follows:

- CMF of 1.0 indicates no impact on safety (reflecting base conditions),
- CMF greater than 1.0 indicates a negative impact on safety, and
- CMF less than 1.0 indicates a positive impact on safety.

CMFs are of a strategic importance to determine the costs and benefits of alternative treatments and to achieve the greatest

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return on investments of road safety agencies. For this reason, they have become increasingly popular and a wide body of research has focused on developing CMFs for different traffic and highway engineering improvements (Highway Safety Manual, 2010). Recently, an online "Crash Modification Factors Clearinghouse" has been established to provide transportation professionals with a repository which collects a wide selection of CMFs classified by star quality rating from 1 (lowest) to 5 (best) (Crash Modification Factors Clearinghouse, 2014). This rating is assigned considering the design, data sources, and sample size of the study that developed the CMF.

Several methods are available in literature for estimating high-quality CMFs with the most common being: the empirical Bayes (EB) method (Hauer, 1997; Persaud and Lyon, 2007), the comparison-group (CG) method (Hauer, 1997; Harwood et al., 2002), and a combination of the EB and CG methods (Sayed et al., 2004). The three methodologies are supposed to account for the main confounding factors in before and after safety evaluations such as the regression-to-the-mean (RTM) phenomenon and the inclusion of unrelated effects. This is achieved by using a group of non-treatment sites at which the countermeasure of interest has not been implemented (i.e., reference or comparison sites). CMF estimates from these study designs are usually provided with a measure of uncertainty of the estimate, in the form of standard error and confidence interval. In doing so, a CMF is handled as a random variable rather than a universal constant that has always the same value everywhere and at all times (Hauer et al., 2012).

However, the estimation of CMFs in the form of point estimates does not offer a complete understanding of how the implemented countermeasure affect safety at the treated locations, leaving some important questions unanswered. These questions include: (1) how does the treatment effectiveness vary with time? (2) what are the impacts of external or indirect factors such as traffic volume and road geometry on the treatment effectiveness?, (3) are there any novelty effects associated with the implemented countermeasures? and (4) if yes, how long were the novelty effects present? As well, the estimation of CMFs as point estimates can lead to inaccurate analysis of the cost-effectiveness of safety countermeasures and would seem unrealistic. Incorporating a CMF function in time can have a significant effect on the results of benefit-cost analysis of safety countermeasures given the way future benefits are discounted to present values.

In an attempt to account for the temporal effects on safety, some studies have focused on the development of CPMs that account for the variation over time in crash frequency by employing time-varying coefficients (i.e., annual factors for a particular year defined as the rate of observed to predicted crashes for that year) (Srinivasan et al., 2008). Other safety evaluations accounted for a potential time trend in the observed crash series by relaxing the coefficients in the CPM to be all time varying (see for instance Lan and Persaud, 2012). However, the limitation of these approaches is that the effect on road accidents can be only analyzed with a single CMF developed for each post-treatment year without including it in a function (see for instance Lyon and Persaud, 2008).

Other recent research has advocated the use of intervention models developed within a hierarchical full Bayes (FB) context. These models acknowledge that the safety treatment (intervention) effects do not occur instantaneously but are spread over future time periods (Li et al., 2008; El-Basyouny and Sayed, 2010, 2012a, 2012b). The FB approach was shown to have also the advantage of accounting for greater uncertainty in the data; providing more detailed inference; allowing inference at more than one level for hierarchical models; and efficiently integrating the estimation of the safety model and treatment effects in a single step, whereas these are separate tasks in the EB method.

2. Research statement

The main goal of this study is to demonstrate the usefulness of two methodologies, within the FB context, that are able to explain how a safety countermeasure affects collision frequency over time. The methods can also estimate the novelty effects associated with safety countermeasures (if present). This can be pursued through the development of collision modification functions (CMFunctions) which incorporates changes over time of the treatment effectiveness, rather than calculating a single point CMF value.

The two following modeling techniques seem promising to account for time effect in an FB framework: (1) linear intervention models which acknowledge that the safety treatment (intervention) effects do not occur instantaneously, but are spread over future time periods (El-Basyouny and Sayed, 2011, 2012a), and (2) non-linear intervention models (dynamic regressions) to identify the lagged effects of the treatment in order to measure its effectiveness (El-Basyouny and Sayed, 2012b, 2012c). Therefore, the aim of the paper is to employ these two methodologies and compare their results in the form of CMFunctions.

To demonstrate the use of the two techniques, a case study is presented to evaluate the safety effectiveness of the "Signal Head Upgrade Program" recently implemented in the city of Surrey (British Columbia, Canada). The added advantage of this case study was that CMFs were estimated in a previous research (Sayed et al., 2007) using an observational BA study with the combined EB and CG methods. These CMFs constituted a sound starting point for the comparison of the results contained in this study.

Finally, it is worth to note that the term CMFunction used in this study should not be confused with the formulas, available in literature, that compute the CMF for a specific site in such a way that the factor can vary for different scenarios (e.g., for different traffic volumes, geometric design etc.) (Gross et al., 2010).

3. Case study: the Signal Head Upgrade Program

Different municipalities in British Columbia (BC) participated in the Signal Head Upgrade Program between 2001 and 2003, where signal visibility was improved at urban signalized intersections. These improvements included signal lens size upgrades, the installation of new backboards, reflective tapes added to existing backboards, and the installation of additional signal heads.

The data set was provided by the Insurance Corporation of British Columbia (ICBC) which funded the program. Total, fatal-plus-injury (F + I), and property-damage-only (PDO) collisions were available from 1999 to 2004 as well as traffic volumes in the form of average annual daily traffic (AADT). Since in the municipality of Surrey (BC) the program was implemented as early as 2001, a longer post-treatment period (4 years) was available for a subset of signalized intersections. For this reason, this set of locations was considered for the analysis of signal visibility improvement over time.

Therefore, a total of 24 treatment and 41 comparison sites were selected. Comparison sites were chosen according to their geographic proximity and similarity to the treatment sites (traffic, geometry, etc.). Table 1 shows summary statistics for the collision frequency (i.e., the number of collisions at an intersection during a year) at both treatment and comparison sites during the years preceding and following the interventions.

As mentioned before, the same data set was used to estimate CMFs in a previous research with the combined EB and CG methods (Sayed et al., 2007). The evaluation results indicated statistically significant reductions of 12.2% and 10.6% for PDO and total collisions, respectively. Severe collisions showed a non-significant