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Investigating the accuracy of Bayesian techniques for before–after safety studies: The case of a "no treatment" evaluation

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ABSTRACT

The main challenge in conducting observational before–after (BA) studies of road safety measures is to use a methodology that accounts for many potential confounding factors. However, it is usually difficult to evaluate and decide on the accuracy of the different safety evaluation techniques available in literature. This is mainly because the outcome of the comparison has no specific target (i.e., the effect of a specific treatment on safety is not precisely known).

The objective of this paper is to compare the accuracy of some of the commonly used Bayesian methodologies for BA safety studies by applying them to locations where no safety treatment has been implemented (making the target result to be no effect). This goal was pursued within the setting of a specific case study where a recent set of collision data was available for urban signalized intersections in British Colombia (Canada) with no safety treatments implemented during the time frame considered. An assessment of the temporal stability of the data set was undertaken to exclude the presence of significant BA changes as explanation of the results reported in this paper.

Both the well-known empirical Bayes and the full Bayes method with non-linear intervention models were explored for comparison. Two types of selection of the hypothetical treatment sites were used in the analysis: random, to minimize the selection bias effect, and non-random, by selecting sites with abnormal collision frequency (hotspots). Several criteria were used for comparisons including variability among the index of effectiveness for individual treatment locations, the stability of the outcome in terms of the consistency of the results of several experiments and the overall treatment effectiveness.

The results showed that when sites are selected randomly for treatment, all methodologies including the simple (naïve) BA study provide reasonable results (small statistically non-significant change in collision frequency). However, when sites are selected for treatment because of high collision occurrence, the estimated index of treatment effectiveness can potentially be biased by values up to 10%. This finding can have significant impact on estimating safety benefits of treatments, especially on those that have low collision reductions. As well, the FB method seems to perform better than other evaluation techniques including the most commonly used EB method. In particular, the FB method provides higher consistency in the estimated collision reduction among treatment sites.

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1. Introduction

Several different experimental designs can be used to evaluate the effect of safety treatments. These designs include safety experiments (randomised control trials) and observational before–after (BA) studies. Although experiments are considered ideal as they would theoretically control for all confounding factors, the decision of which road sites receive a treatment cannot practically be made randomly. Therefore, safety experiments are rarely used in the field of road safety. The most commonly used approach to determine the effectiveness of road safety treatments is the use of an observational BA study. Observational studies are much more widespread in road safety literature since treatment sites are usually selected where concerns about safety performance arise (collision-prone locations) (Highway Safety Manual, 2010). As such, the main challenge in conducting observational BA studies is to make use of a methodology that accounts for many potential confounding factors. One of the most important confounding factors in safety analysis is the regression-to-the-mean (RTM) effect (Hauer, 1997; Elvik, 2002). This effect refers to the tendency of extreme events to be followed by less extreme values regardless

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a change in the accident occurrence mechanism and it can be clearly observed in the case of sites selected for treatment solely on the basis of high collision records. This high record may be caused partially by random fluctuation and the selected sites are likely to have fewer accidents in future periods even if no treatment is applied. This will likely lead to an overestimation of the treatment effect. Other confounding factors include maturation (time trends), unrelated site-specific factors and changes in traffic volume (exposure).

Traditionally, there are mainly three approaches taken in observational BA studies that are supposed to account for confounding factors: using the well-known empirical Bayes (EB) method (Hauer, 1997), using the comparison-group (CG) method (Griffin and Flowers, 1997), and using a combination of the EB and CG methods (Sayed et al., 2004). Confounding factors are accounted for by using a group of non-treatment sites at which the countermeasure of interest has not been implemented (i.e., reference or comparison sites). Reference sites are used to correct for the RTM phenomenon because of selection bias (Hauer, 1992). Often, the reference group includes a larger number of sites that are similar to the treatment sites, but have not undergone any improvements between the before and the after periods. It is used to develop safety performance functions (SPFs), i.e., a calibrated relationship between collision frequency and annual average daily traffic (AADT) volumes. Comparison sites are a group of similar facilities selected for geographic proximity and comparability (traffic, geometry, etc.) to the treated sites. They are used to account for the unrelated and time trend effects that occur due to causal factors that are not recognized, measured and understood. Underlying this approach is the hope that the unknown factors will affect the comparison group in the same manner that they influence the treatment group. For example, effects such as traffic and driver composition, enforcement level, or weather conditions can change between the before period and the after period.

Recently, researchers have also introduced the use of the full Bayesian (FB) method to evaluate the effect of safety countermeasures (Li et al., 2008; Lan et al., 2009; El-Basyouny and Sayed, 2010, 2012a,b). The FB approach was shown to have several advantages, including the ability to account for greater uncertainty in the data; to provide more detailed inference; to allow inference at more than one level for hierarchical models; and to efficiently integrate the estimation of the safety model and treatment effects in a single step, whereas these are separate tasks in the EB method.

Several studies have compared the results of before and after safety evaluations when applied to evaluate specific treatments. The results showed a general agreement among the resulting treatment effectiveness index especially among the methodologies that make use of Bayesian techniques (Persaud et al., 2010; Sacchi et al., 2014; Ahmed et al., 2015). However, since the outcome of the comparison has no specific target (i.e., the effect of a specific treatment on safety is not known), it is difficult to evaluate and decide on the accuracy of the techniques. The main objective of this paper is to compare some of the commonly used Bayesian techniques for BA safety studies by applying them to locations where no safety treatment has been implemented and targeting the resulting output to be no effect.

2. Techniques included in the comparison

2.1. Empirical Bayes

Consider an observational BA study where collision data are available for a reasonable period of time before and after the intervention. In addition, a set of collision data for the same period of time is available for a group of sites (reference group) that are similar to the treatment sites, but have not undergone any improvements between the before and the after periods. The EB method provides an estimate for the expected collision frequency at the ith site that would have occurred during the time period following the implementation of the treatment (TA) had the treatment not been implemented (π_{TAi}). First, it combines a site's observed collision frequency in the before period (Y_{TBi}) and SPF-based predicted average collision frequency (μ) computed from the reference group. The estimate of the expected average collision frequency for that site in the before period (μ_{TBi}), can be calculated as (Hauer, 1997):

$$\mu_{TBi} = \alpha \times \mu + (1-\alpha) \times Y_{TBi} \tag{1}$$

where α is the weighted adjustment factor, which is a function of the SPF's overdispersion parameter κ and is equal to:

$$\alpha = \frac{1}{1+\mu/\kappa} \tag{2}$$

Afterwards, π_{TAi} is calculated as:

$$\pi_{TAi} = \mu_{TBi} \times r \tag{3}$$

where r is a factor applied to account for the length of the after period and differences in traffic volumes between the before and the after periods (Highway Safety Manual, 2010).

The treatment effectiveness index (θ^*), from which it is possible to estimate the percentage of reduction in predicted collisions counts as $(1-\theta^*) \times 100$, can be calculated as:

$$\theta_{EB}{}^{*} = \frac{1}{\pi_{TA}/Y_{TA}} \tag{4}$$

where π_{TA} represents the sum of the expected collision frequency at the n treated sites that would have occurred during the time period following the implementation of the treatment had the treatment not been implemented and Y_{TA} is the sum of the observed collision frequency at the n treated sites for the entire after period.

Eq. (1) is needed to control for the RTM bias. However, to correct for history and maturation confounding factors, some researchers (Sayed et al., 2004) have advocated the use of the combination of the EB method and the comparison group (CG) method, which makes use of a group of comparison sites in the calculation of θ^*. In this case the overall treatment effectiveness index can be obtained from:

$$\theta^{*}{}_{EB/CG} = \frac{Y_{CB}/Y_{CA}}{\pi_{TA}/Y_{TA}} \tag{5}$$

where Y_{CB} and Y_{CA} are, respectively, the total collision frequency observed in the before and the after periods at the comparison group sites.

2.2. Full Bayes method with non-linear intervention models

Consider the same observational BA study where collision data are available before and after the intervention and a set of collision data for the same period of time for a group of comparison sites. Let Y_{it} denote the collision count recorded at site i ($i=1,2, \ldots, n$) during year t ($t=1,2, \ldots, m$). Using a hierarchical model, such as Poisson-lognormal, with site-level random effects it is possible to write:

$$Y_{it}|\lambda_{it} \sim \text{Poisson}(\lambda_{it}), \tag{6}$$

$$\ln(\lambda_{it}) = \ln(\mu_{it}) + \varepsilon_i, \tag{7}$$

$$\varepsilon_i \sim N(0, \sigma_\varepsilon^2), \tag{8}$$

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