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# Measuring safety treatment effects using full Bayes non-linear safety performance intervention functions

Karim El-Basyouny[a,1], Tarek Sayed[b,*]

[a] Department of Civil and Environmental Engineering, University of Alberta, Edmonton, AB, Canada
[b] Department of Civil Engineering, University of British Columbia, Vancouver, BC, Canada V6T 1Z4

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ABSTRACT

Full Bayes linear intervention models have been recently proposed to conduct before–after safety studies. These models assume linear slopes to represent the time and treatment effects across the treated and comparison sites. However, the linear slope assumption can only furnish some restricted treatment profiles. To overcome this problem, a first-order autoregressive (AR1) safety performance function (SPF) that has a dynamic regression equation (known as the Koyck model) is proposed. The non-linear 'Koyck' model is compared to the linear intervention model in terms of inference, goodness-of-fit, and application. Both models were used in association with the Poisson-lognormal (PLN) hierarchy to evaluate the safety performance of a sample of intersections that have been improved in the Greater Vancouver area. The two models were extended by incorporating random parameters to account for the correlation between sites within comparison–treatment pairs. Another objective of the paper is to compute basic components related to the novelty effects, direct treatment effects, and indirect treatment effects and to provide simple expressions for the computation of these components in terms of the model parameters. The Koyck model is shown to furnish a wider variety of treatment profiles than those of the linear intervention model. The analysis revealed that incorporating random parameters among matched comparison–treatment pairs in the specification of SPFs can significantly improve the fit, while reducing the estimates of the extra-Poisson variation. Also, the proposed PLN Koyck model fitted the data much better than the Poisson-lognormal linear intervention (PLNI) model. The novelty effects were short lived, the indirect (through traffic volumes) treatment effects were approximately within ±10%, whereas the direct treatment effects indicated a non-significant 6.5% reduction during the after period under PLNI compared to a significant 12.3% reduction in predicted collision counts under the PLN Koyck model.



## 1. Introduction

The Empirical Bayes (EB) methodology has been the state-of-the-art for determining the effectiveness of safety treatments. The EB approach was shown to account for confounding factors such as the regression-to-the-mean (RTM) in observational before–after studies (Hauer, 1997; Hauer et al., 2002; Sayed et al., 2004; Persaud and Lyon, 2007). Alternatively, recent advances in statistical modeling techniques have facilitated the application of the full Bayes approach to conduct safety analysis. (Aul and Davis, 2006; Pawlovich et al., 2006; Li et al., 2008; Lan et al., 2009; Persaud et al., 2009; El-Basyouny and Sayed, 2010, 2011; Park et al., 2010; Yanmaz-Tuzel and Ozbay, 2010).

The results of several studies suggest that the FB approach is appealing due to its ability to: account for all uncertainty in the data, provide more detailed inference, allow inference at more than one level for hierarchical models, and efficiently integrating the estimation of the SPF and treatment effects in a single step, whereas these are separate tasks in the Empirical Bayes method (Huang et al., 2009; Lan et al., 2009; Persaud et al., 2009; El-Basyouny and Sayed, 2010). Additionally, the FB approach provides more flexibility in developing SPFs such as the use of intervention models in a before–after road safety evaluation (Pawlovich et al., 2006; Li et al., 2008), the application of the multivariate PLN to model collision counts at different levels of severity (Park et al., 2010; El-Basyouny and Sayed, 2011) and the use of random parameters to gain new insights into how collision counts are influenced by covariates and to account for heterogeneity due to unobserved road geometrics, traffic characteristics, environmental factors and driver behavior (Anastasopoulos and Mannering, 2009; El-Basyouny and Sayed, 2009).

Given these advantages, several studies have proposed using the FB approach to conduct observational before–after studies.

* Corresponding author. Tel.: +1 604 822 4379.
*E-mail addresses:* karim.el-basyouny@ualberta.ca (K. El-Basyouny), tsayed@civil.ubc.ca (T. Sayed).
[1] Tel.: +1 780 492 9564.

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For example, Li et al. (2008) considered various linear forms of intervention and hierarchical models (Poisson-Gamma or Poisson-lognormal) to conduct safety evaluations. These linear intervention models acknowledge that treatment (intervention) effects do not occur instantaneously but are spread over future time periods, and use dynamic regression models to identify the lagged effects of the intervention to describe their response. The forms/models were developed to deal with both immediate and gradual treatment impacts while accounting for countermeasure implementation, time effects, traffic volumes as well as the effects of other covariates representing various site characteristics. Park et al. (2010) extended the univariate linear intervention model to include multivariate dependent variables with multiple regression links and proposed an algorithm for the computation of the treatment effectiveness index to determine the efficacy of the countermeasure. To gain new insights into how collision counts are influenced by covariates and to account for heterogeneity, the use of multivariate linear intervention models with random parameters among matched treatment–comparison pairs was advocated by El-Basyouny and Sayed (2011).

It should be noted that in all of the above studies, linear slopes were assumed to represent the time and treatment effects across the treated and comparison sites. To overcome the linear slopes assumption, this paper advocates the use of the nonlinear 'Koyck' intervention model (Koyck, 1954) to represent the lagged treatment effects that are distributed over time. The Koyck model is an alternative dynamic regression form involving a first-order autoregressive (AR1) SPF that is based on distributed lags (Judge et al., 1988; Pankratz, 1991). The Koyck model affords a rich family of forms (over the parameter space) that can accommodate various profiles for the treatment effects. Therefore, the first objective of the paper is to present the Koyck model as an alternative nonlinear intervention model to estimate the effectiveness of safety treatments in before–after designs.

Besides, it is possible using the Koyck model to isolate an additional component corresponding to the time (novelty) effects. Analyzing such a phenomenon provides valuable insight into whether the overall gain in safety compensates for the short-term confusion caused by the introduction of the new safety countermeasure (Persaud, 1986). Although the assessment of the uncertain duration or stability over time of the effects of road safety measures is important, novelty effects have received little attention in the road safety literature (Elvik, 2010). Therefore, another objective of the paper is to formulate and estimate novelty effects under the Koyck nonlinear intervention model.

In addition, the paper offers a novel approach to compute the various components of the treatment effectiveness index under both the linear and the nonlinear intervention models. The various components are related to direct and indirect treatment effects. The direct effects are further decomposed into long term trend changes and overall mean level changes whereas the indirect effects are imposed on the predicted collisions through traffic volumes and other site characteristics that vary with time. The importance of isolating a component corresponding to the direct treatment effects cannot be over emphasized as it enables analysts to assess the effectiveness of the countermeasures apart from local (site-related) environmental factors. These specific aspects of treatment effectiveness are important for traffic safety applications and help overcome the imperfection of the rather "blind" treatment effectiveness index.

Finally, the paper aims to provide straightforward equations in terms of model parameters for the computation of the treatment effectiveness index and its above-mentioned components without resorting to additional algorithms such as the one proposed by Park et al. (2010).

To demonstrate the differences between the linear intervention model and the nonlinear 'Koyck' intervention model, the full Bayes approach is utilized to determine the effectiveness of certain countermeasures that were implemented in 25 treated intersections in the Greater Vancouver area using an observational before–after design involving comparison groups. The linear and nonlinear 'Koyck' intervention models have been extended by including random parameters to account for the correlation between sites within comparison–treatment pairs. Treatment effectiveness was investigated under both models and the respective components were estimated and compared.

## 2. The models

Let $Y_{it}$ denote the collision count observed at site $i$ ($i = 1, 2, \ldots, n$) during year $t$ ($t = 1, 2, \ldots, m$). It is assumed that the data are available for a reasonable period of time before the intervention (at least two years). Naturally, longer periods are preferable both before and after the intervention.

### 2.1. The Poisson-lognormal linear intervention (PLNI) model

For the PLNI model (M1), it is assumed that the $Y_{it}$ are independently distributed as

$$Y_{it}|\theta_{it} \sim \text{Poisson}(\theta_{it}), \quad (1)$$

$$\ln(\theta_{it}) = \ln(\mu_{it}) + \varepsilon_i, \quad (2)$$

$$\ln(\mu_{it}) = \alpha_0 + \alpha_1 T_i + \alpha_2 t + \alpha_3 (t - t_{0i}) I_{it} + \alpha_4 T_i t + \alpha_5 T_i (t - t_{0i}) I_{it} + \alpha_6 T_i I_{it} + \beta_1 \ln(V_{1it}) + \beta_2 \ln(V_{2it}) + \beta_3 X_{3i} + \cdots + \beta_J X_{Ji}, \quad (3)$$

$$\varepsilon_i \sim N(0, \sigma_\varepsilon^2), \quad (4)$$

where $T_i$ is a treatment indicator (equals 1 for treated sites, zero for comparison sites), $t_{0i}$ is the intervention year for the $i$th treated site and its matching comparison group, $I_{it}$ is a time indicator (equals 1 in the after period, zero in the before period), $V_{1it}$ and $V_{2it}$ denote the annual average daily traffic (AADT) at the major and minor approaches, respectively, $(X_{3i}, \ldots, X_{Ji})$ are additional covariates representing geometric and environmental site characteristics, $(\alpha_0, \ldots, \beta_J)$ are the regression coefficients and $\sigma_\varepsilon^2$ represents the extra-Poisson variation.

The interpretation of the regression coefficients is given by Li et al. (2008) and El-Basyouny and Sayed (2011). In particular, the parameters $\alpha_4$ and $\alpha_5$ allow for different time trends and different intervention slopes across the treated and comparison sites, whereas $\alpha_6$ represents a possible sudden drop (or increase) in collision counts immediately following the intervention. If the changes at the treatment sites were gradual (without a sudden jump), the parameter $\alpha_6$ is dropped from the model ($\alpha_6 = 0$).

Since the matched comparison sites were selected to be as similar to treatment sites as possible, this may induce a correlation in collision count between sites within comparison–treatment pairs. To account for this correlation, suppose that the $i$th site belongs to the pair $p(i) \in \{1, 2, \ldots, N_C\}$, where $N_C$ denotes the number of comparison groups. The variation due to the comparison–treatment pairing can be represented by allowing the regression coefficients in Eq. (3) to vary randomly from one pair to another. This leads to the model M2

$$\ln(\mu_{it}) = \alpha_{p(i),0} + \alpha_{p(i),1} T_i + \alpha_{p(i),2} t + \alpha_{p(i),3} (t - t_{0i}) I_{it} + \alpha_{p(i),4} T_i t + \alpha_{p(i),5} T_i (t - t_{0i}) I_{it} + \alpha_{p(i),6} T_i I_{it} + \beta_{p(i),1} \ln(V_{1it}) + \beta_{p(i),2} \ln(V_{2it}) + \beta_{p(i),3} X_{3i} + \cdots + \beta_{p(i),J} X_{Ji}, \quad (5)$$