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Time-series intervention analysis of pedestrian countdown timer effects

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ABSTRACT

Pedestrians account for 40–50% of traffic fatalities in large cities. Several previous studies based on relatively small samples have concluded that Pedestrian Countdown Timers (PCT) may reduce pedestrian crashes at signalized intersections, but other studies report no reduction. The purposes of the present article are to (1) describe a new methodology to evaluate the effectiveness of introducing PCT signals and (2) to present results of applying this methodology to pedestrian crash data collected in a large study carried out in Detroit, Michigan.

The study design incorporated within-unit as well as between-unit components. The main focus was on dynamic effects that occurred within the PCT unit of 362 treated sites during the 120 months of the study. An interrupted time-series analysis was developed to evaluate whether change in crash frequency depended upon of the degree to which the countdown timers penetrated the treatment unit. The between-unit component involved comparisons between the treatment unit and a control unit.

The overall conclusion is that the introduction of PCT signals in Detroit reduced pedestrian crashes to approximately one-third of the preintervention level. The evidence for this reductionis strong and the change over time was shown to be a function of the extent to which the timers were introduced during the intervention period. There was no general drop-off in crash frequency throughout the baseline interval of over five years; only when the PCT signals were introduced in large numbers was consistent and convincing crash reduction observed. Correspondingly, there was little evidence of change in the control unit.

The pedestrian countdown timer (PCT)is a countdown signal that displays the available crossing time in seconds; it complements the conventional flashing DON'T WALK phase of a traffic signal cycle. The Manual on Uniform Traffic Control Devices provides guidance on the PCT and presents it as the standard pedestrian signal configuration (MUTCD, 2009).

Pedestrian countdown signals are believed to be superior to conventional signals because they communicate the amount of available crossing time at intersections. The Florida Department of Transportation (FDOT), for example, conducted a study to determine pedestrians' understanding of the traditional flashing DON'T WALK signal versus the pedestrian countdown signal. This study suggested that the PCT was more intuitive than the traditional flashing DON'T WALK display, which contributed to pedestrians making better decisions about when to begin crossing and when to wait for the next WALK signal. The study demonstrated that under the traditional flashing DON'T WALK signal, pedestrians were more likely to (a) start crossing during the flashing DON'T WALK phase, (b) run out of time while crossing, (c) return to the starting side of the crossing, or (d) stop in the roadway when the light changed (Huang & Zegeer, 2000).

Similarly, other research has shown that the use of countdown timers leads to a decrease in the probability that pedestrians will cross near the end of a pedestrian WALK phase if it appears that there is insufficient time. Further, pedestrians who cross during the flashing DON'T WALK phase tend to increase their walking speed in an attempt to finish the crossing within the amount of time shown on the countdown signal (ITE, 2007). The Minnesota Department of Transportation measured pedestrian compliance with signal commands and found a 12% average increase in successful pedestrian crossings with the implementation of pedestrian countdown timers (Institute of Transportation Engineers (ITE), 2007).

Perhaps most importantly, several studies have concluded that the introduction of the PCT signals produces a reduction in the number of pedestrian crashes (Eccles, Tao, & Mangum,

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2007; Federal Highway Administration (FHWA), 2007; Markowitz, Sciotino, Fleck, & Yee, 2006; Pulugurtha, Desai, & Pulugurtha, 2010. The FHWA (2007) review of the effects of various pedestrian crash reduction methods suggests that the addition of countdown timers to existing pedestrian signals may result in a 25% decrease in crashes.

In contrast, a study by Camden, Buliung, Rothman, Macarthur, and Howard (2012) concluded that there was no effect of introducing PCT signals in the city of Toronto. Further, a secondary analysis of the Camden et al. data found that the rate of decline in pedestrian crashes at intersections with PCT signals was significantly lower than the rate of decline found at intersections without the PCT signals (Huitema, 2014). That is, the safety improvement across time was greater at intersections having only conventional signals than it was at intersections with both conventional signals and PCT signals.

The inconsistencies in the conclusions reached in various PTC studies have not been systematically investigated. Although the focus of this study is not on these inconsistencies, future work in this area should consider the extent to which the conclusions are determined by methods of design and statistical analysis. The role of these methods in determining the outcome of safety studies is often underappreciated. The purposes of the present study are to (1) describe a time-series intervention method for the analysis of safety interventions in large cities, and (2) to apply it in evaluating the effects of introducing pedestrian countdown timers in Detroit, Michigan.

1. Evaluating program effects

1.1. Empirical Bayes analysis

An inspection of recent methodological literature on the evaluation of crash reduction programs (e.g., Hauer, Harwood, Council, & Griffin, 2002; Fitzpatrick & Park, 2009) reveals a preference for simple Before–After designs and empirical Bayes methods of analysis. The essential purpose of these approaches is to provide a sound estimate of the expected frequency of crashes (or some other outcome) for some entity before exposure to an intervention. Once this estimate is computed, it is used as a baseline against which the after-intervention accident frequency is compared.

A major feature of the Bayesian approach is that the expected frequency estimate is based on two sources of information: (1) the characteristics of a reference population relevant to the entity being studied and (2) the crash history of the entity. The relative weight of these two sources in providing a single crash frequency estimate depends upon the mean and variance of the estimates provided by each source. When a moderate amount of information is available regarding the reference population from which the entities are selected the variance of the crash estimates provided by this source is likely to be large. Similarly, when little information regarding the actual crash history of an entity is available the variance associated with this source is likely to be large. Conversely, when much data regarding either the reference population or the crash history of the entity is available the associated variance is likely to be small. Hence, the empirical Bayes estimate of crash frequency weights the two sources of information by a function of the means and variances of these sources. Ultimately, these weights are such that the influence of a source with a large variance is small and the influence of a source with a small variance is large. If essentially no relevant information is available regarding the reference population, the analysis must focus exclusively on the history of the entity. This is exactly the situation with which we were confronted in Detroit. Adequate data regarding the reference population that could have been useful in building an empirical Bayesian model were simply not available to us. That is, satisfactory detailed data regarding the properties of the sites available for study were unavailable for purposes of establishing a useful multivariate model of crash frequency. This limited data environment led to an alternative analytic approach that capitalized on the extensive time-series crash data that actually were available to the research team

1.2. Time-Series Intervention analysis

Although it is often the case that Bayesian methods are well suited for typical data structures available in safety research, the main approach used in the current study is an extension of what is known as “time-series intervention analysis.” The reasons for adopting this method are that (1) adequate data regarding characteristics of a reference population were not available and (2) extensive longitudinal crash data for the entity (i.e., the city of Detroit) were provided. This means that it was possible and desirable to focus on the historical time-series crash data in the evaluation of the effects of the PCT intervention. Studies with this focus are often described as interrupted time-series designs.

The traditional interrupted time-series design is characterized by many observations sampled at equally spaced time points before and after the introduction of an intervention. Because the data trajectory observed during the total series may be interrupted by the introduction of the intervention, the interrupted time-series label is fitting.

The pre-intervention observations constitute the “baseline” phase of the time series and the post-intervention observations constitute the “intervention” phase. The baseline data are used to estimate counterfactual observations for the intervention phase; that is, the baseline provides a prediction of what the outcome data in the intervention phase will be if there is no effect of the intervention. Acceptable time-series intervention models provide a comparison of (1) the counterfactual level of the post-intervention data (i.e., the level predicted to occur if no intervention is introduced) against (2) the post-intervention data that actually occur after the intervention is introduced.

Many methods of time-series analysis are available for evaluating the effects of interventions. Two useful approaches are “ARIMA” (short for “autoregressive, integrated, moving averages”) intervention models and time-series regression intervention models that accommodate autoregressive errors. Although both approaches apply in many situations, they are quite different with respect to assumptions, complexity, estimation methods, parameters estimated, and transparency of results. Our view is that data of the type analyzed in the present study are best modeled using a version of the second approach. The time-series regression model used for the Detroit analysis is described in detail later in the article.

1.3. Advantages of time-series designs

Time-series designs may be considerably more informative than conventional Before–After designs. The end result of a Before-After analysis is a single estimate of “the effect,” whereas a time-series analysis can provide descriptions of dynamic change throughout the study. The change throughout the intervention phase may be called the outcome function. It involves a description of various aspects of the intervention effect such as (1) immediate change in level, (2) rate of change throughout intervention phase, (3) and ultimate amount of change (relative to baseline projections) observed at the end of the intervention phase. Advantages of providing a thorough description of change throughout the whole study (instead of or in addition to a traditional Before–After effect measure) include greater transparency of the outcome and the ability to diagnose possible regression effects that can threaten the conclusions of a study. For example, when the entity of interest consists of sites selected for study *because* they have unusually high