Accident Analysis and Prevention 93 (2016) 65–74

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

Quantifying the causal effects of 20 mph zones on road casualties in London via doubly robust estimation

Haojie Li[a,*], Daniel J. Graham[b]

[a] *School of Transportation, Southeast University, China*
[b] *Centre for Transport Studies, Imperial College London, UK*

ARTICLE INFO

Article history:
Received 19 October 2015
Received in revised form 25 February 2016
Accepted 5 April 2016
Available online 9 May 2016

Keywords:
20 mph zones
Doubly robust methods
Causal analysis

ABSTRACT

This paper estimates the causal effect of 20 mph zones on road casualties in London. Potential confounders in the key relationship of interest are included within outcome regression and propensity score models, and the models are then combined to form a doubly robust estimator. A total of 234 treated zones and 2844 potential control zones are included in the data sample. The propensity score model is used to select a viable control group which has common support in the covariate distributions. We compare the doubly robust estimates with those obtained using three other methods: inverse probability weighting, regression adjustment, and propensity score matching. The results indicate that 20 mph zones have had a significant causal impact on road casualty reduction in both absolute and proportional terms.

1. Introduction

It is widely thought that a reduction in vehicle speeds can reduce the severity of road casualties and decrease the number of traffic collisions (Soole et al., 2013; Elvik et al., 2004; Elvik, 2009). There are a number of policy interventions that can be used by governments to reduce traffic speeds in the hope of improving road safety. An example of such measure is designation of 20 mph zones, which are widely applied in the UK particularly in residential areas.

While several studies have been undertaken to analyze the impact of 20 mph zones on various outcome of interest, there remains uncertainty regarding the causal effects of 20 mph zones on road safety. A major challenge for evaluation lies in constructing viable counterfactual outcomes that can represent what would have happened to “treated” units in the absence of the treatment (i.e. designation of 20 mph status). Since counterfactual outcomes cannot be observed, regression-based statistical models are usually used to model them, particularly via before–after and time-series methods (e.g. Webster and Layfield, 2003; Grundy et al., 2009). The validity of such methods relies on their ability to control for confounders, which are a set of risk factors for the outcome of interest that are also correlated with treatment assignment. The estimator of treatment effects is consistent and unbiased only if the confounders are properly accounted for. This critical issue, however, is inadequately justified in previous studies.

This research contributes to the literature by tackling the issue of confounding using a doubly robust (DR) estimator and subsequently uses this method to evaluate the effect of 20 mph zones on road casualties in London. The DR approach combines outcome regression (OR) and propensity score (PS) models to obtain an estimator which is consistent and asymptotically unbiased so long as at least one of the component models (i.e. OR or PS) is correctly specified. It thus provides two opportunities for valid treatment effect estimates which is useful in situations when the quality of data or knowledge about the underlying processes is not uniform. The DR method has been used routinely to estimate causal treatment effects in other areas of science such as medicine and epidemiology, but, to the best of our knowledge, has not been applied previously in road traffic safety research.

Another key contribution of our paper lies in development of a panel data sets to capture variance in road network characteristics over time. A limitation of previous research on this topic is that road network effects have been assumed static which could lead to biased treatment effect estimates if such characteristics operate as confounders.

This paper is organized as follows. Section 2 reviews previous literature in the field. Methods are described in Sections 3 and 4. Our results are presented and discussed in Section 5. Conclusions are then drawn in the final section.

2. Literature review

A wealth of empirical evidence shows a clear relationship between traffic collisions and vehicle speeds. In particular, mean

* Corresponding author.
E-mail address: h.li@seu.edu.cn (H. Li).

http://dx.doi.org/10.1016/j.aap.2016.04.007
0001-4575/

vehicle speeds are found to be positively related with the number and severity of traffic collisions (Elvik et al., 2004; Elvik, 2009). Speed limits specify maximum desirable traffic speeds and these can be used to reduce the number of road traffic casualties. An example of such a measure is traffic calming, which is especially prevalent in residential areas.

Numerous studies have been conducted to evaluate the safety impacts of traffic calming. A meta-analysis by Elvik (2001) investigates the effects on road safety of area-wide urban traffic calming schemes from 33 studies, including research reports from Norway, Sweden, Finland, Denmark, Germany, the Netherlands, Great Britain, France, the United States and Australia. The results show that area-wide urban traffic calming schemes reduce the number of injury accidents by about 15% on average, whilst a 25% reduction in the number of accidents is found for residential streets. Another meta-analysis by Bunn et al. (2003) reviews 16 controlled before–after trials of area-wide traffic calming mainly in high income countries. Their review results also suggest that traffic calming can be effective in reducing the number of traffic crashes. However, previous studies reviewed in these meta-analyses tend to use before–after methods with some defined comparison group, which is not able to fully control for confounding effects, such as selection bias, also known as the regression to mean.

A number of studies have examined the impact of traffic calming in the UK, including 20 mph zones, on road safety, traffic speeds, environmental and health outcomes, amenity, traffic volumes, and inequality (Casanova and Fonseca, 2012; Grundy et al., 2009; Steinbach et al., 2011; Tovar and Kilbane-Dawe, 2013; Webster and Mackie, 1996; Webster and Layfield, 2003; Williams and North, 2013)). Webster and Layfield (2003) investigate 78 20 mph zones in London applying before–after methods. Allowing for background changes, total and KSI casualties are found to be reduced by 45% and 57% respectively. Grundy et al. (2009) conduct a time series analysis using data of 399 20 mph zones in London from 1986 to 2006. Time trend effects are taken into account by using conditional fixed effects Poisson models. The authors also suggest that the RTM effect can be controlled for by dropping data for three, four or five years prior to the implementation of the 20 mph zones.

There are two key issues that have not been fully addressed in previous evaluation studies on the impacts of 20 mph zones. First, the methods used in previous work are mainly before–after control studies. Usually, a control group is employed to estimate the counterfactual outcomes of the treatment group. Ideally control groups should have the same or similar characteristics to those of the treatment group, i.e. the control group must be representative of the treated sites. However, in previous research, insufficient attention has been paid to selection of such control groups. For example, Webster and Layfield (2003) use all unclassified roads in London as "control" data for roads in 20 mph zones. However, due to selection bias, the characteristics of treated and "control" units defined in this way may differ.

Second, a fundamental assumption required to draw valid causal inference from observational data is that all confounders are measured and represented adequately. Previous studies on 20 mph zones have largely ignored the potential for road casualties to be associated with the road network characteristics. Yet we know from the literature road casualties are significantly associated with road network characteristics, such as road class, road density and the number of nodes, the connectivity and accessibility of the road network, and the curvature of the road network (e.g. Huang et al., 2010; Marshall and Garrick, 2011; Rifaat et al., 2011; Jones et al., 2008; Quddus, 2008). The failure to account for the effects due to road network characteristics in evaluating traffic calming measures can bias estimates of the safety impacts of 20 mph zones. In this paper we develop a detailed panel data set on road network design to address potential confounding from this source.

The doubly robust estimator, originally proposed by Robins et al. (1995), has been described in the statistical literature (Bang and Robins, 2005; Robins et al., 1995; Robins, 1999; Lunceford and Davidian, 2004), and applied extensively in various areas of science. However, it has not yet been used for road safety research although in our view it has great potential.

3. Methods

The DR estimator combines PS and OR models developed using insights from the potential outcomes framework for causal inference. In this section we first introduce the potential outcomes framework and draw attention to its relevant assumptions. We then discuss how a doubly robust estimator of causal effects can be obtained by combining outcome regression and propensity score models.

3.1. Potential outcome framework

In presenting the potential outcome framework, it is necessary to introduce relevant notation. D_i is an indicator of treatment enrolment for individual or unit i. To facilitate understanding, consider only binary treatments. $D_i = 1$, if unit i received the treatment, and 0 otherwise. Let $Y_i(D_i)$ be the potential outcomes for unit i. Therefore, $Y_i(0)$ denotes the level of outcome that unit i would attain if not exposed to the treatment. Likewise, $Y_i(1)$ denotes the level of outcome that unit i would attain if exposed to the treatment. The individual causal treatment effect for unit i can be defined as $\delta_i = Y_i(1) - Y_i(0)$ (Individual Treatment Effect). The fundamental problem of causal inference is that since unit i can be either treated or not, we can only observe one of these two potential outcomes. If unit i is subject to the treatment then $Y_i(1)$ will be realized and $Y_i(0)$ will be an unobservable counterfactual outcome and vice versa.

In simple control studies, such as those described in the literature review above, the average treatment effect on the treated (ATE), $E[Y(1) - Y(0)|D = 1]$, is estimated by taking comparisons of the average outcomes between treated and control units, which can be defined as:

$$\begin{aligned}\delta_{ATE} &= E[Y(1)|D = 1] - E[Y(0)|D = 0]\\ &= E[Y(1) - Y(0)|D = 1] + \{E[Y(0)|D = 1] - E[Y(0)|D = 0]\}\end{aligned} \quad (1)$$

In the above equation, the term in curly brackets is not zero for most cases due to selection bias, i.e. the treatment assignment is usually associated with the potential outcomes that individuals could attain, with or without being exposed to the treatment.

In randomized experiments, the probability of assignment to treatment does not depend on potential outcomes. That is,

$$(Y(1), Y(0)) \perp D$$

Then $E[Y(0)|D = 1] = E[Y(0)|D = 0]$
and therefore

$$\begin{aligned}\delta_{ATE} &= E[Y(1)|D = 1] - E[Y(0)|D = 0]\\ &= E[Y(1) - Y(0)|D = 1] + \{E[Y(0)|D = 1] - E[Y(0)|D = 0]\}\\ &= E[Y(1) - Y(0)|D = 1] \text{(ATE with randomized assignment)}\end{aligned} \quad (2)$$

Eq. (2) provides an unbiased estimator of ATE. Randomized experiments are straightforward and allow the greatest reliability and validity of statistical estimates of causal effects. Whilst they are a valuable tool for treatment evaluation, it is not always feasible to implement a randomized experiment due to high costs and ethical issues. Consequently, causal analysis with observational data