The Causal Effect of Citywide Speed Limit Reduction on Crash Risk

Guocong Zhai [1], Kun Xie [2], Di Yang [3], Hong Yang [4]

Department of Civil & Environmental Engineering, Old Dominion University, Norfolk, VA, USA, gzhai001@odu.edu
Department of Civil & Environmental Engineering, Old Dominion University, Norfolk, VA, USA, kxie@odu.edu
Department of Civil and Urban Engineering, New York University, Brooklyn, NY, USA, dy855@nyu.edu
Department of Computational Modeling and Simulation Engineering, Old Dominion University, Norfolk, VA, USA, hyang@odu.edu

1. Introduction

In New York City (NYC), a new default speed limit law took effect on November 7th, 2014, which changed the speed limit on all NYC road segments without a posted speed limit from 30 mph to 25 mph. As Tefft [1] indicated, reducing impact speed from 30 mph to 25 mph would approximately reduce fatal risk by half. However, the previous literature has understudied the safety effectiveness of citywide speed limit reduction in an urban setting, such as NYC. In the context of a high-density urban road network in NYC, safety treatment implemented on one site could have a significant spatial spillover effect on its neighboring sites. For instance, lower operating speed in a treated road segment could allow more time for drivers or pedestrians from crossing streets to properly respond to unexpected events. The existence of the spatial spillover effect would violate the stable unit treatment value assumption (SUTVA) of the causal framework proposed by Rubin [2] and lead to biased estimates of the safety effectiveness [3]. Moreover, potential confounding variables (e.g., traffic volume, geometric design) that vary in treatment and control sites should be accounted for via an appropriate matching process due to the potential violation of the proposed ignorability assumption [4]. A simple linear function, commonly used in literature [5-7], may not be enough to depict the complex relationship between covariates and the treatment indicator. Thus, the matching process should also explore the nonlinear relationship. Further, there also exists a time trend in crash observations caused by unobserved factors such as enforcement and driving behavior changes. For instance, along with the speed limit reduction, more vigorous enforcement on dangerous driving behaviors was imposed, leading to fewer crashes in the post-treatment period (a downward trend). A potential time trend should be considered to get a reliable estimate of the effect of speed limit reduction on crash safety performance.

Because previous research that has jointly addressed the three issues mentioned above is relatively limited, this study aims to estimate the safety effectiveness of speed limit reduction in NYC by developing an integrated causal inference approach that can jointly account for spatial spillover effect, confounding bias, and time trend. The propensity score matching (PSM) is used to balance potential confounding variables between treatment and control sites. A logistic generalized additive model (GAM) in the matching process is used to capture the nonlinear relationship between potential confounding variables and the treatment indicator. The spatial difference-in-differences (SDID) approach could decompose the safety effectiveness into the direct treatment effect and spatial spillover treatment effect. The SDID approach could also capture the time trend of the safety effectiveness using the extended difference-in-differences (DID) structure. The safety effectiveness of the speed limit reduction in this paper is measured by frequency changes in fatal crashes, injury crashes, and property-damage-only (PDO) crashes.

2. Methodology

Under the Rubin causal framework proposed by Rosenbaum and Rubin [4], this paper uses a binary treatment indicator $D_{it} \in \{0,1\}$, where $D_{it} = 1$, if the site i receives the treatment in the period t, and 0 otherwise ($i = 1, 2, ..., n; t = 0, 1$). In particular, n is the number of treatment and control sites in NYC, and only two periods t

[2] * Corresponding author.
E-mail address: kxie@odu.edu

are included as the pre-treatment ($t=0$) and post-treatment ($t=1$) periods. In addition, a binary time indicator $T_{it} \in \{0,1\}$ is also involved, denoting the pre-treatment period if $T_{it}=0$ and the post-treatment period $T_{it}=1$. Thus, let Y_{it} denote the observed crash frequency of one specific crash type (i.e., fatal crashes, injury crashes, or PDO crashes) for the road segment i at the period t , defining as the equation (1):

$$Y_{it} = D_{it}Y_{it}(D_{it}) + (1-D_{it})Y_{it}(D_{it}) \qquad (1)$$

where $Y_{it}(D_{it})$ means the potential outcomes of crash frequency. $Y_{it}(1)$ denotes that crash frequency for the site i at the period t would be if exposed to the speed limit reduction and $Y_{it}(0)$ denotes that crash frequency for the site i at the period t would be if not exposed to the treatment.

The PSM process is applied to tackle confounding bias when evaluating the safety effectiveness of the speed limit reduction. Because the pre-treatment confounding variables are common causes for the treatment indicator D_{i0} and the pre-treatment potential outcomes $Y_{i0}(D_{i0})$. We have to block the relationship between the pre-treatment covariates $\mathbf{X}_{i0}$ and the treatment indicator D_{i0} via the PSM process. The estimated propensity score $e_i(\mathbf{X}_{i0})$ is the predicted probability of receiving the treatment ($D_{i0}=1$) given pre-treatment covariates $\mathbf{X}_{i0}$ for the site i. The logistic GAM was proposed to capture the nonlinear relationship with flexible additive functions and calculate the estimated propensity score $e_i(\mathbf{X}_{i0})$. The logistic GAM would significantly improve balance performance and tackle confounding bias, as Woo et al. (2008) indicated. The logistic GAM is denoted as the equation (2):

$$E(\log(\frac{e_i(\mathbf{X}_{i0})}{1-e_i(\mathbf{X}_{i0})})) = \beta_0 + \beta_1 X_{1,i0} + \beta_2 X_{2,i0} + \ldots + \beta_{p-1} X_{p-1,i0} + f_p(X_{p,i0}) \qquad (2)$$

where $(\beta_0, \beta_1, \beta_2, \ldots \beta_{p-1})$ are the coefficients of covariates $(X_{1,i0}, X_{2,i0}, \ldots X_{p-1,i0}) \in \mathbf{X}_{i0}$, such as borough area, one-way street, and number of intersections. Moreover, $f_p(X_{p,i0})$ is a nonparametric smooth function that describes the nonlinear relationship between $X_{p,i0} \in \mathbf{X}_{i0}$ and the treatment indicator D_{i0}. In the matching process, $X_{p,i0}$ only denotes the natural logarithm of VMT.

Then, we develop the SDID model with the matched data to assess the safety effectiveness of the speed limit reduction, which could jointly identify the spatial spillover effect, tackle confounding bias, and capture the time trend of the safety effectiveness. Assuming Y_{it} follows a Poisson distribution with the mean λ_{it}, the probability of y_{it} crashes in the site i at the period t can be given by the equation (3):

$$P(Y_{it}=y_{it}) = \frac{e^{-\lambda_{it}} \lambda_{it}^{\ y_{it}}}{y_{it}!} \quad (3)$$

To specify the Poisson mean λ_{it}, $\{\mathbf{X}_{it}, D_{it}, T_{it}, W_{s,it}\}$ are incorporated into the model in the equation (4):

$$\begin{aligned} \ln(\lambda_{it}) &= \alpha_0 + \alpha_1 \mathbf{X}_{it} + \alpha_2 D_{it} + \alpha_3 T_{it} + \alpha_4 (1+\rho \mathbf{W}_{s,it}) D_{it} T_{it} + \varepsilon_{it} \\ &= \alpha_0 + \alpha_1 \mathbf{X}_{it} + \alpha_2 D_{it} + \alpha_3 T_{it} + \alpha_4 D_i T_t + \alpha_{4,\rho} \mathbf{W}_{s,it} D_{it} T_{it} + \varepsilon_{it} \end{aligned} \qquad (4)$$

where $\alpha_{4,\rho} = \rho\alpha_4$, ρ is a spatial autoregressive parameter. The spatial weight $\mathbf{W}_s$ is a ($2n \times 2n$) block-diagonal row-standardized spatial contiguity matrix as indicated by Delgado and Florax [8], which denotes the local spatial interaction in treatment responses; $\mathbf{W}_{s,it} \in [0,1]$ is defined as the proportion of treated neighboring sites for the site during the period t. Besides, $\exp(\varepsilon_{it})$ is assumed to be gamma-distributed with mean one and variance η to address the over-dispersion issue for the negative binomial model [9]. It should be noticed that the equation (4) would revert to the standard DID structure if $\rho=0$, indicating no spatial spillover effect.

3. Findings

The matched dataset was used to develop the SDID models for fatal, injury, and PDO crash frequencies. Table 1 presents the estimation results of our proposed approach. All variables selected are statistically significant at the 0.10 level. One unit increase in the number of intersections is associated with a 2.02% increase in fatal crashes and a 3.04% increase in injury or PDO crashes. This positive association between the number of intersections and crash frequencies has also been found at El-Basyouny and Sayed [10]. Intuitively, road users would have more interactions and conflicts at intersections than road segments. In addition, more intersections in a road network are associated with shorter spacings between intersections for safer lane change behaviors, consistent with findings in Xie, Wang [9]. Every percent increase in VMT is associated with a 0.58% increase for fatal crashes, a 0.54%

increase for injury crashes, a 0.50% increase for PDO crashes. As a commonly used exposure indicator, a larger VMT is accompanied by more opportunities to be involved in crashes [11]. Borough area indicators are also significant and can capture the effects of unobserved risk factors at the borough level. Further, one-way streets are expected to have 3.92% fewer injury crashes than two-way ones, consistent with findings in Xie, Wang [12]. One-way streets can significantly reduce conflict points at intersections [13]. Thus, it could improve traffic safety in high-density road networks by converting some two-way streets into one-way streets. Arterials are associated with an 8.33% higher PDO crashes than others, consistent with the findings at Alarifi, Abdel-Aty [14]. One potential reason could be that the higher operating speed in arterials gives drivers less time to react to unexpected events.

Table 1: Modeling Results of the Integrated PSM and SDID Approach (PSM+SDID)

		Fatal crashes		Injury crashes		PDO crashes	
		Coeff.	Std. Err	Coeff.	Std. Err	Coeff.	Std. Err
Intercept		-9.39^{***}	0.64	-2.46^{***}	0.09	-1.07^{***}	0.09
Borough areas (base: Brooklyn & Bronx)	Manhattan	-0.33^{*}	0.13	-	-	0.55^{***}	0.03
	Queens	-0.40^{***}	0.12	-0.46^{***}	0.03	-0.29^{***}	0.03
	Staten Island	-1.50^{***}	0.33	-1.18^{***}	0.05	-0.83^{***}	0.05
One-way street		-	-	-0.04'	0.02	0.07^{**}	0.02
Arterial street		-	-	-	-	0.08^{***}	0.02
Number of intersections		0.02^{***}	<0.01	0.03^{***}	<0.01	0.03^{***}	<0.01
Log (VMT)		0.58^{***}	0.05	0.54^{***}	0.01	0.50^{***}	0.01
T_{it}		0.79	0.58	-0.14	0.07	0.06	0.08
D_{it}		1.84^{***}	0.49	0.06	0.05	0.08	0.06
$D_{it}T_{it}$		-0.01	0.73	0.24	0.14	0.22	0.14
$W_{s,it}D_{it}T_{it}$		-1.10^{*}	0.52	-0.19	0.12	-0.19	0.12
η		1.81^{*}	0.78	1.32^{***}	0.03	1.00^{***}	0.02
AIC			3232.25		46841.11		69132.50
Pseudo R-Squared			0.16		0.52		0.51

Significance codes: ' $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

For the comparison purpose, except for our proposed approach, other five commonly used causal inference approaches, such as comparison group (CG), PSM, DID, SDID, and PSM+DID, were also developed to estimate the safety effectiveness of the speed limit reduction. Please refer to the National Research Council [11] for more estimation details about the CG approach. Results of the safety effectiveness estimates are presented in Table 2. This study disentangled the average treated effect for the treated (ATT) into the average direct treatment effect for the treated (ADTT) and average spatial spillover effect (AITT).

All causal approaches consistently suggested a significant negative impact of speed limit reduction on fatal crashes. The average proportion of neighboring treatment sites, $\overline{W_{s,it}D_i}$, equals 0.85 before matching and 0.87 after matching due to dropping the unmatched sites in the matching process. The ATT estimate of the PSM+SDID is -0.97, indicating a 62.09% decrease in fatal crashes after the speed limit reduction. The spatial spillover effect of the treatment was found to be significant in our proposed approach. Similarly, CG, PSM, DID, SDID, and PSM+SDID suggested a decrease in fatal crashes of 44.97%, 46.74%, 45.12%, 39.35%, and 65.35%, respectively. By comparing PSM+SDID with PSM+DID, we found that the omission of the spatial spillover effect would overestimate the impact of the speed limit reduction on fatal crashes. By comparing PSM+SDID with PSM, we found that the ignorance of the time trend underestimated the impact of speed limit reduction on fatal crashes. By comparing PSM+SDID with SDID, we found that the ignorance of confounding bias would also underrate the impact of speed limit reduction on fatal crashes. In addition, we found a similar conclusion on fatal crashes between CG and DID approaches due to similar parallel trend assumptions and covariates. Our proposed approach is more likely to precisely estimate the treatment effect by jointly considering the spatial spillover effect, confounding bias, and the time trend.

However, the PSM+SDID approach did not imply a significant impact of speed limit reduction on injury and PDO crashes. Among alternative approaches, only PSM indicated a significant positive treatment effect on injury (a 19.72% increase) and PDO (24.61%) crashes, likely due to the ignorance of the time trend. Moreover, the estimation results by the CG approach were slightly different from those by the DID approach, which might attribute to the fact that some insignificant covariates were not included in the DID modeling process. In contrast, the CG approach involved all covariates suggested in this paper.

Table 2: Safety Effectiveness of the Speed Limit Reduction

Safety effectiveness	Causal approach	ADTT		AITT		ATT	
		Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error
Fatal crash frequency	CG		-		-	-0.60	-
	PSM		-		-	-0.63^{*}	0.31
	DID		-		-	-0.60^{*}	0.33
	SDID	0.30	0.60	-0.68^{*}	0.33	-0.50^{***}	0.12
	PSM+DID		-		-	-1.06^{*}	0.47
	PSM+SDID	-0.01	0.73	-0.96^{*}	0.39	-0.97^{*}	0.48
Injury crash frequency	CG		-		-	0.05	-
	PSM		-		-	0.18^{***}	0.06
	DID		-		-	0.11	0.07
	SDID	0.16	0.14	-0.04	0.07	0.11	0.07
	PSM+DID		-		-	0.06	0.08
	PSM+SDID	0.24	0.14	-0.17	0.09	0.07	0.10
PDO crash frequency	CG		-		-	0.05	-
	PSM		-		-	0.22^{***}	0.06
	DID		-		-	0.11	0.07
	SDID	0.18	0.14	-0.05	0.07	0.12	0.08
	PSM+DID		-		-	0.04	0.08
	PSM+SDID	0.22	0.14	-0.17	0.09	0.05	0.08

Significance codes: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

4. Conclusions

This study adds to the literature a robust causal inference approach (PSM+SDID) that can jointly account for spatial spillovers, tackle confounding bias, and capture the time trend to evaluate the effectiveness of safety treatments. A critical issue with causal analyses of the safety effectiveness in a dense urban setting like NYC concerns addressing the spatial spillover effect. In this study, the speed limit reduction on one treated site has a significant spatial spillover effect on fatal crashes in its neighboring road segments. Lower vehicle operating speed from crossing streets would allow more time for drivers and pedestrians to respond to unexpected events and thus reduce crashes. To be more specific, the AITT is vital in explaining the safety effectiveness of the treatment of fatal crashes. Secondly, a critical approach to tackling confounding bias is balancing covariates between treatment and control sites (road segments). The logistic GAM is used to identify the nonlinear relationship between covariates and the treatment indicator, blocking relationships between potential confounding variables and the treatment indicator. Thirdly, the time trend identified by the extended DID structure (SDID) could help capture the impacts of unobserved temporal factors such as police enforcement and driving behavior changes.

The proposed causal approach (PSM+SDID) suggests that the NYC speed limit reduction would significantly decrease fatal crashes by 62.09%. Interestingly, as Tefft (2013) indicated, the impact speed reduction from 30 mph to 25 mph would reduce fatal risk by 50%, close to the safety effectiveness estimated in this study. Alternative causal approaches present a range of fatal crash reductions from 39.35% (SDID) to 65.35% (PSM+DID). Moreover, the spatial spillover effect on fatal crashes is found to be statistically significant, likely due to the high-density road network in NYC. However, according to the proposed approach, the speed limit reduction has insignificant impacts on either injury crashes or PDO crashes. Based on findings, we would recommend cities implement speed limit reduction if there is a high risk of fatal crashes. In project appraisal, decision-makers should properly estimate the safety benefits of speed limit reduction by considering not only its direct effect but also the spillover effect. Traffic calming measures, education, and enforcement programs should also be considered along with speed limit reduction to raise the awareness and conformity of drivers.

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