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No association between Safe Routes to school programs and school-age pedestrian or bicyclist collisions in New York State

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ABSTRACT

Introduction: Safe Routes to School (SRTS) programs aim to promote children's active school commuting and to improve traffic safety around schools. Evaluation studies mostly have focused on travel modal shift to active modes. However, traffic safety improvement has been less studied, although it was one of the most important program goals and it could be equally important to policy makers and practitioners. We aim to evaluate whether schools participating in a SRTS program have safety improvement.
Methods: Using a two-group (case-control) pretest-posttest study design, we analyzed SRTS funding in 2008 and 2013 in New York State. Analysis of Covariance models were established to examine if SRTS funding was associated with changes in collision outcomes with adjusting school demographics, area-based socioeconomic characteristics, and built environments around schools. Collision outcomes were vehicle collision count and risk (count adjusted by traffic volume) around school before and after SRTS funding.
Results: In total, 2363 schools were examined. We found that the 2013 SRTS programs were not significantly associated with a decrease in collision involving school-age pedestrians or bicyclists occurring within a 0.5-mile distance from schools during school hours.
Conclusions: The 2013 SRTS funding was not associated with collision reduction, suggesting no evident effect of SRTS on collision reduction among school-age pedestrians and bicyclists.

1. Introduction

In the United States, pedestrian and bicyclist fatalities have increased since 2008. In 2017, there were 5977 pedestrian deaths, of which nearly 19% were children aged 14 or younger. Pedestrian deaths accounted for 16% of all traffic fatalities in 2017, increasing from 12% in 2008 (National Highway Traffic Safety Administration, 2019). A Canadian study found that about 50% of child pedestrian collisions occurred during school commuting times around schools (Warsh et al., 2009). The number of bicyclist deaths also increased from 708 in 2008 to 840 in 2016. Poorly designed streets may produce preventable pedestrian and bicyclist collisions (National Highway Traffic Safety Administration, 2018). Safe street environments for all modes and all street users are especially important for vulnerable populations including children. School-age children are less likely to walk or bike in their neighborhoods if there are many collisions (Liu and Mendoza, 2014). Traffic safety concern is one of the main reasons for parents not allowing their children to walk or

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bike to/from schools (McDonald and Aalborg, 2009).

For safer walking and bicycling and more appealing school commuting modes, a federal program, the Safe Routes to School (SRTS) program was initiated by the US Congress with the 2005 federal transportation bill (Fischer, 2005). Between 2005 and 2012, a total of $1.2 billion was budgeted for the SRTS program including infrastructure enhancement (e.g., sidewalk improvement and pedestrian safety countermeasures) and non-infrastructure interventions (e.g., education, enforcement) (McDonald et al., 2014). The SRTS program initially allocated funding to State transportation departments (DOTs). In 2012, 2015, new transportation bills were passed to combine the existing stand-alone SRTS funding into general walking and bicycling transportation program funding streams. Under the old funding stream, most SRTS funding was awarded in 2008 and 2013. Afterwards, the DOT has had no dedicated funding specifically for SRTS. The SRTS program must compete against other transportation projects (The Safe Routes Partnership, n.d.). Consequently, it is necessary and critical to evaluate whether the SRTS program (when it was a stand-alone program with dedicated funding) had significant impacts and intended outcomes using a pretest-posttest design with longitudinal collision, demographic and built environment data.

Previous studies aiming to evaluate the impacts of SRTS have mostly focused on students' travel mode change (changes in walking and biking rates to/from school). They showed that SRTS slightly increased children's walking or bicycling. According to a national SRTS survey report, 5227 schools participating in SRTS in 2007–2013 had a 3% increase in walking and bicycling (National Center for Safe Routes to School, 2015). Some studies found a moderate increase in walking (from 9.8% to 14.2%) among 53 SRTS schools in four states (Stewart et al., 2014) and a 5–20% increase in walking or biking to/from 14 schools in Oregon after SRTS interventions (McDonald et al., 2013). A systematic review paper summarized that SRTS interventions had a small impact on travel mode change (Cohen's $d < 0.33$) (Chillón et al., 2011).

Another important outcome that needs to be evaluated as part of SRTS impacts is the improvement in traffic safety. However, there are only very few studies that examined longitudinal changes in pedestrian or bicyclist injury associated with SRTS programs, mostly published by the same research group (Dumbaugh and Frank, 2007). DiMaggio and Li (2013) found that the rate of pedestrian injury decreased by 44% for youth aged 5 to 19 in census tracts with SRTS treatments in New York City, while rates were unchanged for census tracts without SRTS (DiMaggio and Li, 2013). Another study analyzed quarterly traffic crash data in Texas to assess the effect of the SRTS program on school-age pedestrian and bicyclist injuries and found that the rates of pedestrian and bicyclist injuries between pre- and post-SRTS periods declined 42.5% (DiMaggio et al., 2015). A recent study found that SRTS intervention was associated with a 23% reduction in pedestrian and bicyclist injuries (DiMaggio et al., 2016). To our knowledge, these are the only published academic papers on SRTS evaluation that specifically focuses on the change in pedestrian or bicyclist safety improvement, even though it was one of the SRTS goals. Other than them, the association between SRTS and collision reduction was rarely tested. Another research gap is that traffic volume, an important and accurate measure of exposure when studying collisions, was not accounted for when pedestrian or bicyclist collision risks were analyzed (Srinivasan et al., 2016; Stewart, 2011).

This study aims to examine whether school-age pedestrian or bicyclist collisions (with traffic volume adjusted) were reduced around schools after SRTS funding, using SRTS eligible schools for 2008 and 2013 SRTS funding in New York State and using a two-group (case-control) pretest-posttest study design.

2. Methods

2.1. School dataset

We identified all public and non-public, K-12 (kindergarten through 12th grade) schools eligible for SRTS funding in New York State with the directory downloaded from the New York State Education Department (NYSED) website (New York State Education Department, 2016). Schools under the categories of 'elementary', 'middle school', 'junior-senior school', and 'K-12 school' were considered eligible for SRTS funding. We excluded schools in New York City because their urban environments, neighborhood-level social and economic characteristics, and traffic volumes are incompatible with those in other parts of New York State. For example, the population density of Buffalo, the second largest city in the state, was 6471 people per square mile, about a quarter of that of New York City's 27,013 people per square mile, according to the 2010 US Census. School density in New York City was 4.49 schools (per square mile), while only 0.07 schools (per square mile) in New York State.

Schools in the NYSED directory constituted the study population. We identified schools' SRTS funding and project information using data from the National Center for SRTS, the official SRTS data clearing house, retrieved in 2018 (National Center for Safe Routes to School, 2018). Data included funding award ID, award amount, SRTS intervention type (infrastructure, non-infrastructure, or combined/both), funding year, and project summary. All SRTS funding awards were announced in either 2008 or 2013. We reviewed SRTS project information and determined not to use the information because sub-type information was unstandardized and insufficient. We reported common intervention types to show details of the SRTS interventions studied in this study. We reviewed the awardee schools and manually matched SRTS information with the NYSED school directory. The funding year was considered as the treatment year when the planned interventions were initiated and occurred.

In this study, we developed two datasets for analyses. The 2008 dataset consisted of schools with 2008 SRTS funding (cases) and all other schools (controls). In the 2013 dataset, we excluded all 2008 SRTS schools and their nearby schools within a 2-mile distance, to avoid potential spatial contamination. If a school was spatially affected by a 2008 SRTS project, it should be excluded from 2013 analysis. The 2-mile distance was determined to make sure that no schools in the 2013 analysis had the spatial contamination issue. Thus, the 2013 dataset consisted of schools with new SRTS funding in 2013 (cases) and schools with no SRTS funding history (controls). Schools receiving SRTS funding in multiple years were excluded in the 2013 dataset, because it is difficult to isolate the effects of multiple funding years.

2.2. School demographics

We obtained the schools' demographic characteristics (enrollment, percent of students in free or reduced lunch, and race/ethnicity composition) from the NYSED's official administrative data, called 'report card' data, originally collected by local school districts. We obtained 2007, 2012, and 2016 report card data (New York State Education Department, n.d.). The time points represent pre-test (1 year before funding) or post-test periods (3–4 years after funding) of the two funding years. Schools were geocoded as points using the New York State Address Geocoder from NYS GIS Clearinghouse.

2.3. Collision data

We used point-level collision data received from the Accident Location Information System (ALIS) in the Safety Program Management and Coordination Bureau, NYS DOT, on January 4, 2019. The data included all vehicle collisions reported by the police and Department of Motor Vehicles offices, from January 2000 to June 2018 (New York State Department of Transportation, 2019). We selected vehicle-to-pedestrian or -bicyclist collisions that involved a pedestrian or a bicyclist, who was aged 5–17 at the time of collision, and defined them as *collisions* of interest in this study (hereafter, "collisions").

2.3.1. Collision count

For each school, we calculated average collision counts per year, occurred during school commuting hours, for the pre-project and the post-project periods, respectively. School commuting hours were defined as 7 a.m.–9 a.m. or 2 p.m.–4 p.m. on Monday through Friday between September 1 and June 30 (DiMaggio and Li, 2013). Next, collisions occurring within a 0.5-mile distance from a school were selected and considered to be associated with the school. We assumed that the 0.5-mile distance is a feasible walking distance for children (Panter et al., 2010; Yu, 2015) and collisions occurred within a 0.5-mile distance from a school are associated with commuting to the school (Abdel-Aty et al., 2007). For the *i*-th school, the average collision counts per year is defined as

$$\mathrm{C}(i,s,t)=\frac{1}{4}\sum_{y}\mathrm{N}(i,\ y) \tag{1}$$

where s is the SRTS dataset year (either 2008 or 2013), t is the time window (either pre- or post-project) explained below, and N (i, y) is the number of collisions in an observation year $y \in Y_{s,t}$. For the 2008 and 2013 datasets, 4-year pre- and post-project time windows were determined as

$$\begin{aligned}
Y_{2008,\mathrm{pre-project}} &= \{2004, \ldots, 2007\}\\
Y_{2008,\mathrm{post-project}} &= \{2009, \ldots, 2012\}\\
Y_{2013,\mathrm{pre-project}} &= \{2009, \ldots, 2012\}, \text{and}\\
Y_{2013,\mathrm{post-project}} &= \{2014, \ldots, 2017\}
\end{aligned} \tag{2}$$

We determined the year time window length as 4 years, the duration gap between 2008 and 2013 SRTS funding announcements. Pre-project periods are 4 years prior to the funding and post-project periods are 4 years subsequent to the funding announcement year. Fig. 1 illustrates the calculation of collisions around schools.

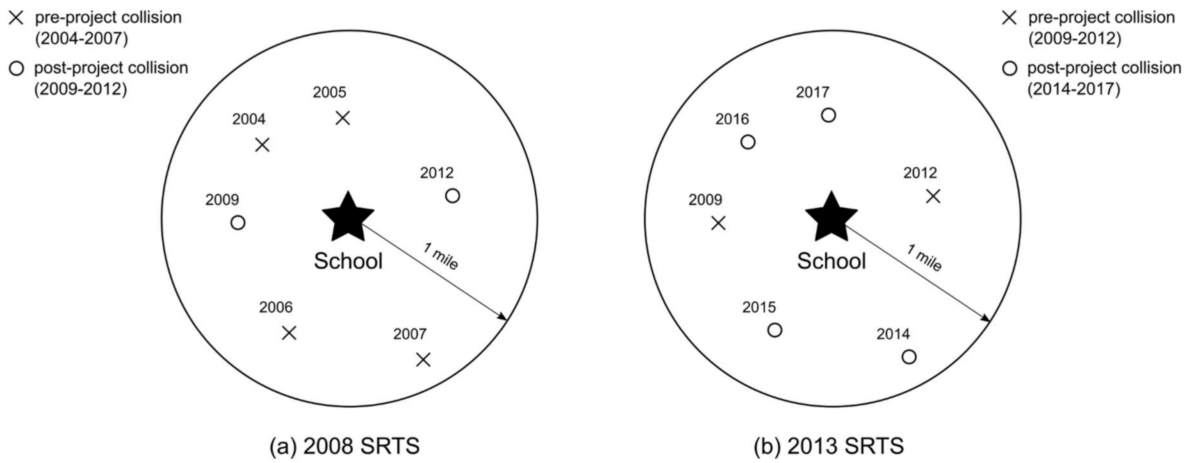

Fig. 1. Calculating collision counts around schools: (a) 1 pre-project collision count per year and 0.5 post-project collision count per year; and (2) 0.5 pre-project collision count per year and 1 post-project collision count per year. The counts are averages over a corresponding 4-year period.

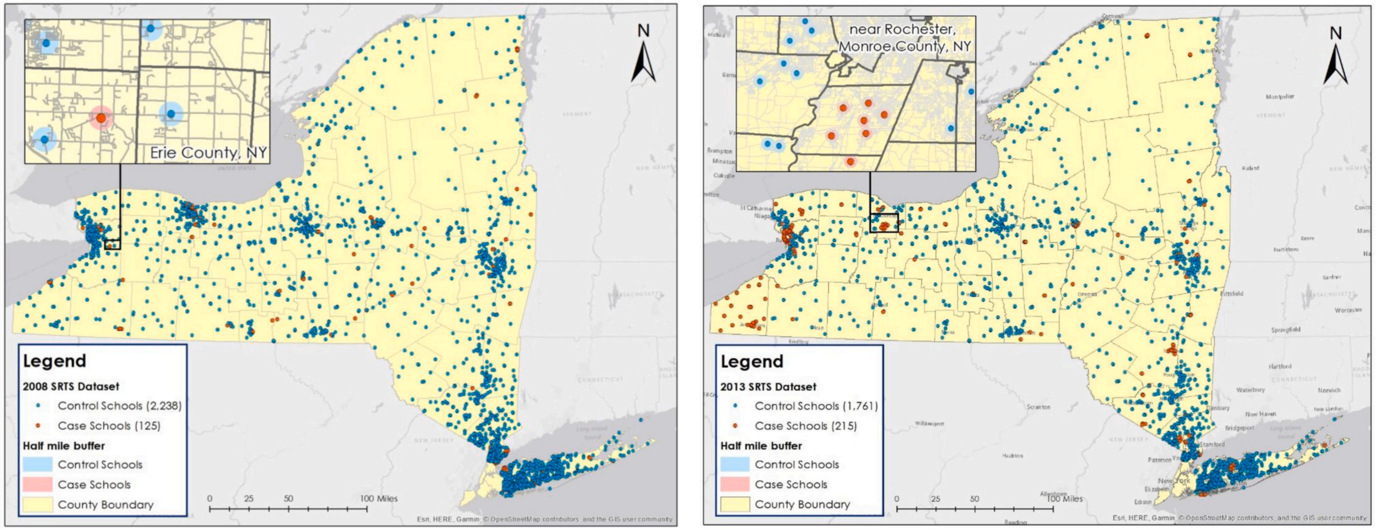

Fig. 2. Locations of Schools: the 2008 dataset (left) and the 2013 dataset (right).

2.3.2. Collision risk

We calculated collision risk by adjusting yearly collision counts with yearly traffic volume as exposure at each school location. Traffic volume at the *i*-th school location, given year *y* and V(*i*, *y*), was estimated from nearby locations' traffic count index, Annual Average Daily Traffic (AADT), and retrieved from the New York State's Open Data Website (New York Open Data, 2019). We used a universal kriging with exponential semi-variogram functions of a straight-line distance between AADT points over school locations, which were adopted from a previous study (Selby and Kockelman, 2013). Traffic volume-adjusted collision risk was defined as

$$\mathrm{R}(i, s, t) = \frac{1}{4}\sum_{y}\frac{\mathrm{N}(i,\ y)}{\mathrm{V}(i,\ y)} \times 1000 \tag{3}$$

2.4. Area-based socioeconomic status and built environment

Area-based socioeconomic status (SES) and built environment characteristics were measured around schools, and the variables were selected based on prior studies (DiMaggio et al., 2015; DiMaggio and Li, 2013; Kerr et al., 2006; Stewart, 2011). They were calculated with area-weighted mean metrics over portions of an available geographic unit (i.e., census tract) within a 1-mile distance from each school, assuming that a school's characteristics are well represented by areas around a 1-mile distance from the school. The number of total population and school-age population, the number of all commuters and active commuters among workers, and the median household income were measured using American Community Survey (ACS) 5-year estimates, which represents an average across the prior 5-year period. We used 2009, 2013, and 2016 5-year ACS data to capture pre- and post-project periods of the 2008 and 2013 datasets. The number of employments was measured using Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics in the best available datasets for the years of 2009, 2013, and 2015.

Street connectivity was defined as the number of intersections within a 1-mile buffer of each school using OpenStreetMap and OSMnx v0.8.1 (Boeing, 2017). The total length of all roads and the total length of non-highway roads (identified with Arterial Classification Codes) were also calculated within 1-mile school buffers. Street connectivity and road lengths were assumed not to change during the study period.

2.5. Analysis

We first conducted univariate analyses to understand longitudinal changes in potential predictors and outcome variables between pre- and post-project periods, using paired *t*-tests and Cohen's *d* tests. Next, we conducted multivariate analysis to examine if SRTS funding was associated with pre-post changes in collision outcomes, after controlling covariates. Selected covariates were related with school commuting behaviors or children's traffic safety, including physical and socioeconomic characteristics of school neighborhoods (McDonald et al., 2010; McDonald et al., 2014; Stewart, 2011). First, pre-project measures that described baseline conditions of the schools and surrounding neighborhood environments were included in the models as covariate candidates. When there were significant changes ($p < 0.05$) and the effect sizes ($|d|$) were $\geq$0.1 between pre- and post-project measures, the difference in measures (e.g., change in total enrollment between pre- and post-project periods) was also counted as the candidates.

In order to address potential multicollinearity issues, any pairs of covariate candidates that were correlated with each other ($\rho > 0.75$), were dropped from the final models. Selected variables include (i) pre-project area-based measures (population density, job density and total road length), and (ii) pre-project school demographics and school demographic change between pre- and post-project measures (percentage of free lunch and total enrollment).

To address the possible regression-to-the-mean (RTM) problem, we employed an analysis of covariance (ANCOVA) model approach (Barnett et al., 2004; Chen et al., 2013; Sterne et al., 2016). Models were established to explain pretest-posttest changes in collision outcomes, with dichotomized SRTS participation as the predictor of interest and pre-project collision status for the RTM problem adjustment. The changes in collision count and collision risk were modeled separately (Model 1 and Model 2).

The significance level was set at $p = 0.05$. Cohen's *d* thresholds were determined as small (<0.2), medium (0.5), and large (0.8). All data processing and analyses were conducted using *R* 3.4.1 (R Core Team, Vienna, Austria) and ArcGIS 10.5 (ESRI, Redland, CA).

3. Results

The NYSED directory included 3723 public and non-public K-12 grade schools. We excluded 1360 schools in New York City and determined 2363 schools eligible for SRTS funding in this study. The National Center for SRTS listed 55 projects that impacted 125 schools in 2008 and 57 projects that impacted 277 schools in 2013. The 2008 dataset includes 125 case schools and 2238 control schools. After excluding the schools that received 2008 funding and their nearby schools located within 2 miles (n = 387), the 2013 dataset had a total of 1976 schools consisting of 215 cases and 1761 controls. SRTS project intervention information was described in the National Center for SRTS report (National Center for Safe Routes to School, 2018). Common infrastructure intervention types include safety improvements, sidewalks improvement (e.g., installation or replacement), crosswalk improvements, ADA ramps, intersection improvement, sign installations (e.g. speed limit signs, school zone signs), multi-use path and guiderail improvements, driver speed feedback trailer deployment. Non-infrastructure types usually include speed data collection study, speed enforcement, and safety education; and there are also a combination type including both infrastructure and non-infrastructure interventions. Fig. 2 shows the locations of schools in two datasets.

From the ALIS database, we identified 82,556 collisions involving a pedestrian or a bicyclist within the study periods of 2004–07, 2009–12, and 2014-17 in the study area (New York State, excluding New York City). Out of them, 2191 occurred with a pedestrian or a bicyclist aged 5–17, within a 0.5-mile distance from the studied schools and were assumed as associated with commuting to/from these schools in the study. Among the studied 2363 schools, 1796 schools (76%) had one collision or more within a 0.5-mile distance from school.

Table 1 shows pre-post comparisons of school characteristics. For both 2008 and 2013 datasets, the *p*-values for paired *t*-tests indicate statistical significance for all characteristics. For the 2008 dataset, most of the school characteristics changed significantly over time. However, their effect sizes were negligible or small ($|d| < 0.2$), except for the percentage of students with a free lunch (+) and area-based median household income (−). From the 2013 dataset, the percentage of students with a free lunch increased significantly over time and the effect size was not negligible ($|d| = 0.40$).

Table 2 shows changes in collision outcomes before and after the SRTS intervention, separated by funding year (2008 vs. 2013 datasets) and funding status (case vs. control). Among the 2008 dataset, case schools had on average 0.21 collisions per year while control schools had 0.17 collisions per year before SRTS intervention. After the intervention, contrary to the expectation, there were no significant changes in both collision count and risk. The effective sizes were all negligible or small ($|d| < 0.2$).

Among the 2013 dataset, case schools had on average 0.21 collisions per year while control schools had 0.14 collisions per year before SRTS intervention. After the intervention, case schools had an average change in collision count (−0.04), which is a larger decrease than that of controls (−0.01). However, they were not statistically significant. On average, collision risk of case and control schools all decreased and the control's decrease was statistically significant. The effect sizes were all negligible or small ($|d| < 0.2$).

We determined to conduct multivariate analysis with the 2013 dataset only. In the 2008 dataset, cases did not have significant differences from controls in terms of the pattern of the change in collision outcomes after controlling for covariates (data not shown). In addition to the main predictor variable (SRTS intervention), we selected covariate variables from school characteristics in Table 1. Selected are shown in Table 4. Percentages of students with limited English proficiency and being White were dropped due to their high correlation with another covariate variable (percentage of students getting a free lunch).

Among the 2013 dataset, we compared case and control schools in terms of pre-project characteristics. As shown in Table 3, cases had higher percentage of students getting free lunch and lower percentage of White students and were located in neighborhoods with lower income and higher job density than controls. There were no significant differences in other characteristics.

Table 1
Pre-post project comparison of school characteristics.

2008 School Dataset (N = 2363)	**Pre-project**		**Post-project**		**Change**	**(% of change)**	**Cohen's *d***	**P-value**
	Mean	**(SD)**	**Mean**	**(SD)**				
School-level demographics								
% Students w/free lunch	23.88	(22.39)	29.29	(23.79)	+4.95	(+21)	0.21	<0.001
% Students w/limited English proficiency	3.77	(7.78)	4.25	(8.03)	+0.43	(+11)	0.05	<0.001
% White	75.79	(28.64)	70.97	(29.47)	−4.28	(-6)	−0.15	<0.001
Total enrollment [person]	449.85	(279.93)	444.46	(260.60)	−11.76	(-3)	−0.04	<0.001
Area-based SES								
Population [person]	8688.22	(10,063.99)	8793.10	(10,088.44)	104.88	(+1)	0.01	<0.001
Median household income [USD]	93,935.46	(115,580.90)	70,820.42	(30,004.23)	−23,115.03	(-25)	−0.25	<0.001
School-age population [person]	2099.83	(5732.51)	2036.45	(5419.52)	−63.38	(-3)	−0.03	<0.001
Job [number]	3872.90	(2591.60)	3781.28	(2486.26)	−91.62	(-2)	−0.02	<0.001
Built environment								
Street connectivity [count]	695	–	–	–	–	–	–	–
Length of all roads [mi]	39.71	(22.23)	–	–	–	–	–	–
Length of non-highway roads [mi]	38.86	(21.93)	–	–	–	–	–	–
2013 SRTS Dataset (N=1976)	**Pre-project**		**Post-project**		**Change**	**(% of change)**	**Cohen's *d***	**P-value**
	Mean	(SD)	Mean	(SD)				
School-level demographics								
% Students w/free lunch	27.50	(21.70)	36.36	(22.14)	+8.86	(+32)	0.40	<0.001
% Students w/limited English proficiency	3.81	(7.27)	4.43	(7.92)	+0.62	(+16)	0.08	<0.001
% Race/ethnicity: White	74.15	(26.95)	69.21	(27.79)	−4.95	(-7)	−0.17	<0.001
Total enrollment	443.10	(250.35)	480.42	(237.08)	+37.32	(+8)	0.16	<0.001
Area-based SES								
Population [person]	7763.28	(9351.87)	7791.53	(9386.76)	+28.25	(+1)	0.00	<0.001
Median household income [USD]	71,914.68	(29,668.49)	74,121.35	(31,052.21)	+2206.67	(+3)	0.07	<0.001
School-age population [person]	3289.49	(4948.71)	3358.26	(5188.55)	+68.77	(+2)	0.01	<0.001
Job [number]	1781.31	(2275.35)	1729.95	(2204.55)	−51.36	(-3)	−0.02	<0.001
Built environment								
Street connectivity [count]	697	–	–	–	–	–	–	–
Length of all roads [mi]	37.42	(21.85)	–	–	–	–	–	–
Length of non-highway roads [mi]	36.64	(21.59)	–	–	–	–	–	–

Table 2
Pre-Post Project Comparison and Case-Control Comparison of Outcome Variables (Collision count and risk).

		Pre- project		Post- project		Diff.	P[a]	Cohen's d
		Mean	SD	Mean	SD			
2008 SRTS Dataset (N = 2363)								
Case (N = 125)	Count[b]	0.212	0.460	0.208	0.392	−0.004	0.882	−0.009
	Risk[c]	0.220	0.795	0.267	0.712	+0.046	0.426	0.061
Control (N = 2238)	Count[b]	0.177	0.382	0.170	0.356	−0.007	0.298	−0.193
	Risk[c]	0.142	0.502	0.149	0.541	+0.006	0.553	0.012
2013 SRTS Dataset (N = 2176)								
Case (N = 215)	Count[b]	0.208	0.345	0.170	0.250	−0.038	0.076	−0.040
	Risk[c]	0.171	0.545	0.169	0.599	−0.002	0.933	−0.062
Control (N = 1961)	Count[b]	0.143	0.328	0.129	0.352	−0.014	0.056	−0.124
	Risk[c]	0.136	0.545	0.104	0.481	−0.032	0.002	−0.004

[a] Paired *t*-test.
[b] Collision count per year within 0.5 mile from school.
[c] Collision count divided by AADT per year within 0.5 mile from school (per 1000).

Table 3
Case-control comparison of pre-project variables (2013 SRTS dataset).

	Mean (Case Schools)	Mean (Control Schools)	Diff.	Cohen's d	P-value
School-level demographics					
% Students w/free lunch	37.42	26.29	11.13	0.52	<0.001
% Students w/limited English proficiency	4.52	3.73	0.79	0.11	0.22
% Race/ethnicity: White	69.28	74.75	−5.47	−0.20	0.01
Total enrollment	447.92	442.51	5.40	0.02	0.74
Area-based SES					
Population [person]	8793.10	8688.22	28.30	0.00	0.96
Median household income [USD]	70,820.42	93,935.46	−17,431.59	−0.60	<0.001
School-age population [person]	3781.28	3872.90	−61.05	−0.03	0.67
Job [number]	2036.45	2099.83	1084.27	0.22	0.03
Built environment					
Length of all roads [mi]	38.61	37.28	1.33	0.06	0.37
Length of non-highway roads [mi]	37.53	36.53	1.00	0.05	0.49

Table 4
Multivariate regression model results (2013 dataset only).

Outcome Variable	Model 1		Model 2	
	Y = Change in Collision Count		Y = Change in Collision Risk	
Predictor Variables	Coeff.	S.E.	Coeff.	S.E.
(Intercept)	0.0278	0.0199	0.0142	0.0297
Population, pre-project (per 1000 people)	0.0223	0.0012 *	0.0124	0.0018 *
Job, pre-project (per 1000 jobs)	0.0046	0.0016 *	−0.0003	0.0024
Students w/free lunch, pre-project [%]	0.0011	0.0003 *	−0.0001	0.0004
Change between pre- and post-project	0.0019	0.0006 *	0.0010	0.0009
Total enrolment, pre-project	0.0000	0.0000	0.0000	0.0000
Total road length	−0.0052	0.0005 *	−0.0028	0.0008 *
SRTS intervention	0.0096	0.0184	0.0532	0.0275
Pre-project collision level (baseline)				
Collision count	−0.6204	0.0210 *		
Collision risk			−0.4261	0.0160 *
Adjusted R^2	0.34		0.27	

* Significance level p-value = 0.05.

Table 4 shows the ANCOVA model results. In both models, pre-project collision level was statistically significant. However, SRTS intervention was not significantly associated with change in collision outcomes. In terms of the goodness of fit, Model 1 had a high adjusted R^2 value (0.34) and Model 2 also had a high value (0.27), showing that the change in collision outcomes were relatively well explained in these models. Pre-project population density and total road length were consistently associated with collision reduction in both models.

4. Discussion

In this study, we attempted to assess the SRTS effectiveness using all SRTS eligible schools within New York State (except New York City). Collision counts and risk associated with school commuting were longitudinally examined. According to our data, schools with 2013 funding had no changes in collision count or in collision risk after SRTS interventions. This is inconsistent with previous studies showing that SRTS interventions were associated with a decrease in pedestrian or bicyclist injury rate by 23%–44% (DiMaggio et al., 2015, 2016; DiMaggio and Li, 2013). Based on our findings, we conclude that SRTS interventions had no effects on collision reduction around schools.

It is noteworthy that pre-project (baseline) collision level was significant in both models, suggesting that the RTM phenomenon may present in our data. When we did not adjust for the potential RTM phenomenon, using a general regression model, not an ANCOVA model, SRTS intervention was significantly associated with collision reduction (data not shown). However, adding the factor of pre-project collision levels as a baseline condition, the significant associations of SRTS intervention disappeared. Studies on traffic safety pointed out that failing to address this issue may lead to overestimation of treatment effects because the effects may not be resulted from the treatment but from the RTM phenomenon (Barnett et al., 2004; Retting et al., 2003). However, many SRTS studies do not consider pre-project or existing collision levels, which may yield treatment effect overestimation.

Our findings, no effects of SRTS on collision reduction, suggest changing future directions of SRTS projects. Promoting stakeholder partnership and engagement has been reported to be a key strategy in successful SRTS programs (Macridis and Garcia Bengoechea, 2015). However, under limited budget, it may be difficult to have active community engagement which requires substantial time and cost. A SRTS evaluation study recommended that successful SRTS programs should have funding to provide on-site, paid staff dedicated to a project because it is difficult to recruit community volunteers (Cooper and McMillan, 2010). Another SRTS study reported difficulties of parents' and other stakeholders' engagement in developing social SRTS programs, although they may be more effective than conventional infrastructure-type interventions (Kang and Diao, 2018). A recent SRTS study found that adding a citizen science engagement model to a SRTS project doubled engagement events and was more effective in increasing children's active transportation than a SRTS project alone (Rodriguez et al., 2019). Technology may be useful to encourage engagement. For example, a research team developed a smartphone app to help parent volunteers organizing a Walking School Bus SRTS program (Ferron et al., 2019).

We focused on collision reduction to evaluate SRTS program's effectiveness. The outcome measures used in this study may be useful for systematic program evaluation and monitoring processes. For example, SRTS program managers may create a logic model that strategically evaluates SRTS activities and their intended results (WK Kellogg Foundation, 2004). Measures like collision reduction are easy to understand and are perhaps more important for program stakeholders including school administrators, police, and children's caregivers. A logic model provides stakeholders with a program's road map describing the sequence from activities to the program's desired results. Because collision outcome measures are objective, easily understood and meaningful, they may serve as a good performance measure when examining effectiveness of SRTS programs.

The presence and quality of infrastructure at baseline may affect collision outcome changes over the study period (e.g., existing sidewalk quality and configuration). However, such detailed data were not available over the entire state in a consistent manner. We instead used urbanization factors (population density, job density, and total road length) as proxy variables. Some of the factors were significant in the regression models, suggesting that it is necessary to include them to explain collision outcome changes. Micro-scale studies are needed to examine qualitative aspects of built environment and their impact on traffic safety.

In the multivariate analysis, we controlled for socioeconomic characteristics of school neighborhoods (the percentage of students with free lunch) because they may affect the relationships between SRTS intervention and street safety (Cooper and McMillan, 2010). The percentage of students with free lunch was significant in the association with collision count while it was not with collision risk, after the traffic volume adjustment. In addition, our ANCOVA models controlled for baseline (pre-project) collision levels which may deal with some uncertainties not explained by existing covariates.

The current study has a two-group pretest-posttest design with defining cases as SRTS schools and controls as non-SRTS schools. Among cases, some SRTS intervention types may have bigger safety effects than others (Stewart, 2011). The report published by the National Center for SRTS provides some details on each project's intervention types (National Center for Safe Routes to School, 2018). However, intervention type information was not standardized across projects. For example, a project had "crosswalk improvement" and another had "crosswalk markings". A project was simply labelled as "safety education" while another was explained with descriptive details as "bike and pedestrian safety awareness campaigns". In our state-scale analysis, we decided to use SRTS intervention as one factor (a dichotomous variable) without further classifying SRTS into sub-types as infrastructure (or engineering) or different kinds of non-infrastructure interventions (education, enforcement, encouragement, or evaluation). As micro-scale study found that different traffic calming countermeasures had different safety effects (e.g., curb extensions, pedestrian refuge islands, raised medians) (Kang, 2019; King et al., 2003), future SRTS studies are needed to focus on detailed intervention types.

In our models, we controlled pre-project built environments (population and job densities and total road length) which may work as proxies of infrastructure qualities at baseline. Pre-project infrastructure qualities (e.g., sidewalk coverage) may affect the association with collision outcomes (Stewart, 2011). In our data, school neighborhood with lower road density was associated with a decrease in collision (Models 1 and 2). Such neighborhoods with low road densities may have poor sidewalk coverage. It is possible that even a small SRTS project may have bigger effect in such neighborhoods.

When assessing collision risk, we did not account for the amount of school-age pedestrians or bicyclists, which could affect collision exposure and consequently collision risk, with two reasons. First, there is no longitudinal standardized data available to estimate the number of school-age pedestrians and bicyclists around studied schools. Second, more importantly, the relationship between collision risk and amount of children's walking and bicycling is not clear. When more children walk, collision risk could increase because more children are exposed to car traffic. Or, it could decrease if drivers become more cautious with the increased presence of pedestrians (safety-in-numbers phenomenon) (Jacobsen, 2015). In fact, a study found that the association between the amount of walking and school-age collision was not significant (Rothman et al., 2014). Because of this possible data unavailability and non-linearity or unclarity, we decided not to adjust the amount of walking and bicycling in assessing collision risk.

Our analysis covered the New York State, aiming to offer some policy guidance and implications for state-run funding and programs. We excluded New York City schools from our dataset because it has the built environment incomparable to other parts of the state and because the city has its own DOT. In our study area, we did not stratify urban and rural areas because more than 90% of schools were located in the US Census-defined urban areas and because an urban-rural dummy variable did not improve our models which already include more detailed built environment factors (e.g., population density). Further studies are needed to focus on specific location and school types.

We used a 0.5-mile airline buffer in counting collisions around each school. A half mile was assumed as a walkable distance for school commuting (McDonald and Aalborg, 2009) and collisions occurred within the distance from a school were spatially associated with the school (Abdel-Aty et al., 2007; Panter et al., 2010; Yu, 2015). In fact, there is no standard buffering distance for SRTS studies (Stewart, 2011). We tested different buffer sizes (e.g., 1 mile and 2 miles) and selected 0.5 miles which may reduce potential spatial mis-association to nearby schools. As for the buffering shapes, we used airline buffers for several reasons. First, studies found that there were no significant differences across buffering methods when explaining the relationship between environments and walking behaviors (Frank et al., 2017; James et al., 2014). Second, because our study covered a large area of the entire state, using a simple method may produce consistency if street network data had varying accuracies and resolutions over the area.

The current study has limitations. First, this study is an observational before-and-after study, not a natural experiment with random assignment. We attempted to adjust the RTM phenomenon or potential selection bias with using ANCOVA models and a relatively long-term statistics based on 4-year time window (Barnett et al., 2004; Chen et al., 2013; Sharma and Datta, 2007). Second, there were no data available on school-level funding allocation when an award has impacted multiple schools. In this case, we assumed that each SRTS-funded school has equally benefitted from the award. Third, we assumed the funding announcement year as treatment year (2008 and 2013) and defined the pre- and post-project period 4 years before and after the treatment year for our study design (2004–2007, 2009–2012, and 2014–2017). However, the completion of the intervention, particularly for infrastructure type with any engineering changes might have been completed a few years after the funding was announced. In addition, some of the datasets from which we calculated the variables were not aligned perfectly with our study design. For example, ACS 5-year estimates are only available from 2005 until 2016 (at the time of submitting the manuscript) and we used the most recent, available dataset. Fifth, we used NYS DOT's official collision data from ALIS, which may have under-reporting issues or misclassification of pedestrian/bicyclist-related collisions with other types of collisions (Noland et al., 2017). Lastly, other qualitative factors that might better explain the reasons for collision or the impact of collisions (e.g., injury severity, contributing factors, and other contextual information) were not considered.

Despite the limitations, our study is a first attempt to examine safety impact of SRTS using longitudinal data and control group study design.

5. Conclusions

Our study found that the SRTS projects in New York State were not associated with the reduction of collisions involving school-age pedestrians or bicyclists occurring school commuting time around schools.

Author statement

B. Kang designed the study, conducted analyses, drafted the article, and was responsible for all aspects of the study. S. Back designed the study and contributed substantively to interpretation and article revision. C. Wang processed and prepared the data for analysis and contributed substantively to interpretation and article revision.

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