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ORIGINAL ARTICLE

Neighborhood Violent Crime and Academic Performance: A Geospatial Analysis

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Highlights

- Research on children's exposure to violence in communities is limited by measurement approaches.
- Geospatial analytic strategies offer a new way to capture experiences with community violence.
- Violence around school buildings relates to average achievement of students in those buildings.

Abstract Decades of empirical work have confirmed that experiences with violence are associated with a variety of adverse behavioral and mental health as well as academic outcomes for children and adolescents. Yet this research largely has relied on indirect measures of exposure. In this study, we apply geospatial analysis to examine the relation between neighborhood violent crime (via police reports) and academic performance (via school-level standardized test proficiency rates). Findings suggest that greater numbers of crimes proximal to school buildings relate to lower levels of academic performance. These results persisted even when controlling economic disadvantage in the student body. Implications for research and policy are discussed.

Keywords Community violence · Geospatial analysis · Academic achievement

Introduction

The research literature on children's exposure to community violence is enormous. Decades of empirical studies have confirmed that both direct (i.e., victimization and in-person witnessing) and indirect (via hearsay, family or friend involvement, or the media) experiences with violence are associated with a variety of adverse behavioral and mental health as well as academic outcomes for children and adolescents (for review see Boxer & Sloan-Power, 2013). Findings regarding the impact of violence exposure are critical given that exposure rates have remained quite high over time (Finkelhor, Turner, Shattuck, Hamby, & Kracke, 2015). For example, via their National Survey of Children's Exposure to Violence (NatSCEV), Finkelhor et al. (2015) reported that in 2011 about 58% of children experienced at least one of five forms of direct victimization, or witnessed violent victimization, in the prior year (physical assault, sexual victimization, maltreatment, property victimization, or witnessing family or community violence). About 41% reported victimization by physical assault and about 22% reported witnessing violence in the prior year, with little change in exposure rates from the 2008 NatSCEV (Finkelhor et al., 2015). Although violence is present in rural and suburban communities, and white youth report exposure, studies suggest that the group with the greatest risk of exposure to violence is youth of color residing in urban communities (Zimmerman & Messner, 2013).

Despite the breadth and depth of the literature on children's exposure to community violence, a number of critical methodological challenges to understanding more precisely how exposure impacts outcomes remain. Perhaps most prominently, very little research has considered the problem of whether children's reports of community violence exposure reflect actual lived experiences veridically or are instead the product of meaningful perceptual biases (Boxer, Sloan-Power, Piza, & Schappell, 2014; Brandt, Ward, Dawes, & Flisher, 2005; Guterman, Cameron, & Staller, 2000; Trickett, Durán, & Horn, 2003). Fowler et al. (2009) have shown that relations between exposure

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and outcomes are stronger when youth self-reports are used for both, and other researchers have observed little agreement between parents and children on ratings of community violence exposure (Boxer et al., 2014; Lewis et al., 2012; Zimmerman, 2014). The apparent majority of studies examining children's exposure to violence have relied on youth self-reports, typically through well-established survey instruments (e.g., Richters & Martinez, 1993). However, there is essentially no evidence to indicate that youth reports of exposure line up well with actual reports of violent crime. Boxer et al. (2014) observed little overlap between children's reports and police reports of violent crime in their neighborhood save for reports of neighborhood homicides. The authors found no significant relations between children's reports of physical assaults, sexual assaults, or robberies, and geocoded police reports of those incidents covering the same timeframe and similar physical location around the child's home address. The authors also observed that child reports of exposure did not correlate with any child- or parent-rated indicators of psychopathology or traumatic stress.

Other researchers also have attempted to bring geocoded police data to bear on the problem of measuring children's exposure to violence, at varying levels of proximity and precision. For example, Tolan, Gorman-Smith, and Henry (2003) examined the role of violent crime in communities in the development of violent behavior in the Chicago Youth Development Study. Tolan et al. (2003) specified violent crime rates within census tracts as community-structural predictors of individual youth involvement violence over time. Sharkey (2010) relied on police indicators of homicide specified at the level of census block groups (smaller than tracts) and evaluated the impact of homicides on children's performance in cognitive tests as the function of temporal and spatial proximity to events. In both cases, exposure to violence via police indicators was inferred as a macro-level background characteristic of a youth's lived experiences, and the researchers were able to draw important conclusions about the deleterious role of violent crime in communities on different aspects of youth development. Yet in neither case did the researchers make direct inferences about whether it was the youths' actual exposure to violence, or their perception thereof that linked to adverse outcomes – or even whether youth participants had any knowledge of the violent crimes having occurred.

Recently, Heissel, Sharkey, and their colleagues (Heissel, Sharkey, Torrats-Espinosa, Grant, & Adam, 2018) integrated geocoded reports of violent crime with experience-sampling and biobehavioral data collection methods to examine the impact of violence exposure on youths' stress reactions and sleep habits. They reported that on nights following local (on a family's home police beat) incidents of violent crime (i.e., physical or sexual assaults, robberies, or homicides), youth had later bedtimes, and on the morning after those incidents they showed dysregulated cortisol patterns. Heissel et al. (2018) were not able to draw inferences based on whether the youth in their sample directly witnessed the crimes logged in the local police beats. However, they found somewhat larger effects of violent crime on sleep patterns as the function of crime proximity: Violent crimes occurring within a half mile of participants' homes (four city blocks, according to the authors) corresponded to significantly later bedtimes (about 30 minutes, $p < .05$) and significantly shorter sleep durations (about 39 minutes, $p < .05$; Heissel et al., 2018, p. 329). Thus, whereas closer proximity does not imply exposure, it certainly increases the likelihood of direct exposure to or at least indirect knowledge of violent crimes, and the results reported by Heissel et al. permit this inference while underscoring the essential importance of measuring the temporal and spatial characteristics of violence.

Indeed, one of the more pressing considerations in advancing developmental research on the impact of violence exposure is how violence in the social context should be conceptualized and operationalized. As Boxer and Sloan-Power (2013) have outlined, there are multiple dimensions to the experience of violence in the social environment – including the exact context and modality of exposure, the specific nature of violent acts, and the duration or persistence of exposure. Yet the vast majority of published literature on youths' exposure to violence has relied on just a small handful of simple metrics – limited almost entirely to whether and how often youth have witnessed violence directly within some prescribed time frame (often over one year, or over the lifetime). The studies employing such measures typically rely on some form of survey methodology that construes violence exposure as a characteristic of the individual – youth either are or are not exposed to violence as the function of their own experiences, and consequently they are or are not affected by this exposure.

Studies on the consequences of exposure to episodic violence – such as direct witnessing of known incidents of serious violence – bear out the value of this construction. For example, in their classic work, Nader, Pynoos, Fairbanks, and Frederick (1990) found that the best predictor of children's post-traumatic stress reactions to a sniper attack at their school was their proximity and level of exposure to the event. But most of the research on the impact of exposure to violence on children and adolescents has relied on reports of more generalized or chronic exposure – in other words, youth reports of exposure and subsequent impacts are not tied to known, discrete events. This approach is not completely limiting – indicators of more chronically experienced violence have been linked via theory-driven analyses to a variety of outcomes including traumatic stress, aggressive behavior, academic difficulties, and emotional symptoms (Boxer & Sloan-Power, 2013; Fowler, Tompsett, Braciszewski, & Jacques, 2009). Yet, we still cannot know what the actual predictors are in those analyses: the actual, lived experiences perfectly or even approximately remembered, or the perceptions of those experiences via memory traces colored by emotional reactions?

Along with the lack of clarity regarding the precise nature of the predictors used to estimate the effect of violence exposure on various outcomes, we also lack critical information about the precise nature of the exposure experiences including where and when they occurred. In terms of "where," although many common instruments ask youth about violence in their neighborhoods, it is difficult to discern what the boundaries of respondents' perceived neighborhoods might actually be. In terms of "when," though we might know reportsinclude the preceding year or a respondent's lifetime, we have no other clear sense of how temporally proximal or distal the exposures were. As noted, Sharkey and colleagues' (Heissel et al., 2018; Sharkey, 2010) use of geocoded and temporally detailed police reports has afforded more precise assessments of exposure in relation to putative individual youth experiences. But through their focus on discrete, episodic events and their immediate outcomes, these findings are relatively less informative with respect to understanding violence in youths' broader community contexts.

In the present study, we consider community violence as a quality of the temporal and physical spaces youth inhabit in their daily lives, and youth outcomes in the aggregate as the potential consequences of differential exposure to community violence in terms of temporal persistence and physical proximity. This represents a meaningful innovation in how violence exposure experiences are captured and operationalized across a wide social ecology. Whereas previous studies have measured violence exposure via individual or police reports in terms of its relation to individual experiences, we utilized police reports to indicate violence across whole communities. We also used aggregated indicators of student performance on school-wide standardized tests in order to examine the cumulative impact of violence on a school community. Our basic hypothesis was that the presence of violent crime would be significantly and negatively associated with standardized test performance. However, the precision of our spatial-temporal assessment of violent crime permitted us to explore a number of corollaries to that assertion. Specifically, we also considered whether incidents of violence that were more spatially (physically closer to school buildings) and temporally (occurring during the school day) proximal to schools would relate more robustly to test scores.

Method

Data Sources

This study was conducted using data on crime and school achievement during academic year 2013–2014 in a medium-sized city in the state of New Jersey (population ~250,000) and was part of a larger project examining risk factors and prevention strategies for violent crime. Data for this study were obtained from two sources: (a) crime incident data were provided by the municipal police department; and (b) school standardized test data were obtained through publicly available online resources maintained by the New Jersey Department of Education.

Crime Incident Data

Violent crime data were collected from the police department's computer-aided dispatch system. Violent crimes consisted of homicides, shots fired, robberies, and aggravated assaults. These included subcategories of deadly weapon, knowingly pointing a firearm, serious bodily injury, and extreme indifference. Violent crime incident data were obtained from August, 2013, through June, 2014, resulting in a total of 1041 violent crimes that could be geocoded (91.5%). As seen in Table 1, many violent crimes occur on the weekends and later in the evenings with lower counts during the day. We aggregated crime incident data over two different time frames based on the academic calendar. First, an *Overall Exposure* indicator accounted for violent crime occurring from the start of August through the end of June (i.e., general exposure to violence across all days and hours; n = 1,041). The second indicator, *School Exposure,* was limited to violent crimes occurring only during the academic year, only during school hours (8 am to 4 pm, conservatively), and only during school days (i.e., weekdays with all public holidays removed; n = 130, 12.49% of Overall Exposure crimes).

To determine how many violent crimes (count) were occurring around each school, the address of each school was joined to city parcel data rather than using a point location. A multiple ring, non-dissolved, buffer was utilized to determine how many violent crimes occurred within 1-block (382 ft), 2-blocks (764 ft), 3-blocks (1146 ft), and 4-blocks (1,528 ft) of each school. The average block length in the target city was computed (382 ft) and applied as the buffer distances. The violent crimes were counted for both the Overall and School Exposure time considerations. Descriptives by buffer zone are shown in Table 2. The ArcGIS program was used for all geospatial mapping and calculations.

Table 1 Temporal heat map of violent crime incidents August 2013 through June 2014

Hour of Day	Day of Week Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	Grand Total
0	9	6	8	7	5	14	10	59
1	7	2	2	3	11	11	15	51
2	6	3	3	5	1	14	13	45
3	3	2	5	2	3	14	14	43
4	1	3	4	2	3	9	11	33
5		1	4		2	5	8	20
6	3	1	1	6	1	3	5	20
7	3	2	1	4	5	2	1	18
8	7		4	2	5	7	1	26
9	3	4	3	5	3	2	2	22
10	5	3	5	3	4	4		24
11	4	4	4		2	2	6	22
12	5	7	9	6	3	3	5	38
13	2	1	6	1	3	2	2	17
14	4	3	4	8	3	8	11	41
15	9	8	2	7	9	5	8	48
16	4	11	11	11	5	7	5	54
17	7	6	6	7	4	5	7	42
18	11	9	15	5	8	6	4	58
19	12	10	11	11	12	6	10	72
20	13	5	6	12	12	5	5	58
21	10	9	9	10	13	6	6	63
22	7	7	13	7	16	12	10	72
23	14	8	10	13	19	16	15	95
Grand Total	**149**	**115**	**146**	**137**	**152**	**168**	**174**	**1041**

Note Heat map includes all 1041 violent crimes recorded city-wide during the study period. Using our 4-block buffer, 970 (93%) of these crimes occurred in spatial proximity to schools.

Table 2 Descriptive statistics

Variables	Minimum	Maximum	Mean	*SD*
Dependent				
Language Art	0.2700	0.9000	0.5062	0.1502
Mathematics	0.2900	0.9100	0.6278	0.1428
Independent				
Economically Disadvantaged %	0.1130	0.9400	0.6914	0.1725
Overall 1-Block	0	20	6.32	5.54
Overall 2-Blocks	1	64	16.05	13.34
Overall 3-Blocks	6	92	31.16	20.76
Overall 4-Blocks	9	136	49.16	31.00
School 1-Block	0	6	1.24	1.57
School 2-Blocks	0	8	2.08	2.09
School 3-Blocks	0	12	3.51	2.79
School 4-Blocks	0	18	5.76	3.99

School Standardized Test Data

We accessed scores from the New Jersey Assessment of Skills and Knowledge (NJASK) test. This is a standardized test administered to students in 3rd–8th grades who attend public school. Upon completion, publicly available school “report cards” are generated to show percentages of students in each school scoring at or above proficiency in two content areas: English Language Arts and Mathematics. These report cards are made available online through the NJ Department of Education’s website. NJASK cut-scores to determine levels of proficiency were set by the state’s Commissioner of Education and the statewide Board of Education (New Jersey Assessment of Skills and Knowledge, 2014, p. 20; see https://www.nj.gov/education/assessment/ms/5-8/ref/SIM14.pdf). The proficiency percentages for these two content areas were used as two separate dependent variables. We were able to recover NJASK scores for all 37 public schools in the city serving 3rd through 8th graders for our current analyses.

Proportion of Economically Disadvantaged Students

Information about economically disadvantaged students per school also was sourced from the publicly available school "report cards." This information appears as a percentage of students classified as "economically disadvantaged," based on the percentage who have qualified for free or reduced school lunches.

Analysis Overview

We start by examining the bivariate correlations between the buffer crime counts and school testing. Next**,** the violent crime counts (sums) per spatial buffer zone and within each temporal indicator (Overall Exposure and School Exposure, as per above) were fixed as independent variables to predict the percentage of students at a school testing at or above proficiency in Language Arts and Mathematics, with and without percentage of economically disadvantaged (ED) students included as a covariate. These analyses resulted in 16 predictive models for Language Arts (i.e., 4 for Overall Exposure and 4 for School Exposure, with and without the ED covariate) and 16 predictive models for Mathematics (again, 4 for Overall Exposure, 4 for School Exposure, with and without the ED covariate).[1]

Results

Descriptive statistics are presented in Table 2. As shown, the number of violent crimes captured in the buffers generally increases as distance from school increases and more area is covered. The average percentage of students by school testing at or above proficiency in Language Arts was 50.62% and 62.78% for Mathematics. The percentage of students economically disadvantaged by school ranged from 11.3% to 94%. Correlations (Table 3) indicated the general negative association between the

[1] The Overall Exposure 2-blocks buffer and percent students economically disadvantage were leptokurtic. A natural log transformation was used for the Overall Exposure 2-blocks and an arcsine transformation for the economically disadvantage variable, bringing the values between +-2. The values seen in the Descriptive table reflect the pre-transformation values.

Table 3 Correlations

	Language Arts	Mathematics	Econ. Dis	School 1	School 2	School 3	School 4	Overall 1	Overall 2	Overall 3	Overall 4
Language Arts	1	0.803**	−0.433**	−0.002	−0.075	−0.020	−0.162	−0.303	−.371*	−0.323	−0.359*
Mathematics		1	−0.364*	−0.176	−0.263	−0.179	−0.248	−.426**	−0.443**	−.398*	−0.387*
Economic Disadvantage By School			1	−0.023	−0.026	−0.070	−0.034	0.138	0.317	0.070	0.135
School 1				1	0.858**	0.733**	0.564**	0.652**	0.434**	0.483**	0.447**
School 2					1	0.910**	0.797**	0.680**	0.589**	0.638**	0.593**
School 3						1	0.917**	0.734**	0.599**	0.710**	0.684**
School 4							1	0.728**	0.633**	0.725**	0.733**
Overall 1								1	0.810**	0.833**	0.824**
Overall 2									1	0.836**	0.812**
Overall 3										1	0.980**
Overall 4											1

**Correlation is significant at the .01 level (2-tailed).
*Correlation is significant at the .05 level (2-tailed).

Table 4 OLS: exposure to crime and language art proficiency

	Overall exposure				School exposure			
	b	*SE*	β	Adj R^2	*b*	*SE*	β	Adj R^2
Model 1a								
Overall 1-Block	−.008†	0.037	−.303	.066	.000	0.016	−.002	−.029
Model 1b								
Overall 1-Block	−.007†	0.004	−.248		−.001	0.015	−.012	
% Economically Disadvantaged	−.269*	0.102	−.398	.203	−.293**	0.105	−.433	.140
Model 2a								
Overall 2-Blocks	−.063*	0.027	−.371	.113	−.005	0.012	−.075	−.023
Model 2b								
Overall 2-Blocks	−.044†	0.027	−.260		−.006	0.011	−.087	
% Economically Disadvantaged	−.237*	0.106	−.350	.204	−.294**	0.104	−.435	.147
Model 3a								
Overall 3-Blocks	−.002*	0.001	−.323	.078	−.001	0.009	−.020	−.028
Model 3b								
Overall 3-Blocks	−.002*	0.001	−.294		−.003	0.008	−.051	
% Economically Disadvantaged	−.279**	0.099	−.412	.230	−.295**	0.105	−.436	.142
Model 4a								
Overall 4-Blocks	−.002*	0.001	−.359	.104	−.006	0.006	−.162	−0.002
Model 4b								
Overall 4-Blocks	−.001*	0.001	−.306		−.007	0.006	−.177	
% Economically Disadvantaged	−.265*	0.099	−.391	.237	−.297**	0.103	−.439	.172

*$p < .05$; **$p < .01$; †$p < .1$.

violent crime measures and the separate dependent variables. The measure of percent economically disadvantaged students by school was negatively and significantly associated with Language Arts and Mathematics scores at or above proficiency, as expected. The correlation matrix also indicated there was not a significant relation between percent economically disadvantaged students by school and any of the crime-block variables.

Findings from the Overall Exposure to violent crime are presented in the left sides of Tables 4 (Language Arts) and 5 (Mathematics). Two models were run for each block, one containing crime only and the second including percentage of economically disadvantaged students by school. Across all models including only Overall Exposure to violent crime, there was a significant and negative relationship found. Generally, as the number of violent crimes increased, the proficiency percentage decreased by school. The variation explained by only Overall Exposure ranged from 6.6% to 11.3% for Language Arts and 12.6% to 17.3% for Mathematics. With the addition of the economically disadvantage measure, the variation explained increased with both measures remaining significantly and negatively associated with proficiency percentage for Language Arts and Mathematics. When percentage of economically disadvantaged students by school was included, the variation explained for percentage of student proficient or above by school for Language Arts ranged from 20.3%–23.7% and 20.5%–23.4% for Mathematics.

Again, the Overall Exposure captures violent crime around schools more broadly but does not distinguish between crimes occurring when school is in session. Predictive analyses using the *School Exposure* measure addressed this distinction directly. Mirroring the Overall Exposure models, School Exposure models found percentage of economically disadvantaged students by school to remain significant in each model. When School Exposure crime by block is included in each model by itself, it was not found to be significantly associated with proficiency percentages across Language Arts (Table 4) and Mathematics (Table 5), and in many instances, an adjusted r^2 indicated no explanatory value with School Exposure by itself. When School Exposure 2-Blocks and 4-Blocks are examined for Mathematics, there is a marginally significant ($p < .1$) relationship between School Exposure crime counts and proficiency percentage while accounting for the percentage of economically disadvantaged students by school. Overall, the percentage of economically disadvantaged students by school explained 14.0%–17.2% of the variation in Language Arts Proficiency and between 11.8% and 16.1% of Mathematics Proficiency.

Discussion

In this study, we applied geospatial analytic methods to examine relations between violent crime rates and aggregated student academic performance in urban neighborhoods. Relying on data sourced from a municipal police department (crime incident reports) and a state office of education (proficiency rates in English Language Arts and

Table 5 OLS: exposure to crime and mathematics proficiency

	Overall exposure				School exposure			
	b	*SE*	β	Adj R^2	*b*	*SE*	β	Adj R^2
Model 1a								
Overall 1-Block	−.011**	0.004	−.426	.158	−.016	0.015	−.176	.003
Model 1b								
Overall 1-Block	−.010*	0.004	−.383		−.017	0.014	−.184	
% Economically Disadvantaged	−.200*	0.095	−.312	.234	−.237*	0.101	−.369	.118
Model 2a								
Overall 2-Blocks	−.072**	0.025	−.443	.173	−.018	.011	−.263	.043
Model 2b								
Overall 2-Blocks	−.059*	0.025	−.364		−.019†	0.010	−.273	
% Economically Disadvantaged	−.160	0.101	−.249	.208	−.239*	0.098	−.372	.161
Model 3a								
Overall 3-Blocks	−.003*	0.001	−.398	.134	−.009	0.009	−.179	.004
Model 3b								
Overall 3-Blocks	−.003*	0.001	−.374		−.011	0.008	−.205	
% Economically Disadvantaged	−.217*	0.094	−.338	.230	−.244*	0.400	−.379	.126
Model 4a								
Overall 4-Blocks	−.002*	0.001	−.387	.126	−.009	0.006	−.248	
Model 4b								
Overall 4-Blocks	−.002*	0.001	−.344		−.009†	0.005	−.261	
% Economically Disadvantaged	−.205*	0.096	−.318	.205	−.240*	0.099	−.373	.154

*$p < .05$; **$p < .01$; †$p < .1$.

Mathematics on standardized tests), we observed significant links between the presence and extent of violent crime surrounding a school building and rates of aggregated student academic performance. Higher levels of violent crime in physical proximity to school buildings were linked fairly consistently to lower levels of proficiency in both English Language Arts and Mathematics. Relations were attenuated somewhat when rates of economically disadvantaged students were taken into account such that overall violent crime rates still predicted academic proficiency rates but not crime rates during school hours. The results are essentially consistent with the literature but have meaningful implications for advancing methods for studying children's experiences with community violence. Further, these findings suggest new ways to think about how and why community violence exposure might impact children's school adjustment and educational achievement.

Although a large volume of research has confirmed links between children's exposure to violence in their communities and a wide range of psychological and behavioral outcomes, this literature rests primarily on self-reported indicators of exposure. That is, most of what we know about how encounters with violence in communities affects children is based on the children's reports of what they have seen, heard, and experienced – their perceptions of exposure. On one hand, an argument could be made that this is all that should matter from the standpoint of refining theory and developing intervention practices. Theories reliant on cognitive (e.g., the development of normative beliefs supporting the use of violence; Guerra, Huesmann, & Spindler, 2003) or emotional (e.g., dysregulated coping in response to violence; Boxer, Sloan-Power, Mercado, & Schappell, 2012) pathways linking violence exposure to child outcomes do not hinge on whether perceptions are veridical to lived experiences. Interventions targeting symptom reduction or wellness promotion in the wake of community violence exposure need not consider whether children's recall of their experiences is exactly accurate.

On the other hand, however, moving existing theory forward and broadening the targets of intervention both require a clearer and more precise understanding of what it means to say a child was exposed to community violence, and the present study makes substantive strides in this regard. Our application of geospatial analysis at the broad, community level to consider the potential impact of violence exposure on children's development is novel and represents an important innovation. As Boxer and Sloan-Power (2013) observed, documenting and examining children's experiences with violence requires a multidimensional framework that allows for knowing not only the context (e.g., community) of exposure but also the content (intensity, severity), channel (method of exposure), and chronicity (e.g., episodic, persistent) of exposure. The results presented here thus reify the importance of proximity and highlight the utility of geospatial methods for describing the nature of exposure (see also Boxer et al., 2014). Applying geospatial analytic methods to examining the consequences to children of violent crime exposure also connects this area of inquiry to the wider field of contemporary communitywide crime prevention (Caplan, Kennedy, Piza, & Barnham, 2019; Garnier, Caplan, & Kennedy, 2018; Kennedy, Caplan, & Piza, 2018). Modern urban law enforcement is increasingly reliant on geospatial analytics to assess neighborhood-level dynamics of crime, improve the efficiency of directed patrols, and guide the development of police-led and community-supported interventions (Caplan, 2011; Caplan & Kennedy, 2016; Caplan, Kennedy, & Miller, 2011; Kennedy, Caplan, Piza, & Buccine-Schraeder, 2016).

Despite our use of newer methods, our findings are consistent with the consensus of the vast extant literature linking community violence exposure to adverse outcomes for children and adolescents. To be sure, most of this research has considered mental and behavioral health outcomes such as traumatic stress reactions, depression, anxiety, and aggressive behavior (Fowler et al., 2009) along with sleep problems (Heissel et al., 2018; Kliewer & Lepore, 2015) and problems in emotion regulation and desensitization (Gaylord-Harden, Bai, & Simic, 2017; Gaylord-Harden, Cunningham, & Zelecik, 2011), but some has shown impacts on academic achievement as well (Borofsky, Kellerman, Baucom, Oliver, & Margolin, 2013; McCoy, Roy, & Sirkman, 2013; Schwartz & Gorman, 2003). Our findings suggest that schools situated in communities marked by higher levels of violent crime serve students who are, in the aggregate, less academically proficient. These findings, however, require some qualification when considering the additional role of economic disadvantage, which we incorporated with an indicator reflecting the percentage of students in each school receiving free or reduced lunches. When this indicator was included as another predictor, only the Overall Exposure measure (violent crime incidents on any day, any time) but not the school-day measure (violent crime incidents only during school hours and on school days) retained a significant effect on academic proficiency outcomes. This suggest that violence exposure as a broader socialization factor (i.e., attending school in a generally violent neighborhood) impacts academic performance more than does violence exposure as a situational contextual factor (i.e., proximal violent incidents occurring throughout the school day). Of course, crime and economic disadvantage often go hand-in-hand (Sampson, Raudenbush, & Earls, 1997) and generally yield both independent and additive impacts on academic performance (Leventhal & Brooks-Gunn, 2000).

Observing fairly consistent links between violent crime and academic outcomes is unsurprising, but our measurement strategy permits us to move beyond this relatively common finding. Unlike prior research in this vein, which has relied on analysis of the broader social ecologies of students in drawing links between community factors and educational outcomes (e.g., Milam, Furr-Holden, & Leaf, 2010; Tolan et al., 2003), we were able to pinpoint violent crimes to the immediate physical surroundings of school buildings. This suggests a more direct effect of exposure to violent crime on children's academic status although we do not have data available to indicate the extent to which children were aware of any specific incidents. Other research suggests that children might only be sensitive to high-profile violent crimes such as homicides (Boxer et al., 2014), but our findings here raise the possibility that children might be responsive to persistent ambient violence in their social ecologies.

Of course, our data span an academic year and our analyses test unidirectional effects of neighborhood violent crime on aggregated academic outcomes across schools. It might be the case that struggling student populations influence increases in crime within a given neighborhood. For example, Steinberg, Ukert, and MacDonald (2019) recently showed that the closure of underperforming schools in Philadelphia led to reductions over time in violent crime. These authors utilized Census block-level indicators of violent crime supplemented with school-level data and suggested that the displacement of youth with propensities to offend led to the drop in crime rates. This might indeed be the direction of effect; but as Sharkey (2010) has noted, individual behaviors and ecological phenomena operate transactionally and the findings reported by Steinberg and colleagues raise a critical "chicken and egg" issue of which came first – the struggling schools, or the violent crime? The Steinberg et al. (2019) analysis implies that crime reduction can follow from school closures; ours suggests that academic gains might follow from crime reduction. Still, because our violent crime data span the entire academic year while our academic performance data were generated at various time points throughout the spring, any causal inferences are necessarily circumscribed. Future studies using these methods should include clear causal ordering and consider incorporating additional measures of student information as covariates, such as total school population sizes, proportion of students receiving punitive sanctions (e.g., suspensions and expulsions), or proportion of students receiving special education for behavioral health conditions could further clarify the nature of effects.

At a time when the study of human development appears to be moving ever-inward, toward more detailed explication of brain and body processes, research seeking to capture more accurately the nature of the social environment of the community remains a critical direction. Prior work has utilized extensive observation and coding of social-physical spaces effectively (Furr-Holden et al., 2008; Milam et al., 2010; Raudenbush & Sampson, 1999). Yet geospatial analytic methods leveraging administrative data such as police incident reports (Caplan et al., 2019; Heissel et al., 2018; Kennedy, Caplan, & Piza, 2011) represent an efficient and innovative set of tools for operationalizing and measuring environmental characteristics. This might be particularly useful in tandem with mixed-method approaches integrating data from sources such as in-person surveys, Census records, and ethnographies (e.g., Boxer et al., 2014; Pratt, King, Burash, & Tompsett, 2019). These tools and the associated theoretical frameworks that guide their use can help to shape developmentally informed policies promoting community safety, academic achievement, and positive youth development more broadly.

Compliance with Ethical Standards

The authors of this manuscript have complied with APA ethical principles in their treatment of individuals participating in the research, program, or policy described in the manuscript. The research has been approved by the Rutgers University IRB.

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Conflict of Interest

The authors have no conflicts of interest to declare with respect to the research presented in this article.

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