No Crime Left Behind:

Exposure to Neighborhood Violence and School Performance in New York City

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ABSTRACT

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Educational policy has increasingly focused on holding teachers and schools accountable for student performance. Yet popular and academic writers have long connected exposure to neighborhood violence to poor student performance. Newly available datasets, statistical methods and computer technology allow for greater power and additional control in analyzing this relation. Using school and neighborhood data (N = 792,374 students from 1,240 school neighborhoods) from New York City between 2006 and 2010, multilevel models were used to test whether exposure to violence in the school neighborhood (the number of police-reported felony assaults, homicides, rapes and robberies) predicts student performance (scaled scores on annual English and math tests). Violent crime is significantly associated with negative students outcomes controlling for a host of student and school neighborhood level variables including poverty and prior violent crime. Effect sizes were larger when predicting math outcomes than English, and for students in middle school as opposed to elementary school. These findings suggest that educational policymakers must distinguish exposure to violence from teacher and school effects and that neighborhood violence must be addressed by stakeholders of child development whether in schools or in society at large.

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CHAPTER I. INTRODUCTION

Federal funding of K-12 public schools has been increasingly tied to student performance since the passage of No Child Left Behind (NCLB) in 2001. Schools must have all (at least 95% of) students, regardless of background, pass annual subject-area tests by 2014. Failure to meet pre-determined benchmarks results in student out-transfers, staff reassignments, and even school closure. Evaluation of individual teachers has also been tied to student test scores as a part of the Race to the Top program implemented in 2009. This present education reform movement is popularly referred to as “No Excuses” for emphasizing that schools must be accountable for student performance.

Such policies may have unintended consequences, however, if factors that are external to education – such as exposure to neighborhood violence (ETV) – are considered endogenous. Present educational analyses account for student-level characteristics such as race and poverty. Yet ETV and other neighborhood dynamics are rarely included, even as a number of studies have linked ETV with a number of negative child outcomes. If ETV predicts lower student performance independent of existing controls, failure to acknowledge ETV results in schools and teachers being held accountable for these gaps. That is to say, differences due to ETV are assumed to come from within schools (and thus endogenous), rather than from outside of the school (exogenous).

This study uses administrative data for New York City from 2006 through 2010 to analyze the relation between exposure to violence in the school neighborhood and student performance. The participant sample included 792,374 students attending 1240 New York City public schools serving grades three through eight from 2006 through 2010. Student performance data were collected from the New York City Department of Education (NYCDOE) and verified using records from the New York State Education Department. These data are disaggregated by grade and by year, as well by student gender, race, and eligibility to receive English language learner services, special education services, and free or reduced price meals. Data on violent crime and community disorder were originally collected for by the New York Police Department (NYPD), the New York City Department of Sanitation (DSNY), the Administration for Children's Services (ACS), the Mayor's Office for Operations and the New York City Department of Health and Mental Health (DOHMH) and are publicly available from the New York City Department of Information Technology and Telecommunications (DIIT). Additional neighborhood data on poverty, immigrant concentration and residential stability were derived from the United States Census' American Community Survey.

The research questions for this study were as follows: (a) Is ETV associated with lower student performance in school? (b) Does ETV improve existing models of predicting student performance? (c) Does the relation between ETV and student performance differ for students by gender, race, age, poverty, English language learner status, or special needs status? (d) Is ETV a better predictor of student performance than community disorder? (See Figure 1.)

It was hypothesized that: (a) higher rates of ETV will be associated with lower student performance. (b) ETV will be a significant predictor and improve model fit over existing models which include only student level factors. ETV will also remain significant across a robust battery of models independent of concentrated disadvantage, past violence and other neighborhood characteristics. (c) Associations between ETV and student performance will be smaller for students with a number of known risk factors including being older, being male, being black or Latino, and being an English Language learner or a student with special needs. Past research has argued that these weakened links reflect a weathering effect, where more proximal risk factors have already negatively conditioned individuals so as to be less impacted by more distal risk factors. (d) ETV will remain a significant predictor of student performance in comparison with and controlling for community disorder.

Across all tested models, ETV significantly predicted negative school outcomes. This relation was significant when controlling for student-level characteristics including family poverty status. It remained significant when controlling for school neighborhood-level risk factors including concentrated disadvantage and prior violence. As hypothesized, interaction terms between violence and known risk factors tended to be positive reflecting a potential weathering effect due to prior or more proximal experiences. Given that all tested interactions were two-interactions, however, these should be interpreted with caution. The major exception regarding interactions involved stronger negative associations for students in middle school as opposed to elementary school. Finally, comparisons of model fit statistics and coefficient estimates for ETV and community disorder proved inconclusive as the two measures were highly correlated.

Taken together, these findings suggest that stakeholders in children's education and development must address ETV. Failure to account for ETV in educational evaluation produces biased estimates of teacher and school effectiveness. Furthermore, the present "No Excuses" paradigm has resulted in a lack of specifically tailored responses to unique stressors such as ETV. Policymakers and researchers must also ask if schools are the ideal treatment setting for ETV and policies designed to curb ETV and its potential links to student performance.

CHAPTER II. LITERATURE REVIEW

The Present Educational Paradigm

Public education has played an increasing role in child development and social policy over the last half century (Hochschild & Scovronick, 2003). Advocates have argued that schools represent a means of developing a skilled workforce, repaying veterans, competing with other countries, and even solving social inequality (Cross, 2004). Some of these goals have proven more daunting than others. Coleman’s (1966) seminal Equality of Educational Opportunity Study placed in stark relief just what public education was challenged with addressing. Twelve years after court-ordered desegregation, contextual factors such as student race and socioeconomic status (SES) were stronger predictors of student performance than school quality and funding.

Today, many schools continue to reflect neighborhood dynamics of de facto racial segregation (Balfanz, 2009) and growing socioeconomic disparity (Massey & Denton, 1987, 1993). Over time, this persistence of intergenerational poverty has resulted in increasingly concentrated disadvantage (Anderson, 1978, 1990; Wilson, 1987, 1996). Yet policymakers continue to insist that public schools can be the source of social and economic uplift.

While testing has been part of federal education policy since 1965, the 2001 NCLB/ESEA Reauthorization Act firmly mandated this belief. Testing is no longer optional. All (at least 95% of) students must pass core subject tests by 2014. A school’s Annual Yearly Progress (AYP) goal is defined as the difference between its prior year pass rate and 95% divided by the number of years remaining until 2014. Schools not meeting AYP for two consecutive years are placed on notice. Schools not meeting AYP for three consecutive years are required to provide additional services for failing students. Repeated failing schools must also allow students to transfer to other schools. Finally, states are required to close schools consistently failing to meet AYP.

In 2009, the Obama administration's Race to the Top program further increased pressure on schools by tying teacher evaluations to student test scores. Such evaluations attempt to estimate individual teacher's contribution to student outcomes by controlling for student characteristics that are exogenous to the classroom (Wright, Horn & Sanders, 1997). This belief that teacher and school effects can be isolated from context and should be used as leverage to improve student outcomes has been popularly referred to as 'no excuses' (Thernstrom & Thermstrom, 2003).

If certain factors are unintentionally excluded from these analyses, however, these evaluative metrics will produce biased estimates. Given the present educational paradigm, such findings might negatively impact school staffing and future policies. New educational research must focus on finding any such confounding variables to prevent this.

Exposure to Violence

Exposure to violence is one such variable and has long been linked to negative developmental outcomes (for a review, please see Foster, & Brooks-Gunn, 2009). ETV includes being a victim of or witnessing acts of physical, emotional, and sexual violence and can occur within multiple ecological contexts such as at home, in one's neighborhood, or at one's school or job (Zielinski, & Bradshaw, 2006). While neighborhood violence may seem more distal, both non-victim and non-perpetrator youth are highly attuned to acts of neighborhood violence (Aneshensel & Sucoff, 1996). These perceptions of ETV, in turn, have been correlated with poor mental health outcomes. Others have found ETV at school and in the community to be a stronger predictor of trauma symptoms than ETV at home (Springer, & Padgett, 2000).

ETV represents a source of stress for individuals across the life course (Macmillan, 2001) and can be modeled as a single traumatic event or a constellation of life stressors operating concurrently or sequentially (Osofsky, 1995; Pearlin, 1989). ETV in one domain or as a witness is associated with increased likelihood of ETV in other domains or as a victim (Hanson et al., 2006; Mrug, Loosier, & Windle, 2008; Osofsky, 1995). Individuals' responses to ETV vary based on personal characteristics, timing, severity, and social and physical context with the potential for ETV to interrupt or shift developmental trajectories (Margolin, & Gordis, 2000).

Children represent unique targets of ETV in that the experience of such stress potentially incapacitates not only their ability to function, but also their parents' and other adults' (such as teachers) ability to care for them (Margolis, & Gordis, 2000). Similarly, additional risk factors can interact with ETV to influence child development both directly and indirectly through parents and other adults (e.g. parental drug use, Hanson et al., 2006). Children can be victims of or witnesses to violence in communities as well as in schools, further increasing the likelihood of ETV as they age into adulthood (Lambert, Ialongo, Boyd, & Cooley, 2005). School transitions, in particular, have been identified as a potentially critical time for elevated risk of victimization (Stewart, Livingston, & Dennison, 2008). Furthermore, as peer influences are more prevalent during childhood and adolescence, ETV has been found to have larger effect sizes for youth with strong peer bonds (Kliewer, Murrelle, Mejia, de Torres, & Angold, 2001).

Much research suggests that children and families living in poverty disproportionately experience ETV (Pearlin, 1989). ETV can serve as a mediator for the relation between poverty and child outcomes (McLeod, & Shanahan, 1993) or independently of poverty as a part of the systemic inequality facing disadvantaged children (e.g. Delaney-Black et al., 2002). A number of studies have found that ethnic minorities, boys, and urban residents also experience higher levels of ETV, but there is no consensus as to differential effects of ETV on developmental outcomes (for contrasting reviews and analyses, please see Buka, Stichick, Birdthistle, & Earls, 2001, and O'Keefe, & Sela-Amit, 1997, versus Guerra, Huesmann, & Spindler, 2003, and Sternberg, Baradan, Abbott, Lamb, & Guterman, 2006). Much of this research suggests that racial, gender and age differences do exist, but vary in significance and directionality depending on witnessing versus victimization (e.g. Hanson et al., 2006), on domain (e.g. physical versus sexual, Schilling, Aseltine, & Gore, 2007), on context (e.g. family versus neighborhood, McCart et al., 2007), on exposure to violence versus associated behavior (e.g. Rosario, Salzinger, Feldman, & Ng-Mak, 2008), or on outcome measured (e.g. depression versus anxiety, Hammack, Richards, Luo, Edlynn, & Roy, 2004).

For developing children and adolescents, researchers have identified socioemotional well-being as a key behavioral outcome linked to ETV that can be measured by clinical diagnoses or symptom or behavior counts (Margolin, & Gordis, 2000; Sternberg et al., 2006). These associations can be quite longstanding, with family violence witnessed during preschool predicting behavioral outcomes at 16 years of age (Yates, Dodds, Sroufe, & Egeland, 2003). It should also be noted that these associations have been found to be bidirectionally (Boyd, Cooley, Lambert, & Ialongo, 2003; Storr, Ialongo, Anthony, & Breslau, 2007) and perhaps even transactionally (Lynch, & Cicchetti, 1998). Coping styles have also been found to moderate these associations (Rosario et al., 2008), which, in turn, predict reports of violence (e.g. Guerra et al., 2003) and juvenile delinquency at home, in the community, and in students' schools (e.g. Harris, Duncan, & Boisjoly, 2002).

Other studies have found socioemotional processes and problem behaviors to mediate the association between ETV and cognitive and school-based academic outcomes (Delaney-Black et al., 2002; Schwartz, & Gormon, 2003). Academic results associated with ETV were found for children as young as age 6 to 7 years old with reading and IQ scores (Delaney-Back et al., 2002) through adolescence with educational attainment and GPA (Hagan, & Foster, 2001; Macmillan, & Hagan, 2004). School attendance has also been linked to ETV and represents another potential mediator for academic outcomes (Hurt, Malmud, Brodsky, & Giannetta, 2001). As will be discussed later, a number of school-based dynamics and processes such as connectedness and teacher and peer support serve potentially as protective factors for youth in schools (e.g. Crooks, Scott, Wolfe, Chiodo, & Killip, 2007).

Methodologically, the majority of ETV studies have relied on child self-report (e.g. the Conflict Tactics Scale in Straus, 1979; the Survey of Exposure to Community Violence in Richters & Saltzman, 1990). The question of reliability has been raised, though, with a number of studies reporting mixed results in measuring parent-child agreement with regard to child ETV (for poor correlations, please see Kuo, Mohler, Raudenbush, & Earls, 2000; Shahinfar, Fox, & Leavitt, 2000; Thomson, Roberts, Curran, Ryan, & Wright, 2002). Video sequences have also been used reliably to help children talk about ETV (Shahinfar, et al., 2000). Finally, a smaller group of studies have utilized administrative data such as child welfare files and police crime reports, at the family and neighborhood level to measure ETV (Bingenheimer, Brennan, & Earls, 2005; Herrenkohl, Tajima, Whitney, & Huang, 2005). Geographic analyses have been used in at least one study to verify the correlation between such administrative data and participant reports of community violence (O’Donnell, Schwab-Stone, & Muyeed, 2002).

ETV is a multi-faceted construct with the potential to function in conjunction with other stressors and to carryover from one developmental domain to another and from one developmental stage to another (Thoits, 1995). ETV has been associated with outcomes ranging from behavior problems for children as young as three years of age (Linares et al., 2001) to employment status and wages during early adulthood (Macmillan, & Hagan, 2004; Schilling et al., 2007). Links between ETV and schools have been found, with one study even showing the intergenerational educational consequences of ETV (Tajima, 2004). In surveying the range of studies across different populations and outcome variables, one should see these widely varying findings as evidence of the complexity of ETV and its relevance as a broader and more general, rather than specific, influence on developing individuals (McMahon, Grant, Compas, Thurm, & Ey, 2003; Schilling et al., 2007).

Additional Neighborhood Predictors

In researching ETV, several additional neighborhood factors must be considered as possible counterfactuals to control for. Concentrated disadvantage and community disorder are highly correlated with exposure to violence (Sampson, Raudenbush, & Earls, 1997). Immigrant concentration and residential stability will also be discussed as important counterbalancing protective neighborhood factors so as to avoid framing neighborhoods from a deficit-based perspective (Bronfenbrenner, 1979). Researchers must attempt to tease apart whether these factors operate independently, simultaneously or sequentially (Evans, Pilyoung, Ting, Tesher, & Shannis, 2007).

Concentrated disadvantage. That individual poverty predicts poor socioemotional and cognitive functioning is well documented (e.g. Bolger, Patterson, Thompson, & Kupersmidt, 1995; Hoff, 2003; McLeod, & Shanahan, 1993). Additional research has also found that neighborhood poverty significantly predicts developmental outcomes over and above individual poverty (Duncan, Brooks-Gunn, & Klebanov, 1994; Duncan & Magnuson, 2005; Evans, 2004).

Often referred to as 'concentrated disadvantage,' this geographically-situated poverty limits educational and economic opportunities of residents who are trapped into perpetuating their conditions (Crane, 1991; Wilson, 1987, 1996). Controlling for individual level poverty, concentrated disadvantage has also been associated with the increased likelihood of adult coronary disease (Sundquist, Winkleby, Ahlen, & Johansson, 2004) and mental health disorders (Beard et al., 2009; Silver, Mulvey, & Swanson, 2002). For children, racial and poverty composition in schools have been found to be as strong predictors of reading scores as family demographic factors (Aikens & Barbarin, 2008).

Concentrated disadvantage also can explain why some risk factors are more prevalent than others in certain neighborhoods and why the cumulative risk of these factors present increasingly staggering odds for poor development (Evans & English, 2002; Evans, Gonnella, Marcynyszyn, Gentile, & Salpekar, 2005). For example, concentrated disadvantage has been linked to child dietary intake (Florence, Asbridge, & Veugelers, 2008) and air pollution (Pastor, Sadd, & Morello-Frosch, 2004), which, in turn, have been linked to lower cognitive functioning for children.

Methodologically, researchers have advocated for operationalizing concentrated disadvantage as more than just a neighborhood's aggregate socioeconomic status (Aber, Bennett, Conley & Li, 1997). Unemployment (Stafford, Bartley, Mitchell, & Marmot, 2001), income disparity (Galea et al., 2003; Sawhill, & McLanahan, 2006), racial and family structure composition (Sampson et al., 1997) have all been utilized before. Another line of research involving housing mobility projects, have found that changes in concentrated disadvantage but not individual poverty status were associated with significant improvements in parental mental health (Leventhal & Brooks-Gunn, 2003).

Immigrant concentration. Immigrant families often cluster in neighborhoods and schools (Lauen, 2007). Immigrant concentration can be viewed as an additional risk factor or as a protective factor in spite of its correlation with concentrated disadvantage. Children from immigrant families often face the challenge of being English language learners in non-English speaking homes, a risk factor that may be amplified at the neighborhood level. English proficiency has been linked to school performance in other subject areas such as math for children of immigrants (Robert & Bryant, 2011). Children of immigrants have also been found to live in neighborhoods and attend schools with lower social cohesion that non-immigrants and be more negatively affected by neighborhood and school conditions (Pong & Hao, 2007).

From another perspective, however, close cultural identification may strengthen protective informal dynamics in the neighborhood, a perspective that is often overlooked by deficit-based models of thinking about immigration. For instance, in a predominantly immigrant subsample in Chicago, being Latino was associated with reduced likelihood of having asthma (Cagney & Browning, 2004). In another urban study, Latino youth from neighborhoods with higher immigrant concentrations were less likely to use substances, even as Latinos were more likely to use substances than whites overall (Kulis, Marsiglia, Sicotte & Nieri, 2007). Similar findings have been reached in Chicago, where immigrant concentration serves as a protective factor against depressive symptoms for foreign-born Mexicans (Almeida, Subramanian, Kawachi, & Molnar, 2011) and against self-reported perpetration of violence (Sampson, Morenoff & Raudenbush, 2005).

Residential stability. The longer residents stay in the same neighborhood and the more residents who do so, the more likely it is that neighborhood norms will develop. Similar to immigrant concentration, residential stability is a potentially protective neighborhood factor that can counteract and operate independently from concentrated disadvantage (Pinderhughes, Nix, Foster & Jones, 2007). That is, while residents of a neighborhood may be predominantly poor, a high degree of residential stability may produce higher degrees of informal social control and be associated with stronger enforcement of positive social norms (Sampson et al., 1997). Stability-associated cohesion is not necessarily protective, however, as other research has found that such norms can accelerate contagion effects for risky behavior such as smoking and drinking (Ahern, Galea, Hubbard, Midanik, & Syme, 2008; Ahern, Galea, Hubbard, & Syme, 2009).

Community disorder. Neighborhood researchers have constructed community disorder to include physical and social factors such as abandoned housing, dirty streets, drug use and informal public gatherings (Sampson et al., 2005). Factors associated with community disorder are non-randomly geographically distributed and clustered within certain neighborhoods (Ahern et al., 2008; Galea, Hall & Kaplan, 2009). Some research has treated physical and social disorder as distinct constructs (e.g. Sampson et al., 2005). Research in New York City, however, has found physical and social disorder to be highly correlated (Hembree et al, 2005). For instance, external building conditions, including the number of structural fires, to be significantly associated with the number of deaths due to drug abuse in neighborhoods (Hembree et al., 2005). Conversely, clean streets were associated with a small but significant reduction in the number of deaths due to drug abuse (Nandi et al., 2006). These relations reflect the latent nature of community disorder as both physical and social.

Other researchers have debated whether community disorder exists because of neighborhood norms or because of structural inequality. Ross and Jang (2000) found community disorder to be correlated with resident mistrust and fear of victimization. On the other hand, while drug abuse deaths are associated with poorer neighborhoods in New York City, drug abuse is associated with wealthier neighborhoods, potentially revealing differential emergency medical treatment (Galea, Ahern, Tracy & Vlahov, 2007). Similarly, Wallace (1982, 1988, 1990) argued that increased community disorder in the Bronx during the 1970s and 1980s could be explained by changes in government service provision. These increases led to the outmigration of thousands of youth from the Bronx and an ongoing cycle of concentrated disadvantage (Wallace & Wallace, 1990). In such a way, disadvantage becomes more concentrated, more segregated, and more racially homogeneous over time (Williams & Collins, 2001).

Community disorder is also highly correlated with both poverty and ETV (Cohen et al., 2000; Marzuk et al., 1997; Sampson et al., 1997). Reductions in community disorder, in contrast, have been linked with benefits for neighborhood residents. For instance, increased trash collection has been associated with improved self-reported health (Cummins, Stafford, MacIntyre, Marmot & Ellaway, 2005).

To summarize, exposure to neighborhood violence is one of a number of neighborhood characteristics and dynamics that have been linked to developmental processes. These associations to development vary across predictors and outcomes. This study seeks to further elucidate the potential role of exposure to violence in the context of school neighborhoods in New York City and also to understand how exposure to violence operates in relation to other neighborhood characteristics including concentrated disadvantage, immigrant concentration, residential stability, and community disorder.

CHAPTER III. METHOD

Participants

Student (N = 792,374) demographic and achievement data for the academic years ending in 2006 through 2010 were obtained from the New York City Department of Education. Demographic data included gender, ethnicity, grade, and designation and eligibility for free or reduced price meals, English Language Learner services and special education services (see Table 1). Students were excluded if there were inconsistent data on student gender or ethnicity or if students were enrolled in one grade but took tests for another grade. Also a small group of students were home-schooled or serving long-term suspensions, and these students were excluded as well. Even as all student data were de-identified and school neighborhood data publicly available, this research study was submitted to and approved by the Teachers College, Columbia University, and the N.Y.C. D.O.E. institutional review boards (I.R.B.).

Measures

School data. State standards tests for grades 3 through 8 in English Language Arts (ELA) and math are the outcome of interest for this study. These tests are domain referenced based on established learning standards, with students receiving scaled scores (400-800) that are also converted to pass/fail scores (1-4 with 3 or 4 being passing). Written by the New State Department of Education since 2006, teachers administer the tests to their own students on the same day each year statewide, and individual districts oversee scoring of the exams so that teachers do not score their own students' tests.

Also, while NCLB regulations require testing in other subjects and grades as well, these tests lack construct validity. Tests in science and social studies for grades 3 through 8 have been designed and piloted but have faced challenges regarding content validity as well as budgetary constraints and are now on hold. High school Regents exams are taken by students in grades 9 through 12, but the test design has changed several times in recent years and scoring of Regents exams has been questioned as teachers score their own students' exams. Finally, students in the first and second grade are assessed using McGraw-Hill's ECLAS-2, which is an ordinal teacher-response checklist of child competencies and skills. Similar to the Regents, there is the potential for teacher bias in assessing their own students.

It should be acknowledged that the ELA and math exams for grades 3 through 8 have also been subject to scandal (Medina, 2010; Otterman, 2010). Because of critical press coverage and an external audit, state education officials acknowledged that between 2006 and 2009 there had been a general easing in the pass/fail – but not scaled score – scoring of ELA and math tests. Using a national educational assessment, the NAEP, to recalibrate scoring, an internal evaluation found that approximately 30% of students who had been scored as passing the ELA and math tests should not have passed. Again, standards for generating the scaled score remained consistent over this time period, however, and it is these scores that will be used for these analyses. Scaled scores were standardized by subject, year, and grade as the tests were not designed vertical equation (i.e. grade to grade comparisons) (for scaled scores and standardized scores by student demographic group, see Table 2).

School neighborhood data. ETV in the school neighborhood is the primary predictor of interest for this study with additional neighborhood factors – concentrated disadvantage, immigrant concentration, residential stability, and community disorder – serving as control variables. A list of all public schools were retrieved from the NYCDOE website as a part of a larger study in the fall of 2010. School geographic data were collected in 2010 and validated in 2011 using both the NYCDOE website and Google Maps street view. Geographic data were matched with Census and NYC DIIT administrative files to confirm each school's census tract, police precinct, and community district. A total of 1240 schools were found to have served students in grades three through eight at some point from 2006 through 2010.

Neighborhood predictors were constructed using publicly available data provided by NYC DIIT and the Census (for factors, original variables and data sources, see Table 3). These data, available at the precinct (n = 76), community district (n = 59) and census tract (n = 2217) level, were matched to each schools geographic location. While each of these data sources utilizes different sets of geographic boundaries, for each type of data these represent the best approximation of school catchment area available (see Figure 2). Many variables are published as percentages or standardized frequencies per 1,000 or 100,000 residents. Count data were converted into rate/100,000 resident to account for variance in precinct, community district and census tract populations. Data were then standardized by year and averaged across the 2006 through 2010 fiscal years (July 1-June 30); although for certain variables, the data were reported for the calendar year. Census data were retrieved as the state file 3 (SF3) package for New York from the 2006-2010 American Community Survey.

ETV. Exposure to violence in the school neighborhood was constructed using DIIT-provided NYPD data. These data include annual counts by precinct of reports of seven major felony categories. Principle components analysis (PCA) with oblique factors and Varimax rotation determined that these data could be reduced into two factors: violent crime (murder and non-negligent manslaughter, forcible rape, robbery, felonious assault) and commercial crime (burglary, grand larceny, and grand larceny auto). PCA was then used to create a single ETV factor with the four violent major felonies.

Community disorder. Physical and social community disorder was constructed using DIIT-provided data from a number of city agencies. These data include annual counts by community district of reported: child abuse/neglect, infant mortality, deaths due to drug abuse, clean sidewalks, and recycling rates. Records on substantiated cases of child abuse/neglect are maintained by the Administration for Children's Services (ACS). Reports alleging child neglect or abuse are first collected by the New York State Central Registry, which then provides cases to the ACS to substantiate by investigations before referring individuals for intervention and case management. Records on infant mortality and deaths due the drug abuse are maintained by the Department of Health and Mental Hygiene and include both accidental and non-accidental deaths. Acceptably clean sidewalks are evaluated by the Mayor's Office of Operations, which employs field inspectors to rate a sample of 6, 000 blocks per community district utilizing a seven-point picture-based rating scale. Sample block inspections occur bimonthly and are averaged across the fiscal year. Recycling diversion rates are computed by the New York City Department of Sanitation (DSNY) as the number of tons of recyclable material collected divided by the number of tons of recyclable material and refuse collected.

As with ETV, non-crime DIIT data, including a number of variables not reported here, were analyzed using PCA for oblique factors with Varimax rotation. After several iterations, five factors were identified: community disorder (deaths due to drug abuse, child abuse/neglect, infant mortality, clean sidewalks, recycling diversion), government assistance (public health insurance, food stamps, public assistance, public housing construction), environmental and medical emergencies (fires, medical emergencies, air complaints, asbestos complaints, emergency building complaints), parks and playgrounds (acceptable and clean parks and playgrounds) and citizen efficacy (resolved consumer complaints and non-emergency building complaints). While future studies will consider the latter four community district factors, this study will utilize on community disorder, which was independently reconstructed as a single PCA factor using the five variables described above.

Concentrated disadvantage. Concentrated disadvantage was constructed as a single PCA factor using rates of single-parent households, unemployment, poverty, having less than a high school diploma, and the proportion of children to adults in each census tract.

Immigrant concentration. Immigrant concentration was constructed as a single PCA factor using rates of being foreign born and households not speaking English in each census tract.

Residential stability. Residential stability was constructed as a single PCA factor using rates of owner occupied housing and living in the same residence for the past five years in each census tract.

Construction of concentrated disadvantage, immigrant concentration and residential stability was modeled on a major research project constructing similar neighborhood factors in Chicago (Sampson et al., 1997; Xue, Leventhal, Brooks-Gunn & Earls, 2005). Principal components analysis of the same and similar census variables used in the Chicago study produced similar factors, with some variation depending on geographic unit of analysis (block group, tract or zip code) and weighting by population. A fourth factor, affluence (median per capita income, home value, and college graduation rates) appeared in several iterations of our factor construction and will be considered in future analyses.

Also, while a number of studies have considered ethnic composition in constructing neighborhood factors (e.g. Sampson et al., 1997), this study maintains that such data are already considered at the student level and by the variables already fit into the factors. In both Chicago and New York City, neighborhood factors including and excluding ethnic composition were highly correlated, indicating that in each city ethnic composition is conflated with other variables. It is also posited that assuming racial and ethnic bases for such factors is dangerous given differences across cities. Concentrated disadvantage is associated with the Latino population in New York City but with the black population in Chicago, and immigrant concentration is associated with the Asian population in New York City but with the Latino population in Chicago.

Analytic Strategy

Computing. To test for linkages between ETV in the school neighborhood and student performance, the data were modeled for multilevel analysis with consideration for mixed and random effects as well as for cross-classification. We consider the data to be multilevel in that we have years, i, within students, j, within schools, k, such that any ELA or math score can be described as ELA_{ijk} or $Math_{ijk}$. Given the nested nature of the data, it is important to consider the possibility that individual level predictors such as gender, ethnicity, or service eligibility may be associated with varying effect sizes in across different schools, necessitating the testing of both fixed effects and random effects. Also because students within the sample move across schools, it becomes important to consider the cross-classification of students across schools with specific years occurring within specific schools but all belonging to the same student (Luo & Kwok, 2012).

Given the size of the data set, however, a number of challenges arose with regard to computing power. That is, with 2,124,619 school years nested in 792,374 students, nested in and moving across 1240 schools, multilevel models must first calculate intercepts for each student and each school before any additional predictors are added. And while fixed effects models provide a single coefficient for each predictor, random effects models compute coefficients for each unique context for a predictor. Also, while the same coefficients are computed for cross-classified data, an exponentially larger covariance matrix is required and drastically increases the computing power necessary to calculate estimates.

High-power computing (HPC) provides for a partial solution to this quandary. Columbia's HPC system, Hotfoot, brings together over 600 computer cores with a total of 72 TB of storage memory and allows for a single computing job to use up to 256 GB of RAM memory. Utilizing a Torque/Moab job submission and management system, users can access Hotfoot remotely, manipulating statistical syntax and reading output from models being run simultaneously across multiple computer cores. Even with such a system, however, cross-classified models that allow for students to move between schools could not be evaluated.

By considering schools to simply be fixed intercept predictors (dummy-coding all 1240 schools as unique variables), the memory required for analyses was reduced to 172 GB overall. Most of these analyses were terminated, however, given the 72-hour time limit allowed for jobs at this memory level. A limited number of analyses using cross-classified models were completed, and while showing improved fit, also show similar parameter estimates, which will be discussed later.

Another solution was then attempted, splitting the entire sample into elementary (grades 3-5) and middle school (grades 6-8) subsamples. This reduced the percentage of students who switched schools from 2006-2010 from 35% of the sample to just under 10%. While it is understood that this does not eliminate the need for or benefits of cross-classified models, assuming strict hierarchical nesting does not seem to be altogether unreasonable. Luo and Kwok (2012), advocates for cross-classification over hierarchical modeling, found that effect size estimates using each method were all similarly significant, in the same direction (positive/negative) and varied by an average of only 4% (range .08%-14.6%).

This study will rely primarily on findings from these split analyses of elementary and middle school subsamples. As a robustness check, all analyses were also run on the full sample with similar parameter estimates, but without improved model fit due to student movement across schools.

Modeling. A series of statistical models were analyzed to answer the five research questions. All models were run using STATA-MP (2 processor) version 12.0 utilizing the ".xtmixed" command. All models were tested using both maximum likelihood and reduced maximum likelihood with no differences found with regard to model fit, predicted coefficients or significance. All models were tested using both fixed and random effects for student-level variables. While both fixed and random effects models largely had matching results, random effects models consistently had better model fit statistics and it is these findings that will be reported here. The progression of models will now be explained as well as how the models answer the research questions.

Model 1: Empty model. The empty model is required in multilevel models as covariance analyses are used to produce interclass correlations (ICC), partitioning error variance by nesting level. For each year *i* for student *j* in school *k*, the standardized ELA/Math score, ELA/Math_{ijk}, is initially predicted by an intercept, γ_{000}, which in this model represents the mean ELA/Math score across all years, all students and all schools, as well as an error term for each school, u_{00k}, each student, r_{0jk}, and each year, e_{ijk}. This is represented by the equation:

$$\text{ELA/Math}_{ijk} = \beta_{0jk} + e_{ijk}$$

(1)

$\beta_{0jk} = \eta_{00k} + r_{0jk}$

$\eta_{00k} = \gamma_{000} + u_{00k}$

or:

$\text{ELA/Math}_{ijk} = \gamma_{000} + u_{00k} + r_{0jk} + e_{ijk}$.

Model 2: Student level predictors. This model includes student-level variables that are included in current educational metrics used to evaluate teachers and schools. This is represented by the equation:

$\text{ELA/Math}_{ijk} = \beta_{0jk} + \beta_{1jk}\text{Meals} + \beta_{2jk}\text{ELL} + \beta_{3jk}\text{IEP} + e_{ijk}$

(2)

$\beta_{0jk} = \eta_{00k} + \eta_{01k}\text{*Gender} + \eta_{02k}\text{*Latino} + \eta_{03k}\text{*Black} + \eta_{04k}\text{*Asian} + r_{0jk}$

$\eta_{00k} = \gamma_{00} + u_{00k}$

or:

$\text{ELA/Math}_{ijk} = \gamma_{00} + \eta_{01k}\text{*Gender} + \eta_{02k}\text{*Latino} + \eta_{03k}\text{*Black} + \eta_{04k}\text{*Asian} + \beta_{1jk}\text{*Meals} +$

$\beta_{2jk}\text{*ELL} + \beta_{3jk}\text{*IEP} + u_{00k} + r_{0jk} + e_{ijk}$.

Note that one set of parameter coefficients, β_{1jk}, β_{2jk}, and β_{3jk}, corresponds to variables – receiving free/reduced price meals (meals), English language learner (ELL) or special education services (IEP) – that can vary from year to year as well as across students and schools. Another set of parameter coefficients, η_{01k}, η_{02k}, η_{03k}, and η_{04k}, corresponds to variables – gender and ethnicity – that are stable across years but can vary across students and schools.

Model 3: Adding ETV and school neighborhood factors. This model adds ETV and the three census-based neighborhood control factors, which we will test against the current educational paradigm in Model 1.

$$\text{ELA/Math}_{ijk} = \beta_{0jk} + \beta_{1jk}\text{Meals} + \beta_{2jk}\text{ELL} + \beta_{3jk}\text{IEP} + e_{ijk}$$

(3)

$$\beta_{0jk} = \eta_{00k} + \eta_{01k}{*}\text{Gender} + \eta_{02k}{*}\text{Latino} + \eta_{03k}{*}\text{Black} + \eta_{04k}{*}\text{Asian} + r_{0jk}$$

$$\eta_{00k} = \gamma_{000} + \gamma_{001}{*}\text{Violence} + \gamma_{002}{*}\text{ Concentrated Disadvantage} + \gamma_{003}{*}\text{Immigrant Concentration} + \gamma_{004}{*}\text{Residential Stability} + u_{00k}$$

or:

$$\text{ELA/Math}_{ijk} = \gamma_{000} + \gamma_{001}{*}\text{Violence} + \gamma_{002}{*}\text{ Concentrated Disadvantage} + \gamma_{003}{*}\text{Immigrant Concentration} + \gamma_{004}{*}\text{Residential Stability} + \eta_{01k}{*}\text{Gender} + \eta_{02k}{*}\text{Latino} + \eta_{03k}{*}\text{Black} + \eta_{04k}{*}\text{Asian} + \beta_{1jk}{*}\text{Meals} + \beta_{2jk}{*}\text{ELL} + \beta_{3jk}{*}\text{IEP} + u_{00k} + r_{0jk} + e_{ijk}.$$

If the addition of ETV and the other school neighborhood-level predictors results in improved model fit relative to Model 2 as well as significant parameter estimates, this would suggest that current evaluation metrics are potentially biased and that ETV should be acknowledged by educators and educational policymakers.

Additional models: Robustness checks and interaction terms. Since ETV cannot be experimentally manipulated, three additional models were analyzed separately as robustness checks. First, γ_{001}*Violence was modeled as γ_{001}*Prior Year Violence + γ_{002}*Change in Violence to test if changes in ETV are associated with changes in student performance (Model 4). Second, a set of terms was added to test for interactions between ETV and student-level predictors (e.g. γ_{011}*Gender*Violence or γ_{111}*Meals*Violence) (Model 5). Finally, γ_{005}*Disorder was both added in lieu of (Model 6) and along with (Model 7) γ_{001}*Violence in order to compare significance levels, model fit statistics and parameter estimate sizes comparing ETV and disorder. While these additional models are not the primary focus of this dissertation, they help provide a stringent battery of tests to evidence the uniqueness and significance of the link between ETV and student performance.

CHAPTER IV: RESULTS

Here, we begin by presenting sample demographics followed by inter-class correlations justifying the use of multilevel models for our analyses and between school-level predictor correlations. We continue by comparing overall model fit statistics: Akaike Information Criteria (AIC, Akaike, 1974) and Bayesian Information Criteria (BIC, Schwarz, 1978) for models predicting ELA and math outcomes within our elementary and then middle school subsamples. We then consider the progression of individual variables across all analyses focusing on violence and disorder before moving to the Discussion section.

Sample Demographic Data

Year by year demographic data are available for sample participants in Table 1. As a percentage of the overall number of student years (N = 2,141,011 for 792,374 students), 51.0% of students were reported as female and 49.0% as male. By ethnicity, 40.0% of students were reported as Latino, 32.0% as black, 14.0% as Asian, and 13.9% as white. By grade and school level, 49.4% were reported as being in elementary school, and 50.6% were reported as being in middle school. In terms of services received, 71.5% of students were reported as receiving free or reduced price meals, 13.8% of students were reported as receiving English Language Learner services, and 16.0% of students were reported as receiving special education services as reported in an Individual Education Plan.

Demographic group mean scaled scores and standardized scaled scores for ELA and for math are reported in Table 2. On average, female students scored higher than male student on both ELA (.13 to -.10) and math (.05 to -.01). Latinos (ELA: -.19, math: -.18) and blacks (ELA: -.16, math: -.25) scored lower on average than Asians (ELA: .49, math: .72) and whites (ELA: .51, math: .48). Finally, students receiving additional services scored lower on average than students not receiving services with students receiving free or reduced price meals (ELA: -.11, math: -.09) doing better on average than students receiving English Language Learner services (ELA: -.76, math: -.50) who in turn did better than students receiving special education services (ELA: -.81, math: -.80). It should be noted that these final three categorizations are not mutually exclusive.

Inter-Class Correlations

Using variance and residual error results from Model 1, between-student variance accounted for between 49.61% and 55.22% of overall variance depending on outcome and grade levels considered (See Table 4). Similarly, between-school variance accounted for between 20.11% and 27.79% of overall variance depending on outcome and grade levels considered (See Table 5). From these results, we can infer that within student variance accounts for approximately 30% of the overall variance in student test scores across years. These inter-class correlations at both the student and school level strongly suggest the value of utilizing all three levels of data available (years within students within schools) (Rowan, Raudenbush, & Kang, 1991).

School-Neighborhood Level Predictor Correlations

Zero-order correlations were calculated for the two student performance outcomes and ETV and the four other school neighborhood level predictors. The correlations presented in Table 5 are at the student-year level. Zero-order correlations calculated at the student level (N = 792,374) and at the school level (N = 1,250) were similar in significance and direction.

Model Fit

Accounting for ETV and other school neighborhood factors improved fit statistics in almost all models tested (Model 3 versus Model 2 in Table 6). Both AIC and BIC statistics improved for ELA and math in elementary school (with similar improvements in fixed effects models). AIC but not BIC statistics improved for ELA and math in middle school (but both statistics showed improvement in fixed effects models).

Controlling for prior year ETV further improved fit statistics in all models tested (Model 4 versus Model 3 in Table 6). These improvements should be interpreted with caution, however, as they are potentially largely or fully explainable by reduction in sample size (as only students with at least two years of data were included in these analyses). Adding interaction terms for ETV with student-level predictors also further improved fit statistics in all models tested (Model 4 versus Model 3 in Table 6).

Substituting community disorder for ETV (Model 5 versus Model 3) resulted in mixed model fit findings. Random effects models for ELA in elementary and middle school showed improved fit (although fixed effects models showed worse fit). Random effects models predicting math in elementary and middle school did not show improved fit (with similar findings for fixed effects models). Adding community disorder to Model 3 also resulted in mixed model fit findings. Random effects models for elementary school ELA and math had improved fit, but fixed effects models showed improved fit for only one statistic for (AIC for ELA). Similarly in middle school, only AIC for ELA showed improved fit in both random and fixed effects.

Results by Variable

ETV. Exposure to violence in the school neighborhood was significantly and consistently negatively associated with student outcomes (ELA: elementary: -.011; middle school: -.031; math: elementary: -.026; middle school: -.033). When including both prior year's ETV and change in violence over the past year, both prior and change in ETV were consistently and significantly negatively associated with student outcomes (prior violence: ELA: elementary: -.053; middle school: -.045; math: elementary: -.058; middle school: -.058; change in violence: ELA: elementary: -.017; middle school: -.021; math: elementary: -.018; middle school: -.036).

Student-level predictors. Unless otherwise noted, all reported coefficients are from our principle model, Model 3, which seeks to answer the primary research question, should ETV be considered in models predicting student performance.

***Gender*.** On average, female students attended school in more dangerous neighborhoods (-.060 to -.071, see Table 4) than male students. Similarly, female students attended school in neighborhoods with higher concentrated disadvantage (.288 to .284), lower residential stability (-.089 to -.087), lower immigrant concentration (.077 to .080) and higher community disorder (.064 to .054) Female students scored significantly higher than their male peers on ELA tests in both elementary (.096) and middle school (.144). Female students scored significantly lower than their male peers on math in elementary school (-.047) with no significant differences on math tests in middle school (.002). Interaction terms for ETV by female were non-significant for elementary school ELA (-.002) and middle school math (-.002) and significantly negative for middle school ELA (-.013) but positive for elementary school math (.011).

Ethnicity. On average, black students were likely to attend public schools in more violent neighborhoods than Latino, Asian or white students (.354 to .050 to -.641 to -.784, respectively, see Table 7). Yet Latino students, on average, lived in neighborhoods with higher concentrated disadvantage than black, Asian or white students (.632 to .438 to -.197 to -.576, respectively) and with lower rates of residential stability (-.383 to -.066 to .140 to .483, respectively). Immigrant concentration was largely driven by Asian and Latino families and therefore students over whites and blacks (.628 to .265 to -.234 to -.260 respectively). Trends for community disorder matched

ETV except for reversing the position of Asian and white children (.345 to 2.65 to -.554 for white children to -.579 for Asian children).

Parameter estimates for white students are not reported as white students served as the reference group for all multilevel analyses.

Black students scored significantly lower than white students (ELA: elementary: -.260; middle school: -.211; math: elementary: -.311; middle school: -.245). Interaction terms for ETV by black were positive and generally significant (ELA: elementary: .028; middle school: .017, $p > .05$; math: elementary: .097; middle school: .037).

Asian students scored significantly higher than white students (ELA: elementary: .099; middle school: .103; math: elementary: .306; middle school: .342). All interaction terms for ETV by Asian were non-significant (at $p > .05$, ELA: elementary: -.013; middle school: -.025; math: elementary: .008; middle school: -.014).

Latino students scored significantly lower than white students (ELA: elementary: -.171; middle school: -.130; math: elementary: -.158; middle school: -.113). Interaction terms for ETV by Latino were non-significant for ELA ($p > .05$, elementary: .011; middle school: .012) and positive and significant for math (elementary: .077; middle school: .044).

Free/Reduced Price Meals. Students receiving free and reduced price meals attended school in neighborhoods with higher rates of violence (.051, see Table 7), concentrated disadvantage (.447), and immigrant concentration (.121), and community disorder (.184) than students not receiving this service, and attended schools in neighborhoods with lower levels of residential stability (-.183).

Receipt of free and reduced price meals is significantly and consistently associated with poorer academic performance (ELA: elementary: -.085; middle school: -.057; math: elementary:

-.045; middle school: -.020). Interactions between violence and socioeconomic status are consistently and significantly positive (ELA: elementary: .030; middle school: .021; math: elementary: .027; middle school: .015).

Immigrant status. Students receiving English Language Learner services on average attended schools with below average levels of violence (-.051, see Table 7) and residential stability (-.373) but higher than average social disorder (.115), poverty (.609), and immigrant concentration (.522).

Receipt of English language learner services is significantly and consistently associated with drastically poorer academic performance (ELA: elementary: -.510; middle school: -.643; math: elementary: -.426; middle school: -.429). Interactions between violence and English Language learner status are consistently and significantly positive (ELA: elementary: .064; middle school: .054; math: elementary: .045; middle school: .014).

Special education status. Students receiving of special education services, on average, attended school in neighborhoods with above average rates of violence (.016), social disorder (.176), and poverty (.360) and below average immigrant concentration (-.041) and residential stability (-.145).

Receipt of special education services is significantly and consistently associated with the largest drop in academic performance of any predictor (ELA: elementary: -.700; middle school: -.643; math: elementary: -.610; middle school: -.656). Interactions between violence and special education status were significantly positive (ELA: elementary: .029; middle school: .017; math: elementary: .020) with the exception of middle school math (.010, $p > .05$).

School neighborhood level controls.

Concentrated disadvantage. Concentrated disadvantage was consistently and significantly associated with lower student performance (ELA: elementary: -.072; middle school: -.050; math: elementary: -.066; middle school: -.028).

Immigrant concentration. With the exception of ELA scores in elementary school (.014, $p > .05$), immigrant concentration was significantly associated with higher student outcomes (ELA: middle school: .042; math: elementary: .033; middle school: .046).

Residential stability. With the exception of ELA scores in middle school (.023, $p > .05$), immigrant concentration was significantly associated with higher student outcomes (ELA: elementary: .038; math: elementary: .046; middle school: .058).

Community disorder. When substituting community disorder for ETV, community disorder was non-significant for elementary ELA (.005, $p > .05$) and slightly negative and significant otherwise (ELA middle school: -.012; math: elementary: -.007; middle school: -.005). When adding community disorder to ETV, community disorder was slightly positive for ELA in elementary (.007), slightly negative for ELA in middle school (-.007), and not significant for math (elementary: -.003; middle school: .000).

CHAPTER V: DISCUSSION

Taken together, these findings suggest that higher rates of ETV in school neighborhoods are associated with lower student performance. This relationship generally improves model fit over existing educational metrics including only student level predictors. Also while ETV is associated with concentrated disadvantage and community disorder, there is consistent evidence that it operates independently of concentrated disadvantage and some evidence that it operates independently of community disorder in predicting student performance. ETV even remains significant even when controlling for prior years crime. There also exists some evidence that students already exposed to more proximal risk factors are buffered to a certain extent from these negative associations.

Exposure to Violence as a Unique Predictor of Student Performance

In every model tested, ETV in the school neighborhood was significantly associated with lower student performance in English and math tests. These models were an improvement over existing educational metrics, showing improved fit on at least one if not both model fit statistics. In a series of robustness checks, ETV remained significant after controlling for not only student-level predictors but also neighborhood-level factors as well including concentrated disadvantage and prior violence. Findings on community disorder were mixed and will be discussed more later. That ETV matters corroborates previous research showing that youth are attuned to neighborhood violence (Aneshensel & Sucoff, 1996).

Controlling for prior ETV was also critical for two reasons. First, from an ETV perspective, it is the best control for selection of individuals into more violent neighborhoods. Secondly from an educational perspective, it shows that newer educational models controlling for unaccounted for factors by including prior year performance are not adequate. That is, value-added models calculating teacher effects assume that including a student's prior year performance will account for variance due to factors beyond student demographics. As Model 4 showed, however, while such models might account for ETV up to the prior year, they do not account for changes in violence that are significant as well. That both prior ETV and change in ETV were consistently significant in Model 4 is also impressive because we know that violence tends to be relatively stable across time (Sampson et al., 2005). This would also suggest that changes in violence due to policy change might have potentially restorative effects. Such analyses match more rigorously tested findings controlling for past violence (Sampson et al., 1997), which have not always remained significant (Sharkey, 2012).

ETV and Poverty

ETV significantly predicted lower student performance independent of both student and neighborhood poverty and was also highly correlated with them, matching the extant ETV literature (Pearlin, 1989). It is then not surprising that poverty also was a strong predictor of achievement gaps in this study, matching prior research on poverty (Duncan et al., 1994). While others have tested violence as a mediator for the impact of poverty on youth (McLeod & Shanahan, 1993), this study followed the approach of treating poverty as a controlled-for counterfactual as done in other studies (Delaney-Black et al., 2002). Students living in poverty are more likely to attend schools in more violent neighborhoods, with each factor representing a unique stressor on student performance. We will address the potential interactive relation between poverty and exposure to violence in our following section on exposure to violence across different populations.

The Challenge of Community Disorder

Considerations of community disorder in lieu of and added to ETV resulted in mixed findings with regard to model fit statistics but generally larger parameter estimates for ETV. Prior research has linked ETV with disorder (Hanson et al., 2006; Mrug, Loosier, & Windle, 2008; Osofsky, 1995). Sampson and colleagues (1997; 1999) have argued that this correlation is spurious as both are related to community norms. Future research will need to consider available data on community norms as well as use multilevel structural equation modeling.

Exposure to Violence Across Populations

Gender. Our mixed findings regarding the interaction of gender and violence are not surprising given the extant literature. While past research has found that male children are more likely to be exposed to violence (Buka et al., 2001), research has not found significant gender differences with regard to associations between exposure to violence and mental health outcomes (McCart et al., 2007; Sternberg et al., 2006). Other studies have found differential effects by gender, but these are inconsistent as to direction. For instance, Singer and colleagues (1995) found women reported higher rates of trauma report and Moses (1999) reported females but not males were more likely to be clinically depressed following exposure to violence. Some researchers have theorized that male youth may have identified better coping strategies such as maternal support, peer support and even avoidant coping to reduce the association between exposure to violence and delinquent behavior (Hammack et al., 2004; Rosario et al., 2003). Differences in peer support by gender also potentially reflect different processes such as co-rumination (Schwartz-Mette & Rose, 2012) and will be discussed further later. On the other hand, Schilling et al. (2007) found that boys had a stronger relation between exposure to violence and antisocial behavior, which Guerra and colleagues (2003), would explain is mediated through the creation of violent schema with regards to social cognition.

It is important to note, however, that unlike residential neighborhood studies, girls were found to be exposed to higher levels of violence in the school neighborhood than boys. One potential explanation for this is that parents in more violent neighborhoods are more willing to invest in private independent school education for sons but not daughters because of either perceived increased threat to boys or because of greater investment in the education of male children (Alderman & King, 1998).

Ethnicity. Prior research has shown that Black and Latino youth are more likely to be exposed to violence (Hanson et al., 2006) but that white children experience stronger associations between violence and negative mental health outcomes (Schilling et al., 2007). Our findings support these prior conclusions with black and Latino students showing weaker associations between exposure to violence and poor school performance relative to white students.

In a surprising finding, however, Asian students were found to have significantly stronger and therefore worse associations between exposure to violence and school performance (these were only found in the fixed effects models across grades). While prior studies have reported that Asian students tend to be exposed to lower levels of exposure to violence (O'Keefe & Sela-Amit, 1997; Ozer & Weinstein, 2004), only single ethnic group studies have been done on Asians (Ho, 2008) with significant but non-comparative findings. These findings suggest that culturally specific processes may be involved in explaining why Asian American coping strategies offer less protection against exposure to violence.

Poverty. As already discussed students living in poverty were exposed to higher levels of violence than their non-poor peers. Yet, a significant weathering effect was found between poverty and violence indicating that children not living in poverty experienced larger reductions in school performance in school neighborhoods with higher levels of violence. These findings contribute a mixed body of existing research. Gladstein, Rusonis, and Heald (1992) found adolescents living in lower SES neighborhoods reported not only higher rates of exposure to violence but also higher rates of trauma through being the victim, knowing the victim, or actually witnessing acts of live-threatening violence. O’Keefe and Sela-Amit (1997), however, found no interaction between SES and it should be emphasized that even with a weathering effect, exposure to violence was still associated with negative changes in student achievement, matching findings from other studies of children living in poverty (Guerra et al., 2003).

English language learner and special education status. Similar to poverty, English language learner status and receipt of special education services both provided small buffers against the associations between exposure to violence and negative school performance. There are two potential interpretations for this. First, immigrant families and families of students who have advocated for their students to receive special education services can be seen as having higher degrees of efficacy (Hoover-Dempsey & Sandler, 1997) and may exert more informal social control over these students, especially in neighborhoods where violence is known to be higher. Such parents, in the case of immigrants, may even live in communities of like-minded and similarly efficacious families. Immigrant concentration has previously been found to be associated with lower rates of violent crime (Sampson et al., 1997) indicating potential neighborhood dynamics seeking to limit the presence and thereby influence of violence.

Secondly, in a similar fashion to advocating parents serving as an additional buffer, (which may also apply to receipt of free and reduced price meals, but which is less likely given that the majority of students in the sample received this service) students receiving ELL and IEP services receive additional adult supervision, allowing for these students to receive a double-dose of adult support relative to students not receiving such services. This can also be understood in terms of student to teacher ratio. While prior research has found that teachers in schools with higher populations of students of color and poor students have lower teacher efficacy (Goddard & Goddard, 2001), a lower student-teacher ratio has been associated with improved efficacy, which is in turn associated with higher student performance. While this argument may not hold in terms of overall main effects for being designated ELL or requiring an IEP, the additional adult support might provide the psychological support necessary to offset the effects of exposure to violence but not the cognitive burden of being an English language learner or requiring special education services.

Middle school. Whereas most existing research has tested only ETV in only one age group, this study is unique in its consideration of ETV effect sizes at different ages. Being a middle school as opposed to an elementary school student was associated with larger effect sizes for exposure to violence. These empirically-measured differences support prior research in residential neighborhoods theorizing that older children spend more time socializing outside of homes and travel more frequently in their neighborhoods resulting in higher exposure to violence (Lambert et al., 2005). Children spend more time in neighborhoods and are more likely to commute to school unaccompanied by parents as they age. Older children spending more time with peers who are exposed to the same crimes and without proper support can potentially amplify stress-based reactions (Kliewer et al., 2001) through processes such as co-rumination (Schwartz-Mette & Rose, 2012). Additional research has discussed how transitions to middle and high school represent periods of development where youth as especially vulnerable to neighborhood violence (Stewart et al., 2008).

CHAPTER VI. CONCLUSION

Limitations

A number of challenges for doing school and neighborhood research have been previously described (Jencks & Mayer, 1990; Kawachi & Berkman, 2003; Leventhal & Brooks-Gunn, 2000), and several primary concerns will be discussed here referencing more recent research.

Schools and neighborhoods? As discussed, a number of students moved between schools and school neighborhoods. Besides representing a statistical challenge with regard to cross-classifying students, this also represents a theoretical challenge of students switching school neighborhoods but not necessarily residential neighborhoods. Future research should also contrast school versus residential neighborhood although this has proven informative but challenging (Vertanen et al., 2009). For instance, higher rates of asthma in middle schools have been associated with poorer census tracts in Chicago, which is an association that theoretically could be attributed to neighborhood or school conditions (Persky et al., 1998). At times, in fact, schools seem to represent the causal mediator for neighborhood effects. Another study of Chicago neighborhoods found three to four times as many fast-food restaurants located within walking distance (1. 5 kilometers) of schools (Austin et al., 2005). It makes more sense that fast-food restaurants place themselves proximally to schools than officials locating schools near fast-food restaurants.

What about families? Another limitation of this study is the lack of consideration of the home environment, which has been linked to child socio-emotional (Dodge, Pettit & Bates, 1994) and cognitive (Rafferty, Griffin & Lodise, 2011) development and performance beginning at infancy. Home factors, such as poverty at the family level, low maternal education, and poor maternal mental health, help explain why the achievement gap targeted by federal policy exists even before children school in kindergarten (Sektnan, McClelland, Acock & Morrison, 2010). Other family-level variables such as parenting style also have been found to predict degree of deviant peer association and collective socialization at the neighborhood level in a sample of African-American 10-12 year olds (Brody et al., 2001).

What counts as a neighborhood? The operationalization of school neighborhoods in this study was based on the best available data. This included data associated with a range of differing geographic boundaries which should be tested as cross-classified nests rather than an individual level of data. A limited number of cross-classified fixed effects models were run and are presented in Tables 13-16 with results being largely consistent with hierarchical models. Multiple perspectives have been utilized to define neighborhoods. Whereas certain studies have utilized geographic boundaries (e.g. Hoxby, 2000), others have utilized administrative boundaries that take into account population counts in addition to geography (e.g. Sampson et al., 1997).

Others have also argued that neighborhoods can be identified by social and ethnic boundaries instead of geographic boundaries (Kulis et al, 2007). In the study of ETV, immigrant concentration protecting against depressive symptoms (Almeida, Kawachi, Molnar, & Subramanian, 2009) and against self-reported perpetration of violence (Sampson et al., 2005). Future research should consider potential interactions between ETV and immigrant concentration.

Some have also argued that certain administrative borders fail because researchers often divide neighborhoods down the middle of a street so that neighbors living across the street from one another would be considered as residents of two distinct neighborhoods (Clapp & Wang, 2006). Such can be the case, too, for schools that are lie on the border of an administrative neighborhood (Patel, Mayer, Slymen, Weeks & Hurd, 2007). Some researchers have adapted by using walkable distances from schools (e.g. Sturm, 2008; Zenk & Powell, 2008) or by expanding tract boundaries (e.g. Patel et al., 2007, expanded each census tract in all directions by 1000 feet).

The present study seeks to resolve these concerns by using data from multiple sources and for multiple geographic boundaries (police precincts, community districts, zip codes, and census tracts). Thus shared-method variance with regard to administrative boundaries is eliminated. This is especially true in considering the census data where schools will be considered at the tract level and at the zip code level. Furthermore, it will also be possible to test for nestedness at each of the administrative levels.

How do we account for selection bias and other confounds? With the exception of housing mobility studies, all neighborhood research must be observational in nature. This is because residents, to varying degrees, can self-select into neighborhoods. Research has found homebuyers to be potentially influenced by the desire to racially self-segregate (Bayer, Gerreira, & McMillan, 2007). This association has also been found in school selection and at both the neighborhood (DeSena, 2006) and city level (Clark, Dieleman & Deklerk, 1992) by parents of differing racial and ethnic backgrounds as well as of immigrant status (Lauen, 2007).

In one particularly poignant study illustrating the danger of assuming random student distribution, Boado (2007) found that assuming immigrant concentration to be randomly distributed would result in statistical inferences suggesting that French secondary schools with higher immigrant populations would have students who attained fewer years of education, had worse academic performance, and were less likely to pursue higher education. Assuming for immigrant self-selection, however, showed that for students in schools with more immigrants there was no significant difference for years of secondary education or lower academic performance, however there were higher rates of pursuing higher education. Unfortunately for experimental scientists, students and families will self-select even after having been randomly assigned, as found in a study of Korean middle school students (Kang, 2007).

While this study cannot do anything to ameliorate the self-selection of residents into neighborhoods, it does hope to illuminate how crime might be one potential factor in predicting resident self-selection. At present, existing internal and academic analyses of school data considers such variables as racial, immigrant, and socioeconomic distribution to be a random function (e.g. Hoxby, 2000). Furthermore, the analysis of these data at the school level, using school neighborhood as a proxy for student neighborhood, has been previously done using a more limited range of data and scope of neighborhood level variables (Whipple, Evans, Bary, & Maxell, 2010).

How valid are administrative data and analyses of a single city? Many researchers using quantitative methods to test for neighborhood effects focus at the city level both as a matter of practicality and as a matter of theorized between-city variance (Riva, Gauvin & Barnett, 2007). (For a review of the challenges involved in neighborhood research, please see Table 1 from Riva et al., 2007). While use of administrative data, and especially administrative data from multiple sources, in addition to subject data can serve to improve the validity of a study, many studies, including this one, do not cross-validate these data (Riva et al., 2007; for counter-examples see validation of crime data from Sampson et al., 1997 and for social and physical disorder see Sampson & Raudenbush, 1999).

Furthermore, given that most neighborhood-level data are extant and administrative in nature, it has also made understanding interpersonal dynamics and non-government related processes more difficult. Research involving social dynamics such as informal social control

(Drukker, Kaplan, Feron & van Os, 2003) and collective efficacy (Sampson et al., 1997) all require continued replication and take additional resources beyond what is typically allocated for analyses using secondary data. Such data will become even more critical as researchers continue to pursue meditational pathways through which development in context can be elucidated. Greater specificity is also needed in delineating what neighborhood characteristics in which areas are predictive of which human development outcomes at what stages of life (Cummins et al., 2005).

Additional neighborhood factors. Finally, data for a number of additional moderators and potential mediators are becoming increasingly available. Various N.Y.C. departments have begun collecting additional community level data on a number of indicators, although these data have yet to be compiled by community board and made publicly available. Some of these measures potentially represent multiple dynamics (business practices, civic efficacy, and government responses) such as the number of complaints concerning a person or establishment violating a smoking law or rodent complaints as recorded by DOHMH. Other measures potentially reflect on intra-neighborhood dynamics between residents including quality of life complaints to the NYPD such as blocked driveways, illegal parking (double parking, commercial vehicles in residential neighborhoods, or vehicles blocking a sidewalk ramp or crosswalk, hydrant, or bus stop), derelict vehicles, and disorderly youth.

Affluence has been uniquely linked to positive cognitive development independent of poverty (Klebanov, Brooks-Gunn, McCarton & McCormick, 1998). Similarly neighborhood cohesion has been found to be a type of socio-emotional wealth that operates independently of material wealth in positive youth development (Kohen, Brooks-Gunn, Leventhal, & Hertzman, 2002). Also tempering any perspectives on neighborhood protective factors are findings that risk factors such as ETV and negative peer associations are stronger predictors of youth violent behavior than social capital, cohesion or information social control (De Coster, Heimer, & Wittrock, 2006; Sampson et al., 2005; Wickrama & Bryant, 2003).

Future Directions

As such, moderators, mediators, coping mechanisms and interventions must be studied across contexts and life transitions as well (Schilling et al., 2007; Zielinski, & Bradshaw, 2006). Such research should focus on understanding systems and pathways through which stress, coping and resilience operate (Luthar, Cicchetti, & Becker, 2000). That is, while it is necessary to understand that ETV serves as a manifestation of systemic inequality, there are processes that individuals and families take, such as future-orientation (Harris et al., 2002) and family cohesion (Kliewer et al., 2001), which provide a more comprehensive perspective on the interplay between stress and human development (Aneshensel, 1992; Margolin, & Gordis, 2000). In particular, we are interested the role that teachers play in exhibiting stress-related outcomes (Margolis & Gordis, 2000). Such outcomes can be operationalized as teacher turnover due to teachers leaving schools in violent neighborhoods at higher rates or teacher credentials due to potential teachers selecting to work in such schools at lower rate leaving schools with less qualified applicants.

Research programs and intervention designs must also consider differences across the lifespan and further utilize longitudinal data (Ozer, Richards, & Kliewer, 2004). One potential pathway is through school connectedness. A latent construct combining disciplinary policies, classroom management style, school size and participation in extracurricular activities, school connectedness has been linked to lower levels of self-reported deviant behavior (McNeely, Nonnemaker & Blum, 2002). Other school-based factors such as support and space to discuss violence can serve as protective factors against ETV (Benhorin, & McMahon, 2008; Brookmeyer, Fanti, & Henrich, 2006). For instance, a students' sense of school safety moderated the relation between ETV and violent delinquency in a sample of high school students (Crooks et al., 2007). Classmate support also has been identified as a protective moderator between ETV and reports of aggressive behavior, even as teacher, peer and parent support did not (Benhorin, & McMahon, 2008). Additionally, students' sense of satisfaction with the value of education has been found to buffer against antisocial behavior for youth exposed to violence (Herrenkohl et al., 2005). In this study, support from across domains, including in the school setting, was also found to potentially have an additive effect for youth exposed to violence (Herrenkohl et al., 2005). Their study also found that victims of violence received less support than witnesses and non-victim-non-witnesses.

We must also question if schools are best place for interventions. O'Donnell and colleagues (2002) reached similar findings writing that the potential influence of schools increased across early adolescence and that family support was a stronger buffer against ETV for younger children than schools. Similarly neighborhood norms research suggests a protective effect for informal social control on adolescent risk-taking behavior (Drukker et al., 2003). In general, political responses to ETV tend to be neighborhood rather than school based (Cooper, Bossak, Tempalski, Des Jarlals & Friedman, 2009).

It is only with a more thorough understanding of these pathways over time, that researchers and practitioners will be able to interrupt the cyclical progression of violence. Otherwise, to simply provide palliative care for the negative developmental outcomes associated with ETV will only serve as an exercise without end (Luthar, & Goldstein, 2004).

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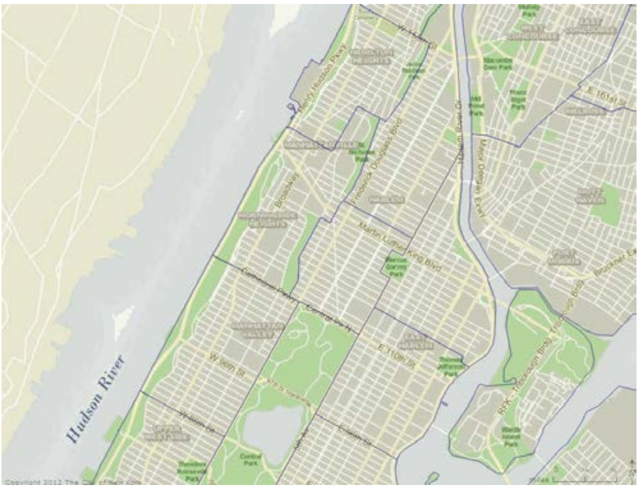
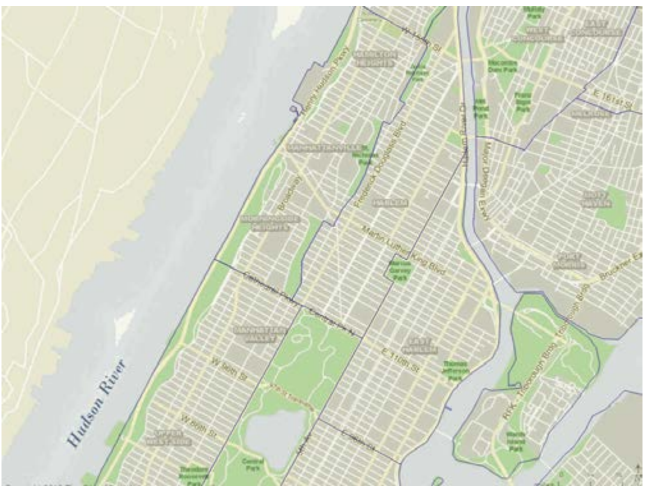
Research Questions
Is ETV associated with lower student performance in school?
Does ETV improve existing models of predicting student performance?
Does the relation between ETV and student performance differ for students by gender, race, age, poverty, English language learner status, or special needs status?
Is ETV a better predictor of student performance than community disorder?

Figure 1. Research questions.



(a)



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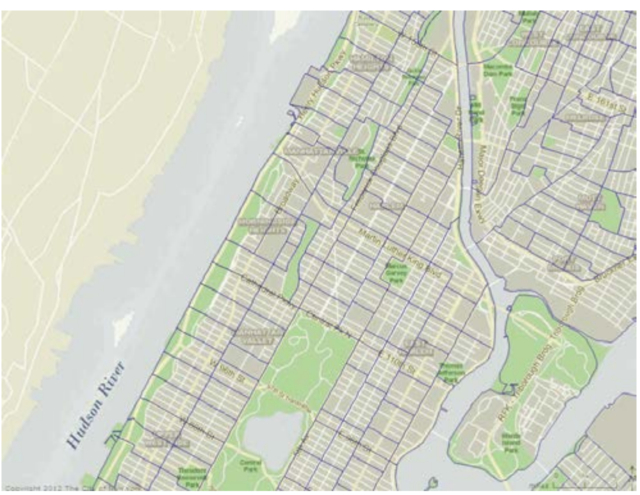

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Figure 2. Examples of varying geographic boundaries for (a) police precincts, (b) community districts, and (c) census tracts in New York City.

Table 1

Student demographic information by student year.

	Elementary School		Middle School		Total	
	Total	Percent	Total	Percent	Total	Percent
Gender						
Female	539,841	51.1%	552,953	51.0%	1,092,794	51.0%
Male	517,338	48.9%	530,875	49.0%	1,048,213	49.0%
Ethnicity						
Latino	423,487	40.1%	433,578	40.0%	857,065	40.0%
Black	331,569	31.4%	354,132	32.7%	685,701	32.0%
Asian	150,228	14.2%	147,447	13.6%	300,171	14.0%
White	151,748	14.4%	148,423	13.7%	297,675	13.9%
Grade						
Elementary	1,057,180	100.0%	0	0.0%	1,057,180	49.4%
Middle	0	0.0%	1,083,831	100.0%	1,083,831	50.6%
Service Designation/Eligibility						
Free Meals	752,752	71.2%	778,392	71.8%	1,531,144	71.5%
ELL	167,162	15.8%	128,849	11.9%	296,011	13.8%
Special Education	175,853	16.6%	166,878	15.4%	342,731	16.0%
TOTAL	1,057,180		1,083,831		2,141,011	

Table 2
Mean ELA and math scaled and standardized scores by group.

	ELA				Math			
	Scaled Score		Z-Score		Scaled Score		Z-Score	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Gender								
Female	660.06	34.59	.13	.98	672.04	39.72	.05	.97
Male	652.44	35.76	-.10	.99	669.69	41.52	-.01	1.01
Ethnicity								
Latino	649.28	33.03	-.19	.91	663.27	37.65	-.18	.90
Black	650.09	32.16	-.16	.88	660.23	37.31	-.25	.89
Asian	672.75	36.49	.49	1.07	698.64	39.47	.72	1.00
White	673.57	36.73	.51	1.05	688.90	38.69	.48	.95
Service Designation/Eligibility								
Free Meals	652.16	33.67	-.11	.94	666.97	39.46	-.09	.96
ELL	631.73	33.68	-.76	.91	652.99	39.33	-.50	.94
Special Education	628.09	35.50	-.81	.93	640.58	40.24	-.80	.94
TOTAL	656.18	35.39	.01	.99	670.84	40.67	.02	.99

Table 3

School neighborhood factors, original variable and source.

School Neighborhood Factor	Original Variable	Data Source	Geographic Level
ETV	Assault	NYPD	Police Precinct
	Homicide	NYPD	Police Precinct
	Rape	NYPD	Police Precinct
	Robbery	NYPD	Police Precinct
Community Disorder	Child Abuse Neglect	ACS	Community District
	Clean Sidewalks	MOO	Community District
	Drug Abuse Deaths	DOHMH	Community District
	Infant Mortality	DOHMH	Community District
	Recycling Rate	DSNY	Community District
Concentrated Disdvantage	Child to Adult Ratio	ACS	Census Tract
	Living in Poverty	ACS	Census Tract
	No High School Diploma	ACS	Census Tract
	Single Parent Households	ACS	Census Tract
	Unemployed	ACS	Census Tract
Immigrant Concentration	Non-English Speaking Household	ACS	Census Tract
	Foreign Born	ACS	Census Tract
Residential Stability	Home Ownership	ACS	Census Tract
	Lived in Residence for Past 5 Year	ACS	Census Tract

Table 4

Inter-class correlations by outcome and by grade level.

		Elementary	Middle
ELA	Student Variance	0.5261	0.5312
	School Variance	0.218	0.2454
	Residual Variance	0.3164	0.2702
	ICC Student	49.61%	50.74%
	ICC School	20.55%	23.44%
Math	Student Variance	0.5738	0.5597
	School Variance	0.2365	0.2925
	Residual Variance	0.2503	0.2002
	ICC Student	54.10%	53.18%
	ICC School	22.30%	27.79%

Table 5

Correlations of school-neighborhood-level predictors to outcomes.

	1.	2.	3.	4.	5.	6.	7.
1. ELA	1.000						
2. Math	.661	1.000					
3. ETV	-.212	-.244	1.000				
4. Community Disorder	-.202	-.225	.859	1.000			
5. Concentrated Disadvantage	-.225	-.226	.641	.674	1.000		
6. Immigrant Concentration	-.011	.049	-.165	-.153	.182	1.000	
7. Residential Stability	.134	.137	-.374	-.388	-.509	-.247	1.000

Note: All relationships are significant at $p < .001$.

Note: N = 2,141,011 student years

Table 6
Model number by included variables.

Variable	Model 1	2	3	4	5	6	7
Intercept	x	x	x	x	x	x	x
Female		x	x	x	x	x	x
Latino		x	x	x	x	x	x
Black		x	x	x	x	x	x
Asian		x	x	x	x	x	x
Meals		x	x	x	x	x	x
ELL		x	x	x	x	x	x
Special Education		x	x	x	x	x	x
Concentrated Dis.			x	x	x	x	x
Immigrant Con.			x	x	x	x	x
Res. Stability			x	x	x	x	x
Violence			x	x	x	x	
Δ Violence				x			
Violence Interactions					x		
Disorder						x	x

Table 7
Model fit statistics for fixed and random effects models.

			Elementary School		Middle School	
			ELA	Math	ELA	Math
Model 2: Current Educational Model	Fixed	AIC	2326950	2331369	2294150	2216237
		BIC	2327080	2331500	2294280	2216367
	Random	AIC	2317059	2319596	2280547	2201311
		BIC	2317603	2319691	2280642	2201406
Model 3: Adding ETV and Census Controls	Fixed	AIC	2325362	2329495	2293990	2216052
		BIC	2325540	2329673	2294168	2216231
	Random	AIC	2315601	2317911	2280513	2201262
		BIC	2316193	2318505	2281106	2201857
Model 4: Controlling for Past ETV	Fixed	AIC	1226071	1144504	1769726	1615918
		BIC	1226249	1144683	1769912	1616103
	Random	AIC	1220104	1137635	1758846	1605231
		BIC	1220674	1138205	1759425	1605753
Model 5: Adding ETV Interactions	Fixed	AIC	2324332	2328249	2292182	2214577
		BIC	2324593	2328510	2292443	2214839
	Random	AIC	2315378	2317709	2280366	2201146
		BIC	2315602	2318373	2280592	2201372
Model 6: Adding Community Disorder to ETV	Fixed	AIC	2325360	2329495	2293981	2216054
		BIC	2325549	2329685	2294171	2216245
	Random	AIC	2315595	2317836	2280506	2201264
		BIC	2316186	2317990	2281111	2201870
Model 7: Community Disorder Replacing ETV	Fixed	AIC	2325369	2329541	2294028	2216151
		BIC	2325546	2329719	2294206	2216330
	Random	AIC	2315530	2317954	2280481	2201351
		BIC	2315672	2318547	2280624	2201946

Table 8

Mean school neighborhood characteristics by demographic groups.

	Exposure to Violence		Community Disorder		Concentrated Disadvantage		Immigrant Concentration		Residential Stability	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Gender										
Female	-.060	.877	.064	1.004	.288	1.058	.077	.991	-.089	.939
Male	-.071	.877	.054	1.003	.284	1.054	.080	.994	-.087	.943
Ethnicity										
Latino	.050	.824	.265	1.040	.632	1.086	.265	.972	-.383	.802
Black	.354	.887	.345	1.023	.438	.987	-.260	.752	-.066	.916
Asian	-.641	.512	-.579	.574	-.197	.738	.628	1.077	.140	.941
White	-.784	.458	-.554	.533	-.576	.669	-.234	1.062	.483	1.029
Grade										
Elementary	-.062	.863	.049	.980	.289	1.048	.092	1.002	-.077	.936
Middle	-.069	.891	.068	1.025	.282	1.063	.065	.984	-.099	.945
Service Designation/Eligibility										
Free Meals	.051	.895	.184	1.041	.447	1.051	.121	.967	-.183	.895
ELL	-.051	.811	.115	1.006	.609	1.039	.522	1.019	-.373	.800
Special Education	.016	.906	.176	1.055	.360	1.091	-.041	.944	-.145	.936
TOTAL	-.065	.877	.059	1.003	.286	1.056	.079	.993	-.088	.941

Table 9
Parameter estimates and fit statistics for elementary school ELA.

	Model 2 Random	Model 3 Random	Model 4 Random	Model 5 Random	Model 6 Random	Model 7 Random
Intercept	0.271	0.309	0.389	0.318	0.309	0.310
	(.018)	(.017)	(.016)	(.016)	(.017)	(.017)
Female	0.096	0.096	0.083	0.097	0.096	0.096
	(.002)	(.002)	(.003)	(.002)	(.002)	(.002)
Black	-0.259	-0.260	-0.272	-0.265	-0.260	-0.260
	(.011)	(.011)	(.011)	(.011)	(.011)	(.011)
Asian	0.099	0.099	0.114	0.098	0.099	0.099
	(.009)	(.009)	(.011)	(.011)	(.009)	(.009)
Latino	-0.171	-0.171	-0.170	-0.175	-0.171	-0.171
	(.010)	(.010)	(.011)	(.011)	(.010)	(.010)
F/RP Meals	-0.083	-0.085	-0.113	-0.084	-0.085	-0.085
	(.004)	(.004)	(.005)	(.004)	(.004)	(.004)
ELL	-0.511	-0.510	-0.592	-0.512	-0.510	-0.510
	(.007)	(.007)	(.008)	(.006)	(.007)	(.007)
IEP	-0.698	-0.700	-0.734	-0.702	-0.700	-0.700
	(.008)	(.007)	(.008)	(.007)	(.007)	(.007)
Concentrated		-0.072	-0.063	-0.085	-0.075	-0.080
Disadvantage		(.010)	(.009)	(.010)	(.010)	(.010)
Immigrant		0.014*	0.003*	0.023**	0.015*	0.018*
Concentration		(.010)	(.009)	(.010)	(.010)	(.010)
Residential		0.038***	0.029***	0.043	0.038***	0.040***
Stability		(.012)	(.010)	(.012)	(.012)	(.012)
ETV		-0.011***	-0.053	-0.066	-0.014***	
		(.004)	(.007)	(.012)	(.004)	
Change in ETV			-0.017***			
			(.006)			
Violence*Female				-0.002*		
				(.003)		
Violence*Black				0.028**		
				(.011)		
Violence*Asian				-0.013*		
				(.013)		
Violence*Latino				0.011*		
				(.011)		
Violence*Meals				0.030		
				(.004)		
Violence*ELL				0.064		
				(.006)		
Violence*IEP				0.029		
				(.006)		
Disorder					0.007**	0.005*
					(.003)	(.003)
Deviance	2316968	2315502	1220002	2315340	2315496	2315506
AIC	2317059	2315601	1220104	2315378	2315595	2315530
BIC	2317603	2316193	1220674	2315602	2316186	2315672

Note: all coefficients are significant at p < .001 unless otherwise noted, * p > .05, ** p < .05, *** p < .01
Note: indicates a model fit statistic that is larger than the previous model.

Table 10
Parameter estimates and fit statistics for middle school ELA.

	Model 2 Random	Model 3 Random	Model 4 Random	Model 5 Random	Model 6 Random	Model 7 Random
Intercept	0.165	0.210	0.240	0.226	0.210	0.212
	(.020)	(.020)	(.020)	(.020)	(.020)	(.020)
Female	0.144	0.144	0.142	0.146	0.144	0.144
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
Black	-0.207	-0.211	-0.205	-0.220	-0.211	-0.211
	(.011)	(.011)	(.012)	(.012)	(.011)	(.011)
Asian	0.106	0.103	0.100	0.097	0.103	0.103
	(.012)	(.012)	(.013)	(.013)	(.012)	(.012)
Latino	-0.126	-0.130	-0.129	-0.138	-0.130	-0.130
	(.011)	(.011)	(.012)	(.012)	(.011)	(.011)
F/RP Meals	-0.057	-0.057	-0.063	-0.059	-0.057	-0.057
	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)
ELL	-0.645	-0.643	-0.675	-0.652	-0.643	-0.643
	(.010)	(.010)	(.012)	(.010)	(.010)	(.010)
IEP	-0.641	-0.643	-0.631	-0.646	-0.643	-0.643
	(.009)	(.009)	(.009)	(.009)	(.009)	(.009)
Concentrated		-0.050	-0.044	-0.059	-0.047	-0.057
Disadvantage		(.011)	(.011)	(.011)	(.011)	(.011)
Immigrant		0.042***	0.036***	0.050	0.041***	0.049
Concentration		(.013)	(.012)	(.013)	(.013)	(.013)
Residential		0.023*	0.021*	0.027**	0.022*	0.025*
Stability		(.014)	(.013)	(.014)	(.013)	(.014)
ETV		-0.031	-0.045	-0.062	-0.028	
		(.004)	(.005)	(.011)	(.004)	
Change in ETV			-0.021			
			(.005)			
Violence*Female				-0.013		
				(.003)		
Violence*Black				0.017*		
				(.011)		
Violence*Asian				-0.025*		
				(.013)		
Violence*Latino				0.012*		
				(.011)		
Violence*Meals				0.021		
				(.004)		
Violence*ELL				0.054		
				(.009)		
Violence*IEP				0.017**		
				(.007)		
Disorder					-0.007***	-0.012
					(.003)	(.002)
Deviance	2280532	2280412	1758746	2280328	2280404	2280458
AIC	2280547	2280513	1758846	2280366	2280506	2280481
BIC	2280642	2281106	1759425	2280592	2281111	2280624

Note: all coefficients are significant at p < .001 unless otherwise noted, * p > .05, ** p < .05, *** p < .01
Note: indicates a model fit statistic that is larger than the previous model.

Table 11

Parameter estimates and fit statistics for elementary school math.

	Model 2 Random	Model 3 Random	Model 4 Random	Model 5 Random	Model 6 Random	Model 7 Random
Intercept	0.261	0.301	0.429	0.293	0.301	0.304
	(.018)	(.017)	(.016)	(.016)	(.017)	(.017)
Female	-0.047	-0.047	-0.072	-0.047	-0.047	-0.047
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
Black	-0.309	-0.311	-0.355	-0.302	-0.311	-0.311
	(.011)	(.011)	(.011)	(.011)	(.011)	(.011)
Asian	0.307	0.306	0.303	0.314	0.306	0.306
	(.011)	(.011)	(.012)	(.012)	(.011)	(.011)
Latino	-0.155	-0.158	-0.190	-0.146	-0.158	-0.158
	(.010)	(.010)	(.011)	(.011)	(.010)	(.010)
F/RP Meals	-0.044	-0.045	-0.080	-0.044	-0.045	-0.045
	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)
ELL	-0.426	-0.426	-0.414	-0.427	-0.426	-0.426
	(.007)	(.007)	(.007)	(.006)	(.007)	(.007)
IEP	-0.608	-0.610	-0.703	-0.611	-0.610	-0.610
	(.007)	(.007)	(.008)	(.007)	(.007)	(.007)
Concentrated		-0.066	-0.073	-0.077	-0.065	-0.073
Disadvantage		(.011)	(.011)	(.011)	(.011)	(.011)
Immigrant		0.033***	0.024**	0.038***	0.032***	0.037***
Concentration		(.011)	(.011)	(.011)	(.011)	(.011)
Residential		0.046	0.030**	0.049	0.046	0.049
Stability		(.013)	(.012)	(.013)	(.013)	(.013)
ETV		-0.026	-0.058	-0.144	-0.025	
		(.004)	(.006)	(.011)	(.004)	
Change in ETV			-0.018***			
			(.005)			
Violence*Female				0.011		
				(.003)		
Violence*Black				0.097		
				(.011)		
Violence*Asian				0.008*		
				(.013)		
Violence*Latino				0.077		
				(.010)		
Violence*Meals				0.027		
				(.004)		
Violence*ELL				0.045		
				(.006)		
Violence*IEP				0.020***		
				(.006)		
Disorder					-0.003*	-0.007***
					(.003)	(.002)
Deviance	2319580	2317812	1137533	2317596	2317810	2317854
AIC	2319596	2317911	1137635	2317709	2317836	2317954
BIC	2319691	2318505	1138205	2318373	2317990	2318547

Note: all coefficients are significant at p < .001 unless otherwise noted, * p > .05, ** p < .05, *** p < .01
Note: indicates a model fit statistic that is larger than the previous model.

Table 12
Parameter estimates and fit statistics for middle school math.

	Model 2 Random	Model 3 Random	Model 4 Random	Model 5 Random	Model 6 Random	Model 7 Random
Intercept	0.156	0.199	0.261	0.209	0.199	0.201
	(.022)	(.022)	(.022)	(.022)	(.022)	(.023)
Female	0.002*	0.002*	-0.001*	0.002*	0.002*	0.002*
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
Black	-0.242	-0.245	-0.277	-0.247	-0.245	-0.245
	(.012)	(.012)	(.012)	(.012)	(.012)	(.012)
Asian	0.343	0.342	0.322	0.342	0.342	0.342
	(.012)	(.012)	(.013)	(.013)	(.012)	(.012)
Latino	-0.110	-0.113	-0.143	-0.117	-0.113	-0.113
	(.012)	(.012)	(.011)	(.011)	(.012)	(.012)
F/RP Meals	-0.020	-0.020	-0.034	-0.022	-0.020	-0.020
	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)
ELL	-0.431	-0.429	-0.391	-0.431	-0.429	-0.429
	(.008)	(.008)	(.008)	(.008)	(.008)	(.008)
IEP	-0.655	-0.656	-0.668	-0.658	-0.656	-0.656
	(.010)	(.010)	(.009)	(.010)	(.010)	(.010)
Concentrated		-0.028**	-0.017*	-0.038***	-0.028**	-0.040***
Disadvantage		(.014)	(.014)	(.014)	(.014)	(.014)
Immigrant		0.046***	0.029*	0.053***	0.046***	0.056
Concentration		(.016)	(.016)	(.016)	(.016)	(.016)
Residential		0.058	0.056***	0.061	0.058	0.063
Stability		(.017)	(.017)	(.017)	(.017)	(.017)
ETV		-0.033	-0.058	-0.082	-0.033	
		(.003)	(.005)	(.011)	(.003)	
Change in ETV			-0.036			
			(.004)			
Violence*Female				-0.002*		
				(.003)		
Violence*Black				0.037		
				(.010)		
Violence*Asian				-0.014*		
				(.013)		
Violence*Latino				0.044		
				(.010)		
Violence*Meals				0.015		
				(.004)		
Violence*ELL				0.014**		
				(.007)		
Violence*IEP				0.010*		
				(.007)		
Disorder					0.000*	-0.005**
					(.002)	(.002)
Deviance	2201296	2201162	1605141	2201108	2201162	2201252
AIC	2201311	2201262	1605231	2201146	2201264	2201351
BIC	2201406	2201857	1605753	2201372	2201870	2201946

Note: all coefficients are significant at p < .001 unless otherwise noted, * p > .05, ** p < .05, *** p < .01
Note: indicates a model fit statistic that is larger than the previous model.

Table 13

Fixed Effects Comparison of Hierarchical Linear Models Versus Cross-Classified Linear Models in Predicting Elementary ELA

	Model 1		Model 2		Model 3		Model 6		Model 7	
	HLM	CC	HLM	CC	HLM	CC	HLM	CC	HLM	CC
Intercept	-0.067	-0.441	0.389	0.095	0.390	0.094	0.390	0.094	0.271	0.096
	(.016)	(.045)	(.011)	(.041)	(.011)	(.041)	(.011)	(.041)	(.018)	(.041)
Female			0.100	0.103	0.100	0.103	0.100	0.103	0.096	0.103
			(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
Black			-0.354	-0.358	-0.354	-0.358	-0.354	-0.358	-0.259	-0.358
			(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.011)	(.004)
Asian			0.045	0.042	0.045	0.042	0.045	0.042	0.099	0.042
			(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.009)	(.004)
Latino			-0.260	-0.267	-0.260	-0.267	-0.260	-0.267	-0.170	-0.267
			(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.010)	(.004)
F/RP Meals			-0.087	-0.084	-0.087	-0.084	-0.087	-0.084	-0.083	-0.084
			(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.004)	(.002)
ELL			-0.537	-0.534	-0.538	-0.534	-0.538	-0.534	-0.511	-0.534
			(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.007)	(.003)
IEP			-0.723	-0.695	-0.723	-0.695	-0.723	-0.695	-0.698	-0.695
			(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.008)	(.003)
Violence					-0.022	-0.006	-0.023	-0.009		
					(.004)	(.004)	(.004)	(.004)		
Disorder							0.001	0.010	0.001	0.008
							(.003)	(.003)	(.003)	(.003)
Deviance	2450058	2423650	2326928	2310078	2326896	2310076	2326894	2310064	2316968	2310068
AIC	2450067	2425356	2326950	2311797	2326919	2311797	2326921	2311787	2316985	2311790
BIC	2450114	2435443	2327080	2321968	2327061	2321979	2327075	2321981	2317092	2321972

Note: Mean difference for non-intercept coefficients from hierarchical models to cross-classified models: 0.015

Table 14

Fixed Effects Comparison of Hierarchical Linear Models Versus Cross-Classified Linear Models in Predicting Middle School ELA

	Model 1		Model 2		Model 3		Model 6		Model 7	
	HLM	CC	HLM	CC	HLM	CC	HLM	CC	HLM	CC
Intercept	-0.096	-0.182	0.325	0.267	0.331	0.255	0.334	0.259	0.170	0.270
	(.018)	(.105)	(.013)	(.104)	(.013)	(.104)	(.013)	(.104)	(.020)	(.104)
Female			0.156	0.161	0.156	0.161	0.156	0.161	0.144	0.161
			(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.003)	(.002)
Black			-0.341	-0.354	-0.341	-0.354	-0.341	-0.354	-0.208	-0.354
			(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.011)	(.004)
Asian			0.066	0.059	0.065	0.059	0.065	0.059	0.105	0.059
			(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.012)	(.004)
Latino			-0.249	-0.264	-0.249	-0.264	-0.249	-0.264	-0.127	-0.264
			(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.011)	(.004)
F/RP Meals			-0.072	-0.070	-0.072	-0.069	-0.072	-0.069	-0.056	-0.069
			(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.004)	(.002)
ELL			-0.752	-0.748	-0.752	-0.748	-0.752	-0.748	-0.645	-0.748
			(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.010)	(.003)
IEP			-0.675	-0.659	-0.675	-0.659	-0.675	-0.659	-0.642	-0.659
			(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.009)	(.003)
Violence					-0.036	-0.029	-0.032	-0.026		
					(.004)	(.004)	(.004)	(.004)		
Disorder							-0.010	-0.008	-0.014	-0.012
							(.002)	(.002)	(.002)	(.002)
Deviance	2430816	2398552	2294128	2270120	2294032	2270060	2294014	2270050	2280498	2270096
AIC	2430825	2400024	2294150	2271606	2294056	2271548	2294041	2271541	2280515	2271584
BIC	2430872	2408751	2294280	2280415	2294198	2280370	2294195	2280374	2280622	2280406

Note: Mean difference for non-intercept coefficients from hierarchical models to cross-classified models: 0.021

Table 15

Fixed Effects Comparison of Hierarchical Linear Models Versus Cross-Classified Linear Models in Predicting Elementary Math

	Model 1		Model 2		Model 3		Model 6		Model 7	
	HLM	CC	HLM	CC	HLM	CC	HLM	CC	HLM	CC
Intercept	-0.073	-0.498	0.383	0.029	0.385	0.022	0.386	0.022	0.264	0.028
	(.017)	(.043)	(.012)	(.040)	(.012)	(.040)	(.012)	(.040)	(.018)	(.040)
Female			-0.044	-0.040	-0.044	-0.040	-0.044	-0.040	-0.047	-0.040
			(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.003)	(.002)
Black			-0.398	-0.410	-0.398	-0.410	-0.398	-0.410	-0.309	-0.410
			(.004)	(.005)	(.004)	(.005)	(.004)	(.005)	(.011)	(.005)
Asian			0.269	0.267	0.269	0.267	0.269	0.267	0.307	0.267
			(.004)	(.005)	(.004)	(.005)	(.004)	(.005)	(.011)	(.005)
Latino			-0.249	-0.262	-0.249	-0.262	-0.249	-0.262	-0.156	-0.262
			(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.010)	(.004)
F/RP Meals			-0.046	-0.044	-0.045	-0.044	-0.045	-0.044	-0.044	-0.044
			(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.004)	(.002)
ELL			-0.445	-0.437	-0.445	-0.437	-0.445	-0.437	-0.426	-0.437
			(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.007)	(.003)
IEP			-0.623	-0.585	-0.623	-0.585	-0.623	-0.585	-0.609	-0.585
			(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.007)	(.003)
Violence					-0.035	-0.024	-0.033	-0.024		
					(.004)	(.004)	(.004)	(.004)		
Disorder							-0.006	-0.001	-0.010	-0.004
							(.003)	(.003)	(.002)	(.002)
Deviance	2450058	2423650	2326928	2310078	2326896	2310076	2326894	2310064	2316968	2310068
AIC	2450067	2425356	2326950	2311797	2326919	2311797	2326921	2311787	2316985	2311790
BIC	2450114	2435443	2327080	2321968	2327061	2321979	2327075	2321981	2317092	2321972

Note: Mean difference for non-intercept coefficients from hierarchical models to cross-classified models: 0.017

Table 16

Fixed Effects Comparison of Hierarchical Linear Models Versus Cross-Classified Linear Models in Predicting Middle School Math

	Model 1		Model 2		Model 3		Model 6		Model 7	
	HLM	CC	HLM	CC	HLM	CC	HLM	CC	HLM	CC
Intercept	-0.111	-0.145	0.327	0.322	0.334	0.309	0.334	0.309	0.158	0.323
	(.020)	(.091)	(.014)	(.091)	(.014)	(.091)	(.014)	(.091)	(.022)	(.091)
Female			0.009	0.015	0.009	0.015	0.009	0.015	0.002	0.015
			(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.003)	(.002)
Black			-0.381	-0.400	-0.381	-0.400	-0.381	-0.400	-0.242	-0.400
			(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.012)	(.004)
Asian			0.347	0.343	0.347	0.343	0.347	0.343	0.343	0.343
			(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.012)	(.004)
Latino			-0.250	-0.269	-0.250	-0.269	-0.250	-0.269	-0.110	-0.269
			(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.012)	(.004)
F/RP Meals			-0.033	-0.031	-0.033	-0.031	-0.033	-0.031	-0.020	-0.031
			(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.004)	(.002)
ELL			-0.467	-0.465	-0.467	-0.465	-0.467	-0.465	-0.431	-0.465
			(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.008)	(.003)
IEP			-0.694	-0.674	-0.694	-0.674	-0.694	-0.674	-0.655	-0.674
			(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.010)	(.003)
Violence					-0.038	-0.035	-0.037	-0.035		
					(.003)	(.003)	(.003)	(.003)		
Disorder							-0.002	0.000	-0.006	-0.005
							(.002)	(.002)	(.002)	(.002)
Deviance	2430816	2398552	2294128	2270120	2294032	2270060	2294014	2270050	2280498	2270096
AIC	2430825	2400024	2294150	2271606	2294056	2271548	2294041	2271541	2280515	2271584
BIC	2430872	2408751	2294280	2280415	2294198	2280370	2294195	2280374	2280622	2280406

Note: Mean difference for non-intercept coefficients from hierarchical models to cross-classified models: 0.019