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Estimating the Effect of Green Space on Academic Achievement
in New York City

A Plan B Paper

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John Lyle Anderson

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Advisor: Professor Stephen Polasky (Chair)

Committee Members: Professor Elizabeth Davis

Affiliate Faculty Geoffrey Maas

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DEDICATION

I dedicate this study to the hundreds of grade school students and educators from New York City whom I met when I worked at Ramapo for Children in Rhinebeck, NY from 2016 to 2018.

ABSTRACT

This paper investigates the relationship between urban green space and academic achievement (standardized test scores) for public elementary schools in New York City. In 2010 and 2017, I find evidence of a neighborhood-level positive association of tree canopy with test scores. However, there is little evidence of any association when only tree canopy close to schools is considered. Results are robust to hierarchical mixed-effects model specifications. I also conduct one of the first longitudinal analyses of the green space-educational outcomes relationship. I find initial evidence that increases in tree canopy around elementary schools between 2010 and 2017 were associated with decreased grade-average test performance for high-poverty schools and were not significantly associated with changes in test performance of non-high poverty schools, a result that somewhat contradicts the positive comparative static results. To reconcile my findings, I construct an extended econometric model detailing potential bias in the green space-educational outcomes relationship that might arise from unobserved changing dimensions of inequality, with the adoption of Common Core curricula starting in 2013 serving as a pertinent example. Standard econometric approaches do not capture time-varying unobserved characteristics associated with observational data, so omitted factors that covary both with changes in green space and changes in test scores may bias the estimated green space-educational outcomes relationship. Future researchers should intentionally consider the co-development of urban green space with salient unobserved factors when estimating and interpreting the effect of changes in green space on educational outcomes over time.

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Introduction

The impacts of natural green spaces on human behavior and well-being began as a multidisciplinary field of research a couple of decades ago, and associated research agendas have both deepened and broadened over time (IPBES 2019; Millenium Ecosystem Assessment 2005). Researchers are often interested in how green space influences behavior and well-being in an urban context, a topic that has gained in importance given the global trend of increasing urbanization¹ (“68% of the World Population”). Markevych et al. (2017) codify three known types of mechanisms that govern how green space affects human health – *harm reduction* (i.e., heat and air pollution reduction), *capacity restoration* (i.e., attention restoration), and *capacity-building* (i.e., physical activity). Twohig-Bennett and Jones (2018) review observational and interventional studies that provide evidence of multiple health benefits caused by greenspace exposure, including decreased heart rate, decreased blood pressure², low-frequency heart rate variability, decreased risk of type II diabetes, and decreased risks of all-cause mortality and cardiovascular mortality. Other studies find evidence for improved mental health outcomes (Alcock et al. 2014; Berman et al. 2012; Beyer et al. 2014; Bratman et al. 2019; Engemann et al. 2019, South et al. 2018), healthier stress biomarkers (Egorov et al. 2017), reduced overall morbidity (Maas et al. 2009), better self-reported health or well-being (Reid et al. 2017; Reid et al. 2018; White et al. 2017), improved happiness (White et al. 2013a), and reduced crime (Kuo and Sullivan 2001)³. White et al. (2013b) use a longitudinal panel survey to offer evidence of improved mental health outcomes from living near coastal areas. Lastly, since urban green space reduces “heat island” effects (Li et al. 2012; Sun and Chen 2017), it may mitigate heat’s negative impact on student learning in urban areas (Goodman et al. 2018; Graff Zivin, Hsiang, and Neidell 2018).

The association of green space (usually urban green space) with the cognitive functioning/development and academic achievement of grade-school students is a relatively understudied subfield of the human-greenspace literature. Nature-based learning has been shown

¹ Estimated global urban population increased from 751 million in 1950 to 4.2 billion in 2018. Fifty-five percent of global population is estimated to live in urban areas, and this is expected to increase to sixty-eight percent by 2050.

² See Grazuleviciene et al. (2014) and Bijnens et al. (2017).

³ The authors use police crime reports to examine the relationship between vegetation and crime in an inner-city neighborhood. Although residents were randomly assigned to different levels of nearby vegetation, the greener a building’s surroundings were, the fewer crimes (both property and violent) were reported.

to enhance educational and developmental outcomes for children (Jordan and Chawla 2019), and multidisciplinary research consistently concludes that any contact that children have with nature induces positive outcomes (Kuo and Jordan 2019). A sizable literature addresses children's cognitive functioning and development amidst natural environments. Ulrich et al. (1991) posit Stress Recovery Theory (SRT) as one independent mechanism that governs the relationship between green spaces and cognitive functioning, suggesting that humans have evolved and retain a psycho-physiological response to nature that lowers stress while in natural environments. SRT is similar to but independent from Attention Restoration Theory (ART) offered by Kaplan (1995) and Kaplan and Berman (2010), which hypothesizes that natural environments restore executive functioning and self-regulation by replenishing voluntary/directed attention. Li and Sullivan (2016) provide experimental evidence of both SRT and ART – they exposed high school students to green landscapes through a randomized controlled trial and conclude that exposure to green environments in school significantly improves attention and stress recovery through independent processes.

Several additional experimental studies support SRT by concluding that green landscapes and environments improve stress recovery, whether measured as self-reported stress (Tyrväinen et al. 2014), ambulatory blood pressure and emotion (Hartig et al. 2003), or a standardized stress test (Jiang et al. 2016). Other studies support ART by demonstrating how green environments improve measures of attention, such as spatial working memory (Flouri, Papachristou, and Midouhas 2019; Schutte, Torquati, and Beattie 2017), performance on computerized cognitive tests (Dadvand et al. 2015), and other attention-demanding tasks (Berto 2005; Hartig et al. 2003). As a whole, these experimental studies find that stress recovery and attention restoration are greater in green environments than they are in either non-restorative environments (Berto 2005; Hartig et al. 2003; Schutte, Torquati, and Beattie 2017; Tyrväinen et al. 2014) or similar restorative environments (Dadvand et al. 2015; Flouri, Papachristou, and Midouhas 2019; Jiang et al. 2016; Li and Sullivan 2016; Tyrväinen et al. 2014). This suggests that greener environments may be particularly beneficial for stress recovery and attention restoration, even when compared to similar restorative activities. As a counterexample, Reuben et al. (2019) conclude that green spaces may not directly impact children's cognitive functioning despite appearing to; the authors assert that although there is evidence that children who grow up in greener neighborhoods have better cognitive abilities relative to children who grow up in less green neighborhoods as a whole, this difference is largely

explained by family and neighborhood socioeconomic factors. However, there is widespread experimental evidence and scientific consensus that natural environments provide stress recovery and attention restoration to humans, in addition to the set of health benefits mentioned previously.

Developing from the natural science literature, the social science literature on the green space-educational outcomes relationship focuses on the link between green space and the measurable “downstream” human capital outcomes associated with cognitive capacity and development. These studies almost all utilize observational research designs. Academic achievement metrics, predominantly test scores but occasionally graduation rates and college readiness, are the outcomes investigated in this subfield. Causal inference of the impact of green space on educational outcomes is difficult to obtain, in contrast to the natural science literature on the impact of green space on stress recovery and attention restoration⁴.

Research on the green space-educational outcomes relationship is multidisciplinary⁵, so existing research approaches and methodologies vary widely. Researchers have analyzed the green space-educational outcomes relationship in several different geographic contexts, including Michigan (Matsuoka 2010), Minneapolis (Hodson and Sander 2017), Chicago (Kuo et al. 2018; Li et al. 2019), Massachusetts (Leung et al. 2019), California (Tallis et al. 2018), Washington DC (Kweon et al. 2017), Toronto (Sivarajah, Smith, and Thomas 2018), Maryland (Browning and Locke 2020), Portland (Donovan et al. 2020), and the continental US (Hodson and Sander 2019). Most of the literature uses an observational cross-sectional research design to investigate the green space-educational outcomes relationship for a set of years between 2005 and 2015.

Researchers typically use standardized test scores as the educational outcome of interest (Beere and Kingham 2017; Donovan et al. 2020; Hodson and Sander 2017; Kuo et al. 2018; Kweon et al. 2017; Sivarajah, Smith, and Thomas 2018; Tallis et al. 2018), although some studies use graduation rates (Li et al. 2019; Matsuoka 2010) or college readiness and freshman-on-track (Li et al. 2019). Most studies use test data averaged at the school-grade level, with the exception of Donovan (2020), who uses individual student data. Researchers use several definitions of green space, most commonly tree cover or total green space (tree cover plus shrub and grass cover) but

⁴ See Browning and Rigolon (2019) for a useful theoretical framework that synthesizes confounders (socioeconomic status, gender, ability, urbanicity, neighborhood, school features) and mechanisms (attention, mental health, time outdoors, physical activity) that mediate the green space-educational outcomes relationship.

⁵ Studies from urban planning, psychology, forestry, and environmental science exist, among others.

occasionally “green land use” (Leung et al. 2019) or normalized difference vegetation index (NDVI) (Browning and Locke 2020; Leung et al. 2019; Tallis et al. 2018). Studies employ varying scopes of spatial analysis, from school grounds exclusively to two-kilometer radii around schools or school attendance areas, largely because the hypothesized green space-educational outcomes mechanism is not well-defined⁶.

Most cross-sectional analyses find evidence of a positive green space-educational outcomes association after controlling for confounding factors. Having more tree cover close to school buildings (Donovan et al. 2020; Kuo et al. 2018; Kweon et al. 2017; Matsuoka 2010) or in the neighborhood (Hodson and Sander 2017; Li et al. 2019; Sivarajah, Smith, and Thomas 2018; Tallis et al. 2018) is largely positively associated with educational outcomes, all else equal. A couple studies report either a negative association (Beere and Kingham 2017; Browning and Locke 2020) or a positive “impervious surface”⁷ – educational outcome relationship (Hodson and Sander 2017). Additionally, studies often cite evidence that not all types of green landscapes have the same positive relationship (Browning and Locke 2020; Hodson and Sander 2017; Kuo et al. 2018; Kweon et al. 2017). Researchers most frequently conclude that tree cover in particular, not green space in general⁸, is positively associated with educational outcomes. Hodson and Sander (2019) conduct a nationwide analysis of the green space-educational outcomes relationship and conclude that the relationship may be context-specific and not testable on a wide geographic scale.

I am aware of two longitudinal studies of the green space-educational outcomes relationship. Leung et al. (2019) conduct an analysis of Massachusetts schools from 2006 to 2014 and conclude that tree canopy, not lower-growing vegetation, is associated with better educational outcomes. However, Markevych et al. (2019) utilize data on German adolescents from two time periods between 2005 and 2014 and conclude that there is no evidence of a positive green space – educational outcomes association when considering the influence of both residential and school green space.

This paper investigates the relationship between green space (specifically tree canopy cover) and academic achievement (standardized Math and English Language Assessment (ELA) test scores)

⁶ i.e., is having more trees “outside the classroom window” important, having more trees at the neighborhood level, or both?

⁷ i.e., sidewalks, roads, buildings.

⁸ “Green space” also includes park fields, athletic fields, and low-lying vegetation such as shrubs and bushes.

in a previously unstudied context – public elementary schools (grades three through five) in New York City. I use temporally matched test score and land cover data from 2010 and 2017, in addition to data on confounders, to conduct both comparative static and longitudinal analyses – this combination of empirical approaches has not been used in any case study to date, to my knowledge. This study utilizes the finest-scale land cover data in the green space – educational outcomes literature to date (six-inch LiDAR data). I begin by describing the data used (including land cover data, test score data, and other covariate data), summarize green space trends in New York City from 2010 to 2017 to provide evidence of sufficient variation in my explanatory variables of interest, and describe my estimation sample. I then present my cross-sectional and longitudinal results, synthesize my findings, and conclude.

Data

I use two essential pieces of data in my analysis. I use geospatial data to define elementary school locations and natural land cover areas in New York City, and I use grade-average standardized test scores as educational outcomes. I also control for a diverse set of confounding factors, the majority of which are school characteristics and school-grade characteristics, that likely covary with test scores and may also covary with urban green space.

Land Cover Data

For land cover data, I use raster files created from remotely-sensed LiDAR (Light Detection and Ranging) data collected in 2010 and 2017 for the entire extent of New York City, which is publicly available through New York City Open Data⁹ (New York City Department of Information 2018a; New York City Department of Information 2018b). In both 2010 and 2017, flyovers were conducted between mid-April and mid-May in leaf-on season. Quantum Spatial, The University of Vermont Spatial Analysis Laboratory, and New York City used quality control procedures to identify whether any measured change in tree canopy between 2010 and 2017 could be attributed

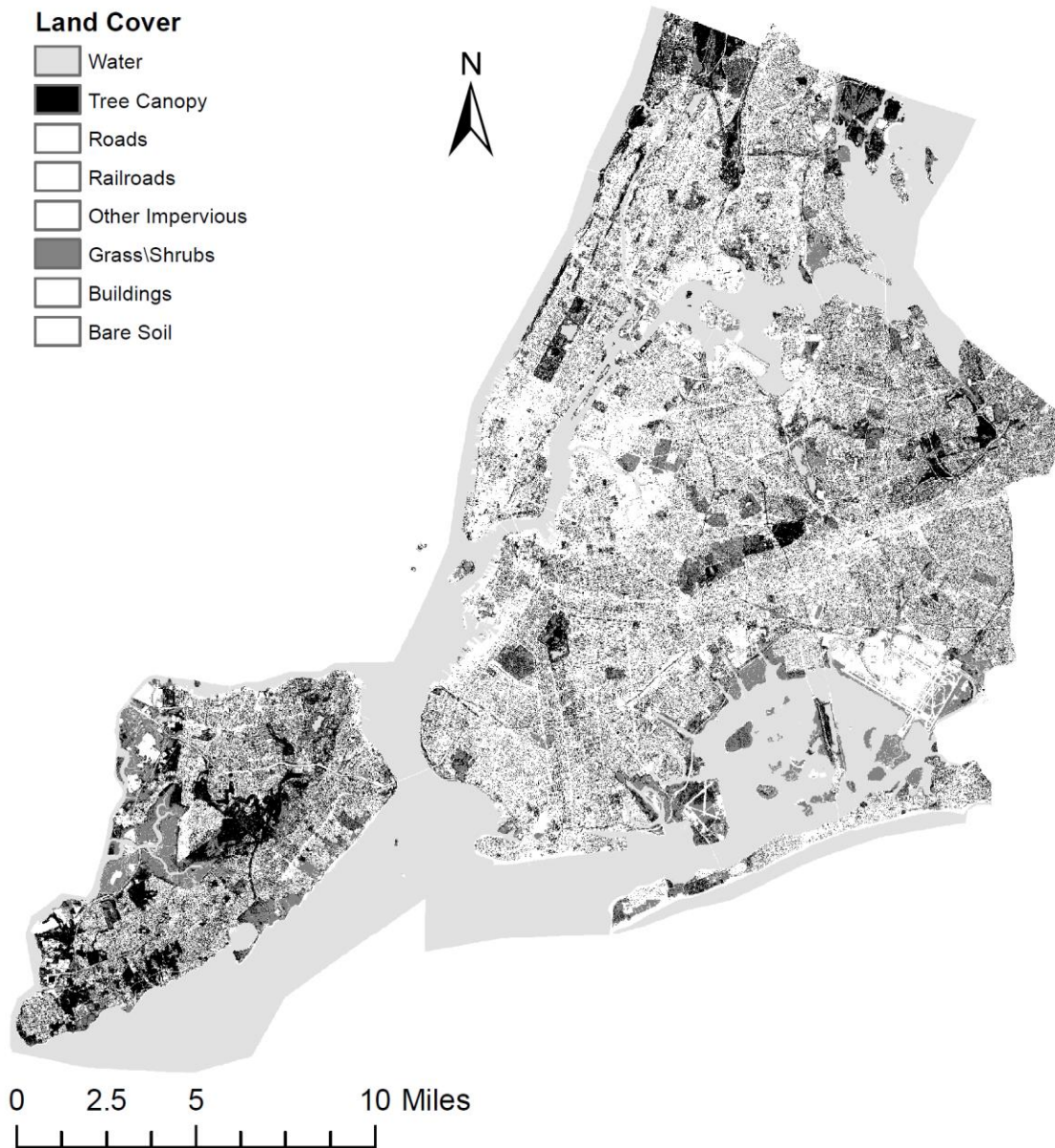
⁹ NYC Open Data catalogs public data generated by city agencies and organizations – it offers access to a large of number of data sets and accompanying documentation. The official NYC Open Data website promotes its content in the following way: “Anyone can use these data sets to participate in and improve government by conducting research and analysis or creating applications, thereby gaining a better understanding of the services provided by City agencies and improving the lives of citizens and the way in which government serves them.”

to variance in the LiDAR capture times or technology (New York City Department of Information 2020). The University of Vermont Spatial Analysis Laboratory and the New York City Urban Field Station developed Object-Based Image Analysis (OBIA) methods to convert the LiDAR images into raster datasets, combining them with other geospatial data provided by New York City Department of Information Technology and Telecommunications. This OBIA classification was estimated to be 96% accurate in 2010 and 98% accurate in 2017. Land cover classes included in the resulting raster data are (1) tree canopy, (2) grass/shrubs, (3) bare soil, (4) water, (5) buildings, (6) roads, (7) other impervious surfaces, and (8) railroads (2017 data only). Land cover is assigned at a six-inch resolution, which is finer-scale than all previous observational studies of the green space-educational outcomes relationship, most of which use between one-meter and two hundred fifty-meter resolution data. Map 1 displays the LiDAR-based land cover map of New York City in 2017. Tree canopy features are signified in black, grass and shrub features in dark gray, and water features in light gray. All geospatial editing and analysis was conducted with ArcGIS 10.7.1 (ESRI 2019).

School Location Data

In addition to the land cover data, I utilize a shape file of school point locations based on the official address of public schools in the city (New York City Department of Education 2019a). I use elementary schools (grades three to five) only, since younger students (especially elementary school students) are more likely to attend their zoned school than older students are (Corcoran 2018). Map 2 displays the distribution of public elementary schools in New York City in 2017. The Spatial Join tool in ArcGIS (ESRI 2020d) was used to assign school information to building polygons, in order to accurately define buffer zones for geospatial analysis around schools. The Buffer tool (ESRI 2020a) was used to define seven concentric buffer zones surrounding school buildings: twenty-five, fifty, one hundred, two hundred and fifty, five hundred, seven hundred and fifty, and one thousand-meter zones. This array of buffer zones is meant to capture any difference in near-school or neighborhood associations of green space with educational outcomes. Map 3 provides an illustration of twenty-five, fifty, one hundred, and two hundred and fifty-meter buffer zones around an elementary school.

Map 1. LIDAR-based Land Cover of New York City (2017)



Lyle Anderson, February 18 2020

Data Source: University of Vermont Spatial Analysis Laboratory, in collaboration with New York City Department of Information Technology and Telecommunications (NYC DoITT), Applied Geographics (AppGeo), and Quantum Spatial

Map 2. New York City Elementary Schools (2017)

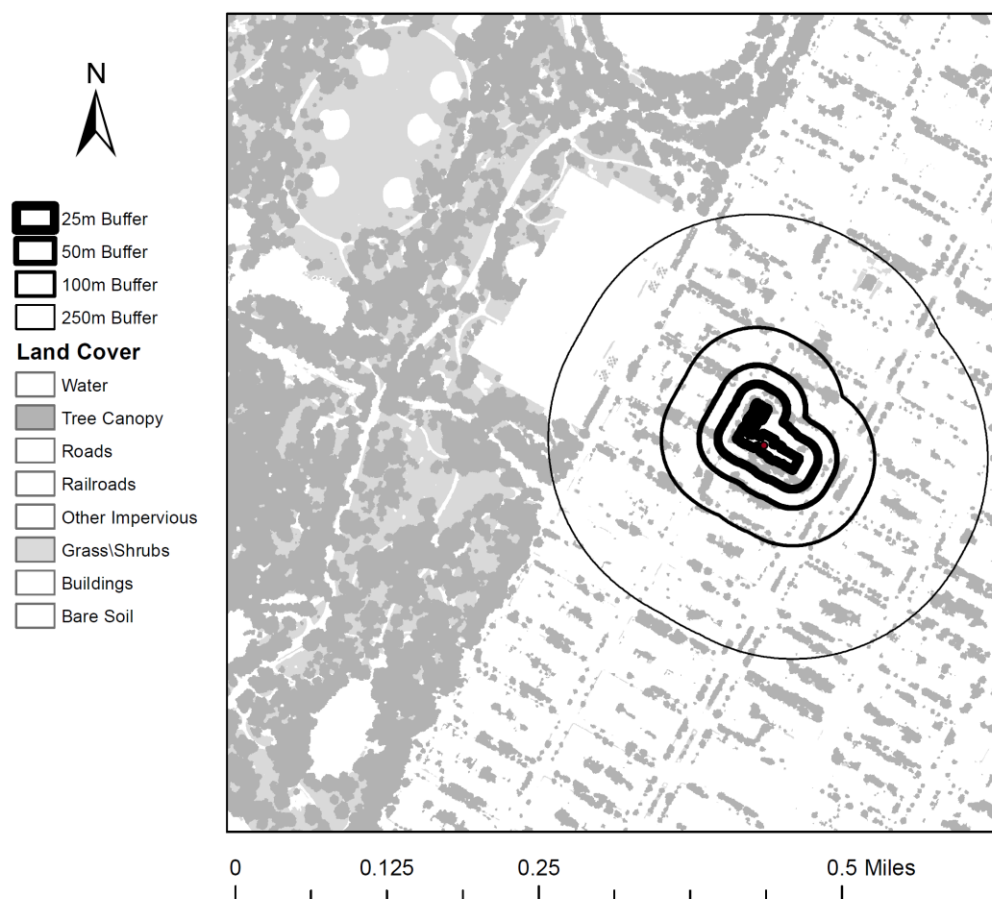


Lyle Anderson, February 18 2020

Data Sources:

- (1) New York City Department of Education
- (2) University of Vermont Spatial Analysis Laboratory, in collaboration with New York City Department of Information Technology and Telecommunications (NYC DoITT), Applied Geographics (AppGeo), and Quantum Spatial

**Map 3. 25m to 250m Buffer Zones Around Elementary School, 2017
(M006 - Lillie D. Blake)**



Lyle Anderson, February 21 2020

Data Sources:
(1) New York City Department of Education
(2) University of Vermont Spatial Analysis Laboratory,
in collaboration with New York City Department of
Information Technology and Telecommunications (NYC DoITT),
Applied Geographics (AppGeo), and Quantum Spatial

Land Cover Variable Creation

I use “percent tree cover”, “percent green space” (tree cover plus grass and shrub cover), and “percent nature space” (tree cover plus grass and shrub cover plus water features) as my baseline measures of the natural environment in New York City. For example, one estimation uses “percent green space within fifty meters of elementary schools”, while another uses “percent tree cover within five hundred meters of elementary schools”. I analyze “nature space” since the association

of water features with educational outcomes has only been studied once, to my knowledge (Hodson and Sander 2017). The Reclassify tool (ESRI 2020b) was used to create binary land cover classes in order to create percentage variables from the land cover data. For example, while conducting tree canopy analysis, I assign tree canopy cells¹⁰ a value of one and assign all other cells a value of zero – calculating the average value of the cells within a particular buffer zone then gives the percent tree canopy within the zone.

To carry out these percentage calculations of geospatial variables within different buffer zones, I used the Feature Statistics to Table tool developed by the United States Geological Survey (USGS) as part of its National Water-Quality Assessment (NAWQA) Area-Characterization Toolbox (Price, Nakagaki, and Hitt 2010). The tool computed the average cell value for areas surrounding each elementary school (i.e., computed the percent of green space within a particular distance of each school). Although Feature Statistics to Table is not a tool included with ArcGIS software, it was more appropriate for my analysis than similar tools provided by ArcGIS because it separately computes statistics for overlapping zones, which occur frequently at larger buffer distances. Zonal Statistics to Table and Tabulate Area are comparable tools provided directly in ArcGIS, but they do not account for overlapping zones when calculating statistics (ESRI 2020e; ESRI 2020f). I compare Zonal Statistics to Table results with Feature Statistics to Table results and discover up to twenty percent discrepancies in percent tree canopy for two hundred and fifty-meter and five hundred-meter calculations, and up to thirty to fifty percent discrepancies in percent tree canopy for one thousand-meter calculations.

Test Score Data

Test score data is reported at the school-grade level by the New York City Department of Education (DOE) (New York City Department of Education 2018a; New York City Department of Education 2019c; New York City Department of Education 2019f; New York City Department of Education 2019g). I use grade-average Math and ELA test scores for grades three through five. Mean test scores cannot be directly compared between 2010 and 2017 because the DOE

¹⁰ In the 2010 and 2017 land cover data, which are both LiDAR-based raster datasets, a “cell” is a six-inch by six-inch spatial unit (a quarter of a square foot) that is assigned a land cover class based on the LiDAR imagery. Therefore, a tree canopy cell is a six-inch by six-inch spatial unit that is identified as tree canopy in the dataset.

implemented Common Core testing standards in 2013 and changed the scale of standardized tests during implementation (New York City Department of Education 2019f)¹¹.

Covariate Data

I control for multiple factors that are likely associated with grade-average test performance of elementary school students. If these factors also correlate with the amount of green space around elementary schools, then controlling for them removes bias in the estimated green space-educational outcomes relationship¹². For example, if wealthier neighborhoods in New York City systematically have more green space (i.e., parks) than poorer neighborhoods, and elementary school students in wealthier neighborhoods systematically perform better on standardized tests than elementary school students in poorer neighborhoods do, then the estimated green space-educational outcomes relationship would be positive but upward-biased if the average income of school grades is not somehow controlled for. In other words, the estimated association between green space and grade-average test scores after controlling for income would be lower than it would have been if income was not controlled for. Similarly, if higher-quality schools are typically located in neighborhoods with more green space than neighborhoods in which lower-quality schools are located, and students in these higher-quality schools typically perform better on tests than students in lower-quality schools do, the estimated relationship between green space and educational outcomes would be upward-biased if some measure of school quality is not accounted for. Similar arguments can be made for all confounders included in the analysis, including demographic variables, classroom structures, school expenditures, and crime incidence.

I gather most school data from New York City Open Data¹³. Demographic data is collected at the school level by the DOE – variables include the racial and gender composition of each school, the percent of the student body that are English Language Learners (ELL), the percent of students that qualify for free or reduced-price lunch, and the percent of students that are enrolled in special education (New York City Department of Education 2018b; New York City Department of Education 2019b). Additional data are collected at the school-grade level by the DOE and include

¹¹ This fact is found in supporting documentation for the dataset – “2010-2017 ELA Test Results.xlsx”.

¹² See Browning and Rigolon (2019) for a useful theoretical framework.

¹³ General URL: <https://opendata.cityofnewyork.us/>

total enrollment, pupil-teacher ratio, and average class size (New York City Department of Education 2019d; New York City Department of Education 2019e).

Another important confounder I control for is a measure of educational quality at the school. The DOE conducts an external Quality Review process to evaluate “how well schools are organized to support student learning and teacher practice” (New York City Department of Education 2020). Although schools do not receive a quality review every year, I generate a most-recent quality review year for each school for the 2008 – 2010 period and the 2015 – 2017 period (i.e., the three-year periods prior to the educational outcomes observed in 2010 and 2017) (New York City Department of Education 2019h). I include three different quality review scores in my analyses: “Curriculum”, “Pedagogy”, and “High Expectations”. Schools are ranked as either “underdeveloped”, “underdeveloped with proficient features” (only an option for the 2008 – 2010 score), “developing”, “proficient”, “well developed”, or “outstanding” (only an option for the 2008 – 2010 score) in each quality category.

I also control for school-level per-student expenditure on classroom instruction and other direct service expenditures. This data is publicly provided by the DOE Division of Finance (New York City Department of Education Division 2020a; New York City Department of Education Division 2020b). Per-student classroom instruction expenditures comprise the bulk of direct service expenditures and include expenditures on teachers, education paraprofessionals, other classroom staff, librarians and books, instructional supplies and equipment, professional development, contracted instructional services, and summer and evening school. Other direct service expenditures per student include instructional support services such as after school activities and counseling, leadership/supervision such as principals and secretaries, ancillary support services like food services and transportation, and building services.

Lastly, I control for the total number of crimes (major felonies and misdemeanors) occurring during the calendar year for the police precinct in which each school is located. These data are publicly available through the New York Police Department from 2000 to 2019 (New York Police Department). I use a publicly available shapefile of police precincts (New York City Department of City 2019) to match schools with police precincts. Controlling for the presence of crime near schools is not only important because it is likely to negatively associate with academic

achievement, but also because it has also been estimated that the contribution of green space to well-being may actually depend on the level of crime in the area (Ambrey and Shahni 2017).

Green Space Change in New York City

To frame my analysis at a high level and provide evidence of sufficient variation in green space variables, I present information on green space and tree canopy in New York City in 2010 and 2017 and changes in green space and tree canopy between the two years, which I calculate from the raster data files. Before I summarize these calculations, it is important to highlight one likely policy driver of tree canopy and green space change in the city.

MillionTreesNYC

Some significant changes in tree canopy levels and distribution between 2010 and 2017 were likely a result of the MillionTreesNYC project, one of the 127 PlaNYC initiatives undertaken in 2007 to make New York a sustainable and resilient city in the coming decades (“PlaNYC Progress Report”). MillionTreesNYC was a citywide public-private partnership to plant one million new trees in the city by 2017 (“I’m Half Way There”), a goal that was completed two years ahead of schedule in 2015. Although trees were planted in all neighborhoods of the city at some point between 2007 and 2015, public implementation of the initiative focused on six Trees for Public Health neighborhoods identified by the Department of Parks and Recreation as having fewer than average street trees and higher than average rates of asthma among young people. It was believed that targeted tree planting in these neighborhoods would reduce the pollutants that trigger respiratory disorders and contribute to healthier living standards in the communities (New York City Department of Parks 2020). These neighborhoods were Hunts Point and Morrisania (Bronx), East New York (Brooklyn), East Harlem (Manhattan), Rockaways (Queens), and Stapleton (Staten Island). Map 4 supplies a graphic of these target neighborhoods (New York City Department of Parks 2020).

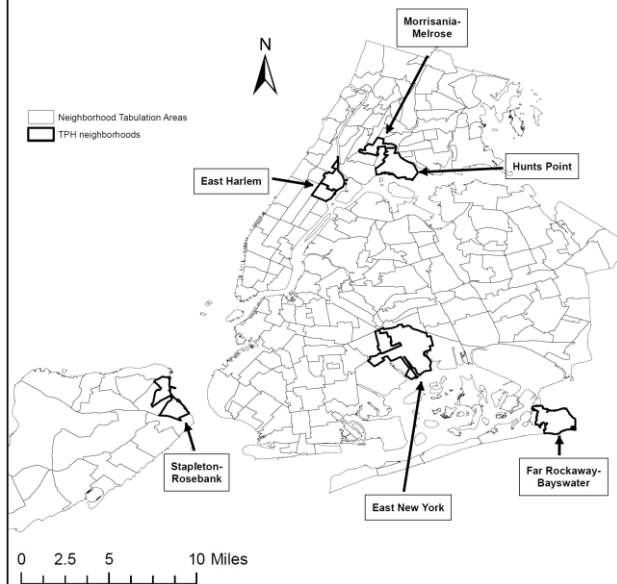
The Department of Parks and Recreation documented progress on street tree planting for the MillionTreesNYC project from 2007 to 2015. I utilize a publicly available shapefile of recorded street block tree plantings from fall 2007 to fall 2015 to inspect the citywide distribution of tree plantings by season and year (New York City Department of Parks 2018). To this end, Map 5

Map 4. *MillionTreesNYC Trees for Public Health Neighborhoods*



highlights the six TPH neighborhoods, and Maps 6 through 8 display the distribution of street tree plantings (in gray) by season and location within the time periods 2007-09, 2007-12, and 2007-15, respectively (this segmentation is meant to show the progression of tree plantings over time). We can gain a few general observations from these maps. First, not all neighborhoods in New York City received street tree plantings. Secondly, the most-targeted planting areas mostly overlap with the TPH neighborhoods. Lastly, the TPH neighborhoods largely received street tree plantings early on in the MillionTreesNYC program compared to other neighborhoods. Overall, this analysis provides an initial sense that the MillionTreesNYC project may have contributed to increased

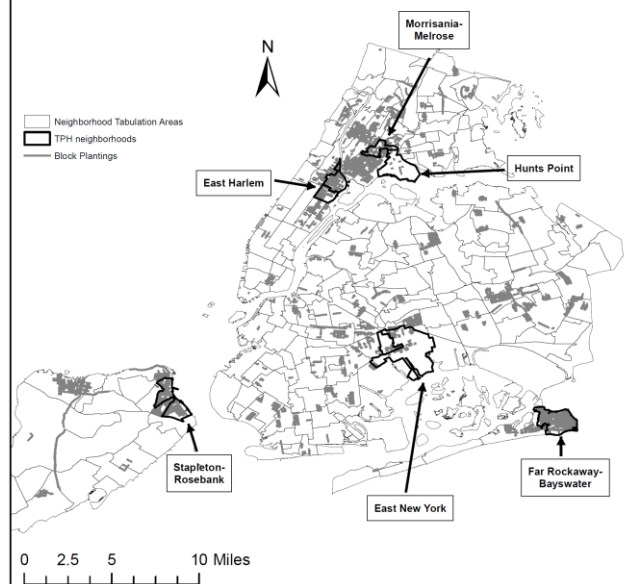
**Map 5. Trees for Public Health Neighborhoods
(MillionTreesNYC)**



Lyle Anderson, April 10 2020

Data Sources:
(1) New York City Department of Parks and Recreation (DPR)
(2) New York City Department of City Planning

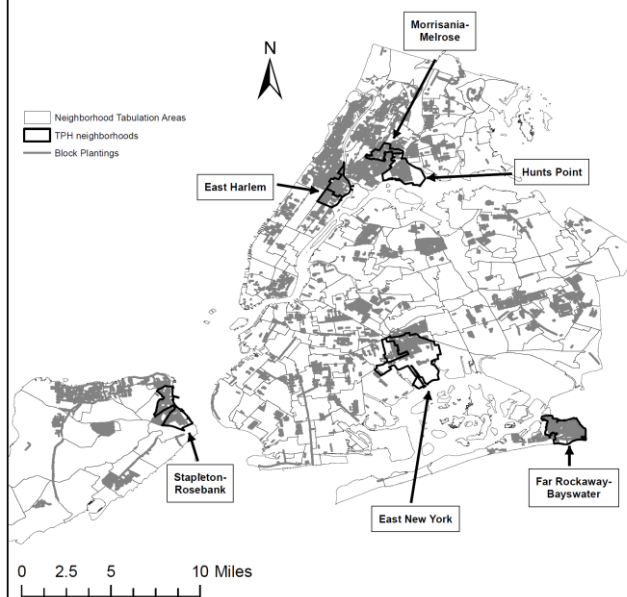
**Map 6. MillionTreesNYC Block Plantings
(2007 - 2009)**



Lyle Anderson, April 10 2020

Data Sources:
(1) New York City Department of Parks and Recreation (DPR)
(2) New York City Department of City Planning

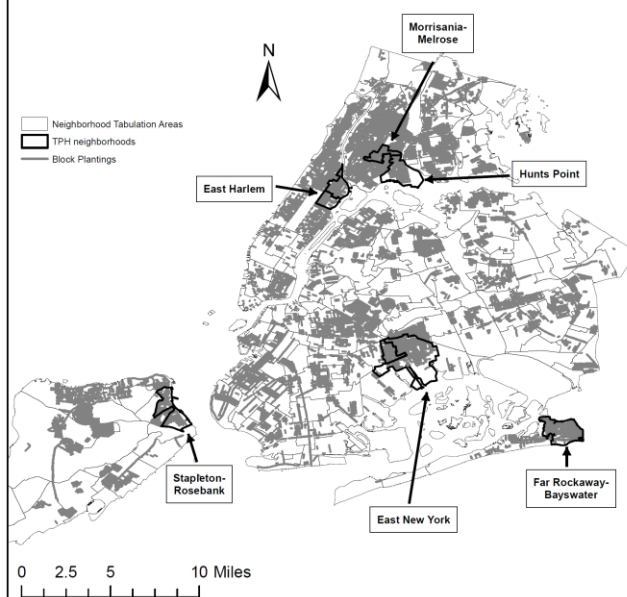
**Map 7. MillionTreesNYC Block Plantings
(2007 - 2012)**



Lyle Anderson, April 10 2020

Data Sources:
(1) New York City Department of Parks and Recreation (DPR)
(2) New York City Department of City Planning

**Map 8. MillionTreesNYC Block Plantings
(2007 - 2015)**



Lyle Anderson, April 10 2020

Data Sources:
(1) New York City Department of Parks and Recreation (DPR)
(2) New York City Department of City Planning

urban greening in New York City between 2010 and 2017, albeit at different rates across neighborhoods.

LiDAR-Based Land Cover Calculations

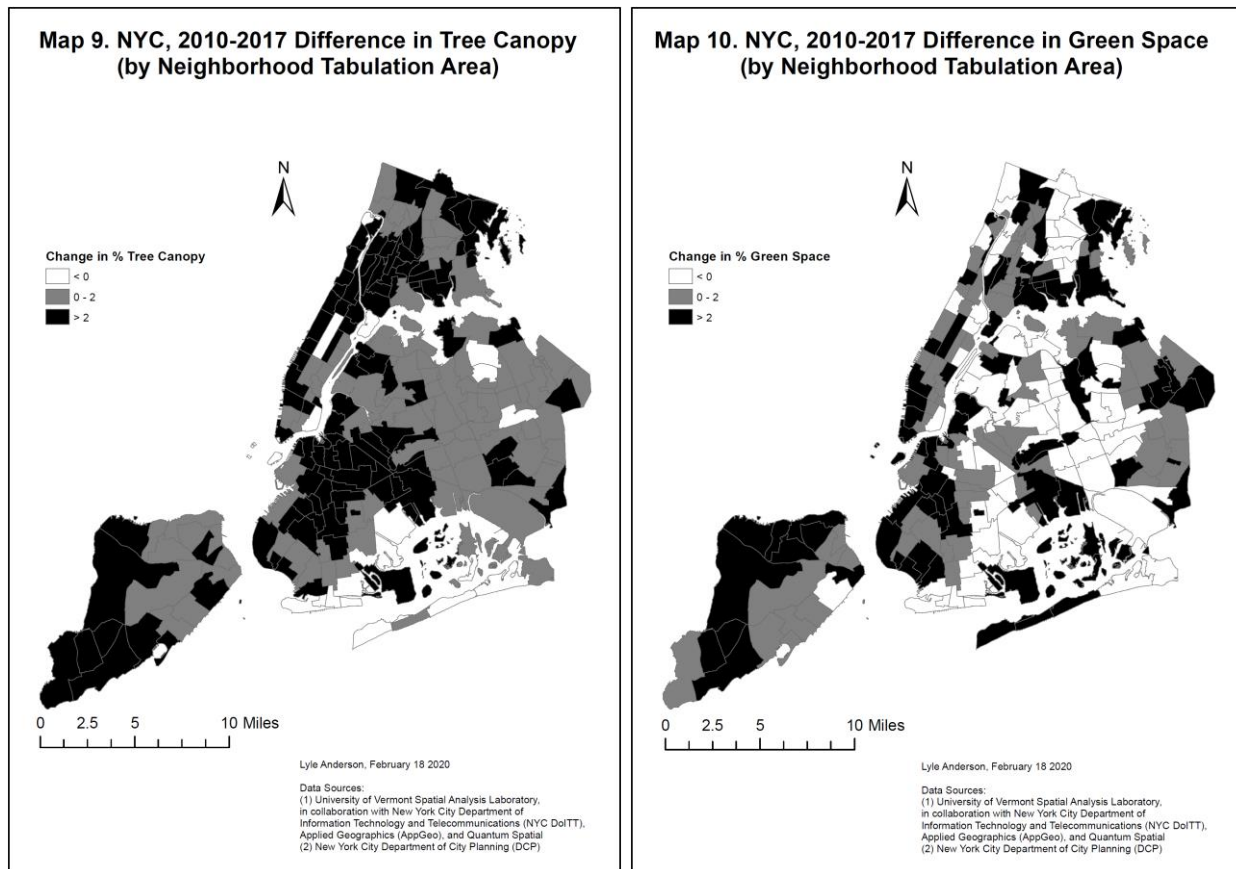
I calculate the citywide change in tree canopy, grass/shrub cover, and overall green space (the sum of tree canopy and grass/shrub area) from the LiDAR-based raster data to provide more explicit proof of the change in New York City's green space. Table 1 shows the amount of tree canopy area, grass/shrub area, and green space (the sum of tree canopy and grass/shrub area) citywide for each year and the difference between the two years. Tree canopy comprised more of New York City's total area than grass/shrub area in both years, and this difference increased over the seven-year period as the city gained fourteen square kilometers of tree canopy but lost thirteen square kilometers of grass/shrub area. As a result, total green space, which comprises just over one-third of city area, barely changed. I compare my tree canopy statistics to the official statistic published by New York City and find that while I calculate a citywide gain of 8.8 percent tree canopy cover, the City concludes that total tree canopy gain over the two years was 8.3 percent (New York City Department of Information 2020)¹⁴. Thus, although my calculated increase in tree canopy cover from 2010 to 2017 is slightly higher, it is certainly in line with official figures.

Table 1. Aggregate Land Cover Statistics for New York City (Own-Calculation)			
	2010	2017	2010 – 2017
Tree Canopy Area (% of total NYC area*)	159 km ² (20.3 %)	173 km ² (22.1 %)	+14 km ² (+1.8 %)
Grass/Shrub Area (% of total NYC area*)	141 km ² (18.0%)	128 km ² (16.3%)	-13 km ² (-1.7 %)
Green Space Area (% of total NYC area*)	300 km ² (38.3%)	301 km ² (38.4%)	+1 km ² (+0.1 %)

* Calculated as the percent of total NYC land area (water features not included).

¹⁴ This discrepancy probably exists because the City and its partners conducted additional robust analysis beyond a simple comparison between 2010 and 2017 raster datasets (my only feasible approach) and identified whether any change in tree canopy could be attributed to variance in the LiDAR capture times or technology (New York City Department of Information 2020).

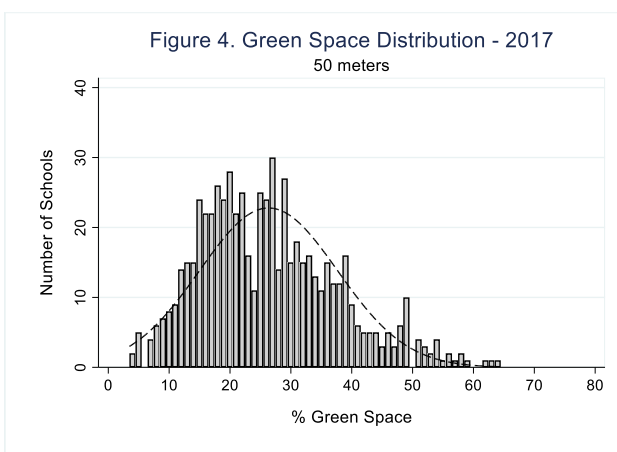
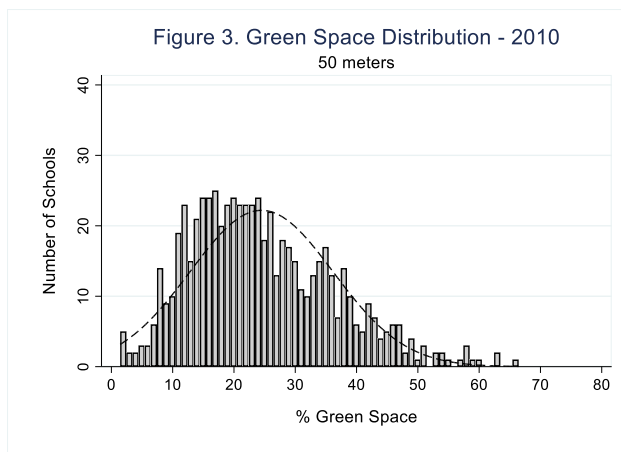
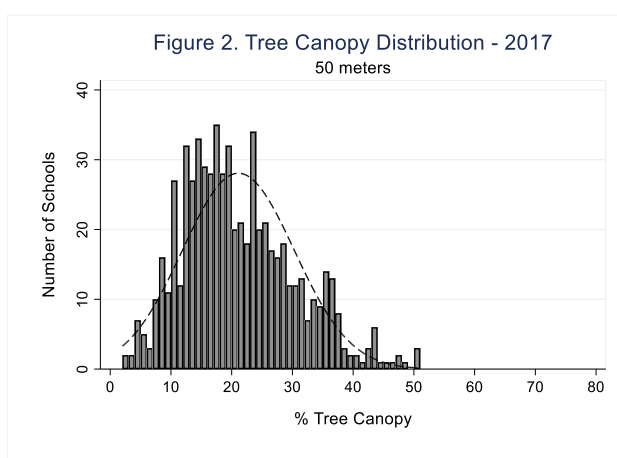
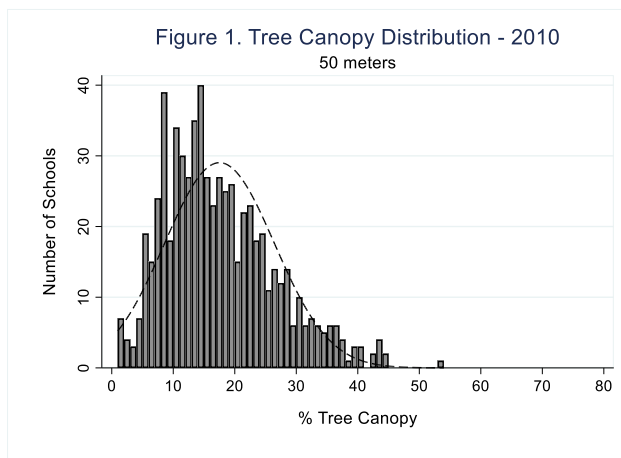
Next, I investigate the distribution of the citywide increase in tree canopy and negligible increase in green space. I utilize publicly available shapefiles of Neighborhood Tabulation Areas (NTAs), New York City-specific aggregations of census tracts, to calculate changes in tree canopy and green space from 2010 to 2017 by neighborhood (New York City Department of City 2020). Maps 9 and 10 display the change in tree canopy and green space by NTA.



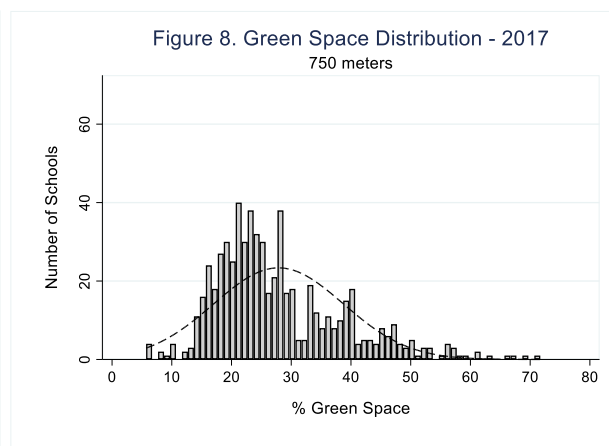
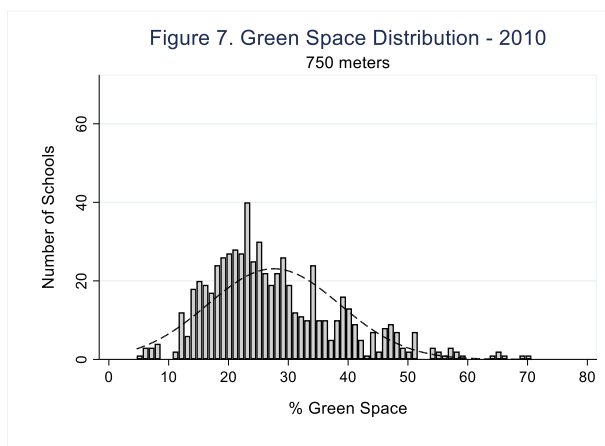
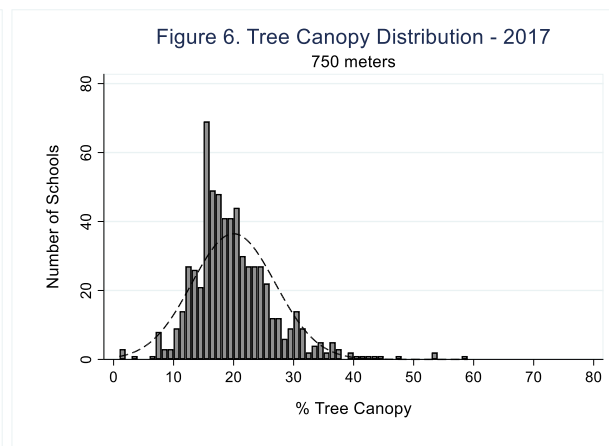
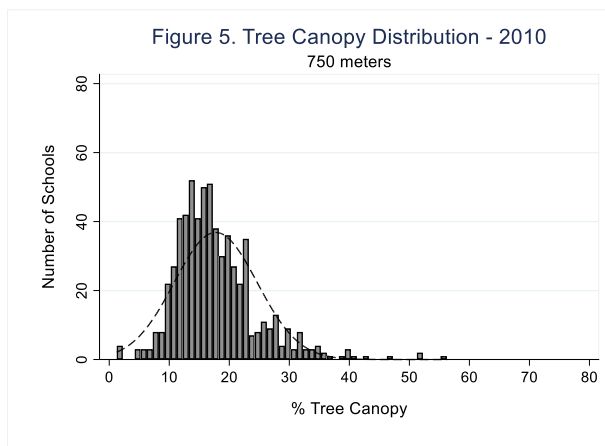
These data are presented by NTA to provide a more granular vision of changes in land cover than the vision provided by looking at the community school district level (there are one hundred and ninety-five NTAs and only thirty-two community school districts). White indicates a negative change, dark gray indicates a positive change of up to two percentage points, and black indicates a positive change of more than two percentage points. It is evident that tree canopy typically increased more across the city than green space did, which aligns with Table 1 statistics.

The citywide increase in tree canopy between 2010 and 2017 and the smaller increase in overall green space are mirrored when we look at the distribution of tree canopy cover and green space at different buffer distances from public elementary schools in New York City. I present these distributions at fifty-meter and seven hundred and fifty-meter buffer distances.

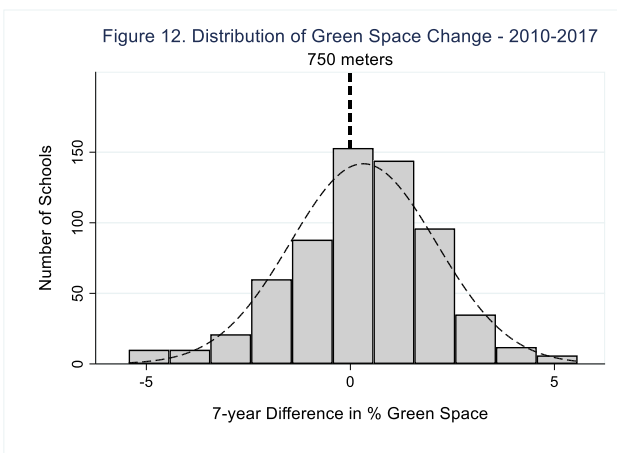
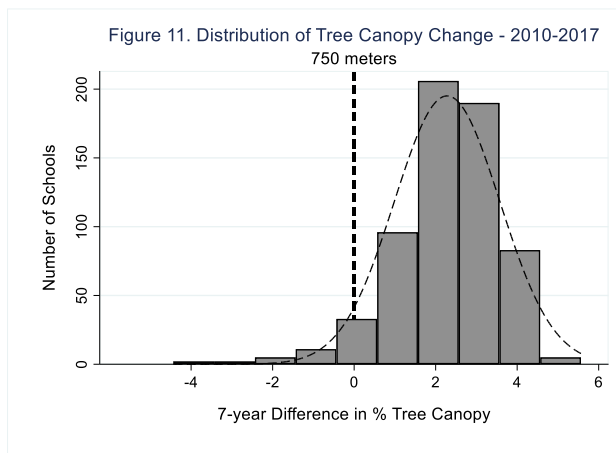
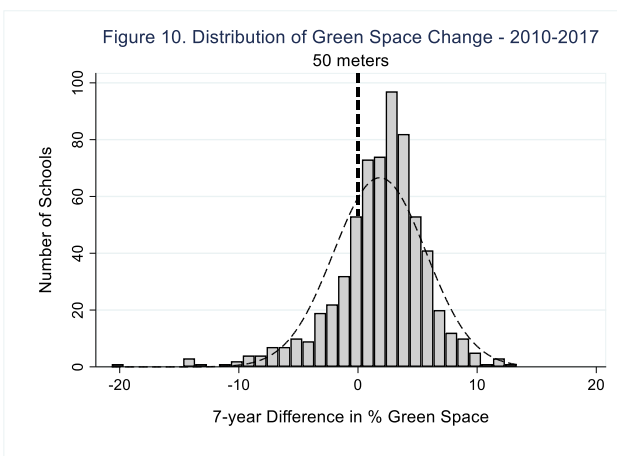
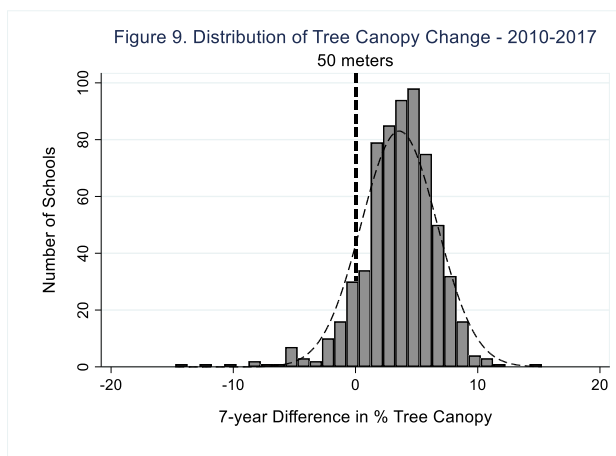
Figures 1 through 4 display the distributions of tree canopy (dark gray) and green space (lighter gray) in 2010 and 2017 within fifty meters of schools. The green space distributions in both years were slightly less concentrated than the tree canopy distributions, and the average or median amount of green space around schools in both years was somewhat larger than the average or median amount of tree canopy around schools. These observations make intuitive sense – the amount of green space close to schools varies more than the amount of tree canopy since it includes grassy areas, and the average amount of green space close to school is somewhat larger than the average amount of tree canopy.



Figures 5 through 8 display the distributions of tree canopy and green space in 2010 and 2017 within seven hundred and fifty meters of schools. These distributions retain the same characteristics as the fifty-meter distributions, with two notable differences. First, the difference between the average amount of green space and the average amount of tree canopy within seven hundred and fifty meters was larger than the difference between the average amount of green space and the average amount of tree canopy within fifty meters. This might be considered a “compounding” phenomenon – the small typical difference in tree canopy and green space close to schools compounds as we consider areas farther from schools. Secondly, the distribution of tree canopy and green space within seven hundred and fifty meters was more concentrated than the distribution of tree canopy and green space within fifty meters. This phenomenon likely reflects the fact that when larger buffer regions are considered, schools increasingly share proximity to expansive park spaces (i.e., Central Park).

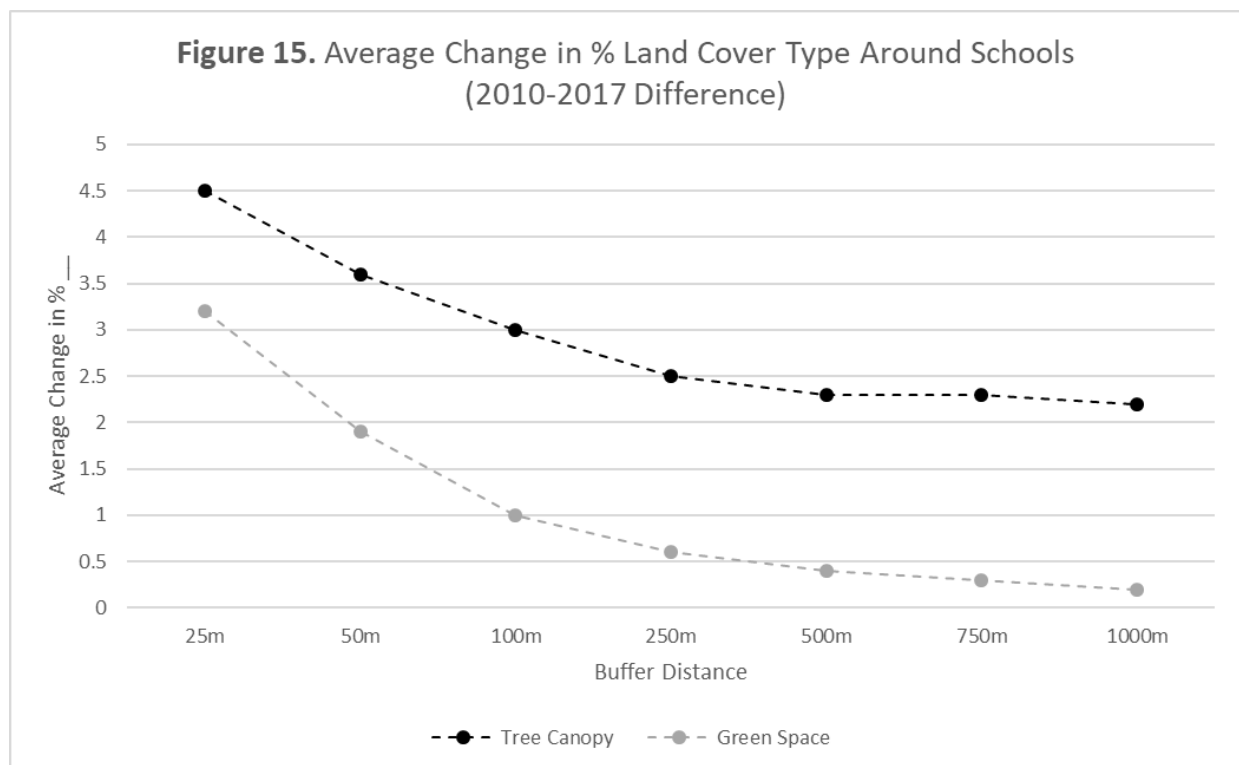
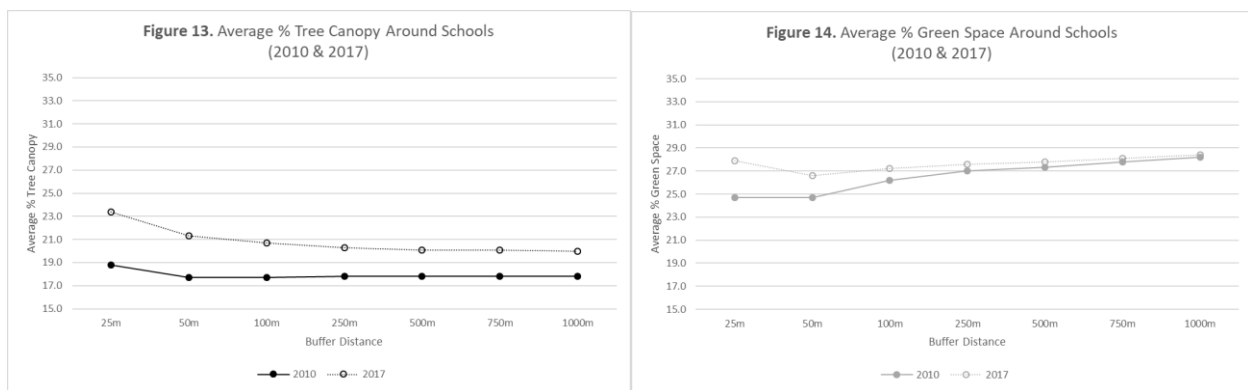


Figures 9 through 12 somewhat synthesize the cross-sectional distributions of land cover and display the change in distributions of tree canopy and green space from 2010 to 2017 within fifty meters and within seven hundred and fifty meters of schools. The overall positive seven-year change in tree canopy close to schools persists as we include areas farther from schools, whereas the positive change in green space close to schools reverts to a near net of zero change as we include areas farther away. These distributions provide more empirical evidence that citywide tree canopy increased significantly from 2010 to 2017 but citywide green space barely increased.



Figures 13 through 15 summarize and conclude the overview of natural land cover in New York City by now including information from all seven buffer distances which I use for my analysis. Figure 13 displays the average amount of tree canopy around schools for 2010 (solid line) and 2017 (dotted line) at all buffer distances, and Figure 14 displays equivalent information for the

average amount of green space. Average amount of tree canopy was two to four percent higher at all buffer distances in 2017, while average amount of green space was one to three percent higher up to a one hundred-meter buffer distance but asymptotically approached 2010 levels at higher buffer distances. These observations closely match earlier results. Figure 15 displays the average change in amount of tree canopy (dashed black line) and green space (dashed gray line) between 2010 and 2017 at all buffer distances. Echoing the patterns shown in Figures 13 and 14, positive changes in tree canopy and green space are more noticeable closer to schools and decrease farther



from schools, with tree canopy retaining positive change throughout and green space approaching zero at larger distances.

Sample Description

There were just over eight hundred public elementary schools in New York City in the 2018-2019 school year (New York State 2019), but my sample only includes public elementary schools that were (1) in operation in both 2010 and 2017, and (2) are geocoded appropriately in the school location shapefile provided in New York City Open Data (New York City Department of Education 2019a). I drop three schools from the sample in 2010 and six schools from the sample in 2017 because they were incorrectly geocoded (i.e., they were not associated with a building but with a different land cover type such as impervious surfaces or tree canopy). I also remove several schools from the sample when analyzing land cover at larger buffer distances because buffer zones began to include data-less regions of the land cover raster layers (a.k.a. regions coded as “No Data” since they lie outside the official city boundaries¹⁵). As a result, my sample statistics reflect characteristics of schools that are in the sample when analyzing twenty-five-meter buffers around schools. These statistics would likely change slightly for samples used in analyses above two hundred and fifty meters.

Table 2 displays descriptive statistics for the cross-sectional analyses for 2010 and 2017. There are 1,499 school-grade observations associated with 535 public elementary schools that each contain data from 2010 and 2017. I report minimum, median, maximum, mean, and standard deviation values for all variables for each year. Mean test scores cannot be directly compared between the two years because the NYC DOE implemented Common Core testing standards in 2013 and changed the scale of standardized tests during implementation (New York City Department of Education 2019f)¹⁶.

¹⁵ Six schools (two from the Bronx and four from Queens) were dropped for five hundred-meter analyses, seven more schools (one from the Bronx and six from Queens, thirteen total) were dropped for seven hundred and fifty-meter analyses, and six additional schools (five from Queens and one from Staten Island, nineteen total) were dropped for one thousand-meter analyses.

¹⁶ This fact is found in supporting documentation for the dataset – “2010-2017 ELA Test Results.xlsx”.

Looking at the three geospatial variables in the third to fifth rows, it is clear that schools typically experienced an increase in tree canopy and green space close to school between 2010 and 2017 (nature space is approximately equal to green space since there are close to zero water features within twenty-five meters of schools). The typical percentage of students eligible for free lunch decreased between the two years, although the median percentage of eligible students was still nearly eighty percent in 2017. Demographic variables such as percent English Language Learner

Table 2. Descriptive Statistics, 2010 & 2017

N = 1499*

	Min		Med		Max		Mean		SD	
	2010	2017	2010	2017	2010	2017	2010	2017	2010	2017
<i>Mean Math Score</i>	31.0	5.0	66.0	53.0	121.0	120.0	66.8	54.9	15.4	20.9
<i>Mean ELA Score</i>	28.0	4.0	54.0	42.0	103.0	102.0	56.1	43.5	12.5	17.0
<i>% Tree Canopy</i>	0.1	1.0	16.7	21.7	63.4	57.1	19.1	23.4	11.4	11.3
<i>% Green Space</i>	0.9	2.6	22.7	26.4	72.4	65.2	25.0	28.0	12.8	12.4
<i>% Nature Space</i>	0.9	2.6	22.7	26.4	72.4	65.2	25.0	28.0	12.8	12.4
<i>% Free Lunch</i>	7.5	2.9	86.2	77.8	99.5	100.0	78.1	71.1	21.9	24.0
<i>% ELL</i>	0.3	0.0	13.0	12.8	61.7	66.2	16.3	15.8	12.5	11.7
<i>% Special Ed</i>	5.3	6.7	15.3	19.7	44.4	40.3	15.7	20.0	5.0	5.6
<i>% Asian</i>	0.0	0.0	4.8	6.1	91.9	94.4	15.0	16.1	20.3	21.1
<i>% Black</i>	0.0	0.0	17.2	13.0	96.0	94.9	28.1	24.7	28.9	27.0
<i>% Hispanic</i>	1.0	1.5	31.1	33.9	98.4	97.6	38.3	40.4	26.6	26.6
<i>% Female</i>	41.3	40.5	48.8	49.0	57.7	58.8	48.8	49.0	2.3	2.4
<i>Pupil-Teacher Ratio</i>	5.7	5.5	13.7	14.0	18.9	19.4	13.7	13.9	2.0	2.1
<i>Average Class Size</i>	11.0	10.0	24.0	25.5	34.5	34.5	24.0	25.2	3.9	4.1
<i>Total Enrollment</i>	11.0	10.0	79.0	56.0	275.0	272.0	85.8	65.8	43.0	40.2
<i>Curriculum Score</i>	1.0	2.0	4.0	3.0	5.0	4.0	3.7	3.3	0.7	0.6
<i>Pedagogy Score</i>	0.0	0.0	4.0	3.0	5.0	4.0	3.6	3.0	0.9	0.6
<i>Expectations Score</i>	1.0	2.0	3.0	4.0	5.0	4.0	3.4	3.6	0.8	0.5
<i>\$ Per Student** (Class Instruction)</i>	504	7,433	9,079	10,020	19,377	23,763	9,291	10,310	1,469	1,729
<i>\$ Per Student** (Other)</i>	4,511	4,394	7,353	7,993	24,084	19,189	7,665	8,374	2,047	2,209
<i>Number of Crimes (Precinct)</i>	2,980	2,318	7,633	6,119	19,300	14,252	8,238	6,499	3,680	2,521

*School-grade observations

**2017 values are inflation-adjusted using a CPI of 1.12¹⁷

¹⁷The CPI Inflation Calculator from the Bureau of Labor Statistics website was used to identify the appropriate inflation adjustment: <https://data.bls.gov/cgi-bin/cpicalc.pl?cost1=1.00&year1=201005&year2=201705>. Specifically, when adjusting nominal per-pupil expenditures in 2017 into 2010 dollars, I adjust for inflation that is estimated to have occurred between May 2010 and May 2017.

students, percent black students, and percent female students display little change over time. Hispanic students comprised most of a typical elementary school student body (between thirty and forty percent on average), and black students comprised the second most (between fifteen and thirty percent on average). Pupil-teacher ratios and average class sizes marginally increased over time on average, while total enrollment per grade typically decreased. On average, schools typically improved their high expectations score between 2010 and 2017 but declined in their curriculum and pedagogy scores. Corrected for inflation, schools typically spent more across the board on their students in 2017 compared to 2010 – for example, median per-pupil spending on classroom instruction increased by nearly one thousand real dollars over time on average, and median per-pupil spending on other direct services increased by about five hundred real dollars on average. Finally, total crimes committed by precinct declined on average from 2010 to 2017, which is in line with existing assessments of declining crime in New York over the past couple of decades (Dobrin 2017; Southall 2017). Specifically, the median number of total crimes in a precinct during the year decreased by about 1,500 crimes from 2010 to 2017 (nearly twenty percent).

Table 3 displays descriptive statistics for changes in variables between 2010 and 2017. The observations from Table 2 also apply here. Schools typically experienced an increase in tree canopy and green space close to school between the two years, the percent of students eligible for free lunch typically decreased, schools spent more per pupil on both classroom instruction and other direct services, and total annual crime substantially decreased on average. Pedagogy scores typically decreased, with a median change in pedagogy score of negative one. All other variables remained relatively constant over time on average (recall that mean test scores cannot be directly compared between the two years).

Having characterized green space and tree canopy coverage in New York City between 2010 and 2017, and having confirmed the quality of the data associated with public elementary schools in both years, a robust empirical analysis of the green space-educational outcomes relationship in New York City is possible. I next present the results of this analysis, which addresses the green space-educational outcomes relationship in both a comparative static context (between-school 2010 and 2017 assessments) and a longitudinal context (a within-school assessment between 2010 and 2017). To my knowledge, this is the first study of the green space-educational outcomes relationship to utilize both empirical approaches.

Table 3. Descriptive Statistics, 2010-2017 Difference

N = 1499*

	Min	Med	Max	Mean	SD
<i>Δ in Mean Math Score</i>	- 61.0	- 12.0	+ 48.0	- 11.9	13.8
<i>Δ in Mean ELA Score</i>	- 65.0	- 13.0	+ 35.0	- 12.6	12.3
<i>Δ in % Tree Canopy</i>	- 21.6	+ 4.5	+ 22.1	+ 4.3	4.2
<i>Δ in % Green Space</i>	- 27.1	+ 3.7	+ 20.2	+ 3.1	5.1
<i>Δ in % Nature Space</i>	- 27.1	+ 3.7	+ 20.2	+ 3.1	5.1
<i>Δ in % Free Lunch</i>	- 60.7	- 2.2	+ 24.6	- 7.1	15.1
<i>Δ in % ELL</i>	- 28.1	- 0.1	+ 22.3	- 0.5	5.8
<i>Δ in % Special Ed</i>	- 10.2	+ 4.4	+ 19.2	+ 4.3	4.8
<i>Δ in % Asian</i>	- 23.6	+ 0.4	+ 22.0	+ 1.1	4.8
<i>Δ in % Black</i>	- 27.4	- 2.2	+ 12.2	- 3.4	5.0
<i>Δ in % Hispanic</i>	- 23.4	+ 2.4	+ 23.7	+ 2.0	5.9
<i>Δ in % Female</i>	- 10.7	+ 0.1	+ 12.5	+ 0.2	3.1
<i>Δ in Pupil-Teacher Ratio</i>	- 6.0	+ 0.1	+ 7.2	+ 0.2	1.8
<i>Δ in Average Class Size</i>	- 14.0	+ 1.3	+ 16.7	+ 1.2	4.6
<i>Δ in Total Enrollment</i>	- 132.0	- 20.0	+ 91.0	- 20.0	30.4
<i>Δ in Curriculum Score</i>	- 3.0	0.0	+ 3.0	- 0.4	0.9
<i>Δ in Pedagogy Score</i>	- 4.0	- 1.0	+ 3.0	- 0.6	1.0
<i>Δ in Expectations Score</i>	- 2.0	0.0	+ 3.0	+ 0.1	0.9
<i>Δ in \$ Per Student** (Class Instruction)</i>	- 3,886	+ 875	+ 10,551	+ 1,020	1,378
<i>Δ in \$ Per Student** (Other)</i>	- 11,587	+ 657	+ 9,158	+ 709	1,810
<i>Δ in Number of Crimes (Precinct)</i>	- 5,358	- 1,168	+ 595	- 1,738	1,520

*School-grade observations

**2017 values are inflation-adjusted using a CPI of 1.12¹⁸

Results

I focus on results estimating the association of tree canopy with test scores. The estimated associations of green space and other natural areas with test scores are mostly colinear with the estimated association of tree canopy and test scores because these other two measures include tree canopy coverage as a major component. My results indicate that conclusions reached by employing the three distinct measures of natural spaces are largely redundant. Results estimating the associations of green space and other natural areas with test scores are available upon request.

¹⁸ See footnote 17 on pg. 23.

Comparative Statics: 2010 and 2017

OLS Estimation

I begin my estimation of the association between tree canopy coverage and test scores by conducting cross-sectional OLS regressions separately for 2010 and 2017. All statistical analysis was done in STATA 16.0 (StataCorp 2019). Equation 1 is the cross-sectional OLS specification:

$$Y_{ij,s} = \beta_0 + \beta_1 T_{j,b} + \pi X_j + \theta Z_{ij} + \alpha_1 \rho_j + \alpha_2 \mu_j + \alpha_3 \delta_j + \alpha_4 \gamma_{ij} + \varepsilon_{ij} \quad (1)$$

$Y_{ij,s}$ is the grade-average test score for subject s (Math or ELA) for grade i (third, fourth or fifth grade) in school j . $T_{j,b}$ is the percent tree canopy around school j at buffer distance b (twenty-five, fifty, one hundred, two hundred and fifty, five hundred, seven hundred and fifty, or one thousand meters). β_1 , the estimated coefficient of interest, estimates the between-school association of test scores and higher tree canopy around school j up to a specific distance b , all else constant. X_j is a vector of school-level covariates for school j , including the percent of students eligible for free lunch, percent English Language Learners, percent special education students, percent Asian students, percent black students, percent Hispanic students, percent female students, the school's most recent curriculum, pedagogy, and high expectations ratings, and per-student expenditures on classroom instruction and other direct services. These factors likely associate with grade-average test performance of elementary school students and could conceivably correlate with the amount of green space around elementary schools, so controlling for them may remove bias in the estimated green space-educational outcomes relationship. Z_{ij} is a vector of school-grade-level covariates for grade i in school j , including pupil-teacher ratio, average class size, and total enrollment. I control for these factors for the same reasons that I control for the school-level covariates. ρ_j is the annual number of crimes in the precinct in which school j is located, μ_j , δ_j , and γ_{ij} are variables controlling for the borough, community school district, and grade number of each school grade, and ε_{ij} is the error term. I use robust standard errors after implementing standard heteroscedasticity tests.

Table 4 contains 2017 OLS estimates for Math and ELA test scores for all seven buffer distances. For each buffer distance, mean math test scores are the dependent variable in column (1) and mean ELA test scores are the dependent variable in column (2). Standard errors are denoted in parentheses. R-squared values are above 0.7 for all regressions, and the number of school-grade observations by regression decreases above two hundred and fifty-meter analyses due to omission of schools close to New York City borders.

As expected, estimated coefficients for all variables except percent tree canopy remain approximately constant from left to right as buffer distance increases. Percent tree canopy is always positively associated with test scores (although the coefficients are not statistically significant for twenty-five, fifty, and one hundred meter buffers), and it consistently exhibits a higher estimated association with Math scores than with ELA scores. Estimated associations of percent tree canopy with both Math and ELA scores are not statistically different from zero until buffer distances reach two hundred and fifty or five hundred meters, although estimated associations increase in magnitude as buffer distance increases. Specifically, students whose school has a one percent higher tree canopy coverage close to school (i.e., within twenty-five meters or fifty meters) are not expected to score appreciably higher on tests on average compared to students at otherwise similar schools (all else constant), but if a school has a one percent higher tree canopy coverage in a wider surrounding area (i.e., within the neighborhood), its students are expected to score higher on tests on average (particularly Math tests) compared to students at otherwise similar schools, all else constant. This result aligns with existing literature concluding that neighborhood-level effects of tree canopy coverage may be more beneficial for student outcomes than schoolyard-level effects.

Most covariates exhibit statistical significance, and most do so at the one percent level. Most variables also possess expected signs. Students in a school with one percent more students eligible for free lunch than otherwise equivalent schools are estimated to score 0.14 points lower on Math tests and 0.16 points lower on ELA tests on average. Students in a school with one percent more ELL students or black students than otherwise equivalent schools are estimated to score 0.2 to 0.3 points lower on tests on average. Having a higher percentage of Asian students or female students increases expected test scores, particularly Math scores for Asian students and ELA scores for female students. If a school scores one point higher on curriculum quality, pedagogical quality, or high expectations culture versus similar schools, its students are estimated to score between one

Table 4. 2017 OLS Estimates														
(1) Math test scores														
(2) ELA test scores														
	25m		50m		100m		250m		500m		750m		1000m	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
% Tree Canopy	.020 (.027)	.017 (.022)	.045 (.034)	.040 (.028)	.039 (.039)	.023 (.031)	.129*** (.041)	.066* (.034)	.181*** (.044)	.100*** (.036)	.181*** (.044)	.109*** (.036)	.162*** (.045)	.116*** (.036)
% Free Lunch	-.143*** (.022)	-.162*** (.018)	-.141*** (.022)	-.159*** (.018)	-.142*** (.022)	-.162*** (.018)	-.147*** (.021)	-.163*** (.017)	-.136*** (.022)	-.161*** (.018)	-.142*** (.021)	-.162*** (.017)	-.141*** (.022)	-.160*** (.017)
% ELL	-.282*** (.040)	-.314*** (.033)	-.281*** (.040)	-.313*** (.033)	-.280*** (.040)	-.313*** (.033)	-.265*** (.040)	-.306*** (.033)	-.265*** (.040)	-.305*** (.033)	-.282*** (.040)	-.308*** (.033)	-.285*** (.041)	-.311*** (.033)
% Special Ed	-.233** (.081)	-.193*** (.066)	-.236** (.081)	-.195*** (.066)	-.237** (.081)	-.195*** (.066)	-.251*** (.081)	-.202*** (.066)	-.246*** (.081)	-.192*** (.066)	-.226** (.081)	-.173*** (.065)	-.220*** (.082)	-.174*** (.066)
% Asian	.142*** (.024)	.040** (.020)	.143*** (.024)	.041** (.020)	.143*** (.024)	.040** (.020)	.144*** (.024)	.041** (.020)	.147*** (.024)	.044** (.020)	.157*** (.025)	.042** (.020)	.156*** (.025)	.041** (.020)
% Black	-.312*** (.022)	-.220*** (.018)	-.312*** (.022)	-.220*** (.018)	-.312*** (.022)	-.219*** (.018)	-.307*** (.022)	-.217*** (.018)	-.313*** (.022)	-.221*** (.018)	-.313*** (.022)	-.221*** (.018)	-.315*** (.022)	-.225*** (.018)
% Hispanic	-.219*** (.023)	-.191*** (.019)	-.218*** (.023)	-.191*** (.019)	-.219*** (.023)	-.191*** (.019)	-.213*** (.023)	-.188*** (.019)	-.211*** (.023)	-.184*** (.019)	-.208*** (.023)	-.186*** (.019)	-.212*** (.023)	-.189*** (.019)
% Female	.227* (.124)	.335*** (.101)	.226* (.124)	.334*** (.101)	.222* (.125)	.333*** (.101)	.192 (.124)	.319*** (.101)	.165 (.125)	.293*** (.101)	.193 (.127)	.316*** (.103)	.227* (.127)	.343*** (.103)
P-T Ratio	.736*** (.254)	.583*** (.207)	.726*** (.254)	.574*** (.206)	.735*** (.254)	.586*** (.206)	.714*** (.253)	.582*** (.206)	.764*** (.255)	.613*** (.208)	.739*** (.257)	.548*** (.208)	.782*** (.259)	.563*** (.209)
Avg. Class Size	-.039 (.085)	-.006 (.069)	-.036 (.085)	-.003 (.069)	-.037 (.085)	-.005 (.069)	-.029 (.085)	-.007 (.069)	-.051 (.085)	-.018 (.069)	-.035 (.086)	-.001 (.069)	-.055 (.086)	-.013 (.070)
Total Enroll.	-.002 (.010)	-.015* (.008)	-.002 (.010)	-.015* (.008)	-.002 (.010)	-.015* (.008)	-.001 (.010)	-.015* (.008)	.001 (.010)	-.013 (.008)	.001 (.010)	-.011 (.008)	-.0004 (.010)	-.011 (.008)
Curriculum	3.531*** (.654)	2.498*** (.532)	3.514*** (.654)	2.483*** (.532)	3.511*** (.655)	2.489*** (.532)	3.371*** (.656)	2.414*** (.535)	3.352*** (.659)	2.376*** (.535)	3.489*** (.665)	2.484*** (.538)	3.531*** (.669)	2.439*** (.539)
Pedagogy	2.354*** (.607)	1.981*** (.493)	2.359*** (.606)	1.985*** (.493)	2.340*** (.607)	1.971*** (.493)	2.394*** (.605)	1.999*** (.493)	2.399*** (.611)	2.048*** (.497)	2.283*** (.612)	1.951*** (.495)	2.265*** (.618)	1.945*** (.498)
Expectations	1.717** (.663)	1.882*** (.534)	1.740*** (.662)	1.905*** (.538)	1.711** (.661)	1.866*** (.537)	1.754*** (.660)	1.894*** (.537)	1.854*** (.663)	1.952*** (.539)	1.831*** (.667)	2.044*** (.539)	1.756*** (.671)	1.992*** (.541)
\$ - Class	.0003 (.0003)	.0003 (.0003)	.0003 (.0003)	.0003 (.0003)	.0003 (.0003)	.0003 (.0003)	.0003 (.0003)	.0003 (.0003)	.0003 (.0003)	.0003 (.0003)	.0002 (.0003)	.0002 (.0003)	.0003 (.0003)	.0003 (.0003)
\$ - Other	-.0001 (.0002)	-.0003* (.0002)	-.0001 (.0002)	-.0003* (.0002)	-.0001 (.0002)	-.0003* (.0002)	-.0001 (.0002)	-.0003* (.0002)	-.0001 (.0002)	-.0003* (.0002)	-.0001 (.0002)	-.0002 (.0002)	-.0002 (.0002)	-.0003* (.0002)
Total Crimes	-.0005*** (.0001)	-.0002* (.0001)	-.0004** (.0001)	-.0002* (.0001)	-.0004** (.0001)	-.0002* (.0001)	-.0004** (.0001)	-.0002 (.0001)	-.0004** (.0001)	-.0001 (.0001)	-.0003** (.0001)	-.0001 (.0001)	-.0003** (.0001)	-.0002 (.0001)
Grade	.097 (.350)	-2.58*** (.284)	.094 (.350)	-2.58*** (.284)	.094 (.350)	-2.58*** (.284)	.080 (.349)	-2.59*** (.284)	.089 (.351)	-2.59*** (.285)	.151 (.353)	-2.51*** (.286)	.133 (.356)	-2.52*** (.287)
CSD	-.107*** (.034)	-.091*** (.028)	-.109*** (.034)	-.094*** (.028)	-.111*** (.035)	-.094*** (.028)	-.114*** (.035)	-.095*** (.028)	-.124*** (.035)	-.098*** (.028)	-.131*** (.035)	-.108*** (.028)	-.139*** (.035)	-.119*** (.028)
Borough	-.893*** (.226)	-.413** (.184)	-.922*** (.228)	-.439** (.185)	-.925*** (.229)	-.431** (.186)	-.1.03*** (.229)	-.478** (.187)	-.1.20*** (.234)	-.597*** (.190)	-.1.24*** (.236)	-.634*** (.191)	-.1.20*** (.237)	-.645*** (.191)
Constant	56.0*** (10.1)	49.2*** (8.2)	55.8*** (10.1)	49.0*** (8.2)	56.4*** (10.1)	49.6*** (8.2)	56.9*** (10.0)	49.8*** (8.2)	57.5*** (10.1)	50.3*** (8.2)	56.8*** (10.1)	49.8*** (8.2)	55.6*** (10.2)	49.1*** (8.2)
R-squared	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.73	0.74	0.73	0.73	0.73
N	1499	1499	1499	1499	1499	1499	1496	1496	1464	1464	1455	1455	1445	1445

Table 5. 2010 OLS Estimates														
(1) Math test scores														
(2) ELA test scores														
	25m		50m		100m		250m		500m		750m		1000m	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
% Tree Canopy	.026 (.022)	.028 (.018)	.031 (.029)	.026 (.024)	.041 (.033)	.029 (.027)	.046 (.035)	.009 (.028)	.069* (.038)	.024 (.031)	.095** (.038)	.034 (.031)	.106*** (.038)	.047 (.031)
% Free Lunch	-.140*** (.024)	-.177*** (.019)	-.140*** (.024)	-.178*** (.019)	-.138*** (.024)	-.177*** (.020)	-.135*** (.024)	-.179*** (.020)	-.121*** (.025)	-.171*** (.020)	-.119*** (.025)	-.179*** (.020)	-.121*** (.025)	-.179*** (.020)
% ELL	-.193*** (.034)	-.189*** (.027)	-.193*** (.034)	-.190*** (.027)	-.193*** (.034)	-.190*** (.027)	-.198*** (.034)	-.193*** (.027)	-.190*** (.034)	-.185*** (.028)	-.192*** (.034)	-.192*** (.028)	-.194*** (.034)	-.194*** (.028)
% Special Ed	-.348*** (.078)	-.239*** (.063)	-.348*** (.078)	-.238*** (.063)	-.347*** (.077)	-.237*** (.063)	-.352*** (.077)	-.238*** (.063)	-.336*** (.079)	-.231*** (.064)	-.341*** (.078)	-.228*** (.064)	-.344*** (.078)	-.232*** (.064)
% Asian	.163*** (.022)	.088*** (.018)	.164*** (.022)	.089*** (.018)	.164*** (.022)	.090*** (.018)	.165*** (.022)	.091*** (.018)	.151*** (.023)	.085*** (.018)	.148*** (.023)	.095*** (.018)	.151*** (.023)	.095*** (.019)
% Black	-.213*** (.020)	-.131*** (.016)	-.213*** (.020)	-.130*** (.016)	-.215*** (.020)	-.131*** (.016)	-.215*** (.020)	-.129*** (.016)	-.217*** (.021)	-.135*** (.016)	-.225*** (.021)	-.128*** (.017)	-.225*** (.021)	-.131*** (.017)
% Hispanic	-.108*** (.023)	-.064*** (.019)	-.108*** (.023)	-.064*** (.019)	-.109*** (.023)	-.064*** (.019)	-.108*** (.023)	-.063*** (.019)	-.124*** (.024)	-.070*** (.019)	-.123*** (.024)	-.060*** (.019)	-.122*** (.024)	-.061*** (.019)
% Female	.192* (.109)	.289*** (.088)	.193* (.109)	.288*** (.088)	.197* (.109)	.290*** (.088)	.198* (.109)	.286*** (.088)	.217* (.110)	.291*** (.089)	.205* (.112)	.257*** (.091)	.218* (.111)	.270*** (.090)
P-T Ratio	-.778*** (.245)	-.473** (.198)	-.782*** (.245)	-.476** (.198)	-.790*** (.245)	-.480** (.198)	-.784*** (.245)	-.471** (.198)	-.854*** (.248)	-.504** (.201)	-.851*** (.251)	-.473** (.204)	-.874*** (.251)	-.483** (.204)
Avg. Class Size	-.084 (.075)	.056 (.061)	-.084 (.075)	.057 (.061)	-.082 (.075)	.058 (.061)	-.073 (.075)	.063 (.061)	-.068 (.076)	.062 (.061)	-.088 (.076)	.051 (.062)	-.087 (.076)	.050 (.062)
Total Enroll.	-.014 (.008)	-.010 (.006)	-.013* (.008)	-.010 (.006)	-.013* (.008)	-.010 (.006)	-.014* (.008)	-.010* (.006)	-.011 (.008)	-.011* (.006)	-.009 (.008)	-.010 (.006)	-.009 (.008)	-.009 (.006)
Curriculum	1.106** (.435)	.846** (.351)	1.101** (.435)	.843** (.351)	1.093** (.435)	.840** (.351)	1.086** (.435)	.853** (.352)	1.087** (.448)	.865** (.363)	1.132** (.449)	.823** (.366)	1.167** (.450)	.808** (.366)
Pedagogy	1.949*** (.367)	1.047*** (.296)	1.952*** (.367)	1.049*** (.296)	1.948*** (.367)	1.045*** (.296)	1.961*** (.366)	1.050*** (.296)	2.008*** (.369)	1.067*** (.300)	1.974*** (.374)	1.022*** (.304)	1.949*** (.374)	1.031*** (.304)
Expectations	.970*** (.317)	1.011*** (.256)	.964*** (.316)	.999*** (.256)	.955*** (.316)	.990*** (.255)	.934*** (.316)	.968*** (.255)	.972*** (.317)	1.009*** (.257)	.855*** (.320)	.996*** (.260)	.810** (.320)	.963*** (.260)
\$ - Class	-.002*** (.0002)	-.001*** (.0002)	-.002*** (.0002)	-.001*** (.0002)	-.002*** (.0003)	-.001*** (.0002)	-.002*** (.0003)	-.001*** (.0002)	-.002*** (.0003)	-.001*** (.0002)	-.002*** (.0003)	-.001*** (.0002)	-.002*** (.0003)	-.001*** (.0002)
\$ - Other	.0006*** (.0002)	.0002 (.0002)	.0006*** (.0002)	.0002 (.0002)	.0006*** (.0002)	.0002 (.0002)	.0006*** (.0002)	.0002 (.0002)	.0006*** (.0002)	.0002 (.0002)	.0006*** (.0002)	.0002 (.0002)	.0006*** (.0002)	.0002 (.0002)
Total Crimes	-.0001 (.0001)	-.0001 (.0001)	-.0001 (.0001)	-.0001 (.0001)	-.0001 (.0001)	-.0001 (.0001)	-.0001 (.0001)	-.0001 (.0001)	-.0001 (.0001)	-.0001 (.0001)	-.0001 (.0001)	-.0001 (.0001)	-.0001 (.0001)	-.0001 (.0001)
Grade	-3.13*** (.302)	3.29*** (.243)	-3.13*** (.302)	3.29*** (.244)	-3.13*** (.301)	3.28*** (.244)	-3.14*** (.301)	3.28*** (.244)	3.14*** (.305)	3.26*** (.247)	-3.07*** (.306)	3.28*** (.249)	-3.05*** (.307)	3.29*** (.249)
CSD	-.061** (.030)	-.096*** (.024)	-.062** (.030)	-.097*** (.024)	-.066** (.031)	-.099*** (.025)	-.064** (.031)	-.095*** (.025)	-.083*** (.031)	-.100*** (.025)	-.082*** (.031)	-.098*** (.025)	-.089*** (.031)	-.108*** (.026)
Borough	-.799*** (.195)	-.886*** (.158)	-.812*** (.196)	-.895*** (.159)	-.824*** (.197)	-.901*** (.159)	-.818*** (.199)	-.874*** (.161)	-.852*** (.204)	-.891*** (.165)	-.885*** (.205)	-.922*** (.167)	-.895*** (.205)	-.954*** (.166)
Constant	121.5*** (8.1)	72.9*** (6.5)	121.7*** (8.1)	73.3*** (6.5)	121.7*** (8.1)	73.3*** (6.5)	121.1*** (8.1)	73.4*** (6.5)	120.6*** (8.2)	73.2*** (6.7)	121.7*** (8.3)	75.4*** (6.7)	121.5*** (8.2)	75.1*** (6.7)
R-squared	0.66	0.66	0.66	0.66	0.66	0.66	0.66	0.66	0.65	0.65	0.65	0.65	0.66	0.66
N	1499	1499	1499	1499	1499	1499	1496	1496	1464	1464	1455	1455	1445	1445

and a half and three and a half points higher on tests on average, with the greatest association seen in curriculum quality. One puzzling result is the estimation that having one student per teacher more compared to similar school grades increases expected test scores by between half a point and a full point on average, although this could conceivably reflect a phenomenon where class sizes were somehow larger in schools where students systematically performed better on tests.

Table 5 presents the 2010 analogue to Table 4. The magnitudes of percent tree canopy coefficients are generally smaller compared to the estimated 2017 coefficients, but they are still all positive. None are statistically significant until five-hundred meter distances around schools are considered, and tree canopy is only ever estimated to statistically associate with Math scores. These results suggest that in both 2010 and 2017, there is evidence of a neighborhood-level positive association of tree canopy with test scores but not much evidence of a schoolyard-level effect.

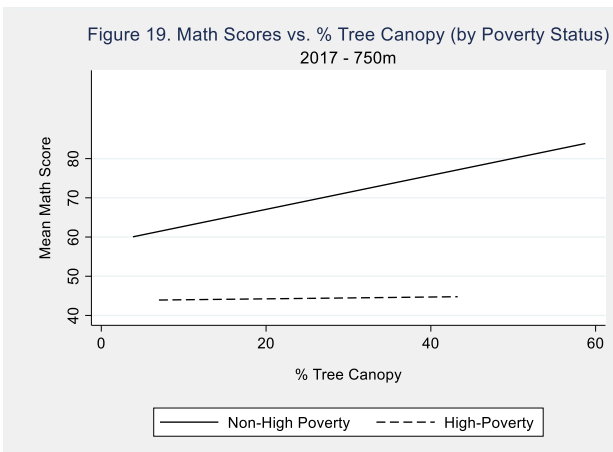
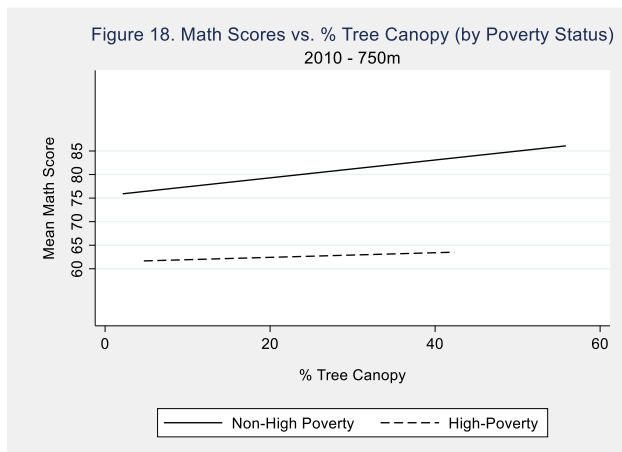
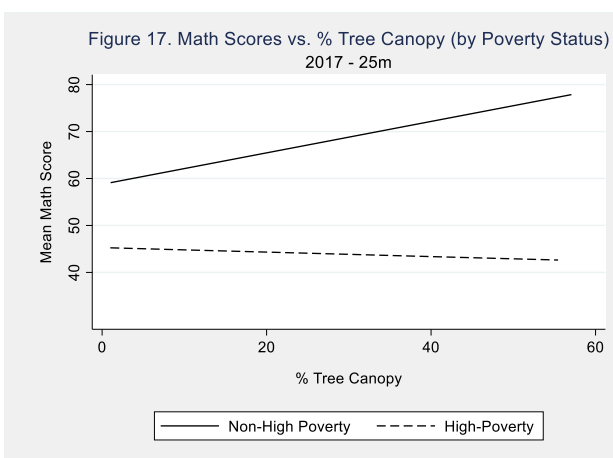
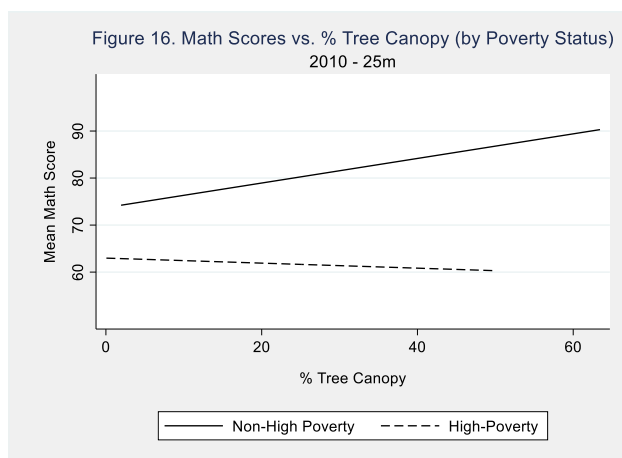
When considering the covariates in the model in 2010, the difference in expected test scores for students in a school with a one-percent higher percentage of ELL, Hispanic or black students compared to other schools is smaller in 2010 compared to 2017, suggesting that these demographic factors may have grown in importance over time. Higher quality review scores are still estimated to have statistically significant positive associations with test scores, but the magnitude of these associations in 2010 is roughly half the magnitude of the associations observed in 2017, suggesting that school quality may have had a larger influence on testing in 2017 compared to 2010. The significantly stronger associations between these explanatory variables and test scores in 2017 compared to 2010 suggest that increasing dimensions of inequality may have differentially impacted test outcomes for public elementary schools in New York City over time, a theme that is consistent with existing assessments¹⁹ and a phenomenon that will be revisited later in the paper. Counter to evidence from 2017, an increase in the pupil-teacher ratio in 2010 has the expected negative and statistically significant relationship with test scores. The puzzling relationship observed in 2010 is that increased expenditures on classroom instruction is estimated to have a negative and significant relationship with test scores; however, this could easily be a case of reverse causality where under-performing schools commanded above-average increases in expenditures.

¹⁹ In particular, see Abel and Deitz (2019) and Liu et al. (2012) for relevant studies that document rising inequality over the past couple decades, particularly in New York City.

Testing the Relationship by Poverty Level

Hodson and Sander (2019), who author one of the most recent studies of the relationship between green space and educational outcomes, find that tree canopy is negatively associated with graduation rates in poorer communities but is slightly positively associated with graduation rates in wealthier communities. They cite literature stating that higher tree canopy levels in poor communities might be driven by trees in abandoned or vacant lots ill-suited for recreation, and that higher tree canopy levels in wealthier communities may reflect areas conducive for recreation and re-energizing. In the same spirit, the next part of my comparative static analysis implements a specific test of the relationship between tree canopy and academic achievement, namely whether the direction and/or magnitude of this relationship depends on the poverty level of schools.

Figures 16 through 19 are linear best-fit lines of the bivariate relationship between test scores and percent tree canopy. I present plots for fifty-meter and seven hundred and fifty-meter buffers in 2010 and 2017, only for the relationship between tree canopy and Math scores (plots of tree canopy



against ELA scores are nearly identical). In all four cases, tree canopy appears to be more highly associated with test scores of non-high poverty schools than with scores of high-poverty schools. Tree canopy is noticeably positively associated with Math scores for non-high poverty schools, but it is slightly negatively associated with Math scores within twenty-five meters of schools and slightly positively associated with Math scores within seven hundred and fifty meters for high-poverty schools. This result corresponds to the finding of Hodson and Sander (2019). Although these simple bivariate correlations may mostly reflect the influence of confounders such as income, they nonetheless support interacting percent tree canopy variables and an indicator of poverty status in the regression specifications. This interaction term will test whether the green space-educational outcomes relationship differs by poverty status of schools.

I test the hypothesis that more tree canopy coverage has zero or negative influence on academic achievement for high-poverty schools but has a positive influence on achievement for non-high poverty schools by incorporating an interaction term into the OLS regressions. Equation 2 is identical to Equation 1 except for the inclusion of the interaction term $(T_{j,b} * highpov)$.

$$Y_{ij,s} = \beta_0 + \beta_1 T_{j,b} + \beta_2 (T_{j,b} * highpov) + \pi X_j + \theta Z_{ij} + \alpha_1 \rho_j + \alpha_2 \mu_j + \alpha_3 \delta_j + \alpha_4 \gamma_{ij} + \varepsilon_{ij} \quad (2)$$

As in Equation 1, $T_{j,b}$ is the percent tree canopy around school j at buffer distance b . The dummy variable *highpov* equals one if the school-grade observation is within a school whose percent of students eligible for free lunch is greater than seventy-five percent, which is the national standard for a high-poverty school (U.S. Department of Education 2019). *highpov* equals zero if the percent of students eligible for free lunch is less than or equal to seventy-five percent. β_1 is thus the estimated association of tree canopy with test scores for non-high poverty schools, and β_2 represents the additional association of tree canopy with test scores for high-poverty schools. The association of tree canopy with test scores for high-poverty schools is then $\beta_1 + \beta_2$.

Table 6 compares tree canopy coefficients estimated without the *highpov* interaction term and tree canopy coefficients estimated with the interaction term. Analysis of Math scores comprises the top

Table 6. 2010 and 2017 OLS Estimates (including high-poverty interaction)

(1) Regression with no interaction term

(2) Regression with interaction term

MATH

	25m		50m		100m		250m		500m		750m		1000m	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
β_1 (2010)	.017 (.024)	.087** (.031)	.019 (.031)	.096** (.040)	.032 (.035)	.103** (.044)	.043 (.036)	.062 (.042)	.069* (.039)	.065 (.044)	.096** (.040)	.086* (.044)	.113*** (.040)	.105** (.044)
β_2	--	-.095*** (.034)	--	-.098** (.041)	--	-.096** (.044)	--	-.029 (.044)	--	.010 (.046)	--	.018 (.046)	--	.001 (.046)
β_1 (2017)	.022 (.028)	.013 (.032)	.047 (.035)	.041 (.039)	.039 (.040)	.029 (.043)	.123*** (.043)	.100** (.045)	.178*** (.046)	.148*** (.047)	.180*** (.046)	.151*** (.048)	.165*** (.047)	.138*** (.048)
β_2	--	.015 (.036)	--	.009 (.041)	--	.024 (.044)	--	.069 (.045)	--	.088* (.047)	--	.084* (.047)	--	.069 (.048)
N	1499	1499	1499	1499	1499	1499	1496	1496	1464	1464	1455	1455	1445	1445

ELA

	25m		50m		100m		250m		500m		750m		1000m	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
β_1 (2010)	.015 (.019)	.071*** (.025)	.010 (.025)	.067** (.032)	.021 (.028)	.059* (.035)	.001 (.029)	-.001 (.034)	.018 (.032)	-.006 (.035)	.030 (.032)	-.001 (.036)	.044 (.033)	.016 (.036)
β_2	--	-.067** (.028)	--	-.062* (.033)	--	-.047 (.035)	--	.018 (.035)	--	.061* (.037)	--	.073* (.037)	--	.065* (.038)
β_1 (2017)	.009 (.023)	.006 (.026)	.030 (.029)	.033 (.031)	.018 (.032)	.012 (.035)	.057 (.035)	.042 (.037)	.099*** (.037)	.070* (.038)	.106*** (.038)	.079** (.039)	.111*** (.038)	.090** (.039)
β_2	--	.023 (.029)	--	.017 (.034)	--	.027 (.036)	--	.057 (.037)	--	.080** (.038)	--	.083** (.038)	--	.075* (.038)
N	1499	1499	1499	1499	1499	1499	1496	1496	1464	1464	1455	1455	1445	1445

half of the table, and analysis of ELA scores comprises the bottom half. The green space-educational outcomes relationship is again analyzed at all seven buffer distances, so two analyses (one without the *highpov* interaction and with the *highpov* interaction) are conducted at each buffer distance.

The first insight from this analysis involves coefficients at lesser buffer distances (i.e., between twenty-five and one hundred meters). Just as before, analysis without separating the green space-educational outcomes association by poverty status (column ones) show positive but statistically insignificant associations of tree canopy with test scores in both 2010 and 2017. However, analysis that separates the association by poverty status (column twos) estimates that in 2010, having more tree canopy close to schools is positively and statistically significantly related to test performance for non-high poverty schools (i.e., β_1 is positive and statistically significant) but exhibits a slightly negative or non-existent relationship with test scores for high-poverty schools (i.e., β_2 is negative and statistically significant). Conversely, in 2017, having more tree canopy close to schools is marginally positively related to test performance for non-high poverty schools (β_1 is positive) and is more positively related to test performance for high-poverty schools (β_2 is also positive). Why does tree canopy close to school appear to “matter” more for non-high poverty schools in 2010 and appear to “matter” more for high-poverty schools in 2017? There is no evident answer, but one potential explanation may be tied to the MillionTreesNYC project summarized previously. If tree canopy increased more between 2010 and 2017 in high-poverty neighborhoods relative to non-high poverty neighborhoods, which is likely the case (see Maps 5-10), it is feasible to think that high-poverty schools may have received a positive and/or bigger “return on investment” from street tree planting than non-high poverty schools did²⁰. Unfortunately, this is not a testable hypothesis with my data.

The second insight from this analysis involves coefficients at greater buffer distances (i.e., between two hundred and fifty and one thousand meters). Analysis without accounting for poverty status shows some evidence of a positive and statistically significant green space-educational outcomes relationship in 2010 and rather robust evidence for such a relationship in 2017. When poverty

²⁰ Recall: it was hoped that targeted tree planting in TPH (high-poverty) neighborhoods would reduce the pollutants that trigger respiratory disorders and contribute to healthier living standards in the communities (New York City Department of Parks 2020). This is the type of “return” on street tree “investment” that I reference. Of course, another relevant ROI could be educational outcomes like test scores.

status is accounted for through the interaction term, it is estimated that having more tree canopy at a neighborhood level is largely positively related to test scores for non-high poverty schools in both years (i.e., β_1 is positive and statistically significant), and that this relationship is usually stronger for high-poverty schools (i.e., β_2 is usually positive and often statistically significant). Also, estimated associations for all schools are greater in 2017. Why does tree canopy at a neighborhood-level around schools appear to “matter” more for high-poverty schools than for non-high poverty schools in both years, even though tree canopy seems to “matter” more for all schools in 2017 compared to 2010? One potential answer adds to the schoolyard-level story: having more tree canopy at a neighborhood level has a stronger influence on test outcomes for high-poverty schools than non-high poverty schools (i.e., has a bigger “return on investment”), and street tree plantings through the MillionTreesNYC project may have benefited *all* schools at a neighborhood level. Of course, this is also not a testable hypothesis with my data.

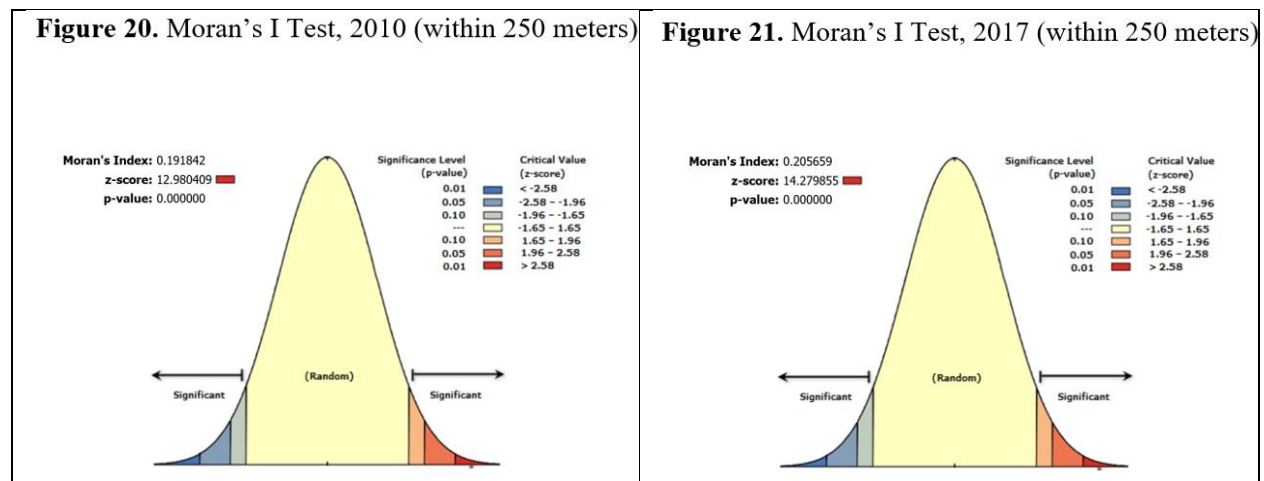
The comparative static green space-educational outcomes story thus far for New York City can be summarized by the following narrative: there is no evidence that having more tree canopy coverage close to elementary schools has an appreciable relationship with how students perform on standardized tests, although it may have been associated with better performance for non-high poverty schools a number of years ago (specifically in 2010), a difference between high-poverty and non-high poverty schools that has disappeared in the seven years since. However, there is substantial evidence that having more tree canopy coverage on a neighborhood scale is positively associated with how elementary school students perform on tests, and this association may be stronger for high-poverty schools, particularly in recent years.

Mixed-Effects Estimation

An important factor in green space-educational outcomes analysis has been neglected thus far – spatial autocorrelation. Spatial autocorrelation describes the degree to which observations located close to each other spatially are similar or correlated, since they are likely to exhibit clustering on various characteristics. This clustering phenomenon has implications for statistical inference. Specifically, typical OLS standard errors are likely to be biased downward (Antweiler 2001; Moulton 1986; Moulton 1990; Wooldridge 2003), and statistical significance tests are likely to be inflated (Dale and Fortin 2002; Pepper 2002). Spatial autocorrelation violates the OLS assumption

of independently sampled observations and may significantly bias the estimated green space-educational outcomes relationship.

There is significant evidence that elementary schools in New York City exhibit spatial autocorrelation in their tree canopy coverage (i.e., schools that are closer together have more similar amounts of surrounding tree canopy than do schools that are farther apart). I compute Moran's I for percent tree canopy within two hundred and fifty-meters of schools in both 2010 and 2017 (ESRI 2020c). Figures 20 and 21 are reports generated from the Spatial Autocorrelation (Moran's I) tool for 2010 and 2017, respectively. Z-scores ($z = 12.98$ ($p < 0.001$) in 2010; $z = 14.28$ ($p < 0.001$) in 2017) are positive and highly statistically significant in both years, providing strong evidence that spatial autocorrelation exists.



Other observable characteristics of elementary schools are also likely to be spatially autocorrelated – schools in the same borough are more likely to have students from similar demographics and socioeconomic backgrounds, schools in the same community school district (CSD) are more likely to command similar per-student expenditures, etc. In this last segment of my comparative static analysis, I model spatial autocorrelation in my regression specifications and evaluate any implications for the estimated green space-educational outcomes relationships.

A multilevel mixed model is one standard method of appropriately estimating relationships with hierarchical or nested observational data, including accounting for spatial autocorrelation (Arcaya

et al. 2012; Corrado and Fingleton 2011; McNeish and Kelley 2019). In these models, the observational data is assumed to be hierarchical or nested, with the dependent variable of interest measured at the lowest level of the hierarchy and explanatory variables measured at multiple levels of the hierarchy. One can model *random* effects by assuming that average unobservable determinants of the outcome of interest (random intercept) and/or the estimated coefficients (random slopes) are different for each group in a given level, instead of using a population average across all levels during estimation. One can also model *fixed* effects by assuming that average unobservable determinants and/or the estimated coefficients are the same for each group in a given level, or for the population in general (Hox 1995; Hox and Kreft 1994). Mixed models employ a combination of random effects and fixed effects. Allowing the estimation of random effects parameters to vary by group and level can address the downward bias in OLS standard errors and the resulting bias in statistical inference by no longer treating individual observations as completely independent.

Multilevel mixed models can be particularly useful when one estimates the effects of certain factors on educational outcomes, where observational data is often hierarchically nested (i.e., students are “nested” within classes which are “nested” within schools). Since I use school-grade level observations in my analysis, boroughs are the highest upper level of the observational data hierarchy, community school districts are the middle upper level (nested within boroughs), and schools are the lowest upper level (nested within community school districts). I fit multilevel linear mixed models using the STATA *mixed* command and, assuming that schools exhibit the base level of spatial autocorrelation, specify borough, CSD, and school random intercepts (i.e., I assume that average unobservable determinants of test scores differ by schools within the same CSD, average unobservable determinants of test scores differ by CSDs within the same borough, and average unobservable determinants of test scores differ by borough). I specify all other variables as fixed effects (i.e., I assume that the *ceteris paribus* relationships between all other observable explanatory variables and grade-average test scores are constant regardless of school, CSD, or borough).

I estimate a three-level multilevel mixed linear model where grade-average test outcomes Y_{ijkms} are measured for i grades (one, two, or three grades) in $j \in [1, 2, \dots, J_k]$ schools in $k \in [1, 2, \dots, K_m]$ school districts in $m \in [1, 2, \dots, M]$ boroughs for both s subjects (Math and ELA). Equation 3 is

identical to Equation 2 except that instead of controlling for borough and community school district as fixed effect variables, I model random intercepts at the school, CSD, and borough level:

$$Y_{ijkms} = \beta_0 + \beta_1 T_{jkm,b} + \beta_2 (T_{jkm,b} * highpov) + \pi X_{jkm} + \theta Z_{ijkm} + \alpha_1 \rho_{jm} + \alpha_2 \gamma_{ijkm} + u_{jkm} + u_{km} + u_m + \varepsilon_{ijkm} \quad (3)$$

Test score outcomes Y_{ijkms} for grade i in school j in CSD k in borough m for subject s are now modeled as a combination of fixed effects (tree canopy effects $T_{jkm,b}$ and $(T_{jkm,b} * highpov)$, school-level effects X_{jkm} , school-grade-level effects Z_{ijkm} , precinct-level crime ρ_{jm} , and grade number γ_{ijkm}) and random intercepts (random intercept u_{jkm} for school j in CSD k in borough m , random intercept u_{km} for CSD k in borough m , and random intercept u_m for borough m). By assuming that average unobservable determinants of grade-average test scores vary between groups within each of the three levels of my data hierarchy, I no longer treat separate school-grade observations as completely independent. This mixed model addresses issues of statistical inference caused by spatial autocorrelation by correcting the downward bias in OLS standard errors. Stated in terms of the nested data hierarchy, my estimation sample is 1499 school grades associated with 535 elementary schools ($J_k = 535$) in thirty-two school districts ($K_m = 32$) in five boroughs ($M=5$).

Table 7 compares OLS and mixed-effects results for tree canopy coefficients (both β_1 , the non-high poverty coefficient, and β_2 , the added association for high-poverty schools). Analysis of Math scores comprises the top half of the table, and analysis of ELA scores comprises the bottom half. The green space-educational outcomes relationship is again analyzed at all seven buffer distances. χ^2 statistics are presented for each mixed-effects regression and represent a test of the mixed-effects model versus a one-level ordinary linear regression model. The χ^2 tests all soundly reject the null hypothesis that an ordinary OLS model is the correct estimation method.

As expected, mixed-effects estimates (column twos) exhibit consistently less statistical significance than the OLS estimates (column ones). Twenty-eight of the fifty-six OLS coefficients are statistically significant, while only seven mixed-effects coefficients are statistically significant

Table 7. 2010 and 2017 OLS and Mixed-Effects Estimates (w/ high-poverty interaction)

(1) OLS

(2) Mixed

MATH

	25m		50m		100m		250m		500m		750m		1000m	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
β_1 (2010)	.087** (.031)	.066 (.044)	.096** (.040)	.059 (.056)	.103** (.044)	.059 (.063)	.062 (.042)	.042 (.060)	.065 (.044)	.070 (.064)	.086* (.044)	.108* (.065)	.105** (.044)	.133** (.067)
β_2	-.095*** (.034)	-.086* (.048)	-.098** (.041)	-.086 (.057)	-.096** (.044)	-.082 (.062)	-.029 (.044)	-.015 (.062)	.010 (.046)	.024 (.065)	.018 (.046)	.020 (.065)	.001 (.046)	-.001 (.066)
χ^2	--	362.0	--	363.6	--	364.4	--	362.7	--	366.0	--	362.8	--	364.7
β_1 (2017)	.013 (.032)	-.004 (.045)	.041 (.039)	.013 (.054)	.029 (.043)	-.009 (.060)	.100** (.045)	.074 (.064)	.148*** (.047)	.144** (.068)	.151*** (.048)	.158** (.069)	.138*** (.048)	.140** (.071)
β_2	.015 (.036)	.011 (.049)	.009 (.041)	-.001 (.057)	.024 (.044)	.014 (.061)	.069 (.045)	.059 (.063)	.088* (.047)	.065 (.065)	.084* (.047)	.059 (.066)	.069 (.048)	.053 (.067)
χ^2	--	312.7	--	312.8	--	312.3	--	304.7	--	302.1	--	300.5	--	301.3
N	1499	1499	1499	1499	1499	1499	1496	1496	1464	1464	1455	1455	1445	1445

ELA

	25m		50m		100m		250m		500m		750m		1000m	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
β_1 (2010)	.071*** (.025)	.052 (.035)	.067** (.032)	.032 (.045)	.059* (.035)	.018 (.054)	-.001 (.034)	-.017 (.048)	-.006 (.035)	-.009 (.051)	-.001 (.036)	-.001 (.052)	.016 (.036)	.019 (.054)
β_2	-.067** (.028)	-.066* (.038)	-.062* (.033)	-.055 (.045)	-.047 (.035)	-.038 (.049)	.018 (.035)	.030 (.049)	.061* (.037)	.073 (.052)	.073* (.037)	.081 (.052)	.065* (.038)	.070 (.053)
χ^2	--	350.0	--	352.0	--	352.3	--	346.1	--	338.7	--	340.2	--	344.5
β_1 (2017)	.006 (.026)	-.005 (.037)	.033 (.031)	.015 (.045)	.012 (.035)	-.016 (.050)	.042 (.037)	.025 (.054)	.070* (.038)	.056 (.056)	.079** (.039)	.074 (.057)	.090** (.039)	.086 (.058)
β_2	.023 (.029)	.028 (.040)	.017 (.034)	.023 (.047)	.027 (.036)	.035 (.050)	.057 (.037)	.056 (.053)	.080** (.038)	.077 (.054)	.083** (.038)	.083 (.054)	.075* (.038)	.082 (.055)
χ^2	--	405.2	--	405.2	--	405.2	--	419.4	--	390.5	--	388.8	--	388.5
N	1499	1499	1499	1499	1499	1499	1496	1496	1464	1464	1455	1455	1445	1445

Figure 22. Estimated Association of +1% Tree Canopy with Math Test Scores (2010)

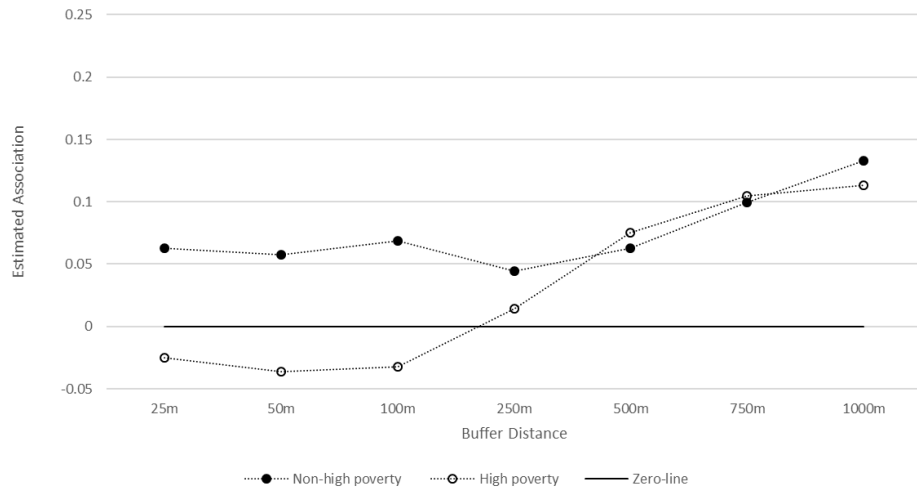


Figure 23. Estimated Association of +1% Tree Canopy with ELA Test Scores (2010)

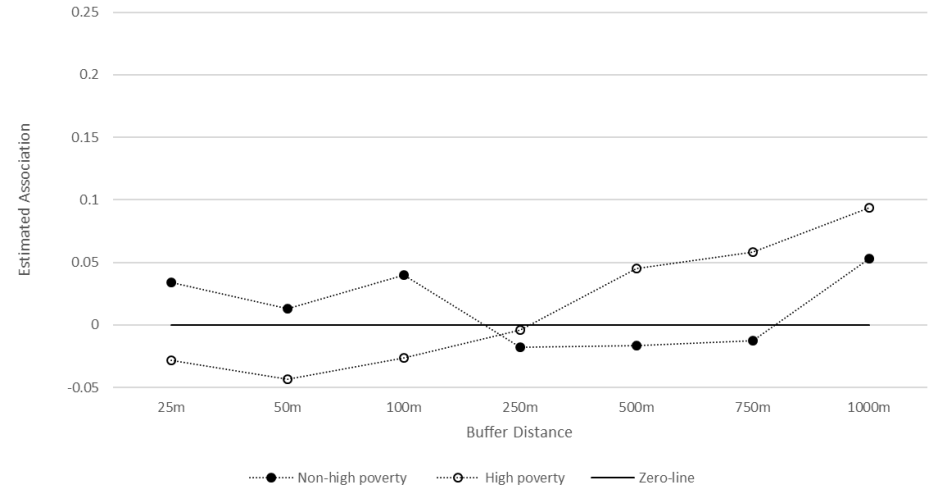


Figure 24. Estimated Association of +1% Tree Canopy with Math Test Scores (2017)

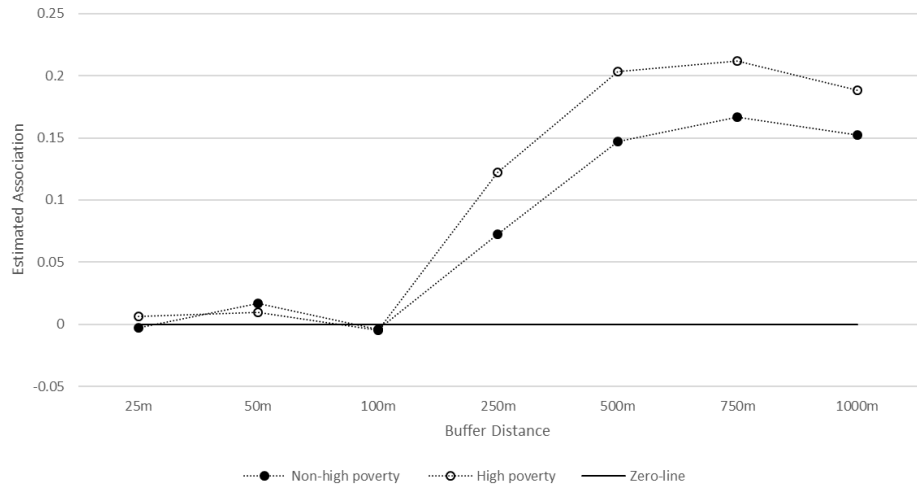
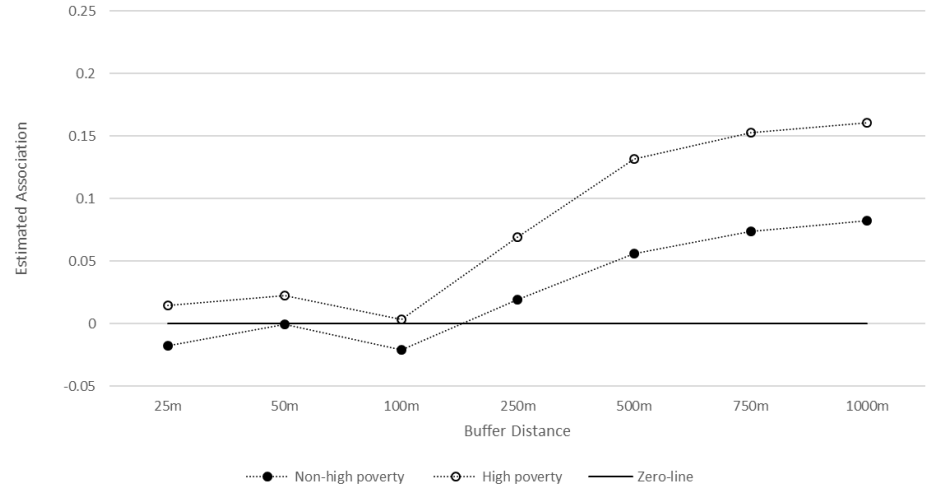


Figure 25. Estimated Association of +1% Tree Canopy with ELA Test Scores (2017)



(mostly for analysis of Math scores in 2017 at larger buffer distances, and only one for the analysis of ELA scores in either year). Mixed-effects coefficients are also mostly smaller in magnitude, and some coefficients at smaller buffer distances are slightly negative and statistically insignificant. Given that mixed-effects is the appropriate estimation method, Figures 22 through 25 plot the mixed-effects tree canopy coefficients against buffer distance separately for high-poverty and non-high poverty schools.

Mixed-effects estimation still provides evidence that more tree canopy at a neighborhood level (considering at least two hundred and fifty meter buffers around schools) is statistically significantly related to test scores for all schools, particularly for Math test scores. However, there is no longer evidence that this neighborhood-level positive association is significantly more beneficial for high-poverty schools than for non-high poverty schools. The high-poverty interaction coefficients do not exhibit the same statistical significance that they do in the OLS analysis, but they largely retain the same signs across years, test subjects, and buffer distances (positive at all buffer distances for 2017 analyses but positive at higher buffer distances and negative for lower buffer distances for 2010 analyses). Therefore, the claim that the direct estimated coefficient β_1 is statistically different for high-poverty and non-high poverty schools (i.e., the claim that the green-space educational outcomes relationship at a neighborhood level is higher for high-poverty schools relative to non-high poverty schools) is no longer clear. Finally, mixed-effects estimation no longer provides evidence that the green space-educational outcomes relationship is ever positive and statistically significant at the schoolyard-level (within at most one hundred meters of schools) for either high-poverty or non-high poverty schools.

Given that the mixed-effects analysis is the appropriate estimation method, the comparative static green space-educational outcomes analysis concludes with the following observations: there is no robust evidence that having more tree canopy coverage close to elementary schools has an appreciable relationship with how students perform on standardized tests (all else equal), but there is some evidence, largely in the association with Math test scores, that having more tree canopy coverage on a neighborhood scale is positively associated with how elementary school students perform on tests (all else equal).

Longitudinal Analysis: The Seven-Year Difference

Most existing studies of the green space-educational outcomes relationship follow a similar research methodology up to this point, employing static variation in measures of academic achievement, green spaces, and confounders across space to determine a *ceteris paribus* association between green space and academic achievement. Since temporally matched green space and academic achievement data is rarely available over time, longitudinal analyses are typically not feasible. Two existing examples of longitudinal analyses that I am aware of are Leung et al. (2019), who conclude that tree canopy is a driver of a positive green space-educational outcomes relationship for Massachusetts public schools, and Markevych et al. (2019), who find no evidence of any positive green space-educational outcomes relationship over time for German adolescents.

Since I observe test scores and relevant time-varying confounders in 2010 and 2017 and also have data on tree canopy for both years, I am able to implement a longitudinal research design in addition to my comparative static analysis. I transition from a between-school analysis (i.e., asking the question whether schools with more surrounding tree canopy have higher expected test scores than schools with less surrounding tree canopy, all else constant) to a within-school analysis (i.e., asking the question whether an increase in tree canopy around a school over time is associated with an increase in expected test scores for a school over time, on average). This approach arguably provides a more causal interpretation of the green space-educational outcomes relationship, as long as standard assumptions hold.

The main desirable property of longitudinal studies, assuming that we observe the same subjects over time (more on the implications of this assumption for this study later), is that they “difference out” time-invariant characteristics of observational units, which is particularly useful if these characteristics are unobserved or unmeasured *and* if these characteristics are correlated with both the outcome and explanatory variable of interest. If our observational units are students, longitudinal studies can control for individual characteristics that don’t change over time, such as inherent ability. If these units are schools, longitudinal studies can control for school-level characteristics that don’t change over time, potentially characteristics like culture and administration. The main implication for this study of the green space-educational outcomes relationship, which relies on school-grade-level observations, is controlling for school-grade-level

characteristics that don't change over time *and* are correlated with both test scores and tree canopy coverage. Potential examples could be unobserved administrative preferences for schools in neighborhoods that commit to “greening” consistently and also provide better student support for standardized testing, unmeasured neighborhood effects such as cultural attitudes towards education, income-related measures not fully captured by the percent of free or reduced-price lunch students at a school, and other time-invariant aspects of a student's learning and living environment.

Mixed-Effects Estimation

Since multilevel mixed models appropriately account for spatial autocorrelation, I continue to utilize a mixed-effects estimation method and do not report OLS results. Similar to the comparative static analysis, mixed-effect estimates are typically smaller in magnitude and less frequently statistically significant than OLS estimates. Additionally, I normalize test score variables in 2010 and 2017 and use the differences in normalized test scores between 2010 and 2017 as my dependent variables. This adjustment accounts for the implementation of Common Core testing in New York starting in 2013, which changed the scoring scale, structure, and implementation of Math and ELA standardized tests. A straight difference in mean test score for a particular school grade between 2010 and 2017 would not necessarily illustrate a true change in academic achievement but instead illustrate a true change in achievement confounded by an observed change in achievement due to a scale scoring change and changes in testing structure and implementation. Computing the difference in normalized mean test score as the dependent variable allows me to estimate the association of changes in tree canopy with real changes in academic achievement.

I begin my longitudinal analysis by estimating a mixed-effects regression of the change in normalized test score between 2010 and 2017 on the change in tree canopy and changes in other covariates, given by Equation 4:

$$\begin{aligned} \Delta Y_{ijkms} = & \beta_1 \Delta T_{jkm,b} + \boldsymbol{\pi} \Delta \mathbf{X}_{jkm} + \boldsymbol{\theta} \Delta \mathbf{Z}_{ijkms} + \alpha_1 \Delta \rho_{jm} \\ & + u_{jkm} + u_{km} + u_m + \varepsilon_{ijkms} \end{aligned} \quad (4)$$

The change in normalized test score ΔY_{ijkms} for grade i in school j in CSD k in borough m for subject s is regressed on the change in tree canopy $\Delta T_{jkm,b}$, changes in school-level effects ΔX_{jkm} (i.e., the change in percent of students eligible for free lunch), changes in school-grade-level effects ΔZ_{ijkm} (i.e., the change in pupil-teacher ratio), and the change in precinct-level crime $\Delta \rho_{jm}$. Like I do in the cross-sectional mixed-effects model, I incorporate a random intercept u_{jkm} for school j in CSD k in borough m , a random intercept u_{km} for CSD k in borough m , and a random intercept u_m for borough m .

Table 8 displays mixed-effects estimates for the association of an increase in tree canopy with the change in normalized Math score (column ones) and the change in normalized ELA score (column twos) at all seven buffer distances. χ^2 statistics are presented and support the use of mixed-effects models in lieu of a standard first-differenced OLS specification.

The first main insight from these longitudinal results involves the regression results for Math test scores (column ones). Since test scores in 2010 and 2017 are normalized, coefficients now have a standard-deviation interpretation instead of a straight-score interpretation. A positive change in percent tree canopy cover is consistently estimated to have a negative association with a change in Math test score for the average student, although this result is only statistically significant when considering a one thousand meter buffer around schools. It is estimated that a one percent increase in tree canopy within one thousand meters of school from 2010 to 2017 is associated with a .040 standard deviation decrease in expected Math score, holding changes in all other observable fixed-effects constant, such as changes in school demographics or changes in school quality metrics. It is estimated that a one percent increase in tree canopy within at most five hundred meters of school is associated with a negligible decrease in expected Math score.

Regression results for ELA test scores (column twos) provide similar estimates – when controlling for changes in fixed effects, a positive change in tree canopy is estimated to have a negative association with a change in expected ELA test score, a statistically significant result when seven hundred and fifty and one thousand meter buffers around schools are considered. Using the one thousand-meter buffer as our case again, it is estimated that a one percent increase in tree canopy cover within one thousand meters of school from 2010 to 2017 is associated with a .061 standard deviation decrease in expected ELA score (when holding all observable changes in fixed effects constant). A one percent increase in tree canopy within at most five hundred

Table 8. 2010-2017 Mixed-Effects Estimates

(1) Math scores

(2) ELA scores

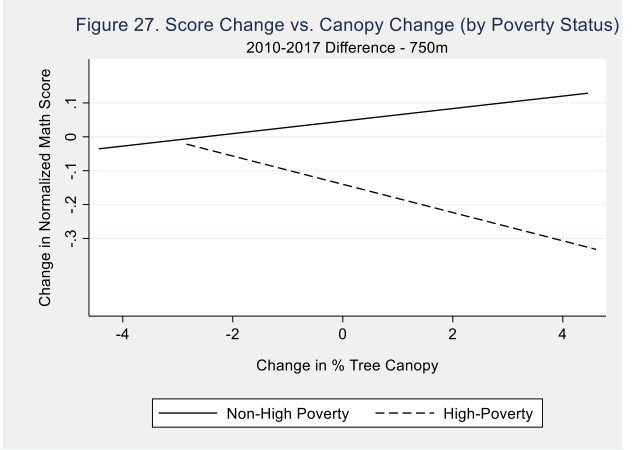
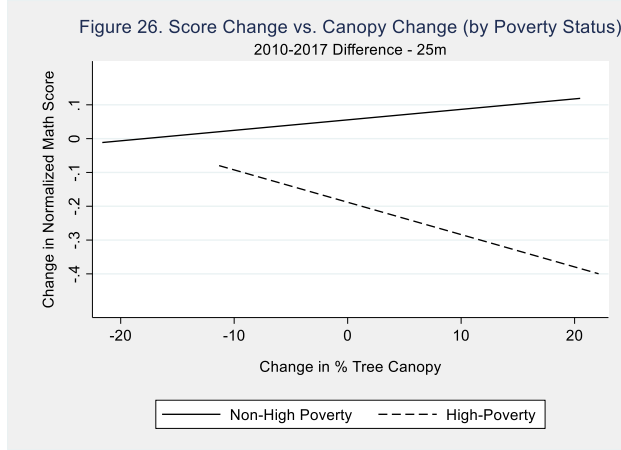
	25m		50m		100m		250m		500m		750m		1000m	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Δ Tree Canopy	-.003 (.005)	-.006 (.005)	-.005 (.007)	-.009 (.007)	-.004 (.008)	-.006 (.009)	-.007 (.011)	-.015 (.012)	-.010 (.014)	-.024 (.015)	-.024 (.017)	-.048*** (.018)	-.040** (.020)	-.061*** (.021)
Δ Free Lunch	-.002 (.002)	-.001 (.002)	-.002 (.002)	-.001 (.002)	-.002 (.002)	-.001 (.002)	-.003* (.002)	-.001 (.002)	-.002 (.002)	-.001 (.002)	-.002 (.002)	-.001 (.002)	-.002 (.002)	-.001 (.002)
Δ ELL	-.009** (.004)	-.013*** (.004)	-.009** (.004)	-.013*** (.004)	-.009** (.004)	-.013*** (.004)	-.009** (.004)	-.013*** (.004)	-.009** (.004)	-.013*** (.004)	-.009** (.004)	-.014*** (.004)	-.010** (.004)	-.014*** (.004)
Δ Special Ed	-.015*** (.005)	-.013** (.005)	-.015*** (.005)	-.013** (.005)	-.015*** (.005)	-.013** (.005)	-.015*** (.005)	-.013** (.005)	-.014*** (.005)	-.013** (.006)	-.014*** (.005)	-.013** (.006)	-.014** (.005)	-.012** (.006)
Δ Asian	.005 (.005)	-.0002 (.005)	.005 (.005)	-.0004 (.005)	.005 (.005)	.0001 (.005)	.007 (.005)	.002 (.005)	.007 (.005)	.001 (.005)	.007 (.005)	.001 (.005)	.005 (.005)	.001 (.005)
Δ Black	-.019*** (.005)	-.019*** (.005)	-.019*** (.005)	-.019*** (.005)	-.019*** (.005)	-.019*** (.005)	-.017*** (.005)	-.018*** (.005)	-.017*** (.005)	-.018*** (.005)	-.018*** (.005)	-.019*** (.005)	-.019*** (.005)	-.020*** (.005)
Δ Hispanic	-.014*** (.005)	-.011** (.005)	-.014*** (.005)	-.011** (.005)	-.014*** (.005)	-.011** (.005)	-.012*** (.005)	-.010** (.005)	-.014*** (.005)	-.011** (.005)	-.014*** (.005)	-.009* (.005)	-.014*** (.005)	-.010** (.005)
Δ Female	-.002 (.007)	.003 (.007)	-.002 (.007)	.003 (.007)	-.002 (.007)	.003 (.007)	-.002 (.006)	.003 (.007)	-.002 (.007)	.003 (.007)	-.001 (.007)	.003 (.007)	-.001 (.007)	.003 (.007)
Δ P-T Ratio	-.016 (.015)	.015 (.015)	-.016 (.015)	.015 (.015)	-.016 (.015)	.015 (.015)	-.016 (.015)	.015 (.015)	-.015 (.015)	.017 (.015)	-.017 (.015)	.017 (.015)	-.019 (.015)	.015 (.015)
Δ Avg. Class Size	-.003 (.003)	.002 (.003)	-.003 (.003)	.002 (.003)	-.003 (.003)	.002 (.003)	-.002 (.003)	.002 (.003)	-.003 (.003)	.002 (.003)	-.002 (.003)	.002 (.003)	-.002 (.003)	.002 (.003)
Δ Total Enroll.	-.0001 (.0006)	-.0001 (.0006)	-.0001 (.0006)	-.0001 (.0006)	-.0001 (.0006)	-.0001 (.0006)	-.0002 (.0006)	-.0002 (.0006)	.0001 (.0006)	-.0001 (.0006)	.0002 (.0006)	.00004 (.0006)	.0001 (.0006)	.00005 (.0006)
Δ Curriculum	.030 (.030)	.028 (.030)	.032 (.030)	.030 (.030)	.032 (.030)	.030 (.030)	.035 (.030)	.033 (.030)	.034 (.031)	.036 (.031)	.042 (.031)	.037 (.031)	.046 (.031)	.041 (.031)
Δ Pedagogy	.074*** (.025)	.063** (.025)	.074*** (.025)	.062** (.025)	.074*** (.025)	.062** (.025)	.074*** (.025)	.062** (.025)	.075*** (.025)	.065** (.025)	.075*** (.025)	.063** (.025)	.070*** (.025)	.059** (.026)
Δ Expectations	.046* (.024)	.058** (.024)	.045* (.024)	.056** (.024)	.045* (.024)	.058** (.024)	.043* (.024)	.056** (.024)	.048** (.024)	.057** (.024)	.045* (.024)	.060** (.024)	.044* (.024)	.059** (.024)
Δ \$ - Class	-.002 (.002)	.001 (.002)	-.002 (.002)	.001 (.002)	-.002 (.002)	.001 (.002)	-.002 (.002)	.001 (.002)	-.002 (.002)	.001 (.002)	-.002 (.002)	.001 (.002)	-.002 (.002)	.001 (.002)
Δ \$ - Other	-.0001 (.001)	-.002 (.001)	-.0001 (.001)	-.002 (.001)	-.0001 (.001)	-.002 (.001)	-.0002 (.001)	-.002 (.001)	.0002 (.001)	-.002 (.001)	.0001 (.001)	-.002 (.001)	.0001 (.001)	-.002 (.001)
Δ Total Crimes	.0001*** (.00002)	.0001*** (.00002)	.0001*** (.00002)	.0001*** (.00002)	.0001*** (.00002)	.0001*** (.00002)	.0001*** (.00002)	.0001*** (.00002)	.0001*** (.00002)	.0001*** (.00002)	.0001*** (.00002)	.0001*** (.00002)	.0001*** (.00002)	.0001*** (.00002)
Constant	.103* (.062)	.049 (.067)	.107* (.063)	.057 (.069)	.104* (.063)	.044 (.068)	.098 (.062)	.046 (.063)	.126* (.067)	.090 (.074)	.150** (.068)	.101 (.062)	.168** (.068)	.119* (.064)
Borough	.006 (.008)	.007 (.015)	.007 (.008)	.007 (.017)	.007 (.008)	.007 (.016)	.006 (.008)	.003 (.013)	.008 (.008)	.009 (.018)	.008 (.009)	1.9E-12 (2.2E-9)	.006 (.009)	4.8E-15 ()
CSD	.002 (.006)	.013 (.009)	.002 (.006)	.012 (.009)	.002 (.006)	.012 (.009)	.002 (.006)	.014 (.011)	3.12E-9 (2.48E-6)	.010 (.009)	.001 (.006)	.013 (.006)	.002 (.006)	.014 (.006)
School	.130 (.014)	.122 (.013)	.130 (.014)	.122 (.013)	.131 (.014)	.122 (.013)	.128 (.014)	.121 (.013)	.133 (.014)	.125 (.014)	.132 (.014)	.123 (.014)	.131 (.014)	.123 (.014)
χ^2	198.81	209.19	198.69	209.07	198.34	208.16	192.53	204.90	196.60	204.25	194.69	196.11	190.45	198.16
N	1499	1499	1499	1499	1499	1499	1496	1496	1464	1464	1455	1455	1445	1445

meters of school is again associated with a negligible decrease in expected test score. Thus, there is initial evidence that the comparative static estimate of a frequently positive and statistically significant relationship between tree canopy and test scores does not hold up when a longitudinal approach is used.

Testing the Relationship by Poverty Level

Similar to the comparative static analysis, increases in tree canopy may associate differently with educational outcomes depending on whether a school is high-poverty or non-high poverty (recall the “return on investment” concept for street tree planting). The comparative static OLS results show that neighborhood-level tree canopy associates with even better expected test outcomes for high-poverty schools relative to non-high poverty schools, although the comparative static mixed-effects analysis concludes that this differential is not clear once spatial autocorrelation is modeled. However, even if there is not a clearly differential association by poverty level in either 2010 or 2017, we can ask a different question of the green space-educational outcomes relationship in a longitudinal analysis, namely whether a *change* in tree canopy is associated differently with the *change* in expected test scores for students in high-poverty schools and students in non-high poverty schools. Given the comparative static results, the hypothesis might be that a change in tree canopy is positively associated with the change in expected test scores for students in high-poverty schools and is somewhat less positively associated with the change in expected test scores for students in non-high poverty schools.

To motivate this test, I plot linear best-fit lines of the bivariate relationship between the change in normalized Math test score and the change in percent tree canopy within fifty meters and seven hundred and fifty meters of schools in Figures 26 and 27. The simple relationship between increased tree canopy cover and change in math scores is starkly different for non-high poverty schools and high-poverty schools, but in the opposite direction from what we might hypothesize given the comparative static results. An increase in tree canopy from 2010 to 2017 is typically associated with increased Math scores for non-high poverty schools but typically strongly associated with decreased test scores for high-poverty schools. These plots strongly suggest controlling for a differential green space-educational outcomes relationship by poverty level in the longitudinal mixed-effects regressions. They also strongly counter any evidence that increased tree canopy might associate with better expected test outcomes for high-poverty schools relative to



non-high poverty schools.

To operationalize this test of the green space-educational outcomes by poverty level in the longitudinal context, I create a dummy variable $highpov_{both}$ equal to one if the school-grade observation is within a school that was considered high-poverty in both 2010 and 2017 (i.e., in both years, more than seventy-five percent of students were eligible for free lunch). Fifty-two percent of observations meet this criteria. Equation 5 is the full longitudinal mixed-effects specification. It is identical to Equation 4 but includes an interaction of the change in percent tree canopy with $highpov_{both}$.

$$\Delta Y_{ijkms} = \beta_1 \Delta T_{jkm,b} + \beta_2 (\Delta T_{jkm,b} * highpov_{both}) + \pi \Delta X_{jkm} + \theta \Delta Z_{ijkms} + \alpha_1 \Delta \rho_{jm} + u_{jkm} + u_{km} + u_m + \varepsilon_{ijkms} \quad (5)$$

β_1 is thus the estimated association of a one percent increase in tree canopy between 2010 and 2017 with the change in normalized average test score for non-high poverty school grades, and β_2 represents the additional association of the increase in percent tree canopy with the change in normalized average test scores for high-poverty school grades. The full association of the increase in tree canopy with the change in normalized average test score for high-poverty school grades is then $\beta_1 + \beta_2$. Table 9 displays estimated tree canopy coefficients for full regressions *without* the

Table 9. 2010-2017 Mixed-Effects Estimates (w/ high-poverty interaction)

(1) Full regression (no interaction)

(2) Full regression (with interaction)

MATH

	25m		50m		100m		250m		500m		750m		1000m	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
β_1	-.003 (.005)	.009 (.006)	-.005 (.007)	.011 (.008)	-.004 (.008)	.016 (.011)	-.007 (.011)	.017 (.014)	-.010 (.014)	.027 (.018)	-.024 (.017)	.027 (.020)	-.040** (.020)	.023 (.023)
β_2	--	-.026*** (.007)	--	-.036*** (.010)	--	-.040*** (.013)	--	-.051*** (.015)	--	-.069*** (.018)	--	-.092*** (.019)	--	-.104*** (.021)
N	1499	1499	1499	1499	1499	1499	1496	1496	1464	1464	1455	1455	1445	1445

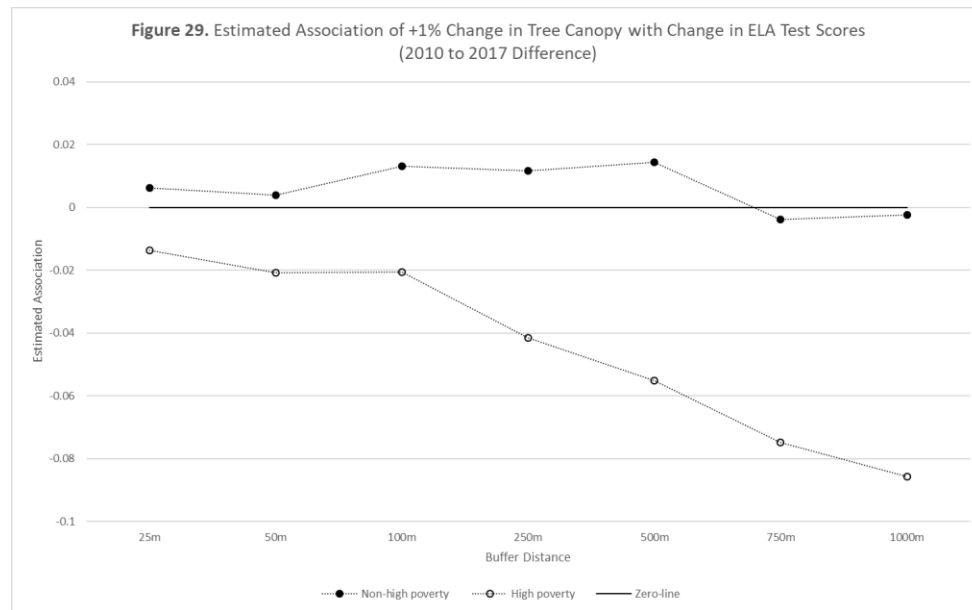
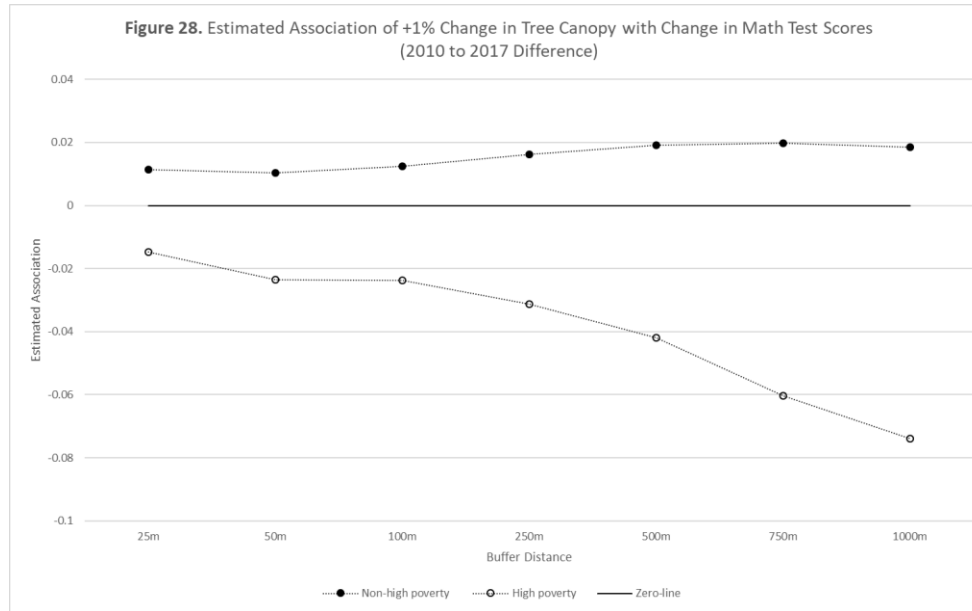
ELA

	25m		50m		100m		250m		500m		750m		1000m	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
β_1	-.006 (.005)	.003 (.006)	-.009 (.007)	.003 (.008)	-.006 (.009)	.013 (.011)	-.015 (.012)	.014 (.014)	-.024 (.015)	.015 (.018)	-.048*** (.018)	-.001 (.021)	-.061*** (.021)	-.004 (.025)
β_2	--	-.019** (.008)	--	-.026*** (.010)	--	-.039*** (.013)	--	-.053*** (.016)	--	-.074*** (.019)	--	-.079*** (.020)	--	-.089*** (.022)
N	1499	1499	1499	1499	1499	1499	1496	1496	1464	1464	1455	1455	1445	1445

high-poverty interaction term (column ones) and *with* the high-poverty interaction term (column twos).

The high-poverty interaction term is unambiguously important in this longitudinal analysis. It is estimated at all buffer distances that an increase in percent tree canopy between 2010 and 2017 is strongly associated with decreases in both Math and ELA expected test scores for high-poverty schools and is associated with either no changes or slight increases in expected test scores (but almost always not statistically significant) for non-high poverty schools. For example, when considering land cover within one hundred meters of elementary schools, it is estimated that a one percentage point increase in tree canopy between 2010 and 2017 is associated with a .040 standard deviation lower expected Math test score and a .039 standard deviation lower expected ELA test score for students in high-poverty schools, a result that is highly statistically significant. The same increase in tree canopy is associated with a .016 standard deviation higher expected Math test score and a .013 standard deviation higher expected ELA test score for students in non-high poverty schools, but these estimates are not statistically significant. More starkly, when considering land cover within five hundred meters of elementary schools, it is estimated that a one percentage point increase in tree canopy between 2010 and 2017 is associated with a .069 standard deviation lower expected Math test score and a .074 standard deviation lower expected ELA test score for students in high-poverty schools but a .027 standard deviation higher expected Math test score and a .015 standard deviation higher expected ELA test score for schools in non-high poverty schools. Figures 28 and 29 plot the tree canopy coefficients against buffer distance separately for high-poverty and non-high poverty schools.

It is important to note that these longitudinal results are still not causal. Since I use school grades as observational units, employing a longitudinal research design (with fixed effects) does not control for time-varying unobserved characteristics of school grades. If time-varying unobserved characteristics of high-poverty school grades caused high-poverty students to do more poorly on standardized tests over time, while analogous characteristics of non-high poverty school grades caused non-high poverty students to retain or improve performance on tests over time, the observed association between increases in tree canopy and changes in grade-average test scores could be partially driven by these unobserved factors and may not reflect the true green space-educational outcomes relationship. Specifically, the strong negative relationship between an increase in tree

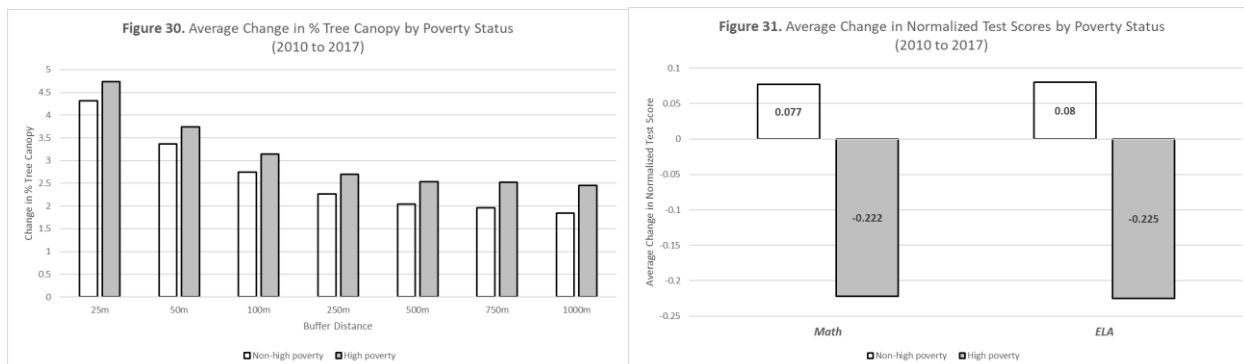


canopy and changes in normalized test score that we observe for high-poverty schools between 2010 and 2017 may be partially spurious and not entirely out of line with the positive (if not clearly statistically significant) neighborhood-level effects that we observe in each year separately.

Synthesizing Conflicting Results

To reiterate, the longitudinal results appear to conflict with the comparative static results. The comparative static analysis concludes that (1) there is no robust evidence that having more tree canopy coverage close to elementary schools has an appreciable relationship with how students perform on standardized tests on average, but (2) there is some evidence, largely in the association with Math test scores, that having more tree canopy coverage on a neighborhood scale is positively associated with how elementary school students perform on tests on average. Longitudinal analysis provides seemingly contradictory evidence that increases in tree canopy around elementary schools over time, whether we consider schoolyard-level distances or neighborhood-level distances, is associated with decreases in the expected test performance of students in high-poverty schools and is not significantly associated with changes in the expected test performance of students in non-high poverty schools.

To illustrate a potential explanation for the discrepancy between the comparative static and longitudinal results, I calculate average seven-year changes in normalized grade-average test scores and average seven-year changes in tree canopy separately by high-poverty status. Figure 30 (average change in percent tree canopy at all buffer distances) and Figure 31 (average change in normalized test scores) show that while tree canopy around schools typically increased at all buffer distances (slightly more for high-poverty schools), grade-average performance on tests changed in substantially different ways by poverty status between 2010 and 2017. Specifically, average Math



scores and ELA scores increased by .077 and .08 standard deviations, respectively, for non-high poverty schools, while average Math and ELA scores decreased by .222 and .225 standard deviations, respectively, for high-poverty schools.

Coupled with the consistent increases in percent tree canopy, there is initial evidence to suggest that spurious negative correlation, caused by time-varying unobserved characteristics of school grades, may influence (1) the strongly negative estimated green space-educational outcomes longitudinal relationship for high-poverty schools and (2) the marginally positive estimated green space-educational outcomes longitudinal relationship for non-high poverty schools.

The Bigger Picture: Inequality and the Common Core

In general, these longitudinal results may reflect well-documented increasing inequality (by many measures) in the United States since 1980 (Chappell 2019; Telford 2019), particularly in urban areas like New York City (Abel and Deitz 2019; Liu et al. 2012; Sommeiller and Price 2018). Changes in housing quality, public utilities provision, school administration, teacher quality, and other aspects of students' living or learning environments are potential unobserved dimensions of inequality that may have widened in New York City between 2010 and 2017 and may have differentially influenced the test performance of students in high-poverty and non-high poverty schools. Although I attempt to capture dimensions of a student's learning environment (i.e., controlling for quality review scores and per-student expenditures), there are likely other unmeasured characteristics of students' learning environments that differed over time, in addition to unmeasured characteristics of students' living environments. The implication of these unobserved factors is that they may bias the estimated impact of increases in tree canopy on changes in expected test scores, particularly since tree canopy increased for almost all areas in New York City during this time period.

Extended Econometric Model: Bias From Unobserved Inequality

I now offer an extended model of the potential bias caused by unobserved time-varying characteristics of school grades. I assume that these characteristics, which I term "unobserved dimensions of inequality", (1) correlate positively with changes in test scores of non-high poverty school grades, (2) correlate negatively with changes in test scores of high-poverty school grades, and (3) correlate positively or negatively with changes in tree canopy around schools depending

on poverty status of the school. The first two assumptions simply reflect what one means by inequality, while the third assumption relies on the evidence that tree canopy empirically increased for almost all areas of New York City between 2010 and 2017 (see Map 9) – I explain this implication further on the next page. This extended model should therefore not be treated as widely applicable to all contexts, but instead one that specifically applies to this study of the green space-educational outcomes relationship in New York City between 2010 and 2017.

Equation 6 is a simplified version of Equation 5 that omits all covariates and random intercept specifications and adds an unobserved “changing dimensions of inequality” term Δv_{ij} (ε_{ij} is the standard disturbance term that does not consistently covary with observed variables by poverty status).

$$\Delta Y_{ij} = \beta_1 \Delta T_{j,b} + \beta_2 (\Delta T_{j,b} * highpov_{both}) + \alpha \Delta v_{ij} + \varepsilon_{ij} \quad (6)$$

In this simplified specification, the change in normalized average test score ΔY_{ij} for school grade i in school j is regressed on the change in tree canopy $\Delta T_{j,b}$ for school j at buffer distance b , the interaction of change in tree canopy with a dummy variable indicating whether a school was high-poverty in both 2010 and 2017, and the unobserved “changing dimensions of inequality” term Δv_{ij} . I assume that, for *non-high poverty* schools,

$$\frac{d(\Delta v_{ij})}{d(\Delta T_{j,b})} \geq 0 \quad (A1)$$

$$\frac{d(\Delta Y_{ij})}{d(\Delta v_{ij})} \geq 0 \quad (A2)$$

I assume that, for *high-poverty* schools,

$$\frac{d(\Delta v_{ij})}{d(\Delta T_{j,b})} \leq 0 \quad (A3)$$

$$\frac{d(\Delta Y_{ij})}{d(\Delta v_{ij})} \leq 0 \quad (A4)$$

Assumptions A1 and A2 assert that (1) changing unobserved dimensions of inequality may *positively* associate with changes in tree canopy for non-high poverty schools, and (2) changes in test scores may *positively* associate with changing dimensions of inequality for non-high poverty schools. Assumptions A3 and A4 assert that (1) changing unobserved dimensions of inequality may *negatively* associate with changes in tree canopy for high-poverty schools, and (2) changes in test scores may *negatively* associate with changing dimensions of inequality for high-poverty schools.

Assumptions A2 and A4 are simply based on what one means by inequality, and they actually do not cause bias in the green space-educational outcomes relationship. Assumptions A1 and A3 are the potential source of bias, and they rest on the fact that tree canopy empirically increased for almost all areas of New York City between 2010 and 2017 (see Map 9). These assumptions basically claim that dimensions of inequality might have widened between 2010 and 2017. Specifically, at the same time tree canopy was increasing between 2010 and 2017, unobserved dimensions of inequality may have *positively* contributed to changes in expected test outcomes for non-high poverty schools and may have *negatively* contributed to changes in expected test outcomes for high-poverty schools.

How does this inclusion of unobservable dimensions of inequality explicitly cause potential bias in the observed green space-educational outcomes relationship? Using Equation 6 and assumptions A1 and A2, for non-high poverty schools,

$$\frac{d(\Delta Y_{ij})}{d(\Delta T_{j,b})} = \beta_1 + \left(\alpha * \frac{d(\Delta v_{ij})}{d(\Delta T_{j,b})} \right) \quad (8a)$$

Equation 8a states that, for non-high poverty schools, the change in normalized average test score associated with a change in tree canopy is the estimated tree canopy coefficient β_1 *plus* the change in test score associated with any marginal change in unobserved dimensions of inequality when tree canopy changed. And for high-poverty schools,

$$\frac{d(\Delta Y_{ij})}{d(\Delta T_{j,b})} = \beta_1 + \beta_2 + \left(\alpha * \frac{d(\Delta v_{ij})}{d(\Delta T_{j,b})} \right) \quad (8b)$$

Similarly, Equation 8b states that, for high-poverty schools, the change in normalized average test score associated with a change in tree canopy is the estimated tree canopy coefficient β_1 , *plus* the high-poverty interaction coefficient β_2 , *plus* the change in test score associated with any marginal change in unobserved dimensions of inequality as tree canopy changed.

We have almost reached the source of potential bias in the longitudinal green space-educational outcomes relationship. Under assumption A1, for non-high poverty schools,

$$\frac{d(\Delta Y_{ij})}{d(\Delta T_{j,b})} = \beta_1 + \alpha \geq \beta_1 \quad (B1)$$

And under assumption A3, for high-poverty schools,

$$\frac{d(\Delta Y_{ij})}{d(\Delta T_{j,b})} = \beta_1 + \beta_2 - \alpha \leq \beta_1 + \beta_2 \quad (B2)$$

Expression B1 states that, for non-high poverty schools, the estimated green-space educational outcomes relationship in the longitudinal analysis may be upward-biased if there were unobserved dimensions of inequality that changed for non-high poverty school grades between 2010 and 2017. Similarly, expression B2 states that for high-poverty schools, the estimated green-space educational outcomes relationship in the longitudinal analysis may be downward-biased if there were unobserved dimensions of inequality that changed for high-poverty school grades between 2010 and 2017.

This extended model example provides evidence that the estimated green space-educational outcomes relationship in the longitudinal analysis may be biased (upward bias for non-high poverty school grades and/or downward bias for high-poverty school grades), specifically due to unobserved “dimensions of inequality” that may have changed in New York City between 2010 and 2017. Therefore, the relationships between an increase in tree canopy and changes in normalized average test scores that we observe between 2010 and 2017 may be not entirely out of line with the positive (if not clearly statistically significant) neighborhood-level tree canopy effects that we observe in each year separately.

The Common Core

One specific time-varying unobserved characteristic of school grades that could have differentially influenced the change in test performance of students in high-poverty and non-high poverty schools between 2010 and 2017 is the implementation of Common Core curricula in New York starting in 2013. The Manhattan Institute for Policy Research notes, using an online survey emailed to more than one thousand New York City public middle and elementary schools, that low-performing schools were more likely than high-performing schools to switch to DOE-recommended Math and ELA curricula since they faced stronger performance-based incentives to do so (Sahm 2015). If implementing Common Core curricula caused high-poverty school grades to perform worse on standardized tests than non-high poverty schools in 2017 compared to 2010, it would be one likely source of bias in the negative longitudinal green space-educational outcomes relationship that we observe for high-poverty schools.

In support of this theory, numerous sources claim that Common Core standards are not appropriate for elementary-school children, particularly for low-performing students. Members of the New York Board of Regents at times expressed concern that the standards were too rigid and unadaptable for disadvantaged students (Disare 2017), and there was concern that low-performing students could not adapt as effectively to the curriculum switch, particularly since they might not be supported as comprehensively as higher-performing students (Barshay 2019). Thus, even if lower-performing (high-poverty) schools adopted Common Core curricula to a greater extent than higher-performing (non-high poverty) schools starting in 2013, there is widespread belief that this adoption would not have necessarily translated into better test outcomes and could actually have induced regression in grade-average learning and achievement between 2010 and 2017.

In terms of the extended model from the previous section, the change to Common Core testing standards for New York City public schools beginning in 2013 would be one possible component of Δv_{ij} (the unobserved “dimensions of inequality”). It would be considered a changing dimension of inequality since high-poverty schools were more likely to adopt Common Core curricula even though there were numerous concerns that such curricula could be detrimental to learning and achievement, particularly for students in high-poverty schools. As a result, $\frac{d(\Delta Y_{ij})}{d(\Delta T_{j,b})}$, the estimated

green space-educational outcomes relationship, would be somewhat biased downward for high-poverty schools.

Discussion

This paper estimates the relationship between green space (particularly tree canopy cover) and academic achievement (standardized Math and ELA test scores) in a previously unstudied context – public elementary schools (grades three through five) in New York City. Six-inch resolution LiDAR-based land cover data is used, which is the highest-resolution data used in the green space-educational outcomes literature to date. After conducting static cross-sectional analyses in both 2010 and 2017, which is the approach most commonly used in the literature due to land cover data limitations, I find no robust evidence that having more tree canopy coverage *only* close to elementary schools (only considering areas within about one hundred meters of schools) has an appreciable relationship with how students perform on standardized tests on average. I do find some evidence, largely in the association with Math test scores, that having more tree canopy coverage on a neighborhood scale, or close to *and* farther from elementary schools (considering at least two hundred and fifty around schools) is positively associated with how elementary school students perform on tests on average. These results are robust to mixed-effects estimation methods, which are meant to address spatial autocorrelation. Although simple bivariate plots suggest that the green space-educational outcomes relationship may be systematically different for high-poverty and non-high poverty schools, there is no consistent cross-sectional evidence that this is the case.

I also conduct what I believe to be just the third longitudinal analysis of the green space-educational outcomes relationship, facilitated by the fact that I have access to land cover data for New York City in both 2010 and 2017 in addition to test score and covariate data. This research methodology is often desirable because it differences out time-invariant characteristics of school grades, which is particularly useful if these characteristics are unobserved or unmeasured *and* if these characteristics are correlated both with grade-average test scores and amounts of tree canopy cover around schools. Examples of these school-grade-level characteristics could be housing quality, public utilities provision, school culture, teacher quality, and aspects of school

administration, although these factors may also vary over time. After conducting a longitudinal mixed-effects analysis, I find initial evidence that increases in tree canopy coverage around elementary schools between 2010 and 2017, whether we consider schoolyard-level distances or neighborhood-level distances, are negatively associated with how average test performance of students in high-poverty schools changes between the two years and are estimated to have marginally positive to no influence on how average test performance of students in non-high poverty schools changes.

At first glance, the longitudinal results seem to conflict with the comparative static results. However, I offer a potential unifying explanation for these results. Since I use school grades as observational units (as most existing studies of the green space-educational outcomes relationship do), employing a longitudinal research design (with fixed effects) does not control for time-varying unobserved characteristics of school grades. If these omitted factors covary both with changes in green space and changes in test scores, the estimated green space-educational outcomes relationship may be biased. I offer several time-varying characteristics of school grades that are unable to be controlled for over time and might have hindered the test performance of high-poverty schools but not the test performance of non-high poverty schools. I also construct an extended econometric model detailing potential bias in the green space-educational outcomes relationship arising from unobserved changing dimensions of inequality. In particular, I posit that since low-performing (high-poverty) schools were more likely than high-performing (non-high poverty) schools to adopt DOE-recommended Common Core curricula starting in 2013, and since concerns surfaced that Common Core curricula and standards might have been particularly challenging for low-performing students to adapt to, adoption of Common Core curricula may have induced unobserved regression in grade-average learning and achievement between 2010 and 2017 for students in high-poverty schools. Therefore, the negative relationship observed between tree canopy change and test score changes for high-poverty schools between 2010 and 2017 may be partially spurious and not irreconcilable with the positive neighborhood-level effects that we observe in each year separately.

Conclusion

This paper supports existing findings in the green space-educational outcomes literature that green space, particularly tree canopy cover, may be positively associated with how elementary school students perform on tests in an urban context, all else constant. In 2010 and 2017, I find some evidence of a neighborhood-level positive association of tree canopy with test scores and no evidence of a schoolyard-level effect, results that are robust to hierarchical mixed-effects model specifications. In contrast, I find initial evidence that increases in tree canopy around elementary schools between 2010 and 2017 were associated with decreased grade-average test performance for students in high-poverty schools and were not significantly associated with changes in test performance for students in non-high poverty schools, a result that somewhat contradicts comparative static results. To reconcile my findings, I construct an extended econometric model detailing potential bias in the green space-educational outcomes relationship that might arise from unobserved changing dimensions of inequality, with the adoption of Common Core curricula beginning in 2013 serving as a pertinent example.

As prior research has noted²¹, these results are not necessarily generalizable across different geographies and spatial scales. Additionally, I focus on elementary school academic achievement, but there is no reason to believe that middle school or high school educational outcomes are not similarly associated with urban green space; future studies should continue to assess the association of green space with various grades and stages of education. Given the estimated existence of a neighborhood-level green space-educational outcomes association, useful analysis of this association could have been conducted by school zone. Future research should consider additional definitions of “neighborhood” at which to analyze the relationship, such as school zones or school attendance areas²². Additionally, I address spatial autocorrelation between schools by estimating hierarchical mixed-effects models, but it is possible that this specification does not capture the full extent of autocorrelation. For example, the mixed-effects model used in this study assumes that schools within the same community school district experience the same average unobservable determinants of test scores, but it can easily be argued that two schools within four blocks of each other in the same school district are more similar along unobserved dimensions than

²¹ See Hodson and Sander (2019), pg. 220.

²² Hodson and Sander (2017), Hodson and Sander (2019), and Kuo et al. (2018) use these areal extents effectively.

are two schools that are five kilometers apart within the same school district. Specifying econometric models with more granular spatial autocorrelation, including constructing and estimating a spatial lag model, could be a useful statistical tool to refine estimates of the green space-educational outcomes relationship.

Future researchers should intentionally consider the implications of using school-level or grade-level observational data, particularly when attempting longitudinal analyses – typical fixed-effects or mixed-effects econometric tools that account for time-invariant unobserved characteristics do not account for time-varying unobserved characteristics, an omission that is less significant if using individual student data but potentially very significant when using grade-average outcomes. This study also highlights the importance of testing and potentially accounting for a systematically different green space-educational outcomes relationship by school poverty level. Finally, this study suggests the importance of locating green space-educational outcomes research within a wider context of factors underlying educational outcomes. Urban green space may exhibit positive associations with educational outcomes of grade school students, but much broader and entrenched unobserved forces may also influence these outcomes. Failing to consider the co-development and co-evolution of urban green space with salient unobserved factors when estimating and interpreting the green space-educational outcomes relationship over time misses the bigger picture and may result in misleading conclusions.

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