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The Relationship Between the Natural Environment and Individual-Level Academic Performance in Portland, Oregon

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Abstract

We tested the hypothesis that exposure to the natural environment is associated with improved academic performance. Specifically, we examined the association between individual-level standardized math and reading test scores and exposure to the natural environment using data from Portland Public Schools (17,918 students attending 83 schools for the math model and 19,459 students attending 90 schools for the reading model). We found that a 1-*SD* increase in tree cover within 200 m of a child's home was associated with moving from the 50th percentile to the 51st percentile on math tests. A 1-*SD* increase in tree cover within 100 m of a child's school was associated with moving from the 50th percentile to the 56th percentile on reading tests. Finally, a 1-*SD* increase in road density within 100 m of a child's home was associated with moving from the 50th percentile to the 47th percentile on reading tests.

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Introduction

A growing number of studies suggest a link between the natural environment and cognitive function (Bratman, Hamilton, & Daily, 2012; de Keijzer, Gascon, Nieuwenhuijsen, & Dadvand, 2016). However, few of these studies have focused on the influence of the natural environment on academic performance, despite academic performance being an important measure of cognitive function and the well-established links between academic performance and a range of short- and long-term health outcomes (Currie & Thomas, 1999; DeWalt, Berkman, Sheridan, Lohr, & Pignone, 2004; St. Clair-Thompson & Gathercole, 2006). In addition, all but one of these studies have used aggregate school-level measures of academic performance (Matsuoka, 2010; Wu et al., 2014), and all have exclusively focused on the natural environment around a child's school and not the child's home. Failing to account for the home environment may be problematic, as recent research has shown that environmental measures that fail to account for a person's entire "activity space" mis-specify environmental exposure and lead to inaccurate estimates of effect (Perchoux, Chaix, Cummins, & Kestens, 2013). We address this gap in the literature by quantifying the relationship between residential and school greenness and individual-level standardized test scores for 17,000 children in Portland, Oregon.

Children's Academic Performance and the School Environment

In the education literature, numerous studies have investigated the determinants of children's academic performance. The majority have focused on attributes of children, parents, and teachers; teaching methods, class size, and school funding (Brooks-Gunn, Klebanov, & Duncan, 1996; Card & Payne, 2002; Hake, 1998; Jencks & Phillips, 2011; Mosteller, 1995). A smaller number of studies have looked at the role of a school's environment. For example, several studies have found that air pollution is associated with decreased academic performance (Mohai, Kweon, Lee, & Ard, 2011; Wang et al., 2009). Similarly, research has found links between school test scores and noise (Shield & Dockrell, 2008), exposure to crime, and school age and architecture (Schwartz & Gorman, 2003).

Children's Academic Performance and the Natural Environment

Building on research demonstrating that a school's environment can impact academic performance, several studies have examined the relationship between exposure to the natural environment and academic performance. Specifically, Matsuoka (2010) looked at aggregate school-level tests scores for 101 schools in six southeast Michigan counties. Unlike other studies that relied on remotely sensed data, the author visited each school and classified the views on a 4-point scale from all built to all natural. He found that schools with more natural views had higher aggregate test scores, higher graduation rates, higher rates of planned college attendance, and lower rates of criminal behavior. Wu et al. (2014) studied the relationship between greenness and aggregate school-level test scores at 905 Massachusetts schools from 2006 to 2012. They measured greenness around each school 3 times a year in buffers ranging from 250 m to 2,000 m using the Normalized Difference Vegetation Index (NDVI), which is a greenness index based on satellite imagery. Their outcome was the proportion of third-grade students in each school who scored above proficient in standardized math and English tests. They found that greener schools had higher test scores after controlling for confounders. Notably, the strongest relationship between greenness and academic performance was in March, which is when children take standardized tests. Hodson and Sander (2017) also modeled the proportion of third-grade students in each school who scored above proficient in standardized math and English tests as well as school-level averages. Unlike previous studies, they considered the natural environment in larger school attendance areas around 222 schools in the Twin Cities, Minnesota. They found no relationship between the natural environment and math scores, but they did find a positive association between the natural environment and both average English test scores and the proportion of children who scored above proficient on English tests. Finally, Kweon, Ellis, Lee, and Jacobs (2017) examined the relationship between greenness and test scores at 219 public schools in Washington, D.C. Their outcome was the percent of students who scored proficient or advanced on standardized math and reading tests. They found that greenness on a school's grounds was positively associated with both math and reading scores. Unlike previous studies that relied on NDVI, the authors used higher resolution land-cover data derived from LiDAR and multispectral imagery.

Finally, Benfield, Rainbolt, Bell, and Donovan (2015) examined the performance of students ($n = 567$) in an introductory college reading class that had multiple sections. All sections followed the same syllabus and were evaluated identically. Some sections were held in a classroom with a view of a natural scene, while other sections were held in classrooms with a view of a concrete retaining wall. Students in classrooms with a natural view had higher final grades and rated the class more highly. This is the only study, to our knowledge, that used individual-level, as opposed to school-level, test scores and suggests that the positive association between greenness and school-level test scores, found in other studies, is not merely an artifact of ecological bias.

A few studies have quantified the relationship between greenness and measures of cognitive development other than school test scores. Notably, Dadvand et al. (2015) measured the cognitive development of 2,593 children attending 36 schools in Barcelona. They measured greenness around each child's home, school, and commute to school using 5-m-resolution NDVI derived from RapidEye imagery. Past studies more commonly used 30-m-resolution NDVI derived from Landsat imagery (Dadvand et al., 2012; Hystad et al., 2014; Laurent, Wu, Li, & Milesi, 2013). They found that more greenness around schools as well as higher total greenness (a weighted average of home, commute, and school greenness) were associated with improved working memory, superior working memory, and reduced inattentiveness. Furthermore, the authors found that 20% to 65% of this effect was mediated by improved air quality.

Wells (2000) studied 17 children enrolled in a program to help low-income families buy homes. Using questionnaires administered by the parents, she tested the children's cognitive function before and after they moved into their new homes. Children who moved into homes with the greenest surroundings showed the greatest improvement in cognitive function.

Not all studies of the relationship between exposure to the natural environment and cognitive function have been observational. (I'm not sure why you added a D. in front of Li) D. Li and Sullivan (2016) experimentally tested the effect of classroom views on attention restoration and stress reduction at five public high schools in Illinois (n = 94 students). Students who were randomly assigned to a classroom with a view of a natural scene had better attention, and lower stress, after conducting a series of stressful tasks, than students assigned to a classroom with no natural view. They also found that stress reduction did not mediate attention restoration.

De Keijzer et al. (2016) reviewed the literature on the relationship between exposure to the natural environment and cognition. For children, they concluded that the evidence was suggestive of a positive association between greenness and cognitive function. However, they went on to conclude that "The existing body of evidence on the association between green spaces and cognitive function through the life course is still inadequate" (p 475).

Gaps Addressed by Current Research

To improve our understanding of the association between exposure to the natural environment and academic performance, we quantify the relationship between greenness and school test scores in Portland, Oregon. Our study is novel in a number of important ways. First, we simultaneously consider greenness around a child's home and school, which is an improvement on past studies that have only considered greenness around schools, which misspecifies children's exposure to the natural environment in their activity space (accounting for a child's school and home environment does not, however, fully specify the child's activity space). Second, we use individual test scores not school-level averages, which avoids the well-documented problems associated with analyzing aggregate data (ecological bias, for example). Third, we use a larger sample size than previous studies. Fourth, rather than recruiting children to a study, which limits generalizability of results, we include all children enrolled in Portland Public Schools (PPS) in our analysis. Fifth, we use higher resolution (1 m) imagery than previous studies, which allows us to better characterize highly heterogeneous urban vegetation. Sixth, we do not use an aggregate measure of greenness. Rather, we decompose greenness into trees and grass-and-shrubs, which helps us determine whether different elements of the natural environment—mature trees versus grass sports fields, for example—have different effects on test scores.

Hypotheses Statements

Our primary research question is determining whether exposure to the natural environment, around a child's home and school, is associated with improved performance on standardized math and English tests:

> **Hypothesis 1**
> $\mathbf{H_0}$: Exposure to the natural environment, at a child's home and school, is unrelated to academic performance.
> $\mathbf{H_A}$: Exposure to the natural environment, at a child's home and school, is positively associated with academic performance.

In addition, we address a secondary research question: whether proximity to major roads is a risk factor for poor academic performance, because past research suggests that improved air quality may mediate, at least partly, our hypothesized relationship between the natural environment and academic performance (Dadvand et al., 2015).

Hypothesis 2
H_0: Proximity to major roads, at a child's home and school, is unrelated to academic performance.
H_A: Proximity to major roads, at a child's home and school, is negatively associated with academic performance.

Method

Participants

Our sample consists of all students in Grades 3 to 8 and Grade 11 enrolled in PPS during the 2013-2014 academic year (21,107 students attending 93 schools living in 160 census tracts). Note that there was no recruitment to this study. Rather, all students who met the selection criteria were included.

Constructs and Measures

Academic performance. We measured academic performance using individual-level scores on standardized math and reading tests. Students at PPS take standardized math and reading tests during Grades 3 to 8 and Grade 11 known as OAKS (Oregon Assessment of Knowledge and Skills) tests. Tests are scored on a Rausch equal interval scale and are designed to be comparable across grades. Scores are distributed similarly in each grade, with mean test scores increasing by grade. Mean math and reading scores (across all grades) are 228 (SD = 14.1) and 226 (SD = 22.7), respectively. Our sample consists of all students in Grades 3 to 8 and Grade 11 enrolled in PPS during the 2013-2014 academic year (21,107 students attending 93 schools living in 160 census tracts).

Exposure to the natural environment. We used the EPA EnviroAtlas (U.S. Environmental Protection Agency, 2016) to calculate metrics describing a child's exposure to the natural environment at home and at school. EnviroAtlas provides 1-m-resolution geographic information system (GIS) layers of vegetation for several U.S. cities including Portland. These layers decompose vegetation into two classes: grass-and-shrubs and trees. We used EnviroAtlas data to calculate percent vegetation cover in 100-m and 200-m buffers around schools and homes (Table 2). The buffers were centered on the centroid of a house or school's lot. We chose these buffer sizes based on past research on the health benefits of the natural environment (Dadvand et al., 2015; Donovan, Michael, Butry, Sullivan, & Chase, 2011; Laurent et al., 2013). Figure 1 shows grass-and-shrubs, trees, and roads in 100-m and 200-m buffers around

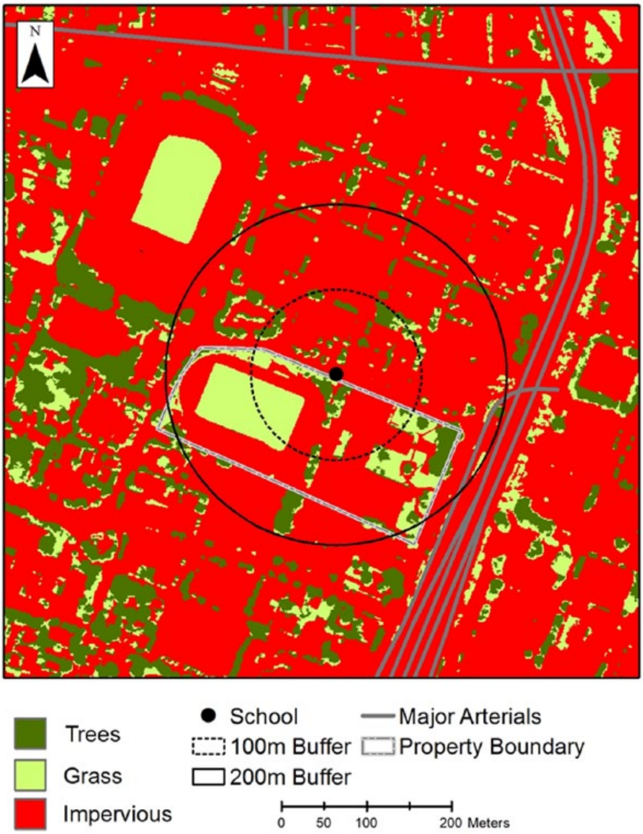

Figure 1. Grass-and-shrubs, trees, and roads around Lincoln High School in Portland, Oregon.

Lincoln High School in Portland. In addition, we used data from Portland Metro (2016) to calculate the network distance from homes and schools to the nearest park and the area of parkland in a 500-m buffer around homes and schools.

Exposure to traffic-related air pollution. We calculated the length of Class 1 and Class 2 roads in 100-m, 200-m, and 500-m buffers around schools and homes based on the U.S. Department of Transportation classification system (2013). Research has found that roads are the most important source of air pollution in Portland (Mavko, Tang, & George, 2008). To give more weight to roads closer to the center of a buffer we applied an inverse-distance weighting scheme (see the appendix). Finally, to make regression coefficients easier to interpret, we standardized all vegetation and road variables by subtracting the mean and dividing by the standard deviation.

Confounders. Research has shown that the natural environment in urban areas is prone to confounding by socioeconomic status (SES; Jesdale, Morello-Frosch, & Cushing, 2013), so it is important that we understand the relationship between SES and the natural environment in Portland and properly control for any potential confounding. We used six variables from the U.S. Census (at the census tract level) to characterize the SES of school and home neighborhoods (Table 2) (percent White, male unemployment rate, percent female head of household, percent renters, median household income, and percent adults who did not graduate from high school). These variables are commonly used to describe the SES of neighborhoods and have been shown to be important determinants of health outcomes (Adler et al., 1994; Cakmak, Hebbern, Cakmak, & Vanos, 2016; Phelan, Link, Diez-Roux, Kawachi, & Levin, 2004). We chose to account for a child's residential neighborhood using Census tracts rather than Census block groups to keep the number of neighborhood-level random effects manageable.

In addition, research has found that exposure to crime is negatively associated with school test scores (Schwartz & Gorman, 2003). Therefore, we calculated the number of violent and property crimes that occurred during the 2013-2014 academic year in 200-m and 500-m buffers around homes and schools. We chose to use larger buffers than those used for vegetation, because crime counts are low, so 100-m buffers often had no crimes, especially violent crimes (Table 2).

To ensure that we adequately controlled for confounders, we examined a matrix of correlation coefficients of variables describing the natural environment, road density, and SES that we would, a priori, expect could be correlated. Road density was uncorrelated with any SES variables. Tree cover is moderately correlated with median income and the proportion of adult residents of a child's home census tract that did not graduate from high school. Therefore, we took particular care to adequately control for income and education in our regression models.

Table 1 provides school-level descriptive statistics, and Table 2 provides individual-level descriptive statistics for the sample. In Table 2, variables above the dotted line are based on a student's residential address, whereas variables below the dotted line are based on a student's residential census tract. Access to individual-level data was approved by Drexel University's Institutional Review Board (approval # 1607004692).

Table 1. School-Level Descriptive Statistics, for Students in Grades 3 to 8 and Grade 11, Attending Portland Public Schools During the 2013-2014 Academic Year (93 Schools, 21,107 Students).

	M	*SD*	Minimum	Maximum
Race White (%)	56.9	22.2	0	86.9
Race African American (%)	10.2	12.8	0.201	83.6
Race Asian (%)	7.77	7.04	0	30.9
Race Hispanic (%)	15.7	12.4	3.10	56.7
Race Pacific Islander (%)	0.849	0.950	0	4.00
Race Mixed (%)	7.64	3.38	4.11	27.1
Race Native (%)	0.893	0.635	0	3.33
English as a second language (%)	8.71	10.7	0	41.3
Free or reduced-cost school lunch (%)	44.3	27.2	2.00	95.2
Teacher experience (years)	13.9	2.99	2.4	23.6
Class size	24.7	2.20	18.8	30.8
Budget per student ($)	5,761	724	4,767	8,475

Statistical Analysis

We estimated two linear mixed models of student test scores: one for math and one for reading. For each model, we pooled test scores from all grades. Our data are structured hierarchically. Students are nested within schools, but they are also nested within home neighborhoods (schools and residential neighborhoods are not nested within each other). Therefore, we estimated models with a random effect for schools and a separate random effect for residential neighborhoods (we defined neighborhood as the census tract a student lived in). We used an unstructured variance structure for both random effects in which no assumptions are made about the variance or covariance structures of the random effects. All models were estimated using maximum likelihood.

We used a nested backward stepwise process for model selection. We first added individual-level variables that past research had consistently found to be correlated with academic performance. This group of variables included gender, grade, ethnicity, whether a student spoke English as a second language, whether a student transferred schools during the 2013-2014 academic year, and whether a student received a free or reduced-cost school lunch. We then used a backward stepwise process to identify other individual-level variables that were significantly associated with test scores. Variables were dropped using progressively lower p value thresholds with a final threshold of $p < .1$. We chose to use a final p value threshold of .1, rather than the more

Table 2. Individual-Level Summary Statistics for Variables Describing the Neighborhood Around a Student's Home (21,107 Students, 160 Census Tracts).

	M	*SD*	Minimum	Maximum
Tree cover within 50 m (%)	25.5	14.1	0.0383	100
Tree cover within 100 m (%)	25.8	13.4	0.0969	100
Tree cover within 200 m (%)	26.3	12.5	0.235	98.2
Grass-and-shrub cover within 50 m (%)	24.4	8.63	0.102	88.4
Grass-and-shrub cover within 100 m (%)	24.6	8.04	0.23	80.2
Grass-and-shrub cover within 200 m (%)	24.6	7.11	0.0342	74.1
Network distance to closest park (m)	558	357	1.22	3,605
Park area within 500 m (hectares)	0.177	0.503	0	6.24
Annual number of violent crimes within 200 m	0.0787	0.35	0	3
Annual number of violent crimes within 500 m	0.389	0.789	0	9
Annual number of property crimes within 200 m	0.548	1.09	0	17
Annual number of property crimes within 500 m	3.53	4.13	0	75
Home census tract: Race White (%)	78.9	11.1	54.1	97.8
Home census tract: Male unemployment rate (%)	10.0	4.63	0	30
Home census tract: Female head of household (%)	19.6	8.15	2.67	44.6
Home census tract: Rent home (%)	37.0	17.4	3.43	93.1
Home census tract: Median household income ($)	61,964	27,172	12,638	163,435
Home census tract: Did not graduate high school (%)	9.21	7.40	0	34.1

commonly used .05, because of the relative consequences of type I and type II error in this study. We know that exposure to the natural environment has many benefits and few negative consequences, so type I error is less of a concern than in analyses in which the exposure under study has known risks.

In contrast, failing to reject a false null hypothesis (type II error) would mean rejecting the efficacy of a low-cost, benign intervention that could improve children's academic performance.

For groups of correlated variables—those describing crime and vegetation, for example—we included the variable with the highest *R*-squared when regressed individually against test score. To avoid including highly collinear combinations of variables in a model, we referred to a correlation-coefficient matrix of all candidate variables. To detect more complex patterns of multicollinearity, we estimated ordinary least squares versions of each model (without school or neighborhood-level random effects) and calculated variance inflation factors for each independent variable. Having identified a preliminary individual-level model, we used the same backward stepwise process to identify school-level variables that were associated with test scores. Finally, we used the same selection process to identify neighborhood-level variables that were significantly associated with test scores. The model-selection process was necessarily iterative: We reintroduced variables that had been dropped to thoroughly test different combinations of variables. In addition, we retained insignificant variables, if they caused coefficients of interest to change by more than 10% after reintroducing them to the final model (Rothman, Greenland, & Lash, 2008). We took particular care to reintroduce any insignificant income and education variables to ensure that their inclusion did not change coefficients of interest.

Results

Hypothesis 1: Exposure to the Natural Environment, at a Child's Home and School, Is Positively Associated With Academic Performance

More tree canopy within 200 m of a student's home was associated with higher math test scores (Table 3). This relationship is statistically significant, but the magnitude of the effect is modest: A 1-*SD* increase in tree canopy within 200 m of a student's home is associated with a 0.32-point increase in math scores. Tree cover around a student's school was not significantly associated with math test scores.

In contrast, tree canopy around a student's school was associated with higher reading scores: A 1-*SD* increase in tree canopy within 100 m of a student's home is associated with a 2.01-point increase in reading scores (Table 4). However, tree canopy around a student's home was not significantly associated with reading scores.

Table 3. Mixed Linear Model of Math Standardized Test Scores for Students in Portland, Oregon, During the 2013-2014 Academic Year (83 Schools, 147 Census Tracts, 17,918 Students).

			95% CI		
Variable	Coefficient	*SE*	LL	UL	*p* value
Male	0.401	0.143	0.121	0.682	.005
Race (White excluded)					
Asian	3.09	0.295	2.51	3.67	<.001
Black	−5.69	0.286	−6.25	−5.13	<.001
Hispanic	−2.20	0.232	−2.66	−1.75	<.001
Mixed	−0.802	0.263	−1.32	−0.286	.002
Native American	−2.56	0.803	−4.13	−0.986	.001
Pacific Islander	−3.48	0.83	−5.11	−1.85	<.001
Grade (3rd excluded)					
4	8.10	0.239	7.62	8.57	<.001
5	12.1	0.241	11.6	12.6	<.001
6	14.3	0.296	13.8	14.9	<.001
7	21.3	0.301	20.7	21.9	<.001
8	23.7	0.302	23.1	24.3	<.001
11	22.2	0.903	20.4	24.0	<.001
Attendance rate (%)	0.287	0.0137	0.260	0.313	<.001
Free or reduced-cost school lunch [individual]	−4.42	0.190	−4.79	−4.04	<.001
Free or reduced-cost school lunch (%) [school]	−0.0519	0.0113	−0.074	−0.0298	<.001
Did not transfer schools	0.896	0.374	0.164	1.63	.016
English as a second language	−7.62	0.291	−8.19	−7.05	<.001
Median household income ($1,000s) [home]	0.0162	0.00535	0.00573	0.0267	.002
Did not graduate high school (%) [home]	−0.0721	−0.0184	−0.108	−3.61	<.001
Standardized class 1 and 2 roads within 100 m of home	−0.155	0.0790	−3.10	−0.000224	.050
Standardized tree canopy within 200 m of home	0.322	0.108	0.110	0.535	.003

			95% CI	
Random-effects variance	Estimate	*SE*	LL	UL
School	6.63	1.15	4.72	9.31
Neighborhood	0.928	0.300	0.493	1.75
Residual	90.0	0.972	88.1	92.0

Note. LL = lower limit; UL = upper limit.

Table 4. Mixed Linear Model of Reading Standardized Test Scores for Students in Portland, Oregon, During the 2013-2014 Academic Year (90 Schools, 148 Census Tracts, 19,459 Students).

			95% CI		
Variable	Coefficient	*SE*	LL	UL	*p* value
Male	−2.68	0.262	−3.20	−2.17	<.001
Race (White excluded)					
Asian	0.305	0.550	−0.773	1.38	.579
Black	−5.05	0.534	−6.09	−4.00	<.001
Hispanic	−2.14	0.433	−2.99	−1.29	<.001
Mixed	−0.30456	0.489	−1.26	0.653	.533
Native American	−3.78	1.44	−6.60	−0.965	.009
Pacific Islander	−4.15	1.51	−7.12	−1.18	.006
Grade (3rd excluded)					
4	6.07	0.441	5.20	6.93	<.001
5	8.45	0.445	7.58	9.33	<.001
6	12.1	0.553	11.0	13.2	<.001
7	17.6	0.564	16.5	18.7	<.001
8	20.0	0.567	18.9	21.1	<.001
11	30.5	3.066073	24.5	36.5	<.001
Attendance rate (%)	0.238	0.0249	0.189	0.287	<.001
Free or reduced-cost school lunch [individual]	−5.23	0.355	−5.93	−4.53	<.001
English as a second language	−9.60	0.539	−10.7	−8.55	<.001
Did not graduate high school (%) [home]	−31.7	6.24	−43.9	−19.5	<.001
Standardized class 1 and 2 roads within 100 m of home	−0.656	0.147	−0.944	−0.368	.002
Standardized tree canopy within 100 m of school	2.01	1.03	−0.00576	4.02	.051

			95% CI	
Random-effects variance	Estimate	*SE*	LL	UL
School	195	35.4	137	279
Neighborhood	279	13.7	254	307
Residual	291	3.30	285	298

Note. CI = confidence interval; LL = lower limit; UL = upper limit.

Grass-and-shrub cover was not significant in either model, nor was proximity to parks. This lack of significance was not due to multicollinearity, as variables describing trees, grass-and-shrubs, and proximity to parks were only modestly correlated.

Results allow us to reject the null hypothesis that exposure to the natural environment and academic performance are unrelated.

Hypothesis 2: Proximity to Major Roads Is Negatively Associated With Academic Performance

Road density around a student's home was negatively associated with math test scores. Specifically, a 1-*SD* increase in road density within 100 m of a student's home is associated with a 0.15-point decrease in math scores. Road density around a student's school was not significantly associated with math scores.

Road density was also negatively associated with reading scores, and the magnitude of this effect was greater than the association between road density and math scores: A 1-*SD* increase in road density within 100 m of a student's school is associated with a 0.66-point decrease in reading scores. Road density around a student's home was not significantly associated with reading scores.

Results allow us to reject the null hypothesis that proximity to major roads and academic performance are unrelated.

Note that coefficients on road and tree variables are insensitive to the inclusion of crossed random effects to accommodate the nonnested random effects for school and neighborhood. Therefore, all models were estimated without crossed effects.

Confounders

Confirming a priori expectations (Good, Aronson, & Inzlicht, 2003), boys outperformed girls on standardized math tests (Table 4). Asian students did better than White students, whereas as all other races performed worse than White students. Increased attendance and not transferring schools are associated with higher test scores; speaking English as a second language and receiving free or reduced-cost lunches are associated with lower test scores. Free or reduced-cost lunches are also significant at the school level, so if a student attends a school where a higher proportion of students receive free or reduced-cost lunches, then that student scores lower on math tests, even if the student does not personally receive free or reduced-cost lunches. The SES of a student's neighborhood was also related to test scores. Specifically, higher median income is associated with higher test scores, whereas a lower high school graduation rate is associated with lower test scores.

The reading and math models were largely consistent with a number of notable exceptions. Girls scored higher than did boys on reading tests. Again, this gender difference is consistent with past research (Malecki & Jewell, 2003). The gender differences in math and reading were not symmetric. On average, boys' math scores were 0.4 points higher than girls, whereas girls' reading scores were 2.7 points higher than boys. As with math scores, lower high school graduation rates were associated with lower reading tests scores. In contrast to math, median household income was not significantly associated with reading scores.

Sample Size and Missing Data

The sample size for both models is lower than the full sample of 21,107 because of missing data. Three variables accounted for the majority of missing values: test scores (math 2,317 missing, reading 1,624 missing), attendance rate (581 missing), and the proportion of a school's students that receive free or reduced-cost school lunches (227 missing). The reduction in sample size from missing data also reduced the number of schools included in the analysis (especially the math model). However, most of these missing schools were small specialist programs often collocated with larger, traditional schools.

Diagnostic Tests

The largest variance inflation factor for an independent variable in either model was 2.25 (proportion of a school's students that receive free or reduced-cost school lunch in the math model), which is below even the most conservative threshold for problematic multicollinearity (O'Brien, 2007).

Finally, using *t* tests, we found no statistically significant differences between the samples used in the math or reading model and the larger population of 21,107 students in the means of key covariates in Table 1.

Discussion

We investigated the relationship between the natural environment and school test scores in Portland, Oregon. We found a positive correlation between test scores and trees around a student's home and school. A 1-*SD* increase in tree cover around a student's home was equivalent to moving from the 50th to the 51st percentile on math scores, and a 1-*SD* increase in tree cover around a student's school was equivalent to moving from the 50th to the 56th percentile on reading scores. Therefore, we reject the Null Hypothesis 1 that exposure to the natural environment and academic performance are unrelated.

Our results confirm the findings of previous studies that examined the relationship between exposure to the natural environment and aggregate school-level test scores. In particular, our use of individual-level test scores suggests that the results from previous school-level studies are not solely a function of ecological bias.

Differences between the math and reading models may reflect fundamental differences in how the natural environment influences performance on math and reading scores. Our results are consistent with Hodson and Sander (2017), who found that greenness around schools was associated with higher reading scores but not higher math scores. However, these differences may also be due, at least in part, to idiosyncrasies in our data.

Our finding that tree cover around a student's school is associated with higher reading scores is consistent with previous studies (Benfield et al., 2015; Dadvand et al., 2015; Matsuoka, 2010; Wu et al., 2014). However, only Dadvand et al. (2015) considered the natural environment around homes. Therefore, Dadvand et al. provide the more relevant frame of reference for our study. Both this study and Dadvand et al. found a relationship between greenness around a student's home and improved test scores or cognitive function. This suggests that greening efforts around schools that are aimed at improving academic performance may be too narrowly focused. The home environment is also important.

Our failure to find a relationship between the natural environment around a child's school and math scores, or between the natural environment around a child's home and reading scores, is somewhat inconsistent with Dadvand et al. (2015). This difference may be due to a number of factors. The cognitive tests used by Dadvand et al. are a measure of cognitive ability, and ability is less likely to be influenced by SES than test scores, which are a measure of attainment. We used 1-m-resolution imagery, derived from aerial photographs and LiDAR that allowed us to distinguish between grass-and-shrubs and trees. In contrast, Dadvand et al. used 5-m-resolution NDVI, derived from satellite imagery, which provides an overall greenness index. No studies have quantified the effect of using higher resolution imagery or the consequences of using imagery that can decompose vegetation into two classes on cognitive outcomes. However, W. Li, Saphores, and Gillespie (2015) did do a side-by-side comparison of different-resolution imagery in a study of the impact of vegetation on house prices in Los Angeles. The authors compared 0.6-m-resolution classified aerial imagery (similar to the imagery we used) that could distinguish between grass-and-shrubs and trees and 30-m-resolution NDVI derived from satellite imagery. The authors found that regression models using high- and low-resolution imagery gave conflicting results. The authors concluded that these inconsistencies were partly a function of differences in resolution, but they also found that NDVI did a poor job of measuring grass-and-shrubs. Dadvand et al. used 5-m- not 30-m-resolution imagery. Nonetheless, the results from Li et al. show that imagery resolution can affect results.

Unlike Dadvand et al., (2015) we did not have access to high-resolution air quality data. However, we did find that road density, our proxy for air quality, was negatively associated with both math and reading scores. Therefore, we rejected Null Hypothesis 2 that proximity to major roads and academic performance were unrelated.

The relationship between reading scores and road density was nontrivial. The observed decline in reading scores associated with a 1-*SD* increase in road density around a student's home is equivalent to moving from the 50th percentile to the 47th percentile reading score. If road density is a valid proxy for air quality, then our results are consistent with past research showing an inverse relationship between air pollution and school test scores.

Minor differences in results between the two studies should not, however, detract from the important similarities. The only two studies that have simultaneously considered the impact of residential and school greenness both found that residential and school greenness were positively associated with improved cognitive function or higher test scores, and both found that air pollution (or a proxy for air pollution) is associated with reduced cognitive function or lower test scores.

The magnitude of the association we found between tree cover and reading scores is policy relevant. If our results are confirmed, then improving access to the natural environment may be a cost-effective intervention for improving early-life academic performance. However, unlike other interventions—teacher training, for example—improvements to the natural environment have a broader impact than improving test scores. Consider four mechanisms that may mediate the impact of the natural environment on test scores: improved air quality, reduced stress, increased physical activity, and increased social connectivity. All four have been shown to impact a broad range of long-term health outcomes including cardiovascular disease, cancer, lower respiratory disease, asthma, and birth outcomes (Hajat, Haines, Goubet, Atkinson, & Anderson, 1999; Künzli et al., 2000; Maisonet, Correa, Misra, & Jaakkola, 2004; Pope et al., 2002; Pope et al., 2004). Therefore, improvements in academic performance from exposure to the natural environment will likely be accompanied by other health benefits. Of these four mechanisms, theoretical (Kaplan, 1995) and empirical work (D. Li & Sullivan, 2016) suggest that stress reduction is likely especially important.

Our results add to a body of research that is suggestive of a causal link between exposure to the natural environment and academic performance. However, before tree planting can be used as a public-health intervention to improve academic performance, it would be prudent to conduct randomized controlled trials of tree-planting programs. Trees are slow growing, so randomized controlled trials would be unavoidably costly and time-consuming. However, limiting the tree-planting interventions to the school level, would reduce both cost and difficulty.

Our study has several limitations. It is an observational, cross-sectional study, so it cannot establish a causal relationship between the natural environment and academic performance. In addition, we used imperfect measures of greenness. In particular, our two-dimensional measures did not account for tree height, and they could not distinguish between different species of tree. However, we did not hypothesize differences in effects related to species or height. In addition, proximity to major roads is an imperfect proxy for air quality, and we were not able to account for traffic volume. Finally, our individual-level SES measures were limited to a small number of metrics describing the child. We did not have any information about parents' SES beyond knowing whether a child received a free or reduced-cost school lunch, which is a coarse measure of household income. However, it is a good indicator of family-level poverty which is highly associated with academic performance (Ensminger et al., 2000). In addition, we had no information on parental involvement in a student's education. Nonetheless, we believe that our study provides valuable new information about the relationship between the natural environment and academic performance.

Conclusion

This is the first study of the natural environment and academic performance to use individual-level school test scores and to simultaneously consider the environment around a student's home and school. Our results suggest that exposure to the natural environment, at both home and school, may promote children's cognitive development and academic performance.

Appendix

Methods for Inverse-Distance Weighting Road Variables

We created 500-m circular buffers around each sampling location and superimposed these buffers on a binary raster representation of road presence. For each sampling location, the Euclidean distance to the center of each cell within its buffer was calculated, and the reciprocal (inverse distance) was computed. The sum of all inverse distances within a buffer was subsequently used to standardize individual inverse distance quantities leading to a weighting raster (kernel) co-registered to the road raster. Multiplying the kernel cell values with corresponding road raster cell values for each sampling location and computing the sum of all products yielded the inverse-distance weight for that location.

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