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Residential neighborhood greenery and children's cognitive development

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ABSTRACT

Children who grow up in neighborhoods with more green vegetation show enhanced cognitive development in specific domains over short timespans. However, it is unknown if neighborhood greenery per se is uniquely predictive of children's overall cognitive development measured across many years. The E-Risk Longitudinal Study, a nationally representative 1994-5 birth-cohort of children in Britain (n = 1658 urban and suburban-dwelling participants), was used to test whether residential neighborhood greenery uniquely predicts children's cognitive development across childhood and adolescence. Greenery exposure was assessed from ages 5 to 18 using the satellite imagery-based normalized difference vegetation index (NDVI) in 1-mile buffers around the home. Fluid and crystalized intellectual performance was assessed in the home at ages 5, 12, and 18 using the Wechsler Intelligence Scale, and executive function, working memory, and attention ability were assessed in the home at age 18 using the Cambridge Neuropsychological Test Automated Battery. Children living in residences surrounded by more neighborhood greenery scored significantly higher, on average, on IQ measures at all ages. However, the association between greenery and cognitive measures did not hold after accounting for family or neighborhood socioeconomic status. After adjustment for study covariates, child greenery exposure was not a significant predictor of longitudinal increases in IQ across childhood and adolescence or of executive function, working memory, or attention ability at age 18. Children raised in greener neighborhoods exhibit better overall cognitive ability, but the association is likely accounted for by family and neighborhood socioeconomic factors.

1. Introduction

Children who grow up in more versus less affluent neighborhoods exhibit better physical, psychological, and cognitive outcomes (Leventhal et al., 2015). Neighborhood socioeconomic status is one of the most frequently measured and consistent predictors of children's outcomes, even after family-level influences are taken in to account (Brooks-Gunn et al., 1993). For the most part, the specific dimensions of neighborhoods that support healthy child development remain poorly characterized (Minh et al., 2017). Prior research has focused primarily on the influence of negative features of children's built and social neighborhood environments, including physical decay, neighborhood disorder and crime, and a lack of social cohesion (Galster, 2012; Ross et al., 2001; Sampson and Groves, 1989). However, intriguing new findings are emerging regarding the potential role of positive features of children's built environments on cognition and health. A number of recent studies have reported positive associations between neighborhood greenery, or the amount of leafy-green vegetation growing within a neighborhood, and children's scores on cognitive and academic tests in urban and suburban settings (Dadvand et al., 2015, 2017; 2018; Flouri et al., 2018; Hodson and Sander, 2017; Kuo et al., 2018; Kweon et al., 2017; Matsuoka, 2010; Sivarajah et al., 2018; Wu et al., 2014).

These findings raise the exciting possibility that children may experience cognitive benefits from spending time in or near “greenery” (Collado and Staats, 2016; Keijzer et al., 2016), and that “greening” vegetation-deprived urban neighborhoods may result in improved cognitive outcomes for children. However, before investing in neighborhood-level interventions based on these findings, we need to ensure

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that identified associations are due to neighborhood greenery per se rather than to other related features of the neighborhood, or due to the self-selection of individuals into greener neighborhoods.

A number of mechanistic theories have been proposed to explain the associations found between children's exposure to neighborhood greenery and their performance on cognitive and academic tests. Strictly bio-physical theories argue that ambient vegetation improves child cognitive development by reducing environmental stressors, such as noise, heat, and air pollution, which are known to interfere with cognitive performance and learning, particularly in urban spaces with high stressor loads (Bowler et al., 2010; Dadvand et al., 2015; Kuo, 2015; Lee and Maheswaran, 2011; Shanahan et al., 2015). Bio-cognitive theories argue that green vegetation, and vegetated areas, naturally lower emotional arousal through evolutionarily-determined pathways (de Vries et al., 2013; Groenewegen et al., 2006; Kuo, 2015), and may encourage the restoration of cognitive resources that are otherwise required when navigating built human environments, particularly executive functions (Berman et al., 2008; Collado and Staats, 2016; Groenewegen et al., 2006; Kaplan, 1995; Ohly et al., 2016). Finally, bio-social theories argue that neighborhood "greenness" simply reflects the presence of parks and open spaces, which appear to provide children with unique environments for physical activity, risk-taking, mastery, self-regulation, and social-interaction, each of which may boost cognitive development and learning (Bowler et al., 2010; Collado and Staats, 2016; Kahn and Kellert, 2002).

While several studies have linked higher levels of ambient greenery surrounding schools to better school-wide test performance and in-classroom child behavior for both primary and secondary school students (Hodson and Sander, 2017; Kuo et al., 2018; Kweon et al., 2017; Li and Sullivan, 2016; Matsuoka, 2010; Sivarajah et al., 2018; van den Berg et al., 2017; Wu et al., 2014), few studies have examined individual child cognitive outcomes in relation to residential neighborhood greenness. Two studies from Spain have reported positive associations between residential neighborhood greenery (measured through satellite-imagery) and child performance on attention and working memory tests, assessed cross-sectionally at ages 4–5 and 7 (Dadvand et al., 2017), and longitudinally across one year around age 8 (Dadvand et al., 2015). An additional study in the UK recently reported positive associations between residential neighborhood greenery (assessed through land use data) and child performance on a single spatial working memory task, assessed cross-sectionally at age 11 years (Flouri et al., 2018).

Here we seek to extend the emerging evidence base on the relationship between neighborhood greenery and child cognitive development using the Environmental Risk (E-Risk) Longitudinal Twin Study, a nationally-representative sample of children born in 1994–1995 in England and Wales and followed to age 18 (N = 2232 in the full cohort; Moffitt and the E-Risk Study Team, 2002). We drew on objective measures of child neighborhood greenery (using the satellite-imagery-derived normalized difference vegetation index, NDVI) and child cognitive ability, and extend what is known about the association between neighborhood greenery and child development in three ways. First, neighborhood greenery has been related to cognitive abilities only in the specific domains of working memory and attention. Here, we include tests of fluid and crystalized intellectual performance to ask if greenery exposure relates to child cognitive ability more generally using a short-form-derived measure of overall IQ, which captures a child's ability to reason, solve novel problems, and acquire and use knowledge and information (Cattell, 1971). While working memory and attention abilities contribute to child success in learning and school performance (Alloway and Alloway, 2010), the IQ represents a more global measure of ability that is known to predict outcomes of interest to policy makers and parents, including job performance and occupational attainment, physical health and longevity, and general well-being (Caspi et al., 2016; Gottfredson and Deary, 2004; Schaefer et al., 2016; Sternberg et al., 2001; Zax and Reese, 2002). In case IQ tests are too broad to detect subtle greenery effects, executive function, working memory, and attention ability were also measured at age 18 years. Second, while previous studies have reported neighborhood greenery associations with cognitive development outcomes at individual time points in childhood (Dadvand et al., 2017; Flouri et al., 2018) and, in one study, across one year (Dadvand et al., 2015), here we leverage the E-Risk Study's longitudinal design to test cognitive associations with neighborhood greenery across the school-age years up through adolescence, from ages 5–18 years. Third, most epidemiologic studies of neighborhood effects attempt to control for the self-selection of wealthier families into greener neighborhoods by applying analytic models that adjust for measures of family and neighborhood-level socioeconomic status. Here we control for both family and neighborhood socioeconomic status while also adjusting estimates for possible self-selection into greener neighborhoods by families with greater genetic predisposition toward high educational attainment and rapid cognitive development, using a polygenic score for educational attainment derived from genome-wide association studies (GWAS) (Lee et al., 2018).

This study thus sought to determine whether residential neighborhood greenery is uniquely predictive of children's overall cognitive ability at multiple ages across childhood and adolescence or with longitudinal growth in children's cognitive abilities as they develop, using high-quality measures of genetic and socioeconomic factors to adjust for the potential self-selection of children with high cognitive ability into greener neighborhoods.

2. Methods

2.1. Sample

Participants are members of the Environmental Risk (E-Risk) Longitudinal Twin Study, a nationally representative sample of children born in 1994 and 1995 in England and Wales (N = 2232). Details about the sample have been reported previously (Moffitt and the E-Risk Study Team, 2002). Briefly, the E-Risk sample was constructed in 1999–2000, when 1116 families with same-sex 5-year-old twins (93% of those eligible) participated in home-visit assessments. The full sample comprised 56% monozygotic (MZ) and 44% dizygotic (DZ) twin pairs; sex was evenly distributed within zygosity (49% male). Families were recruited to represent the UK population of families with newborns in the 1990s, based on residential location throughout England and Wales and mothers' age (teenaged mothers with twins were over-selected to replace high-risk families who were selectively lost to the register through non-response. Older mothers having twins via assisted reproduction were under-selected to avoid an excess of well-educated older mothers). The study sample represents the full range of socioeconomic conditions in Great Britain, as reflected in the families' distribution on a neighborhood-level socioeconomic index (ACORN [A Classification of Residential Neighborhoods], developed by CACI Inc. for commercial use) (Odgers et al., 2012). E-Risk families' ACORN distribution closely matches that of households nation-wide: 25.6% of E-Risk families live in "wealthy achiever" neighborhoods compared to 25.3% nationwide; 5.3% vs. 11.6% live in "urban prosperity" neighborhoods; 29.6% vs. 26.9% live in "comfortably off" neighborhoods; 13.4% vs. 13.9% live in "moderate means" neighborhoods; and 26.1% vs. 20.7% live in "hard-pressed" neighborhoods. E-Risk underrepresents "urban prosperity" neighborhoods because such households are likely to be childless.

Follow-up home visits were conducted when the participants were aged 7 (98% participation), 10 (96%), 12 (96%), and, most recently, 18 (93%) years. Home visits at ages 5, 7, 10, and 12 years included assessments with participants as well as their mother (or primary caretaker); the home visit at age 18 included interviews only with the participants. Each twin participant was assessed by a different interviewer. The Joint South London and Maudsley and the Institute of Psychiatry Research Ethics Committee approved each phase of the study. Parents gave informed consent and twins gave assent between 5 and 12 years and then informed consent at age 18.

As there are, on average, significant differences between urban/suburban-dwelling and rural-dwelling families in terms of neighborhood greenery and general socioeconomic trends (Galster, 2012; Minh et al., 2017; Mitchell and Popham, 2007; Riva et al., 2009), for this analysis we focused only on the urban and suburban-dwelling members of the E-Risk Study (n = 1658 analysis sample; 74.3% of the full cohort; 52.0% female). This matches the sample characteristics of previous studies of child residential neighborhood greenery exposure (e.g., Dadvand et al., 2015, 2017; Flouri et al., 2018), and avoids potential confounding due to gross urban/suburban vs. rural differences. Urbanicity classification was based on responses from a postal survey sent to residents living alongside E-Risk families when children were aged 12. Residents reported whether their neighborhood was in “a city,” “a town,” “a suburb,” “a small village,” or “the countryside.” Urbanicity was categorized as urban (1: city/town), suburban (2: suburb), and rural (3: small village/countryside); additional details on the classification of residences in the E-Risk Study are provided elsewhere (Newbury et al., 2016). The analysis sample's ACORN distribution is similar to that of the full cohort but represents slightly fewer “wealthy achiever” neighborhoods (19.3% of the analysis sample live in “wealthy achiever” neighborhoods compared to 25.6% in the full cohort) and slightly more “hard pressed” neighborhoods (30.2% of the analysis sample live in “hard pressed” neighborhoods compared to 26.1% in the full cohort).

2.2. Measures

2.2.1. Childhood neighborhood greenery exposure

Greenery exposure was calculated through a measure of the density of ambient leafy vegetation within a 1-mile radius of the child's home: the satellite-image-derived NDVI. Each child received an NDVI score localized to their residence at ages 5, 7, 10, 12, and 18. NDVI scores describe the ratio of near-infrared/green light to visible/red and blue light detected in a satellite image. NDVI gives a standardized measure of the “greenness” of a patch of land, as near-infrared and green light are reflected by healthy, chlorophyll-rich vegetation while visible and red and blue light are absorbed. NDVI values range from -1 to $+1$. Negative values typically represent clouds, snow, or water, values close to zero represent barren areas (e.g., rock, sand, buildings), and values close to one represent dense vegetation zones, like rainforests. For each home assessment year (participant ages 5, 7, 10, 12, and 18), raw MODIS (MOD13Q1) satellite images were retrieved from the U.S.-National Aeronautics and Space Administration's EarthData registry (https://earthdata.nasa.gov/) across 16-day time series during peak vegetation periods for the Study region (August) localized to the Study members home address at those ages. Images were resampled to a 30×30 m resolution. 1-mile home radius buffers were chosen to accommodate the neighborhood activity zone of primary school age children (approximately 800 m) and adolescents (up to approximately 1600 m) (Carver et al., 2008; Jones et al., 2009; Villanueva et al., 2012).

To examine associations between lifelong residential greenery exposure and cognitive outcomes at ages 5, 12, and 18, and across ages 5 to 12 and 12 to 18, NDVI scores were averaged up to each age point of IQ assessment to produce an average childhood NDVI score by that age comprised of at least half of the potential observation time points whenever data was missing. A cross-sectional NDVI score was available for 1574 children at age 5 (94.9% of the analysis sample, 51.8% female, Mean = 0.57, SD = 0.09, Range = 0.14 to 0.85), and childhood average NDVI scores were generated for 1656 children for ages 5–12 (99.9% of the analysis sample, 52.9% female, Mean = 0.58, SD = 0.08, Range = 0.21 to 0.82) and 1651 children for ages 5–18 (99.6% of the analysis sample, 51.8% female, Mean = 0.55, SD = 0.08, Range = 0.21 to 0.82).

2.2.2. Childhood cognitive ability

Overall cognitive ability was assessed at age 5 years using a short form of the Wechsler Preschool and Primary Scale of Intelligence-Revised (WPPSI-R) (Buckhalt, 1990) using standard testing procedure. Using two subtests, Vocabulary (measuring crystallized ability) and Block Design (measuring fluid ability), children's age-5 IQs were computed following the procedure described by Sattler (1992) (Table H-7). Overall cognitive ability was assessed again at age 12 years using a short form of the Wechsler Intelligence Scale for Children-IV (WISC-IV) using standard testing procedure. Using two subtests, Information (measuring crystallized ability) and Matrix Reasoning (measuring fluid ability), children's age-12 IQs were computed following the procedure described by Sattler and Dumont, 2004 (Table A-9). Overall cognitive ability was assessed a final time at age 18 years using a short form of the Wechsler Adult Intelligence Scale–IV (WAIS-IV) using standard testing procedure. Using two subtests, Information (measuring crystallized ability) and Matrix Reasoning (measuring fluid ability), children's age-18 IQs were computed following the procedure described by Sattler (2009) (Table A-11). The WPPSI-R, WISC-IV, and WAIS-IV use matched scales. Executive function, working memory, and attention ability were also measured, independently, at age 18 years using the Cambridge Neuropsychological Test Automated Battery (CANTAB; http://www.cambridgecognition.com/cantab/) using standard testing procedures. Executive function was assessed through the Spatial Span subtest, which assesses the ability to hold in active memory and manipulate information about variable spatial sequences. Working memory was assessed through the Spatial Working Memory subtest, which assesses the ability to hold information about spatial location in active memory while searching for information. Attention was assessed through the Rapid Visual Information Processing subtest, which assesses sustained attentional vigilance for a target sequence within an on-going stream of digits.

2.2.3. Covariates

Covariates measured at the child-genetic, family, and neighborhood level were used to account for selection effects that may influence both child cognition and exposure to greenery.

2.2.3.1. The polygenic score for educational attainment. To adjust for possible self-selection into greener neighborhoods by families of children carrying genes associated with more rapid cognitive development and higher levels of cognitive function, we turned to a polygenic score derived from a recent genome-wide association study (GWAS) of educational attainment. GWAS are large-scale data mining studies that scan common genetic variants across the entire human genome. GWAS of educational attainment have identified hundreds of variants associated with educational attainment and cognitive ability (Lee et al., 2018). A composite measure derived from these GWAS results, called a polygenic score (Dudbridge, 2013), can predict attainment in school, at work, and in the accumulation of wealth across life, including differences between siblings in the same family (Belsky et al., 2016, 2018). This polygenic score is also predictive of the rate of cognitive development in childhood (Belsky et al., 2016). There is also emerging evidence that this polygenic score is associated with family and neighborhood socioeconomic status (Belsky et al., 2018; Domingue et al., 2015). Polygenic scores for educational attainment were created for each child of European descent (90% of full cohort, 88% of analysis sample) using the methods described below.

Genotyping – We used Illumina HumanOmni Express 12 BeadChip arrays (Version 1.1; Illumina, Hayward, CA) to assay common single-nucleotide polymorphism (SNP) variation in the genomes of cohort members. We imputed additional SNPs using the IMPUTE2 software (Version 2.3.1; https://mathgen.stats.ox.ac.uk/impute/impute_v2.html) (Howie et al., 2009) and the 1000 Genomes Phase 3 reference panel (Abecasis et al., 2012). The resulting genotype databases included genotyped SNPs and SNPs imputed with 90% probability of a specific genotype among the European-descent members of the E-Risk cohort (N = 1999 participants in 1011 families). We analyzed SNPs in Hardy-Weinberg equilibrium ($p > .01$).

Polygenic scoring – Polygenic scoring was conducted following the method described by Dudbridge (2013) using the PRSice software (Euesden et al., 2015). Briefly, SNPs reported in the most recent GWAS results released by the Social Science Genetic Association Consortium (Lee et al., 2018) were matched with SNPs in the E-Risk database. For each SNP, the count of education-associated alleles was weighted according to the effect estimated in the GWAS. Weighted counts were summed across SNPs to compute polygenic scores. We used all matched SNPs to compute polygenic scores irrespective of nominal significance for their association with educational attainment.

Additional details on genotyping, imputing, and polygenic scoring are available in the Supporting **Information** and in Wertz et al. (2018).

2.2.3.2. Family socioeconomic status. To adjust for possible self-selection into greener neighborhoods by families with greater socioeconomic status, family socioeconomic status (SES) was measured via a composite of parental income, education, and occupation that was divided into tertiles (i.e., low, middle, high-SES) (Trzesniewski et al., 2006). 37.15%, 32.93%, and 29.92% of the analysis sample were classified as low, middle, and high-SES respectively.

2.2.3.3. Neighborhood socioeconomic status. To adjust for possible confounding of greenery-IQ associations by socioeconomic aspects of the neighborhood environment, which may be related to the density of greenery within the neighborhood, neighborhood socioeconomic status was calculated for each Study member based on their address at ages 5, 7, 10, and 12 using the U.K. Government's 2015 Index of Multiple Deprivation (IMD; https://www.gov.uk/government/statistics/english-indices-of-deprivation-2015) score for the address. The IMD is a linear combination of a set of relative measures of deprivation for small areas ("Lower-layer Super Output Areas") across the U.K., which are based on seven different domains of deprivation: 1) Income Deprivation, the proportion of the population experiencing deprivation relating to low income; 2) Employment Deprivation, the proportion of the working age population in an area involuntarily excluded from the labour market; 3) Education, Skills and Training Deprivation, the lack of attainment and skills in the local population; 4) Health Deprivation and Disability, measures the risk of premature death and the impairment of quality of life through poor physical or mental health; 5) Crime, measures risk of personal and material victimization; 6) Barriers to Housing and Services, measures the physical and financial accessibility of housing and local services; and 7) Living Environment Deprivation, measures the quality of the local environment, with indicators for the 'indoors' living environment (containing measures of the quality of housing) and indicators for the 'outdoors' living environment (containing measures of air quality and road traffic accidents).

The Index of Multiple Deprivation ranks every small area in England (so-called Lower-Layer Super Output Areas, LSOA, containing approximately 650 households or 1500 individuals) from 1 (most deprived area) to 32,844 (least deprived area). Rankings are published alongside deciles, which were used in this analysis, and were available for 2007, 2010, and 2015. There was high correlation among IMD rank scores at each available year: for example, the 2007 and 2015 IMD measures for the children's home address correlate at $r = 0.975$, $p < .005$. Consequently, only the 2015 IMD data, which contained a built in postcode-to-LSOA conversion tool, were used for this study.

2015 IMD decile scores falling within a half-mile radius surrounding the child's home were averaged across ages 5, 7, 10, and 12 to create a childhood average neighborhood socioeconomic status score. The half-mile radius was chosen to match the most commonly used metrics of neighborhood poverty in the UK and the US, the Super Output Area and the Census Block Group, respectively (each containing between 600 and 3000 people). Average IMD scores were then used to control for neighborhood socioeconomic status in regression models examining associations between residential greenery and IQ scores at ages 12 and 18. For tests examining associations between residential greenery and IQ scores at age 5, only the age 5 IMD score was used.

2.3. Statistical analysis

Our analysis followed three steps. First, in a cross-sectional analysis, we tested the association between childhood greenery exposure and child cognitive ability measured at ages 5, 12, and 18 using full information maximum likelihood (FIML) estimated regression models to account for missing data. In an initial model, the outcome was regressed on childhood greenery exposure and sex. Each cognitive outcome was then examined using four covariate-adjusted models, including: (1) a "genetics-adjusted" model in which the outcome was regressed on childhood greenery exposure and the covariates of sex and the child's educational-attainment polygenic score, (2) a "family-adjusted" model in which the outcome was regressed on childhood greenery exposure and the covariates of sex and family socioeconomic status, (3) a "neighborhood-adjusted" model in which the outcome was regressed on childhood greenery exposure and the covariates of sex and residential neighborhood socioeconomic status, and (4) a "fully-adjusted" model in which the outcome was regressed on childhood greenery exposure and the covariates of sex, the child's educational-attainment polygenic score, family socioeconomic background, and residential neighborhood socioeconomic status. Analyses were conducted with Mplus, Version 8 (Muthén and Muthén, 2017). Childhood average greenery exposure scores were utilized for tests involving age 12 and age 18 outcomes in order to examine the influence of cumulative greenery exposure up to that age, matching previously used methodology (Dadvand et al., 2015). As a sensitivity test, these analyses were also run using cross-sectional greenery exposure scores at age 12 and 18. These tests produced similar results to those run with the cumulative childhood average exposure scores, with generally smaller effect sizes found. Only cross-sectional greenery exposure scores were available at age 5.

Second, in a longitudinal analysis, we tested the association between childhood greenery exposure and longitudinal change in child IQ from ages 5 to 12 and from ages 12 to 18 using an analysis of covariance model of IQ change. Age 5 and age 12 child IQ scores were added as covariates to each of the models specified in the first step that predicted age 12 and age 18 IQ scores, respectively. In this way greenery-IQ associations were adjusted for past IQ scores, providing a test of the relationships between cumulative greenery exposure and change in IQ between the two time-points. Additionally, to test the potential influence of longitudinal change in child greenery exposure across assessment waves, we created greenery and IQ change scores from ages 5 to 12 and from ages 12 to 18. These were calculated by subtracting age 5 greenery and IQ scores from their corresponding age 12 scores and by subtracting age 12 greenery and IQ scores from their corresponding age 18 scores. Associations between longitudinal change in greenery exposure and longitudinal change in child IQ were examined using correlation tests.

Third, we tested the association between childhood greenery exposure and executive function, working memory, and attention ability at age 18 years, using the same initial and covariate-adjusted regression models specified in the first step.

Because the E-Risk Study contains a sample of twins, the non-independence of children within families was accounted for at each analysis step by adjusting the standard errors using the Mplus Cluster command. All results are presented in standard deviation units.

Comparing cases with present versus missing greenery exposure data: 100% of the E-Risk Study cohort was seen at age 5, 96% at age 12, and 93% at age 18. In order to best replicate past studies on greenery associations with child cognitive development (Dadvand et al., 2015, 2017; Flouri et al., 2018) this study considered only urban and suburban members of the E-Risk Study; children who were rural dwelling by age 12 (n = 494) or who had missing data on the measure of urbanicity (n = 80) were removed from the analysis sample. Of the remaining 1658 children, a minimum of 95% had present greenery data for each analysis. There were no statistically significant differences between those with and without greenery measurement in terms of children's cognitive abilities, their educational-attainment polygenic scores, or their social class origins, but those children without greenery data did have lower neighborhood socioeconomic status scores (Mean neighborhood socioeconomic status for children with greenery data = 0.175 z-score standardized units, Mean for children without = -0.335, $p < .001$).

All urban and suburban dwelling children were included in the analyses. FIML was used to adjust model estimates for information known to relate to the probability of missingness on study variables. FIML is a widely accepted technique for dealing with missing data (Enders, 2001; Raykov, 2005) that, in most simulation studies, performs equally well to or better than multiple imputation techniques with respect to correcting bias in estimates and recovering known parameters (Schafer and Graham, 2002). For sensitivity tests, FIML analyses were also conducted after removing urban and suburban study members who were missing information on greenery; this did not change the results.

3. Results

3.1. Do children who grow up in greener neighborhoods score higher on overall cognitive ability tests?

Results from the multiple linear regression models testing associations between child greenery exposure and the cognitive outcomes are displayed in Table 1. Children living in greener neighborhoods tended to score slightly higher on measures of cognitive ability at ages 5, 12, and 18 (Table 1, first column), with larger associations found for crystallized cognitive ability (which measures a child's level of acquired knowledge) than for the fluid cognitive ability (which measures a child's ability to reason and solve novel problems), at least at ages 12 and 18; overall, effect sizes were smaller for outcomes measured in adolescence (age 18) than for those measured earlier in childhood (age 5 and age 12). Differences among effect sizes were not statistically significant.

To test whether detected associations may be explained by the self-selection of families into greener neighborhoods, a series of adjusted models were fit to the data. First, controls for children's genetics were entered using the educational-attainment polygenic score. We have previously shown that, in the full E-Risk sample, children with higher educational-attainment polygenic scores exhibit greater overall IQ at age 5 (r = 0.14, 95%CI: 0.09, 0.19, $p < .001$) (Wertz et al., 2018). Here we found that, in the analysis sample, children with higher educational-attainment polygenic scores also tended to have higher overall IQs at age 12 (r = 0.24, 95%CI: 0.18, 0.30, $p < .001$) and at age 18 (r = 0.23, 95%CI: 0.17, 0.29, $p < .001$). However, children's educational-attainment polygenic scores were not associated with their greenery exposures across childhood (r = 0.03, 95%CI: −0.04, 0.10, $p = .463$ by age 18). Consequently, adding the educational-attainment polygenic score to the models testing the associations between cumulative greenery exposure and the cognitive outcomes did not alter the results (Table 1, second column).

Second, we tested whether children's family socioeconomic status may explain the observed associations between greenery exposure and the cognitive outcomes. Children from higher-status families tended to live in homes surrounded by more ambient greenery; the relationship between children's family socioeconomic status and their greenery exposure increased as the children aged and more greenery assessment waves were averaged into the cumulative measure of greenery exposure (r = .12, 95%CI: 0.06, 0.19, $p < .001$ for family socioeconomic status and greenery exposure at age 5 and r = 0.18, 95%CI: 0.12, 0.25, $p < .001$ for family socioeconomic status and greenery exposure by age 18). Adding family socioeconomic status to the multiple regression models reduced the associations between greenery exposure and all cognitive outcomes to non-significance except for those with age-5 fluid

Table 1
Association of child cognitive ability with neighborhood greenery exposure measured from age 5 up to the age of IQ testing.

	Unadjusted		Adjusted for child genotype		Adjusted for family socioeconomic status		Adjusted for neighborhood socioeconomic status		Fully adjusted	
	β (95% CI)	*P*	β (95% CI)	*P*	β (95% CI)	*P*	β (95% CI)	*P*	β (95% CI)	*P*
Age 5 overall IQ	.09 (.03, .16)	.006	.09 (.02, .15)	.009	.05 (-.01, .12)	.095	.02 (-.05, .09)	.560	.03 (-.04, .09)	.417
Age 5 crystallized ability	.06 (-.01, .13)	.069	.06 (-.01, .12)	.082	.03 (-.04, .09)	.379	.01 (-.06, .08)	.841	.01 (-.05, .08)	.730
Age 5 fluid ability	.09 (.03, .15)	.003	.09 (.03, .15)	.005	.06 (.00, .12)	.043	.03 (-.04, .09)	.407	.03 (-.03, .10)	.289
Age 12 overall IQ	.09 (.02, .15)	.007	.09 (.03, .15)	.004	.02 (-.04, .07)	.553	-.001 (-.07, .07)	.975	< .0001 (-.06, .06)	.999
Age 12 crystallized ability	.11 (.04, .17)	.001	.11 (.05, .18)	.001	.03 (-.02, .09)	.255	.01 (-.06, .08)	.771	.01 (-.05, .07)	.708
Age 12 fluid ability	.04 (-.02, .09)	.178	.04 (-.02, .10)	.151	-.01 (-.06, .05)	.814	-.01 (-.08, .05)	.653	-.01 (-.07, .04)	.664
Age 18 overall IQ	.06 (-.003, .12)	.062	.05 (-.01, .12)	.077	-.02 (-.07, .04)	.538	-.06 (-.12, .01)	.117	-.05 (-.11, .01)	.100
Age 18 crystallized ability	.07 (.01, .14)	.028	.07 (.01, .14)	.024	-.01 (-.06, .04)	.742	-.04 (-.11, .03)	.306	-.03 (-.09, .03)	.292
Age 18 fluid ability	.02 (-.03, .08)	.430	.01 (-.03, .06)	.662	-.03 (-.08, .02)	.287	-.05 (-.01, .01)	.096	-.05 (-.11, .01)	.105

Note. 95% confidence interval (CI) reported in parentheses. Neighborhood greenery exposure was measured by taking the average of NDVI scores within a 1-mile radius of the child's home assessed from age 5 years up to the age of IQ assessment for each outcome in the table. Neighborhood socioeconomic status was measured using the UK Government's Index of Multiple Deprivation. All models adjusted for sex. Covariates in the fully adjusted model include sex, child polygenic score for educational attainment, family socioeconomic status, and neighborhood socioeconomic status. Analyses were conducted using full information maximum likelihood (FIML) estimated regression models to adjust estimates for missing data. 205 children (12.4% of the analysis sample) lacked the educational-attainment polygenic score, 38 children (2.3%) were missing the measure of neighborhood socioeconomic status, and no children were missing the measure of family socioeconomic status. On study outcomes, 16 children (1.0% of the analysis sample) were missing the age-5 outcome variables, 84 (5.1%) were missing the age-12 outcome variables, and 136 (8.2%) were missing the age-18 outcome variables.

cognitive ability (Table 1, third column).

Third, we tested whether children's neighborhood socioeconomic status may explain the observed associations between greenery exposure and the cognitive outcomes. Higher socioeconomic status neighborhoods also tended to have greater levels of ambient greenery; the relationship between children's neighborhood socioeconomic status and their greenery exposure grew stronger as the children aged and more greenery assessment waves were averaged into the cumulative measure of greenery exposure (r = .38, 95%CI: 0.31, 0.45, $p < .001$ for neighborhood socioeconomic status and greenery exposure at age 5 and r = 0.49, 95%CI: 0.43, 0.55, $p < .001$ for neighborhood socioeconomic status and greenery exposure by age 18). Adding neighborhood socioeconomic status to the multiple regression models reduced associations between greenery exposure and all cognitive outcomes to non-significance (Table 1, fourth column).

Fourth, all child, family and neighborhood-level potential confounds were entered into the multiple regression models simultaneously. As expected, and shown in Table 1 (fifth column), all associations between cumulative greenery exposure and the cognitive outcomes were reduced to non-significance in the final model.

3.2. Do children who grow up in greener neighborhoods display greater longitudinal change in overall cognitive ability?

We next tested whether cumulative childhood greenery exposure predicted enhanced longitudinal change in cognitive ability for our Study children across childhood and adolescence by 1) predicting age-12 IQ scores while controlling for age-5 scores, and 2) predicting age-18 IQ scores while controlling for age-12 scores. When considering change across childhood, we found that children living in greener neighborhoods scored slightly higher on measures of crystalized cognitive ability at age 12 than they did at age 5 (Table 2, first column), reflecting enhanced acquisition of knowledge relative to children living in less green neighborhoods. Children living in greener neighborhoods did not, however, demonstrate significantly more growth in full-scale IQ or fluid cognitive ability across the same ages relative to peers living in less green neighborhoods. When considering change across adolescence, we found that children living in greener neighborhoods did not tend to show greater growth on any of the IQ measures from age 12 to 18 relative to peers living in less green neighborhoods (Table 2, first column).

To test whether the detected association between cumulative greenery exposure and accelerated longitudinal growth in crystalized cognitive ability from ages 5 to 12 may be explained by the self-selection of families into greener neighborhoods, we applied the same series of adjustments to the longitudinal statistical model as for the cross-sectional analyses. First, we adjusted for the child's genetic predisposition to high educational attainment and rapid cognitive development using the educational-attainment polygenic score. This adjustment did not reduce the size of the original association, although the p-value changed from 0.042 to 0.055 (Table 2, second column). Second, we adjusted for family socioeconomic status. This adjustment reduced the original association to non-significance (Table 2, third column). Third, we adjusted for neighborhood socioeconomic status. This adjustment also reduced the original association to non-significance (Table 2, fourth column).

Finally, as levels of neighborhood greenery are not static across time, particularly for children who move residences, we also tested whether children who experience longitudinal change in greenery exposure across IQ assessment waves displayed corresponding longitudinal change in overall cognitive ability. To do so we created greenery change scores from age 5 to 12 (by subtracting age 5 greenery scores from age 12 scores) and correlated those with IQ change scores from age 5 to 12 (created by subtracting age 5 IQ scores from age 12 IQ scores). These tests were replicated for greenery and IQ change from ages 12 to 18. We found that children whose exposure to residential neighborhood greenery changed over time did not display corresponding changes in overall cognitive ability, either from age 5 to 12 (r = 0.03, p = .187) or from age 12 to 18 (r = −0.01, p = .846).

3.3. Do children who grow up in greener neighborhoods show enhanced executive function, working memory, or attention ability by age 18?

As IQ tests capture individual variability across a broad range of cognitive domains, they may not be sensitive enough to detect the modest changes in ability hypothesized to result from exposure to green-space. Therefore, we also tested the relationship between childhood green-space exposure and child cognitive ability in the specific cognitive domains of executive function, working memory, and attention ability, which were measured at age 18 using the CANTAB Spatial Span, Spatial Working Memory, and Rapid Visual Information Processing subtests, respectively. We found that children living in greener neighborhoods tended to score higher at age 18 on the Spatial Span subtest (**β** = 0.08, 95%CI: 02, 0.14 $p = .007$), but not on the

Table 2
Association of longitudinal change in child cognitive ability from age 5 to 12 and from age 12 to 18 with neighborhood greenery exposure measured from age 5 up to the highest age of IQ testing.

	Unadjusted		Adjusted for child genotype		Adjusted for family socioeconomic status		Adjusted for neighborhood socioeconomic status		Fully adjusted	
	β (95% CI)	P	β (95% CI)	P	β (95% CI)	P	β (95% CI)	P	β (95% CI)	P
Change in overall IQ from age 5 to 12 years	.01 (-.04, .07)	.607	0.01 (-.04, .07)	.858	-.02 (-.06, .03)	.477	-.03 (-.09, .03)	.325	-.02 (-.08, .03)	.392
Change in crystallized ability from age 5 to 12	.06 (.002, .12)	.042	.06 (-.001, .11)	.055	.01 (-.04, .06)	.656	.001 (-.06, .06)	.982	.01 (-.05, .06)	.846
Change in fluid ability from age 5 to 12	−0.01 (-.05, .03)	.858	−0.01 (-.06, .04)	.816	−0.03 (-.08, .02)	.301	−0.03 (-.09, .02)	.240	−0.03 (-.09, .02)	.257
Change in overall IQ from age 12 to 18 years	−0.01 (-.05, .03)	.541	−0.01 (-.05, .03)	.518	−0.03 (-.07, .01)	.128	−0.03 (-.08, .01)	.142	−0.04 (-.08, .01)	.108
Change in crystallized ability from age 12 to 18	−0.01 (-.04, .03)	.735	−0.01 (-.05, .03)	.689	−0.02 (-.06, .01)	.193	−0.03 (-.07, .02)	.224	−0.03 (-.07, .01)	.186
Change in fluid ability from age 12 to 18	−0.01 (-.06, .03)	.611	−0.01 (-.06, .03)	.623	−0.03 (-.07, .02)	.277	−0.03 (-.08, .02)	.243	−0.03 (-.08, .02)	.211

Note. 95% confidence interval (CI) reported in parentheses. Neighborhood greenery exposure was measured by taking the average of NDVI scores within a 1-mile radius of the child's home assessed from age 5 years up to the highest age of IQ assessment for each outcome in the table. Neighborhood socioeconomic status was measured using the UK Government's Index of Multiple Deprivation. All models adjusted for sex. Covariates in the fully adjusted model include sex, child polygenic score for educational attainment, family socioeconomic status, and neighborhood socioeconomic status. Analyses were conducted using full information maximum likelihood (FIML) estimated regression models to adjust estimates for missing data.

Spatial Working Memory (**β** = -0.02, 95%CI: −0.08, 0.04, p = .488) or Rapid Visual Information Processing subtests (**β** = 0.02, 95%CI: −0.04, 0.07, p = .512).

To test whether the association between cumulative greenery exposure and the Spatial Span test of executive function at age 18 may be explained by the self-selection of families into greener neighborhoods, we applied the same series of adjustments to the executive-function-outcome statistical model as for the cross-sectional and longitudinal IQ-outcome analyses. First, we adjusted for the child's genetic predisposition to high educational attainment and rapid cognitive development using the educational-attainment polygenic score. This adjustment did not reduce the original association (**β** = 0.07, 95%CI: 02, 0.13 p = .014). Second, we adjusted for family socioeconomic status. This adjustment did reduce the original association to non-significance (**β** = 0.03, 95% CI: −0.03, 0.09 p = .272). Third, we adjusted for neighborhood socioeconomic status. This adjustment also reduced the original association to non-significance (**β** = 0.002, 95%CI: −0.06, 0.07 p = .960).

4. Discussion

The integration of in-home cognitive testing and satellite imagery data within a well phenotyped and genotyped cohort of children followed across childhood and adolescence advanced our understanding of the relationship between residential neighborhood greenery exposure and child cognitive development in four ways. First, similar to prior studies, we found statistically significant positive associations between children's exposure to residential neighborhood greenery and their performance on cognitive tests yielding overall IQ scores and subscale measures of crystalized and fluid cognitive ability at ages 5, 12, and 18 years. It should be noted that, similar to other neighborhood-level research findings, these associations were small (β = 0.08 to 0.11). At age 5, for example, children in the top quartile of neighborhood greenery exposure tested, on average, 3.18 IQ points higher on their overall IQ than their peers in the bottom quartile of exposure.

Second, we found no evidence that the association between greenery exposure and higher IQ scores was confounded by children's genetic propensity for high educational attainment and rapid cognitive development. In this cohort there was no relationship between children's genetics and their exposure to residential neighborhood greenery; children with a genetic propensity for high educational attainment were not more likely to live in greener neighborhoods.

Third, we found a consistent social gradient in greenery exposure; children growing up in higher socioeconomic status families tended to live in greener neighborhoods, and the magnitude of the family socioeconomic status – greenery exposure association increased as children aged into adolescence. Statistically adjusting the greenery-IQ associations for measures of socioeconomic status attenuated all original associations to such an extent that none remained statistically significant.

Fourth, we found that, after adjusting for socioeconomic factors, children's lifelong exposure to residential neighborhood greenery did not predict longitudinal change in their IQ scores across childhood or adolescence, nor their scores on executive function, working memory, or attention tests at age 18 years.

Collectively, these results suggest that children living in homes surrounded by more vegetation and vegetated areas may tend to outperform their peers from less green neighborhoods on cognitive tests assessing acquired knowledge and the ability to reason and solve novel problems. We found no evidence to support the hypothesis that this phenomenon is the result of children with greater genetic predispositions towards rapid cognitive development living in residences surrounded by more greenery. We did find evidence to suggest, however, that this phenomenon is likely confounded by the unequal distribution of greenery across urban and suburban neighborhoods in the UK, where families living in less deprived areas, and who have high-performing children, tend to enjoy greener residential environments (correlation between neighborhood socioeconomic status and neighborhood greenery scores ranged from r = 0.38 to 0.49). Neighborhood greenery may not, in other words, directly improve children's overall cognitive function despite the appearance of positive associations.

While socioeconomic status of the family and neighborhood fully explained the associations found between neighborhood greenery and children's overall cognitive development in this sample, our findings do not preclude the possibility that targeted greening interventions may impact other important child health and development outcomes. Controlled experiments in classroom settings suggest that children taught outdoors (Kuo et al., 2018), or given views to nature (Li and Sullivan, 2016), may attend to their lessons better. Likewise, a randomized neighborhood greening intervention trial in Philadelphia recently reported that greening vacant lots significantly improved the mental health of nearby residents, with the greatest effects reported for neighborhoods with the most participants living below the poverty line (South et al., 2018). Further research, including randomized intervention trials, is required to understand for whom and under what conditions greenery exposure may influence cognitive outcomes.

What can explain this study's non-significant findings given the recent positive reports at the child-level from Spain (Dadvand et al., 2015, 2017, 2018) and the UK (Flouri et al., 2018)? First, previous studies have only considered the narrow cognitive domains of attention and working memory ability, using cross-sectional measures or those recorded across short time-spans. It is possible that children's residential exposure to neighborhood greenery does not fundamentally alter long-term outcomes in overall cognitive ability, even if short-term beneficial associations with subdomains of ability exist. The finding that, after adjustment for socioeconomic factors, cumulative greenery exposure did not predict executive function, working memory, or attention ability at age 18 years does suggest, however, that greenery associations with these specific cognitive abilities may not extend past the school-age years.

Second, previous child-level studies have tended to measure residential greenery exposure within smaller zones than those considered in the current study. Dadvand et al. assessed NDVI within a 250 m radius of children's homes for those in living Barcelona, for example, and within 100, 300, and 500 m home radii for those living in Valencia and Sabadell (Dadvand et al., 2015, 2017, 2018). Our roughly 1600 m buffer size, chosen to accommodate the neighborhood activity zone of older children (Carver et al., 2008; Jones et al., 2009; Villanueva et al., 2012), likely gathered information about a larger geographical neighborhood space than these past studies would have. This could account for differential findings if greenery in the near-home environment exerts differential influence from greenery in the larger neighborhood, as would be the case if a view to trees matters more, for example, than the general presence of trees. Notably, a recent review of 47 studies and 260 analyses found that the likelihood of neighborhood greenery predicting physical health increased as neighborhood buffer zone size increased, with peak associations found in buffers of between 1000 and 1999m in size (Browning and Lee, 2017).

We acknowledge limitations. First, while NDVI is a consistently used measure of ambient vegetation exposure, it does not capture information about children's use of parks and open spaces. Measures of child park use would have improved our exposure estimates. However, this limitation is common to larger studies with sufficient power to test subtle effects, such as those on cognition. Second, while Study members' exposure to greenery was assessed repeatedly across childhood (from ages 5 to 18) we did not measure exposure before age 5. Thus, early-life greenery exposure may have been misestimated for those children who moved before age 5 or for whom residential neighborhood greenery was not stable year to year. Third, neighborhood greenery was only measured at one buffer radius (1 mile), which precluded testing for differential influence of greenery near the home versus in the wider neighborhood environment. Fourth, our measure of neighborhood socioeconomic status averaged deprivation scores across small areas in the UK, leading to possible misspecification of neighborhood status for areas with highly heterogeneous neighboring parcels. Notably, the results of the study do not change if a smaller-scale neighborhood status measure, such as ACORN, is utilized. Finally, we were not able to fully leverage the E-Risk Study's twin-pair sample to strengthen causal inference because Study twins tended to live in the same home during childhood. As the E-Risk twins move through adulthood, there will greater opportunity to test the influence of neighborhood greenery on those who have discordant exposure – a design recently employed with participants from the University of Washington Twin Registry to identify a significant link between residential neighborhood greenery and mental health at midlife (Cohen-Cline et al., 2015).

Notwithstanding its limitations, our study may hold implications for research. First, our results indicate that childhood exposure to residential neighborhood greenery can be linked to subtle differences in overall cognitive outcomes across childhood and adolescence that are likely best explained as arising from shared relationships with family and neighborhood socioeconomic factors. While most previous studies of neighborhood greenery and cognition adjusted estimates for at least one measure of family or neighborhood-level socioeconomic status, a recent systematic review determined that few controlled for possible confounding at both levels (Keijzer et al., 2016). Future research should describe the extent to which greenery exposure is entwined with participant social class and, further, attempt to adjust for possible confounding at both the family and neighborhood level whenever possible. More research that can decouple the association between affluence and greenery is particularly needed. Second, our findings suggest that child genotype, at least for rapid cognitive development and high educational attainment, may be unrelated to greenery exposure and thus unlikely to exert a confounding effect on associations with cognitive outcome tests. This suggests that while there is documented genetic selection into deprived neighborhoods for factors related to educational attainment (Belsky et al. in press), genetically related selection pressures may be weaker with respect to neighborhood greenery.

As conflicting findings on neighborhood effects on child cognitive ability emerge, the process of integrating these observations into a coherent theory will require an increasing focus on experimentally isolating active components and estimating causal impacts rather than simply documenting robust associations within observational studies. This study did not fully replicate the initial novel findings about neighborhood greenery and child cognitive development reported by others. Rather than a “failure to replicate,” these findings can be viewed as an opportunity to explore the limits of generalizability (Redish et al., 2018). Further research is now required to explore and experimentally test the contexts and conditions in which neighborhood greenery may be beneficial for children's cognitive development. It is appealing to believe that exposure to green vegetation and natural spaces may enhance our children's intellectual growth. Our findings highlight the need to exercise caution, however, when assuming that direct benefits arise from greenery per se, or that benefits from greenery may be uniform across populations and settings.

Declarations of interest

None.

Ethics approval

The Joint South London and Maudsley and the Institute of Psychiatry Research Ethics Committee approved each phase of this study. Parents gave informed consent and twins gave assent between 5 and 12 years and then informed consent at age 18.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2019.04.029.

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