Early Child Development, Residential Crowding, and Commute Time in 8 US States, 2010–2017

Eryn Piper Block, MPP, Frederick J. Zimmerman, PhD, Efren Aguilar, Lisa Stanley, DrPH, and Neal Halfon, MD, MPH

Objectives. To examine relationships of residential crowding and commute time with early child development.

Methods. We used the Early Development Instrument (EDI), a teacher-reported, population-health measure of child development. The sample included child-level observations spanning 8 US states from 2010 to 2017 (n = 185 012), aggregated to the census tract (n= 2793), stratified by percentage of households in poverty. To test the association of commute times, crowding, and child development, we tested overall readiness and 5 EDI domains by using adjusted census tract–level multivariate regression with fixed effects.

Results. In the full sample, a 1-standard-deviation increase in crowding was associated with 0.064- and 0.084-point decreases in mean score for cognitive development and communication skills, respectively. For the high-poverty subsample, a 1-standard deviation increase in commute time was associated with 0.081- and 0.066-point decreases in social competence and emotional maturity.

Conclusions. In neighborhoods with increased crowding or commute time, early child development suffers.

Policy Implications. This study suggests a potential relationship between the changing urban landscape and child health. Children would benefit from more multisector collaboration between urban planning and public health. (*Am J Public Health.* 2018;108:1550–1557. doi:10.2105/AJPH.2018.304680)

See also Galea and Vaughan, p. 1444.

In cities across the United States, high crime and economic disinvestment are being superseded by growing gentrification, displacement of low-income populations, and rapidly increasing housing costs. Thus, understanding the relationship between child well-being and our changing urban landscape is ever more important. From birth to age 5 years, critical child development occurs for brain functioning, health and school readiness.[1] The roles of early childhood experiences and environmental exposures and contexts on these outcomes are increasingly well recognized.[2–5]

By many accounts, our rapidly changing cities have not kept up with increased demand for urban living. As cities become more crowded and expensive, many families respond by moving farther from cities' urban cores to find cheaper housing in the suburbs or by living in smaller, more crowded spaces. Recent research has shown that restrictive zoning policies in major cities have resulted in longer commutes and increased crowding, which may impair child health.[6] This study is the first, to our knowledge, to examine the impact of these 2 indicators of rapidly changing cities—residential crowding and extended commute times—on early child development.

The purpose of this article is to contribute to the investigation of relationships between individual-level child health and ecological-level changes. Following Bronfenbrenner's ecological model, we hypothesized that changes to the urban landscape may have an impact on child development through the interplay among the individual, family, neighborhood, and community domains.[7] Through the lens of the environmental stressors model, we hypothesized that long commutes and residential crowding may affect child development by increasing family and child stress. The environmental stressors model suggests that people experience stress from neighborhood characteristics such as noise, crowding, and pollution,[8] and this stress can lead to social isolation, antisocial behavior, decreased academic performance, depression, aggression, and behavior problems in children (see Wandersman and Nation,[8(p651)] for full model).

Residential crowding has been linked with many adverse outcomes that reinforce the environmental stressors model, such as heightened mental distress.[9,10] For children, overcrowding is linked with poor academic performance,[11] behavioral problems in school,[12] and respiratory problems.[13] However, few of these studies examined outcomes in very young children or more comprehensive measures of early child development.

There is also strong evidence that lengthy commute times can increase stress and thus lead to adverse health and mental health outcomes. Long commute times are associated with increases in hypertension and obesity and decreases in cardiovascular fitness, stress, sleep quality, self-assessed health, and overall energy in adults.[14–16] Adults with longer commute times are more likely to feel time pressure and lower life satisfaction and

ABOUT THE AUTHORS

Eryn Piper Block, Frederick J. Zimmerman, and Neal Halfon are with the Department of Health Policy and Management, School of Public Health, University of California Los Angeles (UCLA). Efren Aguilar, Lisa Stanley, and Neal Halfon are with the Center for Healthier Children, Families, and Communities, Department of Pediatrics, David Geffen School of Medicine, UCLA.

Correspondence should be sent to Eryn Piper Block, 10960 Wilshire Blvd Ste 960, Los Angeles, CA 90024 (e-mail: erynpblock@g.ucla.edu). Reprints can be ordered at http://www.ajph.org by clicking the "Reprints" link.

This article was accepted July 14, 2018.
doi: 10.2105/AJPH.2018.304680

have less time participating in leisure activities.[17–19] Although this literature is specific to adults, children could be adversely affected by parents' long commutes: children may miss out on high-quality parent–child interaction time when parents spend so much of the day away from home. With this evidence in mind, we hypothesized that long commute times can have an indirect effect on child development through quality and quantity of time spent with parents.

We hypothesized that the impacts of residential crowding and commute time on child development are more pronounced for families in low-income neighborhoods. Families in high-income neighborhoods may be protected from the hazards related to these stressors and may have had more autonomy to move on the basis of good schools and high-quality green spaces. Time scarcity is a mechanism through which commute time may adversely affect health and it is more likely that high-income individuals can use financial resources to purchase additional time—for example, by taking private vehicles to work instead of public transportation, ordering food instead of cooking, using grocery-delivery services for shopping, or hiring people to help with household cleaning. Empirical evidence supports the notion that low-income people are especially susceptible to environmental stressors. Commute time and mental health symptoms were positively associated for women in poverty during pregnancy and postpartum but not for those in higher-income groups.[20] For low-income families, shorter commute times are strongly associated with higher chances of upward mobility.[21]

THE EARLY DEVELOPMENT INSTRUMENT

We used the Early Development Instrument (EDI) as a measure of early child development. The EDI is a teacher-reported, population-health measure of child development for midyear kindergarten students with 5 domains: physical health and well-being, social competence, emotional maturity, language and cognitive development, and communication skills and general knowledge.[22] The EDI is distinct from other kindergarten-readiness measures in that it is a population-health measure instead of an individual diagnostic tool.[22,23] Child scores are geocoded to homes, allowing for place-based research.

The EDI was developed in Canada and has been implemented in many countries including Australia and the United States. The EDI has undergone extensive psychometric analysis[22,24] and has high interrater reliability and domain-specific Cronbach alphas: 0.96 for social competence, 0.92 for emotional maturity, 0.93 for cognitive development, 0.95 for communication skills, and 0.84 for physical health.[22] In addition, the EDI is predictive of third-grade reading and math achievement.[25]

Under the 5 domains of child development, there are 16 total subdomains (see Appendix A, available as a supplement to the online version of this article at http://www.ajph.org). Children are categorized as "not ready," "somewhat ready," or "ready" for school. The cut-offs for "not ready" are based on criterion validation.[26] Children considered "not ready" within a subdomain are determined to have developmental challenges in that area. For instance, under the domain "social competence" and subdomain "overall social competence with peers," the "not ready" category includes children who "have average to poor overall social skills, low self-confidence and are rarely able to play with various children and interact cooperatively."[27]

METHODS

We used a cross-sectional associational design. The unit of analysis was the census tract.

Study Population

The EDI population included 301 792 children in kindergarten and occasionally preschool in 16 states and Washington, DC. All data collection sites were established in partnership with local organizations to promote data-driven decision-making to improve developmental needs of child populations.

The data are collected within schools and linked to the child's home address via geocoding. The host organization can use these data, aggregated to the neighborhood level, to look for spatial patterns of vulnerability in child development and plan for better resource allocation.

The full data set includes 71 data collection sites. Site types include neighborhoods (n = 5), multiple neighborhoods (n = 4), districts (n = 14), segments of districts (n = 3), multiple districts (n = 2), Promise Neighborhoods (n = 1), cities (n = 26), multiple cities (n = 2), counties (n = 8), and collections of multiple counties (n = 6). Out of 71 sites, 36 sites successfully collected data from all or almost all kindergartners within the catchment area during at least 1 time point. Total data collection among sites ranged from 140 to 87 753 students. All data were collected between 2010 and 2017.

Sample

We based this analysis on a subsample of the EDI population that met strict inclusion criteria, structured to avoid selection bias, as follows. The sample was first constructed at the child level before being aggregated to the census tract level for analysis. A child's record was valid only if the teacher reported on at least 4 of the 5 EDI domains. The primary sampling unit was the school district, in which the district administration disseminated the survey to teachers in schools throughout the district. We included school districts if at least 90% of schools were represented with valid records for at least 90% of students. Districts were grouped into jurisdictions, defined as the largest geographical unit for which at least 90% of school districts were included. For example, Orange County, California, is 1 jurisdiction because all 24 school districts participated, each of which had more than 90% of schools with valid records for more than 90% of students. Washington, DC, is a jurisdiction of just 1 primary sampling unit (school district). We excluded jurisdictions with fewer than 500 students. We excluded private schools and Head Start programs, jurisdictions that explicitly excluded special education classrooms in their data collection, invalid or

TABLE 1—Sample Descriptive Statistics at the Census Tract Level With Stratification by Level of Neighborhood Poverty: 8 US States, 2010–2017

	Full Sample	High Poverty[a]	Low Poverty[b]
Census tracts, no.	2793	948	1845
Count of "not ready" subdomains by census tract, frequency (%)			
0	296 (10.6)	67 (7.1)	229 (12.4)
1	513 (18.4)	90 (9.5)	423 (22.9)
2	1126 (40.3)	366 (38.6)	760 (41.2)
3	605 (21.7)	308 (32.5)	297 (16.1)
4	132 (4.7)	70 (7.4)	62 (3.4)
5	53 (1.9)	27 (2.9)	26 (1.4)
6	24 (0.9)	5 (0.5)	19 (1.0)
7	17 (0.6)	5 (0.5)	12 (0.7)
8	9 (0.3)	4 (0.4)	5 (0.3)
9	5 (0.2)	1 (0.1)	4 (0.2)
10	6 (0.2)	3 (0.3)	3 (0.2)
12	3 (0.1)	1 (0.1)	2 (0.1)
13	3 (0.1)	1 (0.1)	2 (0.1)
15	1 (0.0)	0 (0)	1 (0.1)
No. of "not ready" subdomains, mean (SD)	2.10 (1.43)	2.45 (1.36)	1.91 (1.43)
Domain scores (range 0–10), mean (SD)			
Physical health	8.75 (0.78)	8.60 (0.72)	8.82 (0.79)
Social competence	8.18 (1.07)	7.99 (1.01)	8.27 (1.09)
Emotional maturity	8.11 (0.90)	8.01 (0.83)	8.16 (0.93)
Language and cognition	8.88 (0.92)	8.61 (0.88)	9.02 (0.90)
Communication skills	7.56 (1.44)	7.17 (1.39)	7.76 (1.42)
% residential crowding, mean (SD)	7.48 (9.20)	12.45 (11.54)	4.92 (6.37)
Average commute time, min, mean (SD)	27.50 (5.84)	26.68 (6.38)	27.91 (5.50)
% bachelor's degree, mean (SD)	29.98 (20.63)	14.70 (12.77)	37.83 (19.46)
Unemployment rate, mean (SD)	9.88 (5.35)	13.10 (6.20)	8.22 (3.93)
% limited English, mean (SD)	10.11 (10.04)	16.53 (11.91)	6.81 (6.91)
% owner-occupied housing, mean (SD)	56.89 (23.40)	43.27 (21.43)	63.89 (21.19)
Population density, pop/sq mile, mean (SD)	7539 (6471)	8858 (7570)	6862 (5711)
% in poverty, mean (SD)	17.01 (12.93)	32.07 (9.92)	9.28 (5.10)
Racial heterogeneity, mean (SD)	0.46 (0.19)	0.38 (0.22)	0.50 (0.16)
Residential instability, mean (SD)	12.08 (6.81)	14.02 (6.69)	11.08 (6.65)

[a]High poverty (top third % of neighborhood poverty [≥ 20%]).
[b]Low poverty (bottom two thirds % of neighborhood poverty [< 20%]).

nongeocoded individual records, and pilot years of data collection.

We started with 71 sites, 5625 census tracts, and 301 792 students. After we implemented all exclusion criteria, the final analysis sample had 25 sites, 8 states (California, Connecticut, Michigan, Mississippi, New York, Oklahoma, South Carolina, and Texas) and Washington, DC, 2793 census tracts, and 185 685 students (see Appendix B, available as a supplement to the online version of this article at http://www.ajph.org, for sample flowchart).

Data

Early child development data. We used the EDI to assess the different domains and subdomains of early child development at the child level for all children in the sample, aggregated to the census tract for analysis.

Neighborhood data sources. Data sources on neighborhood characteristics were linked to the census tract where each child lived. We used population density from the Environmental Protection Agency's Smart Location Database Version 2.0. Other census tract–level variables were from the 2012 5-year American Community Survey (ACS) from the US Census Bureau.

Because the data collection for the EDI spanned 2010 to 2017, most of the children in the study were born between 2005 and 2012. The EDI intends to measure child development up to the point of starting kindergarten, so we used the 5-year estimates from the 2012 ACS survey, which would span most of our years of interest.

Measures

There were 6 dependent variables (each in its own model) for this study: census tract–level average of each of the 5 domain scores and the count of "not ready" EDI subdomains out of 16, a count variable of the number of EDI subdomains for which a child is considered "not ready," aggregated to the census tract level (higher scores mean more vulnerability). We omitted child-level observations with data on fewer than 14 subdomains. At the individual level, domain scores ranged from 0 to 10 (higher scores mean higher levels of development).

There were 2 main predictors: average commute time and percentage residential crowding. These originate from the US Census 2012 5-year ACS survey. Average commute time began as a categorical variable with time categories ranging in 5-minute increments from 0 to 5 minutes to 40 to 44 minutes, and also including 45 to 59, 60 to 89, and 90 minutes or more. To construct the variable, average commute time, we took the midpoint of each of the categories and averaged them over the population of the census tract. Preliminary tests suggest a linear relationship between commute time and child development. Percentage of residential crowding is the proportion of households in the census tract for which there is more than 1 person per room, following Blake et al., who suggest that health and mental health issues arise more frequently above this threshold.[28]

There were 8 control variables: percentage of owner-occupied housing, population density, percentage of residents with

TABLE 2—Census Tract–Level Analyses of Early Childhood Vulnerability With Residential Crowding and Average Commute Time as Main Predictors in Full Sample: 8 US States, 2010–2017

	Average "Not Ready," OLS (95% CI)	Physical Health, OLS (95% CI)	Social Competence, OLS (95% CI)	Emotional Maturity, OLS (95% CI)	Language and Cognition, OLS (95% CI)	Communication Skills, OLS (95% CI)
% residential crowding, *z* score	0.053 (0.013, 0.093)	0.003 (−0.022, 0.029)	0.002 (−0.033, 0.037)	0.009 (−0.021, 0.038)	−0.064 (−0.096, −0.031)	−0.084 (−0.129, −0.040)
Average commute time, *z* score	0.025 (−0.027, 0.076)	−0.003 (−0.030, 0.024)	−0.010 (−0.051, 0.031)	0.000 (−0.038, 0.038)	0.000 (−0.042, 0.043)	−0.011 (−0.067, 0.045)
% in poverty	0.007 (0.002, 0.012)	-0.004 (−0.007, −0.001)	-0.004 (−0.007, −0.001)	−0.002 (−0.005, 0.001)	−0.005 (−0.009, −0.002)	−0.005 (−0.009, −0.001)
% with bachelor's degree	−0.013 (−0.017, −0.010)	0.007 (0.006, 0.009)	0.009 (0.006, 0.011)	0.006 (0.004, 0.008)	0.009 (0.006, 0.013)	0.013 (−0.010, 0.016)
Unemployment rate	−0.003 (−0.014, 0.008)	−0.002 (−0.008, 0.005)	−0.001 (−0.007, 0.005)	0.000 (−0.006, 0.006)	0.006 (−0.001, 0.013)	0.003 (−0.008, 0.013)
% limited English	0.001 (−0.005, 0.007)	0.002 (−0.002, 0.005)	0.001 (−0.004, 0.005)	0.001 (−0.002, 0.005)	−0.003 (−0.008, 0.002)	−0.009 (−0.015, −0.003)
% owner-occupied housing	−0.003 (−0.005, −0.001)	0.002 (0.001, 0.003)	0.003 (0.001, 0.004)	0.002 (0.001, 0.003)	0.001 (−0.001, 0.003)	0.003 (0.001, 0.005)
Population density	−0.000 (−0.009, 0.008)	0.001 (−0.004, 0.007)	0.005 (−0.000, 0.010)	0.002 (−0.003, 0.006)	−0.001 (−0.006, 0.005)	0.000 (−0.009, 0.009)
Racial heterogeneity	0.193 (0.035, 0.351)	−0.033 (−0.135, 0.068)	−0.024 (−0.169, 0.120)	−0.080 (−0.205, 0.046)	-0.152 (−0.262, 0.041)	−0.427 (−0.697, −0.156)
Residential instability	0.004 (−0.001, 0.008)	−0.001 (−0.003, 0.002)	−0.002 (−0.005, 0.001)	−0.002 (−0.004, 0.001)	−0.004 (−0.008, 0.001)	−0.002 (−0.007, 0.003)
Constant	2.810 (2.480, 3.141)	8.631 (8.459, 8.802)	7.474 (7.290, 7.658)	7.486 (7.338, 7.634)	8.713 (8.313, 9.112)	7.112 (6.657, 7.566)

Notes. CI = confidence interval; OLS = adjusted ordinary least squares regression. The sample size was n = 2793 census tracts. These adjusted OLS regression models used analytic weights to adjust for the number of children within each census tract. The analysis included jurisdiction-level fixed effects and clustered standard errors at the primary sampling unit. Control variables in the model included percentage of residents below poverty line, percentage of adults with a bachelor's degree or higher, unemployment rate, percentage of households in which no one older than 14 years speaks English very well, percentage of owner-occupied housing, population density (population/square mile/1000), racial heterogeneity (higher scores = more heterogeneity), and 1-year residential in stability (percentage of residents who have moved within the past year).

a bachelor's degree or higher, unemployment rate, percentage of households with limited English (the percentage of households in which no one older than 14 years speaks English very well), racial heterogeneity, residential instability (percentage of residents within a census tract who have moved within the past year),[29] and poverty level (percentage of households below the federal poverty line, as defined by the US Census Bureau, according to ACS data from 2008 to 2012). Because of the skewed nature of the data, we truncated population density at 30 000 per square mile. We calculated racial heterogeneity by

$$RH_k = 1 - \Sigma_1^{j=J} G_j^2 \quad (1)$$

where J are racial/ethnic groups and G is the proportion of the census tract that each racial group represents.[30] The groups included Asian, Black, Latino, non-Latino White, and other. Larger values represent more heterogeneity. We chose these variables because they may each be independently associated with both child development and either commute times or crowding.

Data Analysis

We used multivariate regression with fixed effects at the jurisdiction level, clustering at the primary sampling unit, and analytic weights to account for varying numbers of children per census tract (ranging from 1 to 1041; mean = 66). We used separate regressions to predict each of the 6 dependent variables based on average commute time and crowding, controlling for neighborhood characteristics. The first model included the full sample and then the sample was stratified by level of poverty at the census tract level (separated at the top-third percentage of households in poverty [20%]) to investigate how neighborhood poverty may moderate the relationship between characteristics of urban mobility and child development. A Chow test suggested that there were differences between models. Average commute time and percentage of crowding are standardized into z scores to have a mean of zero and a standard deviation of 1, and both were included in the same model. The correlation between commute time and crowding was small at 0.12. We ran all analyses with Stata version 14.0 (StataCorp LP, College Station, TX).

RESULTS

Table 1 shows descriptive statistics for the full sample, high-poverty subsample (top-third census tracts by percentage in poverty [at or above 20%]), and low-poverty subsample (below 20% poverty). There were 2793 total census tracts represented by the total sample, 948 and 1845 in the high-poverty and low-poverty subsamples, respectively. Our full sample had census tracts with larger proportions of people with limited English and in poverty, and similar proportions of adults with at least a bachelor's degree and unemployment rates compared with the United States overall. Our sample included children from 7 different states and the District of Columbia, but did not include states in the Great Plains or the Northwest. Thus, our sample offers modest external generalizability to the United States.

TABLE 3—Census Tract–Level Analyses of Early Childhood Vulnerability With Residential Crowding and Average Commute Time as Main Predictors in High-Poverty Subsample: 8 US States, 2010–2017

	Average "Not Ready," OLS (95% CI)	Physical Health, OLS (95% CI)	Social Competence, OLS (95% CI)	Emotional Maturity, OLS (95% CI)	Language and Cognition, OLS (95% CI)	Communication Skills, OLS (95% CI)
% residential crowding, *z* score	0.055 (−0.015, 0.126)	0.002 (−0.042, 0.046)	0.009 (−0.049, 0.067)	0.011 (−0.037, 0.060)	−0.056 (−0.096, −0.015)	−0.068 (−0.125, −0.012)
Average commute time, *z* score	0.110 (0.014, 0.207)	−0.035 (−0.084, 0.014)	−0.081 (−0.146, −0.016)	−0.066 (−0.123, −0.010)	−0.060 (−0.129, 0.009)	−0.070 (−0.170, 0.030)
% below poverty line	0.008 (0.003, 0.013)	−0.004 (−0.008, 0.000)	−0.006 (−0.010, −0.003)	−0.002 (−0.006, 0.002)	−0.007 (−0.011, −0.003)	−0.007 (−0.012, −0.003)
% with bachelor's degree	−0.006 (−0.010, −0.001)	0.001 (−0.003, 0.006)	0.004 (0.001, 0.007)	0.002 (−0.001, 0.005)	0.008 (−0.003, 0.012)	0.004 (−0.001, 0.009)
Unemployment rate	−0.007 (−0.019, 0.005)	−0.001 (−0.010, 0.009)	0.001 (−0.005, 0.007)	0.001 (−0.006, 0.009)	0.010 (−0.002, 0.017)	0.001 (−0.013, 0.015)
% limited English	−0.001 (−0.008, 0.007)	0.000 (−0.004, 0.005)	0.003 (−0.002, 0.007)	0.003 (−0.002, 0.008)	−0.003 (−0.008, 0.003)	−0.008 (−0.016, −0.001)
% owner-occupied housing	0.000 (−0.004, 0.004)	0.001 (−0.002, 0.003)	0.001 (−0.002, 0.004)	0.000 (−0.002, 0.003)	−0.001 (−0.004, 0.002)	−0.002 (−0.006, 0.002)
Population density	0.001 (−0.012, 0.014)	0.003 (−0.004, 0.010)	0.002 (−0.006, 0.009)	−0.001 (−0.009, −0.006)	−0.001 (−0.010, 0.007)	−0.002 (−0.015, 0.011)
Racial heterogeneity	−0.077 (−0.426, 0.272)	0.191 (−0.005, 0.387)	0.167 (−0.093, 0.428)	0.073 (−0.132, 0.277)	−0.160 (−0.315, −0.006)	−0.054 (−0.434, 0.326)
Residential instability	0.008 (0.001, 0.016)	−0.001 (−0.006, 0.005)	−0.005 (−0.011, 0.002)	−0.005 (−0.010, −0.001)	−0.007 (0.014, 0.001)	−0.642 (−0.013, 0.0000)
Constant	2.549 (1.398, 3.701)	8.742 (8.172, 9.311)	7.994 (7.138, 8.850)	7.537 (6.861, 8.214)	8.779 (7.495, 10.063)	7.374 (6.261, 8.487)

Notes. CI = confidence interval; OLS = adjusted ordinary least squares regression. The sample size was n = 948 census tracts. These adjusted OLS regression models used analytic weights to adjust for the number of children within each census tract. The analysis included jurisdiction-level fixed effects and clustered standard errors at the primary sampling unit. Control variables in the model included percentage of residents below poverty line, percentage of adults with a bachelor's degree or higher, unemployment rate, percentage of households in which no one older than 14 years speaks English very well, percentage of owner-occupied housing, population density (population/square mile/1000), racial heterogeneity (higher scores = more heterogeneity), and 1-year residential in stability (percentage of residents who have moved within the past year).

Full Sample Analyses

Table 2 presents the regression results with the full sample (n = 2793), each dependent variable in a different column, including commute time and crowding in the same models. At the census tract level, a 1-standard-deviation increase in residential crowding was associated with a 0.053 increase in number of "not ready" subdomains ($P = .01$), and 0.064- and 0.084-point decreases in aggregate mean score of language and cognitive development ($P < .01$) and communication skills ($P < .01$), respectively. No coefficients for commute time were statistically significant.

High-Poverty Subsample

Table 3 presents regression results for the high-poverty subsample (the top third of census tracts by percentage of residents in poverty). The coefficient for "not ready" was no longer significant. A 1-standard-deviation increase in residential crowding was associated with 0.056- and 0.068-point decreases in aggregate mean score of language and cognitive development ($P = .01$) and communication skills ($P = .02$), respectively. For commute time, a 1-standard-deviation increase was associated with a 0.110 increase in number of "not ready" subdomains ($P = .03$), and 0.081- and 0.066-point decreases in aggregate mean score of social competence ($P = .02$) and emotional maturity ($P = .02$), respectively.

Low-Poverty Subsample

Table 4 presents the results for the low-poverty subsample. A 1-standard-deviation increase in residential crowding was associated with a 0.101- and 0.135-point decrease in aggregate mean score of language and cognitive development ($P < .01$) and communication skills ($P = .01$), respectively.

DISCUSSION

We examined associations between indicators of a changing urban landscape and child development vulnerability at the neighborhood level. Although studies have examined relationships among crowding, commute time, and health, this is the first study that we know of that looks at population-level relationships of commute time and crowding with comprehensive measures of child development. We chose 2 measures that assess aspects of the complex and dynamic ecosystem within which a child and family function, and we saw a significant relationship between those ecosystem measures and child development.

In neighborhoods with higher levels of residential crowding, children have increased vulnerability and decreased language and cognitive development and communication skills. These relationships were apparent regardless of neighborhood poverty level. The relationship between crowding and these development domains aligns with past research that crowding has an impact on academic achievement. However, it was surprising that no relationship was found among social competence, emotional maturity, and crowding, as the literature suggests the potential for those relationships.

TABLE 4—Census Tract–Level Analyses of Early Childhood Vulnerability With Residential Crowding and Average Commute Time as Main Predictors in Low-Poverty Subsample: 8 US States, 2010–2017

	Average "Not Ready," OLS (95% CI)	Physical Health, OLS (95% CI)	Social Competence, OLS (95% CI)	Emotional Maturity, OLS (95% CI)	Language and Cognition, OLS (95% CI)	Communication Skills, OLS (95% CI)
% residential crowding, *z* score	0.072 (−0.004, 0.148)	−0.000 (−0.047, 0.47)	−0.017 (−0.067, 0.033)	0.011 (−0.029, 0.051)	−0.101 (−0.153, −0.048)	−0.135 (−0.237, −0.034)
Average commute time, *z* score	−0.016 (−0.078, 0.046)	0.012 (−0.021, 0.045)	0.018 (−0.027, 0.063)	0.031 (−0.005, 0.067)	0.023 (−0.034, 0.081)	0.007 (−0.060, 0.074)
% below poverty line	0.006 (−0.001, 0.013)	−0.003 (−0.007, 0.002)	−0.005 (−0.013, 0.002)	−0.004 (−0.010, 0.002)	−0.005 (−0.011, 0.001)	−0.002 (−0.013, 0.008)
% with bachelor's degree	−0.014 (−0.018, −0.010)	0.008 (0.007, 0.010)	0.009 (0.007, 0.011)	0.006 (0.004, 0.008)	0.009 (0.006, 0.012)	0.015 (0.011, 0.018)
Unemployment rate	−0.006 (−0.015, 0.003)	0.001 (−0.005, 0.006)	0.001 (−0.008, 0.009)	0.003 (−0.006, 0.011)	0.003 (−0.005, 0.011)	0.011 (−0.001, 0.023)
% limited English	0.001 (−0.010, 0.012)	0.004 (−0.001, 0.009)	−0.002 (−0.009, 0.005)	−0.001 (−0.007, 0.006)	−0.001 (−0.009, 0.006)	−0.007 (−0.016, 0.003)
% owner-occupied housing	−0.005 (−007, −0.002)	0.003 (−0.001, 0.004)	0.004 (0.002, 0.005)	0.003 (0.001, 0.005)	0.002 (0.000, 0.004)	0.006 (0.003, 0.009)
Population density	−0.005 (−0.015, 0.005)	0.003 (−0.004, 0.009)	0.010 (0.002, 0.017)	0.007 (0.002, 0.012)	0.002 (−0.005, 0.009)	0.007 (−0.004, 0.017)
Racial heterogeneity	0.185 (−0.063, 0.433)	−0.078 (−0.245, 0.088)	0.026 (−0.188, 0.239)	−0.104 (−0.294, 0.086)	−0.025 (−0.208, 0.159)	-0.527 (−0.900, −0.155)
Residential instability	0.002 (−0.004, 0.008)	−0.000 (−0.003, 0.003)	−0.002 (−0.007, 0.004)	0.001 (−0.004, 0.005)	−0.002 (−0.005, 0.002)	0.000 (−0.007, 008)
Constant	3.625 (2.869, 4.382)	8.471 (7.986, 8.956)	7.021 (6.484, 7.558)	7.212 (6.726, 7.699)	7.196 (6.714, 7.677)	5.310 (4.757, 5.864)

Notes. CI = confidence interval; OLS = adjusted ordinary least squares regression. The sample size was n = 1845 census tracts. These adjusted OLS regression models used analytic weights to adjust for the number of children within each census tract. The analysis included jurisdiction-level fixed effects and clustered standard errors at the primary sampling unit. Control variables in the model included percentage of residents below poverty line, percentage of adults with a bachelor's degree or higher, unemployment rate, percentage of households in which no one older than 14 years speaks English very well, percentage of owner-occupied housing, population density (population/square mile/1000), racial heterogeneity (higher scores = more heterogeneity), and 1-year residential in stability (percentage of residents who have moved within the past year).

In high-poverty neighborhoods with higher commute times, children have more vulnerability and decreased social competence and emotional maturity. The commute time results align with past studies that commute time predicts outcomes for impoverished families more than those with higher income.[20] In addition, these developmental domains align with our hypothesis that increased commute time might lead to decreased quality and quantity of interactions with parents, which might lead to emotional and social difficulties for children.

Although we hypothesized about the origin of the relationships between specific development domains and urban landscape changes, these can only serve as suggestions as we were unable to directly measure the mediators of this relationship or the direct, individual-level relationships. Future studies should investigate these potential mediators between ecological changes and individual-level child development as well as measure crowding and commute time at the family level.

This study suggests that everyday stressors and adversity predict childhood vulnerability at the neighborhood level. Just as childhood resilience is associated with the "ordinary magic" of day-to-day interactions that children have with their environments,[31] their vulnerability may also be associated with the ordinary, everyday adversity that does not show up on measures of adverse childhood experiences, which are more formal measures of specific kinds of family-level adversities.[32] Future research should seek to better understand how everyday occurrences such as having less time with a parent who is commuting long distances to work contribute to an ecosystem of experiences that results in greater development vulnerability.

Public Health Implications

Although the magnitude of these effects was not large—on the order of a couple of percentage points for every standard-deviation change in either commute time or crowding—at the population level these changes lead to meaningful effects. The vast majority of the nation's poor children live in and around cities, in urban and suburban areas—more than 10 million children, according to US Census data for 2016. Given that an estimated half of all poor children are not ready to start school at age 5 years, there are some 5 million urban poor children who suffer from readiness deficits.[33] The estimates presented here suggest that the roughly 5% increased risk associated with crowding and long commutes affects the school readiness of nearly 200 000 children a year.

Both crowding and commute times are under the control—indirect though it is—of city planners, city councils, mayors, and the citizens that elect and appoint them. In recent decades, restrictive zoning, poor transportation planning, and stagnant wages have combined to put many households into the untenable position of having to work long hours, commute long distances, or squeeze many people into small spaces.[34] Children have been among those whose health and well-being suffers most from these policy failures. This problem is especially pronounced for high-poverty neighborhoods. Our findings emphasize the need for multisectoral integration and collaboration. Children's issues should not just remain in discussions of child welfare, the juvenile justice system, the foster care system, and preschools. Transportation, city planning, and other ecosystem issues are also children's issues, and, thus, it is important for child advocates and researchers to be at the table during a wide variety of policy discussions.[35]

Limitations

There were several limitations in this study. This was a cross-sectional, observational study. We cannot rule out omitted variable bias. We attempted to minimize this by adding several theoretically important control variables to the model.

This is an ecological model that examines associations at the census tract level as individual-level data were not available for our independent variables. Thus, we cannot be sure that the same relationships would hold at the individual level.

The time that these data were collected varied over 7 years (2010–2017), and the census-level data also varied from 2010 to 2012. This may mean that the characteristics at the neighborhood level may not exactly match the neighborhood characteristics of the individual children during the years leading up to kindergarten.

Sites that did not include special education classrooms in their data collection were excluded from the sample, but there may have been others that did so without disclosing it to the study team.

Neighborhoods vary in size. The census tract does not always necessarily characterize a neighborhood, but we used the census tract as a proxy for the neighborhood because it is the most uniform geography type across the country by population size at the level of granularity that we thought would be most appropriate.

The EDI data were not collected as a random sample: sites individually chose to participate for various reasons. The EDI data were also, therefore, not necessarily representative of the entire United States, so generalizability is limited. We attempted to improve internal validity by using a strict set of inclusion and exclusion criteria for sites and only took sites where there was almost a full census of children in the jurisdiction.

CONCLUSIONS

In this study, we found that both more crowding and longer commutes in high-poverty neighborhoods were associated with lower levels of early child development at the neighborhood level. Even in more affluent neighborhoods, crowding was associated with poor child development. The built environment, planning policy, and zoning all seem to have an influence on how children develop. The public health sector should work with advocates in the economic development, urban planning, and transportation planning sectors to take actions that improve the lives of low-income children. AJPH

CONTRIBUTORS

E. P. Block participated in designing the analysis, conducted the analysis, wrote the first draft, and edited each draft. F. J. Zimmerman guided the design of the analysis and reviewed the final article. E. Aguilar consulted on the sample and variable construction and reviewed the final article. L. Stanley consulted on the sample construction and reviewed the final article. N. Halfon obtained funding, consulted on the framing of the article, and reviewed the final article.

ACKNOWLEDGMENTS

E. P. Block wrote this with the financial support of the UCLA Graduate Summer Research Mentorship Award.

The authors would like to acknowledge the publishers of the Early Development Instrument (EDI) at McMaster University, Offord Centre for Child Studies, for their support of the EDI in the United States. Through its license to UCLA to sublicense the EDI in the United States, the EDI has provided communities a common measure to monitor child well-being. Emily Chan contributed substantially to the data collection process, and Joshua L. Bader geocoded all observations.

HUMAN PARTICIPANT PROTECTION

This secondary analysis was covered under UCLA institutional review board 11-000393-CR-00004.

REFERENCES

1. Irwin LG, Siddiqi A, Hertzman C. The equalizing power of early child development: from the Commission on Social Determinants of Health to Action. *Child Health Educ*. 2010;1(3):146–161.

2. Lemelin J-P, Boivin M, Forget-Dubois N, et al. The genetic–environmental etiology of cognitive school readiness and later academic achievement in early childhood. *Child Dev*. 2007;78(6):1855–1869.

3. Hertzman C, Boyce T. How experience gets under the skin to create gradients in developmental health. *Annu Rev Public Health*. 2010;31(1):329–347.

4. Russ S, Garro N, Halfon N. Meeting children's basic health needs: from patchwork to tapestry. *Child Youth Serv Rev*. 2010;32(9):1149–1164.

5. Halfon N, Larson K, Lu M, Tullis E, Russ S. Lifecourse health development: past, present and future. *Matern Child Health J*. 2014;18(2):344–365.

6. Lens MC, Monkkonen P. Do strict land use regulations make metropolitan areas more segregated by income? *J Am Plann Assoc*. 2016;82(1):6–21.

7. Bronfenbrenner U. Developmental research, public policy, and the ecology of childhood. *Child Dev*. 1974;45(1):1–5.

8. Wandersman A, Nation M. Urban neighborhoods and mental health: psychological contributions to understanding toxicity, resilience, and interventions. *Am Psychol*. 1998;53(6):647–656.

9. Gómez-Jacinto L, Hombrados-Mendieta I. Multiple effects of community and household crowding. *J Environ Psychol*. 2002;22(3):233–246.

10. Evans GW. The built environment and mental health. *J Urban Health*. 2003;80(4):536–555.

11. Goux D, Maurin E. The effect of overcrowded housing on children's performance at school. *J Public Econ*. 2005;89(5-6):797–819.

12. Maxwell LE. Multiple effects of home and day care crowding. *Environ Behav*. 1996;28(4):494–511.

13. Mann SL, Wadsworth ME, Colley JR. Accumulation of factors influencing respiratory illness in members of a national birth cohort and their offspring. *J Epidemiol Community Health*. 1992;46(3):286–292.

14. Frank LD, Andresen MA, Schmid TL. Obesity relationships with community design, physical activity, and time spent in cars. *Am J Prev Med*. 2004;27(2):87–96.

15. Hansson E, Mattisson K, Björk J, Östergren P-O, Jakobsson K. Relationship between commuting and health outcomes in a cross-sectional population survey in southern Sweden. *BMC Public Health*. 2011;11(1):834.

16. Hoehner CM, Barlow CE, Allen P, Schootman M. Commuting distance, cardiorespiratory fitness, and metabolic risk. *Am J Prev Med*. 2012;42(6):571–578.

17. Hilbrecht M, Smale B, Mock SE. Highway to health? Commute time and well-being among Canadian adults. *World Leis J*. 2014;56(2):151–163.

18. Venn D, Strazdins L. Your money or your time? How both types of scarcity matter to physical activity and healthy eating. *Soc Sci Med*. 2017;172:98–106.

19. Künn-Nelen A. Does commuting affect health? *Health Econ*. 2016;25(8):984–1004.

20. MacLeod KE, Shi L, Zhang D, Chen L, Chao SM. Association between vehicle time during pregnancy and mental health among women of different income groups. *J Transp Health*. 2018;8:106–111.

21. Chetty R, Hendren N. The impacts of neighborhoods on intergenerational mobility II: county-level estimates. *Q J Econ*. 2018;133(3):1163–1228.

22. Janus M, Offord DR. Development and psychometric properties of the Early Development Instrument (EDI): a measure of children's school readiness. *Can J Behav Sci*. 2007;39(1):1–22.

23. Brinkman S, Stanley F. Public health aspects of child well-being. In: Ben-Arich A, Casas F, Frones I, Korbin JE, eds. *Handbook of Child Well-Being*. Dordrecht, Netherlands: Springer; 2014:317–350.

24. Curtin M, Browne J, Staines A, Perry IJ. The Early Development Instrument: an evaluation of its five domains using Rasch analysis. *BMC Pediatr*. 2016;16(1):10.

25. Brinkman S, Gregory T, Harris J, Hart B, Blackmore S, Janus M. Associations between the Early Development Instrument at age 5, and reading and numeracy skills at ages 8, 10 and 12: a prospective

linked data study. *Child Indic Res*. 2013;6(4): 695–708.

26. Janus M, Walsh C, Duku E. Early Development Instrument: factor structure, sub-domains and multiple challenge index. 2005. Available at: https://edi.offordcentre.com/wp/wp-content/uploads/2015/11/RESULTS.Normative_Data_II.pdf. Accessed September 12, 2018.

27. Offord Centre for Child Studies. Domains and subdomains, Early Development Instrument. 2016. Available at: https://edi.offordcentre.com/researchers/domains-and-subdomains. Accessed October 4, 2017.

28. Blake KS, Kellerson RL, Simic A. Measuring overcrowding in housing. Washington, DC: Department of Housing and Urban Development, Office of Policy Development Research; 2007.

29. Coulton C. *Using Data to Understand Residential Mobility and Neighborhood Change*. What Counts. 2014. Available at: http://www.whatcountsforamerica.org/portfolio/using-data-to-understand-residential-mobility-and-neighborhood-change. Accessed September 12, 2018.

30. Nielsen AL, Hill TD, French MT, Hernandez MN. Racial/ethnic composition, social disorganization, and offsite alcohol availability in San Diego County, California. *Soc Sci Res*. 2010;39(1):165–175.

31. Masten AS. Ordinary magic. Resilience processes in development. *Am Psychol*. 2001;56(3):227–238.

32. Dube SR, Felitti VJ, Dong M, Giles WH, Anda RF. The impact of adverse childhood experiences on health problems: evidence from four birth cohorts dating back to 1900. *Prev Med*. 2003;37(3):268–277.

33. Isaacs JB. Starting school at a disadvantage: the school readiness of poor children. The Social Genome Project, Center on Children and Families at Brookings. 2012. Available at: https://www.brookings.edu/research/starting-school-at-a-disadvantage-the-school-readiness-of-poor-children. Accessed September 12, 2018.

34. Metcalf G. Sand castles before the tide? Affordable housing in expensive cities. *J Econ Perspect*. 2018;32(1): 59–80.

35. Halfon N, Wise PH, Forrest CB. The changing nature of children's health development: new challenges require major policy solutions. *Health Aff (Millwood)*. 2014;33(12): 2116–2124.