Bravo *et al. BMC Public Health (2024) 24:3343*
https://doi.org/10.1186/s12889-024-20846-6

BMC Public Health

RESEARCH

Open Access

Residential instability, neighborhood deprivation, and outcomes for children

Mercedes A. Bravo[1,2*], Dominique Zephyr[2] and Marie Lynn Miranda[2,3*]

Abstract

Background Residential instability and neighborhood conditions may shape children's health and development, but it is unclear whether all residential moves are equally destabilizing, and the extent to which moving to neighborhoods with different conditions can improve children's outcomes. Most studies estimating causal effects of these factors on children's health or development use smaller, geographically constrained, urban cohorts.

Objective In a racially/ethnically and socioeconomically diverse statewide cohort including urban and rural communities, we investigate effects of residential instability, neighborhood deprivation, and their intersection on childhood educational outcomes.

Methods We construct a statewide dataset that links North Carolina birth records (2002–2005) with lead testing data (2003–2015) and 4th grade standardized test scores (2013–2016). A composite census tract-level neighborhood deprivation index (NDI) is linked with individuals based on residence at birth, lead testing, and 4th grade. Outcomes of interest are 4th grade test scores in reading and mathematics. We use multinomial propensity scores to estimate effects of residential instability and neighborhood deprivation on test scores.

Results Children who moved between only high deprivation neighborhoods had lower reading test scores (-0.29 [95% CI: -0.59, -0.015]) compared to children who resided in high deprivation neighborhoods but did not move. Children who resided in a high deprivation neighborhood at birth and subsequently moved to a low deprivation neighborhood(s) had higher test scores compared to those who moved between only high deprivation neighborhoods (1.59 [0.90, 2.28]). Additionally, children who move from high to low deprivation neighborhoods earlier had larger improvements.

Conclusion Being residentially stable, even while residing in a high deprivation neighborhood, is associated with improved educational outcomes. However, there is also a larger positive effect of moving from high to low deprivation neighborhoods. Our findings have important implications, particularly given the increasing segregation of neighborhoods by socioeconomic status and the housing affordability crisis in the United States. Partnerships between housing programs, early childhood education and services, and health care providers, which address evictions and broader issues, may help address health inequalities rooted in childhood exposures and experiences.

Keywords Neighborhood deprivation, Residential instability, Cognitive outcomes, Standardized test scores, Residential instability, Test scores, Early childhood outcomes

*Correspondence:
Mercedes A. Bravo
mercedes.bravo@duke.edu
Marie Lynn Miranda
mlmpi@uic.edu
Full list of author information is available at the end of the article

Background

The Institute of Medicine and National Research Council concluded that "virtually every aspect of early human development, from the brain's evolving circuitry to the child's capacity for empathy, is affected by the environments and experiences that are encountered in a cumulative fashion, beginning in the prenatal period and extending throughout the early childhood years"[1]. Focusing on children is essential for understanding cognitive ability, its malleability, and beneficial or adverse effects of different exposures and experiences [2, 3].

A particularly salient experience is where children live and how stable those living environments are. Residential instability contributes to poor health and developmental trajectories [4]. Children who move more frequently are more likely to have poorer physical health, mental health, and behavioral outcomes [5, 6]. Characteristics of neighborhoods – including poverty, segregation, and crime – may also contribute to shaping outcomes for children and their families. Sampson et al. (2008) studied effects of concentrated neighborhood disadvantage on the verbal ability of 772 children who participated in the Project on Human Development in Chicago Neighborhoods [3]. They posit four possible pathways through which neighborhood environments may affect children's cognition (and, thereby, test scores): (i) inconsistent maternal parenting practices and/or compromised mental health of caregivers;[8–10]; (ii) school quality, which is often linked with neighborhood because public school funding in the US is geographically determined; (iii) restriction of the "speech community" to which a child is exposed [11, 12]; and (iv) limited "communication infrastructure" and interaction with community members, potentially resulting from distrust, violence, and physical features of the neighborhood [13–15]. Other studies have shown that neighborhood context affects verbal ability and that recency of exposure to disadvantaged neighborhoods may affect children's test scores ($n=600$) [7]. However, not all residential moves are necessarily destabilizing for families, as moves that embed children in more highly resourced areas may positively affect their outcomes. Findings from the Moving to Opportunity (MTO) project ($n=5{,}000$) suggest that moving to lower poverty neighborhoods earlier in childhood is more likely to benefit children [16, 17].

Situated in the American South, North Carolina (NC) has marked racial/ethnic, socioeconomic, and urban/rural differences in childhood outcomes [18–20]. We utilize a large, diverse, population-based sample from NC to investigate the effects of residential instability and neighborhood deprivation on 4th grade test scores. We chose to use 4th grade test scores because they: (i) are early indicators of academic achievement, and therefore useful for facilitating earlier identification of and intervention with "at risk" students; (ii) are strong predictors of high school outcomes (e.g., 10th grade test scores, probability of enrolling in advanced courses in high school, and high school graduation); (iii) have, in some cases, been shown to be as predictive of high school outcomes as 8th grade test scores; and (iv) are imperfect but useful proxies for cognitive development [21]. Early educational outcomes are linked with health because overall educational attainment is linked with health (e.g., life expectancy) through various pathways such as income, wealth, insurance status, access to health care, and engaging in health promoting behaviors [22].

Methods

Data

The analytical dataset was constructed from three administrative datasets: (i) the NC detailed birth records (DBR) for 2002–2005; (ii) lead surveillance records for years 2003–2015; and (iii) end-of-grade (EOG) standardized test scores in reading and mathematics for NC public school students in 4th grade for years 2013–2016.

Detailed birth records

We obtained the NC DBR from the NC Department of Vital Statistics/NC Center for Health Statistics (Raleigh, NC). For all recorded live births in NC, the DBR contain data on date and location of birth; maternal health data, demographic data, and residential address at time of birth; and neonate characteristics, including sex, gestational age, birth weight in grams. Studies indicate that DBR generally provide accurate information for demographic characteristics and birth outcomes [23, 24].

Blood lead surveillance data

Records of blood lead testing were obtained from the Childhood Lead Poisoning Prevention Program of the Children's Environmental Health Unit in Department of Health and Human Services (Raleigh, NC). Blood lead records contain individual-level data on child characteristics such as age, date of testing, lead concentration in micrograms per deciliter (μg/dL), and residential address. In the blood lead surveillance data, blood lead levels are recorded as integer values with a limit of detection (LoD) of 1 μg/dL. Any blood lead levels at or below the LoD were given a value of 1 μg/dL. The database does not provide information on why children were screened for lead, however, children should have been screened if they were Medicaid participants or based on their parent's responses to the CDC Lead Risk Assessment Questionnaire [25].

End-of-grade (EOG) standardized testing data

Educational records, including EOG test scores, were obtained from the Education Research Data Center housed at Duke University (Durham, NC). In NC, children enrolled in grades 3–8 in public schools are administered standardized tests in subject areas of reading and mathematics, typically in May or June of the academic year. These are "curriculum-based multiple-choice achievement tests…specifically aligned to the *North Carolina Standard Course of Study*" [26]. End-of-grade tests consist of multiple choice questions in areas of reading and math. The reading portion of the exam is intended to assess interpretation, critical stance, and connections; the math portion assesses geometry, patterns, relationships, numeration, numerical operations, functions, statistics, and probability (Mathematics) [27]. The educational records also include individual-level data on children, including birth date, in addition to demographic and socioeconomic data, English proficiency, and school and district ID.

Neighborhood deprivation

The neighborhood deprivation index (NDI) was constructed using 2000 and 2010 Census data and 2015 ACS data at the census tract level. The NDI was calculated across NC as previously described, using the first factor loadings from a principal components analysis of multiple variables, including percentages of: households in poverty, female-headed households with dependents, households with annual income < $30,000, households on public assistance, males in management/professional occupation, crowded housing, unemployed, and without a high school education [28]. A census tract was classified as "high NDI" if its NDI was in the top two quintiles of NDI and classified as "low NDI" if its NDI was in the bottom two quintiles of NDI (see Supplemental Material [SM] Table S1). Higher values of NDI indicate greater deprivation.

Study area and sample

In 2010, approximately 8.4% of North Carolina's population was Hispanic (of any race); 21.5% was Black or African American; and 68.5% was White [29]. Approximately two-thirds of the population (66.7%) resided in owner-occupied housing, and 66.1% of the population lived in an urban area [29, 30]. The percentage of people in poverty in NC in 2010 was 17.5%, compared to the United States-wide average of 15.3% [31].

There were 88,499 children linked across NC detailed births (2002–2005), lead screening (2003–2015), and education datasets (2013–2016), and geocoded at time of birth, lead testing, and EOG testing. We restricted to children who: were born to self-reported non-Hispanic White (NHW), non-Hispanic Black (NHB), or Hispanic mothers (excluded 3,096 records); did not have limited English proficiency, as it can be complicated to interpret test scores among such children (excluded 5,600 records); had blood lead levels ≤ 80 μg/dL (excluded 8 records); and had blood lead tests between 0 and 6 years of age inclusive (excluded 437 records). We also removed 555 (0.70%) records with missing values for any of the following variables: birthweight percentile for gestational age, preterm birth, Medicaid participation, blood lead test result, child sex, maternal tobacco use during pregnancy, maternal race/ethnicity, maternal age, maternal educational attainment, and maternal marital status at time of child's birth.

We also excluded children who did not reside in the same census tract in 3rd grade as in 4th grade (excluded 14,746 records). This was done in an effort to ensure that the neighborhood conditions present in 4th grade were likely also present in 3rd grade. After implementing this restriction, we did not use the 3rd grade census tract information again, resulting in 64,165 individual children retained in the study sample.

Among children who moved between different census tracts, we sought to identify children who had moved between census tracts that were similar with respect to NDI versus children who had moved between census tracts that were dissimilar with respect to NDI. Using census tract of residence at birth, children were linked to NDI calculated using 2000 Census data. Using census tract of residence at time of lead testing, children were linked to NDI calculated using 2000 Census data if lead testing occurred before 2006. If testing occurred in 2006 or later, they were linked to NDI calculated using 2010 Census data. Using census tract of residence at time of 4th grade EOG testing, children were linked to NDI calculated using 2015 American Community Survey (ACS) data.

NDI distributions in 2000, 2010, and 2015 are shown in SM Figure S1. To classify census tracts as low or high NDI, we first calculated quintiles of scaled NDI at time of birth and applied the same quantile range to scaled NDI at time of lead testing and scaled NDI at time of 4th grade standardized testing. A census tract was classified as "high NDI" if the NDI of the tract was in the top two quintiles of scaled NDI, and classified as "low NDI" if the NDI of the tract was in the bottom two quintiles of scaled NDI. A total of 23,823 records were removed for being in the middle quintile at time of birth, or time of EOG testing, or time lead testing (SM Table S1) (remaining $n = 40{,}342$). NDI at time of birth was used to define ranges delineating high and low NDI because the NDI at time of birth had a wider confidence interval around the mean (compared to NDI at time of EOG testing) and was thus a more conservative approach.

Treatment groups

In the resulting analytical dataset of $n = 40{,}342$ individuals, we estimate exposure to neighborhood deprivation and residential instability, classifying children as those who (i) resided continuously in the same low deprivation neighborhood; (ii) resided continuously in the same high NDI neighborhood; or (iii) moved between census tracts that were similar vs different with respect to NDI. Thus, children were binned into one of eight categories: *high-high-high-stay* ($N = 5{,}171$), *high-high-high-move* ($N = 11{,}537$), *high-high-low-move* ($N = 2{,}398$), *high-low-low-move* ($n = 849$), *low-low-low-stay* ($N = 2{,}603$), *low-low-low-move* ($N = 10{,}620$); *low-low–high-move* ($N = 2{,}956$), and *low–high-high-move* ($N = 1{,}848$) (Table 1). "High/low" represents Census tract NDI at each time point (birth, lead testing, and EOG testing), and "move/stay" indicates whether the child moved Census tracts (SM Table S2). A comparison of characteristics of the original study sample versus the final analytic sample is provided in SM Table S3 and S4.

We excluded individuals who did not fall into one of the eight categories described above ($n = 2{,}063$), primarily because there were small cell sizes in the remaining categories. We also excluded individuals who did not move census tracts but were classified as having changes in neighborhood deprivation. This could result if an individual did not move but the NDI for their census tract changed over time (or the relative ranking of NDI changed over time), which occurred in a relatively small number of individuals, $n = 297$. The final analytical dataset consisted of 37,982 individuals belonging to one of the eight mutually exclusive categories above.

Statistical analysis

We use propensity scores to estimate the effects of residential instability and neighborhood deprivation on test scores, while accounting for differences between children who experience varying degrees of residential instability and/or exposure to neighborhood deprivation. The propensity score represents the probability of receiving the treatment, conditional on observed characteristics at baseline. Specifically, the distribution of observed baseline covariates should be similar between exposed and unexposed individuals, conditional on the propensity score [32]. To address the potential imbalance in the distribution of observed characteristics between treatment groups, we used a multinomial propensity score model for multiple treatments using generalized boosted models via the *mnps* function of the *twang* package in R [33]. We included variables that may be related to the outcome of interest, 4th grade standardized tests scores in reading and mathematics, in propensity score estimation [34, 35]. These include: maternal race/ethnicity (Hispanic, non-Hispanic Black, and non-Hispanic White); birthweight percentile for gestational age; preterm birth, defined as birth prior to 37 weeks gestational age (yes/no); enrollment in Medicaid at the time of the blood lead test (yes/no); blood lead level (μg/dL); sex; maternal smoking during

Table 1 Final classification of individuals in the analytical dataset

Classification	N (%)	Description
Group Comparison 1		
HIGH HIGH HIGH STAY	5,171(25.9%)	Resided in the same census tract at time of birth, lead testing, and standardized testing, and census tract classified as high NDI (high deprivation)
HIGH HIGH HIGH MOVE	11,537 (57.8%)	Moved between only high deprivation census tracts across birth, lead testing, and standardized testing
HIGH HIGH LOW	2,398 (12.0%)	Moved from high deprivation census tracts at birth and lead testing to low deprivation tract at time of standardized testing
HIGH LOW LOW	849 (4.3%)	Moved from high deprivation census tract at birth to low deprivation tract at time of lead and standardized testing
Total	19,955 (100%)	
Group Comparison 2		
LOW LOW LOW STAY	2,603 (14.4%)	Resided in the same census tract at time of birth, lead testing, and standardized testing, and census tract classified as low NDI (low deprivation)
LOW LOW LOW MOVE	10,620 (58.9%)	Moved between only low deprivation census tracts across birth, lead testing, and standardized testing
LOW LOW HIGH	2,956 (16.4%)	Moved from low deprivation census tracts at birth and lead testing to high deprivation tract at time of standardized testing
LOW HIGH HIGH	1,848 (10.3%)	Moved from low deprivation census tract at birth to high deprivation tract at time of lead and standardized testing
Total	18,027 (100%)	

pregnancy (yes/no); maternal educational attainment (not a high school graduate; high school graduate; college graduate); maternal age at time of birth (15–24, 25–34, 35–44 years); and maternal marital status at the time of birth (married or unmarried) [36, 37].

Treatment groups should, conditional on the propensity score, be balanced with respect to baseline covariates. Imbalance between treatment groups was assessed by comparing the absolute standardized mean differences (ASMD) between the treatment groups with respect to the observed characteristics, before and after weighting [33]. We also assess the overlap or common support assumption, that is, each individual must have a positive probability of receiving each treatment [38].

To estimate the effect of exposure to residential instability and neighborhood deprivation on test scores, we fit generalized linear models of 4.th grade test scores across the treatment groups that incorporated multinomial propensity score weights using the *survey* package [39]. One model was fit to compare treatment groups of children that had high NDI at baseline (e.g., *high-high-high stay*, *high-high-high move*, *high-high-low*, and *high-low-low)*. A separate model was fit to compare treatment groups of children that had low NDI at baseline (e.g., *low-low-low stay*, *low-low-low move*, *low-low–high*, and *low–high-high)*. Regression models controlled for birthweight percentile for gestational age, Medicaid participation, blood lead concentration, child sex, maternal tobacco use during pregnancy, maternal race/ethnicity, maternal age, maternal educational attainment, and maternal marital status at time of child's birth. [36, 37].

Reading and math EOG scores were modeled separately. Average treatment effects and their 95% confidence intervals (CI) are reported.

Sensitivity analysis

We conducted multiple sensitivity analyses. First, to explore potential for selection bias by conditioning selection into the study on having a blood lead test, we removed the criteria of having had a lead test and consider only moves between birth and time of 4th grade testing. Second, we examined associations between NDI, residential stability, and test scores, stratified by urbanicity (urban vs. nonurban neighborhood of residence at baseline [birth]) or race/ethnicity (Hispanic, non-Hispanic Black, and non-Hispanic White) to explore heterogeneity of effects across urbanicity and race/ethnicity. Third, we used proportion of the population in poverty, summarized at the census tract level, instead of NDI to proxy neighborhood SES. Finally, we fit models that adjusted for propensity scores and no other covariates.

This research was governed by a research protocol approved by the Institutional Review Board at the University of Chicago Illinois and Duke University.

Results

Baseline characteristics of children (i.e., prior to propensity score matching) who resided in high and low NDI census tracts at birth are summarized in SM Tables S5 and S6, respectively. Prior to implementation of propensity scores, compared to children who were residentially stable in high deprivation neighborhoods (*high-high-high stay*), children who moved between different high deprivation neighborhoods (*high-high-high move*) had, on average, lower reading scores (SM Table S5). They were also more likely to have lower birthweight percentile for gestational age; be enrolled in Medicaid; have mothers of non-Hispanic Black or Hispanic race/ethnicity; and have mothers who were younger, reported smoking during pregnancy, were unmarried at time of birth, or did not graduate from high school.

SM Table S6 summarizes observed characteristics of groups of children who resided in low NDI census tracts at baseline. Again, prior to implementation of propensity scores, compared to children who were residentially stable in low deprivation neighborhoods (*low-low-low stay*), children who moved between different low deprivation neighborhoods (*low-low-low move*) were more likely to be enrolled in Medicaid; have mothers of non-Hispanic Black or Hispanic race/ethnicity; and have mothers who were younger, were unmarried at time of birth, or did not graduate from high school.

After propensity scores were calculated, imbalance between treatment groups was assessed by calculating the ASMD between the treatment groups with respect to observed characteristics, before and after weighting (SM Tables S7 and S8). After weighting, an ASMD < 0.20 suggests that sufficient balance was achieved [33]. After weighting, there were no observed baseline characteristics with an ASMD ≥ 0.20 for children who resided in high (SM Table S7) or low NDI (SM Table S8) census tracts at baseline. Boxplots were used to compare the distribution of propensity scores across groups and determine that the overlap assumption was plausibly met [38] (SM Figures S2 and S3).

Residential instability and 4th grade test scores

Average treatment effects of residential instability for children who resided in high and low NDI neighborhoods at baseline are summarized in Table 2 (full regression results are provided in SM Tables S9 and S10). First, we consider children who resided in high deprivation neighborhoods across all three time points. Those who were residentially unstable (*high-high-high move*) had

Table 2 Average treatment effects comparing children who moved between homogenous neighborhood environments to children who did not move (referent group)

	Reading scores		Math scores	
	Effect estimate (95% confidence interval)	***p*-value**	**Effect estimate (95% confidence interval)**	***p*-value**
HIGH-HIGH-HIGH MOVE vs. HIGH-HIGH-HIGH STAY (referent)	−0.285 (−0.585, 0.015)	0.063	−0.359 (−0.647, −0.071)	0.015
LOW-LOW-LOW MOVE vs. LOW-LOW-LOW STAY (referent)	0.453 (0.056, 0.850)	0.025	0.431 (0.027, 0.836)	0.037

marginally lower reading scores (−0.29 [95% CI: −0.59, 0.015)]; $p=0.063$) and lower mathematics scores (−0.36 [−0.65, −0.071]; $p=0.015$) compared to residentially stable children (*high-high-high stay*). This suggests that residential instability among children who reside in high deprivation neighborhoods only is associated with lower reading and math test scores.

Next, we consider children who resided in low deprivation neighborhoods across all three time points. Those who were residentially unstable (*low-low-low move*) had higher reading scores (0.45 [95% CI: 0.056, 0.85)]; $p=0.025$) and mathematics scores (0.43 [0.027, 0.84]; $p=0.037$) compared to residentially stable children (*low-low-low stay*). These findings suggest that residential moves among children who reside in low deprivation neighborhoods only is associated with higher reading and math test scores.

Changing neighborhood environments and 4th grade test scores

Next, we focus on children who were residentially unstable, comparing groups with different levels and timing of exposure to neighborhood deprivation (see Table 3; full regression results are provided in SM Tables S9 and S10). Those children who moved from a high deprivation neighborhood at birth and lead testing to a low deprivation neighborhood at time of EOG testing (*high-high-low-move*) had higher reading scores (0.93 [0.54, 1.33)]; $p<0.001$) and mathematics scores (0.78 [0.41, 1.16)]; $p<0.001$) compared to those who moved between multiple high deprivation neighborhoods (*high-high-high move).*

Children who moved from a high deprivation neighborhood at birth to low deprivation neighborhoods at time of lead testing and EOG testing (*high-low-low-move*) had higher reading scores (1.59 [0.90, 2.28)]; $p<0.001$) and mathematics scores (1.51 [0.84, 2.19)]; $p<0.001$) compared to those who moved between multiple high deprivation neighborhoods (*high-high-high-move).*

These comparisons suggest that, among children who reside in high deprivation neighborhoods at time of birth, those who subsequently move to a low deprivation neighborhood have higher test scores compared to their counterparts who move only between neighborhoods that measure high in deprivation. Coefficients also suggest that moving to a lower deprivation neighborhood earlier (e.g., at time of lead testing versus time of end of grade testing) may confer a greater benefit in terms of test scores.

Compared to children who moved between multiple low deprivation neighborhoods (*low-low-low move)*, children who moved from low deprivation neighborhoods at birth and lead testing to a high deprivation neighborhood at time of EOG testing (*low-low–high*) had lower reading scores (−0.77 [−1.16, −0.38)]; $p<0.001$) and mathematics scores (−0.68 [−1.08, −0.28)]; $p<0.001$) (Table 3).

Table 3 Average treatment effects comparing children who moved between more heterogeneous neighborhood environments to children who moved between more homogeneous neighborhood environments (referent group)

	Reading scores		Math scores	
	Effect estimate (95% confidence interval)	***p*-value**	**Effect estimate (95% confidence interval)**	***p*-value**
HIGH HIGH LOW vs. HIGH HIGH HIGH MOVE (referent)	0.932 (0.536, 1.328)	< 0.001	0.782 (0.405, 1.159)	< 0.001
HIGH LOW LOW vs. HIGH HIGH HIGH MOVE (referent)	1.592 (0.901, 2.283)	< 0.001	1.513 (0.835, 2.191)	< 0.001
LOW LOW HIGH vs. LOW LOW LOW MOVE (referent)	−0.768 (−1.162, −0.375)	< 0.001	- 0.681 (−1.083, −0.279)	< 0.001
LOW HIGH HIGH vs. LOW LOW LOW MOVE (referent)	−0.616 (−1.243, 0.010)	0.054	−0.722 (−1.339, −0.105)	0.022

Finally, children who moved from a low deprivation neighborhood at birth to high deprivation neighborhood(s) at time of lead testing and EOG testing (*low–high-high*) had marginally lower reading scores (−0.62 [−1.24, 0.010)]; $p = 0.054$) and lower mathematics scores (−0.72 [−1.34, −0.11); $p = 0.022$]) compared to children who moved between multiple low deprivation neighborhood (*low-low-low move*). These comparisons suggest that, among children who reside in low deprivation neighborhoods at time of birth, those who subsequently move to a high deprivation neighborhood have lower test scores compared to their counterparts who move between neighborhoods that are low in deprivation. These results all suggest that moving from a low deprivation neighborhood to a high deprivation neighborhood – whether earlier or later – negatively affects reading and mathematics test scores.

Sensitivity analysis

We conducted multiple sensitivity analyses. First, to explore potential for selection bias by conditioning selection into the study on having had a blood lead test, we removed the criteria of having had a lead test. Thus, we only utilize residential information at birth and time of 4th grade testing. Children who moved between high deprivation neighborhoods between birth and 4th grade had lower reading test scores than children who were residentially stable in high deprivation neighborhoods, but the difference was not statistically significant (SM Table S11). Children who moved between low deprivation neighborhoods between birth and 4th grade had higher reading test scores than children who were residentially stable in low deprivation neighborhoods, but again the difference was not statistically significant. Children who moved from a high deprivation neighborhood at birth to a low deprivation neighborhood at time of EOG testing (*high-low-move*) had higher reading scores (1.25 [0.93, 1.56]; $p < 0.001$) compared to those who moved between high deprivation neighborhoods (*high-high-move)* (SM Table S12). Children who moved from a low deprivation neighborhood at birth to a high deprivation neighborhood at time of EOG testing (*low–high-move*) had lower reading scores (−0.96 [−1.25, −0.67]; $p < 0.001$) compared to those who moved between only low deprivation neighborhoods (*low-low-move).*

For brevity, results of the remaining sensitivity analyses are summarized in Table 4, with detailed results for both reading and math scores provided in the SM. In our second sensitivity analysis, we used proportion of the population in poverty, summarized at the census tract level, instead of NDI to proxy neighborhood SES; results are summarized in Table 4 and SM Tables S13-S14. Third, we examined associations between NDI, residential stability, and test scores, stratified by urbanicity of census tract of residence at time of birth, classified as urban or not urban (e.g., suburban or rural), defined according to Rural–Urban Commuting Area (RUCA) codes [40, 41]. Urbanicity may change over time as the individual moves neighborhoods (or an area becomes more urban). We chose to stratify based on urbanicity at baseline in part because birth was the timepoint with the largest amount of heterogeneity in terms of urbanicity; that is, on average in the analytical dataset, children tended to move into urban rather than rural areas as they aged. Results for urban and nonurban models are provided in Table 4, SM Table 15, and SM Table 16. Fourth, we fit models that were stratified by maternal race/ethnicity (Hispanic, non-Hispanic Black, and non-Hispanic White) to explore heterogeneity of effects across racial/ethnic groups (Table 4; SM Table S17, and SM Table 18). Finally, we re-fit the main analysis models but adjusted only for propensity scores (i.e., models did not include any additional covariates); results are reported in Table 4, SM Tables S19 and S20.

Discussion

Two comparisons were of particular interest, namely assessing the effects on test scores of residential instability and exposure to neighborhood deprivation. To assess the effect of residential instability, we compared test scores in: (i) children who stayed in the same low deprivation census tract (*low-low-low stay)* vs those who moved between different low deprivation census tracts (*low-low-low move*); and (ii) children who stayed in the same high deprivation census tract (*high-high-high stay*) vs those who moved between different high deprivation census tracts (*high-high-high move*).

To assess the combined effect of residential instability and exposure to neighborhood deprivation, we compared test scores in children who moved at different time points and to different neighborhood deprivation environments (i.e., *high-high-high move* vs *high-high-low-move; high-high-high-move* vs *high-low-low-move; low-low-low-move* vs *low-low–high-move*; and *low-low-low-move* vs *low–high-high-move*).

Our results with respect to the impact of residential instability and combined residential instability with neighborhood deprivation are visually summarized in Fig. 1. With respect to residential instability, children who moved between high deprivation neighborhoods had lower reading and mathematics test scores compared to children who resided in high deprivation neighborhoods but did not move. This suggests that even if children reside in high deprivation neighborhoods

Table 4 Summary of sensitivity analysis results

Comparison	Reading								Math							
	Main[b]	**Poverty[c]**	**Urban[d]**	**Nonurban[d]**	**Non-Hispanic Black[f]**	**Hispanic[f]**	**Non-Hispanic White[f]**	**No covariates[e]**	**Main**	**Poverty**	**Urban**	**Nonurban**	**Non-Hispanic Black**	**Hispanic**	**Non-Hispanic White**	**No covariates**
(A) **Average treatment effects comparing children who moved between homogenous neighborhood environments to children who did not move (referent group)**[a]																
HIGH-HIGH-HIGH MOVE vs HIGH-HIGH-HIGH STAY (referent)	–	–	–	–	–	+	–	–	–	–	+	–	–	+	–	–
LOW-LOW-LOW MOVE vs LOW-LOW-LOW STAY (referent)	**+**	+	**+**	–	+	+	+	+	**+**	+	**+**	–	+	+	+	+
(B) **Average treatment effects comparing children who moved between more heterogeneous neighborhood environments to children who moved between more homogeneous neighborhood environments (referent group)**																
Comparison	**Reading**								**Math**							
	Main	Poverty	Urban	Nonurban	Non-Hispanic Black	Hispanic	Non-Hispanic White	No covariates	Main	Poverty	Urban	Nonurban	Non-Hispanic Black	Hispanic	Non-Hispanic White	No covariates
HIGH HIGH LOW vs. HIGH HIGH HIGH MOVE (referent)	**+**	**+**	**+**	**+**	**+**	–	**+**	**+**	**+**	**+**	**+**	+	**+**	–	**+**	**+**
HIGH LOW LOW vs. HIGH HIGH HIGH MOVE (referent)	**+**	**+**	**+**	**+**	**+**	+	**+**	**+**	**+**	**+**	**+**	+	**+**	+	**+**	**+**
LOW LOW HIGH vs. LOW LOW LOW MOVE (referent)	–	–	–	–	–	–	–	–	–	–	–	+	–	–	–	–
LOW HIGH HIGH vs. LOW LOW LOW MOVE (referent)	–	–	–	–	–	–	–	–	–	–	–	+	–	–	–	–

[a] (**+**) indicates positive statistically significant effect on test scores; (+) indicates positive non-significant effect on test scores; (–) indicates negative statistically significant effect on test scores; (–) indicates negative non-significant effect on test scores ($\alpha < 0.05$ for all)

[b] Associations estimated in main models presented in Tables 2 and 3

[c] Associations estimated in models that used proportion of the population in poverty, summarized at the census tract level, instead of NDI to proxy neighborhood socioeconomic status

[d] Associations estimated in models stratified by urbanicity of census tract at birth, classified as urban or not urban (e.g., suburban or rural)

[e] Associations estimated in models stratified by race/ethnicity (non-Hispanic Black, Hispanic, and non-Hispanic White)

[f] Associations estimated in models adjusting only for propensity scores (no additional covariates)

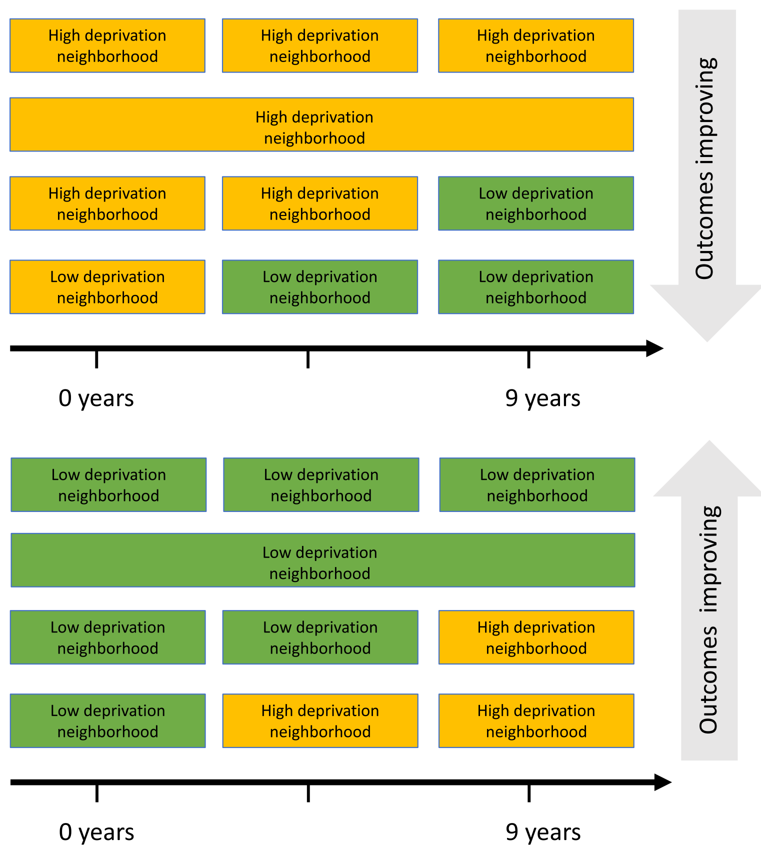

Fig. 1 Visualization of effects of residential instability patterns and exposure to neighborhood deprivation on 4th grade test scores for (top panel) individuals who reside in high deprivation neighborhoods at baseline; and (bottom panel) individuals who reside in low deprivation neighborhoods at baseline

long-term, policies that create greater residential stability may improve educational outcomes.

In contrast, children who moved between low deprivation neighborhoods had higher reading and math scores compared to children who resided in low deprivation neighborhoods but did not move. We are unable to provide a definitive explanation for this phenomenon, but posit that these residential moves are positive moves for the family (e.g., moving to a bigger house or a house with bigger yard).

All of these results, taken together, suggest that the impact of residential instability is highly context dependent. With regard to NDI exposure, among children who moved, those who moved between only low deprivation neighborhoods had higher test scores than children who moved between low and high deprivation neighborhoods. Among children who moved, those who resided in a high deprivation neighborhood at birth and subsequently moved to a low deprivation neighborhood(s) had higher reading and math test scores compared to those who moved between only high deprivation neighborhoods. Thus, exposure to low deprivation neighborhoods is associated with higher test scores, while exposure to high deprivation neighborhoods is associated with lower test scores. Moreover, findings suggest that timing or duration may matter. Namely, children who moved from high to low deprivation neighborhoods earlier in the life course (i.e., by time of lead testing) had larger improvements in test scores compared to those who moved at older ages (i.e., by time of EOG testing).

The estimated effects of residential instability and NDI on test score are consequential. The interquartile range (IQR) in reading and math EOG scores was 13 points for both. Thus, the effects range from 2.2%–12.3% of the IQR. For further perspective, maternal education is widely acknowledged to be an important predictor of academic performance [42]. In our models, the estimated effect of mothers completing high school versus not completing high school range from 16.7%–20.2% of the IQR. In addition, the effect exposure to poverty, as measured by enrollment in Medicaid, ranges from 11.1%–14.0% of the IQR.

To the best of our knowledge, this is the first, or one of the first, studies to use administrative datasets to examine residential instability and changing exposure to neighborhood deprivation simultaneously in a population level dataset. There is a large and growing literature on neighborhood socioeconomic conditions and health, developmental, and cognitive outcomes. In a sample of 772 Black/African American children aged between 6 and 12 years old at baseline in Chicago, IL, Sampson et al. (2008) found that prolonged exposure to neighborhood concentrated disadvantage was associated with lower scores on tests of verbal ability. Propensity score-based methods have also been used in observational studies assessing the impact of: kindergarten retention on social-emotional development [43]; school size on mathematics achievement [44]; and high-quality teacher–child relationships in kindergarten and math and reading achievement in first grade [45], among others [46].

This study is not without limitations. Compared to our study, many experimental, quasi-experimental, and surveys spanning multiple years have richer covariate data. We did not attempt to control for measures of school characteristics, conditions, or "quality". In addition, the children in our dataset are likely biased toward those who are at greatest risk of lead exposure given blood lead surveillance strategies and associated testing patterns employed in the absence of a universal lead screening program in North Carolina. Because the education data are limited to students tested in the North Carolina public school system, we are not able to assess the impact of either residential instability or neighborhood environment on those children enrolled in private school or home-schooled. Additionally, we did not have access to reliable/valid markers of school quality (e.g., student:teacher ratios), or individual- or household-level information regarding home ownership, which would provide important contextual information with respect to residential stability. We did not interpolate NDI values for intercensal years, which may contribute to measurement error (i.e., misclassification). We recognize that standardized test scores are imperfect and incomplete measures of an individual's aptitude, comprehension, and overall cognitive abilities; nevertheless, they represent important outcomes. While our findings may be biased due to unmeasured confounders, we attempted to mitigate potential bias by using propensity scores and controlling for maternal- and child-level covariates.

Despite limitations, this study has important strengths. It is one of the first studies of its kind: an observational study that links and leverages existing administrative datasets to better understand how residential context and residential instability over early years in an individual's life course relate to standardized test scores. While we may lack richness in covariate data, our approach allows for a large and diverse sample size and includes children from communities across the State of North Carolina, including those in urban, suburban, and rural communities. While not a perfect indicator of cognitive impacts, decrements in EOG scores can have significant consequences. Performance on EOG tests is used to inform decisions about children's educational progress and access to augmented resources. Among children on the low end of the test score distribution, one or two points may mean missing the cut-off for progression to the next grade. For those at the high end of the test score distribution, one or two points may restrict eligibility for advanced and intellectually gifted programs, which rely heavily on test scores to identify students. Additionally, we included multiple sensitivity analyses which led to findings that were generally consistent with the main analysis results.

Conclusion

Our findings have important policy implications. In the US, neighborhoods are increasingly segregated by socioeconomic status, and housing affordability hit an all-time low in 2023 [47, 48]. The housing affordability crisis particularly affects first time homeowners and low-income families, who face challenges finding safe, affordable, stable housing [49]. The housing affordability crisis, combined with high levels of inflation and soaring childcare costs (even outpacing inflation) over the last several years has further eroded residential stability for low-income families with children, placing more children at risk for residential instability and even homelessness [50]. A 2023 report on early childhood housing instability in North Carolina specifically recommended policies that: improve shelters' and housing support programs' abilities to serve families with children and children; increase participation of residentially unstable children in early care and education services; and enhance coordination between housing and early care and education services [51]. The reality that low socioeconomic status students tend to have lower test scores combined with the findings of our analysis – namely, that residentially unstable students who move among the highest deprivation neighborhoods have the lowest test scores – underscore the importance of policies to bolster residential stability among lower socioeconomic status families.

Increasingly, researchers, educators, policymakers and health care providers recognize the role of non-clinical factors in shaping health outcomes. Advocating for more equitable housing policy, with an emphasis on both residential stability and the quality of neighborhoods in which children and their families reside, can be an important tool for narrowing health (and educational) inequities and addressing the social correlates of health in concrete ways.

Abbreviations

ASMD Absolute standardized mean differences
DBR Detailed birth records
EOG End of grade
IQR Interquartile range
NC North Carolina
NDI Neighborhood deprivation index

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12889-024-20846-6.

Supplementary Material 1.

Acknowledgements

We thank Claire Osgood for data management expertise and support.

Data sharing plan

Access to the detailed birth records, lead vital statistics data, and educational test score data described in this research are governed by data use agreements and protocols reviewed and approved by the Institutional Review Board (IRB) at the University of Chicago Illinois. The measure of neighborhood deprivation is constructed from publicly available census data are available upon request from the corresponding author. Code to replicate results reported is available upon request from the corresponding author.

Disclaimer

The findings and conclusions in this publication are those of the author(s) and do not necessarily represent the views of the North Carolina Department of Health and Human Services, Division of Public Health.

clinical trial details

Not applicable.

Other

Research reported in this publication was supported by the National Institute on Minority Health and Health Disparities of the National Institutes of Health under Award Numbers R00MD011304 (PI: Bravo) and the National Institute of Environmental Health Sciences under Award Number R01ES028819 (PI: Miranda). The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health. The findings and conclusions in this publication are those of the author(s) and do not necessarily represent the views of the North Carolina Department of Health and Human Services, Division of Public Health, the North Carolina Department of Public Instruction, or the North Carolina Department of Vital Statistics.
Access to the detailed birth records, lead vital statistics data, and educational test score data described in this research are governed by data use agreements and protocols reviewed and approved by the Institutional Review Board (IRB) at the University of Notre Dame. The measure of neighborhood deprivation is constructed from publicly available census data are available upon request. Code to replicate results reported is available upon request.

Authors' contributions

Conceptualization, MAB, MLM; methodology, MAB, DZ; formal analysis, DZ, MAB; writing—original draft preparation, MAB; writing—review and editing, MLM, DZ; visualization, MLM, MAB; funding acquisition, MAB, MLM. All authors have read and agreed to the published version of the manuscript.

Funding

Research reported in this publication was supported by the National Institute on Minority Health and Health Disparities of the National Institutes of Health under Award Numbers R00MD011304 (PI: Bravo) and the National Institute of Environmental Health Sciences under Award Number R01ES028819 (PI: Miranda). The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

Data availability

Access to the detailed birth records, lead vital statistics data, and educational test score data described in this research are governed by data use agreements and protocols reviewed and approved by the Institutional Review Board (IRB) at the University of Chicago Illinois. The measure of neighborhood deprivation is constructed from publicly available census data are available upon request from the corresponding author. Code to replicate results reported is available upon request from the corresponding author.

Declarations

Ethics approval and consent to participate

Not applicable.

Competing interests

The authors declare no competing interests.

Author details

[1]Global Health Institute, Duke University, Durham, NC, USA. [2]Children's Environmental Health Initiative, University of Illinois Chicago, Chicago, IL, USA. [3]Department of Pediatrics, University of Illinois Chicago, Chicago, IL, USA.

Received: 25 April 2024 Accepted: 22 November 2024
Published online: 30 November 2024

References

1. Shonkoff JP, Phillips D. From neurons to neighborhoods: the science of early childhood development. Washington, DC: National Academies Press; 2000.
2. Heckman JJ. Skill formation and the economics of investing in disadvantaged children. Science. 2006;312:1900–2.
3. Sampson RJ, Sharkey P, Raudenbush SW. Durable effects of concentrated disadvantage on verbal ability among African-American children. Proc Natl Acad Sci U S A. 2008;105(3):845–52.
4. Kirby JB, Kaneda T. Access to health care: does neighborhood residential instability matter? J Health Soc Behav. 2006;47(2):142–55.
5. Busacker A, Kasehagen L. Association of residential mobility with child health: an analysis of the 2007 National Survey of Children's Health. Matern Child Health J. 2012;16(1):78–87.
6. Acosta S. Stable housing is foundational to children's well-Being. In: Center on budget and policy priorities: off the charts. 2022. https://www.cbpp.org/blog/stable-housing-is-foundational-to-childrens-well-being.
7. Hicks AL, et al. Sequential neighborhood effects: the effect of long-term exposure to concentrated disadvantage on children's reading and math test scores. Demography. 2018;55(1):1–31.
8. Klebanov PK, et al. The contribution of neighborhood and family income to developmental test scores over the first three years of life. Child Dev. 1998;69(5):1420–36.
9. Kling JR, Liebman JB, Katz LF. Experimental analysis of neighborhood effects. Econometrica. 2007;75(1):83–119.
10. Furstenberg FFJ, et al. Managing to make it: urban families and adolescent success. Chicago: University of Chicago Press; 1999.
11. Ogbu JU. Beyond language: ebonics, proper english, and identity in a Black-American speech community. Am Educ Res J. 1999;36(2):147–84.
12. Griffin P, MS Burns, CE Snow. Preventing reading difficulties in young children. 1998.
13. Klinenberg E. Heat Wave: A Social Autopsy of Disaster in Chicago. (2nd ed.) University of Chicago Press; 2015.
14. Ball-Rokeach SJ, Kim Y-C, Matei S. Storytelling neighborhood: paths to belonging in diverse urban environments. Commun Res. 2001;28(4):392–428.
15. Kim Y-C, Ball-Rokeach SJ. Civic engagement from a communication infrastructure perspective. Commun Theory. 2006;16(2):173–97.
16. Sanbonmatsu L, et al. Neighborhoods and academic achievement: results from the moving to opportunity experiment. J Hum Resour. 2006;41(4):649–91.

17. Chetty R, Hendren N, Katz LF. The effects of exposure to better neighborhoods on children: new evidence from the moving to opportunity experiment. Am Econ Rev. 2016;106(4):855–902.
18. Piontak JR, Schulman MD. School context matters: the impacts of concentrated poverty and racial segregation on childhood obesity. J Sch Health. 2016;86(12):864–72.
19. Skinner AC, Slifkin RT. Rural/urban differences in barriers to and burden of care for children with special health care needs. J Rural Health. 2007;23(2):150–7.
20. Nichol G, Hunt H. The persistent and pervasive challenge of child poverty and hunger in North Carolina, N.C.P.R. Fund, Editor. Chapel Hill: University of North Carolina; 2021. https://law.unc.edu/wp-content/uploads/2021/12/NC-child-poverty_final-web.pdf.
21. Goldhaber D, Wolff M, Daly T. Assessing the accuracy of elementary school test scores as predictors of students' high school outcomes. CALDER Working Paper 2021. No. 235–0821–2. https://files.eric.ed.gov/fulltext/ED605735.pdf.
22. Case A, AAO Deaton. Life expectancy in adulthood is falling for those without a BA degree, but as educational gaps have widened, racial gaps have narrowed. LID. e2024777118. (1091-6490 (Electronic)).https://doi.org/10.1073/pnas.2024777118LID.
23. Buescher PA. Smoking in pregnancy in North Carolina. Maternal characteristics and trends, 1988–1994. N C Med J. 1997;58(5):356–60.
24. Buescher PA, et al. The quality of the new birth certificate data: a validation study in North Carolina. Am J Public Health. 1993;83(8):1163–5.
25. Centers for Disease Control and Prevention. Screening young children for lead poisoning: guidance for state and local public health officials. Atlanta: CDC; 1997.
26. North Carolina Public Schools Accountability Services Division. The North Carolina testing program 2006–2007. Raleigh: North Carolina Department of Public Instruction; 2006.
27. North Carolina Public Schools. Understanding North Carolina end-of-grade testing. In: Assessment brief. Raleigh: North Carolina Division of Public Instruction; 2004.
28. Messer LC, et al. The development of a standardized neighborhood deprivation index. J Urban Health. 2006;83(6):1041–62.
29. US Census Bureau. 2010 Census: North Carolina profile. 2010. Available from: https://www2.census.gov/geo/maps/dc10_thematic/2010_Profile/2010_Profile_Map_North_Carolina.pdf. Cited 2024 September 25.
30. US Census Bureau. 2010 Census urban and rural classification and urban area criteria. 2010. Available from: https://www.census.gov/programs-surveys/geography/guidance/geo-areas/urban-rural/2010-urban-rural.html. December 2, 2019. Cited 2021 September 14.
31. Bishaw A. Poverty: 2010 and 2011. 2012. Available from: https://www2.census.gov/library/publications/2012/acs/acsbr11-01.pdf. Cited 2024 September 25.
32. Austin PC. An introduction to propensity score methods for reducing the effects of confounding in observational studies. Multivar Behav Res. 2011;46(3):399–424.
33. McCaffrey DF, et al. A tutorial on propensity score estimation for multiple treatments using generalized boosted models. Stat Med. 2013;32:3388–414.
34. Brookhart MA, et al. Variable selection for propensity score models. Am J Epidemiol. 2006;163(12):1149–56.
35. Brooks JM, Ohsfeldt RL. Squeezing the balloon: propensity scores and unmeasured covariate balance. Health Serv Res. 2013;48(4):1487–507.
36. Bang H, Robins J. Doubly robust estimation in missing data and causal inference models. Biometrics. 2005;61:692–972.
37. Huppler-Hullsiek K, Louis T. Propensity score modeling strategies for the causal analysis of observational data. Biostatistics. 2002;3:179–93.
38. Garrido MM, et al. Methods for constructing and assessing propensity scores. Health Serv Res. 2014;49(5):1701–20.
39. Lumley T. Survey: analysis of complex survey samples. R package version 4.0, 2020.
40. Hart LG, Larson EH, Lishner DM. Rural definitions for health policy and research. Am J Public Health. 2005;95(7):1149–55.
41. Morrill R, Cromartie J, Hart LG. Metropolitan, urban, and rural commuting areas: toward a better depiction of the U.S. settlement system. Urban Geography. 1999;20(8):727–48.
42. Harding JF, Morris PA, Hughes D. The relationship between maternal education and children's academic outcomes: a theoretical framework. J Marriage Fam. 2015;77:60–76.
43. Hong J, Yu B. Effects of kindergarten retention on children's social-emotional development: an application of propensity score methods to multivariate, multilevel data. Dev Psychol. 2008;44:407–21.
44. Wyse AE, Keesler V, Schneider B. Assessing the effects of small school size on mathematics achievement: A propensity score-matching approach. Teach Coll Rec. 2008;110:1879–900.
45. McCormick MP, et al. Teacher-child relationships and academic achievement: a multilevel propensity score model approach. J Sch Psychol. 2013;51:611–24.
46. Graham SE, Kurlaender M. Using propensity scores in educational research: general principles and practical applications. J Educ Res. 2011;104(5):340–53.
47. Fry R, P Taylor. The rise of residential segregation by income. 2012. Available from: https://www.pewsocialtrends.org/2012/08/01/the-rise-of-residential-segregation-by-income/. Cited 2019 August 22, 2019.
48. Ludden J. Most homes for sale in 2023 were not affordable for a typical U.S. household. United States: National Public Radio (NPR); 2023. https://www.npr.org/2023/12/24/1221480443/most-homes-for-sale-in-2023-were-not-affordable-for-a-typical-u-s-household.
49. Aurand A, et al. Out of reach: the high cost of housing. In: National low income housing coalition. Washington, DC: National Low Income Housing Coalition; 2021.
50. Valle-Gutierrez L. Kashen J. As federal funds expire, child care prices are soaring. Commentary: care economy 2023.
51. Stilwell L, et al. Early childhood housing instability and homelessness in North Carolina: landscape and recommendations to address unmet needs. Durham: Margolis Center for Health Policy at Duke University; 2023. https://healthpolicy.duke.edu/publications/early-childhood-housing-instability-and-homelessness-north-carolina.

Publisher's Note