SSM - Population Health 25 (2024) 101553

Contents lists available at ScienceDirect

SSM - Population Health

journal homepage: www.elsevier.com/locate/ssmph

Unveiling early childhood health inequities by age five through the national neighborhood equity index and the early development instrument

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ARTICLE INFO

Keywords:
Early childhood
Health inequities
National neighborhood equity index
Early development instrument

ABSTRACT

There is growing public urgency to close equity gaps in health and development by addressing inequities at multiple levels of children's developmental ecosystems. Current measurement strategies obscure the dynamic structural and relational patterns of oppression, adversity, and disadvantage that children can experience in their local intimate developmental ecosystem, as well as the leverage points that are necessary to change them. The purpose of this study is to examine the relationship between a universally available measure of neighborhood socio-economic context, the National Neighborhood Equity Index (NNEI), and a population measure of early child development and well-being, the Early Development Instrument (EDI). Data from a convenience sample of 144,957 kindergarteners in neighborhoods across the US demonstrate that children living in neighborhoods with more equity barriers are more likely to be on vulnerable developmental trajectories than those who reside in neighborhoods without any equity barriers. A multi-dimensional measurement approach that incorporates both the EDI and the NNEI can be used to quantify ethnoracialized patterns of structural disadvantage during critical periods of health development. These measures can inform community action to intervene early in the lifecourse to optimize children's health development trajectories at a population level.

1. Introduction

The concept of health equity has gained significant importance in the scientific health literature over the past few decades, reaching an inflection point in 2008 when the World Health Organization's Commission on Social Determinants of Health emphasized the need to address social determinants to achieve health equity (Marmot et al., 2008). Since then, an expanding body of research has revealed persistent and even worsening inequities in the social determinants of health (Bleich et al., 2012; Singh et al., 2017), amid growing recognition of structural factors including institutional racism, cultural racism, and racial discrimination that are contributing to health inequity gradients among different ethnoracial groups (Williams & Mohammed, 2013).

Despite the formidable challenges inherent in disentangling the influences of neighborhood level factors from wider societal patterns of inequity (e.g., wealth inheritance, racial discrimination in employment, access to loans and mortgages, pollution exposure, etc.), it is imperative to understand the relationships between neighborhood disadvantage and health inequalities (Oakes et al., 2015). A recent systematic review of the literature on associations between racial segregation and health disparities revealed a lack of neighborhood-level studies, particularly those that explore different ways of measuring and investigating patterns of segregation, and the underrepresentation of minority groups such as Hispanic and Asian populations (Yang et al., 2020).

At the same time, significant advances in the field of lifecourse health have emphasized the importance of health development in the early years for lifelong well-being. Health development is now understood as an active, dynamic process that starts before conception and is

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https://doi.org/10.1016/j.ssmph.2023.101553
Received 29 April 2023; Received in revised form 27 October 2023; Accepted 29 October 2023
Available online 14 November 2023
2352-8273/

influenced across the lifespan by factors at child, family, neighborhood and community levels of the child's developmental ecosystem (Halfon et al., 2014). Early experiences and exposures can "get under the skin" and embed their impacts in biological processes, behaviors, and life-course patterns of health development (Boyce & Hertzman, 2018; Halfon et al., 2020; Williams & Collins, 2001; Williams & Mohammed, 2013). Understanding all the potential factors that contribute to the early childhood origins of health disparities is essential to address the full impact of social determinants of health across the life course.

Neighborhood characteristics are increasingly understood to have potential for direct and indirect impacts on the health development of children, especially in the sensitive first five years of life (Chetty et al., 2016; Chyn & Katz, 2021). However, there is a lack of reliable and easy-to-use place-based measures of inequalities linked to information on how young children in different neighborhoods are faring. The lack of knowledge of these relationships leads to a situation whereby local communities do not have the data they need to make sense of what is going on and to effect change (Oakes et al., 2015). In this study we address this gap in the literature by using the Early Development Instrument (EDI), a validated population-level measure of five dimensions of early child development at kindergarten entry (Brinkman et al., 2013, 2014; Duncan et al., 2020; Janus, 2007; Woolfson et al., 2013). Additionally, we employ the National Neighborhood Equity Index (NNEI), a novel measurement of neighborhood socio-economic context adapted from the work of Charles Bruner (Bruner, 2017) based on US Census data, and available for every census tract in the nation. We report on the relationships between these two measures, the patterns of early childhood developmental vulnerability that are revealed across neighborhoods, and consider the possible factors underlying these differences. Further, we explore the potential for this linked measurement strategy to engage and empower local communities to work as partners with researchers and local stakeholders in collective sense-making and community transformation to promote child development at the neighborhood level.

Quantifying neighborhood developmental ecosystems is complex. As geographic inequalities have persisted over time, so too have their health impacts, which highlights the importance of actionable measurement strategies. In pursuit of advancing this area of research, a proliferation of indices has emerged at state, national, and global levels. The National Equity Atlas (Henderson, 2018), Opportunity Index 2.0 (Acevedo-Garcia et al., 2020), The Human Development Index (Sagar & Najam, 1998) are a few that have gained some prominence. Rather than resolving these inequities, however, these indices have revealed another fundamental shortcoming in the literature: the field is index rich, but validation poor. This is particularly true for data related to early childhood – the most sensitive period of human development.

In addition, a shortcoming of many existing indices is their inability to identify modifiable, community-level factors. This limitation stems from three prominent challenges that remain unresolved. The first is that many of these measures are constructed using data that are available only at larger geographic scales (e.g., city, county, or even state). These larger geographies can be particularly susceptible to the Modifiable Areal Unit Problem (MAUP), where both the shape and scale of the geographic unit of analysis influences the aggregated results. This issue can introduce statistical bias, potentially impacting the results of any statistical analysis conducted (Wong, 2004). Second, another notable limitation arises from the infrequency of data availability. For example, the Child Opportunity Index has only been calculated for 2010 and 2015. These measures are expensive and difficult to generate and have resulted in sporadic releases of data. This in turn makes them poor candidates to be routinely used to understand changing ecosystems and their dynamic impacts over time. Finally, some indices are not available for every neighborhood in the US. This places undercounted communities at a tremendous disadvantage in pursuing rigorous data informed, place-based prevention and early intervention efforts. The Human Development Index reports data only down to the county or the 25 most populous metropolitan areas, and the National Equity Atlas is available for only the 100 largest cities.

One potential index that resolves all three of the above challenges is the NNEI. Due to its reliance on the US Census, the NNEI benefits from being consistently available through annual releases of five-year aggregated estimates since 2015. Moreover, it covers every census tract in the US and its territories, ensuring comprehensive geographic coverage. Thus, our primary study aim is to assess the strength of the NNEI in predicting early childhood health and development and to explore how neighborhood equity is related to patterns of early childhood vulnerability.

2. Methods

2.1. Study sample

This study used data from the US EDI database that consisted of 223,252 observations of children from 11 states and Washington D.C. collected from 2015 to 2018 (See Appendix A). Since the sampling strategy for various schools or children varies across sites, we employed a series of inclusion and exclusion criteria to address the sampling variation. Special education classes, Head Start programs, private schools, observations without valid EDI data (at least 75% response on at least four out of five domains), and non-geocoded records were excluded. The final analytical sample consisted of 144,957 observations from 3686 census tracts. See Appendix B for the sample flowchart.

2.2. Measures

2.2.1. Early development instrument (EDI)

The EDI is an observational survey filled out by kindergarten teachers on all students in their classroom(s). Because the EDI is based on observational recall, it is required that a child must be in the classroom for at least three months to ensure the teacher's familiarity with each student. For this reason, EDI data is usually collected in the second half of the school year. Each EDI survey contains 103 core items and teachers typically take 10–15 min to fill it out per student. These core items produce measurements in five distinct developmental domains: Physical Health and Well-being, Social Competence, Emotional Maturity, Language and Cognitive Development, and Communication Skills and General Knowledge.

The EDI is scored based on a national normed sample collected in the US in 2009–2010. Normative cutoffs were established for each domain based on the 10th percentile in this pilot dataset. These normative cutoffs have been monitored in the subsequent years to assure that they are still representative. Using the normative cutoff values, each child is categorized as vulnerable for a particular domain if their domain score falls below the cutoff. A composite measure of overall developmental vulnerability, termed "vulnerable on one or more domains", was calculated from the domain categorizations. If a child was vulnerable in any of five developmental domains, they are counted as vulnerable in this measure.

Addresses for each child are obtained from the participating school district and geocoded using ArcGIS 10.7. A composite address locator was created from the most current US Census TIGER relationship files and a proprietary streets dataset from NAVTEQ. Unmatched addresses after the automatic geocoding process were subjected to a round of manual matching. Generally, the geocoding rate each year was greater than 98% for those records with full street addresses and zip codes. The geocoded addresses are then spatially-joined to census tracts so that the NNEI dataset can be linked.

2.2.2. National neighborhood equity index (NNEI)

The NNEI was created from the US Census American Community Survey 5-year estimates and is comprised of 11 variables across the following four dimensions: two educational indicators (percentage of population 25 and older without a high school diploma, and the percentage of the population 25 and older with a college degree); three economic indicators (percentage of households with wage income, percentage of families with children in poverty, and percentage of households with public assistance income); four social indicators (percentage of single-parent family households, percentage of limited English-speaking households, percentage of disconnected youth (ages 16–19 that are unemployed and not in school), and the percentage of children enrolled in preschool/nursery school); and finally, two wealth indicators (percentage of owner-occupied housing and percentage of households with interest, rent, or dividend income).

Data were aggregated for all 11 variables across every census tract in the US. For each variable, an equity barrier cutoff was established based on one standard deviation above or below the national census tract mean. The direction above or below the mean was determined by whether the variable was a positive or negative indicator. The number of variables categorized as an equity barrier in each census tract was summed to give a measure of inequity to each census tract. Census tracts were grouped into four categories based on their number of equity barriers: 0 of the 11 possible equity barriers = Level 0; 1–2 of the 11 possible equity barriers = Level 1 (low); 3–5 of the 11 possible equity barriers = Level 2 (medium); and 6–11 of the 11 possible equity barriers = Level 3 (high). The NNEI, represented by the census tract level score, is then assigned to each individual child's geocoded addresses. The unit of analysis in this study is at the child level (N = 144,957).

2.3. Analysis

We first examined similarities and differences between our sample and national distributions to validate the comparability of the NNEI levels across different racial and ethnic groups in our dataset. The intent of this exploratory analysis was to examine if barriers faced by ethnoracial groups using the NNEI over four years in our study (2015–2018) were consistent with national estimates. We accomplished this by comparing our sample to a national sample that examined equity barriers (using the NNEI) by ethnorace over the same time period (See Appendix C).

For the main analyses, the dependent variable of interest was vulnerability on one or more EDI domains vs no vulnerability on any domains (dichotomized). The independent variable of interest was the NNEI level (categorical) with Level 0 (no equity barriers) as the referent group. The main covariates of interest included ethnorace (categorical: Black/African American, Asian/Native Hawaiian/Other Pacific Islander, Hispanic, White, Other), sex (male/female), and whether the child has an Individualized Education Program (IEP) (yes/no).

To explore the relationship between neighborhood equity domains and their intersections with ethnorace, we conducted a series of generalized linear models in our main analysis. Specifically, we fit four models: the first included only the NNEI variable, the second controlled for sex and IEP, the third added ethnorace, and the fourth included an interaction term between ethnorace and NNEI. By including this interaction term, we aimed to examine how the association between neighborhood equity domains and early childhood development outcomes is influenced by ethnoracial context. This approach allowed us to gain a more nuanced understanding of the combined effects of neighborhood equity and ethnorace on early childhood development outcomes.

We used generalized estimating equations with a binomial distribution and a logistic link function given the outcome was dichotomous. We specified the correlation structure as exchangeable and used the census tract as the cluster variable to estimate cluster-robust standard errors. Exponentiated coefficients were displayed to facilitate interpretation. To assess the interaction between the NNEI variable and ethnorace, we used the STATA margins command to estimate the marginal effects of the predicted probabilities for the outcome of interest. These estimates were used to show the average change in the probability of being vulnerable on one or more developmental domains for each ethnorace group across the levels of the NNEI. Finally, we displayed these estimates by generating a plot to provide a clear visualization of the results.

3. Results

Exploratory analyses comparing our sample (n = 144,957) to the national sample (n = 86,830,194) showed a greater proportion of children living in higher NNEI classification neighborhoods (i.e., neighborhoods with more equity barriers) in the study sample compared to the national data. In other words our sample was in practical terms reflective of an over-sampling of less advantaged neighborhoods, resulting in greater representation in our sample of minoritized ethnoracial groups which may be regarded as a strength of this study. See Appendix C for details. Across the years studied (2015–2018), the highest proportion of white children living in neighborhoods with six or more equity challenges ranged from 1.42% to 1.72%. Comparing this to Black children, the figures ranged from 16.80% to 20.17%. Conversely, in communities with the highest level of opportunity (those with zero equity challenges) the highest (national) proportion was only 25.16% of Black children compared with 63.94%, white children who had this advantageous start in life.

Descriptive statistics for the final analytic sample are presented in Table 1, including percentages and frequencies. The NNEI levels were categorized into four levels: level 0 (n = 49,833), level 1 (n = 38,884), level 2 (n = 36,307), and level 3 (n = 19,933), accounting for 34.38%, 26.82%, 25.05%, and 13.75% of the total sample, respectively. Sex was evenly distributed in the sample, with 50.89% of children identifying as male (n = 73,770) and 49.11% as female (n = 71,187).

The majority (93.08%; n = 134,929) of children did not have an IEP, while a small proportion reported having an IEP (6.68% of the sample, n = 9677). Only a negligible percentage of children had no data on IEP status (0.24%, n = 351). The racial and ethnic composition of the sample consisted predominantly of children identified as Hispanic (56.70% of the sample, n = 82,188), followed by White (19.75% of the sample, n = 28,623), African American/Black (10.16% of the sample, n = 14,734), Asian/Native Hawaiian/Other Pacific Islander (9.15% of the sample, n = 13,257), and Other (4.25% of the sample, n = 6155).

The resulting odds ratios from the series of regression analyses that examined the relationship between the NNEI and EDI, including covariates sex, IEP, ethnorace, and the interaction term between ethnorace

Table 1
Descriptive statistics of sample (N = 144,957).

	Total % (*n*)
NNEI	
Level 0	34.38% (49,833)
Level 1	26.82% (38,884)
Level 2	25.05% (36,307)
Level 3	13.75% (19,933)
Sex	
Male	50.89% (73,770)
Female	49.11% (71,187)
IEP	
Yes	6.68% (9677)
No	93.08% (134,929)93
Not available	0.24% (351)
Ethnorace Group	
African American/Black	10.16% (14,734)
Asian/Native Hawaiian/Other Pacific Islander	9.15% (13,257)
Hispanic	56.70% (82,188)
White	19.75% (28,623)
Other	4.25% (6155)
EDI Outcome	
Low on one or more EDI domains	23.65% (34,286)
Not low on one or more EDI domains	76.35% (110,671)

Table 1 displays the descriptive statistics of the sample (144,957 observations from 3686 census tracts).

and NNEI, are displayed in Table 2. Each model was built based on the previous one to assess the contribution of additional variables. Model 1, which included only the NNEI variable, revealed a statistically significant association between NNEI level and being vulnerable on one or more EDI domains. The odds of being vulnerable on one or more EDI domains increased monotonically with each NNEI level, suggesting that the NNEI measure is predictive of early childhood development. In Model 2, we added sex and IEP as control variables. After controlling for these covariates, the odds of being vulnerable on one or more EDI domains continued to be higher with higher levels of neighborhood deprivation. Model 3 further expanded the analysis by including ethnorace as predictors. The results indicated that ethnorace was significantly associated with the EDI outcomes and the association between the NNEI and the EDI attenuated with the inclusion of race Model 4 included an interaction term between NNEI and ethnorace.

To ease the interpretation of the estimates in Model 4 we used the margins command in STATA to interpret differences in EDI outcomes by ethnorace group shown in Exhibit 1. The predicted probabilities are displayed in Appendix D. We observed substantial variation in developmental vulnerability by ethnorace groups across neighborhood equity levels. Among all ethnorace groups, Black children consistently exhibited the highest educational vulnerability, with a 26% predicted probability of being vulnerable on one or more EDI domains in neighborhoods with the lowest NNEI scores (i.e., with no equity barriers) (NNEI = 0), which increased to 33% at the highest NNEI levels (NNEI = 3), representing a difference of nearly 10 percentage points. In comparison, the predicted probability differences between the lowest and highest NNEI levels were smaller for children who identified as Asian/Native Hawaiian/Other Pacific Islander. At the lowest NNEI levels (NNEI = 0) these children had a 14% predicted probability of being vulnerable in one or more EDI domains compared with 21% at the highest NNEI level. Among Hispanic and Asian children, the predicted probability of being vulnerable in one or more EDI domains did not significantly increase at higher NNEI levels (NNEI = 2 and NNEI = 3). However, steeper differences in EDI outcomes were observed among White children, where predicted probabilities rose from 15% at the lowest NNEI level to 30% at the highest NNEI level. A similar pattern was observed among children identifying as Other, with a predicted probability of 17% at the lowest NNEI level, increasing to 29% at the highest NNEI level.

4. Discussion

This study showed that as levels of neighborhood disadvantage increased, so did the likelihood of early childhood developmental health vulnerability. The NNEI data examined across the years in this study also reveal persistent highly racialized patterns in the exposure to the number of equity barriers across ethnoracial groups. These findings are consistent with what is known about racist structures of selective advantage where extreme ethnoracial disparities exist in children's access to "opportunity neighborhoods" (Acevedo-Garcia et al., 2008). Differential exposures to equity barriers may be contributing to measurable differences in early childhood health and development, and to the early origins of later life health inequities. As such, failure to act on these levels of neighborhood disadvantage may represent a critical lost opportunity for achieving health equity.

The combined use of the EDI and the NNEI provides valuable insights into variations in developmental health across all domains of development. However, the degree to which NNEI classification correlates with the EDI results varies by ethnoracial group. These differences, along with the overall trends observed in our study, provide useful additions to the existing literature. Moreover, our study is novel in that it includes data on Hispanic and Asian children, who are often underrepresented or excluded from similar studies (Yang et al., 2020). By incorporating these ethnoracial groups, we hope to fill a critical gap in the literature and provide a more comprehensive understanding of the developmental health of children living in diverse neighborhoods. Indeed, this

Table 2
Adjusted regression results for early childhood developmental health vulnerability across NNEI levels and sociodemographic factors.

Variables	Model 1	Model 2	Model 3	Model 4
NNEI				
Level 1	1.26*** (1.20–1.31)	1.28*** (1.23–1.34)	1.21*** (1.16–1.26)	1.13** (1.00–1.27)
Level 2	1.59*** (1.52–1.67)	1.57*** (1.50–1.63)	1.35*** (1.29–1.41)	1.33*** (1.19–1.48)
Level 3	1.77*** (1.67–1.86)	1.75*** (1.67–1.84)	1.44*** (1.37–1.51)	1.42*** (1.27–1.59)
Female		0.52*** (0.50–0.53)	0.51*** (0.50–0.53)	0.52*** (0.50–0.53)
No IEP		0.91*** (0.91–0.91)	0.91*** (0.91–0.91)	0.91*** (0.91–0.91)
Asian/Native Hawaiian/Other Pacific Islander			0.47*** (0.44–0.50)	0.45*** (0.40–0.50)
Hispanic			0.74*** (0.71–0.77)	0.76*** (0.70–0.84)
White			0.54*** (0.51–0.57)	0.49*** (0.45–0.54)
Other			0.61*** (0.57–0.66)	0.54*** (0.48–0.62)
Level 0#African American/Black				1.00 (1.00–1.00)
Level 0#Asian/Native Hawaiian/Other Pacific Islander				1.00 (1.00–1.00)
Level 0#Hispanic				1.00 (1.00–1.00)
Level 0#White				1.00 (1.00–1.00)
Level 0#Other				1.00 (1.00–1.00)
Level 1#African American/Black				1.00 (1.00–1.00)
Level 1#Asian/Native Hawaiian/Other Pacific Islander				1.02 (0.87–1.20)
Level 1#Hispanic				1.03 (0.91–1.17)
Level 1#White				1.15** (1.00–1.32)
Level 1#Other				1.22** (1.00–1.48)
Level 2#African American/Black				1.00 (1.00–1.00)
Level 2#Asian/Native Hawaiian/Other Pacific Islander				1.20** (1.01–1.43)
Level 2#Hispanic				0.93 (0.83–1.05)
Level 2#White				1.41*** (1.20–1.66)
Level 2#Other				1.14 (0.92–1.42)
Level 3#African American/Black				1.00 (1.00–1.00)
Level 3#Asian/Native Hawaiian/Other Pacific Islander				1.15 (0.90–1.48)
Level 3#Hispanic				0.92 (0.82–1.04)
Level 3#White				1.76*** (1.37–2.25)
Level 3#Other				1.48*** (1.15–1.91)
Constant	0.24*** (0.23–0.25)	0.71*** (0.68–0.75)	1.14*** (1.07–1.21)	1.17*** (1.07–1.29)

(*continued on next page*)

Table 2 (*continued*)

Variables	Model 1	Model 2	Model 3	Model 4
Observations	144,957	144,957	144,957	144,957
Number of Census tracts	3686	3686	3686	3686

Table 2 shows results of three models that used generalized estimating equations with exchangeable correlation and clustering at the census tract level employing binomial distribution with logistic link function. The unit of analysis was the individual child (114,957 observations from 3686 census tracts). Outcome was dichotomous (1 = low on one or more EDI domains, 0 = not low). All coefficients are displayed as odds ratios. ***p < 0.01, **p < 0.05, *p < 0.1. For all ethnorace comparisons, African American/Black is the reference category.

measurement strategy can be used to explore opportunity segregation, which represents a human development construct with three critical dimensions: the effect of social partitioning and segregation; multi-hierarchical dynamics of social stratification; and lifecourse opportunity pathways that shape social networks, behaviors, educational opportunities, and health outcomes.

These results are consistent with other studies in that as equity barriers increase, the risk of early vulnerability also increases (Ash & Fetter, 2004; Galster, 2012; Minh et al., 2017; Quillian, 2017; Solar & Irwin, 2010). However, these findings also reveal that the impact of this social stratification varies by ethnorace. While studies suggest that children at age eight struggle with how to process their own perceptions of racism (Pachter et al., 2010), our findings raise questions of whether children as young as five may be attuned to social signals that are impacting emergent socio-affective characteristics that are critical to resilience throughout the lifecourse. This raises the important question of whether these young children could in some way be internalizing experiences of racism, setting them early in life on a pathway of "weathering," resulting from repeated cumulative everyday instances of racial stigmatization. Over time, these vulnerabilities in health development that begin in early childhood continue to compound and to diverge such that racially stigmatized populations have worse health outcomes, higher rates of disease and die at earlier ages than their more advantaged counterparts (Williams & Mohammed, 2013). Our data move beyond individual assessments and emphasize the potential population level impacts of neighborhood level inequities present and persistent in many communities. However, lived experience of neighborhood inequity is just one among several possible explanations for the associations observed in this study. Importantly, there are numerous local environmental factors (measured and unmeasured) that might also explain the observed associations. For example, early learning environments, physical/built environments, and a wide range of environmental/chemical exposures have all been found to have an impact on early childhood development (Cummins & Jackson, 2001; Rible et al., 2018; Saracho, 2023). Combinations of all of these factors may also be important.

One interpretation of these results also suggests new avenues for exploring population level patterns of resilience, allowing for explorations of the roots of resilience during this early sensitive period of human development. Previous research using the EDI in a US sample revealed greater vulnerability among children from lower-income neighborhoods, particularly for Black/African American and Hispanic/Latinx children (Halfon et al., 2020). We find more gradual increases in developmental vulnerability across NNEI classification levels for minority ethnoracial communities. This suggests the possibility of resilience patterns for these minority populations, an aspect often underrepresented in current literature.

Finally, our findings have implications for policy and practice. Understanding that children living in neighborhoods with high equity barriers are more likely to demonstrate developmental vulnerability at kindergarten entry highlights opportunities to intervene in the early years through place-based strategies designed to optimize children's developmental ecosystems and support their early developmental trajectories. Providing EDI data at the neighborhood level can be a powerful way to engage local communities in finding solutions to long standing inequalities. For example, one city has embarked on a broad

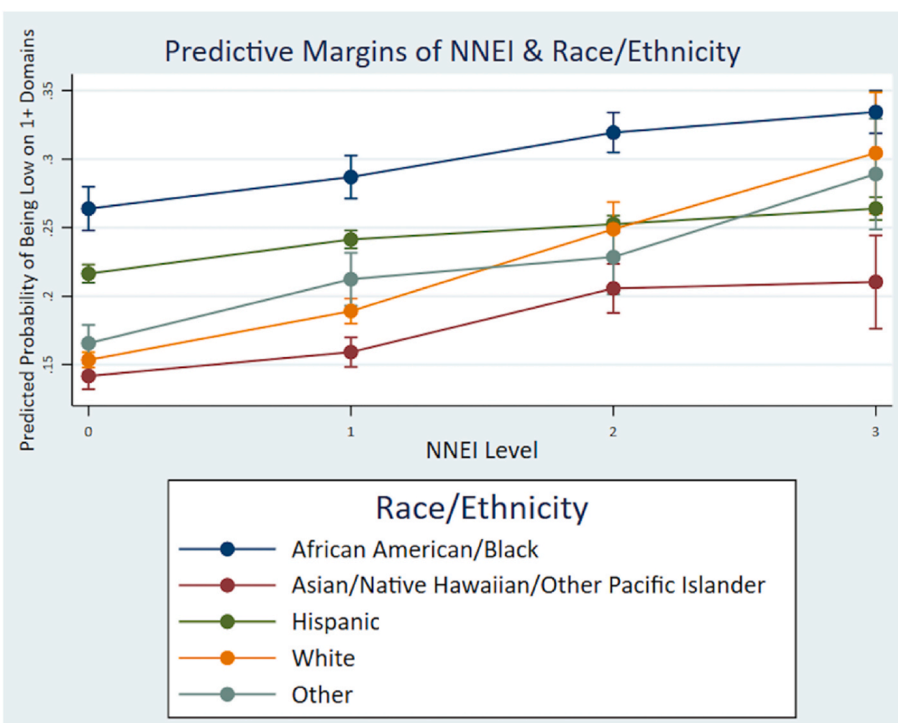


Exhibit 1. Early Childhood Developmental Health Vulnerability Across NNEI Levels, by Ethnorace Categories. Exhibit 1 displays the predicted probabilities of being low on one or more EDI domains by ethnorace categories across the NNEI levels. The individual child was the unit of analysis (144,957 observations from 3686 census tracts). 95% confidence intervals displayed for each predictive probability.

cross-sector effort, passing a resolution to become an “Early Learning City”, using EDI data to engage parents with the formation of an early childhood hub network. Ongoing EDI monitoring can be used for the following purposes: to determine whether developmental interventions are working at a population level; to examine ethnoracial patterns of inequitable developmental outcomes to evaluate whether interventions are working well for all ethnoracial groups; to assess if they are culturally resonant, working best for the groups with the most to gain. In this way, the EDI and NNEI can serve as powerful tools that are useful for local communities working to close equity gaps. Moreover, while it is well recognized that root causes of inequities often lie outside of individual and local control, these data can give residents a powerful tool to open dialogue with local, state and national governance, and advocate for change.

5. Limitations

Neighborhood-level measurements, including the NNEI, come with inherent limitations due to the broad impact of many indicators that extend beyond the boundaries of individual neighborhoods. Some factors, initially observed at the neighborhood level, are influenced by larger forces spanning multiple communities. For instance, socioeconomic complexities like wealth distribution, pollution exposure, and employment opportunities often transcend localized boundaries. In this context, neighborhoods themselves become smaller ecosystems strongly influenced by broader systemic effects. While the components within the NNEI measurement may vary across neighborhoods, the association between the NNEI and child development outcomes are not solely attributed to the concept of opportunity structure. The interconnected nature of these influences underscores the need for a comprehensive strategy that acknowledges collective challenges cutting across neighborhoods. Thus, recognizing effective community action may require operating on multiple scales, encompassing individual neighborhoods, broader geographical regions, and engaging a diverse array of stakeholders across various areas.

Additionally, a prominent limitation is that these results are based on a convenience sample. Collecting EDI data is voluntary and participating communities are interested in developing a better understanding of how well they are preparing children for school entry in the hopes to set them on positive developmental trajectories. This may be due in part to their understanding of the equity barriers their communities face. As a result, the study sample has a higher proportion of children living in neighborhoods with a higher NNEI classification than seen in national data trends (see Appendix C). The sample also has a larger representation of Hispanic children when compared to national data (Alba, 2018). Since the study sample has a higher representation of Hispanic children than seen in the national data, the racialized patterns of exposures to equity barriers results in a sample facing more equity barriers than a nationally representative sample. The data are also focused in certain states and regions that have had the resources to collect EDI data. Finally, while these data are collected across four years, the data are not analyzed taking year into account in this cross-sectional study.

6. Future research

Considering the exploratory nature of our present study, it is imperative for future research to better elucidate the underlying reasons behind the observed patterns. In our current study, we have posited that opportunity structure, racism, and resilience could potentially contribute to these trends. However, to achieve a comprehensive understanding, further research endeavors are warranted.

There is also a need for further research to develop and improve innovative quantitative methods for assessing neighborhood-level resilience. Such analyses have the potential to transform the way communities facing significant structural equity challenges view themselves and their potential for health and resilience, positioning them at the forefront of resolving larger national challenges. Additionally, these tools can aid in the adoption of data-driven practices to evaluate and advocate for the sustainability of effective population-level interventions. By studying the potential roots of early childhood health and developmental vulnerability and resilience, investigating ways to foster resilience and mitigate risks, and engaging communities at the neighborhood level in local responses, we can work together to set all children on a pathway to health and well-being across the life course.

7. Conclusion

Measuring neighborhood ecosystem factors, quantified by the NNEI, that influence early childhood health development as measured by the EDI, provides potential opportunities to identify and mitigate neighborhood risks. This study also highlights the ethnoracialized patterns of structural disadvantage, moving beyond simple descriptions of white versus black outcomes that can contribute to developmental disparities across the lifespan. Further, this approach can inform ethically responsible, community-based, anti-racist policies aimed at undoing health inequities. Ultimately, this combined measurement approach can help to engage communities to act by providing them with locally relevant, highly contextualized information. It can help make health equity a shared vision and value, increase a community’s capacity to respond to data in ways that have potential to improve outcomes, and foster multi-sector collaboration towards common population goals about early child development in their local area to promote human flourishing.

CRediT author statement

efren aguilar: Conceptualization, Methodology, Software, Formal Analysis, Investigation, Data Curation, Writing – Original Draft, Visualization. **Judith L. Perrigo:** Conceptualization, Methodology, Writing – Original Draft, Writing – Review & Editing, Supervision, Project Administration. **Nicole Pereira:** Methodology, Software, Validation, Formal Analysis, Data Curation, Writing – Original Draft, Visualization. **Joshua L. Bader:** Methodology, Software, Formal Analysis, Investigation, Data Curation, Writing – Review & Editing. **Shirley Russ:** Reviewing & Editing. **Neal Halfon:** Conceptualization, Methodology, Writing – Review & Editing, Supervision.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Ethical statement

The University of California, Los Angeles (UCLA) holds FWA number 00004642. With this FWA, UCLA assures that it will meet all requirements of Title 45, Part 46 of the Code of Federal Regulations (45 CFR 46) for all human subjects research supported by the federal government. This study, IRB#11-000393-AM-00039 **The Early Development Instrument (EDI): A Population Based Measure for Communities**, was approved by the UCLA Institutional Review Board (UCLA IRB) with the following regulatory determinations:

1. The UCLA IRB waived the requirement for signed parental permission for the research under 45 CFR 46.117(c)(2).
2. The UCLA IRB waived the requirement for signed informed consent for the teacher participants under 45 CFR 46.117(c)(2). However, the teachers should be provided with an information sheet describing the study.
3. The UCLA IRB determined that the research meets the requirements for expedited review per 45 CFR 46.110 category 7.
4. The UCLA IRB waived the requirement for parental permission under 45 CFR 46.116(d) for the parents who do not opt in or out of the EDI.

5. The UCLA IRB determined that the research meets the requirements of 45 CFR 46.404 for research involving children as subjects.

Declaration of competing interest

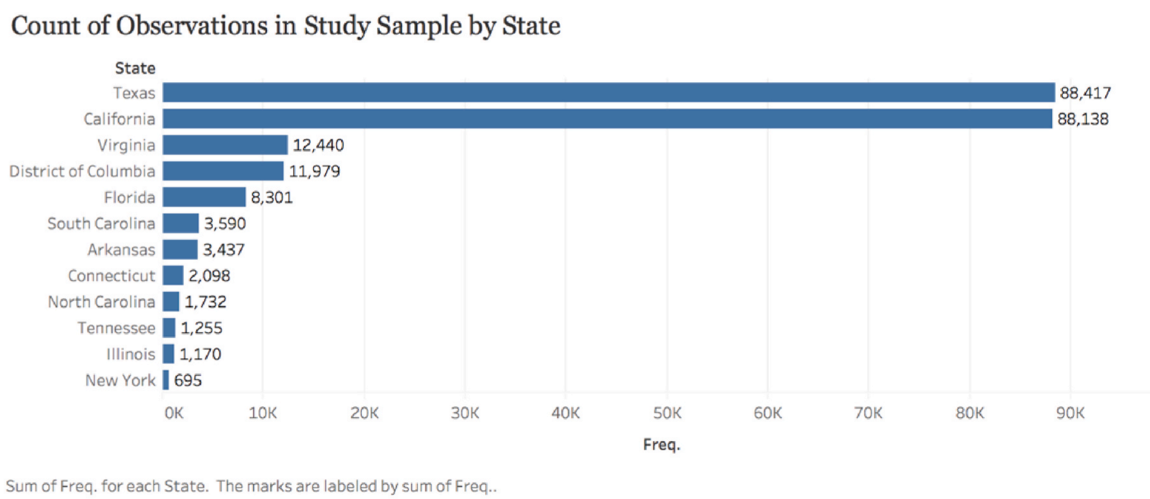
None.

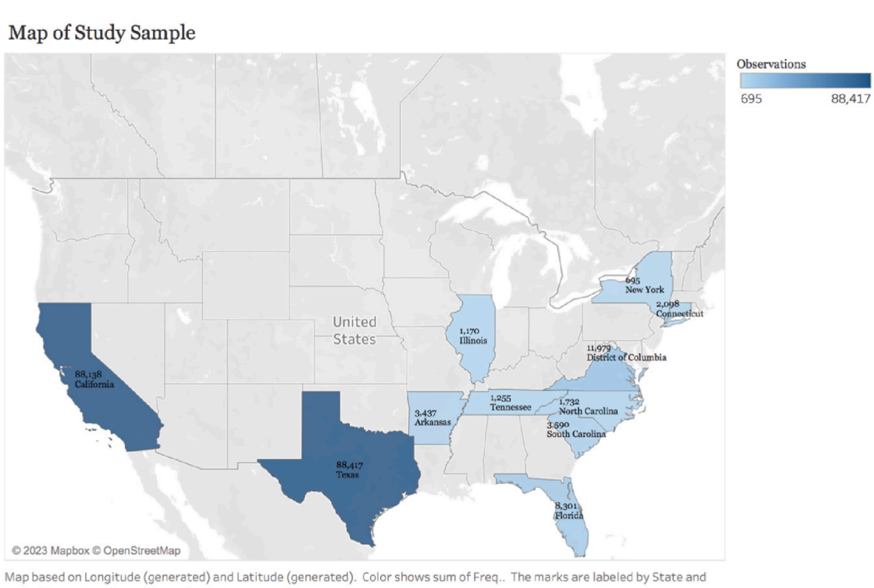
Data availability

The data that has been used is confidential.

Appendix A. Sample

State	Freq.
New York	695
Illinois	1170
Tennessee	1255
North Carolina	1732
Connecticut	2098
Arkansas	3437
South Carolina	3590
Florida	8301
District of Columbia	11,979
Virginia	12,440
California	88,138
Texas	88,417





Appendix A displays the spatial distribution of the study sample by state.

Appendix B. Sample Flowchart

Starting sample: Students =223,252 ; Census tracts= 6785

↓

Exclude Special Ed Classes: Students = 221,245; Census tracts= 6755

↓

Exclude Head Start & Private Schools: Students = 218,506; Census tracts= 6635

↓

Exclude observations with invalid records: Students = 181,809; Census tracts= 6399

↓

Exclude observations with incomplete information: Students =180,419 ; Census tracts= 6004

↓

Included observations in final regression estimation: Students =144,957 ; Census tracts= 3,686

Appendix B displays the sample flowchart.

Appendix C. National vs Sample Equity Barrier Classification by Ethnorace Over Time (2015–2018)

African American/Black								
NNEI Class	2015		2016		2017		2018	
	National	Sample	National	Sample	National	Sample	National	Sample
Zero	25.16%	13.88%	23.35%	24.21%	24.31%	28.75%	24.29%	19.99%
Low	28.22%	20.42%	26.46%	24.36%	28.45%	22.14%	29.01%	22.48%
Medium	29.63%	32.08%	30.02%	26.98%	29.91%	19.92%	29.84%	36.97%
High	16.98%	33.63%	20.17%	24.45%	17.34%	29.19%	16.86%	20.56%
Asian/Native Hawaiian/Other Pacific Islander								
NNEI Class	2015		2016		2017		2018	
	National	Sample	National	Sample	National	Sample	National	Sample
Zero	52.88%	42.14%	48.70%	36.67%	49.77%	42.42%	50.06%	39.66%
Low	31.42%	37.48%	33.52%	37.64%	33.15%	39.30%	33.30%	44.02%
Medium	12.00%	16.46%	13.29%	18.56%	13.23%	13.07%	13.05%	15.26%
High	3.70%	3.92%	4.49%	7.13%	3.84%	5.21%	3.59%	1.06%
Hispanic								
NNEI Class	2015		2016		2017		2018	
	National	Sample	National	Sample	National	Sample	National	Sample
Zero	28.81%	23.01%	26.56%	27.42%	27.89%	24.96%	28.53%	19.35%
Low	28.32%	29.16%	27.81%	26.68%	27.87%	20.46%	28.37%	26.26%
Medium	26.97%	33.44%	28.78%	29.44%	28.68%	34.58%	28.19%	34.66%
High	15.90%	14.39%	16.86%	16.46%	15.56%	20.00%	14.91%	19.72%
White								
NNEI Class	2015		2016		2017		2018	
	National	Sample	National	Sample	National	Sample	National	Sample

(continued on next page)

(*continued*)

White								
NNEI Class	2015		2016		2017		2018	
	National	Sample	National	Sample	National	Sample	National	Sample
Zero	63.94%	64.81%	60.82%	65.56%	62.87%	63.84%	62.95%	68.01%
Low	27.06%	26.10%	28.91%	27.01%	27.75%	26.38%	27.53%	27.18%
Medium	7.58%	7.57%	8.55%	5.92%	7.87%	8.12%	8.00%	4.09%
High	1.42%	1.52%	1.72%	1.50%	1.51%	1.66%	1.52%	0.73%
Some Other Ethnorace								
NNEI Class	2015		2016		2017		2018	
	National	Sample	National	Sample	National	Sample	National	Sample
Zero	28.81%	23.01%	26.56%	27.42%	27.89%	24.96%	28.53%	19.35%
Low	28.32%	29.16%	27.81%	26.68%	27.87%	20.46%	28.37%	26.26%
Medium	26.97%	33.44%	28.78%	29.44%	28.68%	34.58%	28.19%	34.66%
High	15.90%	14.39%	16.86%	16.46%	15.56%	20.00%	14.91%	19.72%

Appendix C displays the distribution of each ethnoracial population of children under 5 of the sample (144,957) compared with the national population (86,830,194).

Appendix D. Marginal Probabilities of Adjusted Regression Results for Early Childhood Developmental Health Vulnerability Across NNEI Levels

NNEI Race/ethnicity# Level	Estimate	Std. Error	z-value	p-value	95% CI Lower	95% CI Upper
African American/Black at NNEI = 0	0.26	0.00	32.56	0.00	0.25	0.28
Asian/Native Hawaiian/Other Pacific Islander at NNEI = 0	0.14	0.00	28.60	0.00	0.13	0.15
Hispanic at NNEI = 0	0.21	0.00	64.26	0.00	0.21	0.22
White at NNEI = 0	0.15	0.00	53.50	0.00	0.15	0.16
Other at NNEI = 0	0.17	0.01	24.23	0.00	0.15	0.18
African American/Black at NNEI = 1	0.29	0.01	35.75	0.00	0.27	0.30
Asian/Native Hawaiian/Other Pacific Islander at NNEI = 1	0.16	0.00	29.05	0.00	0.15	0.17
Hispanic at NNEI = 1	0.24	0.00	71.94	0.00	0.23	0.25
White at NNEI = 1	0.19	0.00	40.49	0.00	0.18	0.20
Other at NNEI = 1	0.21	0.01	21.65	0.00	0.20	0.23
African American/Black at NNEI = 2	0.32	0.01	43.06	0.00	0.30	0.33
Asian/Native Hawaiian/Other Pacific Islander at NNEI = 2	0.21	0.01	22.63	0.00	0.19	0.22
Hispanic at NNEI = 2	0.25	0.00	81.00	0.00	0.25	0.26
White at NNEI = 2	0.25	0.01	24.68	0.00	0.23	0.27
Other at NNEI = 2	0.23	0.01	16.53	0.00	0.20	0.26
African American/Black at NNEI = 3	0.33	0.01	42.16	0.00	0.32	0.35
Asian/Native Hawaiian/Other Pacific Islander at NNEI = 3	0.21	0.01	12.10	0.00	0.18	0.24
Hispanic at NNEI = 3	0.26	0.00	62.49	0.00	0.26	0.27
White at NNEI = 3	0.30	0.02	13.46	0.00	0.26	0.35
3#Other	0.29	0.02	14.02	0.00	0.25	0.33

Appendix D displays the results from the margins command in STATA and displays the adjusted predictions at NNEI level for each ethnorace group controlling for sex, IEP status.

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