9-13-2018

Neighborhood and Social Environmental Influences on Child Chronic Disease Prevalence

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Recommended Citation

Kranjac, A. W., Denney, J. T., Kimbro, R. T., Moffett, B. S., & Lopez, K. N. (2018). Neighborhood and social environmental influences on child chronic disease prevalence. *Population and Environment*. doi: 10.1007/s11111-018-0303-9

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Comments
This is a pre-copy-editing, author-produced PDF of an article accepted for publication in *Population and Environment* in 2018 following peer review. The final publication is available at Springer via DOI:10.1007/s11111-018-0303-9.

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ABSTRACT

We investigate how distinct residential environments uniquely influence chronic child disease. Aggregating over 200,000 pediatric geocoded medical records to the census tract of residence and linking them to neighborhood-level measures, we use multiple data analysis techniques to assess how heterogeneous exposures of social and environmental neighborhood conditions influence an index of child chronic disease (CCD) prevalence for the neighborhood. We find there is a graded relationship between degree of overall neighborhood disadvantage and children's chronic disease such that the highest neighborhood CCD scores reside in communities with the highest concentrated disadvantage. Finally, results show that higher levels of neighborhood concentrated disadvantage and air pollution exposure associate with higher risks of having at least one chronic condition for children after also considering their individual- and family-level characteristics. Overall, our analysis serves as a comprehensive start for future researchers interested in assessing which neighborhood factors matter most for child chronic health conditions.

KEYWORDS

Child Chronic Disease; Concentrated Disadvantage; Pollution Exposure; Neighborhoods

INTRODUCTION

The rates of children with chronic health conditions is on the rise in the United States (Cleave, Gortmaker, & Perrin 2010; Pulcini *et al*. 2017); yet, the upward trends are not uniformly distributed across the population. Instead, low-income children suffer disproportionately from chronic illness and have higher than average comorbidities associated with their conditions (Pulcini *et al*. 2017). Despite clear evidence that chronic health conditions vary by family-level poverty status, existing studies fail to capture important contextual dimensions of residential environments that may have potentially far-reaching consequences for chronic disease prevalence in children (Freedman *et al*. 2011; Patel & Ioannidis 2014).

It is well documented that communities are stratified by dimensions of socioeconomic status (SES; e.g., poverty, educational attainment), family structure (female-headed households), residential stability (home ownership), and racial/ethnic composition (racial segregation; Sampson 2003). This means that central features of the environment are dictated by variation in social and economic conditions (Li *et al*. 2014). For example, air pollution (Pope & Dockery 2006; Crowder & Downey 2010; King 2015), population density (Brooks-Gunn *et al*. 1997; Saelens and Handy 2008), walkability (Leyden 2003; Oakes, Forsyth, & Schmitz 2007; Sundquist *et al*. 2015), and safety (Almgren *et al*. 1998; Sharkey 2010) closely follow socioeconomic lines and may ultimately lead to disparities in the prevalence of childhood chronic health conditions like diabetes, obesity, and asthma, in a particular area (Brown *et al*. 2008, 2016; Kimbro & Denney 2013; Juhn *et al*. 2005).

This is important because exposure to these environmental conditions can influence many mechanisms known to associate with complex chronic health outcomes (see Diez Roux and Mair 2010, for review). In turn, these chronic conditions may have long-term impacts (Juonala *et al*.

2011) on important factors that influence later-life social and economic outcomes, such as physiological development and academic performance (Bullard 2000; Downey 2006; Crowder & Downey 2010; Currie *et al*. 2011). A better understanding of how geographic places influence chronic condition occurrence is needed to isolate the neighborhood-level characteristics that contribute most to health disparities among children.

To this end, we geocode individual records from a network of pediatric clinics and hospitals in the Houston metropolitan area and aggregate them to the census tract level. We then link each record to neighborhood-level social and economic indicators generated using the decennial Census files and American Community Survey (ACS) data to estimate an index of child chronic disease (CCD) prevalence. We organize our analysis by first using latent profile modeling techniques (LPA) to characterize neighborhoods into areas of distinctive physical and social contexts using measures of concentrated disadvantage, air quality, crime, walkability, and population density. Second, we provide a visualization of the distribution of the CCD scores across the city of Houston by neighborhood characteristics and by the LPA neighborhood types. Third, we use spatial data analysis techniques to compare the prevalence of chronic illness among children living under different neighborhood conditions and across different LPA neighborhood types to determine how heterogeneous exposure levels of various neighborhood conditions influence children's disparate chronic health outcomes. We end with multi-level multinomial logistic regression models to examine the impact of neighborhood characteristics, above and beyond individual characteristics, on children's health.

BACKGROUND

Depending on the neighborhood feature and health condition under study, moderate to strong evidence connects various health outcomes to specific environmental exposures (Patel &

Ioannidis 2014; Oakes *et al*. 2015; Arcaya *et al*. 2016). From greater population density (Saelens & Handy 2008) and the economic environment (Brown *et al*. 2008; Grafova 2008) impacting obesity, to the proximity of intersections influencing the relative risk of asthma development (Juhn *et al*. 2005), studies indicate that the neighborhood environment may be linked to individual health outcomes. Much of this work conceptualizes a range of social indicators to explain how measures of neighborhood socioeconomic position relate to health and well-being. Among others, measures of concentrated disadvantage (Diex-Roux *et al*. 1997; Sampson, Sharkey, & Raudenbush 2008), crime rates (Sampson, Raudenbush, & Earls 1997; Foster 2008), and outdoor air pollution (Pope & Dockery 2006; Gaurnieri and Balmes 2014; Akinbami *et al*. 2010), are shown to independently associate with an equally extensive range of health conditions (see Arcaya *et al*. 2016, for review).

A wealth of data further indicate that the effects of neighborhoods reach far beyond the physical characteristics of the community (Sampson & Sharkey 2008; Diez Roux 2001; Diez Roux and Mair 2010) to influence individuals' health through aberrant physiological outcomes brought on by psychosocial stress early in the life course (Berens *et al*. 2017). Brooks-Gunn and colleagues (1993), for example, first pointed to variation in children's psychopathological stressors to explain the association between children's exposure to neighborhood disadvantage and worse developmental outcomes. Others have shown that living in areas characterized by high rates of crime and deprivation may lead to greater risk factors for poor health (Ross & Mirowsky 2001; Diex-Roux *et al*. 1997; O'Campo *et al*. 1997) through mechanisms related to stress and adaptation (Morenoff 2003). What is more, this effect begins to surface early on in childhood (Vartanian & Houser 2010) and has been shown to lead to an accumulation of risk for those who remain in impoverished contexts (Lippert 2016), impacting some well into adulthood (Winning *et al*. 2016).

It follows from this that intervening processes such as geographic isolation among the truly disadvantaged (Wilson 1987) can have potentially far-reaching consequences for chronic health outcomes later in life (Sampson 2001; see Diez Roux and Mair 2010, for review). This is, in part, due to the known association between aspects of neighborhood differentiation (e.g., concentration of poverty) and its contribution to the clustering of health-related indicators (e.g., homicide rates). What is less clear is how these same factors that lead to the spatial cluster of crime and other social problems may work to generate communities where children are at high risk for chronic disease.

In the present analysis, we go beyond prior studies by attending to past methodologic limitations (e.g., small sample size and insufficient chronic condition variation within neighborhoods; Diez Roux and Mair 2010) to clarify how air pollution exposure and neighborhood social and economic conditions uniquely influence an index of child chronic disease prevalence. We do so with data from one of the most culturally diverse cities in the United States (U.S.): Houston, TX. We use our unique data to fill gaps in the literature and estimate the impact of differential neighborhood factors on children's chronic health outcomes to explain the geographic and population patterning of child chronic disease prevalence. Given that place of residence is socially and economically patterned, we expect that differential exposure to concentrated disadvantage and pollution among children in more affluent areas, relative to those who live in more disadvantaged communities, will illuminate chronic health disparities across neighborhoods.

METHODS

Our focal data set is a compilation of electronic medical and administrative records from the largest network of pediatric clinics and hospital admissions in the country in Houston, TX. Medical records include inpatient and emergency room pediatric encounters at a large pediatric hospital as well as outpatient visits to one of 50 pediatric clinics throughout all 13 counties in the Houston metropolitan area. Children who were 2 – 12 years old in 2011 and 2012 were included. We randomly selected one child per family to eliminate household-level effects. Each child record was geocoded using street addresses and linked to the matching residential census tract.

The key outcome measure derived from the focal data set of medical records is an index of child chronic disease (CCD) prevalence that we create by aggregating the medical records in each neighborhood. We base the measure on five common chronic health conditions among children (see Torpy *et al*. 2010). Children were coded as carrying a diagnosis of Type I or Type II diabetes, malnutrition, asthma, respiratory illness (i.e., acute respiratory illness, bronchitis, wheezing), or obesity based on ICD-9 diagnostic codes. For example, those ICD-9 codes that begin with '493' or if the word "asthma" appeared in any of the first five diagnosis fields in the billing record for any visit between 2011 and 2012, that child was coded as asthmatic. Table 1 shows the number and proportion of children across each chronic health outcome and associated ICD-9 codes.

[Table 1 about here]

An important limitation in using medical records is that it is possible that children with a chronic health condition were not coded as such if they did not receive a billing code for such a diagnosis during the two-year window of our study. We assessed potential bias of selection into chronic disease outcomes by verifying that our data are consistent with hospitalization and prevalence rates provided by the Texas Department of State Health Services (Huang, Li, and Parrish 2008). Still, it is likely that some children (e.g., immigrant children or children without health insurance) are excluded from our sample. We acknowledge that billing data are not perfect, but the ability to use physician diagnoses instead of parental reports significantly reduces potential reporting bias (Gordon and Mellor 2015).

Dichotomous variables for each of the five conditions were created, with a score of 1 assigned to each condition diagnosed. Because not many children suffered from more than 2 chronic conditions at a time (n = 75), we collapsed cumulative scores ≥ 2 into one category, so that the final score for each child record ranges from 0 to 2+. We exclude census tracts with fewer than 20 children (n = 147). Then, we calculate the CCD score for all remaining census tracts by dividing the sum of all chronic index scores in the tract by the number of children in the tract. The result is a CCD score mean of 0.38 (SD = 0.13) across 986 census tracts (or neighborhoods).

Child characteristics also originate from the electronic health record data, and include age at time of visit, gender, race/ethnicity, total number of medical visits across 2011-2012, and insurance type as a proxy for SES. Electronic health records, like most data, come with strengths and weaknesses. We have a large and diverse number of patients with objectively-measured indicators such as height and weight. But the patient record is primarily intended for clinical and administrative use. As such, the variables available for analysis are often limited due to issues of privacy and security. Age is a continuous measure and represents the age of the child when he/she visited the clinic, centered on the mean for ease of interpretation. Gender is a dichotomous variable and represents whether or not the child is male, with female as the reference. Race/ethnicity is a categorical measure representing the parent-reported race/ ethnicity of the child categorized as non-Hispanic White, non-Hispanic Black, Hispanic, and Asian/other race, with non-Hispanic White as the reference. Total visits is a continuous measure indicating the number of medical visits a child made in 2011-2012. Insurance type is a categorical measure indicating the type of medical insurance held by the child at the time of the visit, and is categorized as private provider or public provider (Children's Health Insurance Program (CHIP) and Children's Medicaid), with private provider as the reference. While it is not ideal to use insurance status as a proxy for SES, publicly-provided health care coverage such as Medicaid is only available to children who meet strict income criteria, with the exception of some that suffer from limited medical conditions (Rosenbaum 2002). In addition, insurance coverage is widely used as a marker for individual-level SES with reasonable validity and reliability (Ayanian et al. 1993; Harnick et al. 1998; Shen et al. 2001; Foraker et al. 2010).

Nearly 38% of children were missing on either race/ ethnicity or insurance status. Due to the lack of comprehensive individual-level measures, multiple imputation would not be appropriate (Allison 2001). Consequently, when we conduct analyses with the individual-level data (i.e. multilevel models described below) we exclude children who are missing on race/ ethnicity or insurance type. This results in analysis on 114,535 children in the multilevel models. In supplementary analyses (not shown), we estimated models on the full sample with an indicator for whether the child was missing on race/ ethnicity or insurance type, and results were substantively similar.

The neighborhood data include social, economic, air quality, walkability, and crime indicators known to be independently associated with various health outcomes. Social and economic measures were generated using the 2010 decennial census files and 2009 – 2013 American Community Survey (ACS) data for years between census data. We use an index of concentrated disadvantage and a measure of population density as social and economic indicators of the child's neighborhood of residence. For concentrated disadvantage, we followed Sampson, Raudenbush, and Earls (1997) and used the first dimension of a principal components factor analysis on percent of adults in the census tract living below the poverty line, the percent of households receiving public assistance, the percent of adult residents who are unemployed, and the percent of female-headed households with children. We further classified concentrated disadvantage into quartiles to compare the CCD index score among children in communities with varying levels of exposure to these neighborhood conditions. For example, we compared extremely low levels of concentrated disadvantage in neighborhoods to those with moderately low, moderately high, and extremely high levels of concentrated disadvantage. We control for neighborhood population density in all models. We opted to keep this measure continuous because if we were to categorize population density into only four categories we risk masking additional correlations between population density and CCD scores (Greggo *et al*. 2005).

Historical air quality data were collected from the Texas Commission on Environmental Quality (TCEQ) Texas Air Monitoring Information System (TAMIS) (http://www17.tceq.texas.gov/tamis/) from the years 2010 – 2012. Air pollutants include $PM_{2.5}$ and O_3 exposure centering at each respective mean. We focused on these particular pollutants due to the known inequalities in exposure by social and economic factors (Bell & Ebisu 2012; Bell *et al*. 2014; Miranda *et al*. 2011; Brochu *et al*. 2011; Fann *et al*. 2011; Levy *et al*. 2007). To estimate the air quality measures, we replicated the approach of the California Communities Environmental Health Screening Tool, Version 2.0 (2014) wherein concentrations for particulate matter 2.5 micrometers or less ($PM_{2.5}$) and daily 8-hour averages of ozone (O_3) were estimated at the centroid of each census tract using ordinary kriging interpolation prediction methods

(Rodriquez and Alexeeff 2014). The quarterly mean is estimated at the geographic center of a census tract to create an annual mean that is then calculated into a three-year average to find a $PM_{2.5}$ concentration value for each census tract. The same steps are taken using daily maximum 8-hour average ozone concentrations to estimate three-year averages of ozone for each census tract. We included ozone exposure as continuous and $PM_{2.5}$ as quartiles because the measures are collinear.

Walkability measures were constructed using 2011 – 2012 data from WalkScore.com. For each address, WalkScore evaluates walking routes using a decay function to isolate whether, and the extent to which, a pedestrian can access key residential services such as grocery stores, schools, parks, and leisure spaces in a given area with minimal automobile use (Leinberger 2013). Higher scores indicate greater pedestrian accessibility. Given the limited variability in the measure, we dichotomized walkability into neighborhoods of low (WalkScore of 0 – 69) and high (WalkScore of 70 – 100) accessibility.

Crime rates were derived from 24 monthly Uniform Crime Reports (UCR) between 2011 and 2012 provided by the City of Houston police department. We followed the model by Tabarrok, Healton, and Helland (2009) and partitioned the geocoded offenses into violent (i.e murder, rape, robbery, aggravated assault) and non-violent (i.e burglary, theft, auto theft). We then calculated the violent and non-violent rates of crime for a given tract. We further dichotomized crime rates into areas of low (≤ 3.8 violent crime rate and ≤ 26.0 non-violent crime rate, per 1,000 residents) and high (> 3.8 violent crime rate and > 26.0 non-violent crime rate, per 1,000 residents) rates of crime based on the national median to isolate how the variability in crime associates with chronic disease index scores. The research was conducted in accord with prevailing ethical principles and reviewed by the Rice University and Baylor College of Medicine Institutional Review Boards.

Statistical Analyses

We sought to clarify how each neighborhood characteristic uniquely influences chronic disease distribution in children. As such, we first used maximum-likelihood spatial-autoregressive error modeling techniques (Drukker, Prucha, & Raciborski 2013; Chakraborty 2011) to determine which neighborhood indicators significantly predict CCD scores while simultaneously adjusting for spatial autocorrelation evidenced in the data. We use a first-order contiguity matrix to generate the spatial regression results and estimate parameters with Stata 15 software (StataCorp 2017). Our goal here is simply to draw attention to the predictive role of neighborhood characteristics, not to develop an inclusive causal model.

We also aim to shed light on the graded relationship between CCD scores and neighborhood type. To accomplish this, we used a maximum-likelihood latent profile analysis (LPA; Lazarsfeld and Henry 1968) to characterize neighborhoods into clusters of health related conditions based on a range of social, economic, and physical indicators commonly used to describe a child's neighborhood of residence (Jencks and Mayer 1990; Harding *et al*. 2011). We include mean levels of educational attainment, rates of unemployment, median household income levels, median year the house was built, percent foreign born, percent of homes that are vacant in the tract, racial and ethnic composition, crime, and walkability to show the graded relationship of CCD scores by LPA neighborhood types. We first estimated a 1-class model and fit successive models with an increasing number of classes. We used Bayesian information criterion (BIC), p-value-based likelihood ratio tests, entropy R^2, bootstrap p-value, and theoretically-driven evidence to select the most parsimonious model. Analyses indicated that neighborhoods are most appropriately captured by a 3-class solution, which describe the health related conditions of children's neighborhoods. We label the three categories as Disadvantaged, Average, and Advantaged based on the neighborhood characteristics described above and used in the LPA.

Finally, we test the impact of distinct residential conditions on children's relative risk of having one or more chronic health condition beyond their individual and family-level characteristics. To do so, we used multi-level multinomial logistic regression models. We performed a series of conditional models that first include the covariates of child and family sociodemographic characteristics (age, gender, race / ethnicity, total number of medical visits, and insurance type as a proxy for SES) followed by models that add the neighborhood conditions of concentrated disadvantage, air quality, population density, walkability, and crime. The models treat level-1 children as nested within level-2 neighborhoods. All models use maximum marginal likelihood estimation with adaptive multi-dimension quadrature (Bock and Aitkin 1981). This approach adjusts for problems that otherwise downwardly bias estimated standard errors including clustering within neighborhoods, different sample sizes for level-1 and level-2 units, heteroscedastic error terms, and variable numbers of cases within level-2 units (Hedeker 2003). We test the impact of distinct neighborhood conditions by including level-2 neighborhood characteristics (and a level-2 error component u_j) along with the level-1 predictors and an individual error term (e_{ij}).

RESULTS

We organize the results by first visualizing the types of neighborhoods across Houston and show, in Table 2, descriptive information for concentrated disadvantage, air quality, crime, walkability, and population density based on the categories created in the LPA. Second, we provide a visualization of the distribution of the CCD scores across the city of Houston and provide mean scores of CCD by neighborhood characteristics and by the LPA neighborhood types in Table 3. Finally, we provide the regression results for the spatial autoregressive estimation in Table 4 and the multilevel estimation in Table 5.

Figure 1 shows how the 3 neighborhood health related condition types from our LPA cluster in the Houston metropolitan area. The Advantaged neighborhoods make up most of the south and west parts of the city center, whereas Average neighborhoods make up the majority of the outlying areas and the Disadvantaged communities make up the north, east, and southern parts of the city. Table 2 displays corresponding means and standard deviations of pollution exposure and neighborhood conditions in Houston. As expected, compared to Disadvantaged, in Average and Advantaged communities, a significantly smaller proportion of neighborhoods are characterized by high levels of concentrated disadvantage (91% vs. 31% vs. 2%), high levels of $PM_{2.5}$ (54% vs. 13% vs. 12%), and densely populated areas (60 vs. 33 vs. 42 people per sq. mi). Crime rates are fairly similar across Houston communities and Disadvantaged neighborhoods are more walkable than Advantaged neighborhoods (56% vs. 71% are highly walkable), with Average communities being the least walkable. This is in line with existing work that shows that communities with higher proportions of socioeconomically disadvantaged populations are often highly accessible to pedestrians; yet, there is little open and developed space available for actual use (King and Clarke 2015).

[Figure 1 and Table 2 about here]

Figure 2 depicts CCD index scores by Census tract. The highest concentrations of high CCD scores are located on the eastern side of the city center. Located nearby is not only the Houston ship channel that expels high levels of pollution, but also many communities that fall into the Average and Advantaged categories of the neighborhood health related condition types, particularly to the North on the East side of the city.

Table 3 shows mean levels of CCD scores by neighborhood characteristics and by the health related condition types from the LPA. As concentrated disadvantage and particulate matter exposure increase, the CCD score moves from 0.28 to 0.45 and 0.32 to 0.45, respectively. For neighborhoods with the highest levels of O_3, scores of CCD are, on average, 0.41, slightly above the mean CCD score of 0.40 for neighborhoods with the lowest levels of 0_3. We categorized ozone exposure to show that mean levels of CCD are higher in more polluted neighborhoods, although the pattern is variable. For walkability, neighborhoods with the lowest levels of walkability have, on average, a score of 0.40, falling to just 0.37 with highly walkable communities. Scores of CCD increase with greater levels of crime, moving from 0.38 in low crime areas to 0.51 in the highest crime areas. Turning to the LPA generated neighborhood health related condition types, and aligning with what we already see by neighborhood indicators of concentrated disadvantaged and air quality, Disadvantaged communities have the highest CCD score (0.46) relative to Average (0.39) and Advantaged (0.28) neighborhoods.

[Figure 2 and Table 3 about here]

Table 4 displays the total change in the covariates averaged across all spatial units from our spatial autoregressive error models with neighborhood characteristics predicting CCD scores. In Models 1 – 5, we add each characteristic one at a time and adjust only for population density in these models. Across all models, the strength of the spatial parameter is highly significant and positive, ranging from 0.01 to 0.29 (all Wald test's $p \leq 0.001$). This means that positive spatial autocorrelation is present in the CCD scores and that areas with higher scores tend to be near other neighborhoods that are high on the index. Model 1 in Table 4 provides further evidence that CCD scores are positively associated with heightened levels of neighborhood concentrated disadvantage. Compared to neighborhoods with low levels of concentrated disadvantage, the CCD score averages 0.03 ($SE = 0.01$, $p \leq 0.05$) points higher in areas of low-medium disadvantage, 0.07 ($SE= 0.01$, $p \leq 0.001$) points higher in moderately, and 0.17 ($SE= 0.01$, $p \leq 0.001$) points higher in high concentrated disadvantage neighborhoods. Model 2 in Table 4 shows a similar pattern with particulate matter exposure. Greater mean levels of $PM_{2.5}$ are associated with higher average chronic index scores—0.11 units higher in low-medium and high-medium exposure areas and 0.20 higher in the most polluted communities, relative to the least polluted communities, respectively. Ozone exposure is also associated with higher average CCD scores (Model 3 in Table 4). With every 1-unit increase in O_3, CCD scores, on average across all neighborhoods, are 0.02 points higher ($SE = 0.00$, $p \leq 0.001$). Models 4 and 5 in Table 4 show that walkability and crime are not significantly associated with CCD scores.

[Table 4 about here]

In Models 6 – 9, we move toward a fully specified model. Model 6 in Table 4 indicates that concentrated disadvantage attenuates the association between PM and the CCD score but both measures are significantly associated in the same direction; in line with our expectations, higher concentrated disadvantage and PM independently associate with a higher CCD score for the neighborhood. Similarly, Model 7 in Table 4 shows that when we add $PM_{2.5}$ and O_3 in the same model, the impact of outdoor air pollution remains significant with concentrated disadvantage included in the model. Models 8 and 9 show that the adjusted associations between walkability, crime and CCD scores for the neighborhood do not reach significance and do little to impact the associations between concentrated disadvantage, $PM_{2.5}$, or ozone and neighborhood CCD scores. Finally, Model 10 in Table 4 shows the graded distribution of CCD scores by LPA generated neighborhood types. Relative to CCD scores in Advantaged communities, scores are significantly higher for those living in Average (0.09, SE = 0.01, $p \leq 0.001$) and Disadvantaged (0.19, SE = 0.02, $p \leq 0.001$) health related condition neighborhood types.

Turning to the multilevel multinomial logistic regression models, Table 5 shows results of the individual and neighborhood predictors on whether a child has 1 or 2 or more chronic health conditions, relative to having none. The random effects estimate across models indicates that the risk of chronic conditions for children does indeed vary across neighborhoods. Model 1 of Table 5 estimates the risk of having one chronic condition, relative to having zero, and includes age at visit, gender, race/ ethnicity, total number of visits, and insurance status at level-1. Model 2 of Table 5 adds the neighborhood characteristics of concentrated disadvantage, $PM_{2.5}$, O_3, population density, walkability, and crime at level-2. Model 3 of Table 5 assesses the risk of having two or more chronic conditions, relative to having zero, with individual-level characteristics included at level-1 and Model 4 of Table 5 adds the neighborhood characteristics at level-2.

Model 1 in Table 5 shows that older children, Non-Hispanic black and Hispanic children, publicly-insured children, and those who visit the doctor more frequently have greater risk of having one chronic condition, relative to having zero. Model 2 in Table 5 accounts for neighborhood and air quality features and slightly attenuates the race/ ethnic and insurance type differences in the risk of having a chronic condition, indicating that some of the heightened risk for chronic disease among Non-Hispanic blacks and Hispanics, relative to whites, and publicly-insured children, relative to privately-insured children, is due to neighborhood context. This model further shows that higher levels of concentrated disadvantage associate independently with the risk of having a chronic condition. Relative to children living in neighborhoods characterized by low levels of concentrated disadvantage, children in high disadvantaged areas have nearly one and a half times greater risk of having a chronic condition. Living in a community with higher levels of ozone exposure is also associated with a higher risk of having a chronic condition, independent of level 1 characteristics. Models 3 and 4 in Table 5 largely mirror Models 1 and 2. Model 4 suggests that after accounting for all individual- and family-level factors, children residing in a more disadvantaged community have greater risk of having two or more chronic conditions, relative to having none. Notably, Model 4 of Table 5 also shows that higher levels of $PM_{2.5}$, but not O_3, associate with significantly higher risk that a child will have two or more chronic conditions, relative to having none.

< Table 5 about here>

DISCUSSION

Empirical research and theory suggest that environmental exposures should be considered when isolating the impact of distinct neighborhood conditions on child chronic disease outcomes (Brown *et al*. 2008; Patel and Ioannidis 2014). Separating these associations, however, introduces several challenges for neighborhood researchers that exploit large survey or experimental data sets (Sampson 2008). Our unique data source, geocoded pediatric medical records from a large network of clinics in Houston, Texas, allows us to overcome past methodologic limitations and more thoroughly investigate the relevance of neighborhood factors for the most common chronic health conditions in children (Diez Roux and Mair 2010). As a study site, Houston, TX represents the racial/ ethnic demographic future of the U.S. (Lewis *et al*. 2011), and although socioeconomically and racially segregated with distributional environmental injustices (Sexton *et al*. 2006) like most major urban areas, Houston’s lack of zoning results in an eclectic mix of residents living near one another. We are able to take advantage of this heterogeneity and the large sample size to fill a substantial gap in the literature and estimate the impact of differential neighborhood factors on children's chronic health outcomes to explain the geographic and population patterning of child chronic disease prevalence.

We set out to illuminate which neighborhood conditions associate with chronic disease prevalence to better understand how places influence chronic disease patterning (see Arcaya *et al*. 2016, for review). We expected that because neighborhoods are socially and economically patterned, variation in exposure to concentrated disadvantage and pollution among children in more affluent areas, relative to those who live in more disadvantaged communities, would drive chronic health disparities across neighborhoods. To accomplish this goal we took a thorough approach in our analyses.

In line with our expectations, using individual measures and indices of neighborhood characteristics, we show for the first time that high levels of concentrated disadvantage and air pollution exposure have robust associations with neighborhood CCD scores. Neighborhood measures of crime and walkability did little to influence the CCD scores, by comparison. Further, we provide analytical strength by creating unique profiles of Houston neighborhoods using these and other neighborhood health related conditions in our Latent Profile Analysis to uncover a graded relationship between level of neighborhood health related disadvantage and prevalence of chronic health conditions in children. Communities with the highest levels of concentrated disadvantage suffer from the highest chronic health conditions among children. We provide further evidence of the importance of particular characteristics of children's neighborhoods through a multilevel analysis. Indeed, children's risk of being diagnosed with one or more chronic conditions was higher if they resided in parts of the city with more socioeconomic disadvantage and/or higher levels of particulate matter in the air, net of individual and family level characteristics.

Importantly, our analysis adds to the literature by revealing that some more advantaged neighborhoods in Houston may experience higher than expected levels of environmental risk factors. For example, in Table 2 we show that while the most Advantaged Neighborhoods are under-represented in the High PM category they are also potentially over-represented in Medium-High PM. This may be important because, at least at the neighborhood-level, living in a socioeconomically advantaged community may not completely protect against factors contributing to chronic conditions among children. In other words, though pollution may disproportionately associate with the most vulnerable populations, affluence alone may not eliminate environmental risks for child health, at least in large urban areas such as in Houston, TX.

We have provided a comprehensive description of the patterns between air pollution exposure, neighborhood social and physical conditions and chronic disease for children in a large and diverse urban area in the U.S. Despite that, this study is not without limitations. Although our patient sample is drawn from all 13 counties in the Upper Gulf Coast region, our sample is still limited to the Houston metropolitan area, reducing the generalizability of our findings to a portion of children in the Houston, TX region between the years of 2011-2012. Related to this limitation is the cross-sectional nature of our data, which attenuates our ability to make causal claims. Similarly, we follow prior work and use census tracts to represent neighborhoods (Massey *et al*. 1994). Although census tracts are by no means a perfect operationalization of residential contexts (Tienda 1991), they remain a useful spatial entity available to us in the approximation of a neighborhood (Arcaya et al. 2016; Jargowsky 1997; White 1987). In addition, air quality in Houston, like most cities, is highly heterogeneous, highlighting the need for multiple measurement techniques to quantify risks associated with pollution; however, our goal was not to precisely capture air quality risk but rather to compare general representations of neighborhood disadvantage, air quality, walkability, and crime for a broad array of risks. Further, the highly restrictive nature of our electronic health records access prevented us from incorporating and linking several different environmental data sets.

Despite these limitations, our study addresses a deficit faced by many researchers, whom generally lack access to data that explicitly link neighborhood social determinants of health to child chronic conditions. We use more than 200,000 medical records to construct an index of child chronic disease prevalence at the neighborhood-level, and link this measure to several sources of contextual data. We show that concentrated disadvantage and exposure to air pollution is associated with the prevalence of chronic health conditions in children. Our analysis of the neighborhood associations with chronic conditions in Houston serves as a substantial jumping off point for future researchers interested in parsing out which neighborhood factors matter most for chronic health conditions in children. Indeed, future analyses might incorporate techniques, such as geographically weighted regression (GWR), that illuminate the most important factors for chronic illnesses in children. Finally, the current study highlights the increasing need for collaboration between academic and medical institutions, each focused on the social determinants of child health.

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Table 1. The Total Number of Children with Each Condition used to Construct the Child Chronic Disease (CCD) Index Score

	Freq	Proportion
Respiratory Disease	50,872	0.25
Asthma	11,383	0.05
Diabetes	1,449	0.01
Malnutrition	1,832	0.01
Obesity	16,600	0.08
Total	207,500	

Source: Data are from the Authors' Compilation of Pediatric Health Records

Note: ICD-9 codes are as follows: Respiratory Disease (460.00-488.00); Asthma (493.00-493.92); Diabetes (250.00-250.93); Malnutrition (262.00); Obesity (278.00)

Table 2. Descriptive Characteristics by Neighborhood Types Created through LPA (n = 986)

		Disadvantaged		Average		Advantaged	
		Mean	SD	Mean	SD	Mean	SD
Concentrated Disadvantage							
	Low Disadvantage	0.00	0.50	0.04	0.49	0.48	0.10
	Low-Medium Disadvantage	0.01	0.31	0.22	0.49	0.34	0.43
	Medium-High Disadvantage	0.08	0.47	0.43	0.47	0.16	0.20
	High Disadvantage	0.91	0.49	0.31	0.35	0.02	0.09
$PM_{2.5}$							
	Low PM	0.02	0.45	0.28	0.48	0.28	0.40
	Low-Medium PM	0.19	0.43	0.36	0.49	0.23	0.42
	Medium-High PM	0.25	0.46	0.23	0.39	0.37	0.50
	High PM	0.54	0.50	0.13	0.33	0.12	0.39
O_3		25.02	0.79	26.30	1.17	25.73	1.08
Population Density		59.61	52.40	33.03	27.85	42.41	29.09
Walkability							
	Low Walkability	0.29	0.43	0.61	0.50	0.44	0.50
	High Walkability	0.71	0.48	0.39	0.48	0.56	0.49
Crime							
	Low Crime	0.47	0.42	0.48	0.36	0.49	0.41
	High Crime	0.53	0.43	0.52	0.35	0.51	0.43

Source: Data are from the Census, American Communtiy Survey (ACS), Texas Commission on Environmental Quality (TCEQ), Houston Crime Data, and Walkscore.com

Table 3. Mean Levels of Child Chronic Disease (CCD) Index Scores Overall and by Neighborhood Characteristics and Types (n = 986)

		Mean	SD
Overall		0.38	0.13
Concentrated Disadvantage			
	Low Disadvantage	0.28	0.11
	Low-Medium Disadvantage	0.32	0.11
	Medium-High Disadvantage	0.36	0.11
	High Disadvantage	0.45	0.12
$PM_{2.5}$			
	Low $PM_{2.5}$	0.32	0.09
	Low-Medium $PM_{2.5}$	0.39	0.13
	Medium-High $PM_{2.5}$	0.36	0.13
	High $PM_{2.5}$	0.45	0.14
O_3			
	Low O_3	0.40	0.15
	Low-Medium O_3	0.36	0.12
	Medium-High O_3	0.37	0.11
	High O_3	0.41	0.14
Walkability			
	Low Walkability	0.40	0.13
	High Walkability	0.37	0.13
Crime			
	Low Crime	0.38	0.13
	High Crime	0.51	0.17
LPA Neighborhood Types			
	Disadvantaged	0.46	0.12
	Average	0.39	0.11
	Advantaged	0.28	0.10

Source: Data are from the Census, American Communtiy Survey (ACS), Texas Commission on Environmental Quality (TCEQ), Houston Crime Data, and Walkscore.com

Table 4. Average Total Impact of Neighborhood Characteristics and Types Predicting Child Chronic Disease (CCD) Index Scores (n = 986)

	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**		**Model 6**		**Model 7**		**Model 8**		**Model 9**		**Model 10**	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE		
Intercept	0.282***	0.01	0.300***	0.01	-0.214***	0.12	0.322***	0.01	0.323***	0.01	0.288***	0.01	-0.923***	0.12	-0.880***	0.14	-0.099***	0.10	0.010***	0.01
Concentrated Disadvantage (Low Disadvantage, ref)																				
Low-Medium Disadvantage	0.030*	0.01									0.021	0.01	0.014	0.01	0.013	0.01	0.014	0.01		
Medium-High Disadvantage	0.070***	0.01									0.056***	0.01	0.049***	0.01	0.047***	0.01	0.047***	0.01		
High Disadvantage	0.173***	0.01									0.142***	0.01	0.109***	0.01	0.106***	0.01	0.105***	0.01		
$PM_{2.5}$ (Low $PM_{2.5}$, ref)																				
Low-Medium PM			0.114***	0.02							0.088***	0.01	0.047**	0.01	0.052***	0.01	0.049***	0.01		
Medium-High PM			0.111**	0.02							0.083***	0.01	0.033*	0.02	0.063***	0.02	0.056***	0.02		
High PM			0.199***	0.02							0.137***	0.01	0.131***	0.02	0.135***	0.02	0.132***	0.02		
O_3					0.024***	0.00							0.049***	0.01	0.047***	0.01	0.048***	0.01		
Walkability (High Walkability, ref)																				
Low Walkability							0.009	0.01							-0.001	0.01	-0.001	0.01		
Crime (Low Crime, ref)																				
High Crime									0.123	0.06							0.093	0.04		
LPA Neighborhood Types (Advantaged, ref)																				
Average																			0.089***	0.01
Disadvantaged																			0.189***	0.01
Spatial Autocorrelation Parameter, ρ	0.273***	0.02	0.293***	0.03	0.184***	0.03	0.150***	0.03	0.153***	0.02	0.223***	0.02	0.079***	0.02	0.091***	0.02	0.088***	0.02	0.249***	0.02

****p<.001; **p<.01; *p<.05*

Note: Neighborhood population density is included in all models.

Source: Data are from the Authors' Compilation of Pediatric Health Records, the Census, ACS, Texas Commission on Environmental Quality (TCEQ), Houston Crime Data, and Walkscore.com

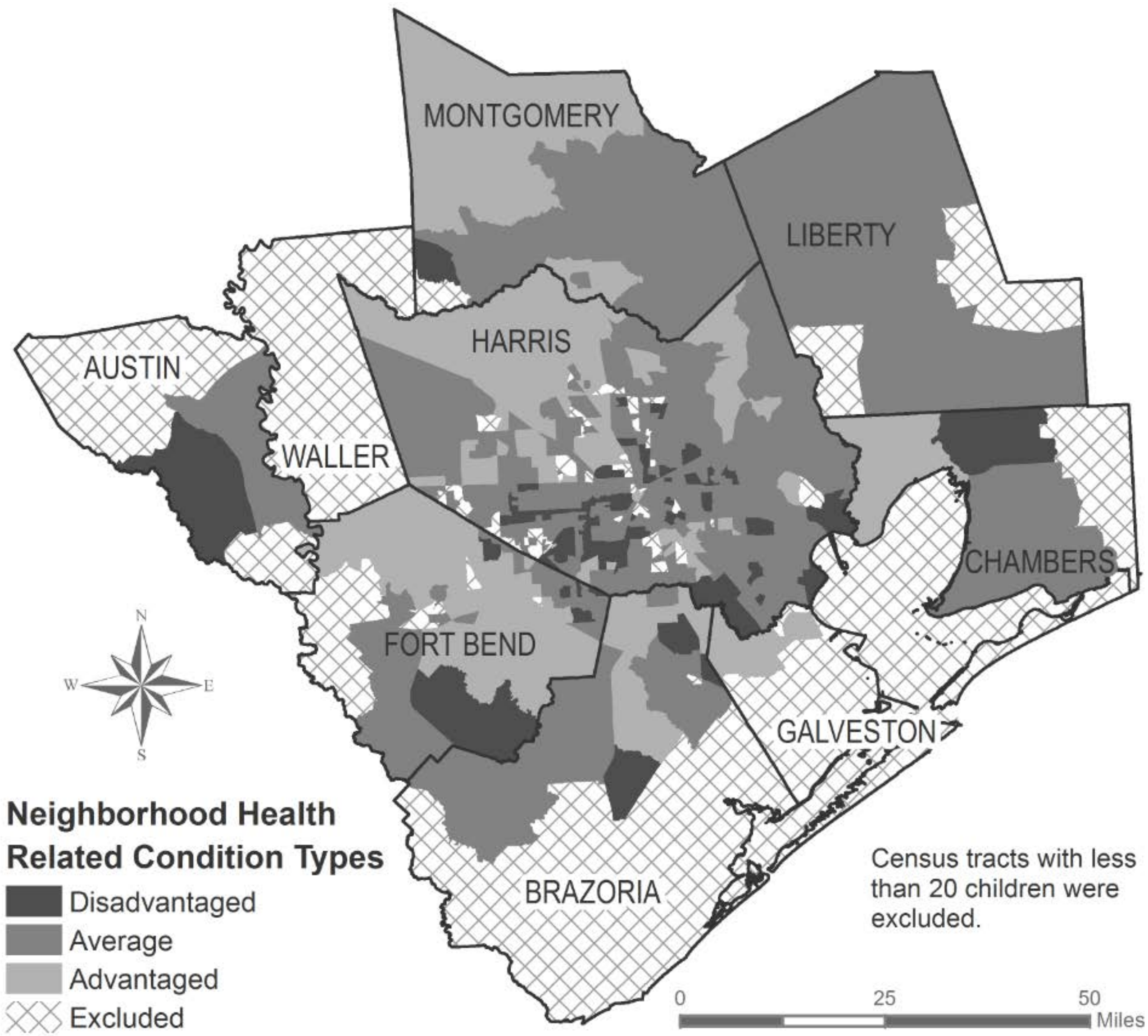
Table 5. Multi-Level Multinomial Logistic Regression Models Predicting Child Chronic Disease (CCD) Index Scores (n=114,535)

	Model 1 0 vs 1			Model 2 0 vs 1			Model 3 0 vs 2+			Model 4 0 vs 2+		
	Coefficient	SE	RRR	Coefficient	SE	RRR	Coefficient	SE	RRR	Coefficient	SE	RRR
Intercept	-3.013***	0.03	0.049***	-4.374***	0.55	0.013***	-6.658***	0.09	0.001***	-8.535***	1.44	0.013***
Demographics												
Age at visit	0.141***	0.00	1.151***	0.135***	0.00	1.144***	0.230***	0.01	1.259***	0.231***	0.01	1.260***
Gender (female, ref)												
Male	0.170***	0.02	1.185***	0.190***	0.02	1.209***	0.190**	0.06	1.209**	0.257***	0.07	1.293***
Race/ ethnicity (non-Hispanic white, ref)												
Non-Hispanic Black	0.781***	0.03	2.184***	0.681***	0.04	1.976***	1.390***	0.09	4.015***	1.098***	0.11	2.998***
Hispanic	0.597***	0.03	1.816***	0.516***	0.03	1.675***	1.079***	0.08	2.942***	0.905***	0.10	2.472***
Asian/ Other	0.005	0.05	1.005	-0.049	0.07	0.952	0.180	0.18	1.197	0.312	0.23	1.366
Child is publically insured	0.382***	0.02	1.465***	0.284***	0.03	1.328***	0.718***	0.07	2.050***	0.597***	0.08	1.817***
Total Visits	0.155***	0.00	1.168***	0.151***	0.00	1.163***	0.274***	0.01	1.315***	0.261***	0.01	1.298***
Neighborhood Characteristics												
Concentrated Disadvantage												
Low-Medium Disadvantage				0.108*	0.05	1.114*				0.312	0.17	1.366
Medium-High Disadvantage				0.284***	0.05	1.328***				0.687***	0.16	1.988***
High Disadvantage				0.384***	0.06	1.468***				1.084***	0.17	2.956***
$PM^{2.5}$												
Low-Medium PM				-0.045	0.05	0.956				-0.054	0.16	0.947
Medium-High PM				-0.051	0.05	0.950				-0.172	0.16	0.842
High PM				0.086	0.06	1.090				0.761***	0.16	2.140***
O^3				0.047*	0.02	1.048*				0.061	0.05	1.063
Population Density				-0.000	0.00	1.000				-0.000	0.00	1.000
Walkability (High Walkability, Ref)												
Low Walkability				0.018	0.08	1.018				-0.249	0.19	0.780
Crime (Low Crime, Ref)												
High Crime				0.030	0.05	1.030				0.077	0.16	1.080
Random Effects												
Tract	0.057***	0.01		0.029***	0.01		0.375***	0.05		0.130***	0.04	
Model Fit												
-2LL	-39710.79			-6206.07			-24063.16			-4030.78		
ICC	0.017			0.009			0.102			0.038		

*p < 0.05; **p < 0.01; ***p < 0.001; RRR= Relative Risk Ratio

Source: Data are from the Authors' Compilation of Pediatric Health Records, the Census, American Community Survey (ACS), Texas Commission of Environmental Quality (TCEQ), Houston Crime Data, and Walkscore.com.

Figure 1: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LIBERTY
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Neighborhood Health
Related Condition Types
Disadvantaged
Average
Advantaged
Excluded
Census tracts with less
than 20 children were
excluded.
0
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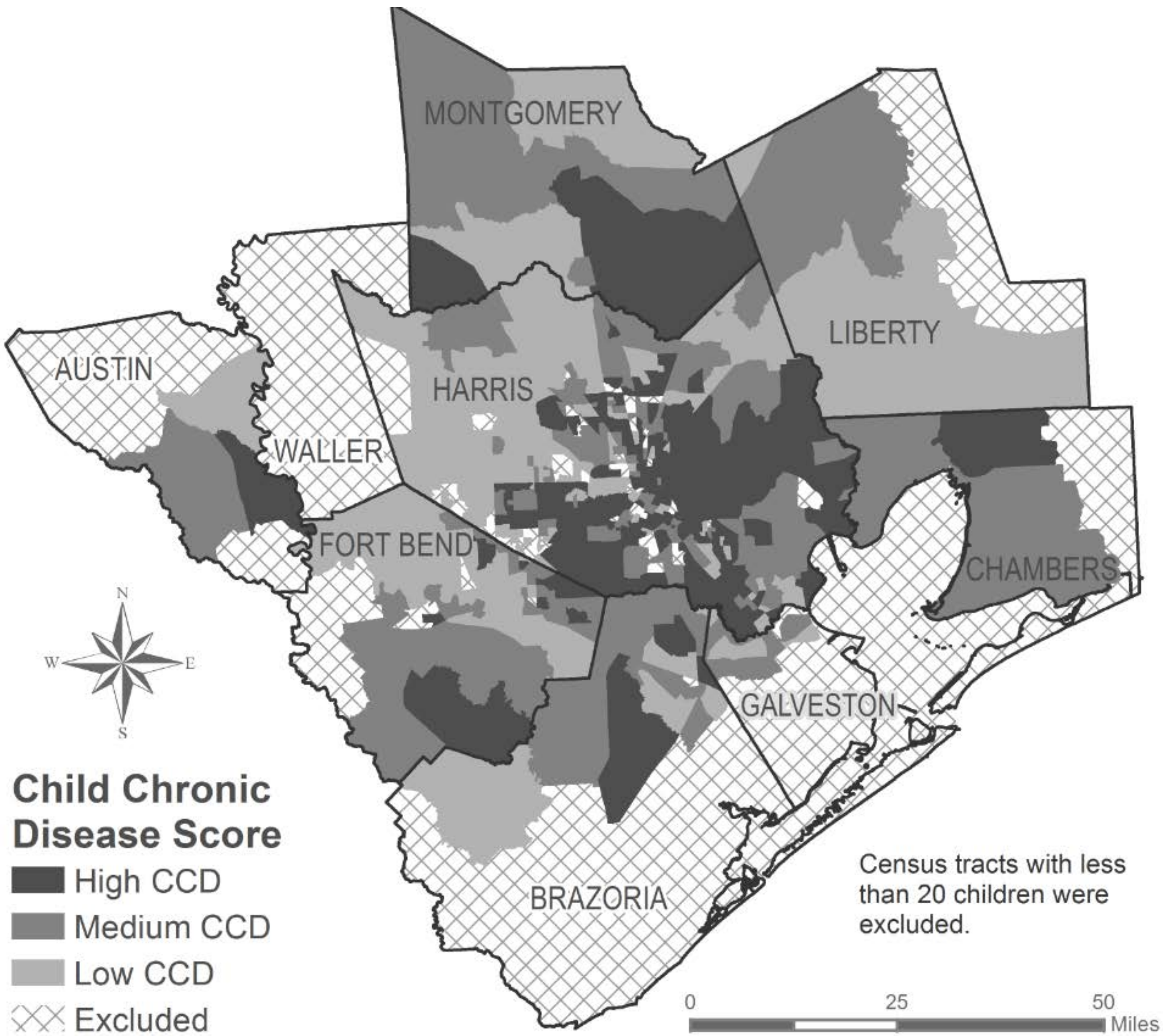
Figure 2:



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S
Child Chronic Disease Score
High CCD
Medium CCD
Low CCD
Excluded
Census tracts with less than 20 children were excluded.
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