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Identifying Geographic Differences in Children's Sugar-Sweetened Beverage and 100% Fruit Juice Intake using Health System Data

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Abstract

Background: Identifying areas with higher sugar-sweetened beverage intake could help tailor policy and public health efforts intended to reduce sugary beverage consumption.

Objective: Demonstrate the feasibility of using health system data to examine the geographic distribution of sugar-sweetened beverage intake and evaluate neighborhood characteristics associated with intake.

Methods: We extracted electronic health record data from a sugar-sweetened beverage and 100% fruit juice screener used for children ages 1–17 years in 8 pediatric practices in North Carolina (March 2017–2018) and dichotomized intake to high (≥ 3 sugar-sweetened beverages/day) versus not. We geocoded addresses and mapped the proportion of consumers in each census tract. We combined electronic health record data with U.S. census data and evaluated associations of census tract income and race/ethnicity with intake. We used multivariable models to evaluate the association between geographic concentrations of income and race/ethnicity and sugar-sweetened beverage intake, controlling for demographics extracted from the electronic health record and clustering by tract.

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Results: Of 19,451 patients, 4,579 (23.5%) reported consuming 3 sugar-sweetened beverages/day. In multivariable models, children living in tracts with high concentrations of low-income (OR: 1.45, 95% CI: 1.26, 1.68) and non-white residents (OR: 1.44, 95% CI: 1.21, 1.71) were more likely to consume 3 sugar-sweetened beverages/day than children in tracts with a high concentration of high-income and white residents.

Conclusion: We demonstrate how health system data could be used to characterize geographic variation in sugar-sweetened beverage and 100% fruit juice consumption. This approach could help target public health efforts and monitor the effects of community-level interventions.

Keywords

Sugar-sweetened beverages; public health; electronic health records; population health

Background

Despite national healthcare organizations recommending that children consume zero sugar-sweetened beverages (SSB) and only one serving of a 100% fruit juice a day, over half of children in the U.S. consume sugary drinks daily.¹⁻⁴ SSB contribute to half of all added sugars in children's diets in the U.S.^{3,5} Increased consumption of SSBs has been shown to lead to adverse health consequences, including weight gain, cardiometabolic disease, and dental caries in both children and adults.⁵⁻¹¹ Children from low-income and minority populations are also more likely to regularly consume SSB, and these differences in SSB consumption are an important contributor to racial and socioeconomic disparities in obesity rates.¹²⁻¹⁴

Given the prevalence of SSB consumption and the potential negative effects on health, there has been a growing number of policy and public health interventions, such as taxes on sugary drinks and media campaigns, focused on reducing SSB intake.^{5,15-18} Identifying neighborhoods or communities with higher SSB intake could help tailor some of these policy and public health efforts. To date, studies evaluating differences in SSB consumption in local areas have primarily relied on community surveys or sales data. These sources have limitations with surveys requiring extensive time and effort to collect, thus limiting the scale of data collection, and sales data lacking individual-level covariates important for public health research.¹⁶⁻¹⁸ Electronic health records (EHR) are emerging as a source for public health research, allowing for the merging of data collected for routine clinical care with some patient-reported information, such as SSB consumption. EHRs could overcome some of the existing challenges with other data sources.

As part of a comprehensive approach to obesity prevention and treatment, pediatric guidelines recommend clinicians routinely screen patients for SSB consumption.¹⁹⁻²¹ The National Academy of Medicine also recommends that health systems routinely capture social and behavioral domains in the EHR to improve population health and reduce health disparities.²² Because health systems also have access to patient-level geographic information, data available in these systems could help identify communities with increased SSB consumption particularly with the use of geospatial modeling tools, such as geographic information systems (GIS). Prior studies have used geospatial tools to examine access to

primary care, understand the environmental factors affecting asthma, and determine the impact of neighborhoods on obesity.^{23–27} Although not previously done, geospatial tools could also be used to identify communities with high SSB intake and understand the social context in which these families live.

We used data from an electronic health record (EHR) SSB and 100% fruit juice screening program in 8 pediatric primary care clinics to examine consumption patterns by geography.²⁸ The primary objective of this study was to demonstrate the feasibility of using health system data to examine the geographic distribution of children's SSB and 100% fruit juice intake in a large, diverse area. The secondary objective was to evaluate the neighborhood characteristics associated with intake.

Methods

Study design

We conducted a cross-sectional study of children screened for SSB and 100% fruit juice intake at 8 pediatric primary care clinics that are affiliated with Wake Forest Baptist Health (WFBH). All children who had been screened for SSB/100% fruit juice intake at these clinics were eligible for inclusion. All 8 clinics used the EpicCare (Verona, WI) EHR. We combined this EHR data with census data from the American Community Survey (ACS) at the census tract level.

Data Sources

EHR data: To increase routine and standardized screening of children for SSB and fruit juice intake in our health system, we created and implemented a point-of-care EHR-based SSB and fruit juice consumption screener in 8 pediatric primary care clinics in March of 2017.²⁸ Participating clinics provide care for a diverse patient population of over 20,000 children annually in urban, suburban, and rural settings. Clinic staff conduct screening at any in-person clinic visit for children 6 months through 17 years of age. The screening was done using a “best practice alert” to remind clinic staff to document consumption information; the prompt automatically triggers after vital signs are entered. Staff (e.g. nurses, medical assistants) administer the screening question in English, with Spanish translation available as needed. We extracted the responses to the SSB/fruit juice screener and demographic data from the EHR for children 1–17 years of age screened between March 2017 and March 2018. We also extracted residential geocode from a database maintained by the Wake Forest Clinical and Translational Science Institute for each child screened.

American Community Survey (ACS): The ACS is a national survey conducted by the U.S. Census Bureau. The ACS collects population estimates for small geographical areas, such as income and employment, and we utilized the 2016 ACS five-year annual average data at the census tract-level to calculate Index of Concentration at the Extremes (ICE) for income and race/ethnicity.²⁹ Census tract areas include between 1200 and 8000 people, a size that is smaller than zip code areas.

Study sample

We included 24,677 children who met inclusion criteria. All analyses were done based on the first time children were screened. We excluded 74 children (0.3%) whose parents refused the questionnaire; 1,206 (4.9%) who responded with “other” to the intake questionnaire; 1,503 (6.1%) whose home address was not located in the three primary counties (Forsyth, Davidson, and Davie) served by the 8 clinics; and 2,266 whose households (9.2%) could not be matched to a geocode due to incomplete address data in the EHR. Because inclusion of census tracts where a small number of children were screened could result in greater risk of miscategorizing area-level consumption patterns, we further excluded children living in census tracts where fewer than 25 children had been screened (N=177). The final study population was 19,451 children, which represented 78.8% of all children screened. Children who were excluded were significantly more likely to be younger age, white, and prefer English (all $p < 0.001$).

Measures

SSB/100% fruit juice Consumption: The screener was worded as follows “*In the past month, how often did _____ (child’s name) drink a sugar-sweetened beverage or 100% fruit juice? Sugar-sweetened beverages include things like fruit-flavored drinks, juice from concentrate, punch, Kool Aid, soda, sports drinks, sweet tea or flavored milks.*” For young children (under age 10), parents/caregivers provide the response data; for older children and adolescents, staff elicit a response from the parent and child as appropriate. Response options for frequency of consumption are selected from a fixed drop-down menu as: “Never,” “Once per week or less,” “Several per week but not every day,” “1 per day,” “2 per day,” “3 per day,” “4 or more per day,” or “Refused.” This 1-item question has been validated against beverage items from the 2013–14 National Health and Nutrition Examination Survey (NHANES) dietary screener with moderate agreement, and at the population level, produces prevalence estimates for consumption that align well with NHANES data.²⁸ Our primary outcome was SSB intake evaluated using two separate dichotomous categories; low SSB/fruit juice intake and high SSB/fruit juice intake. Because of the small number of individual responses per category in certain census tracts and in order to understand the extremes of consumption, we dichotomized responses to these 2 separate categories. Low SSB intake was dichotomized into “once per week or less/never consume” or not. High intake was categorized into >3 or more SSB/fruit juice times per day or not.

Index of Concentration at the Extremes: Our primary predictors were the Index of Concentration at the Extremes (ICE) for income and race/ethnicity, identified at the census-tract level. The ICE is designed to measure the extent to which residents of an area are concentrated at the extreme of deprivation and privilege.^{30–32} The ICE is measured on a scale of -1 to 1 , and it is determined by subtracting the number of poor households from the number of affluent households and dividing by the total number of households in the area $((\text{affluent households} - \text{poor households}) / \text{total number of households})$. A score of -1 means that 100% of the population is concentrated in the most deprived group and a value of $+1$ means that 100% of the population is concentrated in the most affluent. Unlike another commonly used measure of neighborhood socioeconomic status, the percent of households with incomes below the federal poverty level, the ICE provides a measure of spatial social

polarization at the extreme of privilege and deprivation.^{30,31} The same is true for the ICE measure for race/ethnicity and the percent of non-white households in a census tract.

We calculated the ICE separately for income and race/ethnicity for all census tracts included in this study based on the 2016 ACS values. The ICE for income was determined by subtracting the number households with incomes less than \$25,000 from the number of households with incomes greater \$100,000, divided by the total number of households. The ICE for race/ethnicity was determined by subtracting the number of non-Hispanic Black households from the number of non-Hispanic White households, divided by the total number of households. We categorized the ICE variable into quartiles for income (bottom quartile most deprived; top quartile most affluent) and race/ethnicity (bottom quartile most concentrated non-Hispanic Black population; top quartile most concentrated non-Hispanic white population).

Covariates: We extracted child demographics from the EHR. We obtained gender, age at the time of screening (categorized as <6, 6–11, and ≥11 years of age), race/ethnicity (White, African American, Hispanic, or other/unknown), and the families' preferred language (English or not). We also included the clinic where the child had been screened and the type of visit screening was done at (well-child visit, urgent visit, behavioral health, nurse visit, or other).

Statistical analysis

We performed bivariate analyses testing the association between SSB/fruit juice intake with ICE and other covariates using chi-square tests. We used multivariable logistic regression to evaluate the association between geographic concentrations of income and race/ethnicity and low intake (defined as children whose screening indicated consumption frequency of either “once per week or less” or “never consume”), controlling for gender, age, race/ethnicity, language, clinic, visit type, and clustering by census tract. We conducted separate multivariable logistic regression analyses to evaluate the association between geographic concentrations of income and race/ethnicity and high intake, controlling for all covariates and clustering by census tract. We did not include weight as a covariate because we would expect child weight to be the result of area-level deprivation or privilege and SSB intake as opposed to a confounder between the two. We conducted sensitivity analyses that included child body-mass index z-scores as a covariate and found similar results (data not shown). We also evaluated SSB intake as a categorical variable using ordinal logistic regression and controlling for covariates (see Tables S1 and S2). For our main analysis, we evaluated children who lived in a census tract in which 25 children or more had been screened. We conducted sensitivity analyses limiting to census tracts with 50 or more screened children and those with 100 or more screened children. We conducted all statistical analyses using Stata version 15.0 (StataCorp, College Station, TX) and used ArcGIS Desktop (10.5.1; ESRI, Redlands, CA) for all geographic visualization. We used a two-sided hypothesis test, and considered an alpha <0.05 significant. The Wake Forest School of Medicine Institutional Review Board approved this study.

Results

Study population characteristics

Of the 19,451 children included in the study, 33.9% were non-Hispanic White, 37.4% were 11 years of age, and for 76.3% the preferred language was English (Table 1). Over 70% of the study population lived in Forsyth County. The majority of children were screened for SSB/100% fruit juice intake at either a well-child (46.8%) or urgent care visit (49.4%). Among the study population, 17.6% reported drinking a SSB or 100% fruit juice one time a week or less and 23.5% reported drinking 3 or more times a day.

In bivariate analysis, children who were younger age, female, non-Hispanic White, and English speaking were more likely (all $p < 0.001$) to have low SSB/100% fruit juice intake (Table 2). Males and non-Hispanic African Americans were more likely to report high intake (3 or more times per day). The neighborhood assessment demonstrated that children in the most deprived areas, as measured by income, were less likely to have low intake (9.8% for lowest ICE quartile vs 29.6% for highest; $p < 0.001$) and more likely to have high intake (30.2% for lowest ICE quartile vs 13.6% for highest, $p < 0.001$). Results were similar with ICE measured for race/ethnicity (Table 2).

Geographic distribution of SSB and 100% fruit juice intake

The Figure represents the geographic distribution of the census tracts where at least 25 households were screened for SSB/100% fruit juice intake. Screening was available for at least 25 households in 125 of the 134 census tracts (93.2%) in the 3-county area covered by our data. Consistent with bivariate results, census tracts in the lowest or most deprived ICE quartile for income had a lower percentage of children who reported drinking one time a week or less (Figure 1, A). Children in census tracts in the lowest ICE quartile for income had a higher percentage of children who reported drinking 3 or more times a day (Figure 1, B). Results were similar for ICE measure by race/ethnicity (C and D, Figure 1).

Multivariable analysis

In multivariable analyses controlling for all covariates and clustering at the census tract level, we found that children in the lowest ICE quartile for income had a lower odds of drinking one SSB/100% fruit juice per week or less (OR: 0.70, 95% CI: 0.60, 0.81; $p < 0.001$) and a higher odds of drinking 3 or more times a day (OR: 1.45, 95% CI: 1.26, 1.68; $p < 0.001$) compared to children living in the highest ICE quartile for income (Table 3). Similarly, children living in the lowest ICE quartile for race/ethnicity were found to have a lower odds of drinking one time per week or less (OR: 0.70, 95% CI: 0.59, 0.84; $p < 0.001$) and higher odds of drinking 3 or more times a day (OR: 1.44, 95% CI: 1.21, 1.71; $p < 0.001$) compared to children in the highest ICE quartile for race/ethnicity. Sensitivity analyses limiting to census tracts with 50 or more screened children and those with 100 or more screened children found similar results (data not shown).

Discussion

In this study, we evaluated EHR data from 8 pediatric primary care practices in a large, diverse area of Western North Carolina to demonstrate the feasibility of using health system data to identify areas of SSB/100% fruit juice intake. This study shows the feasibility of combining health system data with publicly available data to characterize neighborhood factors that could be associated with health behaviors. We found that children living in a census tract in the lowest ICE quartile for income (OR: 1.45, 95% CI: 1.26, 1.68) and race/ethnicity (OR: 1.44, 95% CI: 1.21, 1.71) had significantly higher odds of drinking 3 or more times a day. This method of combining health system and publicly available data could be used more widely to target population and public health efforts addressing unhealthy behaviors, such as SSB consumption.

The high SSB intake among low-income and minority populations, which has been documented previously and is demonstrated at the neighborhood level in this study, is an important contributor to disparities in obesity rates.^{12–14} The determinants of SSB consumption are complex and include individual, parental, and environmental factors.³³ Pediatric clinical care settings have a high potential to address SSB intake as children regularly interact with the healthcare system accompanied by a parent or caregiver.³⁴ Continued research is needed to develop interventions to systematically screen and address SSB intake in clinical care settings.

Population level interventions are also needed to address the environmental contributors of SSB intake.⁵ Previous studies have utilized geospatial tools, such as GIS, to improve primary care access, understand factors affecting asthma, and determine the effect of neighborhoods on obesity.^{23–27} A growing number of health systems are also beginning to geocode patient data to help understand how geography and environmental factors affect health and patient care.^{24,35} This is the first study to utilize geocoded health system data to characterize SSB and fruit juice consumption across a large, diverse area. In a year, the 8 pediatric practices included in our study were able to screen at least 25 households in over 90% of census tracts in three counties in Western North Carolina. This method could be used with other health system data across different geographic areas. Although we did find significant differences in neighborhood characteristics and SSB/fruit juice intake, and included some individual-level variables as covariates in models, it is possible some of these differences are driven by unmeasured individual characteristics of the population living in these neighborhoods, or area-level factors such as the food environment. Future research using geocoded health data though, could help further elucidate the contribution of environmental (e.g. healthy food access) and individual (e.g. parental education level) drivers of SSB consumption.

The results of our study have important public health implications in two ways. First, this study demonstrates how health system data can be used to identify and characterize areas of high SSB/100% fruit juice intake, which could be used to target public health interventions. The majority of studies assessing SSB consumption have relied on conducting large surveys or evaluating sales data from stores.^{3,12,14,16} Both of these methods can be time consuming and labor intensive. In a year, the 8 practices were able to screen approximately 20,000

children at minimal cost because the screening was conducted as part of routine pediatric primary care. As an increasing number of clinical practices and health systems begin to screen for SSB intake, this geocoded health system data could be used to target public health efforts, such as billboards or media campaigns, to reduce SSB intake in specific areas with high consumption. This method of geocoding health system data could be used in other counties, cities, and states to identify 'hot spots' of SSB consumption.

Second, health system data could be used to evaluate the effect of public policies on SSB intake over time. A growing number of local and state governments are interested in enacting policies limiting SSB intake, such as taxes on the sale of SSB.^{5,15,16} Data from health systems and practices that routinely screen for SSB consumption could be used to evaluate the effect of these policy changes. For example, one study recently found a reduction in sales of SSB after Philadelphia implemented a 1.5-cent excise tax on these beverages.¹⁶ Geocoded health system data could be used to evaluate the effect of the Philadelphia excise tax on self-reported consumption and differences in consumption between demographic groups and by neighborhood over time.

There are several limitations to this study that should be acknowledged. First, the rates of SSB/100% fruit juice intake are based on children who were seen in clinic and screened and not the total population in a census tract; children screened may not represent the overall population of children in those census tracts or the results generalizable to other populations. We limited the analyses to census tracts where at least 25 children had been screened to help ensure that we had a minimum level of census tract representation. Geographic coverage should increase, though, as an increasing number of clinics begin to screen. Second, SSB/100% fruit juice intake was determined by either parental or self-report. It is possible parents or patients did not feel comfortable reporting or were not able to accurately assess the number of times a child consumed a drink. However, the EHR SSB screening question produces prevalence estimates of consumption that align well with the NHANES dietary screener, which is one of the few national surveys that collects data on SSB intake.²⁸ Third, the screening question includes SSB, 100% fruit juice, and flavored milk together, which may have different health effects and patterns of consumption. Because the question combined SSB and 100% fruit juice, we cannot specify how much of the differences in intake were due to SSB or fruit juice. The health system has recently moved to a two item screen that separately assess SSB and fruit juice, and future studies could evaluate differences in consumption. Fourth, because the screening question is administered in a busy clinical setting and many adults and children are unable to accurately assess volumes of consumption, the screener assess the frequency and not the amount of SSB/100% fruit juice intake. Frequency of SSB consumption, though, is highly correlated with the volume of consumption.²⁸ Fifth, although we controlled for a number of individual covariates and clustered at the census tract level, this was an observational study, so there may be unmeasured confounders that we could not include. Sixth, the race/ethnicity ICE measure compares only black and white residents in a census tract. Although, we controlled for individual child race/ethnicity and segregation remains most stark between black vs white residents, future studies should consider constructing ICE measures using other racial/ethnic constructs.^{30–32} Seventh, the geographic location of children was based on the address

listed in the EHR. Front desk staff, though, routinely verify address information at the time children present for visits, it is possible some of the families' addresses were incorrect.

Conclusion

Pediatric practice guidelines recommend that healthcare providers routinely screen children for SSB intake as part of a comprehensive approach to obesity prevention and treatment. We combined EHR data from 8 pediatric primary care practices with publicly available data to demonstrate how health system data could be used to identify areas of high and low SSB/fruit juice intake and determine the neighborhood characteristics associated with consumption. Our results suggest that geospatial health system data could provide a novel source of information to target public health efforts to areas of high SSB consumption. In the future, these methods could be used to evaluate the effect of public health or population-level interventions over time.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Abbreviations:

ACS	American Community Survey
EHR	electronic health record
GIS	geographic information systems
ICE	index of concentration at the extremes
NHANES	National Health and Nutrition Examination Survey
SSB	sugar-sweetened beverages

References

1. Vos MB, Kaar JL, Welsh JA, et al. Added Sugars and Cardiovascular Disease Risk in Children: A Scientific Statement From the American Heart Association. *Circulation*. 592017;135(19):e1017–e1034. [PubMed: 27550974]
2. Heyman MB, Abrams SA, Section On Gastroenterology, Hepatology, and Nutrition, Committee On Nutrition. Fruit Juice in Infants, Children, and Adolescents: Current Recommendations. *Pediatrics*. 62017;139(6). pii: e20170967

3. Powell ES, Smith-Taillie LP, Popkin BM. Added Sugars Intake Across the Distribution of US Children and Adult Consumers: 1977–2012. *J Acad Nutr Diet*. 102016;116(10):1543–1550 e1541. [PubMed: 27492320]
4. Rosinger A, Herrick K, Gahche J, Park S. Sugar-sweetened Beverage Consumption Among U.S. Youth, 2011–2014. *NCHS Data Brief*. 12017(271):1–8.
5. Muth ND, Dietz WH, Magge SN, Johnson RK. Public Policies to Reduce Sugary Drink Consumption in Children and Adolescents. *Pediatrics*. 42019;143(4).
6. de Ruyter JC, Olthof MR, Seidell JC, Katan MB. A trial of sugar-free or sugar-sweetened beverages and body weight in children. *N Engl J Med*. 10112012;367(15):1397–1406. [PubMed: 22998340]
7. Malik VS, Pan A, Willett WC, Hu FB. Sugar-sweetened beverages and weight gain in children and adults: a systematic review and meta-analysis. *Am J Clin Nutr*. 102013;98(4):1084–1102. [PubMed: 23966427]
8. Bleich SN, Vercammen KA. The negative impact of sugar-sweetened beverages on children's health: an update of the literature. *BMC Obes*. 2018220; 5:6. [PubMed: 29484192]
9. Park S, Lin M, Onufrak S, Li R. Association of Sugar-Sweetened Beverage Intake during Infancy with Dental Caries in 6-year-olds. *Clin Nutr Res*. 12015;4(1):9–17. [PubMed: 25713788]
10. Loh DA, Moy FM, Zaharan NL, Jalaludin MY, Mohamed Z. Sugar-sweetened beverage intake and its associations with cardiometabolic risks among adolescents. *Pediatr Obes*. 20172; 12(1): e1–e5. [PubMed: 26843446]
11. Malik VS, Li Y, Pan A, et al. Long-Term Consumption of Sugar-Sweetened and Artificially Sweetened Beverages and Risk of Mortality in US Adults. *Circulation*. 3182019.
12. Dodd AH, Briefel R, Cabili C, Wilson A, Crepinsek MK. Disparities in consumption of sugar-sweetened and other beverages by race/ethnicity and obesity status among United States schoolchildren. *J Nutr Educ Behav*. May-Jun2013;45(3):240–249. [PubMed: 23414783]
13. Taveras EM, Gillman MW, Kleinman KP, Rich-Edwards JW, Rifas-Shiman SL. Reducing racial/ethnic disparities in childhood obesity: the role of early life risk factors. *JAMA Pediatr*. 812013;167(8):731–738. [PubMed: 23733179]
14. Datar A, Chung PJ. Changes in Socioeconomic, Racial/Ethnic, and Sex Disparities in Childhood Obesity at School Entry in the United States. *JAMA Pediatr*. 72015;169(7):696–697. [PubMed: 25984706]
15. Afshin A, Penalvo JL, Del Gobbo L, et al. The prospective impact of food pricing on improving dietary consumption: A systematic review and meta-analysis. *PloS one*. 2017;12(3):e0172277. [PubMed: 28249003]
16. Roberto CA, Lawman HG, LeVasseur MT, et al. Association of a Beverage Tax on Sugar-Sweetened and Artificially Sweetened Beverages With Changes in Beverage Prices and Sales at Chain Retailers in a Large Urban Setting. *JAMA*. 5142019;321(18):1799–1810.
17. Kansagra SM, Kennelly MO, Nonas CA, et al. Reducing sugary drink consumption: New York City's approach. *Am J Public Health*. 42015;105(4):e61–64.
18. Boles M, Adams A, Gredler A, Manhas S. Ability of a mass media campaign to influence knowledge, attitudes, and behaviors about sugary drinks and obesity. *Prev Med*. 102014;67Suppl 1:S40–45. [PubMed: 25066020]
19. Davis MM, Gance-Cleveland B, Hassink S, Johnson R, Paradis G, Resnicow K. Recommendations for prevention of childhood obesity. *Pediatrics*. 122007;120Suppl 4:S229–253. [PubMed: 18055653]
20. Krebs NF, Himes JH, Jacobson D, Nicklas TA, Guilday P, Styne D. Assessment of child and adolescent overweight and obesity. *Pediatrics*. 122007;120Suppl 4:S193–228. [PubMed: 18055652]
21. Spear BA, Barlow SE, Ervin C, et al. Recommendations for treatment of child and adolescent overweight and obesity. *Pediatrics*. 122007;120Suppl 4:S254–288. [PubMed: 18055654]
22. Committee on the Recommended Social and Behavioral Domains and Measures for Electronic Health Records. Capturing Social and Behavioral Domains in Electronic Health Records: Phase 1. Washington DC. National Academy of Sciences; 2014.

23. Dulin MF, Ludden TM, Tapp H, et al. Using Geographic Information Systems (GIS) to understand a community's primary care needs. *J Am Board Fam Med.* Jan-Feb2010;23(1):13–21. [PubMed: 20051538]
24. Bazemore A, Phillips RL, Miyoshi T. Harnessing Geographic Information Systems (GIS) to enable community-oriented primary care. *J Am Board Fam Med.* Jan-Feb2010;23(1):22–31. [PubMed: 20051539]
25. Beck AF, Huang B, Chundur R, Kahn RS. Housing code violation density associated with emergency department and hospital use by children with asthma. *Health Aff.* 112014;33(11):1993–2002.
26. Beck AF, Sandel MT, Ryan PH, Kahn RS. Mapping Neighborhood Health Geomarkers To Clinical Care Decisions To Promote Equity In Child Health. *Health Aff.* 612017;36(6):999–1005.
27. Saelens BE, Sallis JF, Frank LD, et al. Obesogenic neighborhood environments, child and parent obesity: the Neighborhood Impact on Kids study. *Am J Prev Med.* 52012;42(5):e57–64. [PubMed: 22516504]
28. Lewis KH, Skelton JA, Hsu FC, Ezouah P, Taveras EM, Block JP. Implementing a novel electronic health record approach to track child sugar-sweetened beverage consumption. *Prev Med Rep.* 92018;11:169–175. [PubMed: 29988772]
29. United States Census Bureau. American Community Survey. <https://http://www.census.gov/programs-surveys/acs/about/information-guide.html>. Accessed September 11, 2019.
30. Krieger N, Waterman PD, Spasojevic J, Li W, Maduro G, Van Wye G. Public Health Monitoring of Privilege and Deprivation With the Index of Concentration at the Extremes. *Am J Public Health.* 22016;106(2):256–263. [PubMed: 26691119]
31. Krieger N, Waterman PD, Batra N, Murphy JS, Dooley DP, Shah SN. Measures of Local Segregation for Monitoring Health Inequities by Local Health Departments. *Am J Public Health.* 62017;107(6):903–906. [PubMed: 28426303]
32. Huynh M, Spasojevic J, Li W, et al. Spatial social polarization and birth outcomes: preterm birth and infant mortality - New York City, 2010–14. *Scan J Public Health.* 22018;46(1):157–166.
33. Mazarello Paes V, Hesketh K, O'Malley C, et al. Determinants of sugar-sweetened beverage consumption in young children: a systematic review. *Obes Rev.* 112015;16(11):903–913. [PubMed: 26252417]
34. Vercammen KA, Frelrier JM, Lowery CM, McGlone ME, Ebbeling CB, Bleich SN. A systematic review of strategies to reduce sugar-sweetened beverage consumption among 0-year to 5-year olds. *Obes Rev.* 7182018.
35. Palakshappa D, Strane D, Griffis H, Fiks AG. Determining Food-Insecure Families' Resource Access with Health System and Public Data. *J Health Care Poor Underserved.* 2019;30(1):265–279. [PubMed: 30827982]

Figure 1:
Geographic Distribution of Sugar-Sweetened Beverage and 100% Fruit Juice Intake
Geographic distribution of low and high SSB/100% fruit juice intake by ICE quartiles for Income and Race/ethnicity by census tract limited to Forsyth, Davidson, and Davie counties. Darker census tracts represent areas of higher deprivation and lighter census tracts represent areas of higher affluence. Green dots represent low intake. Yellow dots represent areas of higher intake. SSB-sugar-sweetened beverage; ICE-Index of concentration at the extremes

Table 1:

Clinic Study Population Characteristics from 2017–2018

		Total population: N (%)
		19,451
Age group		
	<6 years	6,312 (32.5)
	6 to <11 years	5,868 (30.2)
	>=11 years	7,271 (37.4)
Gender		
	Female	9,825 (50.5)
	Male	9,626 (49.5)
Race/Ethnicity		
	White	6,589 (33.9)
	African American	5,373 (27.6)
	Hispanic	6,101 (31.4)
	Other	1,388 (7.1)
Language		
	English	14,835 (76.3)
	Other	4,616 (23.7)
County		
	Forsyth	14,162 (72.8%)
	Davidson	3,601 (18.5%)
	Davie	1,688 (8.7%)
Clinic		
	1	1,870 (9.6)
	2	3,678 (18.9)
	3	744 (3.8)
	4	1,698 (8.7)
	5	2,970 (15.3)
	6	1,404 (7.2)
	7	3,466 (17.8)
	8	3,621 (18.6)
Visit type		
	Well child	9,105 (46.8)
	Urgent	9,608 (49.4)
	Behavioral health	346 (1.8)
	Nurse	348 (1.8)
	Other	44 (0.2)
Income ICE quartile		
	1 (lowest)	5,147 (26.5)

		Total population: N (%)
	2	4,446 (22.9)
	3	4,968 (25.5)
	4 (highest)	4,890 (25.1)
Race ICE quartile		
	1 (lowest)	4,905 (25.2)
	2	5,235 (26.9)
	3	4,745 (24.4)
	4 (highest)	4,566 (23.5)
Low SSB/fruit juice intake	Yes	3,413 (17.6)
High SSB/fruit juice intake	Yes	4,579 (23.5)

The ICE is measured on a scale of -1 to 1, and it is determined by subtracting the number of poor households from the number of affluent households and dividing by the total number of households in the area ((affluent households-poor households)/total number of households). A score of -1 means that 100% of the population is concentrated in the most deprived group and a value of +1 means that 100% of the population is concentrated in the most affluent. We categorized the ICE variable into quartiles for income (bottom quartile most deprived; top quartile most affluent) and race/ethnicity (bottom quartile most concentrated non-Hispanic Black population; top quartile most concentrated non-Hispanic white population). SSB-sugar-sweetened beverage; ICE-Index of concentration at the extremes

Table 2:

Bivariate Analysis evaluating Patient Characteristics and Intake from 2017–2018

	Low SSB/fruit juice Intake			High SSB/fruit juice intake		
	No	Yes	p-value	No	Yes	p-value
Age group			<0.001			0.06
<6 years	5,105 (80.9)	1,207 (19.1)		4,871 (77.2)	1,441 (22.8)	
6 to <11 years	4,902 (83.5)	966 (16.5)		4,509 (76.8)	1,359 (23.2)	
≥11 years	6,031 (82.5)	1,240 (17.1)		5,492 (75.5)	1,779 (24.5)	
Gender			<0.001			0.001
Female	7,816 (81.2)	1,810 (18.8)		7,458 (77.5)	2,168 (22.5)	
Male	8,222 (83.7)	1,603 (16.3)		7,414 (75.5)	2,411 (24.5)	
Race/Ethnicity			<0.001			<0.001
White	4,973 (75.5)	1,616 (24.5)		5,327 (80.9)	1,262 (19.2)	
African American	4,825 (89.8)	548 (10.2)		3,496 (65.1)	1,877 (34.9)	
Hispanic	5,198 (85.2)	903 (14.8)		4,916 (80.6)	1,185 (19.4)	
Other	1,042 (75.1)	346 (24.9)		1,133 (81.6)	255 (18.4)	
Language			<0.001			<0.001
English	12,065 (81.3)	2,770 (18.7)		11,173 (75.3)	3,662 (24.7)	
Other	3,973 (86.1)	643 (13.9)		3,699 (80.1)	917 (19.9)	
Clinic			<0.001			<0.001
1	1,234 (66.0)	636 (34.0)		1,659 (88.7)	211 (11.3)	
2	3,289 (89.4)	389 (10.6)		2,872 (78.1)	806 (21.9)	
3	596 (80.1)	148 (19.9)		551 (74.1)	193 (25.9)	
4	1,398 (82.3)	300 (17.7)		1,231 (72.5)	467 (27.5)	
5	2,785 (93.8)	185 (6.2)		1,823 (61.4)	1,147 (38.6)	
6	1,155 (82.3)	249 (17.7)		1,314 (93.6)	90 (6.4)	
7	3,262 (94.1)	204 (5.9)		2,076 (59.9)	1,390 (40.1)	
8	2,319 (64.0)	1,302 (36.0)		3,346 (92.4)	275 (7.6)	
Visit type			<0.001			0.07
Well child	7,518 (82.6)	1,587 (17.4)		7,005 (76.9)	2,100 (23.1)	
Urgent	7,868 (82.0)	1,740 (18.1)		7,329 (76.3)	2,279 (23.7)	
Behavioral health	303 (87.6)	43 (12.4)		244 (70.5)	102 (29.5)	
Nurse	313 (89.9)	35 (10.1)		261 (75.0)	87 (25.0)	
Other	36 (81.8)	8 (18.2)		33 (75.0)	11 (25.0)	
Income ICE quartile			<0.001			<0.001
1 (lowest)	4,645 (90.3)	502 (9.8)		3,592 (69.8)	1,555 (30.2)	
2	3,774 (85.0)	672 (15.1)		3,307 (74.4)	1,139 (25.6)	
3	4,177 (84.1)	791 (15.9)		3,749 (75.5)	1,219 (24.5)	
4 (highest)	3,442 (70.4)	1,448 (29.6)		4,224 (86.4)	666 (13.6)	
Race ICE quartile			<0.001			<0.001

	Low SSB/fruit juice Intake			High SSB/fruit juice intake		
	No	Yes	p-value	No	Yes	p-value
1 (lowest)	4,339 (89.7)	506 (10.3)		3,391 (69.1)	1,514 (30.9)	
2	4,411 (84.3)	824 (15.7)		3,930 (75.1)	1,305 (24.9)	
3	3,689 (77.7)	1,056 (22.3)		3,901 (82.2)	844 (17.8)	
4 (highest)	3,539 (77.5)	1,027 (22.5)		3,650 (79.9)	916 (20.1)	

The ICE is measured on a scale of -1 to 1, and it is determined by subtracting the number of poor households from the number of affluent households and dividing by the total number of households in the area ((affluent households-poor households)/total number of households). A score of -1 means that 100% of the population is concentrated in the most deprived group and a value of +1 means that 100% of the population is concentrated in the most affluent. We categorized the ICE variable into quartiles for income (bottom quartile most deprived; top quartile most affluent) and race/ethnicity (bottom quartile most concentrated non-Hispanic Black population; top quartile most concentrated non-Hispanic white population). SSB-sugar-sweetened beverage; ICE-Index of concentration at the extremes

Table 3:

Multivariable analysis Evaluating Sugar-Sweetened Beverage/100% Fruit Juice Intake and Census Tract Level Income and Race/Ethnicity from 2017–2018

Income			
Low Sugar-Sweetened Beverage/100% Fruit Juice Intake			
Income ICE quartile	OR	95% CI	p-value
1 (lowest)	0.70	0.60, 0.81	<0.001
2	0.83	0.71, 0.96	0.01
3	0.84	0.72, 0.97	0.02
4 (highest)	Ref		
High Sugar-Sweetened Beverage/100% Fruit Juice Intake			
Income ICE quartile	OR	95% CI	p-value
1 (lowest)	1.45	1.26, 1.68	<0.001
2	1.56	1.34, 1.83	<0.001
3	1.33	1.15, 1.53	<0.001
4 (highest)	Ref		
Race/Ethnicity			
Low Sugar-Sweetened Beverage/100% Fruit Juice Intake			
Race ICE quartile	OR	95% CI	p-value
1 (lowest)	0.70	0.59, 0.84	<0.001
2	0.83	0.70, 0.99	0.04
3	0.96	0.82, 1.10	0.55
4 (highest)	Ref		
High Sugar-Sweetened Beverage/100% Fruit Juice Intake			
Race ICE quartile	OR	95% CI	p-value
1 (lowest)	1.44	1.21, 1.71	<0.001
2	1.24	1.08, 1.43	0.002
3	1.08	0.94, 1.25	0.27
4 (highest)	Ref		

The ICE is measured on a scale of –1 to 1, and it is determined by subtracting the number of poor households from the number of affluent households and dividing by the total number of households in the area ((affluent households-poor households)/total number of households). A score of –1 means that 100% of the population is concentrated in the most deprived group and a value of +1 means that 100% of the population is concentrated in the most affluent. We categorized the ICE variable into quartiles for income (bottom quartile most deprived; top quartile most affluent) and race/ethnicity (bottom quartile most concentrated non-Hispanic Black population; top quartile most concentrated non-Hispanic white population). ICE-Index of concentration at the extremes