Published in final edited form as:

Obesity (Silver Spring). 2020 January ; 28(1): 65–72. doi:10.1002/oby.22663.

Childhood Obesity and the Food Environment: A Population-Based Sample of Public School Children in New York City

Brian Elbel, PhD, MPH,

Department of Population Health, New York University School of Medicine, New York, NY, and
Wagner Graduate School of Public Service, New York University, New York, NY

Kosuke Tamura, PhD,

Department of Population Health, New York University School of Medicine, New York, NY

Zachary T. McDermott, MA,

Wagner Graduate School of Public Service, New York University, New York, NY

Erilia Wu, MPA,

Department of Population Health, New York University School of Medicine, New York, NY

Amy Ellen Schwartz, PhD

Center for Policy Research, Maxwell School, Syracuse University, Syracuse, NY

Abstract

Objective—To examine the relationship between proximity to healthy and unhealthy food outlets around children's homes and their weight outcomes.

Methods—We used 3,507,542 student-year observations of height and weight data from the 2009–2013 annual FITNESSGRAM assessment of New York City public school students. We then calculated BMI z-scores (zBMI), whether a student had obesity and obesity/overweight using CDC growth chart, and combined these data with the locations of four food outlet types—fast-food restaurants, wait service restaurants, corner stores, and supermarkets—to calculate distance to the nearest outlet. We examined associations between weight status outcomes and distance to these food outlet types using neighborhood (census tract) fixed effects.

Results—Living further than 0.025 miles (about 1/2 of a city block) from the nearest fast-food restaurant was associated with lower obesity, obesity/overweight, and zBMI. Results ranged from 2.5 to 4.4 percent decreased obesity. Beyond this distance there were generally no impacts of the food environment and little to no impact of other food outlet types.

Corresponding Author: Brian Elbel, PhD, MPH, New York University School of Medicine, Department of Population Health, Section on Health Choice, Policy and Evaluation, 180 Madison Ave, New York, NY 10016. Phone: 212-263-4283. Brian.Elbel@nyumc.org.

Kosuke Tamura (current affiliation) Cardiovascular Branch, National Heart, Lung, and Blood Institute, National Institutes of Health, Bethesda, MD

Author Contributions: BE and AS conceived of and designed the study; all authors participated in the acquisition, analysis, or interpretation of data; BE, KT, and ZM drafted the manuscript; all authors provided critical revision of the manuscript; ZM and EW performed statistical analysis; BE obtained funding; BE and AS provided study supervision. BE and AS had full access to all the data in the study and take responsibility for the integrity of the data and the accuracy of the data analysis.

Disclosure: The authors declared no conflict of interest.

Conclusions—Close proximity to fast-food restaurants was inversely related to childhood obesity but no relationships beyond that were seen. These findings can help better inform policies focused on food access, which could, in turn, reduce childhood obesity.

Keywords

Body-Mass Index (BMI); Childhood Obesity; Food; Health Policy

Introduction

Childhood obesity has been on the rise since the 1980s and is now estimated to affect 18.5% of 2–19 year olds in the United States (US).¹ It is disproportionately higher in non-Hispanic Black (19.5%) and Hispanic youth (21.9%), compared to their non-Hispanic white (14.7%) and non-Hispanic Asian counterparts (8.6%).² Maintaining a body mass index (BMI) within a healthy range potentially decreases the risk for chronic diseases, including cardiovascular disease, cancer, and stroke as well as improve psychosocial health.^{3,4} By 2030, if the obesity trend continues, it is estimated that the medical costs attributable to obesity will reach \$48–66 billion each year in the US.⁵

The causes of and solutions to childhood obesity have not been clearly elucidated.⁶ In recent years, attention has been paid to the key role the food environment, including the location of food resources, may play in shaping the obesity epidemic.^{7,8} Research suggests that the gradual weight gain seen in the U.S. population can be attributed to increases in caloric intake, likely attributable to increased consumption of “empty calories” and decreased consumption of nutrient-dense foods.^{9–12} Many studies link fast-food consumption in particular to excess calorie intake and poor diet quality.^{13–17}

Generally, previous research investigating associations between objectively measured food environments (e.g., proximity to food outlets) and a child’s weight status have found few statistically significant associations. The few studies that did find statistically significant results support current understanding of the relationship between the food environment and obesity, in that obesity is positively correlated with close proximity to fast-food restaurants, and inversely so with supermarkets. These studies examined particular aspects of the food environment, i.e., the authors looked at the effect of supermarkets or fast food restaurants on weight outcome.^{18–24} Another key limitation of these is that only a few have examined the food environment around children’s homes,^{24,25} including very small distances (of less than 0.1 miles) in urban areas.^{17,18} Our prior work has found that in New York City (NYC) public school children have enormous access to food outlets (both in terms of proximity to food outlets and the number of outlets available within walking distance), and that disparities exist.²⁶

Equally important, only a small number of studies examine whether the relationship between access and child BMI is biased due to unmeasured neighborhood level confounders or selection into particular neighborhoods.^{18–24} For example, some studies have used fixed effects models at different levels to examine how variation in the food environment around home affects weight outcomes.^{24,27} Others have used an instrumental variable strategy (proximity/access to highway) to address endogeneity when examining the effects of fast-

food restaurant access on BMI.^{28–30} Overall, these studies focused on fast-food access as opposed to broader aspects of the food environment.

Our study examines access to healthy and unhealthy food outlets around children's homes and its relationship to children's obesity, obesity/overweight and BMI. We define "unhealthy" outlets as fast food restaurants and corner stores, and "healthy" outlets as wait-service restaurants and supermarkets. While healthy outlets also sell high-calorie, unhealthy foods and unhealthy outlets sell healthier foods, the majority of corner stores have limited availability of healthy foods, and healthy food availability increases with store size overall.³¹ Importantly, youth consumers tend to purchase high-calorie foods in the stores we consider unhealthy outlets.³² We utilize a population-based sample of public school children in NYC and look at very small distances, including those less than 0.1 miles around residences, with a primary estimation strategy utilizing census tract fixed effect. This allows us to only compare children who live within the same census tract and examine small differences in distances to the nearest food outlet that are more likely to be driven by chance. The primary hypothesis is that children who live very close to unhealthy food outlets (e.g., fast-food outlets and corner stores) will have an increased weight status. In contrast, children who live very close to relatively healthier food outlets (e.g., wait-service restaurants and supermarkets) will have a decreased weight status.

Methods

Participants

Data are from the NYC Department of Education for the 2009–2013 schools years, representing all children in the NYC public school system. Children living within 0.5 miles of NYC borders were excluded due to lack of complete food environment variables (data represent NYC only). Otherwise, children were only excluded for having missing data.

Weight status outcomes

Height and weight data come from the 2009–2013 FITNESSGRAM, an annual, school-based, standardized assessment which measures the BMI of every public school child in grades K–12.³³ Data collection takes place throughout the year, is done by the physical education teacher or school nurse, and has previously proven valid, both in terms of its testing method³⁴ and rates of reporting across different race and ethnicity.³⁵ From this, the z-score of BMI (zBMI) was calculated, standardized by age (in months) and gender. Two binary outcomes were created for having obesity (> 95 percentile of zBMI) and obesity/overweight (> 85 percentile of zBMI) based on the CDC growth charts.

Home food environment variables

Four food retail outlet variables were derived from two data sources: 1) the NYC Department of Health and Mental Hygiene (DOHMH) Restaurant Grading data, which was used to determine the location of fast-food and wait-service restaurants, and 2) the New York State Department of Agriculture and Markets (NYS Ag & Markets), Licensing and Inspection data, which was used to determine the location of supermarkets and corner stores. The four food outlet types were defined as: corner stores (stores with floor area less than

6,000 square feet, representing 90.8% of all non-restaurant food retail stores in NYC); supermarkets (stores over 6,000 square feet, representing 9.2% of all non-restaurant food retail stores); fast-food restaurants (both national chain and non-chain fast-food restaurants without wait service, as well as other restaurants that do not specify service type, representing 60.1% of all restaurants); and wait-service restaurants (both chain and non-chain restaurants with wait/table service, representing 39.9% of all restaurants). Per city and state regulations, restaurants are inspected annually, and retail food stores at least every 18 months. Mobile food outlets such as street vendors and food trucks are not captured in either dataset. Other retail store types such as pharmacies and dollar stores are excluded since they represent a very small portion of the food environment. Our four categories represent 93% of the food outlets in the city. For each food outlet type, an indicator was created based on the presence of the nearest food outlet open at the beginning of the school year. Both DOHMH and NYS Ag & Markets maintain archival data that record inspections conducted in previous years. We were able to obtain these data through Freedom of Information Law (FOIL) requests to create year-specific indicators for the food environment.

Based on our knowledge of the food environment in NYC and to allow for the possibility that small distances can make a meaningful impact on people's food behavior, we created a set of mutually exclusive street network distances as small as feasible to allow us to explore statistically whether such small distances matter. These distances include: 0–0.025 (i.e., approximately 0–0.5 blocks in NYC), 0.025–0.05 (0.5–1 blocks), 0.05–0.1 (1–2 blocks), 0.1–0.15 (2–3 blocks), 0.15–0.2 (3–4 blocks), 0.2–0.25 (4–5 blocks), and 0.25–0.5 miles (5–10 blocks). We primarily chose 0.5 miles as the upper bound of our analysis because this is a reasonable walking distance, or approximately 10 minutes of walking, for people in NYC to access food without having to rely on alternative transportation methods. For example, public school students in grade K-2 who live further than 0.5 miles from their schools are eligible for transportation assistance. Children living within 0.5 miles from city borders are excluded from our analysis, since these families may access food outside of the city border in Westchester and Nassau counties, and our restaurant data do not cover inspections in these areas. It is also noteworthy that relaxing such a constraint, for example, to 0.25 miles, has little impact on our sample size or the results. We used ArcGIS 10.5 to calculate the street network distances between the geographic coordinates of children's homes and the food outlets, and SAS 9.3 (Cary, NC) for Euclidean distances.

Statistical analysis

We described the overall sample characteristics by presence of each food outlet within incremental and exclusive distances around each child's home. We then examined the associations between a child's weight status outcomes (having obesity, obesity/overweight, and zBMI, in three separate regressions. We included the binary outcomes having obesity and obesity/overweight because they have clinical significance, while a continuous zBMI allows us to examine smaller changes over time.) and each food outlet type, using the mutually exclusive network distances. All food types were included in the same model.

We used OLS regression for all of our models. Current literature suggests that it performs as well as, if not better than, a logit / probit estimator for a dichotomous outcome under the

circumstances that the outcome is usually not predicted at the extreme ends³⁶ (i.e. close to 0 or 1), and that the model estimates associations between the independent and outcome variable.³⁷ Such an estimation strategy also allows a simpler interpretation of the results, particularly the coefficients.

Our primary estimation strategy used census tract level fixed effects, or the inclusion of a separate indicator/dummy variable for every tract (minus one excluded tract), which allowed us to only compare children within the same census tract (thereby controlling for unobserved selection into neighborhoods). We also adjusted for year, child characteristics and housing characteristics, along with robust standard errors. Child characteristics included race/ethnicity (Black, Hispanic, White, Asian & Other), age, grade, gender, poverty status (whether the child qualifies for free/reduced price lunch, generally defined as family income below 185% of the Federal Poverty line), whether foreign born, whether receiving special education, and whether classified as having limited English proficiency. Residential housing data came from NYC Real Property Assessment Data (RPAD). We included housing variables because they are potential confounders, and even in the same neighborhood, housing characteristics could be associated with both proximity to food outlets and weight outcomes. These variables included indicators for housing type (1 family residence, 2–4 family residence, 5+ family residence, condo, mixed use building, other residential building or non-residential building) and an indicator for whether the child lived in public housing. In Figures 1–4 we present the results of the regressions as percent change in each outcome, calculated from the predicted mean of each outcome (e.g., probability of having obesity, using Margins command in STATA) minus the reference group's mean (0–0.025 miles), divided by the reference group mean, then multiplied by 100. We present the actual regression coefficients in Table S5 and used STATA version 15 for all analyses.

We also performed a number of supplementary sensitivity analyses, including 1) replacing street network distance with Euclidean distance buffers; 2) separating regressions by grade, kindergarten – 5th and 6th – 12th; 3) separating regressions by boroughs of NYC (that is, counties—Bronx, Kings, New York, Queens and Richmond); 4) removing the top 10% of children in our sample with the most access to commercial space around their homes, as research has shown that retail activities are sometimes more strongly associated with obesity;³⁸ 5) reclassifying restaurants without specified service type into the wait-service category (as opposed to fast food); 6) breaking out non-restaurant food retail stores into finer and smaller categories (bodegas <2K sq. ft., medium supermarkets 2K–6K sq. ft., and large supermarkets ≥6K sq. ft.); 7) accounting for lower density of supermarkets (compared with other food outlet types) by setting the reference group to 0–0.05 miles instead of 0–0.025 miles; 8) comparing regression results with and without census tract fixed effects; 9) separating regressions on non-poor and poor student samples; 10) adding clustered standard errors at student level (since a student could be observed multiple times, and this violates the assumption of independence); 11) introducing a time lagged food exposure in year $t-1$ and $t-2$, respectively, for year t weight outcomes, since the change in food environment may not have an effect on weight outcomes immediately, or within the same year. This approach allows us to continue using our preferred estimation strategy while also better utilizing the longitudinal nature of the food environment data, potentially pointing to more than

associations; 12) examining effect sizes stratified by year, of all three outcomes, instead of the average effect that is presented in our main model.

Results

Our final analytic sample consisted of 3,507,542 student-year observations in 2,111 unique census tracts. In academic year 2012–2013 there were 1,052,807 children in traditional (not special education or charter) schools. Of these, 5.2% (n=54,555) were excluded for missing residential address data, 4.2% (n=44,366) for missing school address data, 10.1% (n=106,307) for missing height or weight data, 0.4% (n=4,430 children) for missing biologically plausible weight status data,¹ 1.4% (n=14,935) for missing home and school census tract information (the home or school addresses of these students could not be successfully recognized in the geocoding software developed by NYC Department of City Planning), 2.1% (n=22,600) for living within 0.5 miles of a NYC border, 3.4% (n=35,977) for being in grades other than K-12 (including Pre-K, ungraded special education, home/hospital instruction, alternative high school), and 3.3% (n=34,445) for not having a fast-food restaurant within 0.5 miles from home (since such isolation is unusual and unrepresentative of NYC). In our sample of 1,188,658 students over five years (3,507,542 observations), 24% were only observed once, 20%, 16%, 18% and 22% were observed twice, three, four and five times, respectively.

Tables S1–S4 shows the child characteristics of our sample from 2013 (we used data from 2013 to describe sample characteristics and full 2009–2013 data for the subsequent regressions). Children were predominantly classified as poor (84.1%; qualified for free or reduced price lunch). Approximately 19.5% of children had obesity (BMI ≥ 95 percentile), and 37.4% at least had obesity/overweight (BMI ≥ 85 percentile). Children were primarily Hispanic (40.4%), followed by Black (25.9%), Asian & Other (18.1%), and White (15.6%). Children lived in all five boroughs: Manhattan (11.5%), Bronx (21.5%), Brooklyn (32.4%), Queens (28.7%), and Staten Island (5.9%). Each of these boroughs is different in terms of its children, density and food environment, and we differentially look at results by borough in sensitivity analysis. We also looked at the overall student characteristics by year, as shown in Table S18, which suggest the sample remained relatively stable in terms of its demographics and weight outcomes between AY 2009 and AY 2013.

Of the 65,491 children whose nearest fast-food restaurant was within 0.025 miles (about half a city block) from home, 38.1% were at least overweight, 50.5% were Hispanic, 85.1% were poor, and the majority of them resided in Manhattan and Brooklyn. Children whose nearest fast-food restaurant was within 0.25–0.5 miles from home were similar by race/ethnicity but more likely to live in the Bronx or Brooklyn. (See also demographic data broken down by wait-service restaurants, corner stores, and supermarkets, Tables S2–S4.)

We found that children who live within 0.025 miles of a fast-food restaurant had a probability of having obesity of 0.19, a probability of having obesity/overweight of 0.37, and a predicted zBMI score of 0.57. Greater distances from home to fast-food restaurants in our sample was associated with lower obesity (percent change range = −4.4% to −2.5%), obesity/overweight (range = −2.9% to −1.3%), and zBMI (range = −5.4% to −2.6%) (Figure

1, Table S5), all $p < 0.01$. Being farther away from corner stores was also associated with better weight outcomes, but generally not until 0.05–0.1 miles (Figure 2, Table S5). The findings for wait-service restaurants and supermarkets were mostly non-significant (Figures 3 and 4, Table S5).

We also performed a series of sensitivity analyses. These analyses are presented in Table S6 through S13, S16 and S17. Results from such analyses were generally consistent with our primary model; such analyses included replacing street network distance with Euclidean distance (or “crow flies”) distance (Table S6), separating the sample by grade (Table S7), removing the top 10% decile of the students who lived near large areas of commercial activities (Table S9), using alternative food categories (Table S10), accounting for relatively lower density of supermarkets (Table S11) and stratified by year (Tables S19 through S21). By-borough analysis returned somewhat mixed results (Table S8a–S8e), and future work should continue to examine these differences. In Table S12 where census tract fixed effects are removed, results were more muted for fast food restaurants, but larger and more likely to be significant for corner stores. And when we estimate regressions separating poor and non-poor students (Table S13), we found the results were more likely to be driven by poor students. However, coefficients for fast-food restaurants showed a similar magnitude for non-poor students, and the effect of corner stores is potentially even more prominent among non-poor students. It is worth noting that with clustered standard errors at student level (Table S17), the results remain consistent with our main model, as does introducing a time lag of food exposure of one or two years (Table S16).

On a separate note, because our estimation strategy relies on differences within tracts, we present in Table S14 data showing that when comparing the SD within tracts to the city average, meaningful variations still exists. It is also worth noting that we looked at the correlation in food outlet measurements over the years in Table S15, with very high year-to-year correlations (pair-wise correlation coefficients at 0.87 or higher) and the multi-year correlations not dropping much lower. Considering such slow changes in the food environment over time, implementing a panel data approach is not feasible. Describing the food environment generally, in AY 2013, the mean distances to the nearest fast food restaurant, corner store, wait service restaurant and supermarket from student’s homes were 641, 710, 1,095 and 1,535 feet respectively²⁶.

Discussion

With our sample of over 3.5 million child-year observations from 2009–2013 in the NYC public school system, we examined associations between the nearest food outlets (i.e., fast-food outlets, wait-service restaurants, corner stores, and supermarkets) from children’s homes and their weight outcomes—obesity, obesity/overweight, and zBMI. Overall, those living very close (less than 0.025 miles) to fast-food restaurants had higher likelihood of obesity, obesity/overweight, and a higher predicted zBMI than those living farther away (in the case of fast food, a 2% difference in obesity between those who live very close versus just farther away). Somewhat similar results were found for corner stores, with consistent results seen for smaller stores (<2k sq. ft.) with greater distances associated with better weight outcomes. Wait-service restaurants and supermarkets were not consistently

associated with obesity. That we did not find significant results for wait-service restaurants may be due to the fact that children and adolescents frequent those types of outlets nearly three times less than they do fast-food restaurants.³⁹ Beyond these very small differences in the two food retail types, the food environment was not found to impact weight status. Of particular note is that supermarkets—a major prior policy focus—were not found to be associated with obesity. Results did differ overall by borough, and future work must disentangle why, and what might be most representative of other urban areas.

There are a large number of studies on the relationship between the food environment and childhood obesity, of mixed quality.^{2,3} A recent review investigating neighborhood food environments and obesity found that most studies used cross-sectional designs and the relationships between food environments and weight status were mostly null.² Furthermore, very few studies contended with endogeneity, and those that did focused on restaurants, mostly fast-food.^{4–6} Our study adds to existing literature by examining multiple food outlet types around each child's home. Additionally, we partially addressed endogeneity with census tract fixed effects, which very few studies are able to do (and has thus far only been done for fast-food).

This work has multiple implications for policy. First, our work implies that for children, food outlets traditionally considered unhealthy are more influential aspects of the food environment than healthy food. Most policies, in contrast, focus on outlets considered to sell healthier foods, namely supermarkets. This has resulted in policies that target increases in such stores, which sell food generally considered to be healthier. New York City launched the Food Retail Expansion to Support Health (FRESH) program in 2009 to promote the creation of supermarkets in underserved and low-income communities through zoning and financial incentives.⁴⁰ Across the United States, federally sponsored Healthy Food Financing Initiatives (HFFI) have been implemented to address a lack in lower-income communities of access to fresh, healthy foods. In 2015, one such initiative allotted \$2 million to the Ohio Department of Jobs and Family Services to oversee the statewide Healthy Food for Ohio (HFFO) program.⁴¹ In California, the state passed the California Healthy Food Financing Initiative to fund partnerships supporting new fresh, healthy food stores in both urban and rural communities.⁴¹

Our study implies that a shift in policies is warranted, and that the focus might do well to pivot to outlets selling less healthy items. At the same time, it is worth noting that policies restricting food access are more difficult to garner support for politically. However, Los Angeles and London both introduced regulations banning new fast-food restaurants in fast-food dense areas. These municipalities were able to implement policies to restrict the availability of less healthy foods, although challenged along the way. In Los Angeles, the one-year ordinance was enacted in 2008, and was the first to consider health concerns and eating behavior based on food environment when regulating restaurant locations.⁴² The London Plan (2017) similarly targeted the density of fast-food restaurants, focusing specifically on preventing an overconcentration of these eateries in low-income boroughs and decreasing their proximity to primary and secondary schools.⁴³

However, the overall impact of the food environment measured in our study is quite limited in NYC. As a result, policymakers must understand that policies must be well targeted, and even those that are will have a small, but potentially important, incremental impact on childhood obesity.

There are some limitations to this work, including that the sample is limited to NYC public school children (in 2014, almost 90% of school-aged children in NYC were enrolled in public school^{44,45}) and not all students have their BMI measured. However, the measurement rates for the period of our study were quite high (almost 90% of all students) as compared with earlier years of the program.³³ We leave to future work examining the cumulative role of the food environment (over time) and the influence of the school food environment, which others have shown to be a potentially important measure influencing childhood BMI.²⁷ We also note that we lack data on food prices in our models, which is beyond the scope of our administrative data but an important factor for future work to consider as it may impact food purchasing behavior. We find some small but statistically significant impacts and frame them as being small throughout. It is important to point out again with our sample size even small effects can be statistically significant and we must be cautious in interpretation. Additionally, while tract fixed effect in our models controls for unobserved differences across tracts, they do not control for within-tract variances. These variances are, however, possibly quite small, given that census tract is a relatively small geographic unit. We also lack information on sibling status within the same household. Finally, we must remember that we are not randomly assigning children to live varying differences to food outlets. While we believe we make significant strides toward this difficult, if not impossible, to achieve ideal study design, results still must be viewed with appropriate caution.

Conclusions

Our findings suggest that policy efforts to create a healthy food environment in close proximity to home could have small but potentially meaningful health implications for at least the subset of children who live very close to such establishments. However, the relatively muted findings on the role of the food environment, at least measured by one aspect of access, show that for urban areas we need to continue to look beyond a single solution and towards a suite of policy solutions to better impact obesity.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

The authors acknowledge the contributions of Courtney Abrams, Olivia Martinez, and Tisheya Ward.

Funding Information: This study was funded by the National Institute of Diabetes and Digestive and Kidney Diseases of the National Institutes of Health (R01DK097347; PI: B. Elbel).

References

1. Skinner A, Ravanbakht S, Skelton J, Perrin E, Armstrong S. Prevalence of Obesity and Severe Obesity in US Children, 1999–2016. *Pediatrics*. 2017;141(3):e20173459.
2. Cheryl F, Carroll M, Ogder C. Prevalence of Overweight and Obesity Among Children and Adolescents Aged 2–19 Years: United States, 1963–1965 Through 2013–2014. *Heal E-Stats*. 2016.
3. Ogden CL, Carroll MD, Lawman HG, et al. Trends in Obesity Prevalence Among Children and Adolescents in the United States, 1988–1994 Through 2013–2014. *Jama*. 2016;315(21):2292. doi: 10.1001/jama.2016.6361 [PubMed: 27272581]
4. Benjamin R Surgeon General 's Perspectives. 2010;125(July-August):514–515.
5. Wang YC, McPherson K, Marsh T, Gortmaker SL, Brown M. Health and economic burden of the projected obesity trends in the USA and the UK. *Lancet*. 2011;378(9793):815–825. doi:10.1016/S0140-6736(11)60814-3 [PubMed: 21872750]
6. Sallis JF, Glanz K. Physical activity and food environments: Solutions to the obesity epidemic. *Milbank Q*. 2009;87(1):123–154. doi:10.1111/j.1468-0009.2009.00550.x [PubMed: 19298418]
7. King AC, Jeffery RW, Fridinger F, et al. Environmental and Policy Approaches to Cardiovascular Disease Prevention Through Physical Activity: Issues and Opportunities. 1995;22(November):499–511.
8. Sallis J, Bauman A, Pratt M. Environmental and policy interventions to promote physical activity. This work was prepared for the CIAR Conference on Physical Activity Promotion: An ACSM Specialty Conference. *Am J Prev Med*. 1998;15(4):379–397. doi:10.1016/S0749-3797(98)00076-2 [PubMed: 9838979]
9. Hill JO. Understanding and addressing the epidemic of obesity: An energy balance perspective. *Endocr Rev*. 2006;27(7):750–761. doi:10.1210/er.2006-0032 [PubMed: 17122359]
10. Hill L Empty Calories: Do they add up? Obesity Action Coalition. http://www.obesityaction.org/wp-content/uploads/Empty_Calories_Do_they_add_up.pdf. Published 2018 Accessed January 1, 2018.
11. Hill JO, Peters JC. Environmental Contributions to the Obesity Epidemic. *Science* (80-). 1998;280(May):1371–1374. doi:10.1126/science.280.5368.1387
12. Hill JO, Wyatt HR, Peters JC. Modifying the Environment to Reverse Obesity. *Obes Environ*. 2003;108–115.
13. An R Fast-food and full-service restaurant consumption and daily energy and nutrient intakes in US adults. *Eur J Clin Nutr*. 2016;70(1):97–103. [PubMed: 26130301]
14. Bowman S, Vinyard B. Fast food consumption of U.S. adults: impact on energy and nutrient intakes and overweight status. *J Am Coll Nutr*. 2004;23(2):163–168. [PubMed: 15047683]
15. French S, Harnack L, Jeffery R. Fast food restaurant use among women in the Pound of Prevention study: dietary, behavioral and demographic correlates. *Int J Obes Relat Metab Disord*. 2000;24(10):1353–1359. [PubMed: 11093299]
16. Paeratakul S, Ferdinand D, Champagne C, Ryan D, Bray G. Fast-food consumption among US adults and children: dietary and nutrient intake profile. *J Am Diet Assoc*. 2003;103(10):1332–1338. [PubMed: 14520253]
17. Schroder H, Fito M, Covas M, REGICOR Investigators. Association of fast food consumption with energy intake, diet quality, body mass index and the risk of obesity in a representative Mediterranean population. *Br J Nutr*. 2007;98(6):1274–1280. [PubMed: 17625027]
18. Leung C, Laraia B, Kelly M, et al. The influence of neighborhood food stores on change in young girls' body mass index. *Am J Prev Med*. 2011;41(1):43–51. [PubMed: 21665062]
19. Lamichhane A, Puett R, Porter D, Bottai M, Mayer-Davis E, Liese A. Associations of built food environment with body mass index and waist circumference among youth with diabetes. *Int J Behav Nutr Phys Act*. 2012;9:81. [PubMed: 22747523]
20. Lee H The role of local food availability in explaining obesity risk among young school-aged children. *Soc Sci Med*. 2012;74(8):1193–1203. [PubMed: 22381683]
21. Shier V, An R, Sturm R. Is there a robust relationship between neighbourhood food environment and childhood obesity in the USA? *Public Health*. 2012;126(9):723–730. [PubMed: 22898435]

22. Sturm R, Datar A. Body mass index in elementary school children, metropolitan area food prices and food outlet density. *Public Health*. 2005;119(12):1059–1068. [PubMed: 16140349]
23. Cobb L, Appel L, Franco M, Jones-Smith J, Nur A, Anderson C. The relationship of the local food environment with obesity: a systematic review of methods, study quality, and results. *Obesity (Silver Spring)*. 2015;23(7):1331–1344. [PubMed: 26096983]
24. Sandy R, Wilson J, Ford OT, Liu G, Ottensmann J, Tchernis R. Studying the child obesity epidemic with natural experiments In: Grossman M, Mocan N, eds. *Economic Aspects of Obesity*. University of Chicago Press; 2011:181–221.
25. An R, Sturm R. School and residential neighborhood food environment and diet among California youth. *Am J Prev Med*. 2012;42(2):129–135. [http://www.ajpmonline.org/article/S0749-3797\(11\)00849-X/abstract](http://www.ajpmonline.org/article/S0749-3797(11)00849-X/abstract). Accessed July 20, 2012. [PubMed: 22261208]
26. Elbel B, Tlamura K, McDermott ZT, et al. Disparities in food access around homes and schools for New York City children. *PLoS One*. 2019. doi:10.1371/journal.pone.0217341
27. Currie J, DellaVigna S, Moretti E, Pathania V. The Effect of Fast Food Restaurants on Obesity and Weight Gain. *Am Econ J-Econ Polic*. 2010;2:32–63.
28. Dunn RA. The effect of fast-food availability on obesity: An analysis by gender, race, and residential location. *Am J Agric Econ*. 2010;92(4):1149–1164. doi:10.1093/ajae/aaq041
29. Dunn RA, Sharkey JR, Horel S. The effect of fast-food availability on fast-food consumption and obesity among rural residents: An analysis by race/ethnicity. *Econ Hum Biol*. 2012;10(1):1–13. doi:10.1016/j.ehb.2011.09.005 [PubMed: 22094047]
30. Anderson ML, Matsa DA. Are restaurants really supersizing America? *Am Econ J Appl Econ*. 2011;3(1):152–188. doi:10.1257/app.3.1.152
31. Laska MN, Borradaile KE, Tester J, Foster GD, Gittelsohn J. Healthy food availability in small urban food stores: a comparison of four US cities. *Public Health Nutr*. 2010;13(7):1031–1035. doi:10.1017/S1368980009992771 [PubMed: 19968901]
32. Borradaile KE, Sherman S, Vander Veur SS, et al. Snacking in children: the role of urban corner stores. *Pediatrics*. 2009;124(5):1293–1298. doi:10.1542/peds.2009-0964 [PubMed: 19822591]
33. Rundle A, Richards C, Bader MDM, et al. Individual-and school-level sociodemographic predictors of obesity among new york city public school children. *Am J Epidemiol*. 2012;176(11):986–994. doi:10.1093/aje/kws187 [PubMed: 23132672]
34. Morrow JR, Martin SB, Jackson AW. Reliability and Validity of the FITNESSGRAM®. *Res Q Exerc Sport*. 2010;81(sup3):S24–S30. doi:10.1080/02701367.2010.10599691 [PubMed: 21049835]
35. D'Agostino EM, Day SE, Konty KJ, Larkin M, Saha S, Wyka K. Individual-Level Fitness and Absenteeism in New York City Middle School Youths, 2006–2013. *Prev Chronic Dis*. 2018;15:E05. doi:10.5888/pcd15.170152 [PubMed: 29324217]
36. Hellevik O Linear versus logistic regression when the dependent variable is a dichotomy. *Qual Quant*. 2009;43(1):59–74. doi:10.1007/s11135-007-9077-3
37. Mood C Logistic Regression: Why We Cannot Do What We Think We Can Do, and What We Can Do About It. *Eur Sociol Rev*. 2010;26(1):67–82. doi:10.1093/esr/jcp006
38. Bader MDM, Schwartz-Soicher O, Jack D, et al. More neighborhood retail associated with lower obesity among New York City public high school students. *Health Place*. 2013;23:104–110. doi:10.1016/J.HEALTHPLACE.2013.05.005 [PubMed: 23827943]
39. Powell L, Nguyen B. Fast-Food and Full-Service Restaurant Consumption Among Children and Adolescents: Effect on Energy, Beverage, and Nutrient Intake. *JAMA Pediatr*. 2013;167(1):14–20. [PubMed: 23128151]
40. New York City Economic Development Corporation, New York City Department of City Planning, New York City Department of Health and Mental Hygiene, Services O of the DM for H and H. *IMPACT REPORT*; 2015 <https://www.nycedc.com/system/files/files/program/FRESH Impact Report.pdf>. Accessed September 18, 2018.
41. The Food Trust. Special Report: HFFI Impacts The Nationwide Success of Healthy Food Financing Initiatives, A Proven, Economically Sustainable Solution. <http://thefoodtrust.org/what-we-do/administrative/hffi-impacts/hffi-impacts-case-studies>. Published 2017 Accessed September 20, 2018.

42. Sturm R, Cohen DA. Zoning For Health? The Year-Old Ban On New Fast-Food Restaurants In South LA. 2009. doi:10.1377/hlthaff.28.6.w1088
43. Mayor of London, London Assembly. London Plan Topic Paper: Hot Food Takeaways.; 2018 https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/366852/PHE_Priorities.pdf. Accessed September 20, 2018.
44. Child Population. <https://data.cccnewyork.org/data/map/98/child-population#10/16/3/16/25/a>. Accessed March 8, 2019.
45. - NYC Data - New York City Department of Education. <http://proxy.nycboe.org/Accountability/data/default.htm>. Accessed March 8, 2019.

Study Importance Questions

What is already known about this subject?

- Some studies that have not been able to address residual confounding and largely focus on broad geographic areas have indicated that the food environment may play a role in shaping childhood obesity in the United States.

What does this study add?

- This study examines the relationship between the food environment and childhood obesity in a way that can inform policy by using a large dataset with detailed address information that more fully considers neighborhood selection and confounding.

Figure 1:

Associations between nearest fast food outlet farther than 0.025 mile from home and weight status outcomes.

Note: Percent change = [(predicted probability [PP] of each buffer - PP of reference group)/PP of reference group]*100. (* p<0.01, + p<0.05, § p<0.10). We use 0–0.025 miles buffer as the reference group. Sample is NYC public school students in grades K-12 with home and school address data, student-level demographic data, and weight data from the FITNESSGRAM in AY 2009–2013 and students with at least one fast food restaurant within 0.5 miles from home. We exclude students who live within 0.5 miles from the city boundaries. Models include year fixed effect, census tract fixed effect, student characteristics and housing characteristics, along with the other three types of food outlets. Student characteristics include race and ethnicity, gender, poverty status, recent immigrant (due to data availability, in 2013 data we use native born as a proxy), special education, LEP, grade and age. Residential housing controls include indicators for housing type (1 family residence, 2–4 family residence, 5+ family residence, condos, mixed used buildings, other residential buildings, non-residential buildings) and a public housing indicator. zBMI is the nationally standardized BMI by gender and age. The sample includes 3,507,542 student-year observations.

Figure 2:

Associations between nearest corner store farther than 0.025 mile from home and weight status outcomes.

Note: Percent change = [(predicted probability [PP] of each buffer - PP of reference group)/PP of reference group]*100. (* $p < 0.01$, + $p < 0.05$, § $p < 0.10$). We use 0–0.025 miles buffer as the reference group. Sample is NYC public school students in grades K–12 with home and school address data, student-level demographic data, and weight data from the FITNESSGRAM in AY 2009–2013 and students with at least one fast food restaurant within 0.5 miles from home. We exclude students who live within 0.5 miles from the city boundaries. Models include year fixed effect, census tract fixed effect, student characteristics and housing characteristics, along with the other three types of food outlets. Student characteristics include race and ethnicity, gender, poverty status, recent immigrant (due to data availability, in 2013 data we use native born as a proxy), special education, LEP, grade and age. Residential housing controls include indicators for housing type (1 family residence, 2–4 family residence, 5+ family residence, condos, mixed used buildings, other residential buildings, non-residential buildings) and a public housing indicator. zBMI is the nationally standardized BMI by gender and age. The sample includes 3,507,542 student-year observations.

Figure 3:

Associations between nearest wait service restaurant farther than 0.025 mile from home and weight status outcomes.

Note: Percent change = [(predicted probability [PP] of each buffer - PP of reference group)/PP of reference group]*100. (* p<0.01, + p<0.05, § p<0.10). We use 0–0.025 miles buffer as the reference group. Sample is NYC public school students in grades K-12 with home and school address data, student-level demographic data, and weight data from the FITNESSGRAM in AY 2009–2013 and students with at least one fast food restaurant within 0.5 miles from home. We exclude students who live within 0.5 miles from the city boundaries. Models include year fixed effect, census tract fixed effect, student characteristics and housing characteristics, along with the other three types of food outlets. Student characteristics include race and ethnicity, gender, poverty status, recent immigrant (due to data availability, in 2013 data we use native born as a proxy), special education, LEP, grade and age. Residential housing controls include indicators for housing type (1 family residence, 2–4 family residence, 5+ family residence, condos, mixed used buildings, other residential buildings, non-residential buildings) and a public housing indicator. zBMI is the nationally standardized BMI by gender and age. The sample includes 3,507,542 student-year observations.

Figure 4:

Associations between nearest supermarket farther than 0.025 mile from home and weight status outcomes.

Note: Percent change = [(predicted probability [PP] of each buffer - PP of reference group)/PP of reference group]*100. (* p<0.01, + p<0.05, § p<0.10). We use 0–0.025 miles buffer as the reference group. Sample is NYC public school students in grades K-12 with home and school address data, student-level demographic data, and weight data from the FITNESSGRAM in AY 2009–2013 and students with at least one fast food restaurant within 0.5 miles from home. We exclude students who live within 0.5 miles from the city boundaries. Models include year fixed effect, census tract fixed effect, student characteristics and housing characteristics, along with the other three types of food outlets. Student characteristics include race and ethnicity, gender, poverty status, recent immigrant (due to data availability, in 2013 data we use native born as a proxy), special education, LEP, grade and age. Residential housing controls include indicators for housing type (1 family residence, 2–4 family residence, 5+ family residence, condos, mixed used buildings, other residential buildings, non-residential buildings) and a public housing indicator. zBMI is the nationally standardized BMI by gender and age. The sample includes 3,507,542 student-year observations.