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Influence of the food environment on obesity risk in a large cohort of U.S. veterans by community type

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Abstract

Objective.—To examine relationships between the food environment and obesity by community type.

Methods.—Using electronic health record data from the U.S. Veterans Administration Diabetes Risk (VADR) cohort, we examined associations between the percentage of supermarkets and fast food restaurants with obesity prevalence from 2008-2018. We constructed multivariable logistic regression models with random effects and interaction terms for year and food environment variables. We stratified models by community type.

Results.—Mean age at baseline was 59.8 (SD=16.1) years; 93.3% identified as men; and 2,102,542 (41.8%) were classified as obese. The association between the percentage of fast food restaurants and obesity was positive in high-density urban areas (OR=1.033; 95% CI: 1.028, 1.037), with no interaction by time (p=0.83). The interaction with year was significant in other community types (p's<0.001), with increasing odds of obesity in each follow-up year. The associations between the percentage of supermarkets and obesity was null in high-density and low-density urban areas, and positive in suburban (OR=1.033; 95% CI: 1.027, 1.039) and rural (OR=1.007; 95% CI: 1.002, 1.012) areas, with no interactions by time.

Conclusions.—Many healthy eating policies have been passed in urban areas; our results suggest such policies might also mitigate obesity risk in non-urban areas.

Keywords

Epidemiology; Food; Health Policy; Obesity; Aging

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INTRODUCTION

In 2017–2018, an estimated 42.4% of U.S. adults were obese.(1) Previous work has shown considerable geographic variation in obesity prevalence across the U.S., with higher obesity prevalence among adults in rural areas than among those in urban areas.(2) The prevalence of diabetes, coronary heart disease, and other chronic diseases is also higher in rural versus urban areas.(3, 4) These geographic disparities in obesity risk may be due to differences in individual- and neighborhood-level sociodemographic characteristics across the rural-urban spectrum,(5) as well as poorer diet behaviors among rural residents.(6) The latter is influenced by a number of community-level characteristics, which provide potentially meaningful targets for policy change and intervention.

One such target for policy change is the neighborhood food environment. A large body of work indicates that the proximity of supermarkets to homes is associated with healthier diets and lower risk of obesity,(7, 8) but results are not always consistent.(9) There is also some evidence to suggest that greater access to fast food restaurants is associated with worse diets and higher prevalence of obesity,(10, 11) but, again, some studies report otherwise.(12, 13) The hypothesized pathway is that those shopping at convenience stores and fast food restaurants, where the availability of energy-dense, nutrient-poor food and beverage items is high,(14-16) are likely to make less healthy food purchases. In contrast, supermarkets and wait-service restaurants sell a mix of healthy and less healthy food and beverage items.(17, 18)

The mixed findings in the literature are potentially due to several methodological differences, including differences in the operationalization of food environment measures. For example, most studies quantify food availability using absolute measures,(19) such as the number of supermarkets or fast food restaurants in a given geographic area. Fewer studies use relative measures (e.g., proportion of a type of food outlet), which capture the range of alternative options in the food environment, and may more closely reflect consumers' food shopping experience compared to absolute measures (e.g., counts).(20) Other studies differ in their definition of areal units and their specification of buffer size, which influences the relationship between the food environment and diet and diabetes outcomes.(21) Furthermore, most of these studies were conducted in small geographic areas, and thus may lack generalizability and have limited statistical power to detect changes in nutrition-related health outcomes. One study examined whether the proximity of supermarkets and fast food restaurants was associated with changes in body mass index (BMI) among 1.7 million veterans across the U.S. between 2009 and 2014, and found no relationship. Yet, this study did not explore differences by community type (e.g., urban, suburban, rural) or associations with obesity prevalence.

There are several reasons why the association between food environment exposures and obesity may differ by community type. A lack of consideration of differences in the range of communities introduces several methodological challenges for food environment studies. Examining differences in the relationship between the food environment and obesity by community type is important because many place-based factors cluster at the community level,(22, 23) and this clustering might differ by community type (e.g., high walkability and healthy food availability may cluster in urban areas but not in rural areas). Some communities may experience little variation in food environment exposures, such as those living in rural areas where supermarkets are scarce,(24) which may result in non-positivity when evaluating these exposures in a statistical model (i.e., not all community types exhibit variation in food environment exposures). It is also possible, for example, that the construct of food availability has a different meaning in urban, suburban, and rural areas (also known as measurement non-invariance, or differential item functioning), which makes it inappropriate to test relationships with health outcomes without taking into account potential effect modification by community type.

Overall, there is a lack of studies accounting for the role of community type, with no national studies to our knowledge assessing the impact of the food environment on obesity prevalence by community type. We sought to address this gap by examining the relationship between the relative availability of fast food restaurants and supermarkets and obesity status over time in a cohort of five million U.S. veterans using the Veteran's Affairs (VA) electronic health record (EHR), and stratifying by community type using a four-level categorization of community type developed by the Diabetes LEAD Network (i.e., high-density urban, low-density urban, suburban/small town, rural).(21, 25)

METHODS

Data sources

Data used for this study were from the U.S. Veterans Administration Diabetes Risk (VADR) cohort, a national diabetes-free cohort of U.S. veterans enrolled in the VA for primary care, constructed by the NYU Grossman School of Medicine and George Mason University through the VA national EHR.(26) Veterans were passively enrolled into VADR if they were free of type-2 diabetes (T2D) as of January 1, 2008 and had at least two primary care visits at least 30 days apart prior to cohort entry (to establish a cohort of patients who seek VA care regularly). Patients were considered to have T2D and were excluded if they met the following criteria prior to entering the cohort: two encounters with T2D ICD-9/10 codes, a prescription for T2D medication other than metformin or acarbose alone, or one in/outpatient encounter with T2D ICD-9/10 codes and two elevated A1C (≥6.5%). The cohort enrolled 7,044,740 veterans and followed them through December 31, 2018; median follow-up time was 5.5 person-years (IQR 2.6-9.8 years).

Addresses were geocoded using ArcGIS StreetMap Premium.(27) P.O. Box addresses and addresses with missing information (n=667,398) and individuals whose addresses were not located in the continental U.S. (n=63,443) were excluded. Patients with first documented address occurring more than two years after the cohort entry date and with inconsistent clinic visit history were excluded due to ambiguity regarding classification of these addresses as baseline addresses (n=1,577,857). The geo-location information of valid baseline addresses were linked to neighborhood characteristics obtained from the Retail Environment and Cardiovascular Disease (RECVD) study and the decennial Census from 2000 and 2010,(28-30) including exposure variables.

We used food establishment data from the Retail Environment and Cardiovascular Disease (RECVD) study,(28) which classified neighborhood amenities using the National Establishment Time Series (NETS) Database. The NETS data were licensed from Walls & Associates (Walls & Associates, Denver, CO), who prepared annual establishment information collected by Dun and Bradstreet (D&B, Short Hills, NJ). The RECVD team re-geocoded the NETS data to improve locational accuracy and assigned establishments to subcategories using Standard Industrial Classification codes, employee and sales information, and chain names obtained from Technomic/Restaurants and Institutions (R&I) and TDLinx®. Details on classification methods have been described elsewhere.(31)

Outcome

To measure obesity, we first calculated body mass index (BMI), defined as weight in kilograms divided by the square of height in meters at each patient visit. If a patient had more than one patient visit in a given year, we used the average of the two most recent weight measurements per year. Then we classified BMI values into four categories, including underweight (<18.5 kg/m^2), normal (18.5 to <25 kg/m^2), overweight (25.0 to <30 kg/m^2), and obese (≥30.0 kg/m^2). Our primary repeated-measures outcome variable was dichotomized into obesity (yes/no). We modeled obesity status because it is a more relevant outcome for clinical practice, and because it is easier to interpret changes in obesity odds as an outcome, than BMI units.

Covariates

Age at baseline was calculated by subtracting the date of birth from cohort entry date. In the EHR, sex was reported as male and female, and marital status as married/living with a partner or single. Race/ethnicity was reported as non-Hispanic American Indian/Alaska Native, Asian, Black, Native Hawaiian and Other Pacific Islander, and white; and Hispanic. Patients in the VA EHR are assigned to different priority groups based on their military service history, disability status, income, and whether or not they qualify for Medicaid or other VA benefits. These priority groups were used to create a proxy for socioeconomic status, categorized hierarchically into three groups: disabled, low income/non-disabled, and none of the above.

Neighborhood socioeconomic environment (NSEE) was defined as the sum of *z*-scores of six Census variables (% persons with less than a high-school education, % persons unemployed, % of households earning less than $30,000/year, % of households in poverty, % of households on public assistance, and % of households with no cars), modeled on previous work and scaled to be between 0 and 100.(32) Land use environment was defined as a the sum of *z*-scores of seven indicators (average block length, average block size, intersection density, street connectivity, household density, % developed land, establishment density); an increase in the land use environment variable indicates more compact development.(33) Using American Community Survey (ACS) 5-year data from 2004-2008 to 2012-2016, we also included percentage Hispanic population and percentage non-Hispanic Black population of participants' Census tracts. To classify community type, we used a measure developed by the Diabetes LEAD Network, which combined Rural Urban Commuting Area codes and land area of participants' residential census tract to create a four-level variable representing high-density urban, low-density urban, suburban/small town, and rural communities; geographically smaller tracts in metropolitan cores were classified as high-density urban and geographically larger tracts were classified as low-density urban.(25)

Exposures

Our exposures included the relative availability of supermarkets and fast food restaurants around participants' residences, including a relative measure of the percentage of supermarkets out of total food stores, and the percentage of fast food restaurants out of total restaurants. The supermarkets category included three mutually-exclusive subcategories: supermarkets, supercenters, and medium-sized grocers. Fast food restaurants were defined as quick-service restaurants offering low-preparation-time foods for take-away or cafeterias (no wait service). The total food stores and total restaurants variables include all types of food stores and restaurants, respectively, including the numerators (i.e., supermarkets, fast food restaurants).

We operationalized the exposures by calculating a network buffer around the population-weighted centroid of the census tracts of participants' home addresses. Street network data was obtained from ArcGIS StreetMap Premium, and network buffers (i.e., using line-based road networks) were created using the "generalized" polygon option and default settings in ArcGIS Pro 2.4.2 and ArcGIS Pro 2.1, respectively. The Diabetes LEAD Network based their buffer distances for network buffers on data from the National Household Food Acquisition and Purchase Survey (FoodAPS),(34) which calculated the average driving distance between participants' residential addresses and their primary food store. The FoodAPS data also assigns participants to rural (yes/no) and non-metro (yes/no) categories, which align with our four-level community-type variable. Based on the FoodAPS mean distances within rural and non-metro categories, 1-, 2-, 6-, and 10-mile buffer distances were assigned to participants residing in high-density urban, low-density urban, suburban/small town, rural census tracts, respectively in order to account for differences in geographic scale across these community types.

Statistical analysis

We excluded participants with fewer than two primary care visits prior to cohort entry (n=1,333,878), those who did not have a valid address (n=667,398), those who did not reside in the contiguous U.S. (n=1,577,857), those with fewer than two BMI values in the follow-up period (n=1,215,361) and those missing covariate data (n=515,034) and exposure data (n=1,463), for a final sample size of 3,067,627 participants. To examine the association between each food environment exposure and repeated measures of obesity status, we used separate generalized linear mixed models with logistic link and a random effect for county and adjusting for covariates, including age at baseline (i.e., cohort entry date). To capture varying associations with duration of follow-up time, a proxy for time since exposure, we included an interaction term for time (year since baseline) and food environment exposure variables. To assess for differences in estimates by community type and mitigate potential confounding bias, we stratified all models by community type. To maximize interpretability, we scaled our exposure variables so that estimates corresponded to a 20 percentage point increase in the relative availability of supermarkets and fast food restaurants. We used R version 4.2.2 for all statistical analyses. We used GGPREDICT in R to visualize the predicted probability of obesity by food environment exposure over time, including zero, 20%, 40%, 60%, 80%, and 100% supermarket and fast food restaurant availability (separately). For ease of interpretation and comparison of association by community types, we further summarized the predicted probability of obesity (using the coefficients from the regression model) at comparable levels of our primary exposures (i.e., 0% and 100%).

To assess whether variation in the frequency of VA clinic visits across participants influenced the distribution of BMI values, we used a Pearson correlation to test the association between participants' BMI value and the time (years) between BMI values recorded at clinic visits.

RESULTS

The mean age of participants was 58.5 (SD=16.0) years; 2,844,774 (92.7%) identified as men and 222,853 (7.3%) identified as women (Table 1). About 0.8% of 37, participants were American Indian or Alaska Native; 0.9%, Asian; 16.8%, Black or African American; 5.2%, Hispanic, Latino, or Spanish; 0.8%, Native Hawaiian or other Pacific Islander; and 75.4%, white. A higher percentage of participants in our study sample resided in low-density urban areas (38.0%) compared to high-density urban (n=516,599 (13.0%)), suburban/small town (21.4%), rural (27.6%) areas. A total of 1,316,027 of total participants (42.9%) were classified as obese, with a lower percentage in high-density urban (39.6%) areas relative to low-density urban (42.1%), suburban/small town (44.0%), and rural (44.6%) areas (Table 2). Similarly, we observed a lower percentage of participants classified as overweight or obese in high-density urban areas (77.8%) relative to low-density urban (80.8%), suburban/small town (82.6%), and rural (82.7%) areas.

The relative availability of fast food restaurants and supermarkets in the total sample was 30.1% (12.8%) and 10.9% (7.2%), respectively (Table S1), with no notable differences by community type (Figures S1, S2). We observed a positive association between the relative availability of fast food restaurants and odds of obesity in all community types, including high-density urban (OR=1.033; 95% CI: 1.028, 1.037), low-density urban (OR=1.041; 95% CI: 1.038, 1.044), suburban/small town (OR=1.033; 95% CI: 1.027, 1.039), and rural (OR=1.010; 95% CI: 1.007, 1.013) areas (Table S1). The interaction between the relative availability of fast food restaurants and time was not significant in high-density urban areas ($p=0.83$), which is reflected by the lack of divergence of observed associations over time in Figure 1. In contrast, the interaction with year was statistically significant in the other community types (p's<0.001), with an increase in the odds of obesity in each subsequent year of follow-up. For example, the predicted probability of obesity for participants residing in suburban/small towns with no fast food restaurants ($\beta=0.472$; 95% CI: 0.468, 0.477) and those residing in suburban/small towns with 20% fast food restaurant availability within the community-specific buffer ($\beta=0.475$; 95% CI: 0.471, 0.478) were not different at baseline; whereas, we observed statistically significantly different predicted probabilities between no fast food restaurants ($\beta=0.456$; 95% CI: 0.452, 0.463) and 20% fast food restaurant availability ($\beta=0.476$; 95% CI: 0.472, 0.480) at the end of the follow-up period (Table S2).

In models without an interaction term for time, we observed a null association between the relative availability of supermarkets and odds of obesity in high-density urban and low-density urban areas (Table S1), whereas we observed a weak association between the relative availability of supermarkets and odds of obesity in suburban/small (OR=1.033; 95% CI: 1.027, 1.039) and rural (OR=1.007; 95% CI: 1.002, 1.012) areas. The interaction between the relative availability of supermarkets and time was not significant in any community type, indicating that null and weak associations between the relative availability of supermarkets and obesity did not differ over time, which is demonstrated graphically by the close overlap in confidence intervals of the associations depicted in Figure 2.

The Pearson correlation coefficient for the association between participants' BMI value and the time (years) between BMI values recorded at clinic visits was −0.02, which indicates a very weak correlation, suggesting frequency of clinic visits did not bias model results.

DISCUSSION

Using 10 years of objective height and weight data from a cohort of over five million U.S. veterans, we found that the relative availability of supermarkets had a weak or no association with odds of obesity across community types, with no significant variation in the magnitude of the associations over time. In contrast, our results suggest that higher relative availability of fast food restaurants was associated with higher odds of obesity in all community types, and, with the exception of veterans in high-density urban areas, the strength of this association increased over time with odds of obesity growing in each subsequent year of follow up, suggesting accumulating effects over time. Taken together, these results suggest that we tailor our obesity prevention strategies to food outlet type, potentially by reducing the availability of fast food restaurants relative to other types of restaurants (e.g., zoning restrictions) and/or supporting healthy choices within fast food restaurants (e.g., added sugar warning labels). The latter may be more feasible, though, especially in areas where changes to public infrastructure are less politically and economically viable. The results also suggest we tailor our approach to community type, given how we see increases in the odds of obesity in low-density urban, suburban/small, and rural areas over time.

There are several potential explanations for the observed effect modification by community type, which may inform intervention and policy solutions. First, many different domains of area-level measures cluster at the community level (i.e., multidimensionality),(32) and the clustering of area-level measures may differ by community type.(32) For example, access to public transportation and restaurant density are typically higher in high-density urban areas relative to other community types, and greater access to public transportation may promote greater access to a mix of restaurant types in high-density urban areas. Furthermore, clustering of area-level measures and the way clustering influences individuals' diet-related behaviors may change over time, with potential differences across community type. Recent work, for example, shows how the relative availability of sit-down restaurants grew over time in urban areas compared to suburban areas in the Midwest region,(35) which may differentially mitigate risk of weight gain from eating out in fast food restaurants in urban areas. It is also possible that veterans living in non-urban areas are less likely than their peers in urban areas to leave their local food environment for alternative options due to a lack of willingness or ability to drive, or other reasons (e.g., time savings); and these differences in food purchasing behaviors may widen over time, especially given how our cohort of veterans is older and has greater health burdens than the civilian population.(36, 37)

Our findings may also be driven by how food environment measures have different meanings in different community types (a form of measurement non-invariance, or differential item functioning).(38, 39) Distributional differences in how veterans access fast food restaurants (e.g., drive-through versus eat-in), the frequency with which veterans visit these establishments, the types of fast food restaurants themselves (e.g., fast causal versus quick service), and the items the fast food restaurants sell (e.g., beverages and desserts with high levels of added sugars) may all inform the differences we observed by community type; and, similarly, temporal changes in the distributional differences in these factors across community types may differentially influence obesity risk over time. For example, it's possible that the veterans in our sample visited fast food restaurants more frequently over time (relative to their cohort entry date), reflecting nationwide increases in food-away-from-home expenditures during this period.(40) Evidence also suggests that restaurants have shifted to selling less healthy food and beverage items over time.(15, 41)

We recently published a longitudinal study of the association between the neighborhood food environment and T2D incidence using data from this cohort of veterans,(42) and we found that the relative availability of supermarkets was associated with lower T2D risk in suburban and rural communities, and the relative availability of fast food restaurants was associated with higher risk of T2D in all community types. These results approximately mirror the results for odds of obesity in the current study, though the previous study did not assess for potential interactions with time, which may have masked meaningful temporal changes in diabetes risk across community types over the follow-up period. Our study is also similar to an analysis of veterans in the Weight and Veterans' Environments Study (WAVES), a retrospective longitudinal cohort study of those who received health care services from the VA between 2009 and 2014. The authors examined the relationship between the relative accessibility of supermarkets – defined as the percentage of supermarkets out of the number of supermarkets and fast food restaurants – and BMI using a model with person fixed effects, and found no meaningful association.(9) It's difficult to make a direct comparison to our findings, though, given the differences in the outcome (BMI vs. obesity status) and differences in modeling approaches. The inclusion of person fixed effects, while a robust strategy for mitigating time-invariant confounding bias, makes comparison especially challenging given how person-level changes in the food environment are only due to either migration to a new address or food outlet openings and closings, which does not reflect associations for non-movers and those for whom the food environment does not change.

Our study had several limitations. The study design was observational, and we lacked key individual-level data due to the use of EHR data, including dietary consumption behaviors and household income. We did, however, have access to objective measures of height and weight, and we used a hierarchical variable of low income and/or disability status as a proxy for socioeconomic status. We lacked data on in-store offerings (e.g., type, prices) or what, if anything, participants purchased at their neighborhood food establishments. We also did not examine the impact of other aspects of the neighborhood built environment on obesity. There was variation in the frequency of follow-up time among cohort participants, though our analyses suggested that the frequency of clinic visits did not bias model results. And we linked neighborhood exposures and covariates to participants' baseline addresses, which overlooks potential changes due to migration. Furthermore, our results may not be generalizable to non-veteran populations, which differ from veterans across a spectrum of characteristics, including key differences in financial, health, and social factors.(36, 37) Our primary strength, however, included our consideration of community type, which is unique relative to other national studies of the food environment and weight-related outcomes. We also leveraged a large sample size and time-varying data, with millions of participant observations, including a sizable number of women and non-white participants.

CONCLUSION

In this study, we found that the relative availability of supermarkets had a weak or no association with odds of obesity, whereas higher relative availability of fast food restaurants was associated with higher odds of obesity in all community types, with an increase in the odds over 10 years of follow-up in low-density urban, suburban/small town, and rural areas. To date, many healthy eating policies (e.g., healthy checkout policies, sugary drink taxes) have passed in urban areas, though our results suggest that such policies might also mitigate obesity risk among veterans residing in non-urban areas. Our results also suggest that initiatives to increase access to supermarkets may not be effective in reducing obesity risk in any community type, and other retail strategies may be needed to change diet-related behaviors (e.g., financial incentives for fruits and vegetables). In the future, it will be important to replicate our results in a different study sample, given the unique demographic characteristics of veterans.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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STUDY IMPORTANCE

- The relationship between the food environment and obesity is not clear, in part due to a lack of studies stratifying by community type (e.g., urban, suburban, rural). This is important to understand potential moderation by place-based factors, potentially due to differences in the meaning of food availability across community type.
- The relative availability of supermarkets had a weak or no association with odds of obesity, whereas higher relative availability of fast food restaurants was associated with higher odds of obesity in all community types, with an increase in the odds over 10 years of follow-up in low-density urban, suburban/small town, and rural areas.
- Many healthy eating policies have been enacted in urban areas, though our results suggest such policies might also mitigate obesity risk in non-urban areas, especially those focused on restaurant settings.

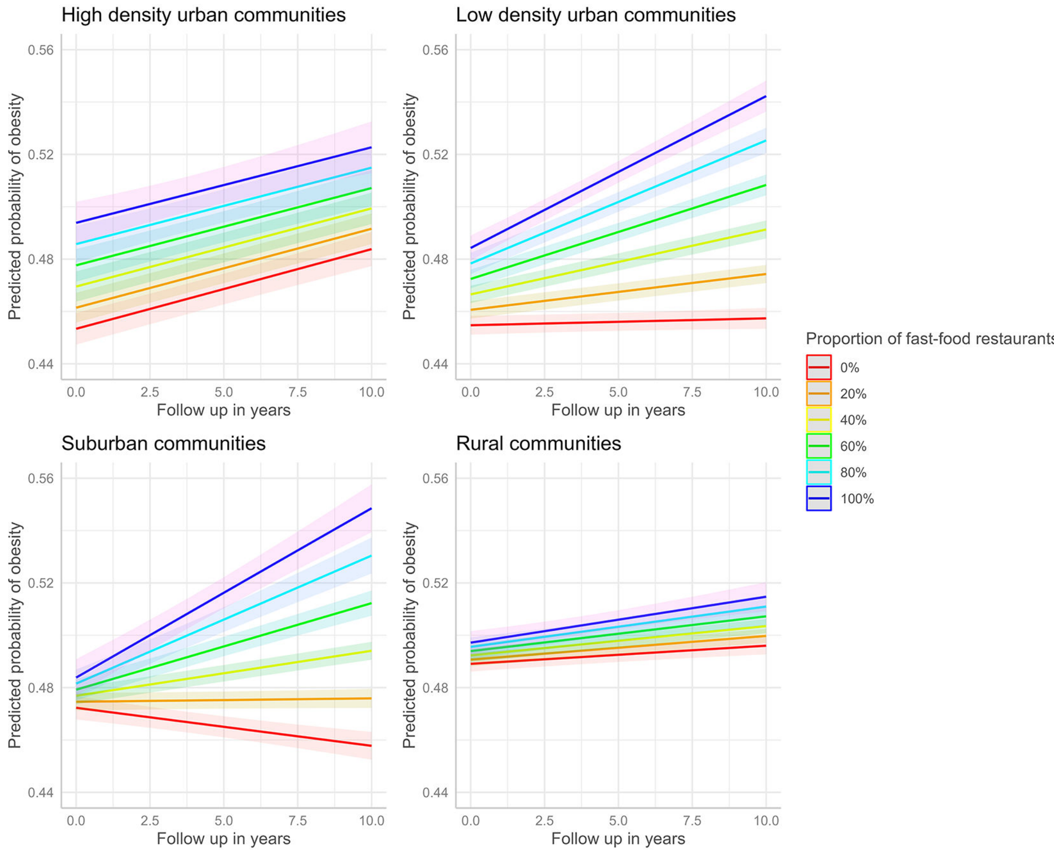

Figure 1. Model-based associations[a] of the relative availability of fast food restaurants and obesity[b] by year and community type

NOTE: p-value reflect statistical significance (α=0.05) of interaction term for time (year since baseline) and food environment exposure variables.

[a]Adjusting for baseline age, sex, race/ethnicity, marital status, income/disability flag, land use environment, neighborhood socioeconomic environment quartiles, percentage Hispanic population and percent non-Hispanic Black population of participants' Census tracts; and interaction with year since baseline (i.e., cohort entry date).

[b]Obesity defined as body mass index of >30.0 kg/m^2.

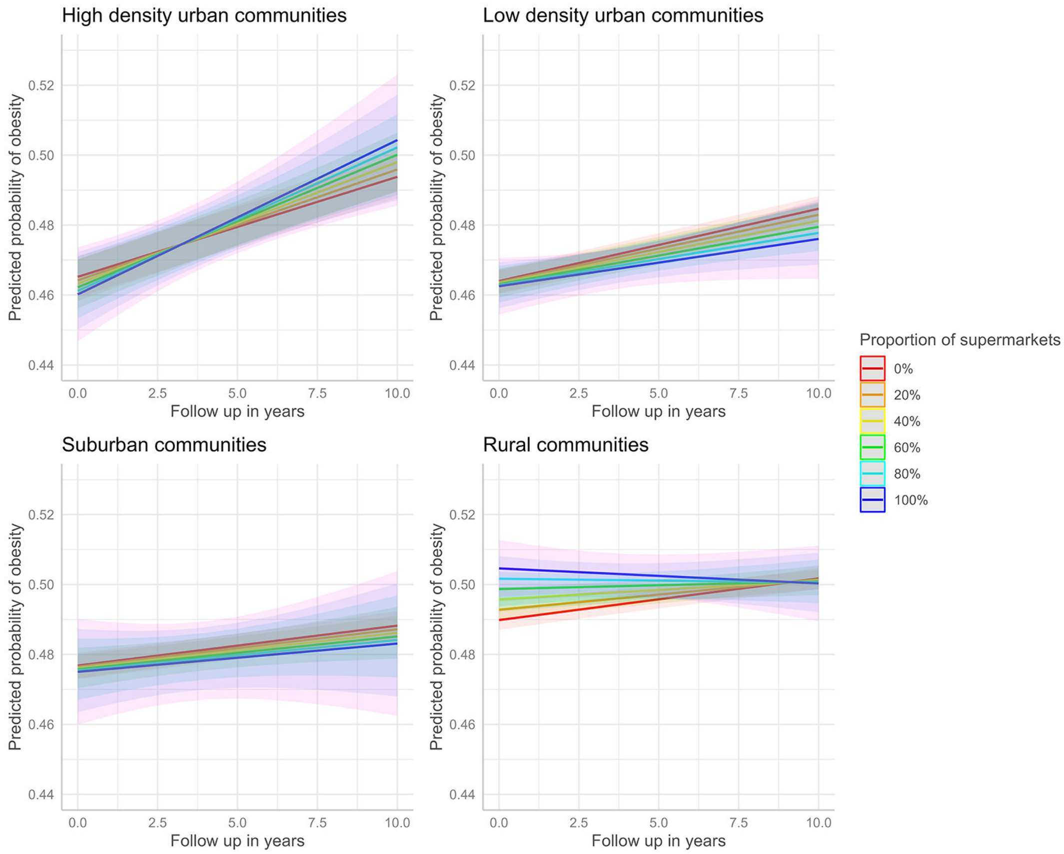

Figure 2. Model-based associations[a] of the relative availability of supermarkets and obesity[b] by year and community type

NOTE: p-value reflect statistical significance (α=0.05) of interaction term for time (year since baseline) and food environment exposure variables.

[a]Adjusting for baseline age, sex, race/ethnicity, marital status, income/disability flag, land use environment, neighborhood socioeconomic environment quartiles, percentage Hispanic population and percent non-Hispanic Black population of participants' Census tracts; and interaction with year since baseline (i.e., cohort entry date).

[b]Obesity defined as body mass index of >30.0 kg/m^2.

TABLE 1.

Individual-level and neighborhood-level characteristics by community type

	All community types n/mean (%/SD)	High density urban n/mean (%/SD)	Lower density urban n/mean (%/SD)	Suburban/small town n/mean (%/SD)	Rural n/mean (%/SD)
	3,067,627	397,916 (13.0)	1,166,343 (38.0)	655,971 (21.4)	847,397 (27.6)
Individual-level variables					
Age	58.5 (16.0)	56.4 (16.2)	58 (16.5)	58.4 (16.1)	60.3 (14.9)
Age categories					
19-39	458863 (15.0)	71103 (17.9)	191652 (16.4)	100724 (15.4)	95384 (11.3)
40-59	926665 (30.2)	139171 (35.0)	362630 (31.1)	195593 (29.8)	229271 (27.1)
60-79	1402894 (45.7)	155387 (39.1)	495555 (42.5)	300475 (45.8)	451477 (53.3)
80+	279205 (9.1)	32255 (8.1)	116506 (10.0)	59179 (9.0)	71265 (8.4)
Gender					
Male	2844774 (92.7)	365978 (92.0)	1069856 (91.7)	606590 (92.5)	802350 (94.7)
Female	222853 (7.3)	31938 (8.0)	96487 (8.3)	49381 (7.5)	45047 (5.3)
Race/eth					
Non-Hispanic white	2311981 (75.4)	213043 (53.5)	819478 (70.3)	524188 (79.9)	755272 (89.1)
Non-Hispanic black	516727 (16.8)	129836 (32.6)	237672 (20.4)	89141 (13.6)	60078 (7.1)
Hispanic	160520 (5.2)	38822 (9.8)	76725 (6.6)	27613 (4.2)	17360 (2.1)
Non-Hispanic Asian	28153 (0.9)	9009 (2.3)	12758 (1.1)	4660 (0.7)	1726 (0.2)
Non-Hispanic Native Hawaiian/other Pacific Islander	25133 (0.8)	4169 (1.1)	10844 (0.9)	5022 (0.8)	5098 (0.6)
Non-Hispanic American Indian/Alaska native	25113 (0.8)	3037 (0.8)	8866 (0.8)	5347 (0.8)	7863 (0.9)
Marital status					
Married/living with a partner	1716936 (56.0)	151943 (38.2)	621197 (53.3)	402827 (61.4)	540969 (63.8)
Single	1350691 (44.0)	245973 (61.8)	545146 (46.7)	253144 (38.6)	306428 (36.2)
Income/disability					
Disabled	1178669 (38.4)	131863 (33.1)	455371 (39)	271002 (41.3)	320433 (37.8)
Low income	1109805 (36.2)	191060 (48)	424484 (36.4)	207113 (31.6)	287148 (33.9)
None of the above	779153 (25.4)	74993 (18.9)	286488 (24.6)	177856 (27.1)	239816 (28.3)
BMI continuous	29.8 (5.6)	29.3 (5.8)	29.7 (5.6)	29.9 (5.6)	30.0 (5.6)
BMI					

	All community types n/mean (%/SD)	High density urban n/mean (%/SD)	Lower density urban n/mean (%/SD)	Suburban/small town n/mean (%/SD)	Rural n/mean (%/SD)
Normal weight (BMI<25)	573061 (18.7)	88635 (22.3)	223438 (19.2)	114367 (17.4)	146621 (17.3)
Overweight (BMI 25 to <30)	1178539 (38.4)	151814 (38.2)	451486 (38.7)	252678 (38.5)	322561 (38.1)
Obese (BMI≥30)	1316027 (42.9)	157467 (39.6)	491419 (42.1)	288926 (44.1)	378215 (44.6)
Prevalence diabetes	1036641 (33.8)	136935 (34.4)	389098 (33.4)	214383 (32.7)	296225 (35.0)
Neighborhood level variables					
Relative fast-food restaurants	0.301 (0.128)	0.256 (0.135)	0.314 (0.122)	0.325 (0.098)	0.286 (0.145)
Relative supermarkets	0.109 (0.072)	0.091 (0.075)	0.103 (0.070)	0.11 (0.051)	0.125 (0.081)
NSEE continuous	16.947 (9.838)	24.809 (13.226)	14.187 (8.873)	14.362 (8.46)	19.054 (7.439)
NSEE quartiles					
1st quartile (most advantaged)	609503 (19.9)	90581 (22.8)	195318 (16.8)	125576 (19.1)	198028 (23.4)
2nd quartile	815284 (26.6)	109105 (27.4)	300479 (25.8)	178543 (27.2)	227157 (26.8)
3rd quartile	883823 (28.8)	104424 (26.2)	351187 (30.1)	193959 (29.6)	234253 (27.6)
4th quartile (least advantaged)	759017 (24.7)	93806 (23.6)	319359 (27.4)	157893 (24.1)	187959 (22.2)
Land use environment	0.06 (0.910)	0.004 (0.810)	0.08 (0.906)	−0.006 (0.962)	0.108 (0.916)
Percent Hispanic	0.103 (0.161)	0.197 (0.228)	0.126 (0.168)	0.08 (0.132)	0.046 (0.094)
Percent NH black	0.136 (0.221)	0.269 (0.323)	0.16 (0.231)	0.101 (0.165)	0.069 (0.137)

NSEE=neighborhood socioeconomic environment

TABLE 2.

Obesity status by individual-level and neighborhood-level characteristics by community type

	All community types		High density urban		Lower density urban		Suburban/small town		Rural	
	n	% (95% CI)	n	% (95% CI)	n	% (95% CI)	n	% (95% CI)	n	% (95% CI)
	1,316,027	42.9 (42.8, 43.0)	157,467	39.6 (39.4, 39.7)	491,419	42.1 (42, 42.2)	288,926	44 (43.9, 44.2)	378,215	44.6 (44.5, 44.7)
Individual-level variables										
Age categories										
19-39	182,781	39.8 (39.7, 40)	25,338	35.6 (35.3, 36)	75,787	39.5 (39.3, 39.8)	41,788	41.5 (41.2, 41.8)	39,868	41.8 (41.5, 42.1)
40-59	449,247	48.5 (48.4, 48.6)	61,727	44.4 (44.1, 44.6)	174,178	48 (47.9, 48.2)	98,310	50.3 (50, 50.5)	115,032	50.2 (50, 50.4)
60-79	618,693	44.1 (44, 44.2)	63,185	40.7 (40.4, 40.9)	215,209	43.4 (43.3, 43.6)	134,683	44.8 (44.6, 45)	205,616	45.5 (45.4, 45.7)
80+	65,306	23.4 (23.2, 23.5)	7,217	22.4 (21.9, 22.8)	26,245	22.5 (22.3, 22.8)	14,145	23.9 (23.6, 24.2)	17,699	24.8 (24.5, 25.2)
Gender										
Male	1,222,415	43 (42.9, 43)	144,484	39.5 (39.3, 39.6)	451,055	42.2 (42.1, 42.3)	268,137	44.2 (44.1, 44.3)	358,739	44.7 (44.6, 44.8)
Female	93,612	42 (41.8, 42.2)	12,983	40.7 (40.1, 41.2)	40,364	41.8 (41.5, 42.1)	20,789	42.1 (41.7, 42.5)	19,476	43.2 (42.8, 43.7)
Race/eth										
Non-Hispanic white	979,120	42.3 (42.3, 42.4)	83,034	39 (38.8, 39.2)	335,224	40.9 (40.8, 41)	225,846	43.1 (43, 43.2)	335,016	44.4 (44.2, 44.5)
Non-Hispanic black	231,578	44.8 (44.7, 45)	52,506	40.4 (40.2, 40.7)	107,907	45.4 (45.2, 45.6)	43,277	48.5 (48.2, 48.9)	27,888	46.4 (46, 46.8)
Hispanic	75,130	46.8 (46.6, 47)	16,873	43.5 (43, 44)	36,092	47 (46.7, 47.4)	13,662	49.5 (48.9, 50.1)	8,503	49 (48.2, 49.7)
Non-Hispanic Asian	7,008	24.9 (24.4, 25.4)	1,971	21.9 (21, 22.7)	3,193	25 (24.3, 25.8)	1,292	27.7 (26.4, 29)	552	32 (29.8, 34.2)
Non-Hispanic Native Hawaiian/other Pacific Islander	11,176	44.5 (43.9, 45.1)	1,710	41 (39.5, 42.5)	4,837	44.6 (43.7, 45.5)	2,275	45.3 (43.9, 46.7)	2,354	46.2 (44.8, 47.5)
Non-Hispanic American Indian/Alaska native	12,015	47.8 (47.2, 48.5)	1,373	45.2 (43.4, 47)	4,166	47 (45.9, 48)	2,574	48.1 (46.8, 49.5)	3,902	49.6 (48.5, 50.7)
Marital status										
Married/living with a partner	782,175	45.6 (45.5, 45.6)	65,760	43.3 (43, 43.5)	277,749	44.7 (44.6, 44.8)	186,107	46.2 (46, 46.4)	252,559	46.7 (46.6, 46.8)
Single	533,852	39.5 (39.4, 39.6)	91,707	37.3 (37.1, 37.5)	213,670	39.2 (39.1, 39.3)	102,819	40.6 (40.4, 40.8)	125,656	41 (40.8, 41.2)
Income/disability										
Disabled	558,333	47.4 (47.3, 47.5)	57,243	43.4 (43.1, 43.7)	212,158	46.6 (46.4, 46.7)	130,956	48.3 (48.1, 48.5)	157,976	49.3 (49.1, 49.5)
Low income	439,936	39.6 (39.5, 39.7)	71,056	37.2 (37, 37.4)	166,235	39.2 (39, 39.3)	84,644	40.9 (40.7, 41.1)	118,001	41.1 (40.9, 41.3)
None of the above	317,758	40.8 (40.7, 40.9)	29,168	38.9 (38.5, 39.2)	113,026	39.5 (39.3, 39.6)	73,326	41.2 (41, 41.5)	102,238	42.6 (42.4, 42.8)
Prevalence diabetes										
Diabetes	608,144	58.7 (58.6, 58.8)	75,168	54.9 (54.6, 55.2)	224,422	57.7 (57.5, 57.8)	128,696	60 (59.8, 60.2)	179,858	60.7 (60.5, 60.9)

	All community types		High density urban		Lower density urban		Suburban/small town		Rural	
	n	**% (95% CI)**	**n**	**% (95% CI)**	**n**	**% (95% CI)**	**n**	**% (95% CI)**	**n**	**% (95% CI)**
No diabetes	707,883	34.9 (34.8, 34.9)	82,299	31.5 (31.4, 31.7)	266,997	34.4 (34.2, 34.5)	160,230	36.3 (36.1, 36.4)	198,357	36 (35.9, 36.1)
Neighborhood level										
NSEE quartiles										
1st quartile (most advantaged)	257,104	42.2 (42.1, 42.3)	35,200	38.9 (38.5, 39.2)	79,307	40.6 (40.4, 40.8)	53,948	43 (42.7, 43.2)	88,649	44.8 (44.5, 45)
2nd quartile	351,431	43.1 (43, 43.2)	43,920	40.3 (40, 40.5)	126,462	42.1 (41.9, 42.3)	78,621	44 (43.8, 44.3)	102,428	45.1 (44.9, 45.3)
3rd quartile	383,745	43.4 (43.3, 43.5)	41,971	40.2 (39.9, 40.5)	150,908	43 (42.8, 43.1)	86,554	44.6 (44.4, 44.8)	104,312	44.5 (44.3, 44.7)
4th quartile (least advantaged)	323,747	42.7 (42.5, 42.8)	36,376	38.8 (38.5, 39.1)	134,742	42.2 (42, 42.4)	69,803	44.2 (44, 44.5)	82,826	44.1 (43.8, 44.3)

NSEE=neighborhood socioeconomic environment