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Geographic Accessibility Of Food Outlets Not Associated With Body Mass Index Change Among Veterans, 2009-14

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Abstract

In recent years, various levels of government in the U.S. have adopted or discussed subsidies, tax breaks, zoning laws, and other public policy instruments to promote geographic access to healthy food. These policies are supposed to reduce obesity. But there is little evidence from large-scale longitudinal or quasi-experimental research suggesting that geographic access to supermarkets, fast food restaurants, and other food outlets actually affect body mass index (BMI). Using a longitudinal design, we examined whether geographic accessibility of food outlets was associated with BMI change between 2009 and 2014 using clinical data for 1.7 million military veterans living in 382 metropolitan areas. We found no evidence that the absolute or relative accessibility of supermarkets, fast food restaurants, or mass merchandisers were associated with individual BMI change. While they may promote equitable access, our findings suggest that policies that alter food outlet accessibility will do little to combat the obesity epidemic.

Introduction

In recent years, various levels of government in the U.S. have adopted or discussed subsidies, tax breaks, zoning laws, and other public policy instruments to promote geographic access to healthy food(1,2). For example, healthy food financing initiatives offer subsidies and tax breaks to open new stores or renovate existing stores in underserved areas(1,3). Most subsidy programs target supermarkets because they offer the widest selection of healthy foods(4–7). In another direction, some governments are trying to reduce access to unhealthy food using fast food restaurant moratoriums and zoning policies that restrict or ban new fast food restaurants in so-called over-served neighborhoods(8–10). In other places, local zoning laws and ordinances include store size restrictions, design guidelines, and formula business regulations(11,12) restrict the entry of the supercenters and other mass merchandisers that are a primary source of food for American households (i.e.,

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Walmart, Target, and other large stores that sell a large variety of food and non-food merchandise)(13,14).

Access to healthier and less healthy food outlets differs across neighborhoods(15–18). Several studies have found that geographic accessibility of supermarkets is negatively associated with local residents' body mass index (BMI) or weight status (e.g., obesity) and geographic accessibility of fast food restaurants is positively associated with BMI(19–23), although evidence on mass merchandiser access-BMI associations is scarce(24–26). Research has also found associations between the relative balance of healthier to less healthy food outlets and BMI(27–30). However, almost all studies of absolute and relative food outlet accessibility used cross-sectional designs(19–21). Results of cross-sectional studies may reflect unmeasured differences in preferences across people who chose to live near food outlets rather than the causal effect of the food outlets themselves(31).

A few quasi-experimental studies have examined supermarket developments and fast food restaurant moratoriums and found little support for the idea that policies that support or restrict food outlets affect BMI(8,32–34). However, these studies were conducted on a small scale and examined the connection between food outlet access and BMI in small geographic areas. Small-scale studies have limited statistical power to detect health changes. Well-designed longitudinal research that supports causal inference and can examine effects of many supermarket, fast food restaurant, and mass merchandiser openings or closings across a wide geographic area can strengthen the evidence base and inform discussions on whether public policies addressing the food environment are likely to be effective in achieving healthier BMI.

This paper reports results from the Weight and Veterans' Environments Study (WAVES), which to our knowledge, is the largest national study of the connection between residential environments and BMI ever conducted in the U.S.(35). The project is at the forefront of "big data" research, linking electronic health records from military veterans nationwide with public and proprietary environmental data. It provides the statistical power needed to detect small effects of the environment on clinical measures of BMI. The data enable research designs that exploit temporal and spatial changes in environmental conditions over a 7-year period and help avoid bias from a broad set of factors that were uncontrolled in earlier research.

The analysis in this paper focuses on supermarkets, fast food restaurants, and mass merchandisers. The premise of the policy debate is that people gain or lose weight because of their geographic access to supermarkets, fast food restaurants, and mass merchandisers. Often the discussion is focused on high-poverty neighborhoods, where obesity is an important health concern, access to healthier food outlets may be limited, and less healthy outlets may be concentrated(15,16,36,37). Our analysis tests the null hypothesis that geographic accessibility of food outlets does not have an important effect on BMI. To shed light on the socioeconomic gradient, we also examined whether the association between the food outlet access and BMI differs by neighborhood poverty level. Rejecting the null hypothesis (statistically and clinically) would provide evidence in favor of the policy view that geographic access to food outlets matters.

Data and Methods

Design

WAVES is a retrospective longitudinal cohort study of American military veterans who received healthcare services from the Department of Veteran Affairs (VA) between 2009 and 2014(35). Here, we linked the first six years of individual-level data from the VA Corporate Data Warehouse, a repository of clinical and administrative data from the electronic health record and other sources, to secondary data on food outlet locations to study the effects of person-level changes in the food environment generated by store openings/closings and individual migration.

Sample

The analytical sample consists of 1.7 million people (ages 20–64 years) residing in 382 metropolitan areas. Excluded were people without at least one VA healthcare encounter in the two years prior to baseline; with long-stay nursing home residence at baseline; without at least one geocoded home address; and without at least one valid height and weight measurement.

Measures

Body mass index—We calculated a BMI measure for each person in each year using height and weight measurements taken during patient encounters. Height was typically based on the modal value across the study period; average weight during the second half of the calendar year was prioritized to align the weight data with the geographic data.

Geographic accessibility of food outlets—We constructed annual measures of the geographic accessibility of chain supermarkets, non-chain supermarkets, supercenters and other mass merchandisers, chain fast food restaurants, and non-chain fast food restaurants for each person and year. Specifically, we measured the number of outlets within a 1-mile (1mi) radius and a larger 3-mile (3mi) radius (inclusive of outlets within 1-mile) of the person's residence. We defined relative accessibility of supermarkets as the number of supermarkets expressed as a percentage of supermarkets and fast food restaurants. In the analysis, the food outlet variables enter as a set of dummy variables and the reference category typically consists of people who live near 0 such outlets.

Covariates—Individual time-invariant variables included age, gender, and race/ethnicity. Individual time-varying covariates included marital status and ten chronic health conditions. Area covariates included: census division, county-level urbanicity(38), census tract demographics (percent of residents below the federal poverty line, median household income, population density), and geographic accessibility of grocery stores, convenience stores, parks, and fitness facilities.

Data analysis

We estimated cross-sectional models with year fixed effects and longitudinal models that incorporated both year and person fixed effects. The person fixed effects adjust for a broad class of potential confounding factors that could undermine the internal validity of cross-sectional regressions. In particular, cross-sectional models are limited by residential self-selection bias, which might mean that cross-sectional associations between food outlet accessibility and BMI reflect preferences or other unmeasured characteristics associated with both food outlet accessibility and BMI. A person fixed-effect model avoids time-invariant biases by focusing on within-person changes in food outlet accessibility. Both the cross-sectional and fixed-effects models account for secular trends.

Person fixed-effect models exploit two different sources of within-person change in food outlet accessibility: changes from *individual migration* that occur when a person moves to a new address with a net change in the prevalence of food outlets; and changes from *neighborhood change* that arise when food outlets open or close. The distinction may be important because residential self-selection may still be a problem among migrants. For example, people may decide to move to a neighborhood where supermarkets are more accessible because of a negative health event that makes it harder for them to travel or because of a change in their lifestyle preferences. In that case, even the fixed-effects model may be biased because unmeasured changes in health status or preferences may affect both BMI and food outlet accessibility. To explore these concerns, we estimated separate fixed-effects models for non-migrants. In the non-migrant sample, the fixed-effects models are based exclusively on variation that comes from the entry and exit of food outlets. Associations for non-migrants are less prone to residential self-selection bias because individual people have very little control over the entry and exit of food outlets. That is, any individual-level changes in health status or preferences that do occur are unlikely to be correlated with the opening or closing of food outlets. The non-migrant fixed-effects models strengthen our inferences about the causal effects of food outlets on BMI.

We fit two specifications of each model. The first set of models is based on food outlets within a 1-mile radius of the person's address. The second set is based on a 3-mile radius. To examine whether associations differed by area economic characteristics, we added interaction terms between the food outlet variables and census tract poverty level. Poverty was categorized using nationwide census tract tertiles. All models accounted for clustering of individuals within counties at baseline. Because men comprise almost 90% of the sample, we estimated separate models for men and women.

Limitations

There are limitations associated with the data and methods. First, we were unable to incorporate measures that capture individual SES. Therefore, while we controlled for multiple census tract socioeconomic characteristics, residual confounding related to within-person changes in SES is possible. Second, our approach to BMI measurement (i.e., modal height measurement across the study period) does not capture real height loss that may occur with aging. Given our study included only those under age 65 at baseline (mean 52 and 43 among men and women, respectively) and the study follow-up time was not more than 6 years, we think undetected measurable height loss was likely infrequent and unlikely to generate bias in effects of food outlet accessibility on BMI. Third, commercial data sources for retail food outlets are prone to error. We carefully cleaned and processed the data to maximize its quality(39). Fourth, this study includes only measures of the geographic accessibility of food outlets and does not consider other dimensions of access or food availability, prices, quality, or marketing inside these outlets, which may impact purchasing and ultimately BMI. Fifth, like most prior studies, we focused on accessibility of food outlets relative to where people live rather than where they spend time, which may more accurately capture exposures(40). Sixth, the VA population may be an important segment of the U.S. population but the 1.7 million VA patients in our study are not a representative sample of the U.S. adult population. For example, our study population has disproportionately more African American and lower income persons, groups at higher risk for obesity(35). And, VA men are older and demographically different from VA women; therefore, our findings for men and women are not directly comparable. While our study's internal validity may be high and VA patients live in diverse neighborhoods nationwide which themselves are broadly representative of the environments in which the bulk of the U.S. population resides, the study's external validity is unknown: it is unclear whether the effects of geographic access to food outlets observed in the VA population are comparable to those in the general population. Finally, our study generally estimates average effects of geographic access to food outlets. While we examine heterogeneity of effects by neighborhood poverty level, we do not rule out the possibility that effects are heterogeneous across other groups of people (e.g., those without a car).

For more information on the data and methods, please see the Appendix Exhibit A(41).

Results

Sample characteristics

Exhibit 1 describes the full sample and non-migrant sample during the baseline year separately for men and women. See Appendix Exhibit B for more descriptive statistics(41). To avoid comparison between men and women, regression results are presented for men, and then women. See Appendix Exhibit C and D for complete regression results(41).

MEN

Food outlet accessibility and BMI associations—Exhibit 2 shows results from cross-sectional and longitudinal regressions of BMI on measures of the geographic accessibility of chain and non-chain supermarkets, mass merchandisers, and chain and non-chain fast food restaurants within 1mi (top panel) and 3mi (bottom panel).

<u>Cross-sectional associations:</u> In the cross-section, neither chain supermarket nor non-chain supermarket access within 1mi was associated with BMI among men (Exhibit 2, column 1). Accessibility of one or more mass merchandisers within 1mi was associated with a 0.123-unit higher BMI ($p<0.001$). Living near more chain fast food restaurants within 1mi was also associated with higher BMI: 0.057 units for 3–6 restaurants ($p<0.01$) and 0.085 units for 7 or more restaurants ($p<0.001$). Living near a moderate or high number of non-chain fast food restaurants were associated with a 0.062 ($p<0.01$) and 0.206 ($p<0.001$) unit lower BMI, respectively.

At 3mi (Exhibit 2, bottom panel), accessibility of 4 or more non-chain supermarkets was associated with a 0.080-unit lower BMI among men in the cross-section ($p<0.05$). Compared to 1mi, associations between mass merchandiser accessibility within 3mi and BMI were generally stronger with coefficients as large as 0.283 (p<0.001). Negative associations between non-chain fast food restaurant accessibility and BMI remained at 3-mi (p<0.001).

Longitudinal associations: Longitudinal results are shown in columns 2 and 3 (Exhibit 2). In the full sample of men (column 2), associations were weak and the relatively few statistically significant associations were not clinically meaningful using either 1mi or 3mi measures. The strongest association with BMI was having 3 or more mass merchandisers. There, the coefficient of 0.026 (p<0.001) is still very small in a clinical sense. To put the effect in context, a 0.026-unit increase in BMI amounts to gaining 0.18 pounds for a man who is 5 feet 10 inches tall. The longitudinal associations were generally weaker and nonsignificant among non-migrant men (column 3).

Relative accessibility of supermarkets to fast food restaurants and BMI associations—Exhibit 3 shows associations between BMI and the relative accessibility of supermarkets to fast food restaurants holding constant the accessibility of other outlet types. In general, relative accessibility of supermarkets to fast food restaurants was not associated with BMI cross-sectionally (column 1) or longitudinally for the full sample of men (column 2) or non-migrant men (column 3).

WOMEN

Food outlet accessibility and BMI associations

Cross-sectional associations: Among women (Exhibit 2, column 4), cross-sectional associations with BMI were not statistically significant for accessibility of chain supermarkets, non-chain supermarkets, and mass merchandisers within 1mi (top panel). Accessibility of chain fast food restaurants within 1mi was associated with higher BMI among women: 0.139 units for 3–6 restaurants (p<0.01) and 0.168 units for 7 or more restaurants (p<0.01). Living near a moderate (3–6) or high (7 or more) number of non-chain fast food restaurants was associated with a 0.130 (p<0.01) and 0.426 (p<0.001) unit lower BMI, respectively.

At 3mi (Exhibit 2, bottom panel), chain supermarket accessibility was not associated with BMI among women in the cross-section. Accessibility of 1 and 2–3 non-chain supermarkets were associated with a 0.073 (p<0.05) and 0.104 (p<0.05) unit higher BMI. BMI tended to increase with more mass merchandisers within 3mi, with coefficients as high as 0.338 (p<0.001) for 3 or more mass merchandisers within 3mi. Chain fast food restaurant accessibility was not associated with BMI, but BMI decreased significantly at higher levels of non-chain fast food restaurant accessibility with coefficients ranging from −0.232 to −0.871 (p<0.001).

Longitudinal associations: There was little evidence from the longitudinal models that BMI was associated with accessibility of chain or non-chain supermarkets, mass merchandisers, or chain or non-chain fast food restaurants in either the full sample of women (column 5) or non-migrant women (column 6) at either 1mi or 3mi (Exhibit 2).

Relative accessibility of supermarkets to fast food restaurants and BMI associations—Among women (column 4), relative accessibility of supermarkets to fast food restaurants was not associated with BMI in the cross-section at 1 mi (Exhibit 3, top panel). At 3mi, women with moderately high and high relative accessibility of supermarkets had BMI 0.100 ($p<0.05$) and 0.140 ($p<0.01$) unit higher than women with low relative accessibility. However, these relative accessibility effects disappeared in the longitudinal models in both the full sample of women (Exhibit 3, columns 5) and the non-migrant women (Exhibit 3, column 6).

Differences by area poverty level—We found no evidence that area poverty level altered the relationship between BMI and food outlet accessibility in either cross-sectional or longitudinal models (not shown).

Discussion

This study found that multiple policy-relevant aspects of the food environment were associated with BMI in cross-sectional comparisons using clinical data on 1.7 million military veterans nationwide. That is, people living in areas with higher accessibility of chain fast food restaurants (1mi) and mass merchandisers (1mi and 3mi men; 3mi women) tended to have higher BMI, while men with high accessibility of non-chain supermarkets tended to have lower BMI (3mi). However, in longitudinal analyses that address important limitations of cross-sectional research particularly residential self-selection bias, we found almost no evidence that absolute or relative geographic accessibility of supermarkets, fast food restaurants, or mass merchandisers affected BMI. Moreover, the significant cross-sectional associations in unexpected directions disappeared in the longitudinal analyses. We also found no support for the idea that food outlet access matters most to people living in high-poverty neighborhoods.

Our study adds to a still small, but accumulating number of longitudinal studies that have generally found that food outlets have either no effect on BMI or effects that are small in magnitude and not clinically meaningful(42–48). Our findings suggest that cross-sectional results should be interpreted with caution and it is unlikely that additional cross-sectional research will provide needed insights into whether geographic accessibility of supermarkets, fast food restaurants, and/or mass merchandisers are promising targets for policy interventions to promote healthier BMI. One important area where additional longitudinal research would be useful is in low-SES populations. Using data from the Panel Study of Income Dynamics, Powell and Han found that each additional supermarket per 10,000 people per 10 square miles was associated with a 0.13-unit lower BMI longitudinally among poor women but was not associated with BMI among non-poor women, or poor or non-poor men(48). Longitudinal associations between fast food restaurant accessibility and BMI were not clinically meaningful in either poor or non-poor women or men in that study(48).

Overall, our findings suggest that public policies to alter residential geographic accessibility of supermarkets, fast food restaurants, or mass merchandisers alone are unlikely to be effective in promoting healthier BMI in adults. Our study does not reveal new information on the possibility that policy-induced changes in food outlet accessibility could have beneficial effects in children or lead to other positive changes such as increased neighborhood economic activity, job creation, and improvements in individual income. Changes in food access may also need to be accompanied by individually-focused health promotion interventions or economic incentives(33). Beyond supporting new food outlets and limiting others, policies addressing the availability, prices, and marketing of food products within food outlets may be useful(33,49). For example, strengthening healthy food stocking requirements for federal nutrition assistance programs, such as the Supplemental Nutrition Assistance Program, could serve as an incentive for lowering prices and transforming the product mix in food stores, which currently favor unhealthy products(7,50–52).

Study Strengths

The strength of the study comes from the large, nationwide, longitudinal, geocoded sample of health care records. That dataset made it possible to construct person-specific measures of the food environment and provided the kind of sample size required to reliably measure even small associations between geographic accessibility of a variety of food outlets and BMI. In addition, the structure of the data allowed us to take advantage of changes in people's exposure to different food outlets that arose through processes of neighborhood change and individual migration. Variation in food environments from neighborhood change seems like a useful way of avoiding many of the sources of potential bias that raise problems in the current literature. Because our study included people living across the country, it was feasible to study the differential effects of the food environment on people living in higher poverty neighborhoods. Unlike many survey-based studies, we were able to study BMI using clinical measurements rather than less accurate self-reports. And because our sample consists of military veterans using VA healthcare, our study implicitly controls for health insurance status and access to healthcare services that might confound associations in other samples.

Conclusion

Public policy may have an important role to play in achieving population-wide reductions in BMI. But the policies currently under discussion, based on assumptions of a causal link between food outlet access and BMI, lack needed robust empirical support. Strategies like the healthy food financing initiative are designed to alter geographic access to supermarkets, fast food restaurants, and mass merchandisers. It is possible that such policies may promote equity in access to healthy foods and reduce the saturation of unhealthy food sources in economically and socially disadvantaged neighborhoods. But our findings suggest that such policies alone are unlikely to lead to healthier BMI over time among adults.

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41. To access the Appendix, click on the Appendix link in the box to the right of the article online.

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Appendix Exhibit A. Technical documentation

Design

The Weight and Veterans' Environments Study (WAVES) is a 7-year retrospective longitudinal cohort study of U.S. adults who were military veterans receiving primary healthcare services in the U.S. Department of Veteran Affairs (VA) between 2009 and 2014 and who were followed to date through 2015. This paper links 6 years (2009–2014) of individual-level data from the VA Corporate Data Warehouse, a repository of clinical and administrative data from the electronic health record and other sources, with non-VA data on food outlet locations.

Linking food outlet data with clinical data is complicated in practice because the home address data, clinical data, and food outlet data are updated on different schedules. At the time we obtained the person-level home address geocodes from the VHA Planning Systems Support Group, the data that were available contained best known addresses as of the end of each VA fiscal year (September 30). To operationalize our work, a first decision was to prioritize the second half of the year (July 1-December 31) for BMI measurement in order to maximize the likelihood that patients were at that address when their weight was measured. Additionally, we pursued the general goal of measuring the environment at a time point preceding the outcome measures in each year. Since our study was designed to evaluate the effects of environmental factors (food outlet accessibility) on BMI, we used the basic policy of temporal precedence to make it clear that changes in environmental factors came before changes in BMI and not the other way around. Specifically, we linked individual BMI to food outlet accessibility measures in the 4^{th} quarter of the previous year. For example, 2009 BMI values were joined to supermarket measures derived from 4^{th} quarter 2008 supermarket location data.

Sample

The sample for the analysis in this paper consisted of 1.7 million working-age adults (20–64 years old) residing in metropolitan counties. The sample is derived from a larger study cohort of 3.2 million U.S. military veterans aged 20–80 years who lived in the continental U.S.(1). The exclusion criteria eliminated patients who did not have at least one VA healthcare encounter in the two years prior to baseline; patients who resided in a long-stay nursing home at baseline; patients who did not have at least one home address (not PO Box address) that could be geocoded to the street or ZIP+4 level during the study period; patients without at least one valid and clinically plausible height and weight measurement during the study period; and patients over the age of 65 because of multiple possible lifestyle, mobility, and socioeconomic differences among older versus younger, working-age adults that might manifest in very different relationships between the residential environment and BMI.

Measures

Body mass index (BMI)

The dependent variable in the paper is the patient's BMI (weight in kg / height in m^2) in a given calendar year. Practical challenges in working with electronic medical record data include having no control over data collection periodicity, frequency, or quality. Ancillary rules were needed to address these issues and to impose an annual structure on the data.

BMI is a weight-for-height measure that is intended to standardize weight measurements in a way that accounts for differences in body structure across individuals that are relatively permanent and that are unrelated to things like diet and exercise. In essence, weight measurements are scaled by the square of a person's height in meters. We cleaned the height measures in the medical records by deleting implausible measurements (<48 inches or >85 inches). We then defined each patient's height to be the modal value of all available height measurements taken during the entire study period. When available height measurements had no modal value, we used the mean instead. Although it is possible that a patient's height changes somewhat over time, we felt that difference in observed height measurements for a patient were more likely to reflect measurement errors or data entry errors than genuine changes in a patient's height. Since small error in height measurement can have outsized effects on BMI (because it is squared in the denominator), use of the most frequently appearing value maximized the likelihood that we would be using the patient's true height (rather than a mean or median which, though a good estimate, would be less likely to exactly equal the patient's true height). Taking a modal value each year was not feasible because the majority of patients did not have enough height measurements within a single year to identify a mode. A limitation of our approach is that it does not capture real changes in height arising from the height loss that may occur with aging. Given that our study sample was limited to patients under age 65 at baseline (mean 52 and 43 among men and women, respectively) and the study follow-up time of not more than 6 years, we think undetected measurable height loss likely was infrequent. Still, among those who lose height over the time period, our approach will underestimate BMI loss and overestimate BMI gain. We can think of no reason why unmeasured losses in height would tend to occur more rapidly in patients exposed to time-varying changes in retail food environments and so we do not expect unmeasured height loss to generate bias in our estimates of the effects of the food environment on BMI. Ultimately our approach reflects our judgement that measurement error was a larger threat to accuracy than time-related decreases in height.

We used a multi-step procedure to define an annual weight measurement for each member of the sample. First, we set each patient's weight in a given year equal to the average value of all of the weight measurements available for the patient during the second half of the calendar year. If no valid weight measurement was available during the second half of the year or if the BMI implied by the average weight in the second half of the year was not 15.0–75.0 kg/m^2, we used the average weight value from the entire calendar year. We were able to compute annual BMI measures using the second half of the year approach for 80.7% of 7,441,544 person-year observations in our analysis. We used the full year averaging approach for the remaining 20.3% of the observations.

Geographic accessibility of retail food outlets

Following our review of validation studies (2), we purchased food store data from InfoUSA and fast food restaurant data from Dun & Bradstreet. After cleaning the home address geocodes and retail food outlet data in order to maximize their accuracy and utility (e.g., reclassifying some records by store type, deduplicating records)(2), we constructed annual (4^{th} quarter) measures of the geographic accessibility of chain supermarkets [standard industrial classification (SIC) codes 541101-541109 (excluding 541103, convenience stores) and >$2M annual sales, or name listed in Supermarket News Top 75 Retailers and Wholesalers in any year between 2010 and 2014]; non-chain supermarkets [SIC codes 541101-541109 (excluding 541103) and >$2M annual sales but name not listed in Supermarket News]; supercenters and other non-membership mass merchandisers (SIC code 53 and Walmart, Kmart, Target, or Meijer in name); chain fast food restaurants including pizza [SIC code 58120601 or 581203 and name listed in National Restaurant News Top 200 between 2007 and 2013 or name listed in Quick Service or Fast Casual or Quick Service Restaurant Top 50 between 2007 and 2013 (but not coffee shops: 58120304)]; and non-chain fast food restaurants (SIC code 58120602 or 581203 and name not in National Restaurant News or Quick Serve Restaurant lists). Most U.S. households shop at mass merchandisers or supermarkets, particularly chain stores(3,4).

We defined the relative accessibility of supermarkets to fast food restaurants as the percentage of food outlets (supermarkets and fast food restaurants) that were supermarkets. Mass merchandisers were not included in the relative accessibility measure because of mixed conceptual and empirical evidence for their potential impact on BMI.

We used an adapted "smartmap" approach(5) to construct our measures of geographic accessibility of retail food outlets. Specifically, we divided the continental U.S. into 30m × 30m grid cells with approximately 9 billion cells. Retail food outlet accessibility measures are based on each grid cell's centroid (geometric center) and calculated as the number of outlets within a 1-mile (1mi) radius and a 3-mile (3mi) radius. For each study year, we assigned the value of each retail food outlet measure to each patient based on the cell in which his or her home geocode was located.

A patient's retail food outlet measures can vary over time for two reasons: (a) individual migration and (b) neighborhood change. Environmental variation over time because of individual migration occurs whenever a patient moves to a new home address and the new address has a different number of nearby retail food outlets. We considered a patient to have moved if home geocodes based on addresses from adjacent years were more than 0.25 miles apart. A patient's environment may change without any migration because of the opening and closing of retail food outlets, which we refer to as neighborhood change. Accessibility within 3 miles may be particularly relevant for food stores, given that multiple studies show that individuals travel between two and four miles from home to shop for groceries (4,6–10). Accessibility within 1 mile may be more relevant for fast food restaurants where individuals often purchase prepared foods or snacks for home consumption.

To avoid strong functional form assumptions about the relationship between the number of nearby food outlets and BMI, we grouped the members of our sample into discrete categories of food outlet accessibility. When categorizing the food outlet variables, we considered several options. Our goal was to compare having different levels of food outlets (e.g., a little, some, a lot) to having no food outlet. The variable distributions shaped whether the variable was dichotomized or categorized based on tertiles or quartiles. We used a hierarchy of decision rules. When more than 50% of people had none of an outlet within the (1- or 3-mile radius) area, we created binary variables (0, 1 or more). This prevented the construction of scarcely populated categories. For other outlets, we created 4-category variables. When at least 10% (and <50%) of the people had no outlet within that distance, we derived a 4-level variable: 0, and then tertiles of the non-zero distribution. When <10% of people had none of the outlet within the specified area, we categorized the variable based on quartiles of the entire distribution to avoid having a scarcely populated reference category. For the relative accessibility there was an additional category of no supermarket or fast food restaurant within that distance because we conceived of having neither a supermarket or a fast food outlet as having potentially different effects than having no supermarket (or a low number of supermarkets within 3 miles) but at least one fast food restaurant. The Table shows how each food outlet was categorized at 1mi and 3mi.

Table

Approach for categorizing food outlets

	Dichotomous (0, 1 or more)	0 and tertiles of the remaining non-zero distribution of values	Quartiles of the distribution of values
Chain supermarkets, 1 mi	X		
Non-chain supermarkets, 1 mi	X		
Mass merchandisers, 1 mi	X		
Grocery stores, 1 mi	X		
Chain fast food restaurants, 1 mi		X	
Non-chain fast food restaurants, 1 mi		X	
Convenience stores, 1 mi		X	
Relative accessibility supermarkets to fast food, 1 mi		X	
Chain supermarkets, 1 mi		X	
Non-chain supermarkets, 3 mi		X	
Mass merchandisers, 3 mi		X	
Grocery stores, 3 mi		X	
Chain fast food restaurants, 3 mi		X	
Non-chain fast food restaurants, 3 mi			X
Convenience stores, 3 mi			X
Relative accessibility supermarkets to fast food, 3 mi			X

Covariates

Individual-level time-invariant variables included baseline age and race/ethnicity (non-Hispanic white, non-Hispanic black, Hispanic, non-Hispanic other/unknown). We supplemented missing race and ethnicity information in the VA data with Medicare data on race from the VA-CMS Data Repository (11,12).

Individual-level, time-varying covariates included marital status (married, separated or divorced, widowed, single, unknown) and ten chronic health conditions associated in prior research with both BMI and independently with diet and/or physical activity (breast cancer, cerebrovascular disease, colon cancer, congestive heart failure, depression, diabetes, hyperlipidemia, hypertension, myocardial infarction, and osteoporosis).

We included several area-level covariates: census division (New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, Pacific) and urbanicity measured at the county level (large central metro, large fringe metro, medium metro, and small metro)(1,13). County urban-rural classification codes were available for 2006 and 2013 only; thus, we assigned 2006 NCHS urban-rural classification codes to patients' residential location for years 2009–2012 and 2013 NCHS urban-rural classification codes to patients' residential location for years 2013–14.

We also adjusted for small-area demographics. Based on census tract of residence, we assigned each patient local tract-level demographic information using the American Community Survey 5-year estimates of SES (percent of residents with annual incomes below the federal poverty line and median household income, both categorized into deciles of the distribution of the values for all continental U.S. census tracts) and population density (number of residents per land area, categorized into quartiles based on all continental U.S. census tracts). Given the delay in annual releases of successive 5-year ACS estimates, we used a 2-year lag based on the ACS 5-year midpoint for linking patient measures to ACS measures (e.g., 2009 patient BMI linked to 2005–2009 ACS data, midpoint 2007; 2014 patient BMI linked to 2010–2014 ACS data).

In addition, we controlled for accessibility of parks (1mi), fitness facilities (1mi), and other retail food outlets (1mi or 3mi depending on the model): grocery stores (SIC codes 541101-541109 [excluding 541103], <$2M annual sales, and name not listed in Supermarket News) and convenience stores (SIC codes 541103, 554101, 554103). We obtained grocery store, convenience store, and fitness facility data from InfoUSA. We combined data from TeleAtlas and NAVTEQ to derive the park measures.

Data analysis

We estimated pooled (all years) cross-sectional models with year fixed effects and longitudinal models that also incorporated individual-level fixed effects to examine associations between food outlet accessibility and BMI.

Cross-sectional models

To understand our statistical modeling strategy in more detail, let BMI_{it} be the BMI associated with patient i in study year t as described above. X_t is a vector of patient-level time-invariant characteristics. Z_{it} is a vector of time-varying patient-level characteristics and characteristics of the patient's environment (small area demographics, accessibility of parks, convenience stores, etc). FE_{it} is a vector of time-varying food environment variables. Depending on the model, FE_{it} may include indicator variables for several different levels of supermarket counts, fast food restaurant counts, mass merchandiser counts, and relative accessibility measures. And depending on the model, these measures may be defined on either a 1-mile radius or a 3-mile radius around the patient's place of residence. With that notation as background, we fit the following regressions using OLS:

$$BMI_{it} = X_i\alpha + Z_{it}\beta + FE_{it}\delta + \theta_t + \varepsilon_{it}$$

In the model, θ_t is a year-specific intercept and ε_{it} is an error term. We estimated standard errors that allowed for observations to be correlated within counties. δ is the vector of coefficients on the food outlet variables. These coefficients measure the cross-sectional association between the food outlet variables and BMI, after controlling for time period effects, time-varying covariates, and time-invariant covariates. Under the strong assumption that there are no unmeasured variables that are associated with both BMI and the food outlet variables, δ captures the causal effects of the geographic accessibility of food outlets on BMI.

Fixed effects models

Residential self-selection bias or omitted variable bias is an important threat to the validity of the cross-sectional regression models. A basic worry is that people decide where to live partly because of their preferences for different food environments. It is possible that a person's food environment preferences are associated with his or her BMI. Together these two points raise concerns that the coefficient on the food outlet variables in the cross-sectional regressions may be biased in ways that make food outlet access look like a more important determinant of BMI than it really is. For example, unmeasured lifestyle preferences that make people like living near fast food restaurants and might also lead them to have higher BMI. In that case, the cross-sectional regression coefficient on measures of fast food restaurant accessibility will reflect both the causal effects of the restaurants and the unmeasured lifestyle factors. The results will imply that fast food restaurant accessibility increases BMI even though most of the relationship may have nothing to do with the restaurants themselves and will merely reflect lifestyle differences between people who choose to live near vs. far from fast food restaurants. It is important to note, though, that this concern arises from any unmeasured factor associated with both where someone lives (e.g., discrimination) and the associated environmental exposures.

To avoid these kinds of confounding interpretations, we took advantage of the longitudinal structure of our data to estimate person fixed effects regression models. These models isolate the causal effect of the food outlet variables among patients who experience a change in their residential food environment. The key assumption required in this type of analysis is that the confounding factors that threaten the validity of the cross-sectional models are time invariant over the study time period. That is, these models work under the assumption that the lifestyle factors that (partially) shape residential choices do not themselves change over time. Arguments like this one apply to any unmeasured confounding patient characteristic that does not change over the study time period. Like the cross-sectional models, the person fixed effects models also allow for a flexible time trend that may which may capture changes in economic conditions, market environments, and health behaviors that could confound food outlet-BMI associations.

The basic form of the fixed effects model that we work with is:

$$BMI_{it} = Z_{it}\beta + FE_{it}\delta + \theta_t + \lambda_i + \varepsilon_{it}$$

In this model, λ_i represents a full set of person fixed effects. The time-invariant covariates contained in X_i are absorbed into the person specific intercepts, along with any unmeasured time-invariant factors that may have generated omitted variable bias in the cross-sectional models. In these models, δ represents the causal effects of the food outlet variables under the assumption that there are no unmeasured time-varying confounders that are associated with both BMI and changes in food outlet accessibility.

These person fixed effect models exploit two conceptually different sources of within-person change in food outlet accessibility in sequential years: change due to individual migration (i.e., a person moving to a new address with a net change in the prevalence of food outlets) and neighborhood change for non-migrants (i.e., the openings and closings of food outlets), which can affect patients whose home address does not change (i.e., non-migrants). The distinction may be important because residential self-selection bias may still be a problem among migrants. For example, patients may decide to move to a neighborhood where supermarkets are more accessible because of a negative health event that makes it harder for them to travel. In that case, even the fixed effects model may be biased because the (unobserved) change in underlying health status may affect both BMI and food outlet accessibility. To explore these concerns, we also estimated separate fixed effects models for non-migrants. Fixed effects models applied to a sample of non-migrants rely only on within-person variation from neighborhood evolution, which may be less prone to bias from time-varying factors that may prompt people to move to a new environment while also changing their BMI.

To test our main hypotheses, we ran each model twice, once for retail food outlet accessibility within 1 mile and again for retail food outlet accessibility within 3 miles of patients' homes. Cross-sectional and fixed effects models include several time-varying individual- and area-level covariates (see Measures). To examine whether associations differed by area economic characteristics, we added interaction terms between the food outlet access variables and area poverty level to the main effects models. Census tract poverty level was categorized using nationwide census tract tertiles as low (0–8.26%; mean=5.00), medium (8.27–17.71%; mean=12.54), or high (17.71–100%; mean=29.19). All models accounted for clustering of patients within counties at baseline using a Huber-White cluster robust variance matrix. Because men comprise almost 90% of the sample, we estimated separate models for men and women.

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Appendix Exhibit B. Descriptive statistics for the total sample and non-migrants at baseline by sex

		Men (n=1,522,803)		Women (n=183,618)	
		Total sample	**Non-migrant sample**	**Total sample**	**Non-migrant sample**
		n=1,522,803	**n=1,034,375**	**n=183,618**	**n=112,670**
		% or Mean (SD)	**% or Mean (SD)**	**% or Mean (SD)**	**% or Mean (SD)**
Body mass index	**Mean (SD)**	**30.2 (6.0)**	**30.3 (6.0)**	**29.5 (6.4)**	**29.6 (6.4)**
Body weight status, %	Underweight or normal weight (BMI ≤ 24.9)	18.2	17.6	26.5	25.9
	Overweight (25 ≥ BMI ≤ 29.9)	35.9	35.9	31.1	31.2
	Obese (BMI ≥ 30)	45.9	46.5	42.4	42.9
Age	Mean (SD)	51.8 (11.5)	52.5 (11.3)	43.4 (11.5)	44.5 (11.3)
Marital status, %	Unknown	1.4	1.6	2.1	2.4
	Married	48.8	53.0	33.3	36.6
	Separated or divorced	26.2	23.8	31.6	30.1
	Widowed	1.8	1.7	2.2	2.2
	Single	21.8	19.9	30.8	28.7
Race/ethnicity, %	Non-Hispanic white	60.5	60.9	50.1	49.8
	Non-Hispanic black	22.5	20.8	32.1	31.1
	Hispanic	6.0	6.0	6.0	5.8
	Other	2.5	2.6	3.3	3.3
	Unknown	8.5	9.7	8.5	10.1
Medical diagnoses, %	Breast cancer	0.0	0.0	1.3	1.4
	Cerebrovascular disease	2.7	2.7	1.2	1.3

		Men (n=1,522,803)		Women (n=183,618)	
		Total sample	Non-migrant sample	Total sample	Non-migrant sample
		n=1,522,803	n=1,034,375	n=183,618	n=112,670
		% or Mean (SD)	% or Mean (SD)	% or Mean (SD)	% or Mean (SD)
Body mass index	**Mean (SD)**	**30.2 (6.0)**	**30.3 (6.0)**	**29.5 (6.4)**	**29.6 (6.4)**
	Colon cancer	0.4	0.4	0.2	0.2
	Congestive heart failure	3.1	3.1	0.8	0.8
	Depression	20.1	18.2	29.2	27.1
	Diabetes	19.1	19.3	8.0	8.1
	Hyperlipidemia	32.4	33.1	17.2	19.1
	Hypertension	41.3	41.4	21.8	22.2
	Myocardial infarction	1.7	1.6	0.4	0.3
	Osteoporosis	0.5	0.5	1.6	1.8
Urbanicity, %	Large central metro	29.9	28.9	30.2	28.9
	Large fringe metro	24.0	24.4	24.1	24.3
	Medium metro	29.9	30.2	30.8	31.2
	Small metro	16.3	16.5	15.0	15.5
Census Division, %	New England	3.7	3.9	2.5	2.6
	Middle Atlantic	9.5	9.9	7.3	7.6
	East North Central	13.4	13.3	10.5	10.1
	West North Central	5.8	5.8	4.8	4.8
	South Atlantic	24.7	24.8	30.8	31.3
	East South Central	7.1	7.2	7.3	7.5
	West South Central	14.0	14.0	15.8	15.7
	Mountain	8.4	8.2	9.0	8.8
	Pacific Alaska	13.3	13.0	12.1	11.6
Median household income, Census tract	Mean (SD)	52334.3 (21346.8)	53374.4 (21462.8)	53192.7 (20672.6)	54160.5 (20930.6)
Poverty rate, Census tract	Mean (SD)	14.9 (11.5)	14.3 (11.0)	14.4 (10.8)	14.1 (10.5)
Population density (per square mile), Census tract	Mean (SD)	4139.5 (8866.6)	4050.6 (8957.9)	4034.3 (8274.4)	3957.9 (8525.6)
Chain supermarkets, 1mi[1]	1 or more stores	41.9	41.1	42.9	41.5
Non-chain supermarkets, 1mi[1]	1 or more stores	25.5	24.7	23.3	22.4
Mass merchandisers, 1mi[1]	1 or more stores	14.7	14.5	16.2	15.5
Grocery stores, 1mi[1]	1 or more stores	48.2	46.8	47.5	45.8
Chain fast food restaurants, 1mi[2]	0 restaurants	19.4	19.8	20.0	20.3
	1–2 restaurants	24.6	24.3	25.3	24.6

		Men (n=1,522,803)		Women (n=183,618)	
		Total sample	Non-migrant sample	Total sample	Non-migrant sample
		n=1,522,803	n=1,034,375	n=183,618	n=112,670
		% or Mean (SD)	% or Mean (SD)	% or Mean (SD)	% or Mean (SD)
Body mass index	**Mean (SD)**	**30.2 (6.0)**	**30.3 (6.0)**	**29.5 (6.4)**	**29.6 (6.4)**
	3–6 restaurants	21.9	20.7	22.6	21.1
	7 or more restaurants	34.2	35.2	32.1	33.9
Non-chain fast food restaurants, 1mi[2]	0 restaurants	23.5	24.4	25.3	26.1
	1–2 restaurants	25.8	25.8	27.0	26.2
	3–6 restaurants	24.2	22.7	22.2	20.5
	7 or more restaurants	26.5	27.1	25.6	27.2
Convenience stores, 1mi[2]	0 stores	22.1	23.1	23.6	24.6
	1–2 stores	24.5	24.6	26.2	26.0
	3–5 stores	30.0	28.3	28.6	26.6
	6 or more stores	23.4	23.9	21.6	22.9
Relative accessibility of supermarkets to fast food restaurants {Supermarkets / (Supermarkets + Fast Food Restaurants) * 100}, 1mi[3]	Low (0)	26.9	27.5	28.7	29.1
	Low-mid (0.4–9.1%)	12.2	11.5	11.8	10.9
	Mid-high (9.1–16.7%)	21.6	21.2	21.8	21.0
	High (16.8–100%)	19.0	19.2	19.1	19.2
	No supermarket or fast food restaurant	20.3	20.7	18.6	19.8
Parks, 1mi	0 parks	17.8	18.3	19.0	19.4
	1 park	22.4	22.4	22.2	21.8
	2–3 parks	26.3	25.3	24.0	23.0
	4 or more parks	33.5	34.1	34.8	35.9
Fitness facilities, 1mi	0 facilities	27.5	28.1	28.7	29.3
	1–2 facilities	17.2	17.2	17.9	17.5
	3–4 facilities	26.8	25.8	26.1	24.6
	5 or more facilities	28.5	28.9	27.2	28.6
Chain supermarkets, 3mi[4]	0 stores	22.3	23.3	23.6	24.7
	1–2 stores	33.6	33.7	35.7	35.4
	3–6 stores	24.6	23.4	24.4	23.1
	7 or more stores	19.5	19.6	16.2	16.8
Non-chain supermarkets, 3mi[4]	0 stores	30.0	21.4	21.2	21.5
	1 store	20.6	20.5	20.8	20.2
	2–3 stores	21.6	20.5	19.4	18.3

		Men (n=1,522,803)		Women (n=183,618)	
		Total sample	Non-migrant sample	Total sample	Non-migrant sample
		n=1,522,803	n=1,034,375	n=183,618	n=112,670
		% or Mean (SD)	% or Mean (SD)	% or Mean (SD)	% or Mean (SD)
Body mass index	**Mean (SD)**	**30.2 (6.0)**	**30.3 (6.0)**	**29.5 (6.4)**	**29.6 (6.4)**
	4 or more stores	36.8	37.6	38.5	40.0
Mass merchandisers, 3mi[4]	0 stores	25.0	25.2	26.3	26.7
	1 store	20.1	20.0	21.7	21.4
	2 stores	18.3	18.1	19.4	18.6
	3 or more stores	36.6	36.8	32.6	33.3
Chain fast food restaurants, 3mi[4]	0 restaurants	28.3	29.6	27.7	29.3
	1–14 restaurants	29.8	30.2	32.0	32.2
	15–32 restaurants	30.7	29.1	31.7	29.6
	33 or more restaurants	11.2	11.0	8.6	8.9
Non-chain fast food restaurants, 3mi[5]	0–5 restaurants	23.5	24.0	21.0	22.3
	6–18 restaurants	25.0	26.2	28.0	29.3
	19–39 restaurants	24.8	24.8	26.5	25.9
	40 or more restaurants	26.7	25.1	24.4	22.5
Convenience stores, 3mi[5]	0–6 stores	23.6	24.1	20.3	21.5
	7–18 stores	23.4	24.5	25.4	26.6
	19–36 stores	24.6	24.7	27.0	26.6
	37 or more stores	28.4	26.7	27.3	25.3
Grocery stores, 3mi[4]	0 stores	27.0	28.1	28.2	29.3
	1–3 stores	26.4	26.6	29.3	29.1
	4–11 stores	28.3	26.6	26.3	24.7
	12 or more stores	18.4	18.6	16.3	17.0
Relative accessibility of supermarkets to fast food restaurants, 3mi[6]	Low (0–7.4%)	23.2	23.3	24.1	24.0
	Mid-low (7.4–10.5%)	24.6	24.5	25.2	24.6
	Mid-high (10.5–14.3%)	23.1	23.0	23.5	23.3
	High (14.3–100%)	23.5	24.0	23.1	23.8
	No supermarket or fast food restaurant	5.6	5.3	4.2	4.3

Authors' analysis of participant data from the VA corporate Data Warehouse, 2009–2014; Census tract demographic data from US Census Bureau (2005–2009, 2006–2010, 2007–2011, 2008–2012, 2009–2013, 2010–2014); Food store data from InfoUSA (2008–2013); Fast food restaurant data from Dun & Bradstreet (2008–2013).

[1]For food outlets for which less than 50% of the sample had an outlet within 1 mile (chain supermarkets, non-chain supermarkets, mass merchandisers, grocery stores), we used a binary variable (0, 1 or more).

[2]For food outlets for which at least 10% of the sample had no outlet within 1 mile (chain fast food restaurants, non-chain fast food restaurants, convenience stores), we used a 4-category variable, constructed as 0 and then tertiles of the non-zero distribution of values.

[3]A 5-category variable was used for relative accessibility: no supermarket or fast food restaurant, low or no supermarket (but at least one fast food restaurant), and then low-mid, mid-high, and high based on tertiles of the remaining non-zero distribution.

[4]For food outlets for which at least 10% of the sample had no outlet within 3 miles (chain supermarkets, non-chain supermarkets, mass merchandisers, chain fast food restaurants, grocery stores), we used a 4-category variable, constructed as 0 and then tertiles of the non-zero distribution of values.

[5]For other food outlets (non-chain fast food restaurants, convenience stores), we used a 4-category variable based on quartiles of the distribution of values.

[6]A 5-category variable was used for relative accessibility: no supermarket or fast food restaurant, and then low, low-mid, mid-high, and high based on quartiles of the remaining distribution of values.

Appendix Exhibit C. Cross-sectional and longitudinal associations between BMI and geographic accessibility of food outlets (1 mile and 3 miles) by sex

	Men			Women		
	Cross-sectional	Longitudinal		Cross-sectional	Longitudinal	
	Total sample	Total sample	Non-migrant sample	Total sample	Total sample	Non-migrant sample
Persons	n=1,522,803	n=1,522,803	n=1,034,375	n=183,618	n=183,618	n=112,670
Person-year observations	n=6,668,033	n=6,668,033	n=4,229,727	n=773,511	n=773,511	n=424,329
	Coefficient (SE)	Coefficient (SE)	Coefficient (SE)	Coefficient (SE)	Coefficient (SE)	Coefficient (SE)
1 mile						
Chain supermarkets						
0 stores	1.000	1.000	1.000	1.000	1.000	1.000
1 or more stores	−0.010	0.007 *	0.001	−0.034	0.009	−0.002
	(0.014)	(0.003)	(0.005)	(0.036)	(0.011)	(0.018)
Non-chain supermarkets						
0 stores	1.000	1.000	1.000	1.000	1.000	1.000
1 or more stores	−0.027	−0.007	−0.002	−0.020	−0.005	−0.033
	(0.017)	(0.004)	(0.005)	(0.039)	(0.011)	(0.021)
Mass merchandisers						
0 stores	1.000	1.000	1.000	1.000	1.000	1.000
1 or more stores	0.123 ***	0.011 *	−0.004	0.081	0.019	−0.000
	(0.016)	(0.005)	(0.007)	(0.043)	(0.014)	(0.025)
Chain fast food restaurants						
0 restaurants	1.000	1.000	1.000	1.000	1.000	1.000
1–2 restaurants	0.027	0.016 ***	0.018 **	0.059	0.009	0.009
	(0.014)	(0.005)	(0.006)	(0.039)	(0.014)	(0.022)
3–6 restaurants	0.057 **	0.015 **	0.012	0.139 **	0.025	0.035

	Men			Women		
	Cross-sectional	Longitudinal		Cross-sectional	Longitudinal	
	Total sample	Total sample	Non-migrant sample	Total sample	Total sample	Non-migrant sample
Persons	**n=1,522,803**	**n=1,522,803**	**n=1,034,375**	**n=183,618**	**n=183,618**	**n=112,670**
Person-year observations	**n=6,668,033**	**n=6,668,033**	**n=4,229,727**	**n=773,511**	**n=773,511**	**n=424,329**
	Coefficient (SE)	**Coefficient (SE)**	**Coefficient (SE)**	**Coefficient (SE)**	**Coefficient (SE)**	**Coefficient (SE)**
	(0.018)	(0.006)	(0.009)	(0.051)	(0.017)	(0.027)
7+ restaurants	0.085 ***	0.025 ***	0.019	0.168 **	0.007	0.030
	(0.025)	(0.007)	(0.012)	(0.062)	(0.021)	(0.034)
Non-chain fast food restaurants						
0 restaurants	1.000	1.000	1.000	1.000	1.000	1.000
1–2 restaurants	−0.014	0.013 ***	0.013 **	−0.035	−0.025 *	−0.032
	(0.014)	(0.004)	(0.005)	(0.037)	(0.011)	(0.019)
3–6 restaurants	−0.062 **	0.013 **	0.015 *	−0.130 **	−0.013	0.002
	(0.020)	(0.005)	(0.007)	(0.047)	(0.014)	(0.025)
7+ restaurants	−0.206 ***	0.010	0.013	−0.426 ***	−0.024	−0.015
	(0.028)	(0.006)	(0.009)	(0.069)	(0.020)	(0.034)
3 miles						
Chain supermarkets						
0 stores	1.000	1.000	1.000	1.000	1.000	1.000
1–2 stores	0.006	0.003	−0.005	−0.078	0.012	−0.024
	(0.020)	(0.006)	(0.008)	(0.050)	(0.018)	(0.027)
3–6 stores	−0.039	0.003	−0.001	−0.106	0.016	−0.033
	(0.029)	(0.007)	(0.010)	(0.063)	(0.021)	(0.031)
7+ stores	−0.078	−0.001	−0.013	−0.156	0.004	−0.048
	(0.045)	(0.008)	(0.011)	(0.082)	(0.025)	(0.039)
Non-chain supermarkets						
0 stores	1.000	1.000	1.000	1.000	1.000	1.000
1 store	−0.001	−0.003	−0.004	0.073 *	0.025 *	0.018
	(0.017)	(0.004)	(0.005)	(0.035)	(0.012)	(0.016)
2–3 stores	0.010	−0.010 *	−0.010	0.104 *	0.026	0.030
	(0.024)	(0.005)	(0.006)	(0.046)	(0.015)	(0.021)
4+ stores	−0.080 *	−0.017 **	−0.015	−0.000	0.006	0.008
	(0.037)	(0.006)	(0.009)	(0.069)	(0.020)	(0.029)
Mass merchandisers						
0 stores	1.000	1.000	1.000	1.000	1.000	1.000
1 store	0.122 ***	0.009 *	0.007	0.158 ***	−0.009	−0.026
	(0.019)	(0.005)	(0.007)	(0.045)	(0.015)	(0.025)

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	Men			Women		
	Cross-sectional	Longitudinal		Cross-sectional	Longitudinal	
	Total sample	Total sample	Non-migrant sample	Total sample	Total sample	Non-migrant sample
Persons	**n=1,522,803**	**n=1,522,803**	**n=1,034,375**	**n=183,618**	**n=183,618**	**n=112,670**
Person-year observations	**n=6,668,033**	**n=6,668,033**	**n=4,229,727**	**n=773,511**	**n=773,511**	**n=424,329**
	Coefficient (SE)	**Coefficient (SE)**	**Coefficient (SE)**	**Coefficient (SE)**	**Coefficient (SE)**	**Coefficient (SE)**
2 stores	0.196***	0.021***	0.016	0.161**	−0.010	−0.018
	(0.022)	(0.006)	(0.009)	(0.054)	(0.017)	(0.031)
3+ stores	0.283***	0.026***	0.012	0.338***	0.019	0.020
	(0.031)	(0.007)	(0.011)	(0.065)	(0.018)	(0.034)
Chain fast food restaurants						
0 restaurants	1.000	1.000	1.000	1.000	1.000	1.000
1–14 restaurants	0.024	0.012	−0.004	0.062	−0.041	−0.063
	(0.020)	(0.007)	(0.012)	(0.069)	(0.026)	(0.051)
15–32 restaurants	0.011	0.011	−0.003	0.069	−0.050	−0.017
	(0.029)	(0.009)	(0.014)	(0.088)	(0.030)	(0.058)
33+ restaurants	0.043	0.011	−0.003	0.111	−0.026	0.015
	(0.038)	(0.010)	(0.016)	(0.106)	(0.034)	(0.067)
Non-chain fast food restaurants						
0–5 restaurants	1.000	1.000	1.000	1.000	1.000	1.000
6–18 restaurants	−0.091***	0.010	0.014	−0.232***	−0.018	−0.009
	(0.022)	(0.005)	(0.007)	(0.057)	(0.016)	(0.022)
19–39 restaurants	−0.228***	0.005	0.009	−0.411***	−0.010	−0.009
	(0.033)	(0.007)	(0.009)	(0.078)	(0.022)	(0.031)
40+ restaurants	−0.370*** (0.044)	−0.002 (0.008)	0.002 (0.011)	−0.871*** (0.104)	−0.027 (0.027)	0.007 (0.039)

Authors' analysis of participant BMI from the VA corporate Data Warehouse, 2009–2014; Urbanicity data from National Center for Health Statistics (2006, 2013); Census tract demographic data from US Census Bureau (2005–2009, 2006–2010, 2007–2011, 2008–2012, 2009–2013, 2010–2014); Food store data from InfoUSA (2008–2013); Fast food restaurant data from Dun & Bradstreet (2008–2013); Park data from TeleAtlas and NAVTEQ (2010, 2014); and Fitness facility data from InfoUSA (2008–2013).

Note: Covariates for cross-sectional and longitudinal models included year, marital status, multiple health conditions, region, population density, median household income, poverty, and accessibility of grocery stores, convenience stores, parks, and fitness facilities. Cross-sectional models also controlled for baseline age and race/ethnicity.

* $p \le 0.05$

** $p \le 0.01$

*** $p \le 0.001$

Appendix Exhibit D. Cross-sectional and longitudinal associations between BMI and relative accessibility of supermarkets to fast food restaurants within 1 mile and 3 miles by sex

	Men			Women		
	Cross-sectional	Longitudinal		Cross-sectional	Longitudinal	
	Total sample	Total sample	Non-migrant sample	Total sample	Total sample	Non-migrant sample
Persons	**n=1,522,803**	**n=1,522,803**	**n=1,034,375**	**n=183,618**	**n=183,618**	**n=112,670**
Person-year observations	**n=6,668,033**	**n=6,668,033**	**n=4,229,727**	**n=773,511**	**n=773,511**	**n=424,329**
	Coefficient (SE)	**Coefficient (SE)**	**Coefficient (SE)**	**Coefficient (SE)**	**Coefficient (SE)**	**Coefficient (SE)**
1 mile						
Low relative accessibility (0)	1.000	1.000	1.000	1.000	1.000	1.000
Low-mid relative accessibility (0.4–9.1%)	−0.037 *	0.009	0.008	−0.094	0.003	0.006
	(0.018)	(0.005)	(0.007)	(0.049)	(0.014)	(0.024)
Mid-high relative accessibility (9.1–16.7%)	−0.000	0.008 *	0.004	0.045	0.013	0.011
	(0.015)	(0.004)	(0.006)	(0.041)	(0.012)	(0.019)
High relative accessibility (16.8–100%)	0.004	0.002	<0.001	0.062	0.012	0.007
	(0.016)	(0.004)	(0.006)	(0.039)	(0.013)	(0.022)
No supermarkets or fast food restaurants	−0.045 **	−0.018 ***	−0.015 *	−0.058	0.015	0.035
	(0.015)	(0.005)	(0.006)	(0.041)	(0.014)	(0.023)
3 miles						
Low relative accessibility (0–7.4%)	1.000	1.000	1.000	1.000	1.000	1.000
Low-mid relative accessibility (7.4–10.5%)	−0.017	−0.002	−0.005	0.043	−0.003	−0.005
	(0.016)	(0.003)	(0.004)	(0.035)	(0.010)	(0.013)
Mid-high relative accessibility (10.5–14.3%)	−0.007	−0.002	−0.010	0.100 *	−0.005	−0.007
	(0.021)	(0.004)	(0.005)	(0.044)	(0.012)	(0.017)
High relative accessibility (14.3–100%)	0.021	−0.001	−0.005	0.140 **	0.025	−0.003
	(0.022)	(0.005)	(0.006)	(0.044)	(0.013)	(0.020)
No supermarkets or fast food restaurants	−0.071 **	−0.021 **	−0.004	−0.063	0.021	0.059
	(0.024)	(0.008)	(0.012)	(0.077)	(0.027)	(0.048)

Authors' analysis of participant BMI from the VA corporate Data Warehouse, 2009–2014; Urbanicity data from National Center for Health Statistics (2006, 2013); Census tract demographic data from US Census Bureau (2005–2009, 2006–2010, 2007–2011, 2008–2012, 2009–2013, 2010–2014); Food store data from InfoUSA (2008–2013); Fast food restaurant data from Dun & Bradstreet (2008–2013); Park data from TeleAtlas and NAVTEQ (2010, 2014); and Fitness facility data from InfoUSA (2008–2013).

Note: Covariates for cross-sectional and longitudinal models included year, marital status, multiple health conditions, region, population density, median household income, poverty, and accessibility of grocery stores, convenience stores, mass merchandisers, parks, and fitness facilities. Cross-sectional models also controlled for baseline age and race/ethnicity.

* $p \leq 0.05$

** $p \leq 0.01$

*** $p \leq 0.001$

Exhibit 1

Descriptive statistics for the total sample and non-migrants at baseline by sex

		Men (n=1,522,803)		Women (n=183,618)	
		Total sample	Non-migrant sample	Total sample	Non-migrant sample
		n=1,522,803	n=1,034,375	n=183,618	n=112,670
		% or Mean	% or Mean	% or Mean	% or Mean
Body mass index	**Mean[1]**	**30.2**	**30.3**	**29.5**	**29.6**
Body weight status, %	Underweight or normal weight (BMI ≤ 24.9)	18.2	17.6	26.5	25.9
	Overweight (25 ≥ BMI ≤ 29.9)	35.9	35.9	31.1	31.2
	Obese (BMI ≥ 30)	45.9	46.5	42.4	42.9
Age	Mean[2]	51.8	52.5	43.4	44.5
Marital status, %	Unknown	1.4	1.6	2.1	2.4
	Married	48.8	53.0	33.3	36.6
	Separated or divorced	26.2	23.8	31.6	30.1
	Widowed	1.8	1.7	2.2	2.2
	Single	21.8	19.9	30.8	28.7
Race/ethnicity, %	Non-Hispanic white	60.5	60.9	50.1	49.8
	Non-Hispanic black	22.5	20.8	32.1	31.1
	Hispanic	6.0	6.0	6.0	5.8
	Other	2.5	2.6	3.3	3.3
	Unknown	8.5	9.7	8.5	10.1
Urbanicity, %	Large central metro	29.9	28.9	30.2	28.9
	Large fringe metro	24.0	24.4	24.1	24.3
	Medium metro	29.9	30.2	30.8	31.2
	Small metro	16.3	16.5	15.0	15.5
Median household income, Census tract	Mean[3]	52334.3	53374.4	53192.7	54160.5

		Men (n=1,522,803)		Women (n=183,618)	
		Total sample	Non-migrant sample	Total sample	Non-migrant sample
		n=1,522,803	n=1,034,375	n=183,618	n=112,670
		% or Mean	% or Mean	% or Mean	% or Mean
Body mass index	**Mean[1]**	**30.2**	**30.3**	**29.5**	**29.6**
Poverty rate, Census tract	Mean[4]	14.9	14.3	14.4	14.1
Population density (per square mile), Census tract	Mean[5]	4139.5	4050.6	4034.3	3957.9
Chain supermarkets, 1mi[6]	1 or more stores	41.9	41.1	42.9	41.5
Non-chain supermarkets, 1mi[6]	1 or more stores	25.5	24.7	23.3	22.4
Mass merchandisers, 1mi[6]	1 or more stores	14.7	14.5	16.2	15.5
Chain fast food restaurants, 1mi[7]	0 restaurants	19.4	19.8	20.0	20.3
	1–2 restaurants	24.6	24.3	25.3	24.6
	3–6 restaurants	21.9	20.7	22.6	21.1
	7 or more restaurants	34.2	35.2	32.1	33.9
Non-chain fast food restaurants, 1mi[7]	0 restaurants	23.5	24.4	25.3	26.1
	1–2 restaurants	25.8	25.8	27.0	26.2
	3–6 restaurants	24.2	22.7	22.2	20.5
	7 or more restaurants	26.5	27.1	25.6	27.2
Relative accessibility of supermarkets to fast food restaurants {Supermarkets / (Supermarkets + Fast Food[8]	Low (0)	26.9	27.5	28.7	29.1
	Low-mid (0.4–9.1%)	12.2	11.5	11.8	10.9
	Mid-high (9.1–16.7%)	21.6	21.2	21.8	21.0
	High (16.8–100%)	19.0	19.2	19.1	19.2
	No supermarket or fast food restaurant	20.3	20.7	18.6	19.8

Authors' analysis of participant data from the VA Corporate Data Warehouse (2009–2014); Census tract demographic data from US Census Bureau (2005–2009, 2006–2010, 2007–2011, 2008–2012, 2009–2013, 2010–2014); Food store data from InfoUSA (2008–2013); Fast food restaurant data from Dun & Bradstreet (2008–2013).

[1]SD for total and non-migrant men = 6.0; SD for total and non-migrant women = 6.4

[2] SD for total men and total women = 11.5; SD for non-migrant men and non-migrant women = 11.3

[3] SD for total men = 21346.8; SD for non-migrant men = 21462.8; SD for total women = 20672.6; SD for non-migrant women = 20930.6

[4] SD for total men = 11.5; SD for non-migrant men = 11.0; SD for total women = 10.8; SD for non-migrant women = 10.5

[5] SD for total men = 8866.6; SD for non-migrant men = 8957.9; SD for total women = 8274.4; SD for non-migrant men = 8525.6

[6] For food outlets for which less than 50% of the sample had an outlet within 1 mile (chain supermarkets, non-chain supermarkets, mass merchandisers, grocery stores), we used a binary variable (0, 1 or more).

[7] For food outlets for which at least 10% of the sample had no outlet within 1 mile (chain fast food restaurants, non-chain fast food restaurants, convenience stores), we used a 4-category variable, constructed as 0 and then tertiles of the non-zero distribution of values.

[8] A 5-category variable was used for relative accessibility: no supermarket or fast food restaurant, low or no supermarket (but at least one fast food restaurant), and then low-mid, mid-high, and high based on tertiles of the remaining non-zero distribution.

Exhibit 2

Cross-sectional and longitudinal associations between BMI and geographic accessibility of food outlets (1 mile and 3 miles) by sex

	Men			Women		
	Cross-sectional	Longitudinal		Cross-sectional	Longitudinal	
	Total sample	Total sample	Non-migrant sample	Total sample	Total sample	Non-migrant sample
Persons	**n=1,522,803**	**n=1,522,803**	**n=1,034,375**	**n=183,618**	**n=183,618**	**n=112,670**
Person-year observations	**n=6,668,033**	**n=6,668,033**	**n=4,229,727**	**n=773,511**	**n=773,511**	**n=424,329**
	Coefficient	**Coefficient**	**Coefficient**	**Coefficient**	**Coefficient**	**Coefficient**
1 mile						
Chain supermarkets						
0 stores	1.000	1.000	1.000	1.000	1.000	1.000
1 or more stores	−0.010	0.007*	0.001	−0.034	0.009	−0.002
Non-chain supermarkets						
0 stores	1.000	1.000	1.000	1.000	1.000	1.000
1 or more stores	−0.027	−0.007	−0.002	−0.020	−0.005	−0.033
Mass merchandisers						
0 stores	1.000	1.000	1.000	1.000	1.000	1.000
1 or more stores	0.123***	0.011*	−0.004	0.081	0.019	−0.000
Chain fast food restaurants						
0 restaurants	1.000	1.000	1.000	1.000	1.000	1.000
1–2 restaurants	0.027	0.016***	0.018**	0.059	0.009	0.009
3–6 restaurants	0.057**	0.015**	0.012	0.139**	0.025	0.035
7+ restaurants	0.085***	0.025***	0.019	0.168**	0.007	0.030
Non-chain fast food restaurants						
0 restaurants	1.000	1.000	1.000	1.000	1.000	1.000
1–2 restaurants	−0.014	0.013***	0.013**	−0.035	−0.025*	−0.032
3–6 restaurants	−0.062**	0.013**	0.015*	−0.130**	−0.013	0.002

	Men			Women		
	Cross-sectional	Longitudinal		Cross-sectional	Longitudinal	
	Total sample	Total sample	Non-migrant sample	Total sample	Total sample	Non-migrant sample
Persons	**n=1,522,803**	**n=1,522,803**	**n=1,034,375**	**n=183,618**	**n=183,618**	**n=112,670**
Person-year observations	**n=6,668,033**	**n=6,668,033**	**n=4,229,727**	**n=773,511**	**n=773,511**	**n=424,329**
	Coefficient	**Coefficient**	**Coefficient**	**Coefficient**	**Coefficient**	**Coefficient**
7+ restaurants	−0.206***	0.010	0.013	−0.426***	−0.024	−0.015
3 miles						
Chain supermarkets						
0 stores	1.000	1.000	1.000	1.000	1.000	1.000
1–2 stores	0.006	0.003	−0.005	−0.078	0.012	−0.024
3–6 stores	−0.039	0.003	−0.001	−0.106	0.016	−0.033
7+ stores	−0.078	−0.001	−0.013	−0.156	0.004	−0.048
Non-chain supermarkets						
0 stores	1.000	1.000	1.000	1.000	1.000	1.000
1 store	−0.001	−0.003	−0.004	0.073*	0.025*	0.018
2–3 stores	0.010	−0.010*	−0.010	0.104*	0.026	0.030
4+ stores	−0.080*	−0.017**	−0.015	−0.000	0.006	0.008
Mass merchandisers						
0 stores	1.000	1.000	1.000	1.000	1.000	1.000
1 store	0.122***	0.009*	0.007	0.158***	−0.009	−0.026
2 stores	0.196***	0.021***	0.016	0.161**	−0.010	−0.018
3+ stores	0.283***	0.026***	0.012	0.338***	0.019	0.020
Chain fast food restaurants						
0 restaurants	1.000	1.000	1.000	1.000	1.000	1.000
1–14 restaurants	0.024	0.012	−0.004	0.062	−0.041	−0.063
15–32 restaurants	0.011	0.011	−0.003	0.069	−0.050	−0.017

	Men			Women		
	Cross-sectional	Longitudinal		Cross-sectional	Longitudinal	
	Total sample	Total sample	Non-migrant sample	Total sample	Total sample	Non-migrant sample
Persons	**n=1,522,803**	**n=1,522,803**	**n=1,034,375**	**n=183,618**	**n=183,618**	**n=112,670**
Person-year observations	**n=6,668,033**	**n=6,668,033**	**n=4,229,727**	**n=773,511**	**n=773,511**	**n=424,329**
	Coefficient	**Coefficient**	**Coefficient**	**Coefficient**	**Coefficient**	**Coefficient**
33+ restaurants	0.043	0.011	−0.003	0.111	−0.026	0.015
Non-chain fast food restaurants						
0–5 restaurants	1.000	1.000	1.000	1.000	1.000	1.000
6–18 restaurants	−0.091 ***	0.010	0.014	−0.232 ***	−0.018	−0.009
19–39 restaurants	−0.228 ***	0.005	0.009	−0.411 ***	−0.010	−0.009
40+ restaurants	−0.370 ***	−0.002	0.002	−0.871 ***	−0.027	0.007

Authors' analysis of participant BMI from the VA Corporate Data Warehouse (2009–2014); Urbanicity data from National Center for Health Statistics (2006, 2013); Census tract demographic data from US Census Bureau (2005–2009, 2006–2010, 2007–2011, 2008–2012, 2009–2013, 2010–2014); Food store data from InfoUSA (2008–2013); Fast food restaurant data from Dun & Bradstreet (2008–2013); Park data from TeleAtlas and NAVTEQ (2010, 2014); and Fitness facility data from InfoUSA (2008–2013).

Note: Covariates for cross-sectional and longitudinal models included year, marital status, multiple health conditions, region, population density, median household income, poverty, and accessibility of grocery stores, convenience stores, parks, and fitness facilities. Cross-sectional models also controlled for baseline age and race/ethnicity.

* $p \leq 0.05$

** $p \leq 0.01$

*** $p \leq 0.001$

Exhibit 3

Cross-sectional and longitudinal associations between BMI and relative geographic accessibility of supermarkets to fast

	Men			Women		
	Cross-sectional	Longitudinal		Cross-sectional	Longitudinal	
	Total sample	Total sample	Non-migrant sample	Total sample	Total sample	Non-migrant sample
Persons	**n=1,522,803**	**n=1,522,803**	**n=1,034,375**	**n=183,618**	**n=183,618**	**n=112,670**
Person-year observations	**n=6,668,033**	**n=6,668,033**	**n=4,229,727**	**n=773,511**	**n=773,511**	**n=424,329**
	Coefficient	**Coefficient**	**Coefficient**	**Coefficient**	**Coefficient**	**Coefficient**
1 mile						
Low relative accessibility (0)	1.000	1.000	1.000	1.000	1.000	1.000
Low-mid relative accessibility (0.4–9.1%)	−0.037 *	0.009	0.008	−0.094	0.003	0.006
Mid-high relative accessibility (9.1–16.7%)	−0.000	0.008 *	0.004	0.045	0.013	0.011
High relative accessibility (16.8–100%)	0.004	0.002	<0.001	0.062	0.012	0.007
No supermarkets or fast food restaurants	−0.045 **	−0.018 ***	−0.015 *	−0.058	0.015	0.035
3 miles						
Low relative accessibility (0–7.4%)	1.000	1.000	1.000	1.000	1.000	1.000
Low-mid relative accessibility (7.4–10.5%)	−0.017	−0.002	−0.005	0.043	−0.003	−0.005
Mid-high relative accessibility (10.5–14.3%)	−0.007	−0.002	−0.010	0.100 *	−0.005	−0.007
High relative accessibility (14.3–100%)	0.021	−0.001	−0.005	0.140 **	0.025	−0.003
No supermarkets or fast food restaurants	−0.071 **	−0.021 **	−0.004	−0.063	0.021	0.059

Authors' analysis of participant BMI from the VA Corporate Data Warehouse (2009–2014); Urbanicity data from National Center for Health Statistics (2006, 2013); Census tract demographic data from US Census Bureau (2005–2009, 2006–2010, 2007–2011, 2008–2012, 2009–2013, 2010–2014); Food store data from InfoUSA (2008–2013); Fast food restaurant data from Dun & Bradstreet (2008–2013); Park data from TeleAtlas and NAVTEQ (2010, 2014); and Fitness facility data from InfoUSA (2008–2013).

Note: Covariates for cross-sectional and longitudinal models included year, marital status, multiple health conditions, region, population density, median household income, poverty, and accessibility of grocery stores, convenience stores, mass merchandisers, parks, and fitness facilities. Cross-sectional models also controlled for baseline age and race/ethnicity.

* $p \leq 0.05$

** $p \leq 0.01$

*** $p \leq 0.001$