Built environment and the purchase of fruits and vegetables in United States households.

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Abstract

Objective: To determine whether neighborhood supermarket and convenience store availability, broader built environment context, is associated with food purchasing behavior in a national population.

Design: We used observational data to perform a cross-sectional study of fruit and vegetable purchases for United States households in 2010. We used 3-level linear mixed-effect regression models to determine whether the associations between the number of neighborhood supermarkets and convenience stores and the self-reported annual household expenditures for fruits and vegetables was affected by regional destination accessibility, neighborhood destination diversity, availability of neighborhood destinations, and neighborhood street connectivity.

Setting: 378 metropolitan statistical areas in the continental United States.

Subjects: 22,448 households.

Results: When we controlled for broader built environment context, there was no significant positive association between availability of neighborhood supermarkets and expenditures on fruits and vegetables; instead, we observed an inverse association between the number of convenience stores and expenditures for fruits ($p=0.001$). The broader built environment context was associated with food purchase, although the magnitude was small: (1) Higher regional destination accessibility was associated with higher expenditures for fruits ($p<0.001$); (2) Higher neighborhood destination diversity was associated with lower expenditures for fruits ($p=0.002$) and vegetables ($p=0.001$); and (3) Higher neighborhood street connectivity was associated with higher expenditures for fruits ($p<0.001$).

Conclusions: The broader built environment factors contribute to understanding how people use neighborhood food stores. However, the relationship between the broader environment context and fruit and vegetable expenditures is small. Policy interventions that focus exclusively on increasing the availability of neighborhood supermarkets likely will not promote fruit and vegetable consumption.

Keywords: food purchase, expenditure, street connectivity, regional accessibility, diversity

Introduction

Many government programs exist to encourage food stores to provide healthful foods and to regulate the types of foods and beverages sold [1-4]. For example, to improve healthy food access, since 2011, the Healthy Food Financing Initiative has provided grants and loans to food outlets (e.g., grocery stores, farmers' markets) in low-income communities nationwide[1]. The Special Supplemental Nutrition Program for Women Infants and Children (WIC) requires stores that accept WIC vouchers to stock a variety of healthy food, and the Supplemental Nutrition Assistance Program requires vendors to sell certain types of food groups to low-income families[2]. These policies and programs are based on a belief that the nutritional quality of diets can be enhanced by increasing the number of stores that sell healthy food, by improving the healthfulness of food sold in stores, and by encouraging people to purchase healthy options. Numerous researchers have investigated factors related to food purchasing decisions, including the types of food stores commonly visited[5-6], the distance between residences and stores[6], and the difference in the foods purchased across store type[5, 7]. This research should inform policy making about how to improve spatial access to healthy food. However, most investigators have focused on the "food store component" (particularly, the spatial access to full-service supermarkets, supercenters, and convenience stores) of the larger "built environment" context.

There are other built environment factors such as transportation infrastructure, number of fast food and sit-down restaurants[8] and other complementary activity locations such as schools, churches, and child care services [9] that affect food purchases. In addition, several studies have linked food store type to the nutritional quality of food purchased. For example, individuals tend to purchase fewer sugar-sweetened beverages and packaged foods in supermarkets than convenience stores [11-12]. Thus, access to transportation and related factors, including street connectivity, the number of parking spaces, and access to public transit may affect which type of store (e.g., full-service supermarkets versus convenience stores) is relatively more convenient[13], and convenience may affect the nutritional quality of food purchased[11-13].

Among studies focusing on only the food store component, Kyureghian et al.[20] and Handbury et al. (unpublished) explicitly assessed the potential access to food stores. These investigators concluded that, at best, food store density explained only a small fraction of the variation in the nutritional quality of food purchased. These researchers documented the availability of food stores in a large geographic area (i.e., 20 km from home or the metropolitan statistical area in which a household resided). Although people purchased outside their closest supermarket[21-22], people were still more likely to use stores closer to home[6, 12, 23]. Here, we examined both availability of neighborhood food stores and potential access to food stores in the region. We defined neighborhood as a small area that provides for daily needs and convenience to shop certain types of foods (but not necessarily by foot). We defined region as an expansive area in which people may combine food purchasing with other needs that must be met by long-distance travel, such as work and entertainment, the area of which may be larger than census-defined places (for example, city, town, and village).

While prior research identified the effect of transportation and land use factors (such as walkability and street connectivity), they focused primarily on characteristics around home[8, 16] without accounting for regional land use patterns and accessibility. Regional scale analysis is important because household shopping activity is far more dispersed rather than concentrated in immediate neighborhood around home[17]. Furthermore shopping activity is often combined with other home support activities such as meeting children after school[18-19]. While these factors have been observed using qualitative analysis and limited to few metropolitan areas, this study is among the first to use a national sample that account for all these factors using quantitative metrics. We studied the association between food shopping behaviors and density of neighborhood supermarkets and convenience stores, broader built environment context of the neighborhood (diversity and density of non-food locations, street connectivity) and regional accessibility.

We used data from the Nielsen Homescan Consumer Panel Dataset for 2010[24] on self-reported household expenditures for fruits and vegetables for 22,448 households in 378 metropolitan statistical areas (MSA) in the continental United States. The large national-level dataset enabled us to examine geographic and market factors related to food purchasing decisions and to generalize and extrapolate our findings to other areas[25]. Our work enhances the understanding of factors that influence where and how people purchase food, and, thus, policies to encourage healthy food purchasing should be implemented with the same considerations[5]. We addressed the following research questions:

1. How does the number of neighborhood supermarkets and convenience stores relate to the purchase of fruits and vegetables?
2. How do other built environment characteristics such as regional destination accessibility, neighborhood destination diversity, availability of neighborhood destinations, and neighborhood street connectivity relate to the purchase of fruits and vegetables?
3. How is the relationship between the number of food stores and the purchase of fruits and vegetables affected by including other built environment factors in the analysis?

Methods

Study sample

Nielsen's National Homescan Consumer Panel Dataset[26] (abbreviated as Nielsen data) is an ongoing, nationally representative survey of 40,000-60,000 U.S. households; the survey includes food and beverage purchase data[24]. We used food purchase data from The Nielsen Company (US), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. Nielsen households (abbreviated as households) reported food purchases in the following types of retail stores: warehouse clubs, mass merchandisers and supercenters, chain grocery stores, non-chain grocery stores, convenience stores, drug stores, dollar stores, ethnic and specialty stores, and others[11].

We selected n=27,422 magnet households from the total of n=60,658 households available for 2010 (analyzed in 2018). Magnet households are households that reported nonstandard Universal Product Code (UPC) products, which included random-weight items such as fruits, vegetables, meats, and in-store baked goods[27-28], in addition to the standard UPC (or branded UPC) products. We focused on magnet households to obtain more information about how people purchase fruits and vegetables because many nonstandard fruit and vegetable UPC products are random-weight. The household-level characteristics of magnet households did not differ greatly from characteristics of non-magnet households (Figure S1 in Appendix A).

We excluded 4,559 households outside the MSAs because individuals in outlying rural areas may commute considerable distances to shop for food; large commuting distances make less reasonable the use of a uniform buffer size (e.g., 5 km) to represent a neighborhood compared with MSAs. We excluded 131 households that lacked covariate information and 284 households that had extremely low or high values of expenditures for both fruits and vegetables (below the 2nd percentile or above the 98th percentile of the expenditures). Our final sample was n=22,448 households (Appendix A provides more details regarding sample construction).

Measures

We aggregated the purchases of fruits and vegetables in each shopping trip over the entire year of 2010 to partially address potential random purchasing behaviors (i.e., impulsive purchases) in a short observational period (e.g., weekly or monthly) for each household in the sample [18]. In total, the households made 418,963 and 700,195 trips to purchase fruits and vegetables and, in turn, recorded 1,198,224 and 1,501,437 expenditures in 2010. Household had an average of 18.7 and 31.2 trips and 53.4 and 66.9 records for fruit and vegetable purchases in 2010. We used expenditure values instead of weight values because magnet households reported expenditures only for nonstandard UPC products. We calculated the self-reported expenditures on fruits and vegetables (separately) as the sum of standard UPC products and nonstandard-UPC products. To address the difficulty of recording expenditures on nonstandard UPC products, Nielsen tracks nonstandard UPCs created by each retailer who assigns them to random-weight products to identify and update food items[29]. Thus, magnet households can either scan the nonstandard UPCs from a reference card accompanying the Nielsen-provided scanner or choose from a list of products in the mobile application to record product type and total price. Although self-reported random-weight products are particularly susceptible to measurement error, the degree of error in Homescan is comparable to the error in other commonly used economic datasets[27]. See Appendix B for the details of developing expenditures for fruits and vegetables.

Because Nielsen disclosed only the zip code tabulation area (ZCTA) in which the households resided, we used the centroid of ZCTA as a proxy for the exact residential location of the households. We used food resource data from the 2010 ReferenceUSA dataset (University of North Carolina at Chapel Hill)[30]. We opted to use ReferenceUSA instead of other food resource data (e.g., Dun & Bradstreet) because of higher accuracy and validity in identifying the type and location of retail food outlets[31-32]. To reflect the potential food sources near home, we characterized neighborhood food availability as the number of supermarkets and convenience stores in a 5-km buffer (abbreviated as neighborhood) around the centroid of a household's residential ZCTA. We classified the supermarkets and convenience stores according to the six-digit primary Standard Industrial Classification (SIC) code. Some private data companies such as Infogroup have appended a 2-4 digit extension to the original SIC to update and expand the system for more precise definition of business classification. See Table S2 in Appendix B for the classification of food stores based on the six-digit Infogroup primary SIC code. We cleaned the longitudinal and latitudinal information of the retail food outlet data to maximize their accuracy (e.g., fix incorrect decimal points). We used ArcGIS 10.5 to calculate the counts of supermarkets and convenience stores in the 5-km buffer.

To measure the regional potential household accessibility to fruits and vegetables, we used regional destination accessibility[33] from Smart Location Database (SLD)[34]. The US Environmental Protection Agency developed SLD to include different indicators for built environment and location efficiency for US Census block groups. The regional destination accessibility measure in SLD was obtained by calculating the number of employees in a 45-minute automobile travel (network travel time, decay weighted). We were constrained by our data source to use the number of employees rather than the number of stores, but employee number is not an unreasonable proxy, assuming that the measurement of the size of food opportunities in such an extensive area is more meaningful after being combined with the size of other types of coexisting opportunities. This measure captures both the size of opportunities and time traveled, and the measure is routinely used in transportation analyses[35]. To generate the value of the regional destination accessibility for households, we spatially linked the centroid of a household's residential ZCTA to the SLD block group in which the centroid fell. See Appendix B for the details of developing regional destination accessibility.

We constructed neighborhood destination diversity to reflect how the attractiveness of other potential daily or weekly routine destinations may affect food purchase. A diverse neighborhood may affect fruits and vegetable expenditures by redirecting food purchasing time to other activities, e.g., eating out[36]. To generate an entropy index of neighborhood destination diversity in the 5-km buffer, we used American Time Use Survey 2010, from which we identified three types of destinations visited before or after grocery shopping: 1) other store/mall, 2) locations for socializing, and 3) restaurants. See Appendix B for details on identifying these destinations. We defined other stores/malls as department store, retail shop, and wholesale club. Locations where people socialized were churches, health care services, and child care services. Restaurants were fast food and sit-down establishments. The entropy equation has been used widely in different land use entropy formulations[33]. The formula we used to calculate neighborhood destination diversity is as follows:

$$Neighborhood\ destination\ diversity = \frac{-1}{\ln(3)} \sum_{i=1}^{3} p_i . \ln(p_i)$$

where p_i is the proportion of the potential destination in one of the three categories in the 5-km buffer. Entropy ranges from zero (homogeneity, all destinations in one category) to one (heterogeneity, an even mixture of type of destinations). Because the entropy value could not reflect the total size of neighborhood destinations, we also incorporated the total number of these three types of neighborhood destinations. We obtained destinations/locations data from the 2010 ReferenceUSA dataset and classified destinations/locations according to their six-digit Infogroup primary SIC codes (Table S2 in Appendix B). We used ArcGIS 10.5 to calculate the count of each type of destination/location in the 5-km buffer.

In addition, we used the SLD measure of neighborhood street connectivity to reflect the directness of traveling to destinations; the degree of directness may increase the convenience of purchasing fruits and vegetables by decreasing transportation costs. The SLD estimated neighborhood street connectivity as the total number of street intersections divided by total land area for each census block group. We generated this street connectivity variable by averaging the connectivity values of block groups with centroids in the 5-km buffer (see Appendix B for the details).

The household-level covariates we used included education level of female head of household (high school or below, college or higher, and no female head)[7, 37], household income (<$20,000, $20,000-$59,999, and ⩾$60,000) [7, 37-40], race (white, black, Asian and other) [37-39], household size (1, 2, 3, 4+) [37-38], marital status of household head(s) (married, widowed, divorced/separated, and single)[37], presence of children (yes/no) [40-41], number of employees in the household (0, 1, 2+, household head excluded), and expenditures for vegetables (in the fruit model) and fruits (in the vegetable model). We retrieved all household-level covariates from the Nielsen Homescan Consumer Panel Dataset for 2010 (see Appendix B for the details). Neighborhood-level variables, assessed via either the residential census block group or census tract, included the percent of zero-car households from the SLD and the percent of households below the poverty line from the 2008-2010 American Community Survey. To obtain the values of percent of zero-car households and percent of households below the poverty line, we spatially linked the centroid of a household's residential ZCTA to the SLD census block group or American Community Survey census tract in which the centroid fell. The area covariate was urbanicity in which the centroid of a household's residential ZCTA fell, which was classified as urbanized area, urban cluster, and non-urban area by the U.S. Census Bureau.

Statistical analyses

We used separate 3-level linear mixed-effect regression models for fruits and vegetables. The 22,448 households were nested in 8,837 ZCTAs, and the 8,837 ZCTAs were nested in 378 MSAs. The median value was 2 (IQR=2) for the number of households that resided in the same ZCTA. The number of households in the same ZCTA ranged from one to fifteen. There were 3,557 (40.3%), 1,941 (22.0%), 1,286 (14.6%), and 2,053 (23.1%) ZCTAs that had one, two, three, and more than three households in the same ZCTA, respectively. We included random intercepts for each ZCTA to enable the responses to vary with the ZCTAs in which the households were nested[42] and, similarly, we included random intercepts for each MSA to enable responses to vary with the MSAs. The distribution of household expenditures for fruits and vegetables was right-skewed (median=99.0 and IQR=133.4 for fruits; median=104.2, IQR=129.6 for vegetables), so we used the logarithmic transformations of expenditures in the final regression models. The exposure variables were number of neighborhood supermarkets and convenience stores, regional destination accessibility, neighborhood destination diversity, availability of neighborhood destinations, neighborhood street connectivity, and the other household-, neighborhood- and area-level covariates. We did not use the Nielsen sampling weight because the initial sample marginal distributions that were used to create the weights were not representative of the sample we retained for our analysis[37]. We performed statistical analyses with R x64 3.5.1 and Rstudio 1.1456, using the R lme4 package to run the linear mixed-effect regression models.

Sensitivity analyses

The centroid of ZCTA may be problematic as a proxy for the real home address, particularly for suburban households in large ZCTAs. ZCTA sizes ranged from 0.02 to 5,037.5 km^2 with a median value of 49.1 km^2 (IQR=108.1). We had 3,068 ZCTAs (34.7%) with a land area below

27.1 km^2 (the average size of ZCTA in Los Angeles-Long Beach-Anaheim, CA). We had 1,006 ZCTAs (11.4%) with a land area equal to or greater than 27.1 and below 41.5 km^2 (41.5 was the average in Chicago-Naperville-Elgin, IL-IN-WI). We had 2,932 ZCTAs (33.2%) with a land area equal to or greater than 41.5 and below 153.5 km^2 (153.5 was the average in Tulsa, OK). Lastly, we had 1,831 ZCTAs (20.7%) with a land area equal to or greater than 153.5 km^2. To examine the severity of using centroid of ZCTA as a proxy for the real home address, we randomly selected a point from a household's residential ZCTA to approximate the "unknown" address of all households in the same ZCTA. We used "create random point" tool in ArcGIS 10.5 and (re)measured the built environmental factors based on these "random points". We compared the results with built environment measures based on ZCTA centroids (see Tables 2 and 3).

Besides the 5-km buffer, we used a 3-km buffer to test the sensitivity of the neighborhood definition on the results because a recent study indicated that 3 km reflects the distance people travel to neighborhood convenience stores[(43)]. In addition, we ran the models on the reduced sample (between 3rd and 97th percentile of the expenditures) to test the effect of outlier definition (purchasers of few or many fruits or vegetables).

Results

Descriptive statistics

The households in our sample were predominantly white and highly educated; 58.3% of households had an annual income greater than US$50,000 (Table 1); the median income was US$51,144[(44)]. Approximately 59% of the households did not have a supermarket in their neighborhood. Their log-transformed expenditures for fruits and vegetables (mean=4.4 for fruits and 4.5 for vegetables) were statistically, but not substantially, different (p=0.007) from their peers who had one neighborhood supermarket (mean=4.5 for fruits and 4.5 for vegetables) or more than one supermarket (mean=4.5 for fruits and 4.5 for vegetables) (data not shown). The median value of the number of neighborhood convenience stores was 6, with 25th percentile and 75th percentile values of 2 and 16.

In our sample, households in Beckley WV had the lowest fruit expenditures (mean = 3.5), while Farmington, NM had the highest (mean = 5.6). Similarly, Hanford-Corcoran, CA, a metropolitan area in the agricultural San Jaoquin valley had the highest average vegetable expenditures (mean = 5.47) while Cape Girardeau–Jackson in MI and IL had the lowest (mean = 3.57). While there are largely no differences in the vegetable expenditures among urban and non-urban households, there are marginal differences in the fruit expenditures, with households in urban clusters having the lowest average expenditure (mean = 4.34) compared to urbanized areas (mean = 4.47) and non-urban (mean = 4.52).

Regression analyses

Analyses including only the availability of neighborhood supermarkets and convenience stores suggested that households in a neighborhood with at least two supermarkets purchased significantly more (by 4.1 percentage points) fruits than households without a neighborhood supermarket (Table 2). Controlling for regional destination accessibility, neighborhood destination diversity, availability of neighborhood destinations, and neighborhood street connectivity, the difference of expenditures on fruits between households with different numbers of neighborhood supermarkets was not significant; and we observed that households purchased significantly more (2.4 percentage points more) fruits if they lived in neighborhoods with fewer (10 fewer) convenience stores (Table 2). Households purchased significantly more (0.3 percentage point more) fruits if they lived in neighborhoods with greater (10, 000 jobs more) regional destination accessibility. Households purchased significantly more (1.3 percentage points more) fruits if they lived in neighborhoods with higher (10 intersections per square mile more) street connectivity. When we controlled for the broader built environment context, we did not find a significant difference in expenditures on vegetables among households with different numbers of neighborhood supermarkets or convenience stores. Controlling for the broader built environment context, we found that households purchased significantly fewer (0.9 percentage point fewer) vegetables if they lived in neighborhoods with greater (10 percentage points of entropy value greater) destination diversity (Table 3).

By controlling for the broader built environment context and also shifting the housing residence from the centroid of household residential ZCTA to a random point in the same ZCTA, we found that the availability of neighborhood supermarkets was not associated with the expenditures on fruits or vegetables (Table 2-3). Similarly, after shifting the housing residence, we found that households purchased significantly more (2.4 percentage points) fruits if they lived in neighborhoods with 10 or fewer convenience stores (Table 2). Conversely, after shifting the housing residence, we found that street connectivity (Table 2) and neighborhood destination diversity (Table 3) were not positively and inversely associated with the expenditures for fruits and vegetables.

Sensitivity analyses using the 3-km buffer to proxy neighborhood and reduced sample (between 3rd and 97th percentile of the expenditures) generated similar results compared to the primary analyses (Appendix Tables S3-S6).

Discussion

We report evidence of cross-sectional associations between availability of neighborhood convenience stores, regional destination accessibility, neighborhood destination diversity, neighborhood street connectivity, and self-reported food purchases. Both the number of convenience stores and broader built environment context of food stores were important to consider when evaluating the relationship between food stores and healthy food purchasing.

Our findings add to the U.S. cross-sectional studies which have indicated that availability of neighborhood supermarkets is not (or only marginally) associated with food purchase[37, 45]. The healthy food purchases of households in neighborhoods with many supermarkets were marginally higher than the healthy purchases in neighborhoods with few supermarkets. However, this marginal effect disappeared when we added broader built environment characteristics to the models. In sum, the data indicated that close proximity to supermarkets likely did not motivate food purchasing after taking into account other shopping trip contexts[46] such as street network and other food and nonfood destinations. Although close to three-fifths of the sample lived in neighborhoods with no supermarkets, households probably used external stores to compensate for inadequate or unsatisfactory resources. One nationally representative study showed that 60% of households still chose supermarkets as the primary type of food store visited[6]. Therefore, for advancing food environment research and intervention, it is important to understand why people choose supermarkets outside of their neighborhoods[46]. The fact that neighborhood supermarkets were not associated with food purchase likely holds because our sample was skewed towards households with higher than national median income and was predominantly white. These households had fewer barriers to access non-neighborhood food stores than low-income households. However, low-income households traveled longer/farther for food shopping if driving or car-sharing was affordable and available[14-15]. Therefore, policy interventions should proceed cautiously if they focus exclusively on increasing the availability of supermarkets in a neighborhood.

Households in a neighborhood with more convenience stores reported purchasing fewer fruits than households in neighborhoods with fewer convenience stores. Only 8% of households had an income under US $20,000 in 2010; the median number of neighborhood convenience stores was similar for households with different income levels (7, 7, and 6 for under $20,000, 20,000-59,999 and 60,000 or above income groups). Therefore, it was unlikely that the inverse association between convenience stores and fruit expenditures was the result of convenience stores targeting poor households or poor households self-selecting to live in neighborhoods with many convenience stores. Our results agree with a previous study that had balanced representation of age, race, gender, and education and which indicated that neighborhood convenience stores were inversely associated with self-reported diet quality[43]. Everyone, not only individuals with poor access to supermarkets, should be considered in future studies of the effect of many neighborhood convenience stores on food purchases. Future work should determine whether convenience stores forestall demand for healthy options by offering unhealthy choices. Does living in a neighborhood with a relatively high availability of convenience stores encourage people to purchase more unhealthy food (e.g., energy dense snacks and sweetened beverages), thus, decreasing purchases of more plentiful healthy options (e.g., fruits) in distant outlets? Some studies have supported this hypothesis by finding that participants tended to purchase foods with poor nutritional quality in small stores such as a corner store, gas mart, pharmacy, and dollar store[47-48], although the evidence was limited to individual cities or subgroups.

Although including other built environment context factors contributed to understanding the relationship between food stores and food purchase, we found that the magnitude was small for associations between other built environment context and food purchase. When the neighborhood street connectivity increased one unit (i.e., the number of road intersections increased ten), the expenditures for fruits increased 1.3 percent. Higher connectivity connotes density of intersections and presumably a more developed area with more types of destinations. Possibly, residents of these neighborhoods had potential destinations other than supermarkets and convenience stores. Thus, it is likely that we did not capture competing stores that sell fruits and vegetables in our study.

With a 10% increase in the diversity of neighborhood destinations, expenditures for vegetables decreased 0.9 percent. This association meant that people in a low diversity neighborhood (for example, entropy=0.36) purchased approximately 2.4 percent ((0.62-0.36)*100/10*0.9=2.4) more vegetables than people in a high diversity neighborhood (for example, entropy=0.62). Possibly, people in neighborhoods with greater destination diversity tended to more frequently patronize restaurants and coffee shops, thus, they purchased less vegetables. We did not find that households purchased more fruits or vegetables if they lived in a neighborhood with a great number of other destinations, such as retail shops, churches, and restaurants. The total number of destinations differed from neighborhood destination diversity. The large number of neighborhood destinations (for example, restaurants, schools) we observed may have been a cluster of similar resources (e.g., restaurants), but the association with food purchase may have been different if the households lived in a neighborhood with diverse and dissimilar destinations, for example two retail shops, one restaurant, and a church, as compared with a neighborhood having five restaurants.

A one unit increase of regional destination accessibility (10, 000 jobs in 45-min automobile travel time) led to a 0.4 percent increase in expenditures for fruits. Our results agree with other findings that food opportunities were linked to other places during weekly or daily routine travels beyond the home neighborhood[14, 18, 54]. The average numbers of food and non-food opportunities in a 45-min automobile travel time were 55,000 and 408,000 for households in Tulsa, OK and those in Los Angeles-Long Beach-Anaheim, CA. *Ceteris Paribus,* households in high accessibility regions (for example, Los Angeles) purchased 14.1 percent ((408,000-55,000)/10,000*0.4=14.1) more fruits than those in low accessibility regions (for example, Tulsa. Future work should be conducted to identify the non-food purchase opportunities that are related to food purchase opportunities and to refine our measurement of regional destination accessibility, which may increase its explanatory power on food purchasing behaviors.

We advocate more research concerning differences in associations between built environment and food purchases in different MSAs because where and what to purchase in food stores in different areas maybe fundamentally different. For example, the median value of expenditures for fruits and vegetables in Los Angeles-Long Beach-Anaheim, CA (n=558) was \$150.6 and \$142.6, compared with \$102.5 and \$131.8 for Tulsa, OK (n=83) (data not shown). Using the Kruskal-Wallis H test (Stata 14.0), we found that the difference was significant ($p<0.001$) in the median value of food expenditures across the two MSAs. Eighty-six percent of households in Los Angeles had at least one supermarket in the 5-km buffer, compared with 30 percent in Tulsa. Households in Los Angeles had, on average, 18 convenience stores in the 5-km buffer, compared with 10 in Tulsa. These suggest that regional differences, along with local land use characteristics might matter for household food choices.

Limitations

We selected only households that reported magnet data, which limited the generalizability of our results to all U.S. households. Our analytic sample was composed of a greater number of middle-income households with a greater average educational attainment than the U.S. national population[61-62]. We used the centroid of the ZCTA as a proxy for a household's exact residential location, which meant that households living in the same zip code tabulation area shared the same built environment characteristics. Our measure of regional destination accessibility may have included destinations unrelated to food purchase. Commercial sources of data for food outlets are error-prone; we carefully cleaned and processed the data to increase their quality, yet errors likely remained. The measure of expenditures for fruits and vegetables may be inaccurate for people who purchase most of these products in nonconventional stores such as farmers' markets. Because nonconventional outlets typically do not provide itemized receipts, households that procured food at nonconventional stores likely incurred a greater reporting burden [29].

Conclusions

The availability of neighborhood supermarkets was not associated with expenditures for fruits or vegetables, but the availability of neighborhood convenience stores was associated with fruit expenditures when we included broader built environment factors in our analysis. The broader built environment contributed to understanding how people used neighborhood food stores, but the association was almost nil when we considered broader built environment context factors with food purchase. Interventions that increase the number of neighborhood supermarkets should proceed cautiously. Households in an area with fewer available convenience stores, less neighborhood destination diversity, greater regional destination accessibility, and greater neighborhood street connectivity may purchase more fruits or vegetables, but an explanation for this behavior requires more thorough study.

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Table 1 Sample characteristics of the study households (n=22,448) in continental United States, 2010

Characteristics	2010
Annual expenditure (log-transformed) on food purchased, $, mean (SD)	
Fruits	4.5 (1.1)
Vegetables	4.5 (1.0)
Availability of neighborhood food stores	
Number of supermarkets, 5-km buffer, %	
0	59.0
1	18.5
2+	22.5
Number of convenience stores, 5-km buffer, 10 counts, median (IQR)	0.6 (0.2-1.6)
Regional destination accessibility	
Jobs in 45 minutes auto travel time, 10,000 jobs, median (IQR)	5.9 (2.3-12.3)
Availability of neighborhood destinations	
Number of other stores/malls, locations where people socialized and communicated with others, and restaurants in the 5-km buffer, 10 counts, median (IQR)	11.2 (3.6-24.9)
Neighborhood destination diversity	
Entropy in the 5-km buffer, 10 percent, mean (SD)	4.8 (2.0)
Neighborhood street connectivity	
Street intersection density (weighted, auto-oriented intersections eliminated) in the 5-km buffer, 10 intersections per square mile, median (IQR)	2.7 (1.0-5.2)
Percent of zero-car households, median (IQR)	3.9 (2.3-6.3)
Percent of population below poverty level, median (IQR)	5.6 (2.6-10.9)
Education level of female head of household [a], %	
≤High school or below	22.9
>High school	68.2
No female head	8.9
Household income, $ [b], %	
Under 20,000	8.0
20,000-59,999	33.7
60,000+	58.3
Race identity of household, %	
White	83.3
Black	9.3
Asian	2.9
Other	4.5
Household size, %	
Single member	21.0
Two members	41.7
Three members	15.7
Four + members	21.7
Marital status of household head(s), %	
Married	64.8
Widowed	5.1
Divorced/separated	15.5
Single	14.5
Presence of children, %	
Yes	26.6

Number of workers in the household (household head excluded), %	
0	86.0
1	11.1
2+	2.9
Urbanicity, %	
Urbanized area	58.4
Urban cluster	4.2
Non-urban	37.4

n, number of observations; IQR, interquartile; SD, standard deviation.

Median and IQR (25^{th}-75^{th} percentile) are presented for continuous variables not normally distributed. Categorical variables are expressed as percentage (%).

Food purchase data and household-level sociodemographic data were derived from the Nielsen Homescan Consumer Dataset in 2010. Copyright © 2018, The Nielsen Company.

[a] For households with two heads of household, Nielsen designates the characteristics of the head of household as whoever makes most of the purchasing decisions.

[b] The value represented ranges of total household income for the full year that is 2 years prior to the panel year.

Table 2 Cross-sectional associations between annual expenditures (log-transformed) for fruits purchased by Nielsen households (between 2nd and 98th percentile of the fruit expenditures, n=21,710 [a]), number of neighborhood (5-km buffer) supermarkets and convenience stores, broader built environment context characteristics, and household-, neighborhood- and area-level covariates

Characteristics	[b] Centroid of residential ZCTA as household's residence				Randomly-selected point in residential ZCTA as household's residence			
	Availability of neighborhood supermarkets and convenience stores only		Availability of neighborhood supermarkets and convenience stores and broader built environment context [b]		Availability of neighborhood supermarkets and convenience stores only		Availability of neighborhood supermarkets and convenience stores and broader built environment context [b]	
	Coefficient (SE)	p-value	Coefficient (SE)	p-value	Coefficient (SE)	p-value	Coefficient (SE)	p-value
Availability of supermarkets, count, 5-km buffer								
0 (Ref.)	---	---	---	---	---	---		
1	0.023 (0.015)	0.122	0.010 (0.015)	0.517	0.014 (0.016)	0.370	0.010 (0.016)	0.539
2+	0.041 (0.018)	**0.022**	0.012 (0.019)	0.538	0.032 (0.018)	0.082	0.023 (0.019)	0.223
Availability of convenience stores, 10 counts, 5-km buffer	0.003 (0.006)	0.599	-0.024 (0.007)	**0.001**	-0.007 (0.005)	0.149	-0.024 (0.006)	**<0.001**
Broader built environment context								
Regional destination accessibility: Jobs in 45-min automobile travel time, 10,000 jobs			0.003 (0.001)	**<0.001**			0.003 (0.001)	**0.001**
Neighborhood destination diversity: Entropy, 10 percent, 5-km buffer			0.001 (0.003)	0.716			0.002 (0.002)	0.434
Availability of neighborhood destinations: Total other stores/malls, locations where people socialized and communicated with others, and restaurants restaurants, 10 counts, 5-km buffer			0.000 (0.000)	0.088			0.000 (0.000)	0.178
Neighborhood street connectivity: 10 intersections per square mile, 5-km buffer			0.013 (0.003)	**<0.001**			0.014 (0.010)	0.172

n, number of observations; SE, standard error; Ref., reference category; ZCTA, zip code tabulation area.
Food purchase data and household-level sociodemographic data were derived from the Nielsen Homescan Consumer Dataset in 2010.
[a] We excluded who reported extremely low or high values for purchases of fruits and vegetables (both simultaneously), defined here as less than the 2nd percentile or greater than the 98th percentile.

[b] Regressions controlled for percent of zero-car households in the residential census block group, percent of population below poverty level in the residential census tract, household income, race identity of household, household size, marital status, if there is at least one child in the family, number of employed household members (household head excluded), expenditure (logarithmic-transformed) on vegetables, and urbanicity (R x64 3.5.1 and Rstudio 1.1456).

Entries in bold mark statistically significant associations ($p<0.05$).

Table 3 Cross-sectional associations between annual expenditures (log-transformed) for vegetables purchased by Nielsen households (between 2^{nd} and 98^{th} percentile of the vegetable expenditures, n=21,686 [a]), availability of neighborhood (5-km buffer) supermarkets and convenience stores, broader built environment context characteristics, and household-, neighborhood- and area-level covariates

Characteristics	[b] Centroid of residential ZCTA as household's residence				Randomly-selected point in residential ZCTA as household's residence			
	Availability of neighborhood supermarkets and convenience stores only		Availability of neighborhood supermarkets and convenience stores and broader built environment context [b]		Availability of neighborhood supermarkets and convenience stores only		Availability of neighborhood supermarkets and convenience stores and broader built environment context [b]	
	Coefficient (SE)	p-value	Coefficient (SE)	p-value	Coefficient (SE)	p-value	Coefficient (SE)	p-value
Availability of supermarkets, count, 5-km buffer								
0 (Ref.)	---	---	---	---	---	---		
1	0.013 (0.014)	0.328	0.017 (0.014)	0.223	0.029 (0.014)	**0.046**	0.028 (0.015)	0.059
2+	0.013 (0.016)	0.429	0.016 (0.018)	0.376	0.027 (0.017)	0.112	0.025 (0.017)	0.158
Availability of convenience stores, 10 counts, 5-km buffer	-0.002 (0.005)	0.732	-0.000 (0.007)	0.976	0.002 (0.004)	0.620	0.001 (0.006)	0.800
Broader built environment context								
Regional destination accessibility: Jobs in 45-min automobile travel time, 10,000 jobs			-0.000 (0.001)	0.586			-0.001 (0.001)	0.517
Neighborhood destination diversity: Entropy, 10 percent, 5-km buffer			-0.009 (0.003)	**0.002**			-0.002 (0.002)	0.410
Availability of neighborhood destinations: Total other stores/malls, locations where people socialized and communicated with others, and restaurants, 10 counts, 5-km buffer			0.000 (0.000)	0.617			0.000 (0.000)	0.824
Neighborhood street connectivity: 10 intersections per square mile, 5-km buffer			0.001 (0.003)	0.881			0.011 (0.009)	0.242

n, number of observations; SE, standard error; Ref., reference category; ZCTA, zip code tabulation area.

Food purchase data and household-level sociodemographic data were derived from the Nielsen Homescan Consumer Dataset in 2010.

[a] We excluded who reported extremely low or high values for purchases of fruits and vegetables (both simultaneously), defined here as less than the 2^{nd} percentile or greater than the 98^{th} percentile.

[b] Regressions controlled for percent of zero-car households in the residential census block group, percent of population below poverty level in the residential census tract, household income, race identity of household, household size, marital status, if there is at least one child in the family, number of employed household members (household head excluded), expenditure (logarithmic-transformed) on fruits, and urbanicity (R x64 3.5.1 and Rstudio 1.1456).

Entries in bold mark statistically significant associations ($p<0.05$)

Appendix A: sample

The annual purchases of fruits and vegetables by a household are high frequency items compared to with low frequency products such as clothes and furniture. However, in our raw study sample, we still observed that, for example, 1,078 and 763 households spent less than $10 for fruits and vegetables, respectively, in 2010. In addition, 14 and 11 households spent more than $ 1,000 for fruits and vegetables, respectively. To avoid undue influence by some outlying points on the regression, we excluded households with extremely large or small expenditures for both fruits and vegetables together. However, households with extremely large or small expenditures for fruits but not for vegetables, or vice versa, were still included. We defined extreme values of expenditure for fruits or vegetables as those below the 2nd percentile or above the 98th percentiles. We did not use “below 1st percentile” and “above the 99th percentile” as cut off points because there would still have been some households with zero purchase of fruits or vegetables with a 1st percentile cut-off point; thus, the narrower cut-offs did not facilitate the log transformation of expenditures.

We used only the data of the magnet households that reported nonstandard UPC products, which included random-weighted (loose) items such as fruits, vegetables, meats, and in-store baked goods; households that did not report nonstandard UPC products were excluded from our models. Thus, we needed to ensure enough overlap (e.g., balance in covariates) between magnet and non-magnet households. If there was enough overlap, the estimated densities of the probability of being magnet household versus non-magnet household would not have too much mass around 0 or around 1[(1)]. We generated the probabilities of being magnet (i.e., propensity scores) for the two subgroups and plotted the probabilities on the same graph. There were enough overlaps between magnet households and non-magnet households (Figure S1), suggesting that all covariates were largely balanced. Thus, we did not necessarily need to exclude some of the magnet households in the expenditure for fruits or vegetables models because of significantly different household-level sociodemographic characteristics. We used kdens command in STATA 14 to draw the plots.

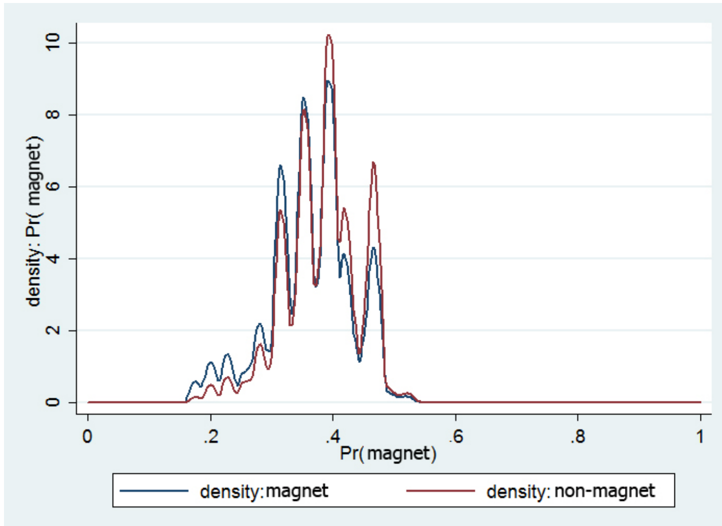

Figure S1. Kernel density estimate: probability of being magnet households

Appendix B: measures

Purchase of fresh fruits and vegetables

The purchases of fresh fruits and vegetables using standard UPC codes were categorized as fresh produce by Nielsen (Table S1). By choosing products from the fresh produce category, we explicitly excluded fruits and vegetables that were dried, tinned, bottled, frozen, or refrigerated; these latter products are classified as dry grocery, frozen food, and deli.

The purchases of fresh fruits and vegetables using nonstandard UPC codes were categorized as magnet by Nielsen (Table S1). From the products of magnet data, we used brand_desr= reference card fruits and brand_desc= reference card vegetables to identify fruits and vegetables, respectively. Other nonstandard UPC (i.e., magnet) products included baked goods, prepared foods, cheese, meat/poultry/fish, coffee, flora, etc., according to the description of products (variable name= brand_desr) in the product file. Items in the categories “reference card fruits” and “reference card vegetables” were not described in detail, i.e., whether the fruits or vegetables were fresh, dried, tinned, frozen, refrigerated, etc. As magnet data were known for random weighted (loose) products, we assumed that we could ignore the proportion of random-weighted magnet dried, frozen fruits or vegetables. Therefore, we specified all the magnet products with brand_descr=reference card fruits and brand_descr=reference card vegetables as fresh fruits and fresh vegetables, respectively.

Appendix Table S1. Fresh produce type and Nielsen production group module description

Food type	Department [a]	Product module/brand [a]
Fruits using standard UPC codes	Fresh produce	fresh apples, fresh cranberries, fresh grapefruits, fresh kiwi, fresh oranges, fresh strawberries, fresh tomatoes, and fresh fruits-remaining.
Fruits using nonstandard UPC codes	Magnet	Magnet data with brand_descr=reference card fruits
Vegetables using standard UPC codes	Fresh produce	fresh carrots, fresh cauliflower, fresh celery, fresh lettuce, fresh garlic, fresh mushrooms, fresh onions, fresh potatoes, fresh radishes, fresh spinach, fresh sprout, and fresh vegetables-remaining.
Vegetables using nonstandard UPC codes	Magnet	Magnet data with brand_descr=reference card vegetables

Note: [a] Department, product module, and brand are all Nielsen defined product codes.

In calculating the annual expenditures for fruits or vegetables by household, we linked the product file to the purchase file using the UPC numbers (variable name 1=upc, variable name

2=upc_ver_uc) as the joint identifying numbers to create a purchase-product file. Upc_ver_uc indicated different versions of upc. We then linked the purchase-product file to the trip file using the trip number (variable name=trip_code_uc) as the joint identifying number to create a trip-purchase-product file. We linked the trip-purchase-product file to the household sociodemographic file using the household number (variable name=household_code) as the joint identifying number to create a household-trip-purchase-product file.

To properly classify self-reported, non-magnet expenditures, we used the departmental category (fresh produce) and the product module description (e.g., fresh apple, fresh lettuce) to identify fruits or vegetables; for the self-reported magnet expenditures, we used the departmental category (magnet) and brand description (e.g., reference card fruits, reference card vegetables) to identify fruits or vegetables. We then calculated the self-reported expenditures for fruits and vegetables (separately) as the sum of standard UPC products (non-magnet) and nonstandard UPC products (magnet) by household for 2010; then, we used these estimates to partially address the potential issue of random purchasing behaviors (i.e., impulsive purchases) in a short observational period (e.g., weekly or monthly)[(2)].

SIC codes from ReferenceUSA

See Table S2 below for the primary six-digit standard industrial classification (SIC) codes used to classify supermarkets, convenience stores, fast food restaurants, sit-down restaurants, child care services, other food and non-food stores, health-care services, and churches.

Appendix Table S2. Primary 6-digit [a] SIC codes from ReferenceUSA used in the analysis for year 2010

Food Resource Type	Description	ReferenceUSA primary SIC code
Supermarkets	Supermarkets	541101
Convenience stores	Variety stores	533100
	Snack products	541102
	Convenience stores	541103
	Gasoline service stations	554100
	Gas stations and convenience stores	554199
Fast food restaurants	Fast food restaurants and stands	581203
	Pizza restaurants	581206
Sit-down Restaurants	Fine dining restaurants	581201
	Family restaurants	581205
	Seafood restaurants	581207

	Steak and barbecue restaurants	581208
Child care services		835101
Churches		866107
Department stores		531102
Retail shops		531104
Wholesale clubs		531110
Miscellaneous general merchandise stores		539900
Offices and clinics of physicians		801101
Offices and clinics of dentists		802101
		802104
Offices and clinics of doctors of osteopathy		803198
Offices and clinics of other health practitioners		804101
		804201
		804301
		804302
		804303
		804901-32, 35-42, 44-47, 50-67, 69, 71-77, 79-81, 83, 84-89, 91-92, 94, 97-99
Health care facilities		805101-02, 805198, 805298, 805901
Hospitals		806904
		806906
		806998

Note: [a] ReferenceUSA has created their own 2-digit extension to the original SIC system as a means to update and expend the system so their customers can more precisely define their business classification.

Regional destination accessibility

The measure of regional destination accessibility is based on a network analysis model that considers the attractiveness (number of employees) of each reachable block group and the travel time between each origin block group and all the destination block groups. The SLD used the employment information in the InfoUSA 2011 and the street network information in the NAVSTREETS to generate measures of job opportunities in each reachable block group and the travel time between each origin block group and all the destination block groups using network analysis models. The SLD then generated the value of regional destination accessibility by decaying the employment at destinations by the distance decay curve and summed for each origin block group[(3)]. Compared to the traditional measure of the total attractiveness of reachable block groups, such as summing the total number of potential destinations in a certain area, by decaying the attractiveness of destinations using distance decay curve, regional destination accessibility calculated by the SLD is a more accurate measure of total attractiveness.

Neighborhood destination diversity

We used American Time Use Survey (ATUS) to identify grocery-chained activities. In 2010, the ATUS had 257,193 observations of activities by 13,260 participants. For each of these participants, the ATUS recorded how many minutes a participant spent time on a specific activity during one observational day (00:00-23:59, 24 hours), in what type of activity the participant attended, and where the participant was when he or she attended the activity. To identify which activities were "chained" with grocery shopping, we retained 2,011 participants who reported at least one grocery shopping in grocery stores. Participants who socialized and communicated in grocery stores or who reported grocery shopping but not in grocery stores (for example, via internet or by telephone) were removed from our sample. We used a 0.5-hour time duration window to identify the activities that occurred before (the start time of) grocery shopping in grocery stores. We also used a 0.5-hour time duration window to identify the activities that occurred after (the end time of) grocery shopping in grocery stores. We defined all activities in such a 1-hour time duration window as grocery-chained activity. We then identified and ranked the locations at which such grocery-chained activities occurred. The locations with high occurrence rates (i.e., the number of grocery-chained activities at one specific location divided by the total number of grocery-chained activities was greater than 10%) were: 1) other store/mall (25.4%); 2) other place (19.2%); 3) someone else's home (14.7%); and 4) restaurants (13.3%), excluding travel activities such as car, truck, motorcycle, walking, bus, etc. According to the activity description linked with such locations, we defined other store/mall as department store, retail shop, and wholesale club. Similarly, we defined locations where people socialized and communicated with others as churches, health care services, and child care services. Similarly, we defined restaurants as fast food and sit-down restaurants. See Table S2 above for the primary six-digit standard industrial classification (SIC) codes used to classify fast food restaurants, sit-down restaurants, child care services, churches, department stores, retail shops, wholesale clubs, miscellaneous general merchandise stores, and six types of health care services. We used these three types of locations (other store, other places, and restaurants) as the potential destinations that were chained with grocery shopping. We calculated the total number of outlets under each type and used the entropy function to calculate the neighborhood destination diversity.

Neighborhood street connectivity

We retrieved the neighborhood street connectivity calculated by the SLD. The SLD used the road network information in the NAVSTREETS to measure neighborhood street connectivity as the total weighted number of street intersections divided by total land area in the block group. The SLD formula to calculate the weighted street connectivity in the block group is as follows:

$$\text{street connectivity} = \mathrm{d1} * 0.667 + \mathrm{d2} + \mathrm{d3} * 0.667 + \mathrm{d4}$$

where d1 is the number of multi-modal intersections having three legs per square mile, d2 is the number of multi-modal intersections having four or more legs per square mile, d3 is the number of pedestrian-oriented intersections having three legs per square mile, and d4 is the number of pedestrian-oriented intersections having four or more legs per square mile. To reflect the connectivity for pedestrian and bicycle travel, the SLD assigned a weight of zero to auto-oriented intersections to reflect the fact that they are a barrier to pedestrian and bicycle mobility[(3)]. Similarly, the SLD assigned lower weights to three-way intersections to reflect the fact that they do not promote street connectivity as effectively as four way intersections[(3)].

Household-level covariates

Households reported the highest degree obtained by the female head of household in one of seven categories. We combined the seven to generate a new education variable with three categories, i.e., high school or below, college or higher, and no female head. We chose the female head of household rather than the male because maternal education has been shown previously to be an important determinant of child diet[(4-7)]. Households reported their income in one of 20 categories, which we combined into a three-category variable, i.e., less than $20,000, $20,000-$59,999, and $60,000 or more. Households reported their race identity in one of four categories, including white, black, Asian and other. Households reported their sizes in one of nine categories; we combined these nine categories into a four-category variable, i.e., one member, two members, three members, and four members or above. Households reported the marital status of the head as four categories, married, widowed, divorced/separated, and single.

Appendix C: data analyses and results

In the sensitivity analysis, we excluded households located in 1,831 largest ZCTAs (with a land area equal to or greater than 153.5 km^2). We used the centroid of residential ZCTA as a household's residence and ran fruit and vegetable models. We used availability of neighborhood supermarkets and convenience stores, neighborhood destination diversity, availability of neighborhood destinations, and neighborhood street connectivity in the 5-km buffer. The model results are shown in Tables S3 and S4.

In the sensitivity analysis, we used the centroid of residential ZCTA as a household's residence and ran fruit and vegetable models. We used availability of neighborhood supermarkets and convenience stores, neighborhood destination diversity, availability of neighborhood destinations, and neighborhood street connectivity in the 3-km buffer. The model results are shown in Tables S5 and S6.

In the sensitivity analysis, we defined an extreme value for expenditure on fruits or vegetables as those below the 3rd percentile or above the 97th percentile. We used the centroid of residential ZCTA as household's residence and ran fruit and vegetable models (n=21,269 for fruit and n=21,249 for vegetable). We used availability of neighborhood supermarkets and convenience stores, neighborhood destination diversity, availability of neighborhood destinations, and neighborhood street connectivity in the 5-km buffer. The model results are shown in Tables S7 and S8.

Appendix Table S3. Coefficients of cross-sectional associations between annual expenditures (logarithmic-transformed) for fruits purchased by Nielsen households (excluding households located in 1,831 ZCTAs with a land area equal to or greater than 153.5 km^2, n=17,420), availability of neighborhood supermarkets and convenience stores (5-km buffer, centroid of residential ZCTA as a household's residence), broader built environment context characteristics, and household-, neighborhood- and area-level covariates

Characteristics	Availability of neighborhood supermarkets and convenience stores only [a]		Availability of neighborhood supermarkets and convenience stores and broader built environment context [a]	
	Coefficient (SE)	p-value	Coefficient (SE)	p-value
Availability of supermarkets, count, 5-km buffer				
0 (Ref.)	---	---	---	---
1	0.011 (0.045)	0.482	-0.000 (0.017)	0.989
2+	0.030 (0.016)	0.104	0.003 (0.020)	0.866
Availability of convenience stores, 10 counts, 5-km buffer	0.025 (0.018)	0.693	-0.023 (0.007)	**0.002**
Broader built environment context				
Regional destination accessibility: Jobs within 45-min automobile travel time, 10,000 jobs			0.003 (0.001)	**0.001**
Neighborhood destination diversity: Entropy, 10 percent, 5-km buffer			0.002 (0.004)	0.570
Availability of neighborhood destinations: Total other stores/malls, locations where people socialized and communicated with others, and restaurants, 10 counts, 5-km buffer			0.000 (0.000)	0.106
Neighborhood street connectivity: 10 intersections per square mile, 5-km buffer			0.014 (0.004)	**<0.001**

n, number of observations; SE, standard error; Ref., reference category; ZCTA, zip code tabulation area.
Food purchase data and household-level sociodemographic data were derived from the Nielsen Homescan Consumer Dataset in 2010. Copyright © 2018, The Nielsen Company.
[a] Regressions controlled for percent of zero-car households in the residential census block group, percent of population below poverty level in the residential census tract, household income, race identity of household, household size, marital status, if there is at least one child in the family, and number of employed household members (household head excluded), expenditure (logarithmic-transformed) on vegetables, and urbanicity (R x64 3.5.1 and Rstudio 1.1456).
Entries in bold mark statistically significant associations (p<0.05).

Appendix Table S4. Coefficients of cross-sectional associations between annual expenditures (logarithmic-transformed) for vegetables purchased by Nielsen households (excluding households located in 1,831 ZCTAs with a land area equal to or greater than 153.5 km^2, n=17,394), availability of neighborhood supermarkets and convenience stores (5-km buffer, centroid of residential ZCTA as household's residence), broader built environment context characteristics, and household-, neighborhood- and area-level covariates

Characteristics	Availability of neighborhood supermarkets and convenience stores only [a]		Availability of neighborhood supermarkets and convenience stores and broader built environment context [a]	
	Coefficient (SE)	p-value	Coefficient (SE)	p-value
Availability of supermarkets, count, 5-km buffer				
0 (Ref.)	---	---	---	---
1	0.013 (0.039)	0.373	0.017 (0.015)	0.265
2+	0.015 (0.015)	0.376	0.021 (0.018)	0.265
Availability of convenience stores, 10 counts, 5-km buffer	-0.005 (0.017)	0.410	-0.002 (0.007)	0.826
Broader built environment context				
Regional destination accessibility: Jobs within 45-min automobile travel time , 10,000 jobs			-0.001 (0.001)	0.589
Neighborhood destination diversity: Entropy, 10 percent, 5-km buffer			-0.010 (0.004)	**0.010**
Availability of neighborhood destinations: Total other stores/malls, locations where people socialized and communicated with others, and restaurants, 10 counts, 5-km buffer			0.000 (0.000)	0.610
Neighborhood street connectivity: 10 intersections per square mile, 5-km buffer			-0.002 (0.003)	0.608

n, number of observations; SE, standard error; Ref., reference category; ZCTA, zip code tabulation area.
Food purchase data and household-level sociodemographic data were derived from the Nielsen Homescan Consumer Dataset in 2010. Copyright © 2018, The Nielsen Company.
[a] Regressions controlled for percent of zero-car households in the residential census block group, percent of population below poverty level in the residential census tract, household income, race identity of household, household size, marital status, if there is at least one child in the family, and number of employed household members (household head excluded), expenditure (logarithmic-transformed) on fruits, and urbanicity (R x64 3.5.1 and Rstudio 1.1456).
Entries in bold mark statistically significant associations (p<0.05).

Appendix Table S5. Coefficients of cross-sectional associations between annual expenditures (logarithmic-transformed) for fruits purchased by Nielsen households (between 2nd and 98th percentile of the fruit expenditures, n=21,710 [a]), availability of neighborhood supermarkets and convenience stores (3-km buffer, centroid of residential ZCTA as a household's residence), broader built environment context characteristics, and household-, neighborhood- and area-level covariates

Characteristics	Availability of neighborhood supermarkets and convenience stores only [b]		Availability of neighborhood supermarkets and convenience stores and broader built environment context [b]	
	Coefficient (SE)	p-value	Coefficient (SE)	p-value
Availability of supermarkets, count, 3-km buffer				
0 (Ref.)	---	---	---	---
1	0.036 (0.017)	**0.033**	0.018 (0.017)	0.295
2+	0.004 (0.023)	0.845	-0.024 (0.023)	0.309
Availability of convenience stores, 10 counts, 3-km buffer	0.001 (0.012)	0.943	-0.044 (0.014)	**0.002**
Broader built environment context				
Regional destination accessibility: Jobs within 45-min automobile travel time, 10,000 jobs			0.004 (0.001)	**<0.001**
Neighborhood destination diversity: Entropy, 10 percent, 3-km buffer			0.001 (0.003)	0.237
Availability of neighborhood destinations: Total other stores/malls, locations where people socialized and communicated with others, and restaurants, 10 counts, 3-km buffer			0.000 (0.000)	0.261
Neighborhood street connectivity: 10 intersections per square mile, 3-km buffer			0.009 (0.003)	**0.001**

n, number of observations; SE, standard error; Ref., reference category; ZCTA, zip code tabulation area.
Food purchase data and household-level sociodemographic data were derived from the Nielsen Homescan Consumer Dataset in 2010. Copyright © 2018, The Nielsen Company.
[a] We excluded who reported extremely low or high values for purchases of fruits, defined here as less than the 2nd percentile or greater than the 98th percentile.
[b] Regressions controlled for percent of zero-car households in the residential census block group, percent of population below poverty level in the residential census tract, household income, race identity of household, household size, marital status, if there is at least one child in the family, and number of employed household members (household head excluded), expenditure (logarithmic-transformed) on vegetables, and urbanicity (R x64 3.5.1 and Rstudio 1.1456).
Entries in bold mark statistically significant associations (p<0.05).

Appendix Table S6. Coefficients of cross-sectional associations between annual expenditures (logarithmic-transformed) for vegetables purchased by Nielsen households (between 2nd and 98th percentile of the vegetable expenditures, n=21,686 [a]), availability of neighborhood supermarkets and convenience stores (3-km buffer, centroid of residential ZCTA as household's residence), broader built environment context characteristics, and household-, neighborhood- and area-level covariates

Characteristics	Availability of neighborhood supermarkets and convenience stores only [b]		Availability of neighborhood supermarkets and convenience stores and broader built environment context [b]	
	Coefficient (SE)	p-value	Coefficient (SE)	p-value
Availability of supermarkets, count, 3-km buffer				
0 (Ref.)	---	---	---	---
1	0.007 (0.015)	0.645	0.008 (0.016)	0.610
2+	0.013 (0.021)	0.526	0.013 (0.022)	0.544
Availability of convenience stores, 10 counts, 3-km buffer	0.003 (0.011)	0.804	0.002 (0.013)	0.907
Broader built environment context				
Regional destination accessibility: Jobs within 45-min automobile travel time , 10,000 jobs			-0.001 (0.001)	0.274
Neighborhood destination diversity: Entropy, 10 percent, 3-km buffer			-0.005 (0.002)	**0.035**
Availability of neighborhood destinations: Total other stores/malls, locations where people socialized and communicated with others, and restaurants, 10 counts, 3-km buffer			0.000 (0.000)	0.325
Neighborhood street connectivity: 10 intersections per square mile, 3-km buffer			0.003 (0.002)	0.263

n, number of observations; SE, standard error; Ref., reference category; ZCTA, zip code tabulation area.

Food purchase data and household-level sociodemographic data were derived from the Nielsen Homescan Consumer Dataset in 2010.

[a] We excluded who reported extremely low or high values for purchases of vegetables, defined here as less than the 2nd percentile or greater than the 98th percentile.

[b] Regressions controlled for percent of zero-car households in the residential census block group, percent of population below poverty level in the residential census tract, household income, race identity of household, household size, marital status, if there is at least one child in the family, and number of employed household members (household head excluded), expenditure (logarithmic-transformed) on fruits, and urbanicity (R x64 3.5.1 and Rstudio 1.1456).

Entries in bold mark statistically significant associations ($p<0.05$).

Appendix Table S7. Coefficients of cross-sectional associations between annual expenditures (logarithmic-transformed) for fruits purchased by Nielsen households (between 3rd and 97th percentile of the fruit expenditures, n=21,269 [a]), availability of neighborhood supermarkets and convenience stores (5-km buffer, centroid of residential ZCTA as household's residence), broader built environment context characteristics, and household-, neighborhood- and area-level covariates

Characteristics	Availability of neighborhood supermarkets and convenience stores only [b]		Availability of neighborhood supermarkets and convenience stores and broader built environment context [b]	
	Coefficient (SE)	p-value	Coefficient (SE)	p-value
Availability of supermarkets, count, 5-km buffer				
0 (Ref.)	**---**	**---**	**---**	**---**
1	0.024 (0.014)	0.103	0.012 (0.015)	0.412
2+	0.040 (0.017)	**0.021**	0.013 (0.019)	0.470
Availability of convenience stores, 10 counts, 5-km buffer	0.004 (0.006)	0.466	-0.019 (0.007)	**0.007**
Broader built environment context				
Regional destination accessibility: Jobs within 45-min automobile travel time , 10,000 jobs			0.003 (0.001)	**<0.001**
Neighborhood destination diversity: Entropy, 10 percent, 5-km buffer			-0.000 (0.003)	0.960
Availability of neighborhood destinations: Total other stores/malls, locations where people socialized and communicated with others, and restaurants, 10 counts, 5-km buffer			0.000(0.000)	0.240
Neighborhood street connectivity: 10 intersections per square mile, 5-km buffer			0.011 (0.003)	**0.001**

n, number of observations; SE, standard error; Ref., reference category; ZCTA, zip code tabulation area.
Food purchase data and household-level sociodemographic data were derived from the Nielsen Homescan Consumer Dataset in 2010. Copyright © 2018, The Nielsen Company.
[a] We excluded who reported extremely low or high values for purchases of fruits, defined here as less than the 3rd percentile or greater than the 97th percentile.
[b] Regressions controlled for percent of zero-car households in the residential census block group, percent of population below poverty level in the residential census tract, household income, race identity of household, household size, marital status, if there is at least one child in the family, and number of employed household members (household head excluded), expenditure (logarithmic-transformed) on vegetables, and urbanicity (R x64 3.5.1 and Rstudio 1.1456).
Entries in bold mark statistically significant associations (p<0.05).

Appendix Table S8. Coefficients of cross-sectional associations between annual expenditures (logarithmic-transformed) for vegetables purchased by Nielsen households (between 3rd and 97th percentile of the vegetable expenditures, n=21,249 [a]), availability of neighborhood supermarkets and convenience stores (5-km buffer, centroid of residential ZCTA as household's residence), broader built environment context characteristics, and household-, neighborhood- and area-level covariates

Characteristics	Availability of neighborhood supermarkets and convenience stores only [b]		Availability of neighborhood supermarkets and convenience stores and broader built environment context [b]	
	Coefficient (SE)	p-value	Coefficient (SE)	p-value
Availability of supermarkets, count, 5-km buffer				
0 (Ref.)	---	---	---	---
1	0.014 (0.013)	0.298	0.017 (0.014)	0.206
2+	0.014 (0.016)	0.363	0.017 (0.017)	0.326
Availability of convenience stores, 10 counts, 5-km buffer	0.021 (0.005)	0.968	-0.001 (0.007)	0.936
Broader built environment context				
Regional destination accessibility: Jobs within 45-min automobile travel time, 10,000 jobs			-0.000 (0.001)	0.820
Neighborhood destination diversity: Entropy, 10 percent, 5-km buffer			-0.008 (0.003)	**0.002**
Availability of neighborhood destinations: Total other stores/malls, locations where people socialized and communicated with others, and restaurants, 10 counts, 5-km buffer			0.000 (0.000)	0.371
Neighborhood street connectivity: 10 intersections per square mile, 5-km buffer			0.001 (0.003)	0.781

n, number of observations; SE, standard error; Ref., reference category; ZCTA, zip code tabulation area.

Food purchase data and household-level sociodemographic data were derived from the Nielsen Homescan Consumer Dataset in 2010. Copyright © 2018, The Nielsen Company.

[a] We excluded who reported extremely low or high values for purchases of vegetables, defined here as less than the 3rd percentile or greater than the 97th percentile.

[b] Regressions controlled for percent of zero-car households in the residential census block group, percent of population below poverty level in the residential census tract, household income, race identity of household, household size, marital status, if there is at least one child in the family, and number of employed household members (household head excluded), expenditure (logarithmic-transformed) on fruits, and urbanicity (R x64 3.5.1 and Rstudio 1.1456).

Entries in bold mark statistically significant associations ($p<0.05$).

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