

RESEARCH REPORT

# Retail Food Access and Obesity Prevalence

Mapping Variation across the United States

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# Executive Summary

Obesity is a significant risk factor for many chronic diseases and higher rates of morbidity and mortality, and its prevalence has increased rapidly during the past few decades. As public health researchers have sought to understand why the rate of obesity in the US has escalated so rapidly in a relatively short period, the role of eating behaviors and individual food choices has received extensive attention, as has the growing array of clinical tools to reduce obesity at the individual level. But the focus on individual actions and tailored clinical management can obscure the ways in which the larger environment shapes the choices and opportunities that are available to all individuals, particularly those in communities where obesity is common. A central feature of that environment is the quality of food access.

We explore how access to different types of retail food stores, which may in turn shape the foods that consumers choose, varies widely across the US, with particular attention to areas with higher rates of obesity. We find the following and use maps to illustrate these trends:

- While obesity is widespread in the US, it is not distributed equally across places. The highest obesity rates in the US are concentrated in Southern counties, particularly those in parts of Texas, Louisiana, Mississippi, Kentucky, and West Virginia. In contrast, the lowest obesity rates are concentrated in Western counties, especially those in Colorado and parts of Wyoming, California, and Nevada.
- On average, counties with high obesity rates have more food establishments per 1,000 residents than counties with low obesity rates.
- We find stark differences in the mix of food establishment types between low-, middle-, and high-obesity counties when we categorize food establishments by whether they are likely to serve healthy or unhealthy food. Among all food establishments, 65.5 percent are considered likely unhealthy in counties with a high percentage of residents with obesity compared with 51.5 percent in counties with a low percentage of residents with obesity. This pattern holds even after controlling for a variety of other county-level characteristics.
- Food establishments more likely to serve unhealthy foods are largely comprised of convenience stores, followed by gas stations, dollar stores, and pharmacies in both low- and high-obesity counties. However, dollar stores represent a substantially larger share of unhealthy food establishments in high-obesity areas than in low-obesity areas.

Using maps to explore the intersections of obesity and retail food stores can assist policymakers and communities in understanding how potential policies and interventions align with areas of higher risk. As an example, we map the locations of recent sites for the Gus Schumacher Nutrition Incentive Program (known as GusNIP), a competitive grant program administered through the USDA, that provides states and localities with funding to increase the value of SNAP benefits when used to purchase fruits and vegetables. The map shows a strong alignment between high obesity prevalence areas and incentive program locations but also makes plain that a significant number of high-obesity counties lack GusNIP grants.

Another opportunity to use mapping to inform policy and practice is looking at the intersection of race and ethnicity and presence of less healthy food options. Although obesity affects individuals from all demographic groups, the burden of obesity and related chronic disease is particularly pronounced in communities of color, stemming from a broad array of factors that can be traced to structural racism. Areas where both obesity and less healthy food access occur at higher rates may be in particular need for prioritizing strategies to improve the food environment.

This is the second report in a series of reports addressing geographic variation in obesity. The first report summarized geographic variation in obesity prevalence and treatment options. This second report builds on these insights by exploring variation in food access, as addressing obesity effectively requires a multifaceted approach that considers both treatment options and improving food access (Waidmann et al. 2022).

# Retail Food Access and Obesity Prevalence: Mapping Variation across the United States

## Obesity Prevalence and Food Access

Obesity is a significant risk factor for many chronic diseases and higher rates of morbidity and mortality, and its prevalence has increased rapidly during the past few decades.<sup>1</sup> In 2020, more than 4 in 10 adults in the US experienced obesity, up from about 15 percent in 1980.<sup>2</sup> As public health researchers have sought to understand why the rate of obesity in the US has escalated so rapidly in a relatively short period, the role of eating behaviors and individual food choices has received extensive attention (Smethers and Rolls 2018), as has the growing array of clinical tools to reduce obesity at the individual level (Khalil et al. 2020; Wolfe et al. 2016). But the focus on individual actions and tailored clinical management can obscure the ways in which the larger environment shapes the choices and opportunities that are available to all individuals, particularly those in communities where obesity is common. A critical part of the conversation about rising obesity and the related burden of chronic disease is about not the individual but what has happened in the environment all around us (Katz 2014). And a central feature of that environment is food and food access.

In this report, we explore how access to different types of retail food outlets (and thus types of food) varies widely across the US, with particular attention to areas with higher rates of obesity. A geographic lens is only one way of understanding how people experience food in their communities, but proximity to similar spaces for acquiring food is an important way to examine shared risk factors as well as potential changes in resources and policies that can disrupt inequities and improve health outcomes on a larger scale. This is the second report in a series of reports addressing geographic variation in obesity. The first report summarized geographic variation in obesity prevalence and treatment options. This second report builds on these insights by exploring variation in food access, as addressing obesity effectively requires a multifaceted approach that considers both treatment options and improving food access (Waidmann et al. 2022).

The overall US food environment is not well aligned with the recommendations for healthier eating—for example, healthier foods like fruits and vegetables are not produced at the level that would

be needed to meet recommended consumption, and the wide availability, marketing, and relatively low cost of many processed foods shape and reflect choices of consumers in less healthy directions (Barnhill 2018; Committee on a Framework for Assessing the Health, Environmental, and Social Effects of the Food System 2015). One recent analysis concluded that almost 60 percent of energy intake among US adults comes from ultraprocessed foods and that these foods account for about 90 percent of added sugars consumed in the US (Eurídice Martínez Steele 2016). High consumption of added sugars has been associated with increased risk of obesity and related chronic diseases.

The immediate local food environment facing consumers may play a particularly large role for people with limited income, transportation access, and/or physical ability to expand their food choices, including options for fresh, healthier options with fewer calories. In fact, previous studies find that disadvantaged consumers lack the financial resources, time availability, and social capital to expand their food choices, and therefore, they are more likely to shop in food stores that are closer to their households compared with higher-income individuals, who have the resources to make more trips and shop at better-resourced supermarkets outside their neighborhoods (Ghosh-Dastidar et al. 2017; LeDoux and Vojnovik 2013; Wang et al. 2007). People who have fewer options for shopping also may pay more than other customers, as research has shown that smaller neighborhood stores have higher prices for staples than do supermarkets (Caspi et al. 2017).

The price of acquiring a healthier diet may play a nontrivial role in individual choices and subsequent health outcomes (Pancrazi et al. 2022). For example, lower prices for fruits and vegetables were positively associated with better dietary quality and lower body mass index (Beydoun et al. 2008). Other research has documented significant geographic variation in food prices for healthier food across the US, and this variation in price may play a role in geographic variation in diet and health outcomes (Todd et al. 2011).

In earlier work on food access, the lack of proximity to grocery stores was identified as a major area of concern, and such locations were deemed “food deserts” (Beaulac et al. 2009). More recent evidence has suggested that physical proximity to grocery stores may not be the most salient aspect of food environments that can affect obesity (Allcott et al. 2019; Lin et al. 2014). The presence of food outlets that are more likely to offer less healthy options may play a critical role. Areas with a higher proportion of these outlets have been described as “food swamps” (Rose et al. 2011), and emerging research has identified an association between higher prevalence of obesity and food swamps. For example, areas with higher rates of fast food outlets and convenience stores have been associated with higher body mass index (Stowers et al. 2017), and geographic variation in obesity among counties has been



associated with several measures of community conditions, including relatively higher access to outlets with less healthy options (Congdon 2017).

Intentional policies that have confined communities of color to specific geographic spaces are well documented, and their historical legacy and continuing contributions are part of understanding the realities of racialized food access and racial/ethnic disparities in obesity and related health outcomes.<sup>3</sup> Farmer and food justice activist Karen Washington coined a new food access term, “food apartheid,”<sup>4</sup> to direct a focus on the root causes of inequity in the food system on the basis of race, class, and geography (Gripper et al.2022; Strings and Bacon 2020).<sup>5</sup>

Food choices are influenced by both supply and demand. In this report, we focus on supply-side access to retail food stores of varying types, which may in turn shape the foods that consumers choose. We focus on food outlets where individuals can purchase food to prepare and eat at home, but food purchased away from home at restaurants and other prepared food outlets also looms large in the community food environment. In 2021, consumers spent 10.3 percent of their disposable income on food, roughly divided between food purchased for at-home consumption (5.2 percent) and food purchased away from home (5.1 percent). However, lower-income households typically spend far less of their household food budget on food purchased away from home than higher income households.<sup>6</sup> In the appendix to this report, we include some additional information on restaurant food access and obesity prevalence, and future research should explore more fully the implications of the mix of places to purchase food to prepare at home and places to eat away from home.

## Using Maps to Understand the Intersection of Obesity and Food Environments

Both obesity and less healthy food environments are widespread in the US. Nevertheless, both obesity and food environments vary significantly by place (Congdon 2017). Attention to geographic variation is an important consideration in identifying and implementing interventions and policies that can shift food environments across the US, particularly in areas of high obesity prevalence. Maps have consistently proven to be an important tool in identifying public health trends for more exploration and translating patterns to both professionals and the general public (Musa et al. 2013). In this report, we use recent data on obesity and food establishments where people can buy food to prepare at home at the county level to map the intersection of obesity and access to different types of food outlets that may constrain or facilitate healthier eating, with the goal of providing data insights to inform considerations

for practitioners, policymakers, and the public. And while food environment changes are needed broadly, these maps can help inform whether interventions are well targeted to the places where they may be most needed.

One limitation of the mapping approach used in this report is the lack of consistently available data below the county-level to explore the intersection of food environments and obesity. County-level data may mask important variations among communities in the same county. As such, these maps are a starting point for unpacking community-level experiences. A deeper understanding of nuances within counties can inform discussions among communities and policymakers about potential strategies to improve healthy food access.

## Data and Methods

### Obesity Rates

Obesity data come from the Behavioral Risk Factor Surveillance System, a large telephone survey that collects information about chronic conditions. Although the survey was designed to collect data at the state and metropolitan statistical area levels, multiple years of Behavioral Risk Factor Surveillance System data are used to report information for smaller geographic areas like counties. To report county-level information, we used the Centers for Disease Control and Prevention's PLACES 2021 release, an effort to release information uniformly on a large scale for local areas. The data sources used to create these estimates include 2017 and 2018 Behavioral Risk Factor Surveillance System data.

It should be noted that measurement of obesity is a contested area of research, and experts increasingly suggest the use of multiple metrics, particularly for individual assessment (Nuttall 2015). This analysis uses public health data that rely on a measure of body mass index, which is often used for population-level analysis.

### Retail Food Environment

To examine the food environment, we use geographic data on food establishments combined with other relevant demographic and economic information from multiple data sources. Information about food establishments is from Data Axle business data, a national database of approximately 25 million business establishments that includes address, industry, number of employees, and sales volume for

each business in 2019. Data Axle categorizes all businesses in the US by the North American Industry Classification System and the Standard Industrial Classification codes. First, we analyze variation in the overall number of establishments per 1,000 residents at the county level. Then, using the North American Industry Classification System, we move beyond a total count of establishments at the county level to differentiate between different types of food establishments—grocery stores, other grocery (including specialty food) stores, convenience stores, warehouse clubs, dollar stores, other department stores (including Walmart, Target, and others selling food), pharmacies, and gas stations. Using the Standard Industrial Classification description, we further limit dollar stores, department stores, pharmacies, and gas stations to include only those whose descriptions (entered in text fields in the data) include “food markets,” “grocers—retail,” “convenience store,” “food products—retail,” “foods—carry out,” or “miscellaneous food stores.” Those that do not sell food are excluded from the analysis. We also use the location name to distinguish dollar stores from other department stores by selecting Dollar General, Dollar Tree, and Family Dollar Store and to ensure that pharmacies include all CVSs, Walgreens, and Rite-Aids, which are known to sell food. Appendix table A.1 includes a crosswalk that maps our food store categories to their 2012 North American Industry Classification System codes.<sup>7</sup> Finally, we categorize each type of retail establishment based on how “likely healthy” and “likely unhealthy” the offerings are likely to be in each, drawing on existing literature that suggests which types of store formats are more likely to offer an array of healthier food options such as fruits, vegetables, lean proteins, and dairy.<sup>8</sup> Table 1 provides a brief description of the major groups of retail food stores we examine. Of course, changing these classifications—or having more precise data on the exact types of foods provided in each type of establishment—might affect our conclusions. It is important to note that less healthy food items can be found across store formats, and research indicates that less healthy options may often be prevalent in price promotions (Bennett et al. 2020). Nevertheless, a store type analysis provides one important framework for generating conversations about local food access options.

We do not include farmers markets in our analysis, although they can be important supplemental sources of healthy food offerings in local communities. Because the majority of food purchases in the US are made in store settings, we have prioritized our analysis of these establishments.

TABLE 1

## Types of Retail Establishments with Food Sales

Store Format	Description	Likely Healthy/Likely Unhealthy Offerings
Grocery store	Establishments typically known as grocery stores and supermarkets that primarily offer a general line of food, including canned and frozen foods; fresh fruits and vegetables; and fresh/prepared meats, fish, and poultry	Likely Healthy
Specialty store	Establishments that focus on a specific line of food items, e.g., meat markets and fruit and vegetable markets	Likely Healthy
Other department store	Retail establishments with separate departments for various merchandise lines, such as apparel, jewelry, home furnishings, and groceries and whose descriptions include “food markets,” “food products—retail,” “foods—carry out,” “grocers—retail,” “miscellaneous food stores,” or “convenience stores,” excluding department stores with “Dollar General,” “Dollar Tree,” or “Family Dollar Store” in the establishment names	Likely Healthy
Warehouse club	Retail establishments that include a general line of groceries along with other lines of goods, such as apparel, appliances, and furniture	Likely Healthy
Convenience store	Usually known as food marts or convenience stores (except those with fuel pumps), these outlets generally offer a limited variety of food items, such as milk, bread, soda, and snacks	Likely Unhealthy
Gas station	Gas stations whose descriptions include “food markets,” “food products—retail,” “foods—carry out,” “grocers—retail,” “miscellaneous food stores,” or “convenience stores”	Likely Unhealthy
Pharmacy	Establishments typically known as pharmacies and drug stores engaged in retailing prescription or nonprescription drugs and medicines and whose descriptions include “food markets,” “food products—retail,” “foods—carry out,” “grocers—retail,” “miscellaneous food stores,” or “convenience stores,” including pharmacies and drug stores with “CVS,” “Walgreens,” or “Rite Aid” in the establishment names	Likely Unhealthy
Dollar store	Include department stores as described above but with “Dollar General,” “Dollar Tree,” or “Family Dollar Store” in the establishment names	Likely Unhealthy

Source: NAICS (one lookup can be found here: <https://www.census.gov/naics/?99967>).

Notes: NAICS = North American Industry Classification System. Our descriptions of retail establishments are primarily from the 2012 NAICS definitions. We categorize each type of retail establishment based on how “likely healthy” and “likely unhealthy” the offerings are likely to be in each, drawing on existing literature that suggests which types of store formats are more likely to offer an array of healthier food options such as fruits, vegetables, lean proteins, and dairy. Changing these classifications—or having more precise data on the exact types of foods provided in each type of establishment—might affect our conclusions.

Although our primary focus in this report is places where people may purchase food to prepare or eat at home, additional maps in the appendix incorporate the availability of restaurants in combination with food stores.

## County-Level Characteristics

We employ data on county-level characteristics to consider other potential influences on food access and population health. We also use data from the 2016–20 American Community Survey five-year county-level estimates<sup>9</sup> to capture county-level place characteristics including median age; percentage of females; percentage of people with a high school diploma; percentage of people with some college; percentage of those with at least a bachelor's degree; percentage of people who are Black, Hispanic, Asian, Native American, or other race or ethnicity; percentage homeowners; median home value; percentage of people living below the federal poverty level; unemployment rate; and total population. We use 2020 county-level food cost data from Feeding America's Map the Meal Gap initiative.<sup>10</sup> Finally, we use the 2013 Rural-Urban Continuum Codes from the US Department of Agriculture (USDA), which distinguishes between metropolitan counties by the population size of their metro areas and nonmetropolitan counties by degree of urbanization and adjacency to metro areas. We designate counties as urban if their USDA classification is metropolitan or nonmetropolitan/urban and as rural if their USDA classification is nonmetropolitan/rural.

## Location of Nutrition Incentive Programs

As one application of how mapping can inform policy and practice, we document the location of the major federally supported nutrition incentive grant program in the context of obesity prevalence. The Gus Schumacher Nutrition Incentive Program is a competitive grant program administered by USDA that provides states and localities with funding to increase the value of Supplemental Nutrition Assistance Program (known as SNAP) benefits when used to purchase fruits and vegetables (Leng et al. 2018). We use a list of grantees from the Gretchen Swanson Center for Nutrition and augment the geographic detail by examining grantee websites and roughly approximating the presence at the county level.<sup>11</sup> Grantees were active as of September 2022 and have variable start and end dates, ranging from 2019 to 2025.

## Analytic Approach

Initially, we examine the distribution of 2019 obesity prevalence by quartiles, a familiar approach to examining the spread of data. As we explore additional factors that intersect with obesity, we divide the 3,142 counties in the United States into three groups based on the percentage of people with obesity in each county: high-obesity counties are those in which obesity rates are in the top 25 percent or quartile of the overall distribution, low-obesity counties are those with rates in the bottom 25 percent of the

distribution, and middle-obesity counties are those in the middle of the distribution. By comparing these three groups of counties—792 high-obesity counties (38.2–50.1 percent), 786 low-obesity counties (15.7–32.6 percent), and 1,564 middle-obesity counties (32.7–38.1 percent)—we hope to gain a better perspective on differences in access to food.

We supplement our descriptive results with findings from simple regressions that we estimate separately using each of our food establishment variables as dependent variables and low and middle obesity indicators as our key independent variables with high obesity counties being the comparison group. We examine obesity as an independent variable because we wanted to test whether food establishments were different between low- and high-obesity counties. We estimate these regressions first without and then with additional controls for county-level characteristics<sup>12</sup> to test whether the relationships we observe between food establishments still hold after controlling for other county-level characteristics that may be correlated with our outcomes of interest. Our reported findings are descriptive and should not be interpreted causally. Figure 1 highlights how these prevalence rates are not randomly distributed across US counties. In future research, regression approaches adjusting for spatial patterning can further inform these insights.

## Using Maps to Examine Data Insights

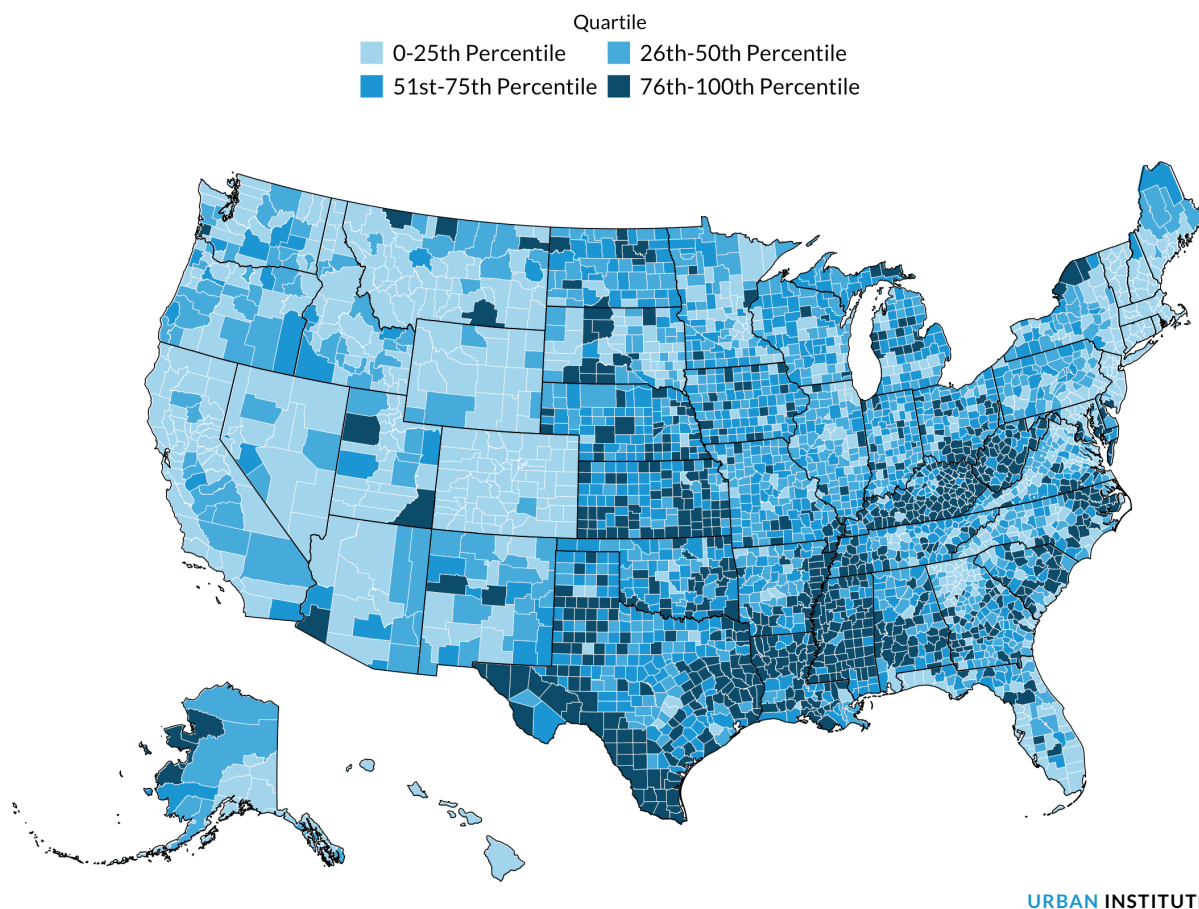
We present data on these intersections in a series of maps below to help foster and inform conversation about food environments as an important lever for improving health and well-being. Mapping can be an important tool for educating policymakers and the public about the places experiencing the highest risk of obesity and the character of local food environments that may shape opportunities and outcomes. Mapping also can assist in assessing whether interventions are prioritizing communities that have poorer food environments and populations that experience chronic health disparities. Maps can aid communities in advocating for changes that promote health and well-being for all residents.

## Geographic Variation in the Prevalence of Obesity

We begin by looking at the geographic distribution of obesity at the county level. While obesity is widespread in the US, it is not distributed equally across place. The highest obesity rates (the darkest blue color) in the US are concentrated in Southern counties, particularly those in parts of Texas, Louisiana, Mississippi, Kentucky, and West Virginia (figure 1). In contrast, the lowest obesity rates (the

lightest blue color) are concentrated in Western counties, especially those in Colorado and parts of Wyoming, California, and Nevada.

**FIGURE 1**  
**Prevalence of Obesity in 2019, by Quartile**



**Source:** Authors' calculations using data from the Behavioral Risk Factor Surveillance System accessed via the Centers for Disease Control and Prevention's PLACES 2021 release. See the Data and Methods section for more information.

**Note:** The map includes all 3,142 counties in the United States in 2019.

## Obesity and Food Access: Mapping Intersections at the County Level

Growing evidence suggests that environments that do not facilitate healthier food access are an important part of higher obesity rates and that these environments are often referred to as “obesogenic” (Lake and Townshend 2006).<sup>13</sup> We first present the distribution of retail food

establishments (regardless of store type) across counties in proportion to population, and we then examine how obesity prevalence intersects with measures of retail food access, breaking down different types of stores. Although the food environment includes a broader array of outlets where food can be purchased, such as restaurants, we first concentrate on places where food can be acquired to prepare at home. The appendix includes additional maps that add types of restaurant establishments to the retail food outlet picture at the county level.

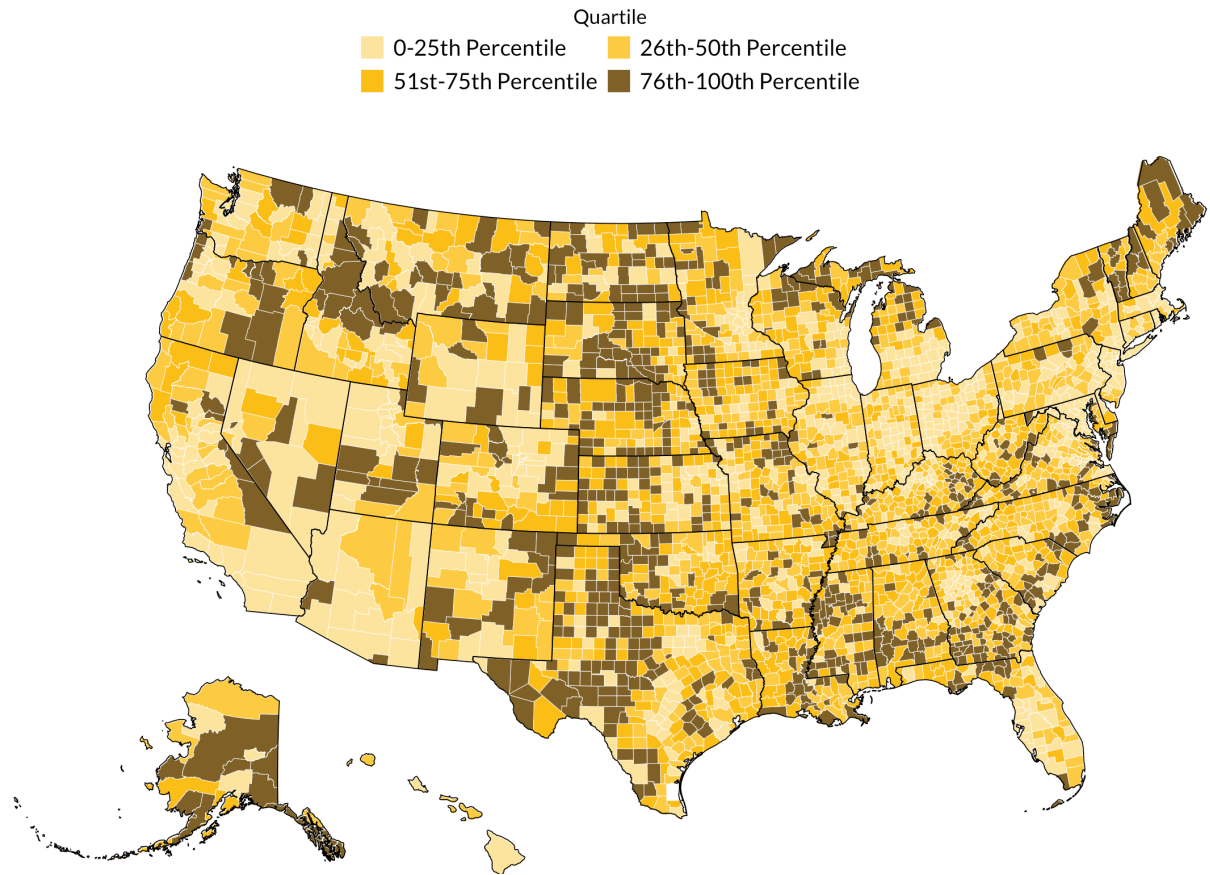
## **Number of Food Establishments across Counties and Obesity Prevalence**

As shown in figure 2, the largest number of food establishments per 1,000 residents (the darkest brown color) are concentrated through the middle of the country, from North Dakota through Texas and in parts of Maine, Idaho, and Oregon. The fewest food establishments per 1,000 residents (the lightest yellow color) are primarily in population-dense areas of the country. To put this into perspective, the median rural county has 9 retail food establishments and a population of 5,732, or roughly 1.57 retail food establishments per 1,000 residents. In contrast, the median nonrural county has 42 retail food establishment and a population of 36,971, or roughly 1.14 food establishments per 1,000 residents.<sup>14</sup>



FIGURE 2

Number of Food Establishments Per 1,000 Residents in 2019, by Quartile



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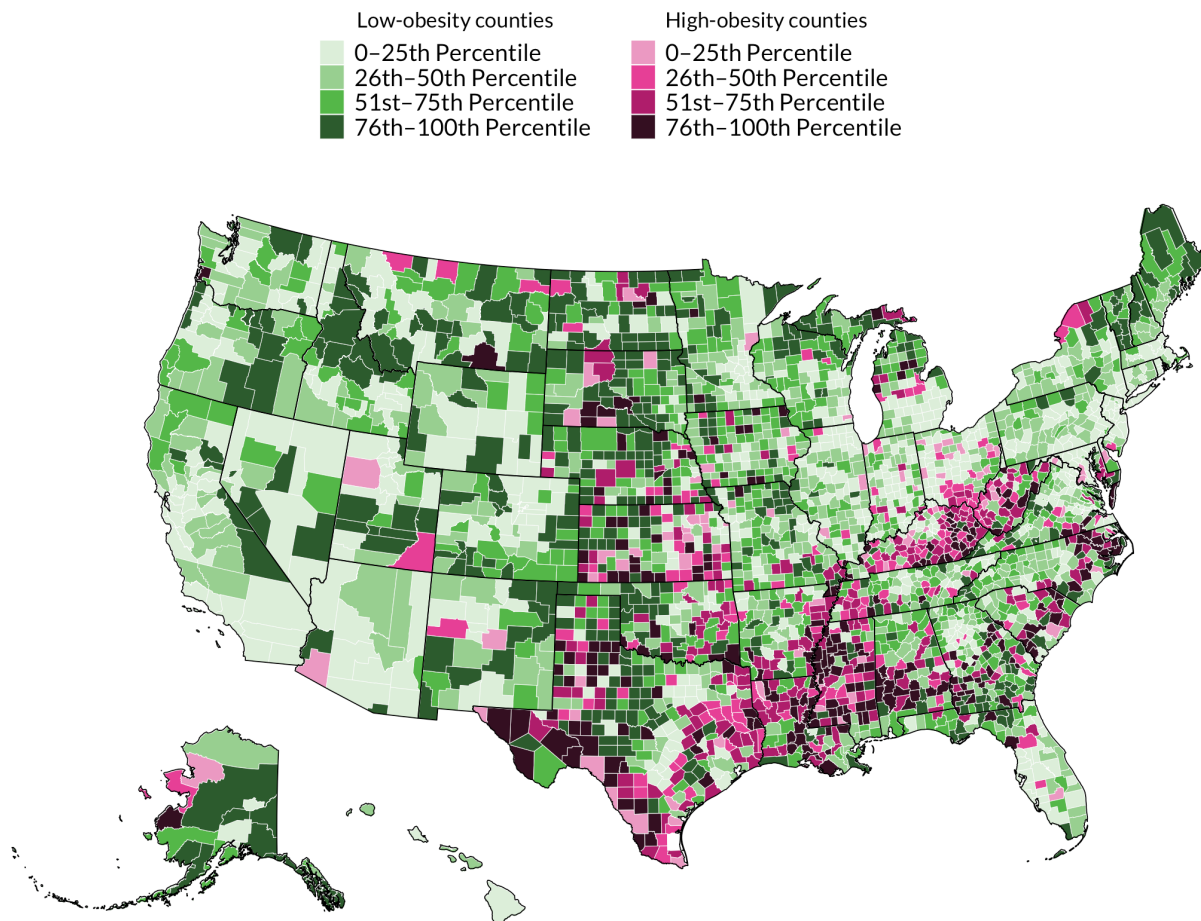
**Source:** Authors' calculations using merged data on obesity from the Behavioral Risk Factor Surveillance System, food establishments from Data Axle, and other county-level characteristics from the 2016–20 American Community Survey five-year county-level estimates and the 2013 Rural-Urban Continuum Codes from the US Department of Agriculture. See the Data and Methods section for more information.

**Note:** Kalawao County, Hawaii, and Kenedy County, Texas, are missing data for the total number of food establishments per capita; these two counties appear white on the map.

We then examine how obesity prevalence intersects with the number of retail food establishments. The map shows parts of the country where high-obesity counties have limited access to food (the lightest pink colors in figure 3). These areas tend to be concentrated in parts of Texas, Louisiana, and Arkansas, where those states border each other, and in the Appalachian region of southern Ohio, West Virginia, and eastern Kentucky, where those states border each other. There are also clusters of such counties in central Mississippi, western Kentucky, and Tennessee as well as parts of Kansas and Oklahoma.

FIGURE 3

Number of Food Establishments per 1,000 People in Lower- and High-Obesity Counties in 2019



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**Source:** Authors' calculations using merged data on obesity from the Behavioral Risk Factor Surveillance System, food establishments from Data Axle, and other county-level characteristics from the 2016–20 American Community Survey five-year county-level estimates and the 2013 Rural-Urban Continuum Codes from the US Department of Agriculture. See the Data and Methods section for more information.

**Notes:** High-obesity counties are those in the top quartile of the obesity prevalence distribution (76th–100th percentile). Lower-obesity counties are those in the bottom three quartiles of the obesity prevalence distribution (0–75th percentile). Both legends are based on the all-county distribution of obesity prevalence. Darker colors indicate a higher number of food establishments per 1,000 people. Kalawao County, Hawaii, and Kenedy County, Texas, are missing data for the total number of food establishments per capita; these two counties appear white on the map.

On average, counties with high obesity rates have more food establishments per 1,000 residents (1.40), while counties with middle obesity rates have 1.29, and those with low obesity rates have fewer establishments for their size of population (1.11 per 1,000 residents; table 2). These differences are statistically significant in our regression analysis even after controlling for other county-level characteristics (table A.2).

TABLE 2

### Average Number of Food Establishments Per 1,000 Residents in 2019, by Counties with Low, Middle, and High Obesity Rates

	Per 1,000 Residents					
	Low-obesity areas		Middle-obesity areas		High-obesity areas	
Grocery	0.32		0.32		0.35	
Other grocery	0.19		0.14		0.11	
Convenience store	0.26		0.35		0.39	
Warehouse club	0.00		0.00		0.00	
Dollar store	0.09		0.18		0.24	
Other department store	0.02		0.03		0.03	
Pharmacy	0.03		0.02		0.02	
Gas station	0.19		0.25		0.27	
<b>Total food establishments</b>	<b>1.11</b>		<b>1.29</b>		<b>1.40</b>	

**Source:** Authors' calculations using merged data on obesity from the Behavioral Risk Factor Surveillance System, food establishments from Data Axle, and other county-level characteristics from the 2016–20 American Community Survey five-year county-level estimates and the 2013 Rural-Urban Continuum Codes from the US Department of Agriculture. See the Data and Methods section for more information.

**Notes:** High-obesity counties are defined as having a share of people with obesity in the top quartile of the nation; low-obesity counties are defined as having a share of people with obesity in the bottom quartile; middle-obesity counties are defined as having a share of people with obesity in the middle two quartiles.

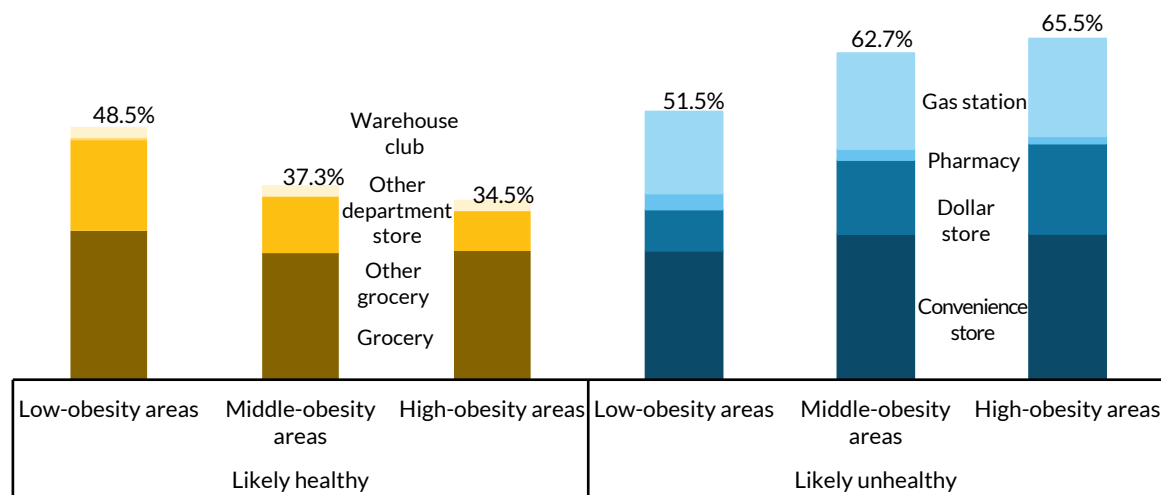
## Classifying Types of Retail Stores as Likely Healthy or Unhealthy in Higher and Lower Obesity Counties

We then turn to the types of retail food stores. Except for other specialty grocery stores, counties with high obesity rates have more of various types of retail food establishments than counties with low obesity rates. These differences are statistically significant, and all except for gas stations remain statistically significant even after controlling for other county-level characteristics. The difference in the number of dollar stores between high- and low-obesity areas is particularly large—with high-obesity areas averaging 0.24 dollar stores per 1,000 residents and low-obesity areas averaging only 0.09 dollar stores per 1,000 residents.

When we categorize food establishments by whether they are likely to serve healthy or unhealthy food, we find stark differences in the mix of food establishment types between low-, middle-, and high-obesity counties (figure 4). We classify “likely healthy” food establishments as all grocery stores (including specialty grocery stores), warehouse clubs, and other department stores and “likely unhealthy” food establishments as convenience stores, dollar stores, pharmacies, and gas stations. Among all food establishments, the percentage that are likely unhealthy is 65.5 percent in counties with a high percentage of residents with obesity compared with 51.5 percent in counties with a low percentage of residents with obesity.<sup>15</sup> Although high-obesity counties have more food establishments

than low-obesity counties *for their population sizes*, they also have a higher share of food establishments that we expect to serve less healthy food. All the differences shown, except for other department stores, are statistically significant (table A.3). Important to note, although the magnitude of the association declines as we control for additional characteristics, the differences between low- and high-obesity counties in the percentage of other grocery stores, dollar stores, pharmacies, and unhealthy and healthy food establishments remains statistically significant. For example, the share of unhealthy food establishments is 14 percentage points higher in high-obesity counties than in low-obesity counties, not controlling for other county characteristics, and is still 2.2 percentage points higher even after controlling for additional characteristics, such as homeownership and poverty rates.

**FIGURE 4**  
**Distribution of Food Establishments in 2019, by Areas with Low, Middle, and High Rates of Obesity**



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**Source:** Authors' calculations using merged data on obesity from the Behavioral Risk Factor Surveillance System, food establishments from Data Axle, and other county-level characteristics from the 2016–20 American Community Survey five-year county-level estimates and the 2013 Rural-Urban Continuum Codes from the US Department of Agriculture. See the Data and Methods section for more information.

**Notes:** High-obesity counties are defined as having a share of people with obesity in the top quartile of the nation; low-obesity counties are defined as having a share of people with obesity in the bottom quartile; middle-obesity counties are defined as having a share of people with obesity in the middle two quartiles. Other department stores account for 2.1 percent of likely healthy food establishments in each of low-obesity areas, middle-obesity areas, and high-obesity areas. Warehouse clubs account for less than 1 percent of likely healthy food establishments. These small shares make these categories difficult to see in the chart.

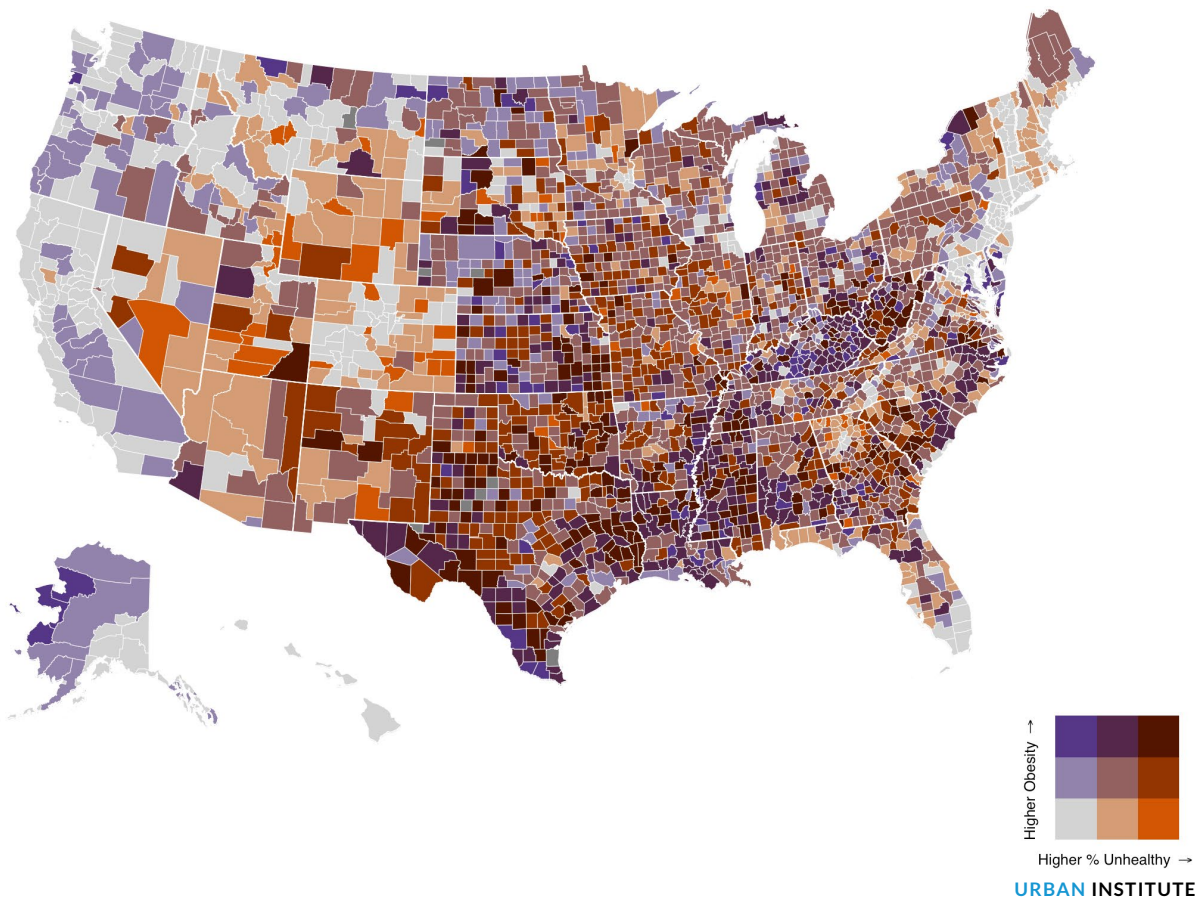
The composition of unhealthy food establishments differs between low- and high-obesity counties. Unhealthy food establishments largely comprise convenience stores, followed by gas stations, dollar stores, and pharmacies in both low- and high-obesity counties. However, dollar stores represent a

substantially larger share of unhealthy food establishments in high-obesity areas than in low-obesity areas (see box 1).

Aggregate numbers mask geographic patterns in these different types of food establishments. In figure 5, we see an especially high density of likely unhealthy food establishments in high-obesity counties (the darkest brown color) scattered throughout the US, but concentrated particularly in the Appalachian region of the country (southern Ohio and West Virginia) and in Mississippi and Texas. We also see low concentrations of unhealthy establishments in low-obesity counties (gray) in the Northeast, Mountain, and Pacific regions.

FIGURE 5

Prevalence of Obesity and Percentage of Likely Unhealthy Food Establishments in 2019



**Source:** Authors' calculations using merged data on obesity from the Behavioral Risk Factor Surveillance System, food establishments from Data Axle, and other county-level characteristics from the 2016–20 American Community Survey five-year county-level estimates and the 2013 Rural-Urban Continuum Codes from the US Department of Agriculture. See the Data and Methods section for more information.

**Notes:** Counties are divided into three groups—bottom quartile, middle two quartiles, and top quartile—based on their obesity rates and also based on their share of unhealthy food establishments. Food establishments that are considered unhealthy include convenience stores, dollar stores, pharmacies, and gas stations.

Our data do not permit us to examine dollar amount of sales per store; additional insights could be gained by understanding the dollar value of purchases across establishments.

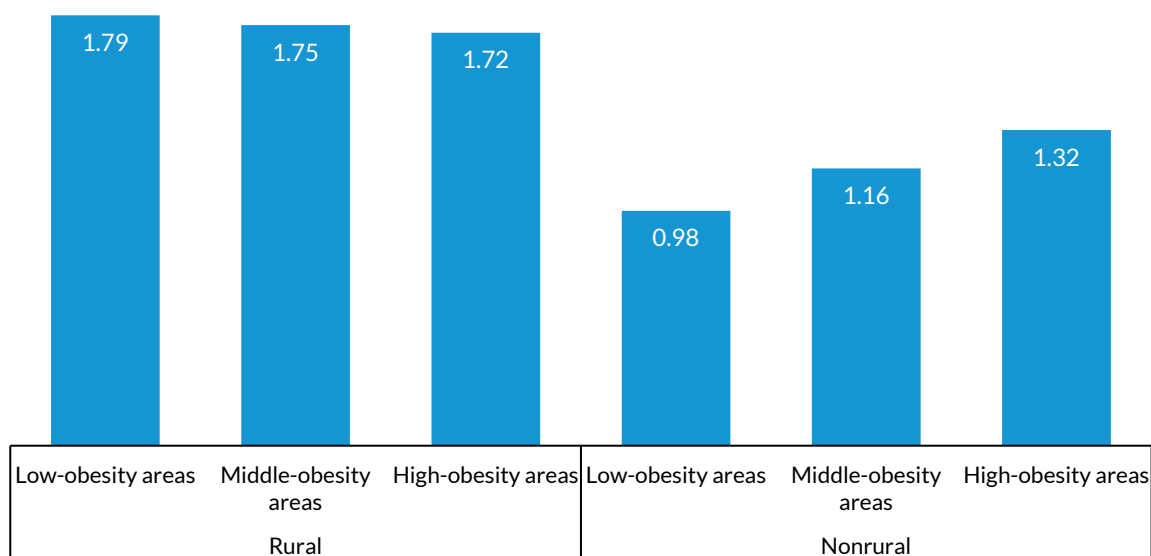
## Differences between Rural and Nonrural Areas

Somewhat different patterns emerge when accounting for differences in urbanization (figure 6).

Overall, rural counties have more food establishments per capita than do nonrural counties, which is not

surprising since rural areas have relatively smaller populations. We observe that retail food store availability is more limited in rural counties with high obesity rates than in those with low obesity rates, but the difference is not statistically significant. On average, there are 1.79 food establishments per 1,000 residents in low-obesity rural counties compared with 1.72 establishments in high-obesity rural counties. In contrast, food availability is much more limited in nonrural counties with low obesity rates than in those with high obesity rates. On average, there are 0.98 food establishments per 1,000 residents in low-obesity nonrural counties compared with 1.32 establishments in high-obesity nonrural counties, and this difference is statistically significant even after controlling for other county-level characteristics. See tables A.4 and A.5 for more information about the types of food establishments by urbanization.

**FIGURE 6**  
**Average Number of Food Establishments Per 1,000 Residents in 2019, by Areas with Low, Middle, and High Obesity Rates and by Urbanization**



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**Source:** Authors' calculations using merged data on obesity from the Behavioral Risk Factor Surveillance System, food establishments from Data Axle, and other county-level characteristics from the 2016–20 American Community Survey five-year county-level estimates and the 2013 Rural-Urban Continuum Codes from the US Department of Agriculture. See the Data and Methods section for more information.

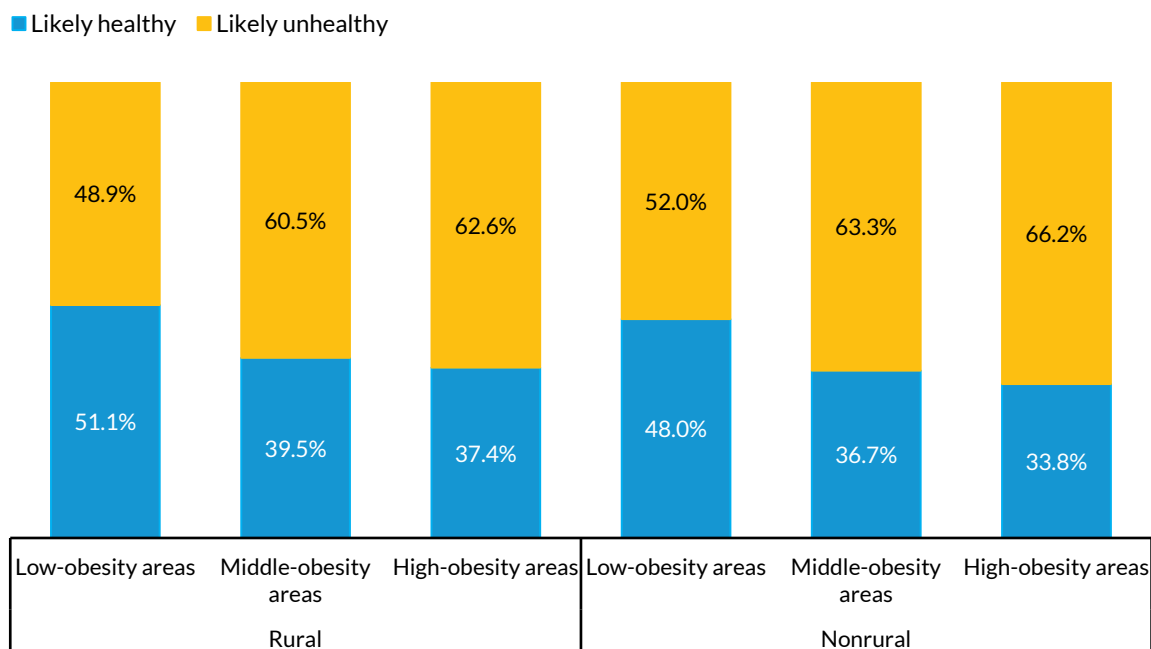
**Notes:** High-obesity counties are defined as having a share of people with obesity in the top quartile of the nation; low-obesity counties are defined as having a share of people with obesity in the bottom quartile; middle-obesity counties are defined as having a share of people with obesity in the middle two quartiles.

As shown in figure 7, we find that counties with high obesity rates have a larger share of food establishments that are likely unhealthy and a smaller share of food establishments that are likely healthy. These differences are similar in both rural and nonrural counties (with a noted gradient of increasing likely unhealthy food establishments as you move from low- to high-obesity areas). In rural counties, for example, food establishments that are likely unhealthy account for 62.6 percent of all food establishments in counties with high rates of obesity and 48.9 percent of all food establishments in counties with low rates of obesity—a difference of 13.7 percentage points. In nonrural counties, food establishments that are likely unhealthy account for 66.2 percent of all food establishments in counties with high rates of obesity and 52.0 percent of all food establishments in counties with low rates of obesity—a difference of 14.3 percentage points. These differences are statistically significant; however, after controlling for other county characteristics, only the difference between nonrural counties remains statistically significant (table A.6).



FIGURE 7

Distribution of Food Establishments in 2019, by Areas with Low, Middle, and High Obesity Rates and by Urbanization



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**Source:** Authors' calculations using merged data on obesity from the Behavioral Risk Factor Surveillance System, food establishments from Data Axle, and other county-level characteristics from the 2016–20 American Community Survey five-year county-level estimates and the 2013 Rural-Urban Continuum Codes from the US Department of Agriculture. See the Data and Methods section for more information.

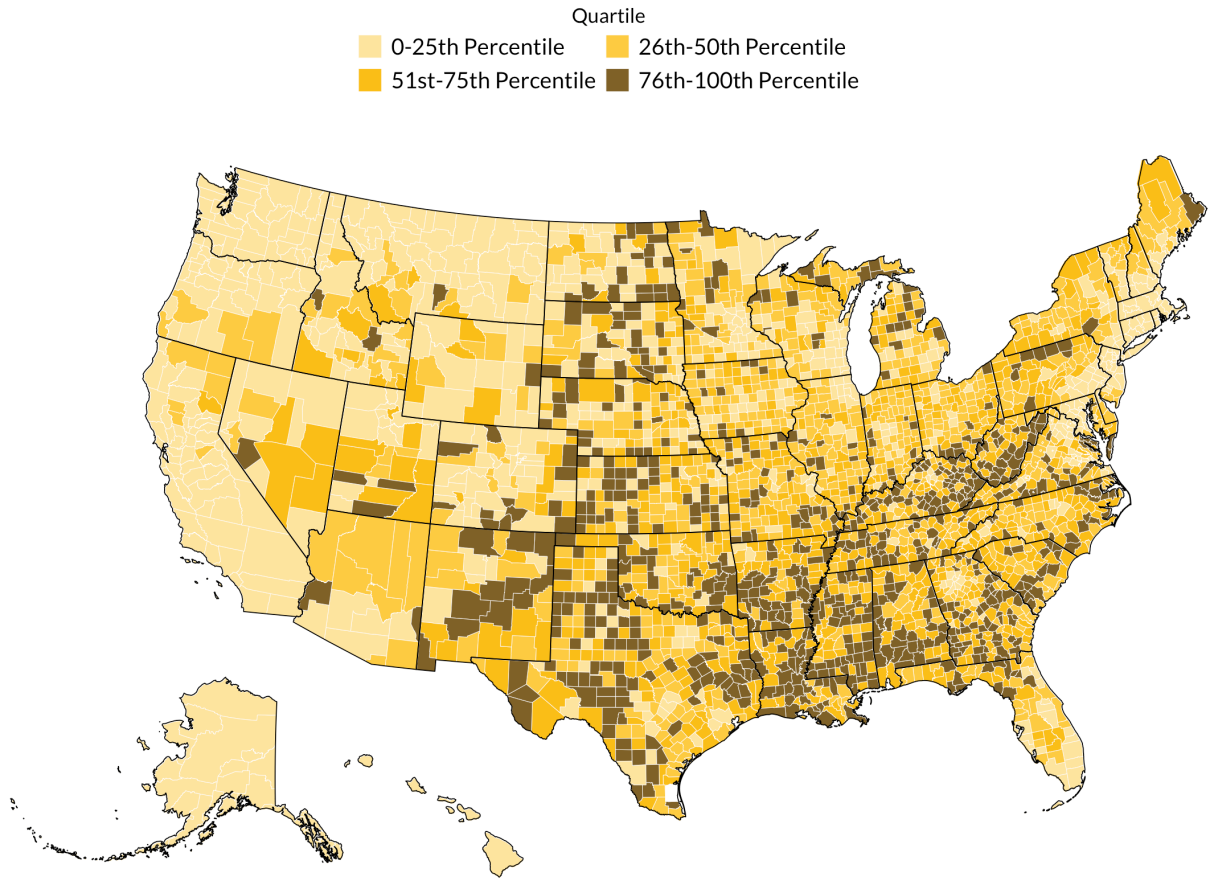
**Notes:** High-obesity counties are defined as having a share of people with obesity in the top quartile of the nation; low-obesity counties are defined as having a share of people with obesity in the bottom quartile; middle-obesity counties are defined as having a share of people with obesity in the middle two quartiles. Food establishments that are considered healthy include grocery stores, department stores (excluding dollar stores), and warehouse clubs. Those that are considered unhealthy include convenience stores, dollar stores, pharmacies, and gas stations.

## Obesity Prevalence and Dollar Stores

The geographic pattern of dollar stores per capita in figure 8 closely follows the pattern of increasing obesity rates in figure 1. Counties with the largest concentration of dollar stores per 1,000 residents (the darkest brown color) are in the South—particularly in West Virginia, Kentucky, Arkansas, Louisiana, Mississippi, Alabama, and Georgia—and run vertically through the center of the country from North Dakota through Texas. In contrast, counties with the smallest number of dollar stores per capita (the lightest yellow color) are concentrated in the West (excluding New Mexico).

FIGURE 8

Number of Dollar Stores Per 1,000 Residents in 2019, by Quartile



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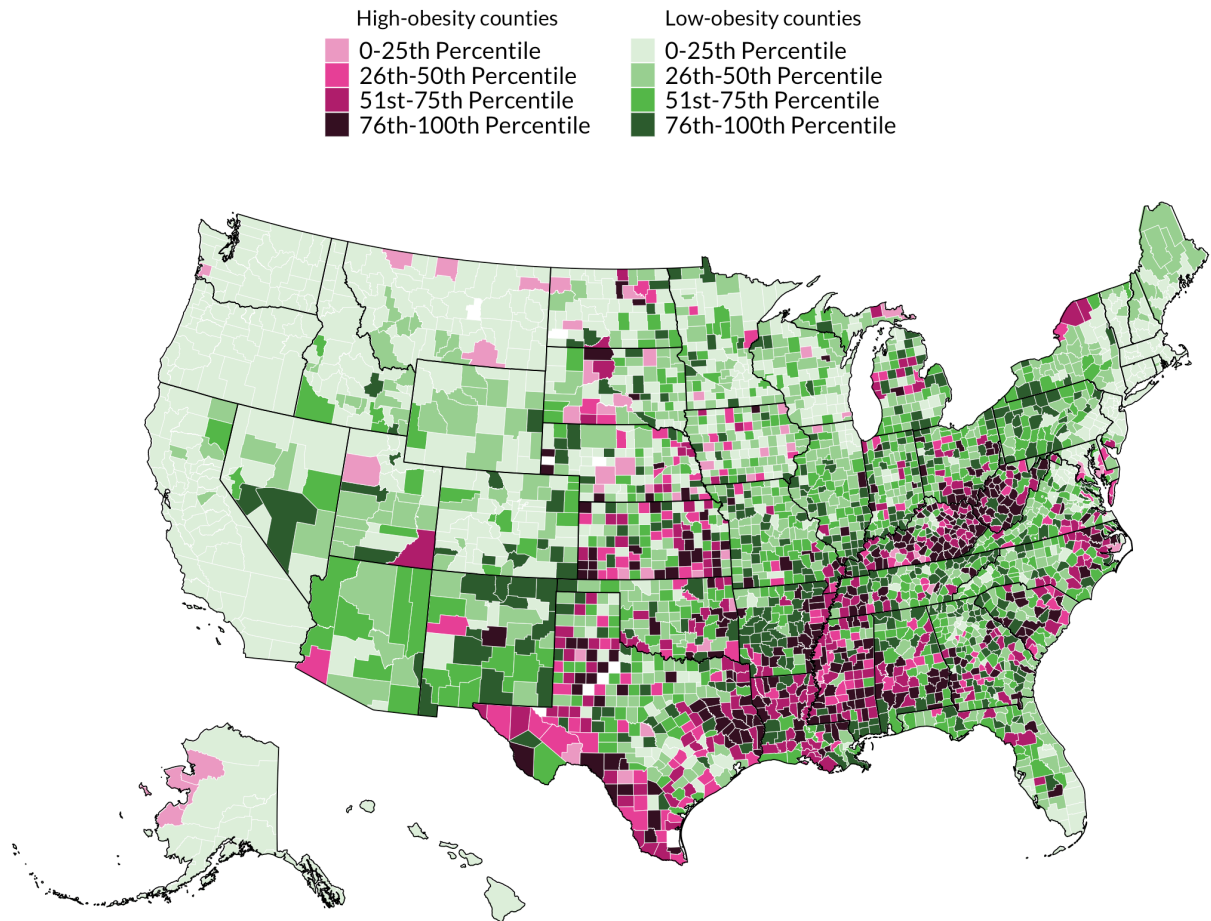
**Source:** Authors' calculations using merged data on obesity from the Behavioral Risk Factor Surveillance System, food establishments from Data Axle, and other county-level characteristics from the 2016–20 American Community Survey five-year county-level estimates and the 2013 Rural-Urban Continuum Codes from the US Department of Agriculture. See the Data and Methods section for more information.

**Note:** Kalawao County, Hawaii, and Kenedy County, Texas, are missing data for the total number of food establishments per capita. These two counties appear white on the map.

As shown in figure 4, on average, dollar stores account for a much lower share of food establishments in lower-obesity counties than in high-obesity counties. High-obesity counties where dollar stores account for an especially high proportion of food establishments are concentrated in the Appalachian region of Ohio, West Virginia, and Kentucky and are scattered throughout parts of Texas, Louisiana, Arkansas, Mississippi, and Alabama (the darkest purple color in figure 9).

FIGURE 9

Percentage of Dollar Stores in Lower- and High-Obesity Counties in 2019



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**Source:** Authors' calculations using merged data on obesity from the Behavioral Risk Factor Surveillance System, food establishments from Data Axle, and other county-level characteristics from the 2016–20 American Community Survey five-year county-level estimates and the 2013 Rural-Urban Continuum Codes from the US Department of Agriculture. See the Data and Methods section for more information.

**Notes:** High-obesity counties are those in the top quartile of obesity prevalence distribution (76th–100th percentile). Lower-obesity counties are those in the bottom three-quarters of obesity prevalence distribution (0–75th percentile). Both legends are based on the all-county distribution of obesity prevalence. Darker colors indicate higher percentages of dollar stores. There are 10 counties with missing values for the percentage of dollar stores. These counties appear white on the map.

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## BOX 1

### A Closer Look at Dollar Stores

Conversations about food access have often focused on the availability of grocery stores but pay less attention to the extent to which retail food trends may have shifted toward other formats that typically offer very few healthier foods. According to a nationally representative survey conducted in 2021 for Consumer Reports, 88 percent of Americans shop at dollar stores, mostly because they are inexpensive and convenient.<sup>1</sup> Dollar stores have proliferated across the country and represent one of the two major categories of retail food store growth in the past decade (the other is supercenters). By contrast, during the past 25 years, the median number of grocery stores per capita has declined by 40 percent, and decreases have been experienced across both rural and nonrural areas.

Dollar stores offer quick access to affordable products that often fulfill daily necessities, such as personal care and household cleaning, as well as other fast-moving consumer goods. (Shrestha 2014) These establishments are characterized by their frequent use and low prices and can be convenient places to acquire necessities in communities with little or no accessibility to large grocery stores or supermarkets. However, they have typically offered limited options for food, especially a variety of fresh and healthy choices, and food offerings skew toward soda, snacks, and processed and packaged foods. One study in a metropolitan area found that candy and soda purchases were particularly common among dollar store customers, even when compared with purchases at other stores like convenience marts and gas marts that do not prioritize healthier food options. (Caspi et al. 2017) Another recent study found that once a dollar store enters a community identified as having low food access (food desert), that geographic area is more likely to remain without a full-service supermarket (Chenarides et al. 2021).

The growth of dollar stores, particularly in lower-income areas, has prompted some policymakers to seek ways to constrain their growth. Since 2018, at least 50 municipalities have passed policies to limit dollar store expansion and density (McCarthy et al. 2022). Opponents have cited the lack of healthier food options and what is perceived as targeting of low-income communities for saturation, which may potentially limit the viability of other formats that could offer a wider variety of foods, such as small grocery stores.

Although dollar stores are less likely to offer healthier food items like fruits and vegetables, a recent study found that, when available, these items were often priced lower than at surrounding grocery stores (Coughenor 2018). The researchers suggested that dollar stores could be considered potential community assets for building affordable access to healthier foods. One dollar store chain, Dollar General, has promoted a strategy for increasing healthier food options in its stores, although the plan does not reach a majority of its outlets in the near term (Dollar General 2022). Dollar stores may be among the few business entities willing to locate in areas with limited demand, so it is important to consider what role they could play in increasing affordable healthy food access in the future.

<sup>1</sup> Brian Vines, "The Truth About Those Dollar Stores," *Consumer Reports*, October 2021, <https://www.consumerreports.org/dollar-stores/the-truth-about-those-dollar-stores/>.

<sup>2</sup> Stevens, Alexander, Clare Cho, Metin Çakır, Xiangwen Kong, and Michael Boland. 2021. *The Food Retail Landscape Across Rural America*, EIB-223. U.S. Department of Agriculture, Economic Research Service.

<sup>3</sup> Shrestha, Sriya. 2014. "Dollars to Dimes: Disparity, Uncertainty, and Marketing to the Poor at US Dollar Stores," *International Journal of Cultural Studies* 19 (4): 373–90. <https://doi.org/10.1177/1367877913515869>.

<sup>4</sup> Caspi, Caitlin E., Kathleen Lenk, Jennifer E Pelletier, Timothy L Barnes, Lisa Harnack, Darin J Erickson, and Melissa N Laska. 2016. "Food and Beverage Purchases in Corner Stores, Gas-Marts, Pharmacies and Dollar Stores," *Public Health Nutrition* 20 (14): 2587–97. <https://doi.org/10.1017/S1368980016002524>.

<sup>5</sup> Chenarides, Lauren, Clare Cho, Rodolfo M Nayga Jr., and Michael R Thompson. 2021. "Dollar Stores and Food Deserts," *Applied Geography*, 134: 102497. <https://doi.org/10.1016/j.apgeog.2021.102497>.

<sup>6</sup> McCarthy, Julia, Darya Minovi, and Chelsea R. Singleton. 2022. "Local Measures to Curb Dollar Store Growth: A Policy Scan," *Nutrients*. 14 (15): 3092. <https://doi.org/10.3390/nu14153092>.

<sup>7</sup> Coughenour, Courtney, Timothy J. Bungum, and M. Nikki Regalado. 2018. "Healthy Food Options at Dollar Discount Stores Are Equivalent in Quality and Lower in Price Compared with Grocery Stores: An Examination in Las Vegas, NV," *International Journal of Environmental Research and Public Health*. 15 (12): 2773. <https://doi.org/10.3390/ijerph15122773>.

<sup>8</sup> "Better for You Options at Dollar General," Dollar General Newsroom, accessed January 9, 2023, <https://newscenter.dollargeneral.com/our-story/blog-posts/better-for-you-options-at-dollar-general.htm>.

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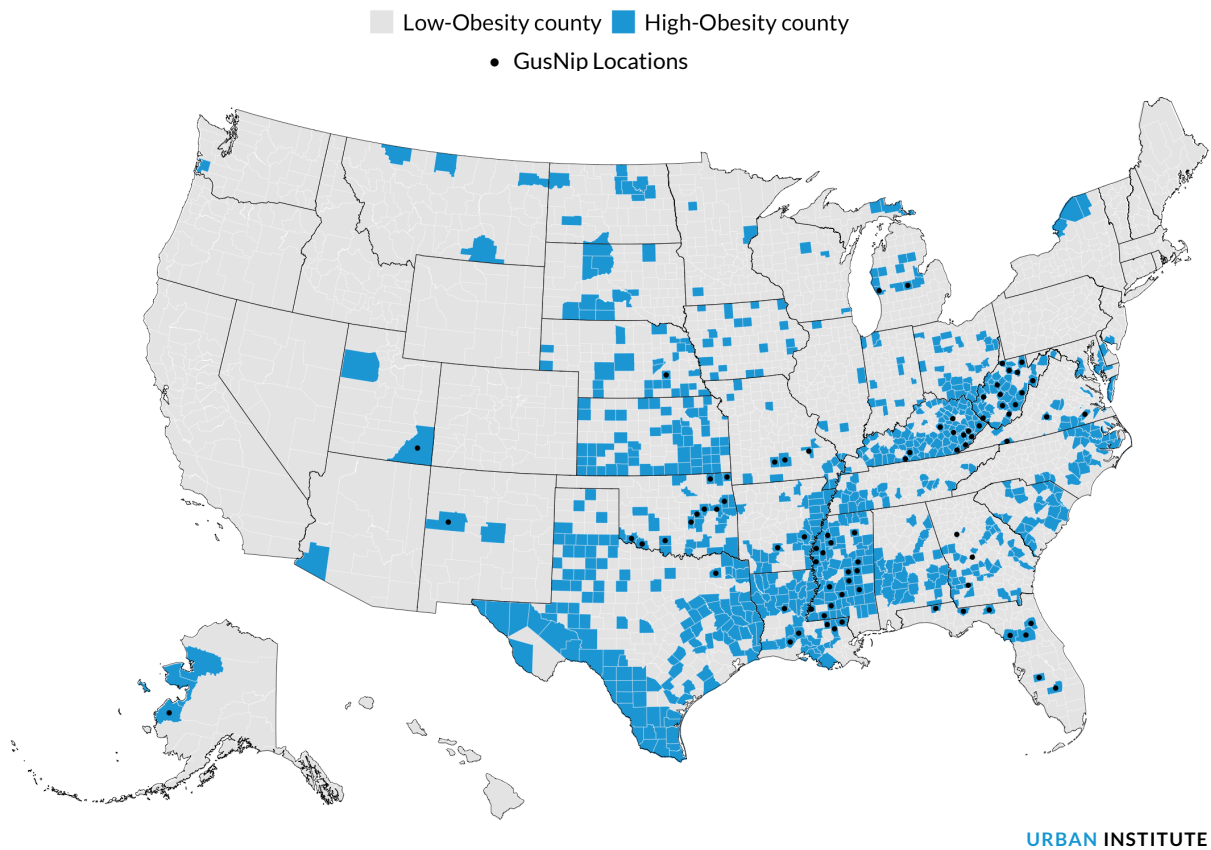
## Using Place-Based Data to Inform Food Access Strategies to Reduce Obesity

Mapping can assist policymakers and communities in understanding how potential policies and interventions align with areas of higher risk. As an example, figure 10 maps the locations of recent nutrition incentive programs in the context of high obesity prevalence. As noted above, the Gus Schumacher Nutrition Incentive Program (known as GusNIP), a competitive grant program, provides states and localities with funding to increase the value of SNAP benefits when used to purchase fruits and vegetables. These may be redeemed in a variety of locations, including farmers markets and retail stores (Leng et al. 2018). Ideally, this evidence-based strategy for increasing fruit and vegetable consumption would be available to all SNAP participants, but in its current form, it is dependent on community initiatives that seek funding and is constrained by the funding amount authorized by Congress.

Figure 10 plots GusNIP locations (represented by black dots) with their associated counties and also highlights high-obesity counties. The map shows a strong alignment between high obesity prevalence and incentive program locations in the current grant funding. However, it also makes plain that a significant number of high-obesity counties lack GusNIP grants. Although there may be other types of initiatives available in these counties, it is important to note the limitations of this federal grant program in reaching high-risk communities and opportunities for further development.

FIGURE 10

SNAP Nutrition Incentive Program Locations in Low- and High-Obesity Counties



Source: Authors' calculations using data from the Behavioral Risk Factor Surveillance System and data collected from the Gretchen Swanson Center for Nutrition and from grantee websites, GusNIP Grantees, "Nutrition Incentive Hub, accessed February 15, 2023, <https://www.nutritionincentivehub.org/grantee-projects>.

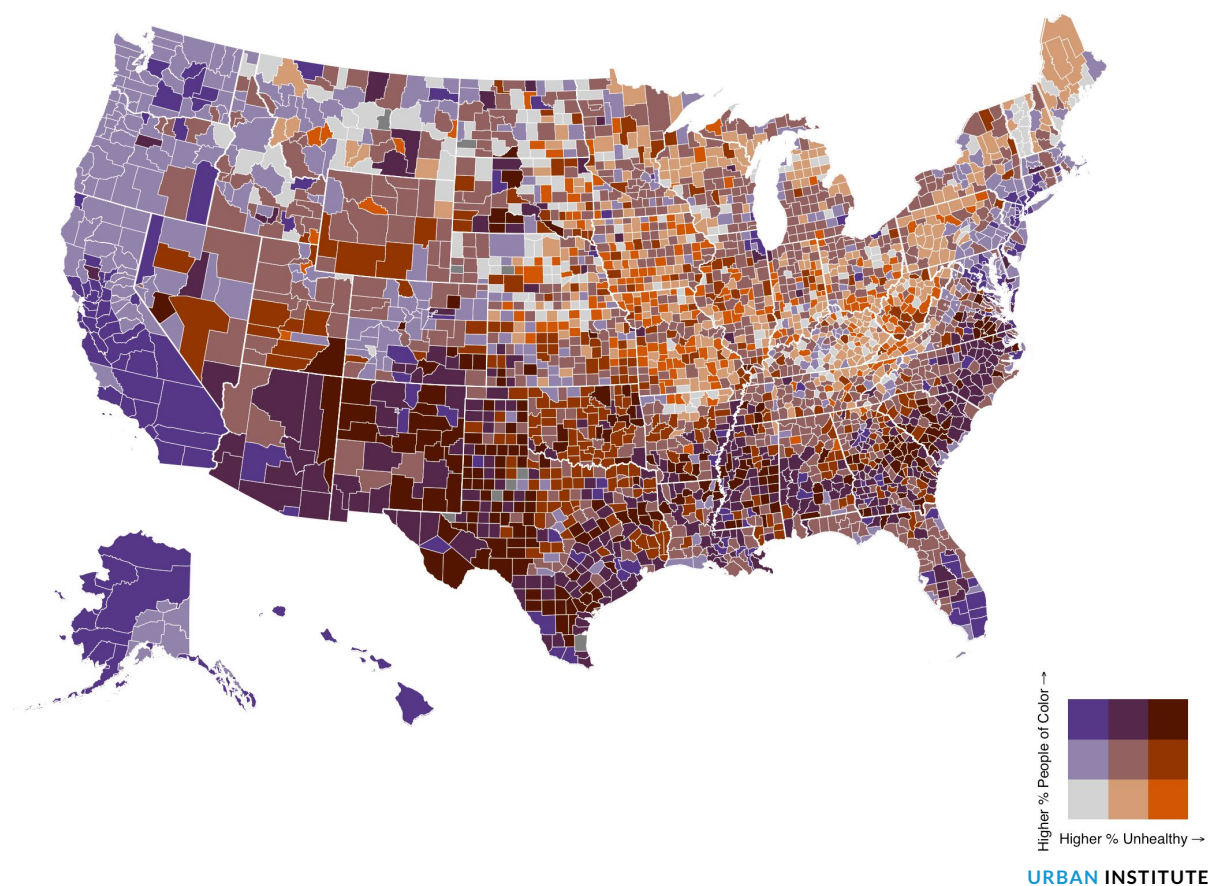
Another opportunity to use mapping to inform policy and practice is looking at the intersection of race and ethnicity and presence of less healthy food options. Although obesity affects individuals from all demographic groups, the burden of obesity and related chronic disease is particularly pronounced in communities of color, including Black, Hispanic/Latinx, and Native American populations (Petersen 2019). The Centers for Disease Control and Prevention highlights several underlying factors that contribute to disparities, including lower high school graduation rates, higher rates of unemployment, higher levels of food insecurity, greater access to poor-quality foods, targeted marketing of unhealthy foods, limited access to areas for physical activity, and poor access to health care and other supportive services. More broadly, these factors can be traced to structural racism and intentional policy choices that have limited opportunities and created significant harms experienced by people of color (Bailey et al. 2017). Using mapping to examine the presence of likely healthy and likely unhealthy food access in

communities with larger percentages of people of color is another tool to help generate conversations about food equity.

Figure 11 provides a snapshot of exposure to less healthy food store options and proportions of people of color at the county level. Counties with higher percentages of residents of color are shown in darker shades of purple while counties with a greater percentage of likely unhealthy food stores are illustrated in darker shades of orange. Areas where both occur at higher rates (darkest brown) may be in particular need for prioritizing strategies to improve the food environment. (An additional map that incorporates restaurants alongside retail food outlets is included in the appendix).

**FIGURE 11**

**Percentage of Communities of Color at the County Level and Percentage of Likely Unhealthy Food Establishments in 2019**



**Source:** Authors' calculations using merged data on obesity from the Behavioral Risk Factor Surveillance System, food establishments from Data Axle, and other county-level characteristics from the 2016–20 American Community Survey five-year county-level estimates and the 2013 Rural-Urban Continuum Codes from the US Department of Agriculture. See the Data and Methods section for more information.

**Notes:** Counties are divided into three groups—bottom quartile, middle two quartiles, and top quartile—based on their share of people who reported their race and ethnicity as anything other than “white” and “non-Hispanic” in the 2016–20 American Community Survey five-year file and also based on their share of unhealthy food establishments. Food establishments that are considered unhealthy include convenience stores, dollar stores, pharmacies, and gas stations.

## Implications for Policy and Practice: Advancing the Conversation about Community-Level Change

Obesity is widespread, and because it is a risk factor for a significant burden of chronic illness, it has been framed as a persistent public health challenge in the US. While advances in treatments for individuals with significant health problems have provided important tools for improving individual outcomes, they do not tackle the policies and practices that contribute to poor health in the first place. The quality of food environments, particularly the prevalence and prominence of less healthy food, is an important consideration for both reducing and preventing obesity, yet these considerations often get lost in a public conversation that can be dominated by narratives about individual choices and personal responsibility.<sup>16</sup>

In the maps and analyses in this report, we examine intersections of obesity prevalence and measures of retail food access at the community level as a means for identifying opportunities for change. We find that areas of higher obesity prevalence are more likely to have greater exposure to the types of food stores likely to offer less healthy options, even when controlling for differences across counties. The association between obesity and unhealthy food establishments holds true in both rural and nonrural areas. In particular, dollar stores account for a much higher share of food establishments in high-obesity counties than in low-obesity counties.

Our emphasis on the food access context for obesity draws from broader efforts in the public health sphere to show how important environments are in shaping individual health. In recent years, much attention has been given to evidence that an individual’s zip code is predictive of health outcomes.<sup>17</sup> While the power of place is a useful lens for focusing on environmental influences, there can be unintended consequences of this framing. There is a risk of stigmatizing the people who live in certain places as well as the potential implication that people should move to places that provide more opportunity instead of demanding an end to disinvestment and exclusion. Most concerning is the potential for “zip code as destiny” to serve as a disempowering frame for people who live in places that are not providing better odds for health and well-being. It is ultimately more powerful to ask who and what can change the distribution of assets that enable people to flourish.



In September 2022, the Biden administration convened the White House Conference on Hunger, Nutrition and Health, the first such gathering since 1968. The administration called for “ending hunger and increasing healthy eating and physical activity by 2030 so fewer Americans experience diet-related diseases—all while reducing health disparities.”<sup>18</sup> The call to action was accompanied by a national strategy document that includes an extensive list of strategies for achieving this vision, a number of which address the role of food environments, for example,

- providing incentives and technical assistance to attract healthier food outlets to underserved areas,
- investing in improvements to healthier food offerings in existing retail stores, and
- increasing the geographic reach and impact of SNAP nutrition incentive programs to defray the costs of fruits and vegetables, which currently leave out many low-income consumers.

A broad array of other policies and interventions are being explored to shift the food access landscape. Some of these policies and interventions focus on changing practices and structures in local communities, while others are intended to challenge existing practices in the broader food environment. For example,

- in addition to working to attract healthy food outlets, some communities have taken steps to limit the density of stores associated with less healthy food offerings, specifically dollar stores; communities could also focus on leveraging these outlets to make changes in inventory offerings,
- proposed policy changes and better practices are also focused on upstream choices by food processors and manufacturers given their influence on what is offered in the retail setting, and
- the role of agricultural policies, including subsidies, that do not align with calls for greater consumption of fruits and vegetables are also receiving growing attention for their role in shaping the food landscape.

Meaningful change in food access that can promote inclusive health and well-being will ultimately require multifaceted strategies. First and foremost among these are strategies to galvanize a collective sense of urgency to change the structures and policies that affect the odds for people’s health. Power mapping is another kind of mapping tool that public health may need to turn to in order to accelerate change (Topp et al. 2021). Those maps can equip communities and their allies to build the power needed to dismantle inequities.

# Appendix: Tables and Figures

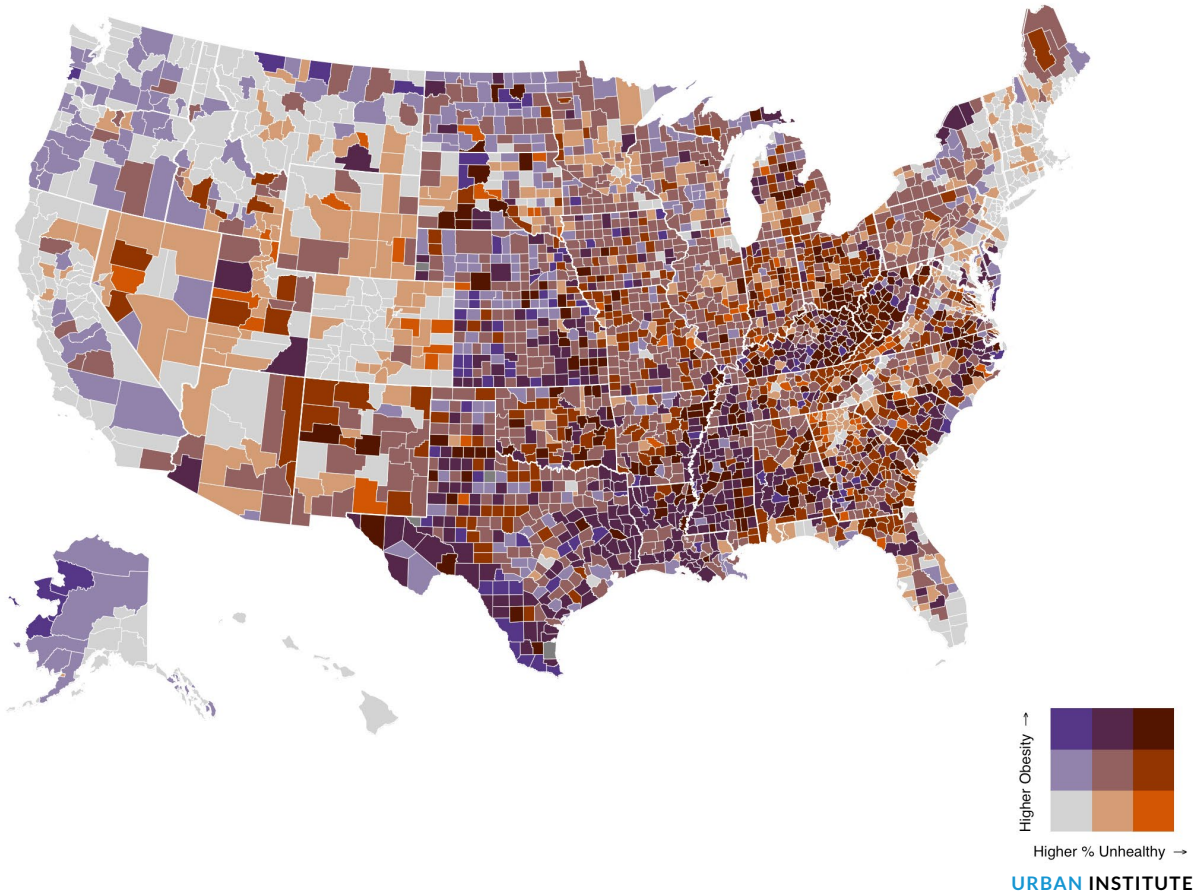
To more fully capture food access and how it relates to obesity rates, we reproduce figure 5 to include restaurants (figure A.1). We classify limited-service (i.e., fast food) restaurants as unhealthy and all other restaurants as healthy. Compared with figure 5, counties in figure A.1 will become darker shades of brown the larger the share of their restaurants that are unhealthy, and they will become more purple or gray the smaller the share of their restaurants that are unhealthy.

The overall impression of figure A.1 is that there are fewer brown counties and more gray/purple counties when restaurants are included, suggesting that most counties' restaurants are likely healthy. More counties in Kansas, Oklahoma, and Texas have relatively healthy food options when accounting for restaurants. Notably, more counties in, Indiana, Kentucky, Michigan, Ohio, and West Virginia have relatively unhealthy food options when accounting for restaurants.

We also reproduce figure 11 to include restaurants (figure A.2). We find that counties in Kentucky, Ohio, and West Virginia with higher percentages of residents of color have an even greater percentage of likely unhealthy food establishments when accounting for restaurants (as illustrated by darker shades of brown in figure A.2 than in figure 11).

FIGURE A.1

Prevalence of Obesity and Percentage of Likely Unhealthy Food Establishments, Including Stores and Restaurants, in 2019

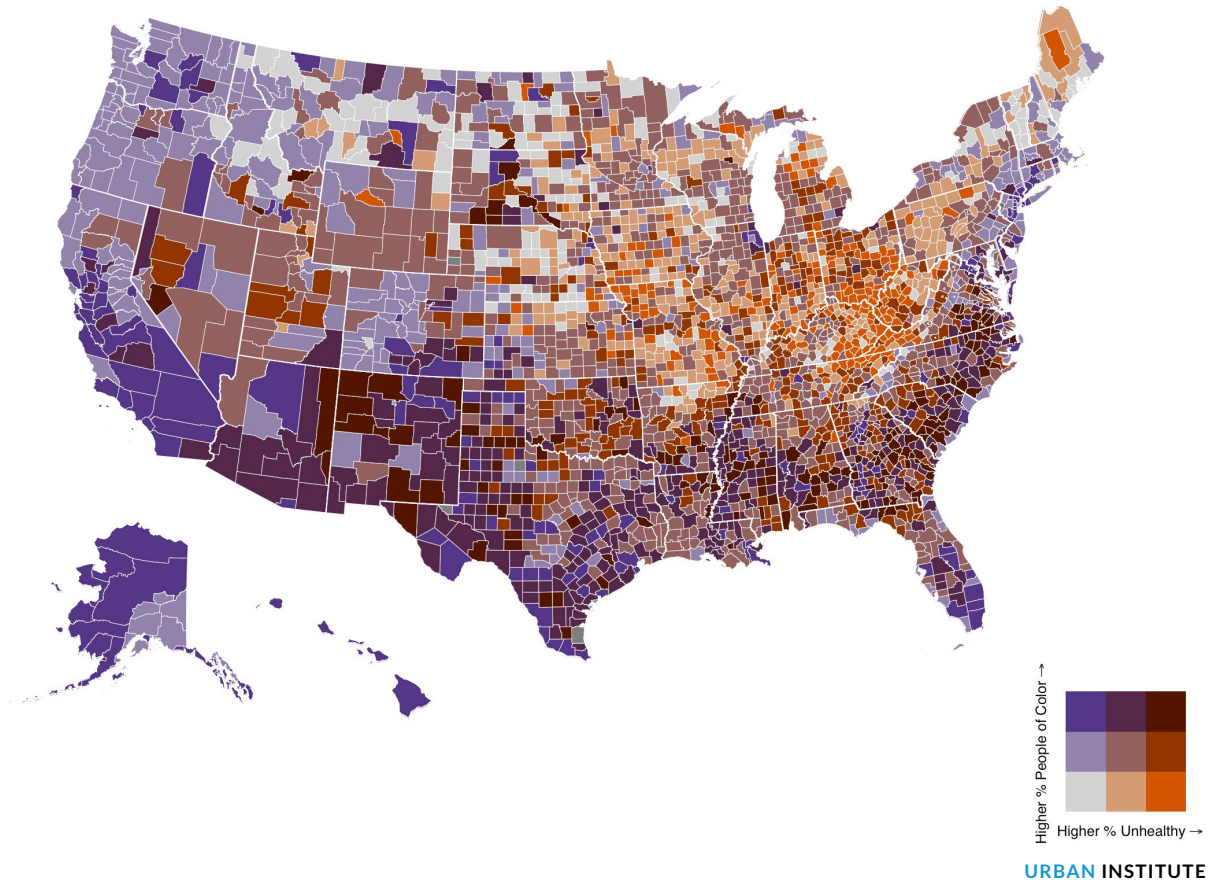


**Source:** Authors' calculations using merged data on obesity from the Behavioral Risk Factor Surveillance System, food establishments from Data Axle, and other county-level characteristics from the 2016–20 American Community Survey five-year county-level estimates and the 2013 Rural-Urban Continuum Codes from the US Department of Agriculture. See the Data and Methods section for more information.

**Notes:** Counties are divided into three groups—bottom quartile, middle two quartiles, and top quartile—based on their obesity rates and also based on their share of unhealthy food establishments. Food establishments that are considered unhealthy include convenience stores, dollar stores, pharmacies, gas stations, and limited-service restaurants.

FIGURE A.2

Percentage of Communities of Color at the County Level and Percentage of Likely Unhealthy Food Establishments, Including Stores and Restaurants, in 2019



**Source:** Authors' calculations using merged data on obesity from the Behavioral Risk Factor Surveillance System, food establishments from Data Axle, and other county-level characteristics from the 2016–20 American Community Survey five-year county-level estimates and the 2013 Rural-Urban Continuum Codes from the US Department of Agriculture. See the Data and Methods section for more information.

**Notes:** Counties are divided into three groups—bottom quartile, middle two quartiles, and top quartile—based on their share of people who reported their race and ethnicity as anything other than “white” and “non-Hispanic” in the 2016–20 American Community Survey five-year file and also based on their share of unhealthy food establishments. Food establishments that are considered unhealthy include convenience stores, dollar stores, pharmacies, and gas stations.

TABLE A.1

## Crosswalk between 2012 NAICS Code and Food Establishment Categories Analyzed

NAICS Code	NAICS Description	Study Category
<b>445</b>	<b>Food and Beverage Stores</b>	
4451	Grocery Stores	
445110	Supermarkets and Other Grocery (except Convenience) Stores	Grocery
445120	Convenience Stores	Convenience Store
4452	Specialty Food Stores	Grocery Other
<b>452</b>	<b>General Merchandise Stores</b>	
4521	Department Stores	
452111	Department Stores (except Discount Department Stores)	Department Store
452112	Discount Department Stores	Department Store
4529	Other General Merchandise Stores	
452910	Warehouse Clubs and Supercenters	Warehouse Club
452990	All Other General Merchandise Stores	Department Store
<b>447</b>	<b>Gasoline Stations</b>	
4471	Gasoline Stations	
447110	Gasoline Stations with Convenience Stores	Gas Station
447190	Other Gasoline Stations	Gas Station
<b>446</b>	<b>Health and Personal Care Stores</b>	
4461	Health and Personal Care Stores	
446110	Pharmacies and Drug Stores	Pharmacy

**Source:** Data Axle and NAICS (one lookup can be found here: <https://www.census.gov/naics/?99967>).

**Notes:** NAICS = North American Industry Classification System. We limit department stores, pharmacies, and gas stations to those whose Standard Industrial Classification descriptions (entered in text fields in the data) include “food markets,” “grocers—retail,” “convenience store,” “food products—retail,” “foods—carry out,” or “miscellaneous food stores.” Those that do not contain any one of these descriptions are excluded from the analysis. We also use the location name to distinguish dollar stores from other department stores by selecting “Dollar General,” “Dollar Tree,” and “Family Dollar Store” and to ensure that pharmacies include all CVSs, Walgreens, and Rite-Aids.

TABLE A.2

**Coefficients from Regressions Testing Differences in Means Reported in Table 2, without and with Other County-Level Controls**

	Difference between Low- and High-Obesity Counties		Difference between Middle- and High-Obesity Counties	
	No Controls	Controls	No Controls	Controls
Grocery	-0.023*	-0.026*	-0.023**	-0.026**
Other grocery	0.086***	0.022*	0.030***	0.017**
Convenience store	-0.132***	-0.045***	-0.042***	-0.020*
Warehouse club	0.002***	0.001***	0.000*	0.000
Dollar store	-0.151***	-0.043***	-0.061***	-0.020***
Other department store	-0.006*	-0.001	-0.003	-0.000
Pharmacy	0.010***	0.002	0.005***	0.002
Gas station	-0.074***	-0.000	-0.019**	0.001
<b>Total food establishments</b>	<b>-0.287***</b>	<b>-0.090***</b>	<b>-0.114***</b>	<b>-0.046**</b>

**Source:** Authors' calculations using merged data on obesity from the Behavioral Risk Factor Surveillance System, food establishments from Data Axle, and other county-level characteristics from the 2016–20 American Community Survey five-year county-level estimates and the 2013 Rural-Urban Continuum Codes from the US Department of Agriculture. See the Data and Methods section for more information.

**Note:** High-obesity counties are defined as having a share of people with obesity in the top quartile of the nation; low-obesity counties are defined as having a share of people with obesity in the bottom quartile; middle-obesity counties are defined as having a share of people with obesity in the middle two quartiles. Regressions with controls also include median age, percentage of females, percentage with a high school diploma, percentage with some college, percentage with at least a bachelor's degree, percentage Black, percentage Hispanic, percentage Asian, percentage Native American, percentage other race, percentage homeowners, median home value, percentage poor, average food price, unemployment rate, and total population.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

TABLE A.3

**Coefficients from Regressions Testing Differences in Means Reported in Figure 4, without and with Other County-Level Controls**

	Difference between Low- and High-Obesity Counties		Difference between Middle- and High-Obesity Counties	
	No Controls	Controls	No Controls	Controls
Grocery	0.039***	-0.000	-0.004	-0.012**
Other grocery	0.098***	0.020***	0.032***	0.014***
Convenience store	-0.032***	-0.012	-0.000	-0.003
Warehouse club	0.003***	0.001***	0.001***	0.000
Dollar store	-0.094***	-0.022***	-0.031***	-0.007**
Other department store	0.000	0.001	-0.000	0.000
Pharmacy	0.017***	0.004**	0.007***	0.003**
Gas station	-0.030***	0.008	-0.004	0.005
Likely healthy	0.140***	0.022**	0.028***	0.002
Likely unhealthy	-0.140***	-0.022**	-0.028***	-0.002

**Source:** Authors' calculations using merged data on obesity from the Behavioral Risk Factor Surveillance System, food establishments from Data Axle, and other county-level characteristics from the 2016–20 American Community Survey five-year county-level estimates and the 2013 Rural-Urban Continuum Codes from the US Department of Agriculture. See the Data and Methods section for more information.

**Notes:** High-obesity counties are defined as having a share of people with obesity in the top quartile of the nation; low-obesity counties are defined as having a share of people with obesity in the bottom quartile; middle-obesity counties are defined as having a share of people with obesity in the middle two quartiles. Regressions with controls also include median age, percentage of females, percentage with a high school diploma, percentage with some college, percentage with at least a bachelor's degree, percentage Black, percentage Hispanic, percentage Asian, percentage Native American, percentage other race, percentage homeowners, median home value, percentage poor, average food price, unemployment rate, and total population.

\* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

TABLE A.4

**Average Number of Food Establishments Per 1,000 Residents in 2019, by Counties with Low, Middle, and High Obesity Rates and by Urbanization**

	Per 1,000 Residents					
	Rural			Nonrural		
	Low-obesity areas	Middle-obesity areas	High-obesity areas	Low-obesity areas	Middle-obesity areas	High-obesity areas
Grocery	0.64	0.55	0.50	0.26	0.26	0.31
Other grocery	0.27	0.14	0.12	0.18	0.14	0.11
Convenience store	0.32	0.42	0.44	0.25	0.33	0.38
Warehouse club	0.00	0.00	0.00	0.00	0.00	0.00
Dollar store	0.13	0.23	0.29	0.08	0.16	0.22
Other department store	0.03	0.02	0.02	0.02	0.03	0.03
Pharmacy	0.01	0.01	0.01	0.03	0.03	0.02
Gas station	0.40	0.38	0.35	0.15	0.21	0.25
<b>Total food establishments</b>	<b>1.79</b>	<b>1.75</b>	<b>1.72</b>	<b>0.98</b>	<b>1.16</b>	<b>1.32</b>

**Source:** Authors' calculations using merged data on obesity from the Behavioral Risk Factor Surveillance System, food establishments from Data Axle, and other county-level characteristics from the 2016–20 American Community Survey five-year county-level estimates and the 2013 Rural-Urban Continuum Codes from the US Department of Agriculture. See the Data and Methods section for more information.

**Note:** High-obesity counties are defined as having a share of people with obesity in the top quartile of the nation; low-obesity counties are defined as having a share of people with obesity in the bottom quartile; middle-obesity counties are defined as having a share of people with obesity in the middle two quartiles.



TABLE A.5

Coefficients from Regressions Testing Differences in Means Reported in Table A.4, without and with Other County-Level Controls

	Difference between Low- and High-Obesity Counties		Difference between Middle- and High-Obesity Counties	
	No Controls	Controls	No Controls	Controls
<b>Rural</b>				
Grocery	0.146***	-0.023	0.052	-0.033
Other grocery	0.151***	-0.002	0.024	-0.013
Convenience store	-0.120***	-0.086	-0.019	-0.036
Warehouse club	-0.001	-0.001	-0.000	-0.000
Dollar store	-0.162***	-0.060**	-0.058***	-0.021
Other department store	0.009	-0.016	0.005	0.002
Pharmacy	-0.000	-0.001	-0.001	-0.003
Gas station	0.049	-0.004	0.028	-0.000
<b>Total food establishments</b>	<b>0.073</b>	<b>-0.192</b>	<b>0.032</b>	<b>-0.105</b>
<b>Nonrural</b>				
Grocery	-0.046***	-0.016	-0.047***	-0.016**
Other grocery	0.074***	0.017*	0.032***	0.024***
Convenience store	-0.131***	-0.032***	-0.049***	-0.017*
Warehouse club	0.003***	0.001***	0.001***	0.000
Dollar store	-0.145***	-0.036***	-0.063***	-0.019***
Other department store	-0.009***	0.001	-0.006**	-0.001
Pharmacy	0.011***	0.002	0.007***	0.003**
Gas station	-0.093***	0.002	-0.034***	0.004
<b>Total food establishments</b>	<b>-0.337***</b>	<b>-0.061**</b>	<b>-0.160***</b>	<b>-0.023</b>

**Source:** Authors' calculations using merged data on obesity from the Behavioral Risk Factor Surveillance System, food establishments from Data Axle, and other county-level characteristics from the 2016–20 American Community Survey five-year county-level estimates and the 2013 Rural-Urban Continuum Codes from the US Department of Agriculture. See the Data and Methods section for more information.

**Note:** High-obesity counties are defined as having a share of people with obesity in the top quartile of the nation; low-obesity counties are defined as having a share of people with obesity in the bottom quartile; middle-obesity counties are defined as having a share of people with obesity in the middle two quartiles. Regressions with controls also include median age, percentage of females, percentage with a high school diploma, percentage with some college, percentage with at least a bachelor's degree, percentage Black, percentage Hispanic, percentage Asian, percentage Native American, percentage other race, percentage homeowners, median home value, percentage poor, average food price, unemployment rate, and total population.

\* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

TABLE A.6

Coefficients from Regressions Testing Differences in Means Reported in Figure 7, without and with Other County-Level Controls

	Difference between Low- and High-Obesity Counties		Difference between Middle- and High-Obesity Counties	
	No Controls	Controls	No Controls	Controls
<b>Rural</b>				
Likely healthy	0.137***	0.021	0.021	-0.011
Likely unhealthy	-0.137***	-0.021	-0.021	0.011
<b>Nonrural</b>				
Likely healthy	0.143***	0.026***	0.030***	0.009
Likely unhealthy	-0.143***	-0.026***	-0.030***	-0.009

**Source:** Authors' calculations using merged data on obesity from the Behavioral Risk Factor Surveillance System, food establishments from Data Axle, and other county-level characteristics from the 2016–20 American Community Survey five-year county-level estimates and the 2013 Rural-Urban Continuum Codes from the US Department of Agriculture. See the Data and Methods section for more information.

**Note:** High-obesity counties are defined as having a share of people with obesity in the top quartile of the nation; low-obesity counties are defined as having a share of people with obesity in the bottom quartile; middle-obesity counties are defined as having a share of people with obesity in the middle two quartiles. Regressions with controls also include median age, percentage of females, percentage with a high school diploma, percentage with some college, percentage with at least a bachelor's degree, percentage Black, percentage Hispanic, percentage Asian, percentage Native American, percentage other race, percentage homeowners, median home value, percentage poor, average food price, unemployment rate, and total population.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

# Notes

- <sup>1</sup> “Obesity Is a Common, Serious, and Costly Disease,” Centers for Disease Control and Prevention, July 20, 2022, <https://www.cdc.gov/obesity/data/adult.html>.
- <sup>2</sup> Obesity is a complex, chronic condition that involves excessive accumulation of fat. The Centers for Disease Control and Prevention typically categorizes obesity as having a body mass index of greater than 30. See “Defining Adult Overweight and Obesity,” Centers for Disease Control and Prevention, last updated June 3, 2022, <https://www.cdc.gov/obesity/basics/adult-defining.html>. Obesity experts increasingly argue for multiple indicators of obesity rather than a single measure. See “Definition of Obesity,” Obesity Medicine Association, August 29, 2017, <https://www.cdc.gov/obesity/basics/adult-defining.html>.
- <sup>3</sup> Julian Agyeman, “How Urban Planning and Housing Policy Helped Create ‘Food Apartheid’ in US Cities,” *The Conversation*, accessed January 9, 2023, <http://theconversation.com/how-urban-planning-and-housing-policy-helped-create-food-apartheid-in-us-cities-154433>.
- <sup>4</sup> “FAQ,” Karen Washington, accessed January 9, 2023, <https://www.karenthefarmer.com/faq-index>.
- <sup>5</sup> Ashley Gripper. “We Don’t Farm Because It’s Trendy; We Farm as Resistance, for Healing and Sovereignty—EHN,” *Environmental Health News* (blog), May 27, 2020, <https://www.ehn.org/black-farming-food-sovereignty-2645479216.html>.
- <sup>6</sup> Jayson L. Lusk and Brandon R. McFadden, “Consumer Food Buying during a Recession,” *Choices Magazine*, 2021, <https://www.choicesmagazine.org/choices-magazine/theme-articles/agricultural-market-response-to-covid-19/consumer-food-buying-during-a-recession>.
- <sup>7</sup> “North American Industry Classification System,” US Census Bureau, accessed February 15, 2023, <https://www.census.gov/naics/?99967>.
- <sup>8</sup> For example, Alessandro Bonanno and Jing Li, “Food Insecurity and Food Access in U.S. Metropolitan Areas,” *Applied Economic Perspectives and Policy* 37 (2015): 177–204; and see citations in Sarah Treuhaft and Allison Karpyn, “The Grocery Gap: Who Has Access to Healthy Food and Why It Matters | PolicyLink,” 2010, <https://www.policylink.org/resources-tools/the-grocery-gap-who-has-access-to-healthy-food-and-why-it-matters>.
- <sup>9</sup> The American Community Survey five-year estimates represent data collected over a period of time—in this case, 2016 through 2020. The primary advantage of using multiyear estimates is the increased statistical reliability of the data for less populated areas and small population subgroups. Important to note, unlike the American Community Survey one-year estimates, geographies do not have to meet a particular population threshold to be published. Thus, these data are representative of all counties in the US. More information is available here: <https://www.census.gov/data/developers/data-sets/acs-5year.html>.
- <sup>10</sup> “Map the Meal Gap Technical Brief,” Feeding America, 2022, <https://www.feedingamerica.org/sites/default/files/2022-07/Map%20the%20Meal%20Gap%202022%20Technical%20Brief.pdf>.
- <sup>11</sup> “GusNIP Grantees,” Nutrition Incentive Hub, accessed February 15, 2023, <https://www.nutritionincentivehub.org/grantee-projects>.
- <sup>12</sup> Covariates include median age, sex, educational attainment, race and ethnicity, homeownership rates, median home values, poverty rates, unemployment rates, rural status, and total population.
- <sup>13</sup> Food is an important aspect of obesogenic environments, but research has identified other community-level conditions, such as the ways in which the built environment may limit physical activity, as important influences as well.

- <sup>14</sup> The per capita number of food establishments here is approximate since the median county in number of food establishments isn't necessarily the median county in population.
- <sup>15</sup> Our taxonomy of food establishments as "likely healthy" and "likely unhealthy" is supported by extant literature (e.g., Bonanno and Li, "Food Insecurity and Food Access" and the citations within Treuhaft and Karpyn, "The Grocery Gap"). Of course, changing these classifications—or having better data on the exact types of foods provided in each type of establishment—might affect our conclusions.
- <sup>16</sup> Julia Belluz, "Opinion | Scientists Don't Agree on What Causes Obesity, but They Know What Doesn't," *New York Times*, November 21, 2022, <https://www.nytimes.com/2022/11/21/opinion/obesity-cause.html>.
- <sup>17</sup> "Life Expectancy: Could Where You Live Influence How Long You Live?" Robert Wood Johnson Foundation, March 9, 2020, <https://www.rwjf.org/en/insights/our-research/interactives/whereyouliveaffectshowlongyoulive.html>.
- <sup>18</sup> "Biden-Harris Administration National Strategy on Hunger, Nutrition, and Health," accessed January 26, 2023, <https://www.whitehouse.gov/wp-content/uploads/2022/09/White-House-National-Strategy-on-Hunger-Nutrition-and-Health-FINAL.pdf>.

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