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Disentangling racial/ethnic and income disparities of food retail Environments: Impacts on adult obesity prevalence

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ABSTRACT

This research aims to assess county food retail environment (FRE) with multifaceted measurements and disentangle how racial/ethnic and income disparities contribute to geographic variations in obesity rates via FRE. County obesity rates, racial/ethnic and income factors, as well as the data of food stores, restaurants, and stores in the Supplemental Nutrition Assistance Program (SNAP) were obtained from the U.S. Department of Agriculture. FRE was assessed with availability (density), healthfulness (ratio of healthy to unhealthy stores), and accessibility (proximity to healthy stores measured by population-weighted distance). Obesity rates and FRE indicators were compared with *t*-test among 3,107 counties stratified by racial/ethnic vs. income factors. We used Varying Coefficient Models to quantify the influences of racial/ethnic and income factors on the FRE and obesity association. Our analysis indicates narrowing disparities in availability but persisting inequalities of healthfulness and accessibility between low- and high-income counties with low and high percentages of racial/ethnic minority populations. Furthermore, racial/ethnic and income factors play essential roles in shaping the obesity and FRE relationship. Among three indicators, healthfulness exhibits relatively consistent relationships with obesity rates as the income or the racial/ethnic factor changes.

1. Introduction

Adult obesity rates have been growing rapidly in the U.S., rising from about 10% in 1960s to estimated 39.8% in 2016 (Rummo et al., 2020). Being obese increases the risk of a series of health problems, such as diabetes, cardiovascular diseases, and cancers (Williams et al., 2015; Yu et al., 2020). Social disparities in obesity persist in the U.S., which disproportionally affects low-income and racial/ethnic minority subgroups (Li et al., 2015; Singleton et al., 2016). Beyond individual socio-demographic factors, studies have found prominent geographic variation in obesity prevalence across the country, which suggests the contextual effects of area-based social determinants of health on obesity (Adachi-Mejia et al., 2017; Rummo et al., 2020; The Center for Disease Control and Prevention, 2020; Yu et al., 2020). For example, county-level food retail environment (hereafter FRE) has been recognized as a critical contextual factor contributing to geographic disparities in obesity (Ahern, Brown, & Dukas, 2011; Maguire et al., 2017; Rummo et al., 2020; Xu et al., 2017; Yu et al., 2020).

Research has consistently documented racial/ethnic and economic inequalities in FRE (Richardson et al., 2012; Morland, 2015; Winkler et al., 2019). Communities with a high percentage of Black or Hispanic residents are less accessible to healthy food outlets (i.e., grocery stores) while are more proximate to unhealthy food stores (i.e., fast food restaurants) (Larson et al., 2009). Low-income communities often have unhealthy food environments with higher barriers to healthy foods (i.e., supermarkets) than those mid- or high-income neighborhoods (Larson et al., 2009; Singleton et al., 2016). Since the late 1970s, many supermarkets in urban low-income neighborhoods have been closed due to limited local purchasing power and other factors (Hosler, 2019; Massey, 2001), which further increased disparities in FRE among communities with different income levels. At the county level, scholars have also observed that variations of FRE are significantly associated with racial/ethnic compositions and economic conditions (Xu et al., 2017; Rummo et al., 2020; Singleton et al., 2016; Yu et al., 2020). Counties with large

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Black or Hispanic population have more fast-food restaurants while less healthy grocery stores and farmer's markets (Singleton et al., 2016; Yu et al., 2020). In contrast, wealthy counties tend to be less exposed to fast food restaurants and therefore have lower obese rates (Xu et al., 2017; Yu et al., 2020). These area-level circumstances, interacting with individual and interpersonal factors, may have greatly contributed to the high prevalence of obesity in the U.S., particularly in those disadvantaged areas. Therefore, it has become increasingly essential to further explore and understand the impacts of these contextual factors (Yu et al., 2020).

It is difficult to distinguish between the impacts of racial/ethnic and economic disparities in FRE on obesity as racially/ethnically segregated minority communities are very likely facing economic deprivation (Massey, 2001; Larson et al., 2009; Li et al., 2019). However, racial/ethnic and economic disparities are two different mechanisms by which the FRE influences obesity prevalence. In the U.S., a long history of institutional racism since the 19th century has caused residential segregation of races/ethnicities and racial/ethnic disparities (Winkler et al., 2019). Institutional policies favoring White population have allocated social capital and resources unevenly among White communities and racial/ethnic minority communities (Riley, 2018; Winkler et al., 2019). For example, a great number of food deserts appeared in racial/ethnic minority communities or counties across the country, lower availability of healthy food leading to less healthy dietary behaviors and higher obesity rates (Dutko et al., 2012; Bell et al., 2019). While county-level economic conditions may influence family income which further limits household food budgets (Slack et al., 2014; Rummo et al., 2020) and increases family members' risks of being obese (Lovasi et al., 2009; Rummo et al., 2020). Despite that many studies have examined racial/ethnic and/or socioeconomic disparities in FRE, few have disentangled how county-level racial/ethnic composition and economic deprivation contribute to explaining uneven FRE and geographic variations of obesity.

The FRE is defined as the places where individuals purchase and/or consume food and beverages (Storr et al., 2019; Walker et al., 2020). A series of measurements have been developed, and the most frequently used type of measure is "the number, type, location, and accessibility of food outlets" (Glanz et al., 2005; Gamba et al., 2015; Herforth & Ahmed, 2015). More specifically, the FRE has been assessed with such spatial measurements as availability, proximity/accessibility, and ratio of different types of food outlets (Shearer et al., 2015; Winkler et al., 2019; Walker et al., 2020). Availability refers to the sufficiency of food supply as measured by the number of food outlets within a predetermined area (Caspi et al., 2012; Shearer et al., 2015) or food stores per capita (Singleton et al., 2016) (e.g., numbers of fast-food outlets, full-service restaurants, supercenters, and grocery stores per 1000 county residents (Ahern et al., 2011; Singleton et al., 2016). Accessibility is defined as the convenience of getting to food outlets, usually reflected by the travel distance or time from a predefined location (i.e., home) to the closest food stores or the number of food outlets within a threshold Euclidian or network distance (Dai & Wang, 2011; Caspi et al., 2012; Bao & Tong, 2017). Scholars have also applied the ratio of healthy food stores to unhealthy ones to reflect the healthfulness of FRE (Li et al., 2019; Walker et al., 2020). Using different measurements has produced mixed findings in the FRE and obesity relationship and made it challenging for direct comparisons among relevant research (Gamba et al., 2015; Kuo, 2020; Rummo et al., 2020; Walker et al., 2020). There is a growing need to further assess community FRE with consistent, reliable, and feasible metrics (Herforth & Ahmed, 2015) and examine the impacts more comprehensively on the obesity epidemic.

To fill the above knowledge gaps, this research aims to: 1) assess county-level FRE in the contiguous U.S. by measuring the density of food stores and restaurants (availability), the ratio of grocery stores/supermarkets to small convenient stores and full-service to fast food restaurants (healthfulness), and the proximity to healthy grocery/supermarkets (accessibility); and 2) to stratify counties based on their racial/ethnic compositions and income levels and disentangle how these two mechanisms explain geographic variations in obesity via uneven FRE.

Table 1
Dependent and independent variables.

	Variables	Description
Dependent variable	Obesity rate (2013)	Age-adjusted obesity rates of counties
Independent variables	Availability	Store count: # stores per 1,000 persons Restaurant count: # restaurants per 1,000 persons SNAP count: # SNAP stores per 1,000 persons
	Healthfulness	Store ratio: grocery stores + super centers + farmer's markets/convenience stores + specialized food stores (store ratio) Restaurant ratio: full-service restaurants/ fast food restaurants SNAP ratio: SNAP grocery stores + supercenters + farmer's markets/ convenience stores + specialized food stores
	Accessibility	Population weighted distance to healthy food stores
	Racial/ethnic factor	% of Black % of Hispanic % of RE-minority (1- % of Non-Hispanic White)
	Income level	Median household income (5-year estimation)

2. Methodology

2.1. Data

The data required for this study were obtained from two sources (Table 1). County obesity rates, aggregated retail food outlet data, as well as information of racial/ethnic compositions and income levels were obtained from the 2018 Food Environment Atlas of the U.S. Department of Agriculture (hereafter USDA) (2018). Addresses of individual food stores were downloaded from the USDA website (2019a).

2.2. Assessment of food retail environment

County-level FRE was assessed by food stores, restaurants, and stores participating in the Supplemental Nutrition Assistance Program (SNAP) with ArcGIS 10.7. Food stores, such as grocery stores, supercenters, local farmer's markets, convenience stores and specialized food stores, were used to assess FRE where residents purchase food for eating at home. Based on the USDA classification, the former three provide more choices of healthy, fresh and nutritious food, while the latter two offer limited options of nonperishable, ready-to-eat, or specialized food (e.g., candy) (Volpe et al., 2017, p. 167). Full-service restaurants and fast-food stores were included to reflect FRE for out-of-home eating. Full-service restaurants have relatively broader menus and provide waiters' services while fast food stores offer limited food options with minimal service (Glanz et al., 2007; Huddleston et al., 2009). The SNAP is a nationwide program which provides modest benefits for low-income families and individuals so as to boost their food purchasing power and afford them a basic diet (USDA, 2019b). In 2019, 248,000 food retailers in this program, including all aforementioned five types of stores, redeemed approximately 56 billion in benefits (Bolen & Wolkomir, 2020). The SNAP stores were included in this study to represent national and social supports for low-income families and individuals to eat healthy.

The FRE was evaluated from three perspectives, availability, healthfulness, and accessibility. The availability of food retail stores at the county level was measured by the number of food stores per 1,000 persons (hereafter store count), the number of restaurants per 1,000 persons (hereafter restaurant count), and the number of SNAP stores per

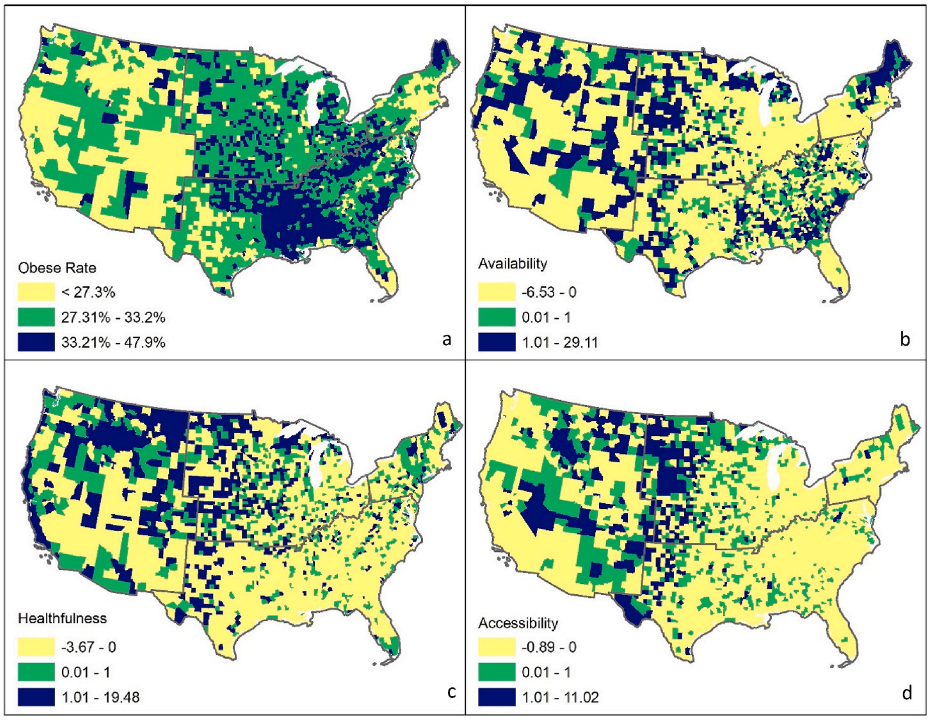

Fig. 1. Obesity rates and food retail environment indexes.

1,000 persons (hereafter SNAP count). The healthfulness of county FRE was assessed by the ratio of the total number of grocery stores, supercenters, and local farmer's markets to the total number of convenience stores and specialized food stores (hereafter store ratio), the ratio of the total number of full-service restaurants to the total number of fast food stores (hereafter restaurant ratio), and the ratio of the total number of SNAP grocery stores, supercenters, and local farmer's markets to the total number of SNAP convenience stores and specialized food stores (hereafter SNAP ratio). The accessibility to healthy food stores was measured by the county-level population-weighted distance (PWD) aggregated by PWDs of block groups to seven (Pellegrini et al., 1997) nearest grocery stores, supercenters, and local farmer's markets (detailed calculation procedures can be found in Zhang et al., 2011).

An index was derived for each of the three indicators. Using composite variables is common for incorporating two or more highly correlated measures into more comprehendible information or reducing multicollinearity for regression modeling (Song et al., 2013). Since all measures of food retail environment in this study are continuous, we used a well-accepted approach, simple averaging, namely summing up z scores of the original measures to create the indexes (Song et al., 2013). Z scores measure how far of each original data point is from the mean in terms of the standard deviation. Transforming original measures with different variances to z scores is necessary to create a composite index without being affected by any original measure with a large variance (Song et al., 2013).

A composite index of availability was obtained by summing up z scores of the three availability indicators: store count, restaurant count, and SNAP count. A larger index reflects better availability of food retail stores in a county.

$$I_{\,availability} = Z_{\,store\ count} + Z_{\,resturant\ count} + Z_{\,SNAP\ count},\ where\ z = (x - \bar{x})/SD \tag{1}$$

A composite index of healthfulness was calculated by summing up z scores of the three healthfulness measurements: store ratio, restaurant ratio, and SNAP ratio. A larger index denotes healthier FRE in a county.

Table 2
Racial/ethnic vs. income disparities of obesity rates and food retail environments indexes across U.S. counties.

	% Black		% Hispanic		% RE-Minority		MHHI		
	Low	High	Low	High	Low	High	Low	High	Average
Obesity rate (%)	30.12	33.52***	31.32	27.9***	30.37	34.12***	31.65	27.54***	30.85
Availability									
Store count	0.98	0.96	0.99	0.9***	0.97	1	1.01	0.83***	0.98
Restaurant count	1.43	1.16***	1.37	1.4	1.41	1.12***	1.34	1.54***	1.38
SNAP count	0.75	0.96***	0.8	0.71***	0.75	1.04***	0.85	0.57***	0.79
Healthfulness									
Store ratio	0.57	0.4***	0.53	0.55	0.55	0.45***	0.53	0.56*	0.53
Restaurant ratio	1.55	1***	1.46	1.28***	1.51	0.93***	1.44	1.41	1.43
SNAP ratio	0.3	0.26***	0.28	0.33**	0.3	0.24***	0.28	0.34***	0.29
Accessibility									
PWD to healthy stores (m)	14,823	8711***	13,435	14,011	13,955	10,519***	14,039	11,338***	13,515

Note:
MHHI—median household income; PWD—population weighted distance.
*Denote p values of two sample *t*-test, ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.
Cutoffs for low and high groups are the national levels: Black –13%; Hispanic—16.3%; RE-minority—36.1%; MHHI–$56,516.

$$I_{\text{healthfulness}} = Z_{\text{store ratio}} + Z_{\text{restaurant ratio}} + Z_{\text{SNAP ratio}}, \text{ where} z = (x - \bar{x}) / SD \quad (2)$$

An index of accessibility was derived by calculating the z score of accessibility to healthy food stores of a county. A smaller index suggests better accessibility to healthy food stores of a county.

$$I_{\text{accessibility}} = Z_{\text{accessibility}}, \text{ where } z = (x - \bar{x}) / SD \quad (3)$$

The maps at the county level were created for obesity rates and indexes of availability, healthfulness, and accessibility in Fig. 1.

2.3. Comparing obesity rates and food retail environments among counties

Obesity rates and FRE indicators were compared among 3,107 counties stratified by median household income (MHHI) and racial/ethnic compositions with two sample *t*-test (Table 2). Because the 2015 county MHHI was used by the 2018 USDA Food Environment Atlas, a county was classified as low-income if the MHHI was lower than the 2015 national MHHI ($56,516) and as high-income otherwise (Proctor et al., 2016). Counties were classified into two groups in terms of the national percentage of Black population (13%), that of Hispanic population (16.3%), or that of racial/ethnic minority (36.1%) in 2010 as the cutoffs, respectively (U.S. Census Bureau, 2011). The reason is that the 2010 census data were used by the 2018 Food Environment Atlas.

2.4. Variables and models

Varying Coefficient Models (VCM) were applied to examine and disentangle how county racial/ethnic compositions and income levels have influenced geographic variations in obesity via uneven FRE. The dependent variable is the age-adjusted obesity rates (hereafter obesity rates) of counties. The independent variables include the indexes of availability, healthfulness, and accessibility as well as indicators of racial/ethnic compositions and income levels. Racial/ethnic compositions of counties were measured by the percentages of racial/ethnic minority population including Black, non-White Hispanic, and others (hereafter RE-minority), Black population, and Hispanic population. The median household income (hereafter MHHI) was used to reflect income levels of counties.

Extended from classical linear models, the VCM integrates generalized additive models and dynamic generalized linear models into one analytical framework, which allows a coefficient to vary as a smooth function of another independent variable (Hastie & Tibshirani, 1993; Fan & Zhang, 1999; Wang et al., 2023). The coefficient functions are estimated with a simple nonparametric regression. Given any fixed Z, the varying coefficient function performs as the coefficient in the simple linear regression model. The VCMs have two advantages to examine how regression coefficients vary over different groups classified by certain covariates (Fan & Zhang, 1999). First, the modeling bias can be significantly reduced and the "curse of dimensionality" can be avoided via allowing coefficients to vary over covariates. Second, the VCM is a powerful tool to understand the dynamic patterns because of its flexibility and interpretability (Fan & Zhang, 2008) as it allows varying coefficient functions to reflect the varying relationships between MHHI and racial/ethnic compositions on the association of county obesity rates and FRE.

Therefore, three VCMs were constructed to estimate how regression coefficients change over such covariates as the MHHI or racial/ethnic compositions. Model 1 was used to explicitly quantify how contributions of county FRE to obesity rates vary with the changes of both MHHI and the percentage of RE-minority.

$$Y_i = \alpha_0(Z_{1i}) + \beta_0(Z_{2i}) + \sum_{p=1}^{3} \alpha_p(Z_{1i})X_{pi} + \sum_{q=1}^{3} \beta_q(Z_{2i})X_{qi} + \varepsilon_i \quad (4)$$

Model 2 was applied to examine how influences of FRE on obesity rates vary with both MHHI and the percentage of Black population.

$$Y_i = \alpha_0(Z_{1i}) + \gamma_0(Z_{3i}) + \sum_{p=1}^{3} \alpha_p(Z_{1i})X_{pi} + \sum_{q=1}^{3} \gamma_q(Z_{3i})X_{qi} + \varepsilon_i \quad (5)$$

Model 3 was utilized to examine how influences of FRE on obesity rates change with both MHHI and the percentage of Hispanic population.

$$Y_i = \alpha_0(Z_{1i}) + \lambda_0(Z_{4i}) + \sum_{p=1}^{3} \alpha_p(Z_{1i})X_{pi} + \sum_{q=1}^{3} \lambda_q(Z_{4i})X_{qi} + \varepsilon_i \quad (6)$$

More specifically in these three models, Y_i represents obesity rates of counties (n=3,107). Z_{1i} is the MHHI for the ith subject, $\alpha_0(Z_{1i})$ represents the varying coefficient function of the income level for the intercept, and $\alpha_1(Z_{1i})$, $\alpha_2(Z_{1i})$ and $\alpha_3(Z_{1i})$ represent varying coefficient functions of the income level for FRE factors such as availability, healthfulness, and accessibility, respectively. Z_{2i} is the percentage of RE-minority for the ith subject, $\beta_0(Z_{2i})$ represents the varying coefficient function of the percentage of RE-minority, and $\beta_1(Z_{2i})$, $\beta_2(Z_{2i})$ and $\beta_3(Z_{2i})$ represent varying coefficient functions of the percentage of RE-minority for availability, healthfulness, and accessibility, respectively. Z_{3i} is the percentage of Black for the ith subject, $\gamma_0(Z_{3i})$ represents the varying coefficient function of the percentage of Black, and $\gamma_1(Z_{3i})$, $\gamma_2(Z_{3i})$ and $\gamma_3(Z_{3i})$ represent varying coefficient functions of the percentage of Black for availability, healthfulness, and accessibility, respectively. Z_{4i} is the percentage of Hispanic for the ith subject, $\lambda_0(Z_{4i})$ represents the varying coefficient function of the percentage of Hispanic, and $\lambda_1(Z_{4i})$, $\lambda_2(Z_{4i})$ and $\lambda_3(Z_{4i})$ represent varying coefficient functions of the percentage of Hispanic for availability, healthfulness, and accessibility, respectively. X_{1i}, X_{2i} and X_{3i} represent availability, healthfulness, and accessibility, respectively. ε_i represents random errors assumed in the model for $3,107$ subjects.

Each varying coefficient function is a function of z, which varies with Z. For any fixed Z, the varying coefficient function can be taken as the coefficient for the corresponding X at Z, and it can be interpreted as in the simple linear regression. For example, $\widehat{\alpha_1}(z)$ reflects the contribution of variable X_1(accessibility) to Y (obesity rate) as the MHHI changes. If we fix a certain amount of MHHI z_0, availability (X_1) will contribute the value of $\widehat{\alpha_1}(z_0)$ to Y (obesity rate) when X_1 increases one unit.

We proposed the regression spline smoothing method to estimate the varying coefficient functions α's, β's, γ's and λ's. All the statistical computation was conducted in the statistical software R. Univariate cubic B-spline was applied to estimate coefficient functions $\alpha_0(z)$, $\alpha_1(z)$, $\alpha_2(z)$, $\alpha_3(z)$, $\beta_0(z)$, $\beta_1(z)$, $\beta_2(z)$, $\beta_3(z)$, $\gamma_0(z)$, $\gamma_1(z)$, $\gamma_2(z)$, $\gamma_3(z)$, $\lambda_0(z)$, $\lambda_1(z)$, $\lambda_2(z)$ and $\lambda_3(z)$ (see 42), denoted by $\widehat{\alpha_0}(z)$, $\widehat{\alpha_1}(z)$, $\widehat{\alpha_2}(z)$, $\widehat{\alpha_3}(z)$, $\widehat{\beta_0}(z)$, $\widehat{\beta_1}(z)$, $\widehat{\beta_2}(z)$, $\widehat{\beta_3}(z)$, $\widehat{\gamma_0}(z)$, $\widehat{\gamma_1}(z)$, $\widehat{\gamma_2}(z)$, $\widehat{\gamma_3}(z)$, $\widehat{\lambda_0}(z)$, $\widehat{\lambda_1}(z)$, $\widehat{\lambda_2}(z)$ and $\widehat{\lambda_3}(z)$, respectively.

3. Results

3.1. Racial/ethnic and income disparities of obesity and food retail environments

The average values of obesity rates and FRE indicators and p values of *t*-test are summarized for counties grouped by county racial/ethnic compositions and MHHI (Table 2). There are 2,443 (78.63%) vs. 664 (21.37%) counties with low and high percentages of Black, 2,675 (86.1%) vs. 432 (13.9%) counties with low and high percentages of Hispanic, and 2,706 (87.09%) vs. 401(12.91%) counties with low and high percentages of RE-minority populations, respectively. Also, 2,503 (80.56%) counties fall in the low MHHI category while 604 (19.44%) in the high MHHI category.

Racial/ethnic and income disparities in obesity exist across counties. In general, higher obesity rates are observed in counties with a high percentage of RE-minority (34.12% vs. 30.37%, $p < 0.001$) or a high percentage of Black population (33.52% vs. 30.12%, $p < 0.001$) compared to those with low percentages of these populations. However, the counties with a larger Hispanic population have lower obesity rates than those with a smaller Hispanic population (27.9% vs. 31.32%, $p < 0.001$). The obesity rates in low-income counties are significantly higher than those in high-income counties regardless of the compositions of Black, Hispanic, or RE-minority populations (31.65% vs. 27.54%, $p < 0.001$).

County racial/ethnic compositions and income levels are associated with FRE as well. We compared three availability indicators including store count, restaurant count, and SNAP count, such healthfulness measurements as store ratio, restaurant ratio, and SNAP ratio, as well as the accessibility reflected by the PDW to healthy food stores with two sample *t*-test. Regarding availability, counties with low and high percentages of Black or RE-minority populations have no significant difference in terms of store count, namely the number of food stores per 1000 persons. But counties with a low percentage of Black or RE-minority populations have more restaurants per 1000 persons than counties with a high percentage of these populations (1.43 vs. 1.16 restaurants/1000 persons, $p < 0.001$; 1.41 vs. 1.12 restaurants/1000 persons, $p < 0.001$). While counties with a low percentage of Hispanic population have higher store counts (0.99 vs. 0.9 stores/1000 persons, $p < 0.001$) but had no significant difference in restaurant count compared to counties with a high percentage of Hispanic. From the perspective of income disparity, we found that low-income counties had significantly higher store counts (1.01 vs. 0.83 stores/1000 persons, $p < 0.001$) while lower restaurant counts (1.34 vs. 1.54 restaurants/1000 persons, $p < 0.001$) compared to high-income counties.

Racial/ethnic disparities are more prominent in terms of healthfulness. Both store ratio and restaurant ratio are significantly higher in counties with a low percentage of Black or RE-minority population compared to counties with high percentages of these populations. For example, the ratio of healthy to unhealthy stores is 0.57 vs. 0.4 ($p < 0.001$) and the ratio of full-service restaurants to fast food restaurants is 1.55 vs. 1 ($p < 0.001$) in counties with low and high percentages of Black population. But counties with a high percentage of Hispanic have a significantly higher restaurant ratio than those with a low percentage of Hispanic (1.46 vs. 1.28, $p < 0.001$). In terms of income inequality, high-income counties have higher store ratios than low-income counties (0.56 vs. 0.53, $p < 0.001$) while no significant difference was found in restaurant ratio.

Despite that SNAP is a program initiated for providing low-income families food purchasing benefits, racial/ethnic and income disparities still exist in the distribution of SNAP stores. Generally SNAP stores are more available in low-income counties with large Black or RE-minority populations, for example, 0.85 vs. 0.57 SNAP stores per 1000 persons in low and high-income counties ($p < 0.001$) and 1.04 vs. 0.75 SNAP stores per 1000 persons in counties with high and low percentages of RE-minority population ($p < 0.001$). Regarding healthfulness, we found an opposite pattern that SNAP ratios are higher in high-income counties with a low percentage of Black or RE-minority population than other counties, for example, 0.34 vs. 0.28 in high and low-income counties ($p < 0.001$), and 0.3 vs. 0.26 in counties with low and high percentages of Black population ($p < 0.001$). However, the counties with a high percentage of Hispanic population have a lower SNAP count (availability, 0.71 vs. 0.8, $p < 0.001$) but a higher SNAP ratio (healthfulness, 0.33 vs. 0.28, $p < 0.01$) than the counties with a low percentage of Hispanic population, which may have contributed to low obesity rates in counties with a high percentage of Hispanic population. Accessibility to healthy SNAP stores, measured by population-weighted distance, is significantly better in the counties with a high percentage of Black (8,711 vs. 14,823 m, $p < 0.001$) or RE-minority population (10,519 vs. 13,955 m, $p < 0.001$) compared to other counties. But high-income counties are generally more accessible to healthy SNAP stores than low-income counties (11,338 vs. 14,039 m ($p < 0.001$).

Table 3
Statistical diagnostics of Vary Coefficient Models.

	Model 1	Model 2	Model 3
Root-mean-squared error (RMSE)	3.48	3.56	3.41
R^2	0.44	0.41	0.46

Apparently, county income level and racial compositions both are strongly associated with obesity rates and FREs, while their contributions to the association of obesity rates and FRE need to be further examined with the VCMs.

3.2. Results of Varying Coefficient Models

All three VCMs perform well with Root-mean-square error (RMSE) values between 3.41 and 3.56 (Table 3). The varying coefficients are displayed in Figs. 2–4 and Tables 4–6. From a statistical point of view, Model 3 with the highest R^2 value (0.46) and the smallest RMSE value (3.41) performs slightly better than Model 1 ($R^2 = 0.44$, RMSE = 3.48) and Model 2 ($R^2 = 0.41$, RMSE = 3.56). R^2 is a statistical measure that represents the proportion of the variance of the dependent variable that's explained by variables in a regression model. RMSE measures the difference between estimated values and actual values. A higher R^2 and a smaller RMSE indicate a better fitted model given the observed data.

Model 1 was constructed to explain how the effect of county FRE on obesity vary with the MHHI and the percentage of RE-minority (Fig. 2 and Table 4). The R^2 value is 0.44, reflecting that the MHHI and the percentage of RE-minority along with three food environment indicators can explain 44% of the variation of obesity rates across counties. More specifically, $\widehat{\alpha_1}(z)$ (-9.03—14.8) is negative if the MHHI of counties is between \$23,925 and \$99,923, \$110,855 and \$120,963 or higher than \$124,515, indicating that one-unit increase of availability can lower $\widehat{\alpha_1}(z_0)$ value in obesity rates for counties which meet any of these conditions. $\widehat{\beta_1}(z)$ (-9.05—1.5) is negative for counties with 68.6%–70% or over 88.5% of RE-minority population, reflecting that one-unit of availability can reduce $\widehat{\beta_1}(z_0)$ value in obesity rates of these counties. $\widehat{\alpha_2}(z)$ (-7.23—9.34) is negative for counties with the MHHI between \$25,785 and \$100,444 or \$110,305—\$120,454, and $\widehat{\beta_2}(z)$ (-17.11–11.99) is negative for counties with RE-minority population of 13.4%–71.8% or higher than 80.7%, reflecting that the increase of healthfulness can reduce obesity rates of these counties. $\widehat{\alpha_3}(z)$ (-22.15–33.32) is positive for counties with the MHHI less than \$25,144 or between \$82,124 and \$103,384, and $\widehat{\beta_3}(z)$ (-71.37—9.56) is positive for all counties no matter of the percentage of RE-minority population, indicating that better accessibility to healthy food stores (smaller accessibility index) can contribute to lower obesity rates for these counties.

Model 2 is run to examine how the MHHI and the percentage of Black population have influenced the association between county FRE and obesity rates (Fig. 3 and Table 5). The R^2 value is 0.41, indicating that the MHHI and the percentage of Black as well as three food environment factors can explain 41% variation of obesity rates. In this model, $\widehat{\alpha_1}(z)$ (-7.73—14.99) is negative for counties with the MHHI between \$25,395 and \$99,653, \$111,055 and \$120,323, or higher than \$124,715, and $\widehat{\beta_1}(z)$ (-6.31—7.58) is negative for counties with 27.2%–36.6%, 39.4%–48.1%, or 68.5%–74.3% Black population, reflecting that better availability is associated with lower obesity rates in these counties. $\widehat{\alpha_2}(z)$ (-8.35—8.64) is negative for counties with the MHHI less than \$100,453 or between \$110,315 and \$122,303, and $\widehat{\beta_2}(z)$ (-13.19—7.71) is negative for counties with less than 14.6%, 19.8%–28.5%, or 33.8%–76.3% of Black population, indicating that one-unit increase of healthfulness can reduce $\widehat{\alpha_2}(z_0)$ and $\widehat{\beta_2}(z_0)$ values in obesity rates for these counties. $\widehat{\alpha_3}(z)$ (-10.11–22.32) is positive for counties with the MHHI less than \$23,404, \$47,954—\$104,814, or \$118,004—\$122,154, and $\widehat{\beta_3}(z)$

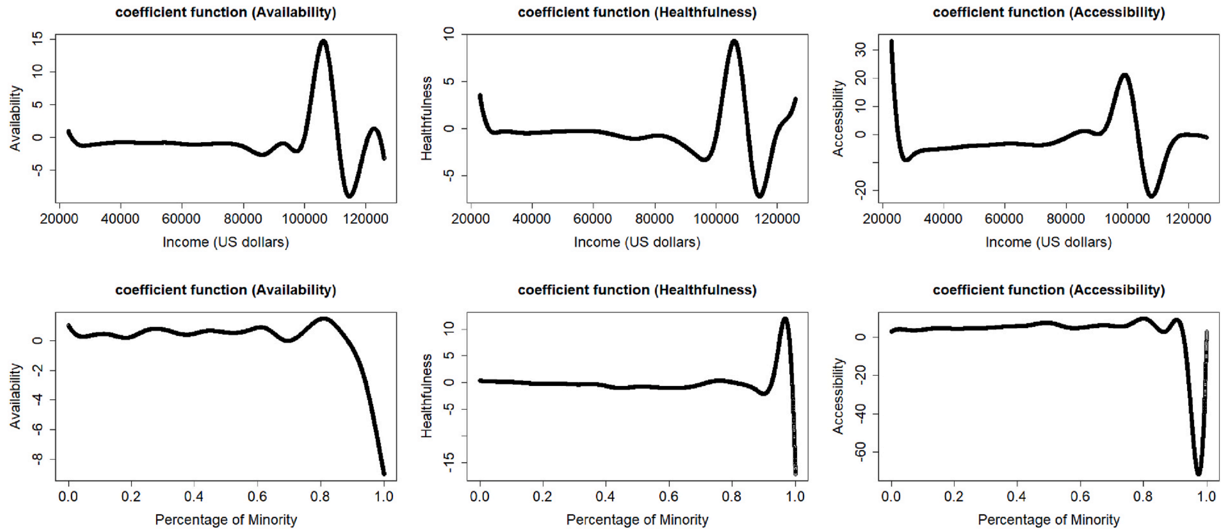

Fig. 2. Varying Coefficient Model of food environment and obesity rate with the changes of county median household income and percentage of RE-minority.

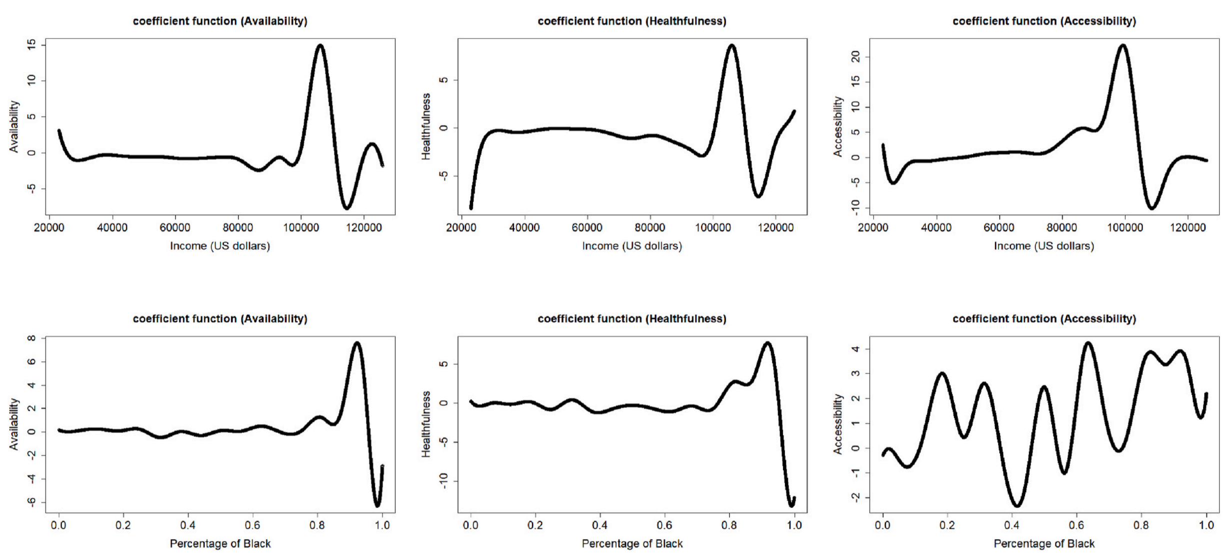

Fig. 3. Varying Coefficient Model of food environment and obesity rate with the changes of county median household income and percentage of Black.

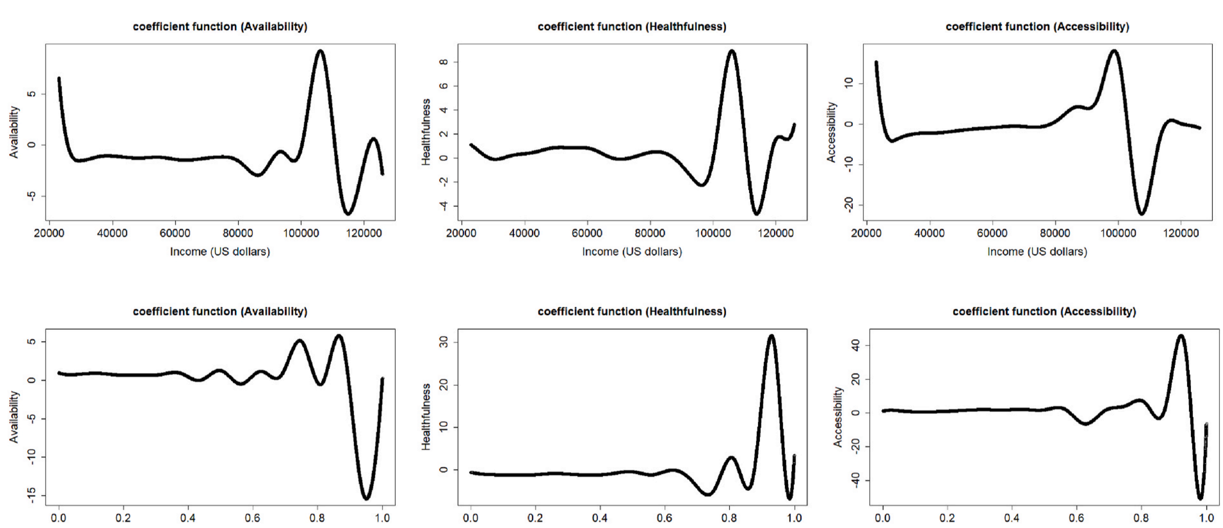

Fig. 4. Varying Coefficient Model of food environment and obesity rate with the changes of county median household income and percentage of Hispanic.

Table 4
Results of model 1.

MHHI	Availability	Healthfulness	Accessibility
	$\widehat{\alpha_1}(z)$	$\widehat{\alpha_2}(z)$	$\widehat{\alpha_3}(z)$
Range	(-9.026, 14.789)	(-7.227, 9.338)	(-22.154, 33.316)
Positive	\$22,894—\$23,924 \$99,924—\$110,854 \$120,694—\$124,514	\$22,894—\$25,784 \$100,444—\$110,304 >\$120,454	\$22,894—\$25,114 \$82,124—\$103,384
Negative	\$23,925—\$99,923 \$110,855—\$120,693 >\$124,515	\$25,785—\$100,443 \$110,305—\$120,453	\$25,115—\$82,123 >\$103,385
% RE-Minority	$\widehat{\beta_1}(z)$	$\widehat{\beta_2}(z)$	$\widehat{\beta_3}(z)$
Range	(-9.023, 1.503)	(-17.107, 11.989)	(-71.370, 9.559)
Positive	<68.8%; 70.1%–88.4%	<13.3%; 71.9%–80.6%;	≤92.6%
Negative	68.9%–70% >88.5%	13.4%–71.8% >80.7%	N/A

Note: MHHI—median household income.

Table 5
Results of model 2.

MHHI	Availability	Healthfulness	Accessibility
	$\widehat{\alpha_1}(z)$	$\widehat{\alpha_2}(z)$	$\widehat{\alpha_3}(z)$
Range	(-7.728, 14.986)	(-8.354, 8.635)	(-10.105, 22.323)
Positive	\$22,894—\$25,394 \$99,654—\$111,054 \$120,324—\$124,714	\$100,454—\$110,314 >\$122,304	\$22,894—\$23,404 \$47,954—\$104,814 \$118,004—\$122,154
Negative	\$25,395—\$99,653 \$111,055—\$120,323 >\$124,715	\$22,894—\$100,453 \$110,315—\$122,303	\$23,405—\$47,953 \$104,815—\$118,003 >\$122,155
% Black	$\widehat{\beta_1}(z)$	$\widehat{\beta_2}(z)$	$\widehat{\beta_3}(z)$
Range	(-6.306, 7.583)	(-13.189, 7.713)	(-2.335, 4.239)
Positive	<27.1%; 36.7–39.3%; 48.2%–68.4%; >74.4%	14.7%–19.7% 28.6%–33.7% >76.4%	<36.3%; 45.9%–53.8%; 58.1%–71.6% >74%
Negative	27.2%–36.6%; 39.4%–48.1% 68.5%–74.3%	<14.6%; 19.8%–28.5%; 33.8%–76.3%	36.4%–45.8%; 53.9%–58%; 71.7%–73.9%

Note: MHHI—median household income.

(-2.34—4.24) is positive for counties with less than 36.3%, 45.9%–53.8%, 58.1%–71.7%, or more than 74% of Black population, reflecting that better accessibility to healthy food stores leads to lower obesity rates for these counties.

Model 3 is utilized to understand how influences of FREs on obesity rates vary with the county MHHI and the percentage of Hispanic (Fig. 4 and Table 6). The MHHI and the percentage of Hispanic as well as three food environment factors can explain 46% of variation of obesity rates ($R^2 = 0.46$). In this model, $\widehat{\alpha_1}(z)$ (-6.74—9.23) is negative for counties with the MHHI between \$25,724—\$100,273, \$110,745—\$121,653, or higher than \$124,324, indicating that better county food outlet availability leads to lower obesity rates for any of these counties. While $\widehat{\beta_1}(z)$ (-15.43—5.82) is negative for counties with 42.7%–43.6%, 54%–58.4%, 79.6%–82.9%, or higher than 89.5% Hispanic population, suggesting that better availability is associated with lower obesity rates in these

Table 6
Results of model 3.

MHHI	Availability	Healthfulness	Accessibility
	$\widehat{\alpha_1}(z)$	$\widehat{\alpha_2}(z)$	$\widehat{\alpha_3}(z)$
Range	(-6.740, 9.233)	(-4.648, 8.933)	(-22.186, 18.103)
Positive	<\$25,724; \$100,274—\$110,744; \$121,654—\$124,324	<\$28,724; \$33,014—\$68,004; \$73,354—\$87,494; \$100,044—\$110,734; >\$118,273	<\$25,234; \$78,474—\$102,904; \$115,104—\$120,464
Negative	\$25,724—\$100,273; \$110,745—\$121,653; >\$124,324	\$28,725—\$33,013; \$68,005—\$73,353 \$87,495—\$100,043 \$110,735—\$118,273	\$25,235—\$78,473 \$102,905—\$115,103 >\$120,464
% Hispanic	$\widehat{\beta_1}(z)$	$\widehat{\beta_2}(z)$	$\widehat{\beta_3}(z)$
Range	(-15.427, 5.822)	(-6.781, 31.565)	(-50.798, 45.801)
Positive	<42.7%; 43.7%–53.9%; 58.5%–79.5%; 83.0%–89.4%	77.9%–82.8%; 87.6%–97.1%	<57.8%; 67.6%–83.3%; 86.7%–95.3%
Negative	42.7%–43.6%; 54.0%–58.4%; 79.6%–82.9%; >89.5%	<77.9%; 82.9%–87.5%	57.9%–67.5%; 83.4%–86.6%; 83.5%–85.9%

Note: MHHI—median household income.

counties. $\widehat{\alpha_2}(z)$ (-4.65—8.93) is negative for counties with the MHHI between \$28,725 and \$33,013, \$68,005 and \$73,353, \$87,495 and \$100,043, or \$110,735 and \$118,273, and $\widehat{\beta_2}(z)$ (-6.78—31.56) is negative for counties with less than 77.9% or 82.9%–87.5% of Hispanic population, reflecting that healthier FRE can lower county obesity rates in these counties. $\widehat{\alpha_3}(z)$ (-22.19—18.1) is positive for counties with the MHHI below \$25,234, \$78,474—\$102,904, or \$115,104—\$120,464, and $\widehat{\beta_3}(z)$ (-50.79—45.8) is positive for counties with less than 57.8%, 67.6%–83.3%, or more than 86.7% Hispanic population, indicating that better accessibility to healthy food stores is associated with lower county obesity rates in these counties.

4. Discussion

This research assesses county FRE from the perspectives of availability, healthfulness, and accessibility to further examine the FRE and obesity association in relation to socioeconomic disparities. Despite that unequal FRE has been considered as one of the crucial predictors of area-based variations in obesity, there is no clear conclusion due to inconsistent findings in the FRE and obesity relationship (Ahern et al., 2011; Jones-Smith et al., 2013; Singleton et al., 2016). A common challenge in this topic is the diverse measures of FRE because of the diversities of data sources of food stores, methods for classifying food outlets, and choices of FRE indicators (Casey et al., 2014; Cobb et al., 2015; Wilkins et al., 2019). To overcome the challenge in literature, this study utilizes a reliable secondary dataset of food outlets collected and classified by the USDA which comprises of multiple types of food stores, restaurants as well as SNAP stores, and assesses FRE with multiple measures including density (availability), ratio (healthfulness), and proximity (accessibility). With the multifaceted FRE measurements, our results reveal the following major findings.

First, our findings confirm that county obesity rates vary greatly with racial/ethnic compositions and income levels, which are generally in line with previous research (Michimi & Wimberly, 2010; Bell et al., 2019; Scheinker et al., 2019; Yu et al., 2020). The highest obesity rates display in non-metro counties within the Deep South where low-income Black population concentrates. In contrast, lowest obesity rates show in counties in the West and the Northeast where have a low poverty rate (Fig. 1). The racial and income disparities in FRE are able to explain over 40% of the variation in county obesity rates. The unexplained proportion could be further explained by other determinants of obesity, such as local culture, dietary structure, physical environment, climatic conditions, etc. (Michimi & Wimberly, 2010; Xu et al., 2017). As a culture identity, the geographic patterns of diets have been recognized and mapped by scholars (Shanahan, 2002; Shortridge, 2003). For example, the consumptions of fruit and vegetable were high in West Coast and the Northeast but very low in the Deep South and the Great Plains (Michimi & Wimberly, 2010). In addition, recent empirical research has found that local physical environment and extreme weather affect residents' engagement in physical activity and increase the risk of being obese (Von Hippel & Benson, 2014; Xu et al., 2017), although energy expenditure is not the focus of our study.

Second, socioeconomic disparities in FRE exist across the U.S. counties, while multifaceted FRE measurements display very complex patterns in relation to county racial/ethnic compositions and income levels. In general, high-income counties with low percentages of RE-minority populations have better availability, healthfulness, and accessibility of FRE compared to those with low-income and/or high percentages of RE-minority populations. While diverse FRE measurements show various patterns, for example, more food stores in low-income counties but more restaurants in high-income counties. Healthfulness (ratio) indicators exhibit relatively consistent patterns, namely high-income counties with a lower percentage of RE-minority populations have higher ratios of healthy to unhealthy food stores and full-service to fast food restaurants generally. When focusing on SNAP stores, they are more available in low-income counties with large RE-minority populations particularly a high percentage of Black population because the SNAP program was initiated for low-income families. While high-income counties with low percentages of RE-minority populations still have better access to healthy SNAP stores. This is generally consistent with the previous findings that areas with high percentage of low-income SNAP participants (Racine et al., 2018) and/or primarily Black (Rigby et al., 2012) are more accessible to limited-variety small or convenience SNAP stores but have less full-variety SNAP stores (e.g., supermarkets). Furthermore, the inconsistent patterns of various FRE indicators reflect narrowing inequalities in the availability of FRE due to the progressive ubiquity of unhealthy food outlets but highlight the persisting disparities in the healthfulness of FRE (Winkler et al., 2019), which therefore stresses the necessity of using multifaceted measurements to assess FRE (Herforth & Ahmed, 2015).

Third, the effect of county FRE on obesity rates varies greatly with county income levels and racial/ethnic compositions. Among three composite FRE indexes, the healthfulness index exhibits relatively consistent relationships with county obesity rates as the MHHI changes while the racial/ethnic factor is controlled or vice versa. Healthier FRE contributes to lower county obesity rates in almost all counties except dozens of counties with extremely high or low MHHI. Similar patterns were observed for most counties with less than 70% of RE-minority, Black, or Hispanic populations. Regarding the composite index of availability, better availability of food outlets is beneficial to lower county obesity rates in the majority counties with the MHHI between around 25 thousand and 90 thousand dollars, while an opposite trend was observed in those extremely poor or wealthy counties. However, the availability and obesity associations fluctuate significantly with varying percentages of RE-minority, Black, and Hispanic populations. For the accessibility index, better accessibility to healthy food stores is associated with high county obese rates for most counties with the MHHI between around 25 thousand and 82 thousand dollars or over 100 thousand dollars. While opposite patterns were found between accessibility and obesity rates for most counties with less than around 70% of RE-minority, Black, and Hispanic populations. These findings echo previous studies that suggest the ratio of mixed food outlets (healthfulness) a more consistent predictor of obesity (Polsky et al., Feng, et al., 2018) compared to those FRE measures with singular food outlet types (e.g., fast food, supermarket) (Fan & Zhang, 1999; Cobb et al., 2015; Gamba et al., 2015). Our analysis also aligns with the literature suggesting that county-level economic and racial/ethnic factors play an essential role in shaping geographic disparities in obesity rates due to their influences on FRE (Singleton et al., 2016; Rummo et al., 2020) and associations with individuals' risk of being obese (Bjornstrom, 2011; Yu et al., 2020). The varying and complex relationships of county-level economic conditions and racial/ethnic disparities and diverse FRE measurements might have both caused previous conflicting results which indicate little or inconsistent association between FRE and obesity (Wilkins et al., 2019).

5. Conclusion

In summary, with data extracted from the USDA, this study contributes to the literature by assessing county-level FRE with multifaceted measurements and disentangling how county income levels and racial/ethnic compositions influence geographic variations in obesity rates via uneven FRE. This research also has practical and policy implications. Our analysis extends the evidence base for economic and racial/ethnic disparities in FRE and obesity. The findings indicate an urgent need for policymakers and planners to increase their awareness of persisting inequalities in the healthfulness of FRE and make every effort to better allocate resources. The government can use the information to encourage or incentivize private sectors to open more healthy food outlets particularly healthy SNAP stores in low-income and RE-minority communities. Furthermore, given the significant influences of county

Table 7
Racial/ethnic vs. income disparities of obesity rates and food retail environments.

	% Black		% Hispanic		% RE-Minority		MHHI		
	Low	High	Low	High	Low	High	Low	High	Average
Obesity rate (%)	30.15	32.76***	31.72	28.23***	30.4	31.64***	32.23	29.02***	30.85
Availability									
Store count	0.99	0.93***	1	0.9***	1.01	0.92***	1.02	0.91***	0.98
Restaurant count	1.44	1.2***	1.34	1.48***	1.45	1.25***	1.29	1.5***	1.38
SNAP count	0.75	0.91***	0.82	0.71***	0.75	0.86***	0.91	0.64***	0.79
Healthfulness									
Store ratio	0.57	0.42***	0.53	0.54***	0.58	0.45***	0.5	0.57***	0.53
Restaurant ratio	1.58	1.02***	1.49	1.28***	1.61	1.11***	1.36	1.523***	1.43
SNAP ratio	0.3	0.26***	0.28	0.33***	0.3	0.28***	0.28	0.31***	0.29
Accessibility									
PWD to healthy stores (m)	15,415	8,360***	13,779	12,719***	15,352	10,300***	13,999	12871*	13,515

Note:
MHHI—median household income; PWD—population weighted distance.
* Denote p values of two sample *t*-test, ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.
Cutoffs for low and high groups are the averages of the data: Black –8.83%; Hispanic–8.33%; RE-minority–16.72%; MHHI–$48,469.

MHHI and racial/ethnic compositions on the FRE and obesity association, governments and other stakeholders should differentiate and tailor relevant policies to fit local situations of counties.

This study has a few limitations that need to be considered. First, given the large study area of this research, the multifaceted measurements in analysis were only based on the types of food outlets while excluding such factors as food prices and food categories provided in stores. Second, county-level data were used to examine the influences of FRE disparities on area obesity rates. This relatively large scale could hide internal variations of FRE as well as income disparities and racial segregation within a county. Future studies that incorporate in-store information and conduct at a finer scale (e.g., neighborhood) would provide new findings on this topic. Third, besides the national levels of racial/ethnic compositions and MHHI, we also used the averages of these factors in the dataset as cutoffs to classify counties into high and low groups. Despite similar results were obtained with these two types of cutoffs (Tables 2 and 7), the selection of cutoffs merits further justification and investigation in future. Lastly, the VCMs are only able to illustrate the contribution of variables by additive varying coefficient functions, leading to a specific model application. The future work would be focusing on a more complex varying coefficient function structure including the interactions among different Zs, such as MHHI and the percentages of minority, Black, and Hispanic populations.

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Ethical standards disclosure

N/A.

Declaration of competing interest

The authors declare no conflict of interest.

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