경제학석사 학위논문

Assessing the Impact of COVID-19 on Disparities in Food Accessibility using Spatial Models

- The Case of New York City -

코로나19가 식품접근성 격차에 미친 영향에 관한 연구

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Sung Eun Sally Oh의 경제학석사 학위논문을 인준함

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Abstract

Assessing the Impact of COVID-19 on Disparities in Food Accessibility using Spatial Models

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Differential access to healthy food has long been a critical public health issue as it perpetuates health disparities among people of different socioeconomic characteristics. Inequities in food access have been further exacerbated by COVID-19, which not only disrupted food production at global levels but also restricted access to food retail venues at neighborhood levels. Vulnerabilities in the food system that have been exposed by COVID-19 highlights a need for equitable and resilient food systems that can withstand shocks.

To inform equitable and resilient food systems planning policies, this study examined the association between food accessibility and neighborhood characteristics in New York City, and analyzed the changes in their association before and during the pandemic, in years 2019 and 2020. Based on 5,712 census block groups, the study first measured food accessibility of each block group by the count of accessible supermarkets and large grocery stores within its 1km-network service area. Then, the food accessibility measure was modeled with socioeconomic and built environment factors using spatial econometric models and geographically weighted regression to appropriately adjust for spatial effects that are present in the food accessibility data.

The results revealed that regression models that do not account for spatial effects in food accessibility could over- or underestimate its association with racial/ethnic and income variables. In detail, the results showed mostly negative association between food accessibility and the percentage of Black or African Americans and racial/ethnic diversity, whereas a positive association was found with the percentage of Hispanic or Latinx origin population. Its association with income became negative in 2020, which diverges from past findings on food accessibility and income levels. Spatially varying relationship corroborated findings on local spillover effects that may have been in play.

Conclusively, results of this study not only emphasize the need to consider spatial effects in studies of food accessibility but also imply that improving network connectivity and promotion of smaller scale food stores may contribute to developing equitable and resilient food systems policy.

Keywords: Food accessibility, COVID-19, local spillover effects
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1. Introduction

With plausible links to dietary health risks such as obesity, diabetes, and heart diseases (Satia, 2009; Hilmers et al., 2012; Petersen et al., 2019), the neighborhood food environment and accessibility have been studied commonly to understand food consumption patterns and nutritional health. Literature on food deserts – areas with poor access to affordable and healthy food – and social determinants of health have gauged the focus of food environment studies on differential accessibility to nutritious food among socioeconomically disadvantaged areas. In the U.S., where diet-related health risks are among the leading causes of death (Murphy et al., 2021), food environments and accessibility have been studied in close relationship with racial/ethnic and economic disparities that shape neighborhood characteristics and dietary patterns (Arcaya et al., 2016), much of which suggest the inequitable existence of food deserts in low-income and minority race neighborhoods (Beaulac et al., 2009).

Since the COVID-19 pandemic, vulnerabilities and inequities in food accessibility have been further exacerbated due to disruptions in all stages of the global food system from production to consumption (Fig. 1). As lower availability of food supply, volatile prices of food, and limited access to food services have been listed as potential food environment disruptions instigated by the pandemic (UNSCN, 2020; Béné, 2020), New York City (NYC), one of the major metropolitan areas in

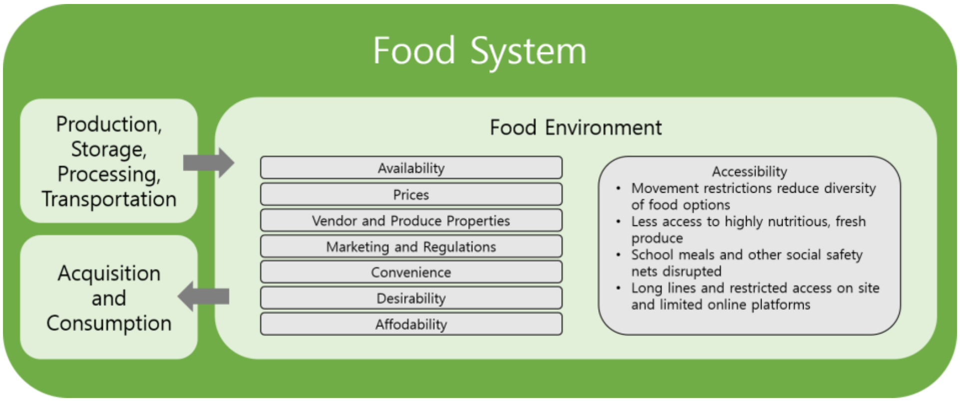

Figure 1 Impact of COVID-19 on food accessibility, redesigned from UNSCN (2018)

the U.S. to have undergone mass COVID-19 outbreaks at the onset of the pandemic, recorded increasing reports of disruptions in food accessibility and prices, especially from racial/ethnic minority residents (Crossa et al., 2021). The weaknesses in the food system that have been exposed by the pandemic reinforce the need for a food system that is not only equitable but also resilient to unforeseen shocks.

To inform equitable and resilient food systems planning policies, the primary objective of this study is to assess the association between neighborhood characteristics and food accessibility with and without the presence of shocks through the case of New York City in the years 2019 and 2020. Unlike most studies that have modeled the association between food accessibility and the socioeconomic and physical characteristics of neighborhoods, this study will apply a spatial modeling approach to appropriately consider the spatial effects that influence the dynamics among food accessibility, race/ethnicity, and wealth. In detail, this study will explore how to define and understand food accessibility, analyze its association with race/ethnicity and income while controlling for other socioeconomic and built environment factors, and compare the differences in the association before and during the COVID-19 pandemic using various spatial models.

Section 2 of this article will review studies on the linkage between health and the food environment, food access disparities and resilience, and spatial modeling methods used to analyze these factors. Then, Section 3 will discuss the data sources and methodology, focusing on spatial model specification. Following the results presented in Section 4, Section 5 will conclude with policy implications and suggestions for future research.

2. Literature Review

2.1 Food Accessibility and Health

The neighborhood food environment has been studied frequently across multiple disciplines, including public health, nutrition, geography, and urban and regional planning. The reason for this interdisciplinary approach is based on the intertwining of individual, household, and environmental factors that affect food purchasing and consumption, food choices and access, and nutritional health outcomes (Committee on Examination of the Adequacy of Food Resources and SNAP Allotments, 2013). Glanz et al. (2005) first conceptualized the physical realm of the food environment by introducing the 'community food environment' at the neighborhood scale and the 'consumer food environment' at the in-store scale. Though other studies have proposed an expansion of this concept to encompass economic, policy, and sociocultural conditions that influence food choices and nutritional health (Swinburn et al., 2013), Glanz et al.'s (2005) conceptualization of the food environment and their evaluation based on Nutritional Environment Measures Survey (NEMS) (Glanz et al., 2017) led much of the empirical studies assessing the health implications of different food retailers.

Following this framework, Cannuscio et al. (2013) conducted a Nutritional Environment Measures Survey in Stores (NEMS-S) of 373 stores in southwestern Philadelphia, U.S., and found that corner and convenience stores had the lowest average NEMS-S scores and that residents were more likely to shop at stores with higher NEMS-S score than those closest to home. For a more detailed understanding of healthy food options at various food retailer types, Cohen et al. (2002) conducted a survey of food availability based on the US Department of Agriculture's (USDA) Thrifty Food Plan (TFP) at 2,400 authorized SNAP retailers, encompassing supermarkets, large grocery stores, small grocery stores, convenience stores, grocery-gas stations, specialty stores, and others. This survey revealed that supermarkets and large grocery stores offered the highest share of the TFP market basket of food of all store types considered (Cohen et al., 2002). In studies without in-person audits, food retailer data categorized by business classification systems were often used (Moore and Diex Roux, 2006; Raja et al., 2008; Kuai and Zhao, 2017; Peng and Kaza, 2019). These empirical studies suggest that better access to large food retailers with more healthful food options is positively associated with better dietary health outcomes, whereas a lack of access to these retailer types is associated with poorer dietary health (Black et al., 2010).

2.2 Food Accessibility and Neighborhood Characteristics

Since household food consumptions encompass money and time expenditure that include both direct prices of food and indirect prices of time spent purchasing, preparing, and consuming food (Becker, 1965), factors constraining financial and time resources for households have been studied in conjunction with food accessibility and associated health outcomes. Typically, these constraints are categorized as socioeconomic, demographic, and built environment factors that characterize households and their environmental surroundings at a neighborhood level.

Moore and Diez Roux (2006) investigated the association between the availability of food and liquor stores and the neighborhood racial/ethnic composition and other socioeconomic characteristics and found a difference in accessibility to grocery stores across predominantly minority race/ethnicity, racially/ethnically mixed, and White census tracts in three American states. In detail, whereas grocery stores were more prevalent in predominantly minority race/ethnicity and racially mixed neighborhoods, supermarkets were less prevalent in predominantly White neighborhoods. Considering income level and race/ethnicity, lower-income and non-White neighborhoods had fewer stores, except liquor stores, than higher-income neighborhoods. Similar findings of a negative association between the share of racial/ethnic minority population and income level were observed by Raja et al. (2008), Ghirardelli et al. (2010), Kwate et al. (2013), and more across the U.S.

In contrast, Elbel et al.'s (2019) study of food environments around homes and schools of NYC public school students found that, regardless of poverty status, students of minority race/ethnicity – Black or African American, Hispanic or Latinx origin, and Asian – lived and attended schools closer to all food retailer types; in fact, non-low-income students of minority race/ethnicity lived and attended schools closer to corner stores and supermarkets than did White students. Further, Galvez et al.'s (2008) study of access to different types of food stores among predominantly Black and Latinx populations in NYC found that predominantly Latinx census blocks had access to more food retailers of all types compared to predominantly Black or racially mixed census blocks, suggesting that inequities exist even within minority race/ethnicity groups.

Peng and Kaza (2019) assessed the association between supermarket and convenience store accessibility and household purchasing behavior and included several built environment factors in the model. As a result, a negative association between destination diversity and vegetable purchases and a positive association between street connectivity and fruit purchases were found. Such findings expanded past studies on spatial shopping behaviors (Ingene, 1984) and retail location choices (Öner, 2018) by contextualizing the built environment and regional analyses with food accessibility issues.

2.3 Spatial Modeling for Neighborhood Effects

In a review of statistical methodologies employed in studies on access to food retailers, Lamb et al. (2015) highlighted the importance of using spatial analysis techniques since many of these studies utilize spatial data when measuring accessibility, whether it pertains to the count of or distant to food retailers. Smiley et al. (2010) used spatial lag and error models to investigate the spatial clustering of health-related resources, like supermarkets and fresh produce stores, in NYC. Using this approach, Smiley et al. confirmed a negative association between the percentage of Black or African American population and resource density, which was not always statistically significant. On the other hand, Wang et al. (2016) found a positive association between the access to supermarkets and grocery stores and the percentage of minority race/ethnic population in their study on two Canadian cities using spatial lag and error models. Spatial models for local spillover effects have been applied to studies of housing prices (Gong et al., 2020), regional trade (Özyurt and Daumal, 2011), and transportation accessibility (Laviolette et al, 2021), but not to those of food accessibility.

Others have used geographically weighted regression (GWR) or a combination of spatial econometric models and GWR to observe the impact of spatial effects and spatial variability. Kuai and Zhao (2017) used GWR to model the relationship between healthy food access and socioeconomic characteristics, such as race, gender, education level, renter housing occupation rate, and poverty rate in Baton Rouge, Louisiana. Through this approach, Kuai and Zhao (2017) found that suburban areas at the periphery of urban regions have the highest access to healthy food. A similar approach was used by Jang and Kim (2018) to examine the intersectional effects of race and income on access to different food stores in the Detroit metropolitan area. Oshan et al. (2020) modeled obesity determinants using GWR and multiscale GWR (MGWR) and analyzed the impact of socioeconomic factors at local, regional, and global levels. Rybarczyk et al. (2019) used both the spatial lag model and GWR to examine the relationship between access to ethnic food outlets by travel mode and the neighborhood socioeconomic and built environment characteristics in Michigan.

2.4 Food Accessibility Resilience

The use of spatial statistical methods has been more limited in studies of food accessibility resilience after disruptive events. Following Hurricane Katrina, Rose et al. (2011) examined the impact of the natural disaster on supermarket availability in neighborhoods of various racial/ethnic compositions in New Orleans, Louisiana. Using Poisson regression methods, a negative association between supermarket access and share of Black or African American population and worsened accessibility in predominantly Black census tracts. Similarly, Kolak et al. (2018) assessed the change in supermarket accessibility from 2007 to 2014 following the Great Economic Recession in Chicago, Illinois. Through spatial analysis of Local

Indicator of Spatial Association (LISA), Kolak et al. (2018) found that higher access to supermarkets persisted in predominantly White neighborhoods whereas predominantly Black, lower-income, and less educated neighborhoods persistently had low access to supermarkets.

Following the COVID-19 pandemic, studies on its impact on the food supply chain, food systems policy, and perceived food environments (Aday and Aday, 2020; Dudek and Spiewak, 2022; O'Meara et al., 2022) have been conducted. As studies on the link between COVID-19 and food systems continue, studies that provide an in-depth and diverse understanding of local food system resilience are in dire need to better prepare for unforeseen stressors related to environmental, economic, and socio-political shocks (Béné, 2020). This study will contribute to this need by using spatial models to assess the relationship between food retailer accessibility with socioeconomic, demographic, and built environment factors and compare any changes before and during the COVID-19 pandemic to shed light on the importance of developing an equitable and resilient food accessibility strategy.

3. Data and Methodology

3.1 Study Area

The study area is NYC, where many past studies on food access in the context of diverse urban areas have been based. NYC is comprised of five boroughs (counties), which include Brooklyn (Kings County), the Bronx (Bronx County), Manhattan (New York County), Queens (Queens County), and Staten Island (Richmond County), and is the most populous city in the U.S. with 8.2 million residents, with Brooklyn and Queens as the most populous boroughs. Citywide, the non-Hispanic or Latinx (HL) White population accounts for 33.3 percent of the entire population, followed by non-HL Black or African Americans (AA) at 22.8 percent, people of HL origin at 28.6 percent, Asians at 12.6 percent, and other categories at 2.8 percent (NYC Dept of Planning).[1] Economically, the median household income from 2015 to 2019 was $63,998, which was higher than the national median household income of $62,843 (U.S. Census Bureau, 2021). NYC, though highly diverse in demographics, is highly segregated with the agglomeration of racial/ethnic enclaves and by income level throughout the city.

Commonly used units of analysis for food environments include zip code tabulation area, census tract, and census block groups to resemble a neighborhood scale. In the context of NYC, where the population and area size of these units vary widely across the five boroughs, the census block group was selected as the unit of analysis to observe micro-level neighborhood effects. Based on the 2010 U.S. Census and New York State map of census block groups, 6,494 block groups were identified in NYC. However, 5,712 block groups remained after water areas and block groups without certain household-level Census data were removed. Figure 2 shows the distribution of the share of Black or African American, Hispanic or Latinx origin, race entropy, and median household income by block group in NYC.

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[1] 2020 U.S. Census indicates an increase of city residents to 8.8 million people. Demographically, the non-HL White population accounts for 30.9 percent of the entire population, followed by people of HL origin at 28.3 percent, non-HL AA at 20.2 percent, Asians at 15.6 percent, and other categories at 5 percent (U.S. Census Bureau, 2021).

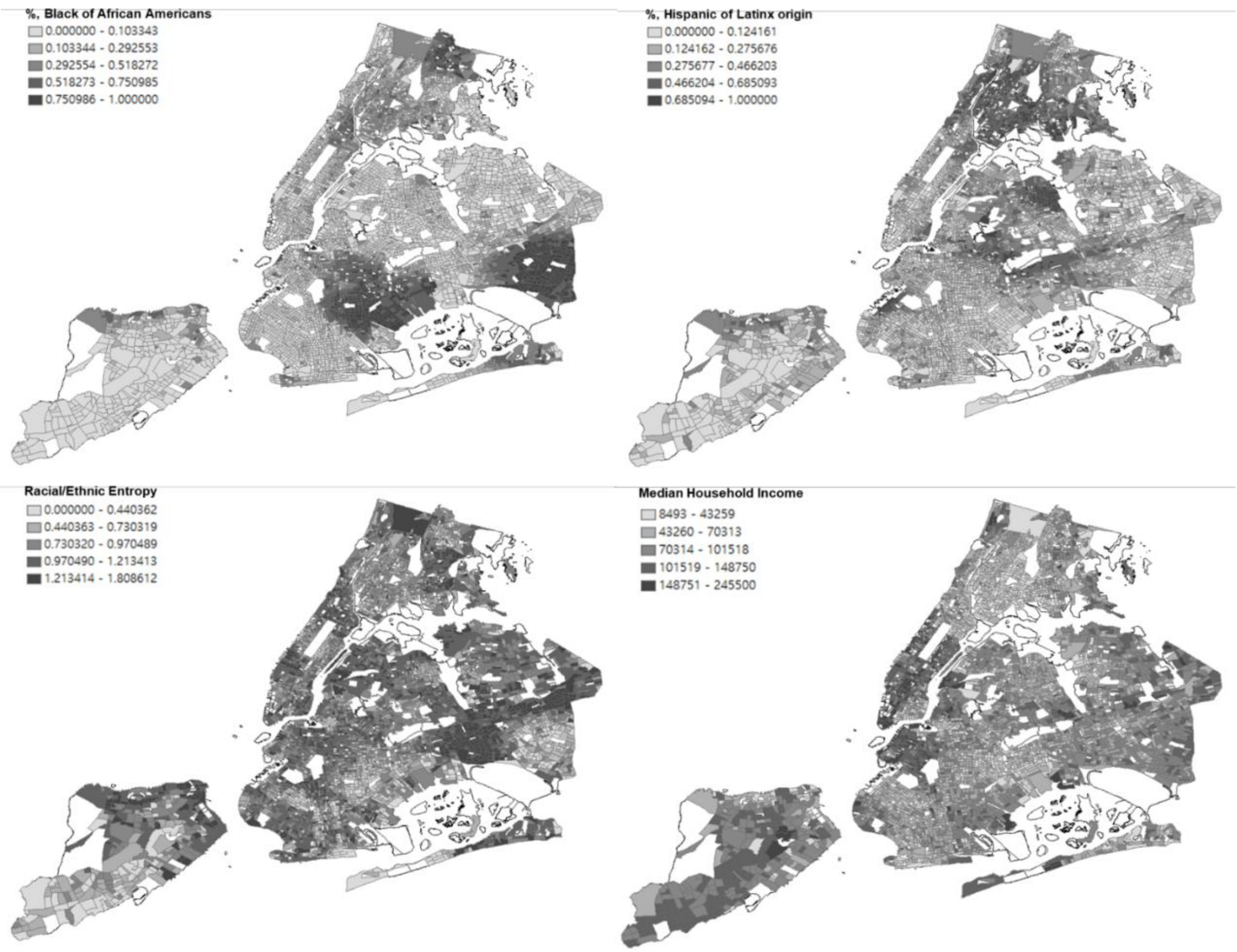

Figure 2 Map of New York City block groups by race/ethnicity and income characteristics

3.2 Data

Table 1 shows the selected variables that were used in this study. The dependent variable is the count of large food retailers, supermarkets and large grocery stores, based on the 2019 and 2020 Reference USA business data, a monthly-updated commercial database that provides detailed information on registered businesses. Following Ohri-Vachaspati et al.'s (2011) guidance on using commercial food outlet databases for food environment studies, the study first obtained data of supermarkets and large grocery stores[2] in 2019 and 2020, which were NYC businesses classified under Standard Industrial Code (SIC) 541105 for Retail Grocers with sales volume above US$ 1 million.[3] Though store classification based on the number of employees is also commonly used (US DHHS and CDC, 2009), such method was not selected due to its higher chances of misclassification (Ohri-Vachaspati et al., 2011). Second, a name recognition scan and google map search was conducted to ensure data validity. Third, service area analysis was conducted by geocoding all selected retailers and obtaining the number of accessible stores within a 1km-street network radius from each block group centroid using ArcGIS. Though 1km, 3km, and 5km have been used in a similar study (Peng and Kaza, 2019), a smaller distance threshold was used to reflect a finer neighborhood scale. The block group polygon data and street network data were obtained from the NYC Department of City Planning Open Data and the New York State GIS Program Office.

Key independent variables are largely classified into socioeconomic and demographic data from the 2019 American Community Survey (ACS) and built environment data from U.S. Environmental Protection Agency's Smart Location Database (SLD). First, race/ethnicity-related variables include the percentage of non-Hispanic and Latinx Black or African American population (AA), the

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[2] Based on Ohri-Vachaspati et al., (2011), supermarkets and grocery stores were considered to sell healthy food items, meaning that they were likely to carry at least three of the four food groupings: five or more fresh fruits, five or more fresh vegetables, fresh or frozen meats, and skim or low-fat milk.

[3] SIC code 541105 pertains to retail grocers like supermarkets and grocery stores, and excludes convenience stores, ethnic foods, health foods, and more. Also, superstores like Walmart, Target, and Costco that also sell food products are excluded as they are classified under SIC codes 5311- for department stores, including wholesale clubs.

Table 1 Variables and Sources

Category	Variable	Variable Description	Source
Dependent	Store count	Number of supermarkets and large grocery stores (SIC code: 541105) within 1km street network service area of census block group	Reference USA (2019, 2020)
Socio-demographic	Total pop	Ln (Total population of block group)	US Census American Community Survey (2019)
	%, AA	Non-HL Black or African American population/Total Pop	
	%, HL	Hispanic or Latinx origin population/Total pop	
	Race entropy	Entropy index of all racial/ethnic groups using Theil's index*	
	%, Elderly	Population of age 65 and older/Total pop	
	%, Family HH	Family households / Total households in block group	
Economic	Med Inc	Ln (Median household income of block group)	
Built Environment	Store entropy	Entropy index of all food retailers by type (supermarkets, large and small grocery stores, convenience stores) in a block group	Reference USA, (2019, 2020)
	LU entropy	Entropy index of five-tier employment sectors (office, retail, industrial, service, entertainment) and residential land-use areas	US EPA Smart Location Database (2021)**
	Network density	Network density in terms of facility miles of multi-modal links per square mile	
	Total LA	Total geometric area of each block group	

* Theil's H or the multigroup entropy index was calculated as $\boldsymbol{h_i = -\sum_{j=1}^{k} p_{ij}\, ln(p_{ij})}$; where k=number of groups, j= group, p_{ij} =proportion of group j in area i
**These variables use data from the 2021 EPA SLD, but were derived from other SLD variables based on prior years' data sources that were available, such as the 2017 Census Longitudinal Employer-Household Dynamics, 2018 Census American Community Survey, 2018 HERE Maps, and more. See SLD's Technical Documentation and User Guide (2021) for more details.

percentage of the population with Hispanic or Latinx origin (HL), and a Theil's index of racial/ethnic diversity (race entropy). in which higher values indicate a greater presence of a diverse racial/ethnic mix. Though the proportion of other racial/ethnic groups like non-Hispanic and Latinx White, Asian, multiple races, other, and non-White groups were considered, they were not selected due to multicollinearity issues. Additionally, block group-level median household income was used as a proxy for economic status. Although poverty rate or unemployment rate have been used commonly in past studies (Deller et al., 2015; Kuai and Zhao, 2017; Elbel et al., 2019), they were not selected due to data availability at block group-level and multicollinearity issues 4. Multicollinearity issues also arose when variables based on income groups – the proportion of households with income less than $35,000 or $40,000, between $40,000 and $125,000, and above $125,000 – were used, so the logarithm of median household income was selected.

The percentage of the population over the age of 65 and the percentage of family households were selected as control variables since other studies have demonstrated that senior population and household types are associated with food accessibility depending on the store type (Wang et al., 2016). Further, built environment factors were also controlled since store locations and retail environments are heavily influenced by urban design and land-use zoning regulations (Rybarczyk et al., 2019). As a proxy for land-use mix, employment and household entropy, in which five-tier employment categories and residential areas are counted, was used. As a proxy for street connectivity relating to automobiles and pedestrians, multi-modal network density was used. Finally, using the store data obtained from Reference USA, Theil's index of all food retailer types, such as supermarkets, large grocery stores, small grocery stores, and convenience stores, was computed to better reflect the retail environment of each block group.

3.3 Spatial Modeling Methodology

3.3.1 Theoretical Considerations for a Spatial Modeling Approach

In their study of neighborhood determinants of car ownership, Laviolette et al. (2021) described three possible causes of spatial dependence in car ownership data, which could be extended to understand spatial dependence in food accessibility. First, it is highly likely that spatial continuity of observed units. In NYC, block groups can be as small as a single block to be as big as a census tract due to varying population density. As such, the unit of analysis for this study is likely to be smaller than the scale at which the spatial layout of food retailers and food accessibility varies despite its appropriateness for studying neighborhood-level effects.

Second, spatial autocorrelation among observed and unobserved factors of food accessibility may exist. Jang and Kim (2018) explained that economies of scale and agglomeration in the retail industry lead food retailers to be clustered in particular areas with a large consumer base and purchasing power. Such studies on agglomeration economies and retail location choices suggest that large food retailers are capable of providing a wider selection of food at lower prices due to economies of scale and locate more densely in higher-income areas (Jang and Kim, 2018; Öner, 2018). In contrast, smaller stores would be more likely to offer a narrower selection of food at possibly higher price levels and disperse across lower-income areas. As such, food retailer location is likely to be influenced by the observable built environment and neighborhood consumer characteristics as well as their unobservable preferences. Since households select neighborhoods that fit their preferences and economic constraints, the distribution of consumer characteristics is likely to be non-random and spatially autocorrelated (Laviolette et al., 2021).

Third, spatial spillover effects in food accessibility need to be considered. The spatial spillover effect is the change in the dependent variable of neighboring units as a result of a change in the observed unit (Elhorst, 2014). In the context of food accessibility, the built environment factors, household characteristics, and consumer preferences are likely to be related to the number of accessible food retailers not only within an observed block group but also across nearby block groups due to varying household food shopping patterns, street connectivity, and zoning criteria. Though food accessibility has been spatially modeled in the past (Larsen and Gilliland, 2008; Smiley et al., 2010; Wang et al., 2016; Kuai and Zhao, 2017; Helbich et al., 2017; Rybarczyk et al., 2019), incorporation of their spatial spillover effects in the study scope has been limited. As such, modeling for spillover effects in the context of spatial dependence in food accessibility will be applied in this study.

Considering these three possible causes of spatial dependence and the endemic spatial effects in spatially referenced data, models that do not consider spatial dependence, such as ordinary least squares (OLS) and Poisson, could result in biased and inconsistent estimates of the relationship between food accessibility and its determinants (Fotheringham, Brunsdon, and Charlton, 2002; Elhorst, 2014). As such, this study will use spatial econometric models and models that allow for

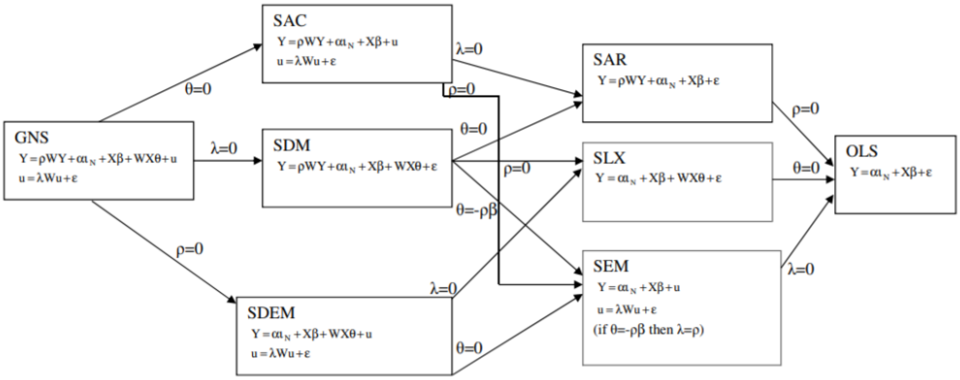

Figure 3 Comparison of different spatial econometric model specification
Note: From "On spatial econometric models, spillover effects, and W," by J.P. Elhorst and S.H. Vega, 2013, 53rd Congress of the European Regional Science Association, p. 24

spatial variation in parametric estimates to improve model specifications (Florax and Nijkamp, 2003).

3.3.2 Spatial Econometric Model Specification

Figure 3 maps how spatial interaction terms are applied in different spatial econometric models. Details about each of these models can be found in Elhorst (2014). LeSage and Pace (2009) suggest that there are three issues to consider for model specification in applied practice: 1) alternative spatial weights matrix specification, 2) alternative sets of explanatory variables, and 3) alternative spatial regression model specifications. The first two issues will be discussed in the following sections, so the third issue will be discussed in depth here.

Based on the prior discussion on spatial dependence, appropriately modeling spatial spillover effects is a key interest in this study. Whereas spatial continuity and autocorrelation can be accounted for in all spatial econometric models presented previously, spillover effects are best observed in select models. The spatial autoregressive (SAR) model, spatial error model (SEM), and spatial simultaneous autoregressive (SAC or SARAR) model, though popularized by Anselin (1988) and Kelejian and Prucha (1998) and may provide interesting theoretical insights, are ill-fitting for observing spatial spillover because they impose restrictions on the magnitude of spillover effects in advance and generate only global spillover or direct effects (Elhorst and Vega, 2013). Considering other critiques of these models such as poor suitability for applied empirical works (LeSage and Pace, 2009; LeSage, 2014; Pace and Zhu, 2012; Pinkse and Slade, 2010), they are not considered further in this study. The spatial lag of X (SLX) model, spatial Durbin error model (SDEM), spatial Durbin model (SDM), and general nesting spatial (GNS) model generate different spillover effects for each explanatory variable that offer insight into local spillover effects apart from their direct effects. Of these, GNS has been subject to overspecification problems that result in weakly identified parameter estimates (Elhorst and Vega, 2013). In contrast, SLX contains only one spatial interaction term like SAR and SEM, which misalign with more contemporary approaches that suggest the superiority of more complex models that involve two spatial interaction terms (Elhorst, 2010).

As such, model selection needs to be made between SDM and SDEM but ambiguities in discerning global and local spillover effects in empirical cases complicate specifying between the two models. A key condition for the presence of local spillover effect is the absence of endogenous feedback effects, in which the impact of a change in region *i* extends to a limited set of neighboring regions *j*, rather than to the neighbors of the neighboring regions and so forth (LeSage, 2014; Elhorst, 2014). In the context of this study, specifying local spillover effects would be more appropriate than modeling global spillover effects since a change in food access and related factors in one block group is not likely to affect all other block groups in the sample; rather, it will likely impact more nearby units resembled by limited endogenous feedback effects due to economic behaviors of food retailers (Jang and Kim, 2018). Empirically, this study observes the neighborhood scale at micro levels since it is assumed that mobility constraints from COVID-19 prevention measure limited individuals' and households' travel distances. As such, this study will use SDEM to observe local spillover effects in food accessibility.

A further consideration for selecting SDEM over SDM was that the dependent variable, the number of accessible large food retailers per block group's service area, already accounts for neighborhood effects and that lagging it will lead to double-counting of its spatial interactive effects. In detail, the dependent variable was formulated by counting the number of supermarkets and large grocery stores that are accessible within a service area that could expand beyond the boundary of the census block group depending on its size. Thus, modeling food access with SDM by lagging the dependent variable that already reflects neighborhood effects will result in biased estimates. Results of model testing that support this model specification process are presented in the next section.

Hence, based on theoretical considerations and the convenience of interpreting direct and indirect effects, SDEM is the final model specification of this study. SDEM follows the form:

$$Y = \alpha t_N + X\beta + WX\theta + u; u = \lambda Wu + \varepsilon;\ \varepsilon \sim N(0, \sigma^2); \qquad (1)$$

where Y is an Nx1 vector consisting of one observation on the dependent variable for every unit in the sample (i = 1, ..., N). t_N is an Nx1 vector associated with the constant parameter α to be estimated. X is an NxK matrix of explanatory variables and β is a Kx1 vector of associated parameters. W is a non-negative NxN spatial weights matrix that describes the structure of spatial configuration between units in the sample, so WX represents the exogenous interaction effects among the explanatory variables and Wu represents the interaction effects among the disturbance terms of different observations. θ is a K x 1 vector of associated parameters, and λ is a scalar parameter denoting the spatial autocorrelation coefficient. Details of this model can be found in Elhorst (2014) for additional reference.

3.3.3. Modeling Spatial Variation of Parameters

To supplement findings from the spatial econometric methods, GWR was incorporated to observe the spatial variation in the magnitude of association among observed factors (Fotheringham, Brunsdon, and Charlton, 2002). Mapping the local parameters of the impact of neighborhood characteristics on food accessibility was expected to enhance the understanding of local spillover effects in play. GWR follows the form:

$$y_i = \beta_0(u_i, v_i) + \Sigma_k \beta_k(u_i, v_i) x_{ik} + \varepsilon_i; \qquad (2)$$

where (u_i, v_i) denotes the coordinates of the *i*-th point and $\beta_k(u_i, v_i)$ represents the continuous function $\beta_k(u,v)$ at point i. Details of this model can be found in Fotheringham et al. (2002).

3.4 Modeling Procedure

The association between the dependent and independent variables was modeled separately for 2019 and 2020 using both spatial econometric models and GWR to observe any changes between the two years. After testing for spatial autocorrelation using Global Moran's I test of OLS estimate residuals, Lagrange multiplier (LM) tests were conducted to specify the spatial econometric models following spatial modeling procedures proposed by Anselin (1988). Since the LM test results indicated that either model of spatially lagged dependent variable and error term is preferred over OLS, estimation using SAR, SEM, SAC, SDM, and SDEM were computed. Then, to decide whether models with more spatial interaction terms should be reduced, the likelihood ratio (LR) test was conducted. Breusch-Pagan (BP) test for spatial heteroscedasticity and Global Moran's I test for spatial dependence in residuals were conducted to consider spatial autocorrelation for each model. Additionally, alternative spatial weights were considered to find the optimal model fit. Specifically, inverse distance thresholds of 0.6km, 0.8km, 1km, 1,2km, 1.4km, 1,6km, and k-nearest neighbors, where k=10, 15, 20, 30, 40, 50 were considered, and the one yielding the optimal Akaike information criterion (AIC) and log-likelihood measures was selected (Stakhovyc and Bijmolt, 2009).

Spatial econometric procedures were conducted in R with *spdep*, *spatialreg*, and *sphet* packages. GWR and MGWR estimation was computed using the MGWR software developed by Oshan et al. (2019). Adaptive bisquare kernel for spatial kernel and golden section search for bandwidth optimization were used for GWR and MGWR. Optimal bandwidths were selected based on minimum corrected AIC (AICc). ArcGIS was used to visualize the distribution of local parameters obtained using GWR.

4. Results

4.1 Variable Selection and Descriptive Statistics

The correlation matrix and variance inflation factors (VIF) are presented in Table 2. The mean VIF for both years was 1.34, which is below the conservative threshold of 5, with 2019 data having a slightly higher VIF for the percentage of HL and logarithm of median household income than those of 2020. The two variables also had the highest absolute value of the correlation estimate with -0.476. Regardless, no correlation measures exceeded the commonly used threshold of 0.5, so the selected variable did not pose serious multicollinearity issues.

The descriptive statistics of the selected variables (n=5,712) are shown in Table 3. The average number of accessible large food retailers per block group increased from 2.6 to 3.1 between 2019 and 2020, and the standard deviation also increased from 2.23 to 2.53. This increase reflects the increase in the total number of supermarkets and large grocery stores from about 800 in 2019 to about 950 in 2020, but with greater disparity among block groups. Store entropy also increased from 0.973 to 0.995 with only a small change in standard deviation from 0.247 to 0.249 between 2019 and 2020.

As for the race/ethnicity and income-related variables that are of key interest, the mean percentage of the AA population was 21.7 percent and that of the HL population was 27.4 percent. The mean race entropy was 0.879 from a range of 0 and 1.808. The mean median household income was about US$74,087 from a range of US$8,493 and US$245,500 or higher. The logarithm of median household income was used for analysis and its mean value was 11.067. Of the control variables, the mean percentage of the elderly population was 13.4 percent and that of family households was 63 percent. The mean land-use entropy was 0.447 from a range of 0 and 0.999, and the mean multi-modal network density was 15.341 from a range of 0 and 56.532.

Table 2 Correlation matrix and variance inflation factors of independent variables

	'19 St. entr.	'20 St. entr.	%, AA	%, HL	Race entr.	Ln(Inc)	Tot pop	Tot LA	%, Elder	%, Fam	LU entr.	Netw. dens.	'19 VIF	'20 VIF
'19 St. entr.	1												1.55	NA
'20 St. entr.	0.9285*	1											NA	1.53
%, AA	0.2960*	0.3009*	1										1.41	1.41
%, HL	0.3492*	0.3317*	-0.1388*	1									1.67	1.66
Race entr.	0.0187	0.0241	-0.1620*	0.0455*	1								1.09	1.09
Ln(Inc)	-0.4253*	-0.4104*	-0.2237*	-0.4756*	0.0483*	1							1.6	1.59
Tot pop	0.0194	0.0066	0.0101	0.1326*	0.1151*	-0.1123*	1						1.12	1.12
Tot LA	-0.2479*	-0.2533*	0.0392*	-0.1822*	0.0614*	0.1354*	0.1630*	1					1.48	1.49
%, Elder	-0.1952*	-0.1888*	-0.0671*	-0.2550*	-0.1078*	0.0361*	-0.1403*	0.1188*	1				1.19	1.19
%, Fam	0.1614*	0.1636*	0.0780*	0.1081*	-0.0926*	-0.0365*	0.1070*	0.2756*	-0.1079*	1			1.24	1.24
LU entr.	-0.1745*	-0.1780*	-0.2480*	-0.1364*	0.0374*	0.2113*	-0.1409*	0.0601*	0.0107	-0.1418*	1		1.17	1.17
Netw. Dens.	0.0829*	0.0825*	-0.1123*	0.0364*	-0.0006	0.0295	-0.0470*	-0.4003*	-0.1257*	-0.1916*	0.1167*	1	1.26	1.26
Mean VIF	NA												1.34	1.34

*p<0.01

Note: Correlation between 2019 store entropy and 2020 store entropy can be dismissed since they are not included simultaneously in regression models

Table 3 Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
Store count, 2019	2.5986	2.2274	0	13
Store count, 2020	3.1043	2.5278	0	16
Store entropy, 2019	0.9733	0.2472	0	1.3863
Store entropy, 2020	0.9948	0.2494	0	1.3863
%, AA	0.2170	0.2833	0	1
%, HL	0.2741	0.2456	0	1
Race entropy	0.8792	0.3256	0	1.8086
Ln (Med Inc)	11.0665	0.5660	9.0470	12.4111
Med Inc	74,086.6	39,534.9	8,493	245,500*
Ln (Total pop)	7.1343	0.4411	4.2627	9.2066
Total pop	1,380.72	650.35	71	9963
Ln (Total LA)	13.2362	0.9998	9.9679	19.2053
Total LA	1,318,928	6,136,221	21,330	219,000,008
%, Elderly	0.1314	0.0792	0	0.7636
%, Family HH	0.6301	0	0	1
LU entropy	0.4474	0.2124	0	0.9999
Network density	15.3413	10.3349	0	56.5316

4.2 Model Specification Tests

First, OLS regression was conducted to obtain the model residuals, which were used for the spatial autocorrelation test and model specification tests. As shown in Table 5 of OLS and SDEM regression results, the 2020 OLS model showed a better model fit with an adjusted-R^2 of 0.366 compared to 0.344 of its 2019 counterpart. Overall, the percentage of AA, HL, and race entropy were all statistically significant with the percentage of AA and race entropy showing negative associations with food accessibility and the percentage of HL showing a positive association across both years. On the other hand, the coefficients of the logarithm of median household income were 0.079 ($p=0.186$) in 2019 and -0.089 ($p=0.157$) in 2020, and both were not statistically significant at $p<0.1$. Considering the statistically significant BP test statistic and Moran's I of the residuals, OLS estimates for both 2019 and 2020 were inconsistent and biased. As such, testing for spatial model specification was conducted.

The result of the LM test is presented in Table 4. For both 2019 and 2020, regular LM error and lag test results were statistically significant, as well as those of the robust LM error and lag tests. As such, all spatial econometric models that

Table 4 Lagrange multiplier test results

	2019		2020	
	Statistic	**P-value**	**Statistic**	**P-value**
LM Error	9237.19	0.000	9150.57	0.000
LM Lag	8372.31	0.000	8292.80	0.000
Robust LM Error	1514.61	0.000	1570.50	0.000
Robust LM Lag	649.73	0.000	712.73	0.000
SARMA	9886.92	0.000	9863.30	0.000

include a spatially autoregressive dependent variable and error term were used. To better specify the model, various spatial weights were tested to find the optimal spatial weights matrix W that yielded the best model fit as detailed in Section 3. Ultimately, spatial weights using k-nearest neighbors, where k=10, were selected. Using this spatial weights matrix, estimates using SAR, SEM, SAC, SLX, SDM, and SDEM were derived. Per the prior explanation for model specification and model performance, only the SDEM results are presented in Table 5, and the results of the other models can be found in Appendix 1-2.

The LR test results (Table 5) justify the rejection of the OLS model estimates in favor of SLX and SEM, indicating that the spatial interaction effects of the explanatory variables and error term should be controlled. Similarly, the LR test results further indicate that SLX and SEM model estimates should be rejected in favor of SDEM, implying that spillover effects need to be controlled even after controlling for spatial autocorrelation among unobserved factors. When comparing OLS and SDEM regression results, model performance improved for both 2019 and 2020 models using SDEM. The AIC of the OLS model was 22,962.85 for 2019 and 24,218.6 for 2020. In comparison, those of the SDEM models reduce to 17,563 and 18,674, respectively. Further, the Nagelkerke pseudo-R^2 of the SDEM estimates was 0.747 for 2019 and 0.761 for 2020, which were higher than that of SDM estimates for both years.

More importantly, the results of spatial autocorrelation tests are not statistically significant at $p<0.1$ using the SDEM model as indicated by the Moran's Index of SDEM residuals. This result signifies that spatial dependence in neighborhood food access may be accounted for by adjusting for disturbances among the observed explanatory factors and unobserved factors. However, the BP statistics remain statistically significant and thereby imply a persistent existence of spatial heteroscedasticity that could cause biased coefficient estimates. In response, a generalized moments (GM) estimator allowing for heteroscedastic innovation was used to derive the SDEM estimates (Kelejian and Prucha, 2010; Laviolette et al., 2021). Coefficients derived with the GM estimator shared the same sign and statistical significance as those derived with maximum likelihood estimation and showed only slight differences in magnitude. As such, the initial results using ML estimation are shown in Table 5. SDEM results using the GM estimator can be found in Appendix 3.

4.3 Spatial Econometric Model: SDEM

The OLS and SDEM estimates for the control variables such as population, land area, the percentage of the population age 65 and older, the percentage of family households, land-use entropy, and network density were all similar in the sign of the association. Although an analysis of the control variables could provide a deeper insight into the association between neighborhood characteristics and food accessibility, only the race/ethnicity and income-related factors will be discussed further in this section.

4.3.1 Food Accessibility and the Share of Black or African Americans

Unlike the OLS results, the SDEM results indicate that the percentage of AA is not statistically significant. However, SDEM portrays a more nuanced context behind the change in estimates between 2019 and 2020. The direct effect estimates of the share of AA were -0.116 ($p=0.412$) for 2019 and -0.198 ($p=0.205$) for 2020. This result could be interpreted as that if the percentage of AA increased by 1 percent in a block group, then its number of accessible large food retailers decreased by 0.12 stores in 2019 and by 0.20 stores in 2020. In contrast to OLS, this result suggests that the negative association between the share of Black and African Americans and food access worsened from 2019 to 2020, despite the global increase in the number of stores.

Table 5 OLS and SDEM regression results for 2019 and 2020

DV = Store count/ BG Service Area	OLS (Robust)						SDEM					
	2019			2020			2019			2020		
	Coeff.	SE	P	Coeff.	SE	P	Coeff.	SE	P	Coeff.	SE	P
Intercept	8.088	0.915	0	12.048	0.947	0	11.805	3.077	0	17.097	3.399	0
Direct												
Store entropy	1.47	0.112	0	1.445	0.132	0	1.783	0.093	0	1.837	0.1	0
%, AA	-0.47	0.088	0	-0.421	0.112	0	-0.116	0.141	0.412	-0.198	0.156	0.205
%, HL	1.118	0.143	0	1.359	0.14	0	0.133	0.128	0.301	0.13	0.141	0.359
Race entropy	-0.639	0.076	0	-0.566	0.086	0	-0.148	0.063	0.019	-0.102	0.069	0.14
Ln (Med Inc)	0.079	0.06	0.187	-0.089	0.059	0.157	0.011	0.044	0.809	0.013	0.049	0.798
Ln (Total pop)	0.773	0.058	0	0.785	0.064	0	0.14	0.041	0.001	0.139	0.045	0.002
Ln (Total LA)	-0.88	0.032	0	-1.013	0.033	0	-0.279	0.023	0	-0.315	0.026	0
%, Elderly	-1.217	0.327	0	-2.091	0.367	0	-0.207	0.236	0.379	-0.154	0.26	0.553
%, Family HH	-2.708	0.146	0	-2.934	0.162	0	-0.334	0.126	0.008	-0.335	0.139	0.016
LU entropy	1.52	0.126	0	1.696	0.136	0	0.623	0.084	0	0.659	0.092	0
Network density	-0.008	0.003	0.003	-0.001	0.003	0.812	-0.01	0.002	0	-0.011	0.002	0
Indirect												
W*Store entropy							0.506	0.376	0.179	0.411	0.407	0.313
W*%, AA							-0.587	0.405	0.148	-0.49	0.446	0.272
W*%, HL							-0.096	0.46	0.835	0.215	0.505	0.67
W*Race entropy							-0.726	0.254	0.004	-0.757	0.28	0.007
W*Ln (Med Inc)							0.054	0.182	0.768	-0.025	0.201	0.901
W*Ln (Total pop)							0.858	0.188	0	0.844	0.207	0
W*Ln (Total LA)							-1.054	0.098	0	-1.269	0.108	0
W*%, Elderly							-2.545	1.092	0.02	-3.957	1.203	0.001
W*%, Family HH							-2.129	0.516	0	-2.633	0.568	0
W*LU entropy							2.249	0.389	0	2.022	0.429	0
W*Netw density							-0.002	0.008	0.755	-0.004	0.008	0.641

Table 5 (cont'd)

DV = Store count /BG Service Area	OLS (Robust)						SDEM					
	2019			2020			2019			2020		
	Coeff.	SE	P	Coeff.	SE	P	Coeff.	SE	P	Coeff.	SE	P
Total												
Store entropy							2.29	0.408	0	2.248	0.441	0
%, AA							-0.702	0.429	0.101	-0.687	0.472	0.146
%, HL							0.037	0.5	0.941	0.345	0.549	0.53
Race entropy							-0.874	0.279	0.002	-0.859	0.308	0.005
Ln (Med Inc)							0.065	0.202	0.749	-0.012	0.222	0.955
Ln (Total pop)							0.998	0.21	0	0.983	0.231	0
Ln (Total LA)							-1.332	0.106	0	-1.584	0.117	0
%, Elderly							-2.752	1.22	0.024	-4.111	1.344	0.002
%, Family HH							-2.462	0.571	0	-2.968	0.63	0
LU entropy							2.872	0.43	0	2.681	0.474	0
Network density							-0.012	0.009	0.159	-0.015	0.01	0.114
Lambda							0.896	0.008	0	0.896	0.008	0
Mult. R-sq		0.345			0.367							
Adj. R-sq		0.344			0.366							
Pseudo R-sq								0.747			0.761	
Log likelihood								-8756.55			-9311.85	
AIC		22962.85			24218.6			17563			18674	
BP stat	321.89	df=11	0	358.72	df=11	0	205.52	df=22	0	187.85	df=22	0
Moran's I	0.534	sd=96.9	0	0.532	sd=96.4	0	0.002	sd=0.39	0.349	0.001	sd=0.16	0.437
LR: SLX/OLS	LR ratio = 823.22, df = 11, p-value<2.2e-16						LR ratio = 887.31, df = 11, p-value<2.2e-16					
LR: SEM/OLS	LR ratio = 5220.6, df = 1, p-value<2.2e-16						LR ratio = 5341.8, df = 1, p-value<2.2e-16					
LR: SDEM/SLX	LR ratio = 4600.5, df = 1, p-value<2.2e-16						LR ratio = 4681.6, df = 1, p-value<2.2e-16					
LR: SDEM/SEM	LR ratio = 203.14, df = 11, p-value<2.2e-16						LR ratio = 227.09, df = 11, p-value<2.2e-16					

On the other hand, the indirect effect estimates were -0.587 (p=0.148) for 2019 and -0.49 (p=0.272) for 2020. Interpretation of these indirect estimates could be that if a block group and its neighboring block groups had an increase of AA by similar proportions, then its number of accessible stores decreased by 0.59 stores in 2019 and 0.49 stores in 2020. Thus, local spillover effects could have mitigated the negative association between these two factors. The SDEM results align with past findings of the negative association between the share of the AA population and food accessibility (Moore and Diez-Roux, 2006; Lewis et al., 2005; Raja et al., 2008; Smiley et al., 2010; Rose et al., 2011; Kwate et al., 2013; Cannuscio et al., 2013; Wang et al., 2016; Kolak et al., 2018).

Comparatively, the OLS coefficients for the percentage of AA were -0.47 at $p<0.001$ for 2019 and -0.421 at $p<0.001$ for 2020; in contrast, the total effect estimates using SDEM were -0.702 (p=0.101) for 2019 and -0.687 (p=0.146) for 2020. Whereas the indirect and total effect estimates align with the OLS estimates in that the absolute value of the coefficients does not decrease from 2019 to 2020, the SDEM direct effect estimates show an increase in the negative association with food accessibility. Additionally, the OLS estimates appear to underestimate the association between the percentage of AA and the access to large food retailers. As such, without considering spatial dependence, neighborhoods with higher proportions of AA may appear to experience less severe access to large food retailers than they do in reality.

4.3.2 Food Accessibility and the Share of People with Hispanic or Latinx Origin

The SDEM results mostly align with OLS findings in that the coefficients for the percentage of HL were mostly positive. However, like the percentage of AA, the estimates were not statistically significant. The direct effect estimates of this variable were about 0.13 for 2019 (p=0.301) and 2020 (p=0.359). On the other hand, the indirect effect coefficient for 2019 was -0.096 (p=0.835) and that for 2020 was 0.215 (p=0.67). Together, the 2019 direct and indirect effects imply that a block group with a higher share of HL could have access to more supermarkets and large grocery stores, but may have experienced reduced access if it was considered with neighboring block groups at a greater neighborhood scale. Regardless, the total effect estimates were positive for both 2019 and 2020 with coefficients of 0.037 ($p=0.941$) and 0.345 ($p=0.530$), respectively.

The different results of the two models suggest that not considering spatial dependence could overestimate the positive association between the neighborhood percentage of HL and food accessibility. These results appear to imply that a block group with a higher share of HL benefits from greater access to supermarkets and large grocery stores than they may experience in actuality. However, it is important to note that findings on the association between the share of HL and food accessibility have been mixed. Moore and Diez Roux (2006) have found a negative association between the proportion of HL and food store access. In contrast, Elbel et al. (2019) found greater access to food stores for Hispanic students in NYC public schools than for White students. Other studies found mixed results on the association between the share of HL and food accessibility by considering various measures of food access and adjusting for factors like crime rates and vehicle ownership, suggesting a need for a more nuanced understanding of this relationship (Galvez et al., 2008; Bader et al., 2015; O'Connell et al., 2016).

Possible explanations for the positive association found in this study could relate to street network connectivity and the role of ethnic food retailers. First, neighborhoods with a higher share of HL may have access to more supermarkets due to better network connectivity. Bader et al. (2015) have found that supermarkets near a high density of expressways tended to be located in predominantly White, Hispanic, and Asian neighborhoods in NYC. Though the multi-modal network density measure that was used as a proxy for network connectivity includes a limited range of expressways, its positive correlation with the share of HL (Table 2) suggests that more supermarkets may have been counted within the 1km network-based service area of block groups with higher shares of HL. Second, ethnic food retailers servicing nutritious, affordable, and culturally acceptable food play a pivotal role in improving food accessibility in ethnic enclaves. Studies on ethnic economies demonstrate how ethnic groups, like Hispanic and Latinx communities, agglomerate in particular neighborhoods and bring forth retailers servicing culturally acceptable goods, which, in turn, employ members of those communities and create economic opportunities (Light and Gold, 2000; Kaplan and Li, 2006). Based on the dynamics of ethnic economies, this study's findings support other findings that highlight the role of ethnic food retailers in neighborhoods with a higher percentage of HL. Future studies could conduct a more detailed survey of supermarkets and large grocery stores to allude to their cultural identity in a greater communal context.

4.3.3 Food Accessibility and Racial Diversity

Both OLS and SDEM coefficients indicate that race entropy is statistically significant and negatively associated with the number of accessible large food retailers at the block group level. The direct effect estimates using SDEM were -0.148 (p=0.019) for 2019 and -0.102 (p=0.14) for 2020. The indirect effect estimates decreased between 2019 and 2020, though by a small difference, from -0.726 (p=0.004) to -0.757 (p=0.007). This result suggests that if a block group and its neighboring block groups had a more even balance of different racial/ethnic groups, then the number of accessible supermarkets and large grocery stores decreased by 0.72 stores in 2019 and by 0.75 stores in 2020. Together, the total effect estimates were -0.874 (p=0.002) for 2019 and -0.859 (p=0.005) for 2020. As such, the negative association between racial/ethnic diversity and the number of accessible supermarkets and large grocery stores could be underestimated if spatial autocorrelation is not modeled appropriately.

Both OLS coefficients and SDEM total effect estimates indicate that racial/ethnic diversity is statistically significant and negatively associated with the number of accessible supermarkets and large grocery stores. This result could appear to suggest that more diverse neighborhoods have lower access to large food retailers and misdirect intervention strategies. However, it is important to note that this study only observed the association of diversity with supermarkets and large grocery stores, excluding other food outlet types that comprise the food environment.

When studying the association between neighborhood racial composition and food environment in Erie County, New York, Raja et al. (2008) found that various food outlets, including grocery stores, fruit and vegetable stores, meat and fish stores, convenience stores, and restaurants, were equally or more prevalent within walking distance of racially mixed neighborhoods than those of predominantly white neighborhoods, except supermarkets. There were 0.69 times as many supermarkets in racially mixed neighborhoods than in predominantly white neighborhoods, whereas there were 1.02 times as many restaurants (Raja et al., 2008). Such context conveys that smaller-scale food outlets like smaller grocery stores, specialty stores, and restaurants could fill the gap left by the absence of large retailers. Given the statistical significance of this factor on access to retailers, future research could apply spatial modeling approaches to observe the association between racial/ethnic diversity and food destination variety in greater depth.

4.4.4 Food Accessibility and Income

Both OLS and SDEM estimates indicate that the median household income (logarithm value) was not statistically significant at $p<0.1$. However, unlike other variables, the sign of the estimates for the income variable changes between 2019 and 2020. The OLS coefficient of the logarithm of median household income were 0.079 ($p=0.187$) for 2019 and -0.089 ($p=0.157$) for 2020, and those for the SDEM total effect were 0.065 ($p=0.749$) for 2019 and -0.012 ($p=0.955$) for 2020.

Though the direct effects produced using SDEM indicate that the logarithm of median household income was consistently positive with estimates of 0.011 ($p=0.809$) for 2019 and 0.013 ($p=0.798$) for 2020, the indirect effect results align with the OLS results with estimates 0.054 ($p=0.768$) for 2019 and -0.025 ($p=0.901$) for 2020. The indirect effect indicated that with an increase in the median household income of a block group and its neighboring block groups, the number of accessible stores increased in 2019 but decreased in 2020. Ultimately, not considering spatial autocorrelation results in the overestimation of the association between the median household income and the number of accessible supermarkets and large grocery stores.

Though the implied magnitude of change is small ($\beta/100$ for a percent increase in median household income), the change from a positive to a negative association between block group income level and access to large food retails between 2019 to 2020 offers an interesting insight that diverges from past findings. The 2019 results align with past findings of a negative association between the percentage of low-income households, poverty rate, the percentage of unemployed individuals, and food accessibility (Moore and Diez Roux, 2006; Lewis et al., 2005; Ghirardelli et al., 2010; Cannuscio et al., 2013), indicating that higher-income neighborhoods have access to more large food retailers. In contrast, the 2020 estimates suggest that even if the income level increases, the number of accessible supermarkets and large grocery stores could decrease.

This departure could be explained by the negative indirect effects of the income variable. As explained earlier, larger food retailers that offer a wider variety of food at lower prices locate more densely in higher-income areas due to market demand and economies of scale (Jang and Kim, 2018). As such, a block group with a higher median household income could have access to more supermarkets and large grocery stores within its service area. However, since such clusters of high-income block groups are neighbored by lower-income block groups as shown in Figure 2, there could have been a reduced concentration of large food retailers on a greater neighborhood scale. The 2019 results hint that, despite possibly being neighbored by lower-income block groups, a higher-income block group could have had access to more large food retailers. However, the negative indirect effect of income in 2020 conveys that access to large food retailers among neighboring block groups could have decreased to the extent that even higher-income block groups nearby could have experienced reduced access to large food retailers due to local spillover effects.

Overall, modeling for spatial dependence demonstrated that OLS estimates often over- and under-estimate the association between various race/ethnicity and income-related factors and food accessibility. Such over-and under-estimation effects incorrectly illustrate and simplify the complex relationship between race, class, and food accessibility. As seen in the SDEM estimates, the sign of the total effect estimates for 2019 more likely resemble their direct effect counterparts, but those for 2020 resemble their indirect effect counterparts. Most notably, the change in the sign of the median household income from positive to negative in 2020 suggests how disruptions in local spillover effects could have negatively affected food accessibility in NYC.

4.4 Geographically Weighted Regression

Table 6 shows the summary of GWR estimates for 2019 and 2020. GWR was conducted to contextualize the local spillover effects revealed through the SDEM estimation process. Results of MGWR were also generated but they are not presented in this section considering the similarity in its result implications and lower model performance for 2020 compared to those of GWR. Instead, bandwidths obtained using MGWR will be discussed and other details can be found in Appendix 4. GWR's bandwidths, the number of units considered to optimize the regression estimate, were 119 for 2019 and 127 for 2020. In model fit, GWR outperformed OLS with an adjusted R^2 of 0.738 (OLS: 0.344) for 2019 and 0.746 (OLS: 0.366) for 2020. Same results were derived using AICc, which were 22,963 with OLS and 19,665 with GWR for 2019 and 24,219 with OLS and 18,263 with GWR for 2020. Compared to SDEM, GWR's AIC is higher for 2019 with 18861(SDEM: 17563) and lower for 2020 with 18116 (SDEM:18674).

The GWR results display interesting shifts in the local estimates of the race and income-related variables. For 2019, the local estimates for the percentage of AA range between -21.642 and 27,977 with a standard deviation of 3.646. In 2020, the estimates shifted downward, ranging between -29.561 and 17.184 with a greater standard deviation of 4.266. For the percentage of HL, the range of local estimates expanded from [-12.982, 10.295] with a standard deviation of 2.635 in 2019 to [-25.145, 20.794] with a standard deviation of 3.03 in 2020. Similarly, the range of local estimates for race entropy expanded from [-5.968, 3.71] with a standard deviation of 1.189 in 2019 to [-6.045, 6.509] with a standard deviation of 1.326 in 2020. Likewise, the range of local estimates for the median household income changed from [-2.975, 3.29] with a standard deviation of 0.798 in 2019 to [-4.144, 3.744] with a standard deviation of 0.86 in 2020. Overall, the standard deviation of these factors increased between 2019 and 2020, possibly indicating a greater disparity in access to large food retailers associated with these factors across block groups in 2020. Since the range of the local estimates for the percentage of AA generally fell, the GWR results corroborate the OLS and SDEM results indicating a consistently negative association between the neighborhood share of AA and access

Table 6 GWR results and MGWR-calibrated bandwidths

DV = Store count/ BG Service Area	2019						2020					
	Mean	STD	Min	Max	BW	MBW	Mean	STD	Min	Max	BW	MBW
Intercept	2.101	13.504	-55.413	46.721	119	270	3.437	14.955	-57.086	46.501	127	43
Store entr.	6.13	7.619	-6.14	52.271	119	43	6.16	7.979	-10.383	51.299	127	261
%, AA	-0.289	3.646	-21.642	27.977	119	1585	-0.193	4.266	-29.561	17.184	127	3184
%, HL	-0.442	2.635	-12.982	10.295	119	2325	-0.063	3.03	-25.145	20.794	127	999
Race entr.	-0.159	1.189	-5.968	3.71	119	1018	-0.108	1.326	-6.045	6.509	127	958
Ln(Inc)	-0.101	0.798	-2.975	3.29	119	43	-0.14	0.86	-4.144	3.744	127	43
Ln(Tot. pop)	0.262	0.543	-1.183	2.805	119	5694	0.286	0.604	-1.744	3.281	127	5708
Ln (Tot. LA)	-0.488	0.619	-3.478	1.279	119	43	-0.573	0.76	-4.282	2.277	127	43
%, Elderly	-0.029	3.138	-15.208	16.295	119	4914	-0.192	3.307	-19.084	12.663	127	4824
%, Fam HH	-0.321	1.995	-7.203	6.02	119	2986	-0.362	2.167	-10.485	7.418	127	2513
LU entropy	1.107	1.459	-1.841	8.564	119	3792	1.207	1.685	-2.918	9.69	127	4051
Netw. Dens.	-0.011	0.029	-0.103	0.077	119	1495	-0.011	0.032	-0.129	0.13	127	1305
Adj. R-sq	0.738					NA	0.746					NA
LL	-8103.946						-8445.291					
AIC	18861.114						18115.851					
AICc	19664.521						18263.323					

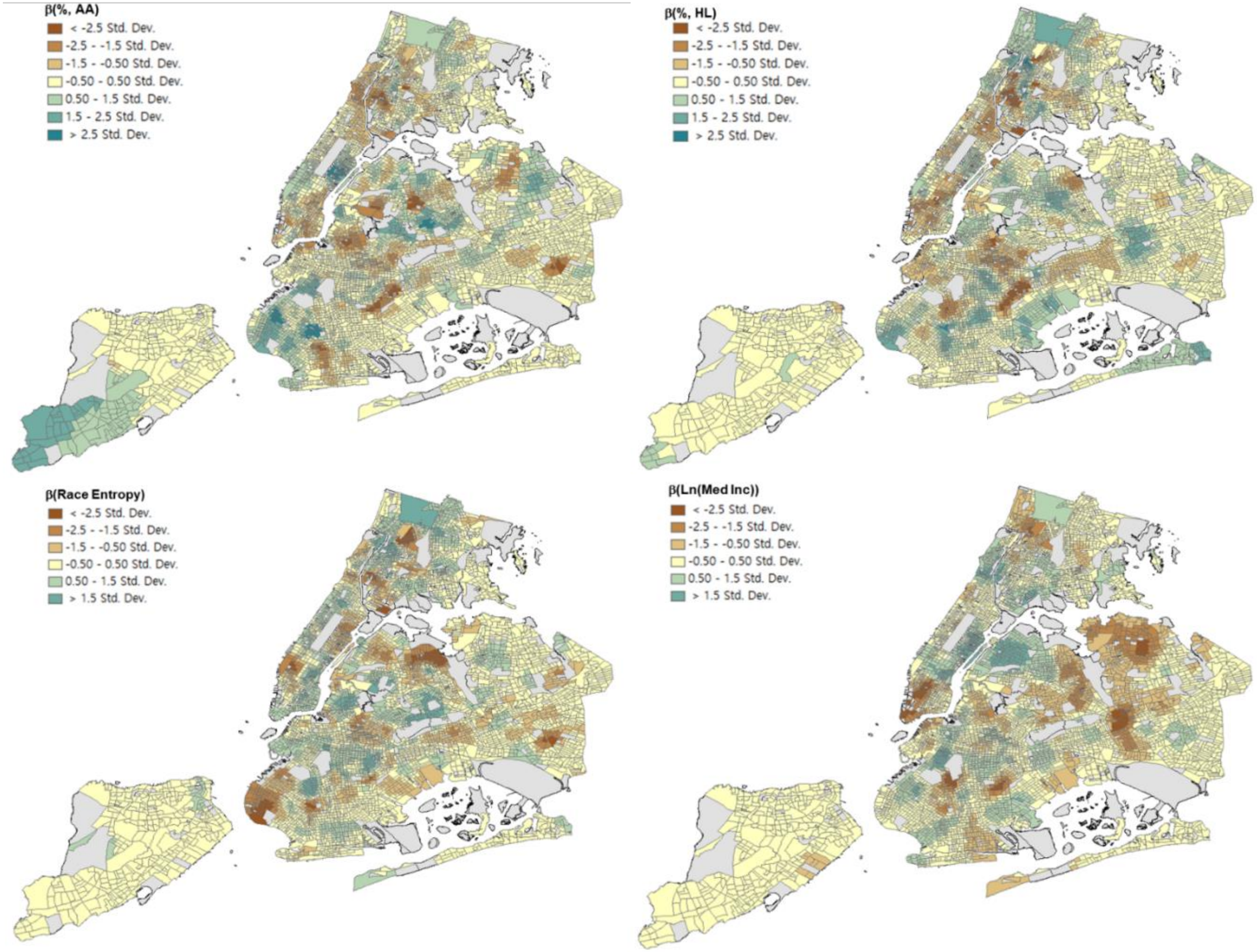

Figure 4 Spatial distribution of 2019 GWR local parameters by standard deviation groups

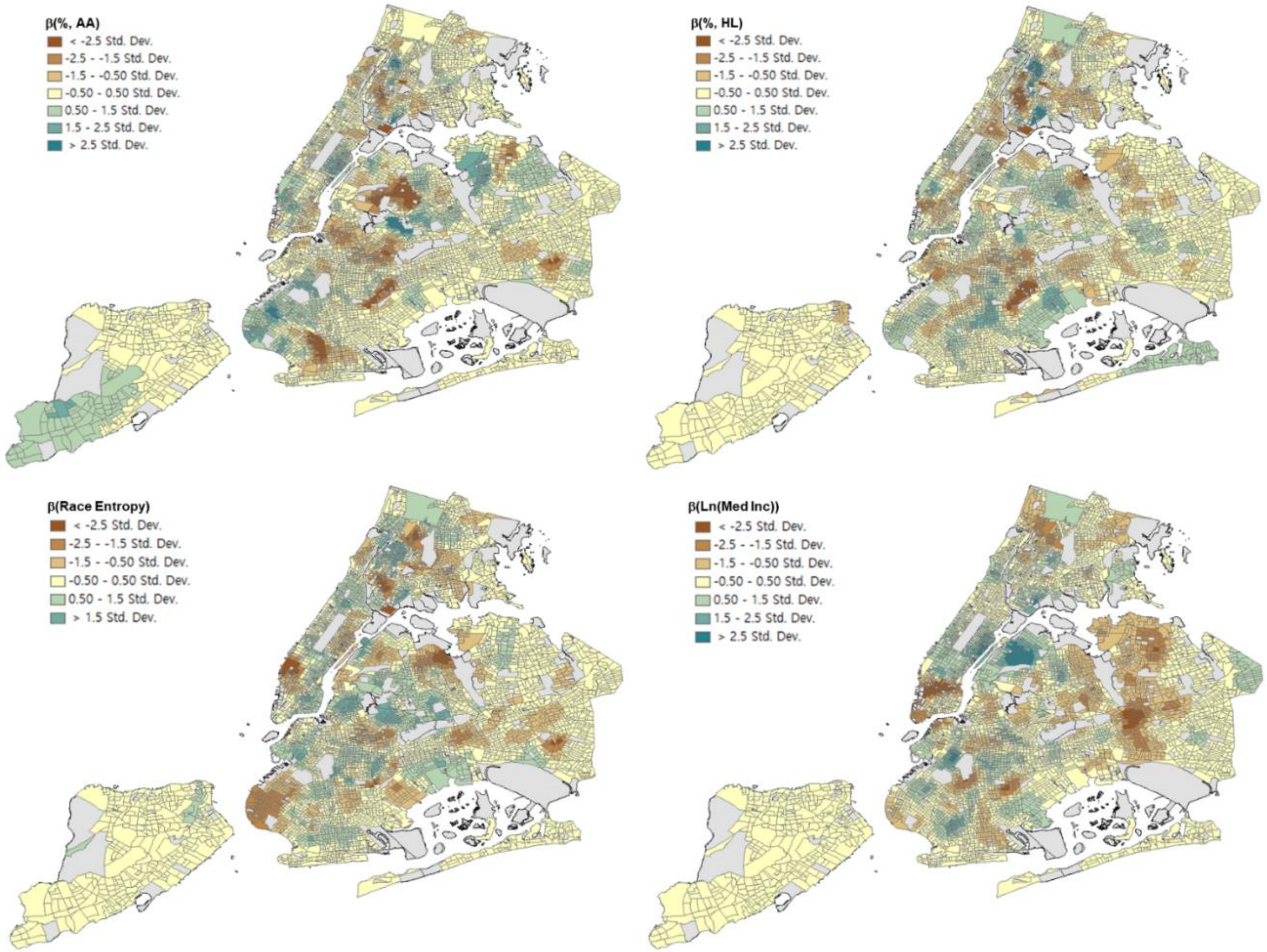

Figure 5 Spatial distribution of 2020 GWR local parameters by standard deviation groups

to large food retailers. For other variables, the increase in the range indicates a polarization of the magnitude of their association with food access.

To visualize the GWR results, the standard deviations of the local parameters are mapped in Figures 4 and 5. For all variables, there exists a clustering of block groups with higher absolute values of the parameters. For the local parameters of the percentage of AA, parameters that fall below -2.5 standard deviation concentrate more in Brooklyn and its border with Queens in 2020, while clusters of estimates above the 1.5 standard deviations shrink globally. For the local estimates of the percentage of HL, the distribution of estimates in the higher and lower standard deviation groups is similar across the two years. However, in 2020, estimates below -2.5 standard deviation and above 2.5 standard deviations are concentrated in the Bronx. The spatial distribution of race entropy's parameters remains mostly similar between 2019 and 2020. Similarly, the spatial distribution of median household income parameters does not change drastically between 2019 and 2020. Generally, block groups with local parameters falling below -1.5 standard deviation or -2.5 standard deviation are located in the Bronx and around the Brooklyn-Queens boundary, possibly suggesting these areas' vulnerability in food accessibility.

Since the aim of MGWR is to improve model fitness and smooth spatial variability, its estimates are optimized to smooth the spatial variation of local parameters, which do not contribute to observing spatially varying relationships across block groups. Thus, its parameter estimates are not discussed in detail, but its bandwidths (MBW) obtained for the race and income variables corroborate findings from the SDEM analysis and are worth exploring. The bandwidth of median household income is 43, which is smaller than the bandwidth used for GWR for 2019 and 2020. Based on Oshan et al.'s (2020) interpretation of MGWR bandwidths in their study of obesity determinants, such small bandwidth of median household income indicates that the impact of income operates at local levels. In contrast, the larger bandwidths of the percentage of AA at 1585 for 2019 and 3184 for 2020 indicate its relationship operating at a broader regional level. Bandwidths of the percentage of HL and race entropy were also higher but decreased between 2019 and

2020. This change highlights how their association with access to large food retailers may have reduced from regional to more local levels, resembling the indirect spillover effects found using SDEM.

5. Conclusion

In sum, telling aspects of food accessibility by vulnerable population characteristics were revealed when spatial dependence in food accessibility was controlled. The association between the share of AA and food accessibility was persistently negative. On the other hand, the share of HL and access to large food retailers were mostly positively associated. Race entropy was persistently negatively associated with access to large food retailers. Lastly, median household income showed a positive and negative association with food accessibility in 2019 and 2020. Though the magnitude of association was small, the change in the sign of association introduced new perspectives on the vulnerability of food access.

Such vulnerability could be attributed to the noticeable impact of local spillover effects in 2020. When spatial dependence was controlled by using SDEM, 2020 results resembled their contemporary indirect effects, whereas 2019 results were more like their direct effect counterparts. Corroborated by MGWR bandwidth calibration, the process of median household income seemed to operate at the local level, and that of the share of AA, HL, and race entropy operated at regional, but more local, levels in 2020 than in 2019. As such, though a global increase in the number of supermarkets and large grocery stores may convey some improvement in food accessibility, spatial modeling revealed that such effects may have spread disproportionately as neighborhoods with underrepresented and underserved population groups may have remained or became more vulnerable in food accessibility.

Local parameter estimates using GWR evince such findings by indicating that areas with polarized negative and positive associations clustered together. Notably, the range of local estimates for the share of AA fell, while that for the share of HL, racial/ethnic diversity, and income level expanded with increases in the standard deviation in 2020. Though the spatial distribution of these clusters varied across different factors, an increase in the concentration of parameters falling below -2.5 standard deviations and above 2.5 standard deviations could be seen.

Considering spatial variability, a widening disparity in food accessibility could be observed.

To address the disparate access to large food retailers among racial/ethnic groups, policies influencing neighborhood demographic characteristics, such as housing policies, could be considered. However, equitable housing policies typically aim at promoting racial/ethnic or economic diversity, which may not alleviate inequities in food access if the primary measure of access centers on large food retailers as demonstrated in the study results. Instead, more sustainable options to promote neighborhood food accessibility would be to focus on diversifying the food environment and improving network connectivity. Though facing critical vulnerabilities in dietary health, Black or African Americans and people of Hispanic and Latinx origin appear to have diverging associations with access to supermarkets and large grocery stores. As previously discussed, the positive association between neighborhoods with a high share of HL may be attributed to better network connectivity and stores serving ethnic economies. Expansion of infrastructure in predominantly AA neighborhoods could boost connectivity that could indirectly improve their access to stores with more healthy food options.

Also, as suggested by other studies, involving ethnic and smaller-scale stores will not only serve the needs of immigrant communities but also fill the gaps in the neighborhood foodscape. Current NYC programs such as Food Retail Expansion to Support Health (FRESH)[4] aims at improving communities' access to healthy and affordable food by providing tax and zoning incentives for developing and renovating supermarkets. However, its incorporation of small-scale stores is limited. Though FRESH utilizes the Supermarket Needs Index, which considers various factors like concentration of stores, walkability, access to cars, and presence of families with children in poverty, to evaluate the number of stores needed to meet communities' dietary needs and has been updated in 2021 to expand the areas where the benefits are applicable, its primary focus on increasing the presence of supermarkets may be insufficient. The FRESH program could reap greater benefits

[4] See 'FRESH Food Store Update' (2021) for details. https://www1.nyc.gov/site/planning/zoning/districts-tools/fresh-food-stores.page

by considering a more diverse set of food retailers in NYC. For instance, its current strategies of providing tax benefits for leasing, acquiring, or renovating retail spaces to carry more healthy food options could be applied to existing small-scale stores such as fresh produce or meat specialty stores, regardless of the retail size. Additionally, zoning incentives that provide additional space for such healthy food servicers, especially in areas that are better connected, could ease local residents' access to more nutritious food options. In communities where food accessibility is lower, these zoning incentives could be accompanied by plans for increasing network connectivity to reduce the disparities across local food environments (Yu et al., 2017).

Especially in the context of shock events like the COVID-19 pandemic, a lack of diversity and quantity of food retailers poses risks to public health as well as to food security. Even neighborhoods that may be well-resourced could experience lower accessibility, which could result in a negative spillover of consumers that will place greater stress on food retailers at local levels. Following the pandemic, NYC initiated the GetFoodNYC program, which established emergency food distribution sites and delivery services to address the increasing risk of food insecurity (Crossa et al., 2021). Compounded with federal policies that expanded existing food assistance programs, such as the Supplemental Nutrition Assistance Program (SNAP) and Special Supplemental Nutrition Program for Women, Infants, and Children (WIC), such measures may have served as effective interventions in response to shocks (Crossa et al., 2021). However, proactive strategies that comprehensively leverage various food store types, consider the cultural and dietary needs of local community members, and improve the means to access food destinations could help achieve a more resilient and equitable food system.

This study contributed to the existing discourse on food accessibility by considering various spatial effects in the context of shock events. However, its faced limitations such as the limited incorporation of the indirect effects of COVID-19 on food retailers, the limited scope of food retailer types and lacking clearer links to health outcomes. First, COVID-19 regulations that affected food businesses pertained to intermittent restrictions on indoor dining at restaurants between 2020 and 2021.[5] Since this study focused on supermarkets and grocery stores that were not subject to COVID-19 restrictions, COVID-19 interventions were not specifically modelled. Instead, this study relied on the assumption that mobility restrictions affecting consumers, price and supply chain disruptions, and changes in or closures of store operations limited the economic and physical access to food retailers during the pandemic. Future studies could better contextualize COVID-19 restrictions by focusing on other food outlets, such as restaurants, or by using surveys on the operational status of stores in observed areas. Expanding on the first suggestion, , future studies could consider different and more diverse measures of food accessibility that are based on distance or self-computed indices. They could also consider more food retailer types, such as convenience stores and restaurants, for a fuller understanding of the food environment. Alternatively, a combination of spatial modeling, in-store audits, and consumer surveys could provide a more accurate picture of food accessibility and dietary health outcomes. Data that show clearer links between food environments, consumption patterns, and community health information will help improve the precision and breadth of future studies on food accessibility.

[5] All updates on New York State's COVID-19 measures could be found at https://coronavirus.health.ny.gov/latest-news?q=

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Appendices

Appendix 1 Spatial econometric regression results for 2019

DV =Store count/ BG Service Area	OLS	SAC	SAR	SEM	SLX	SDM	SDEM
Intercept	8.08795***	1.07064	0.55493	3.25378***	6.35932***	0.84786	11.80547***
Store entropy	1.47040***	1.32159***	1.14531***	1.78180***	1.80339***	1.77057***	1.78335***
% , AA	-0.46993***	-0.29802***	-0.25585***	-0.09953	-0.19669	-0.08592	-0.1159
% , HL	1.11840***	-0.04127	-0.10675	0.13672	0.08187	0.11079	0.13281
Race entropy	-0.63875***	-0.14629**	-0.13865**	-0.07351	-0.15489	-0.07591	-0.14764*
Ln (Med Inc)	0.07926	0.07391*	0.08382**	-0.01062	0.0033	-0.0051	0.01069
Ln (Total pop)	0.77325***	0.15930***	0.15568***	0.07593*	0.20189***	0.07742*	0.14012***
Ln (Total LA)	-0.87998***	-0.26268***	-0.23233***	-0.21733***	-0.28518***	-0.20570***	-0.27878***
% , Elderly	-1.21725***	0.00217	0.0251	-0.04497	-0.1845	-0.02657	-0.20747
% , Family HH	-2.70845***	-0.48444***	-0.39691***	-0.1597	-0.36608	-0.11749	-0.33392*
LU entropy	1.52063***	0.60672***	0.59503***	0.45969***	0.60164***	0.45738***	0.62314***
Network density	-0.00803**	-0.00975***	-0.01020***	-0.00864***	-0.00979***	-0.00909***	-0.00976***
Rho		0.82065***	0.88236***			0.88767***	
Lambda		0.26677***		0.92714***			0.89621***
W*Store entropy					-0.14104	-1.42481***	0.5064
W*% , AA					-0.30202	0.0306	-0.58654
W*% , HL					0.78190**	-0.11552	-0.0957
W*Race entropy					-0.80997***	-0.06388	-0.72632**
W*Ln (Med Inc)					0.13326	0.04698	0.05383
W*Ln(Total pop)					1.75589***	0.20145*	0.85795***
W*Ln (Total LA)					-1.11719***	-0.03244	-1.05369***
W*% , Elderly					-2.30090**	-0.71432	-2.54501*
W*% , Fam HH					-2.69101***	-0.10047	-2.12853***
W*LU entropy					1.96639***	0.20866	2.24923***
W*Netw. density					-0.02203***	0.00034	-0.00247

Appendix 1 (cont'd)

DV =Store count/ BG Service Area	OLS	SAC	SAR	SEM	SLX	SDM	SDEM
Mult. R-sq	0.3455				0.4333		
Adj. R-sq	0.3442				0.4311		
Pseudo R-sq		0.739	0.73743	0.73758		0.74311	0.74675
Log likelihood		-8842.627	-8859.773	-8858.122		-8797.262	-8756.553
AIC	22962.85	17715	17748	17744	22161.63	17645	17563
BP test	273.5***	177.87***	225.64***	24.4*	621.94***	444.19***	205.52***
Moran I test	0.53418***	-0.00555	0.02299***	0.00183	0.57306***	0.01312**	0.00198

*p<0.1, **p<0.01, ***p<0.001

Appendix 2 Spatial econometric regression results for 2020

DV = Store count/ BG Service Area	OLS	SAC	SAR	SEM	SLX	SDM	SDEM
Intercept	12.04765***	1.35304*	0.8936	3.67707***	14.73922***	2.16397*	17.09747***
Store entropy	1.44455***	1.37679***	1.21785***	1.85989***	1.83171***	1.84194***	1.83674***
%, AA	-0.42073***	-0.30056***	-0.26415***	-0.16494	-0.2595	-0.1665	-0.19756
%, HL	1.35851***	-0.01955	-0.08268	0.11799	0.12389	0.08183	0.12963
Race entropy	-0.56560***	-0.11657*	-0.11603*	-0.02264	-0.11221	-0.02663	-0.10234
Ln (Med Inc)	-0.08901	0.06786	0.07651*	-0.00269	0.00476	0.00359	0.01248
Ln (Total pop)	0.78538***	0.16666***	0.16324***	0.07875	0.20395**	0.07921	0.13930**
Ln (Total LA)	-1.01282***	-0.29218***	-0.26382***	-0.23949***	-0.32568***	-0.22709***	-0.31525***
%, Elderly	-2.09061***	0.04499	0.03654	0.15076	-0.20045	0.1489	-0.15416
%, Family HH	-2.93434***	-0.46747***	-0.39354***	-0.11034	-0.393	-0.07	-0.33499*
LU entropy	1.69603***	0.67663***	0.65542***	0.52570***	0.64960***	0.51557***	0.65921***
Network density	-0.00074	-0.01003***	-0.01042***	-0.00980***	-0.01043**	-0.01030***	-0.01104***
Rho		0.83704***	0.88622***			0.88810***	
Lambda		0.23132***		0.93077***			0.89603***
W*Store entropy					-0.59233*	-1.55799***	0.41092
W*%, AA					-0.21003	0.10147	-0.48982
W*%, HL					0.75615**	-0.09927	0.21522
W*Race entropy					-0.70037***	-0.09612	-0.75657**
W*Ln (Med Inc)					-0.25525*	-0.00307	-0.02489
W*Ln (Total pop)					1.63339***	0.17364*	0.84360***
W*Ln (Total LA)					-1.25004***	-0.04882	-1.26920***
W*%, Elderly					-5.33482***	-1.38319**	-3.95720**
W*%, Fam HH					-2.76215***	-0.14425	-2.63347***
W*LU entropy					1.96730***	0.08126	2.02182***
W*Netw. density					-0.00568	0.00265	-0.00407

Appendix 2 (cont'd)

DV = Store count/ BG Service Area	OLS	SAC	SAR	SEM	SLX	SDM	SDEM
Mult. R-sq	0.3668				0.4579		
Adj. R-sq	0.3657				0.4558		
Pseudo R-sq		0.75344	0.75224	0.75147		0.75715	0.76116
Log likelihood		-9402.619	-9416.566	-9425.401		-9359.33	-9311.853
AIC	24218.6	18835	18861	18879	23353.29	18796	18674
BP test	358.72***	176.97***	220.12***	14.923	695.42***	408.41***	187.85***
Moran I test	0.53167***	-0.00474	0.02139***	0.00068	0.58021***	0.01337**	0.0007

*$p<0.1$, **$p<0.01$, ***$p<0.001$

Appendix 3 SDEM results using GM Estimator Robust to Presence of Heteroscedasticity

DV = Store count /BG Service Area	2019			2020		
	Coeff.	**SE**	**P-value**	**Coeff.**	**SE**	**P-value**
Intercept	11.860	3.191	0.000	18.809	3.497	0.000
Store entropy	1.784	0.094	0.000	1.799	0.100	0.000
%, AA	-0.116	0.143	0.414	-0.177	0.157	0.259
%, HL	0.130	0.130	0.315	0.144	0.143	0.314
Race entropy	-0.147	0.063	0.021	-0.095	0.070	0.173
Ln (Med Inc)	0.010	0.045	0.817	0.007	0.049	0.892
Ln (Total pop)	0.139	0.041	0.001	0.139	0.046	0.002
Ln (Total LA)	-0.279	0.023	0.000	-0.318	0.026	0.000
%, Elderly	-0.208	0.237	0.380	-0.160	0.261	0.540
%, Family HH	-0.332	0.128	0.009	-0.320	0.141	0.023
LU entropy	0.623	0.084	0.000	0.658	0.093	0.000
Network density	-0.010	0.002	0.000	-0.011	0.002	0.000
W*Store entropy	0.510	0.388	0.189	-0.307	0.422	0.468
W*%, AA	-0.593	0.446	0.184	-0.347	0.485	0.475
W*%, HL	-0.119	0.492	0.809	0.318	0.538	0.555
W*Race entropy	-0.722	0.266	0.007	-0.704	0.291	0.016
W*Ln (Med Inc)	0.051	0.191	0.791	-0.074	0.210	0.723
W*Ln (Total pop)	0.852	0.192	0.000	0.842	0.211	0.000
W*Ln (Total LA)	-1.053	0.101	0.000	-1.309	0.111	0.000
W*%, Elderly	-2.550	1.116	0.022	-4.012	1.227	0.001
W*%, Family HH	-2.116	0.544	0.000	-2.505	0.596	0.000
W*LU entropy	2.247	0.396	0.000	2.035	0.435	0.000
W*Netw density	-0.002	0.008	0.790	-0.003	0.009	0.702
Lambda	0.917	0.009	0.000	0.915	0.009	0.000
Moran's I test	0.591	sd=106.5	0.000	0.591	sd=106.6	0.000

Appendix 4 MGWR results

DV = Store count/ BG Service Area	2019					2020				
	Mean	STD	Min	Max	Bandwidth	Mean	STD	Min	Max	Bandwidth
Intercept	-1.952	4.87	-10.897	5.518	270	4.787	5.817	-6.063	18.544	43
Store entropy	8.302	3.511	0.425	16.478	43	4.275	1.332	1.421	6.678	261
% , AA	0.235	0.955	-0.832	1.725	1585	0.827	0.859	0.148	2.402	3184
% , HL	0.782	0.563	0.038	1.674	2325	1.019	1.271	-0.299	3.332	999
Race entropy	-0.132	0.43	-0.598	0.894	1018	-0.227	0.537	-0.791	1.227	958
Ln (Med Inc)	0.197	0.306	-0.611	0.814	43	0.192	0.429	-0.881	1.06	43
Ln (Total pop)	-0.121	0.001	-0.122	-0.12	5694	-0.419	0	-0.42	-0.418	5708
Ln (Total LA)	-0.303	0.173	-0.919	0.052	43	-0.247	0.173	-0.728	0.224	43
% , Elderly	-0.769	0.126	-0.963	-0.476	4914	-2.281	0.125	-2.504	-2.023	4824
% , Family HH	-1.227	0.075	-1.358	-1.046	2986	-2.266	0.198	-2.59	-2.017	2513
LU entropy	0.059	0.067	-0.037	0.227	3792	-0.179	0.061	-0.258	-0.01	4051
Network density	-0.025	0.006	-0.032	-0.008	1495	-0.029	0.006	-0.039	-0.013	1305
Adj. R-sq			0.746					0.79		
Log likelihood			-8445.291					-8628.206		
AIC			18115.851					18459.507		
AICc			18263.323					18601.386		

국문초록

코로나19가 식품접근성 격차에 미친 영향에 관한 연구

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불평등한 식품접근성은 사회경제적 특성이 다른 개인 간의 건강격차를 고착시킬수 있어 공중보건 분야에서 중요한 문제가 되고 있다. 코로나19는 식품 공급을 방해하고, 인접한 식료품점으로의 접근을 제한하여 지역 단위의 식품환경 수준을 저해아였다. 코로나19로 드러난 식품체계의 취약성은 식품체계의 평등성 및 회복탄력성 보완을 위한 정책 수립의 당위성을 보여준다.

본 연구는 미국 뉴욕시 사례를 중심으로, 코로나19 팬데믹 전후의 식품접근성과 지역특성 간의 연관성을 비교하여 식품체계의 평등성 및 탄력성 강화 방안에 기여하고자 한다. 이를 위해 5,712개의 미국 센서스 블록그룹을(census block group) 대상으로 도로 네트워크 기반 1km 반경 내 위치한 대형 식료품점의 수를 활용하여 각

블록그룹의 식품접근성을 측정하였다. 본 연구에서는 지역단위의 분석자료에 존재하는 공간효과를 고려하기 위해 공간계량모형 및 지리가중회기분석모형을 활용하여 식품접근성과 사회경제적 특성 및 건조환경 간의 관계를 분석하였다.

분석결과 식품접근성의 공간효과를 고려하지 않을 경우 인종집단 및 소득 변수와의 연관성이 과대 또는 과소 추정될 수 있음을 확인하였다. 변수별 식품접근성과의 관계에 있어 흑인 또는 아프리카계 미국인 비율과 인종 다양성은 음의 관계를, 히스패닉계 또는 라틴아메리카 출신 인구 비율은 양의 관계를 보이는 것으로 나타났다. 중위소득 변수의 경우 2020년 팬데믹 동안 음의 관계를 보이는 것으로 나타나, 식품접근성과 소득 수준 간의 관계에 대한 기존 연구결과와 차이점을 보였다. 또 공간계량모형을 통해 확인된 국지적 파급효과는, 지역특성 간의 관계과 블록그룹별로 상이한 것으로 나타난 지리가중회기모형 결과를 통해서도 뒷받침된다.

본 연구의 결과는 식품접근성에 대한 연구에서 공간효과를 고려할 필요성을 강조할 뿐만 아니라, 네트워크 연결성 개선과 소규모 식료품점 활성화가 평등하고 회복탄력적인 식품체계 개선에 기여할 수 있음을 시사한다.

주요어: 식품접근성, 코로나19, 국지적 파급효과

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