The mobility of food retailers: How proximity to SNAP authorized food retailers changed in Atlanta during the Great Recession

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Abstract

Retailer mobility, defined as the shifting geographic patterns of retail locations over time, is a significant but understudied factor shaping neighborhood food environments. Our research addresses this gap by analyzing changes in proximity to SNAP authorized chain retailers in the Atlanta urban area using yearly data from 2008 to 2013. We identify six demographically similar geographic clusters of census tracts in our study area based on race and economic variables. We use these clusters in exploratory data analysis to identify how proximity to the twenty largest retail food chains changed during this period. We then use fixed effects models to assess how changing store proximity is associated with race, income, participation in SNAP, and population density. Our results show clear differences in geographic distribution between store categories, but also notable variation *within* each category. Increasing SNAP enrollment predicted decreased distances to almost all small retailers but increased distances to many large retailers. Our chain-focused analysis underscores the responsiveness of small retailers to changes in neighborhood SNAP participation and the value of tracking chain expansion and contraction in markets across time. Better understanding retailer mobility and the forces that drive it can be a productive avenue for future research.

Keywords

Food environment; SNAP; Great Recession; Atlanta; retailer mobility

1. Introduction

In recent years, multiple studies have identified disparities in access to food retailers in cities across the United States linked to both race and economic characteristics. Poor access to healthy food may contribute to increasing rates of diet related chronic conditions among vulnerable populations (Black, Moon, & Baird, 2014). The actual impact on health remains unclear, in part due to the complex dynamics shaping food shopping behaviors (Cannuscio, Hillier, Karpyn, & Glanz, 2014; Cummins, Flint, & Matthews, 2014; LeDoux & Vojnovic, 2014; Zenk et al., 2011). Still, a lack of access to healthy and affordable food can increase time costs for low-income households with limited transportation options, adding to daily stress and stretching limited resources (Shannon, 2016).

Most recently, a number of authors have used data on individuals' daily mobility to analyze the dynamic ways that food access can vary within or between days (Shearer et al., 2014; Widener & Shannon, 2014; Chen & Clark, 2015; Ravensbergen, Buliung, Wilson, & Faulkner, 2016; Widener et al., 2017). While valuable, these studies have almost exclusively focused on the daily mobility of food consumers, treating neighborhood environments and food retailers as static. At small time scales, this is a reasonable assumption, with the exception of mobile and pop up sites such as farmers' markets and food trucks (Lucan et al., 2014).

Still, over longer units of time (months or years), food retailers are also mobile, moving in and out of neighborhoods based on economic and social transformations (Wylie, 2015). These changes in stores' spatial distribution are what we define as ***retailer mobility***, and it can vary by store type and neighborhood characteristics. While supermarkets may be more prevalent in low-density suburbs (Ledoux & Vojnovic, 2012), some chains target high-income communities while others focus more on middle and working class ones. Store siting decisions can be shaped by policy guidelines across spatial scales, including local zoning decisions or tax incentives but also federal food subsidies and emergency assistance (Ghosh-Dastidar et al., 2017). Tools for analysis of demographic and economic trends, such as ArcGIS Business

Analyst, can guide location decisions (ESRI, 2018). Retailers' food quality may also vary within store categories depending on target audience and location (Martin et al., 2014).

Framing differences in retailer proximity and quality as retailer redlining rather than food deserts may provide a more accurate conceptual framing (Zhang & Ghosh, 2015). The former term instead highlights how retailers' location decisions are based on the calculation of optimal sites for capital investment based on demographic characteristics and policy environments, rather than the natural process implied by the ecological metaphor of food deserts. Inasmuch as location decisions reflect and reinforce racially segregated landscapes, they are analogous to past redlining practices in housing which limited investment in non-white neighborhoods (Jackson, 1987).

Retailer mobility may be an especially salient concept for chain stores, where corporate actors think explicitly in terms of spatial networks of multiple locations. Chains share a single target demographic group and locational strategy. While previous research on retailer accessibility has grouped stores based on broad categories (*e.g.*, supermarkets, fast food, corner stores), an approach that differentiates between chains may thus provide insight into the factors shaping location decisions.

Within the United States, most policy to improve food access used tax or other monetary incentives to expand or renovate stores within low access neighborhoods. The Healthy Food Financing Initiative, announced by the Obama administration in 2011, is an example of this approach (Office of Community Services, 2011). However, the Supplemental Nutrition Assistance Program (SNAP, formerly food stamps) provides another economic incentive (Chrisinger, 2014). SNAP clients redeemed $66.5 billion in benefits in 2016 (USDA Food and Nutrition Service, 2017b), providing a significant local stimulus for retailers. Many SNAP clients rely on their benefits for much of their monthly grocery shopping (Bartfeld, Gundersen, Smeeding, & Ziliak, 2015), and so authorized retailers play a crucial role in providing food access.

This paper describes the results of a chain-based analysis of geographic proximity to authorized SNAP retailers in the years following the Great Recession (2008-2013). Participation in the SNAP program increased significantly in this period, as did the number of authorized retailers ([citation withheld for review]). Yet the pattern of store expansion was not uniform geographically or across chains. Through analysis of changes in retailer proximity across this time period within the Atlanta urban area, we identify how and where chains responded to increases in SNAP participation, as well as to changing racial and economic characteristics. The rapid changes during this period provide a unique natural experiment to understand how store chains respond to shifting demographic landscapes as well as how SNAP as an economic stimulus can affect neighborhood food environments.

2. Methods

2.1 Study setting

Our research focuses on census tracts within the U.S. Census defined urban area of Atlanta, Georgia. It includes sections of 21 counties (figure 1). This region had a population of 4.7 million people in the 2011-2015 ACS, an increase of 5% compared to the 2008-2012 ACS just three years earlier (United States Census Bureau, 2017). According to the most recent census data, 35% of the urban population identifies as African American, 11% as Hispanic/Latinx, and 6% as Asian American, and diversity is increasing rapidly in many suburban communities (Shaer, 2017; United States Census Bureau, 2017; Vasilogambros, 2015). One recent study identified Atlanta as the most sprawling urban area in the country (Hamidi & Ewing, 2014).

According to data provided to us by Georgia's Department of Family and Children's Services, SNAP enrollment increased dramatically within the Atlanta urban area following the recession, rising from 402,396 in 2008 to a peak of 844,748 in 2012 (Lauren Badger, Georgia Division of Family and Children Services, personal communication, March 26, 2014). Similarly, the number of SNAP authorized retailers increased from 1,913 to 3,543 in the same period, largely driven by the growth of small retailers.

Atlanta's recent growth—in population, diversity, and household participation in the SNAP program—make it an excellent site for this research.

2.2 Retailer data, chain identification, and distance measures

Our analysis focuses on the locations of SNAP authorized retailers within our study area. Authorized retailers are required to provide a basic selection of staple foods (meats, breads, produce, and dairy) as part of their participation in SNAP, as well as purchasing electronic equipment for benefit redemption (USDA Food and Nutrition Service, 2017a). While most supermarkets are SNAP authorized from the time they open, many small retailers receiving authorization during the recession were already in operation prior to our study period [citation removed for peer review].

We obtained yearly data on authorized retailers in the state of Georgia from 2008 through 2013 directly from USDA's Benefit Redemption Division (79,078 total records). These records include retailer names, addresses, geographic coordinates for current retailers, and USDA's retailer classification. We link specific retailer locations across years, reducing the data to 17,761 records for unique locations across years, and created a dichotomous variable identifying retailers in major chains based on retailer name. We also geocoded retailers lacking geographic coordinates using the Google Maps API service (Google, 2017). Selecting only the retailers in our study area reduced our dataset to 6,243 records.

To analyze retailer mobility, we select chain retailers that had at least thirty locations in each year of our study period, a threshold that captured major chains across store categories. We group the resulting twenty chains into three groups based on their classification by USDA. Large retailers, classified by USDA as superstores or supercenters, include supermarkets (Kroger, Publix, and Ingles), smaller groceries (Aldi and Food Depot), and big box stores (Target and Walmart). Convenience stores are mostly made up of gas station chains such as Exxon, QuickTrip, and Texaco. Combination stores include pharmacies (CVS, RiteAid, and Walgreens) and dollar stores (Dollar General, Dollar Tree, and Family Dollar). Our final dataset includes data on 2,147 retailer locations.

Our outcome variable is retailer proximity, a measure of distance that over time allows us to track the entrance and exit of SNAP-authorized retailers within neighborhoods. To create this variable, we compute the Euclidean distance between the 55,901 census block centroids in our study area and their closest five retail locations for each chain in each year (34.4 million records) to assess how this proximity measure varies across spatial scales. We do so using the gDistance function available in the nabor package for the statistical software program R (Elseberg, Magnenat, Siegwart, & Nüchter, 2012). Combined with data from the 2010 census, we then create a population weighted average retailer distance for each chain in each year for the 855 census tracts present within our study area. While we analyzed results for all five distance measures—the first through fifth closest locations—results were similar in all our tests and in this paper we report results based on the middle metric, third closest location. Model results for our other dependent variables are also available in Appendix B.

Lastly, we match identified SNAP retailers with store listings purchased from the commercial database service InfoUSA based on stores' name and address, linking 68% of our stores to these data. InfoUSA includes the year when each location entered its database, allowing us to identify retailers present prior to the recession. As SNAP authorization sometimes lagged one year behind InfoUSA's data, we identify all retailers present prior to 2007 who were also newly authorized to accept SNAP benefits in 2009 or later. These stores were present and operating prior to our study period but did not become SNAP authorized until after 2008. The low match rate between USDA and InfoUSA data may reflect previously identified gaps in the latter's datasets (Gustafson, Wilson, and Jilcott-Pitts, 2012), and our research team did not have access to a better data source to address this issue. Future research could use other commercial providers in an effort to raise this rate.

2.3 Census and demographic clusters

Our analysis measures differences in retailer mobility in part by observing changing proximity across tracts with similar demographics. Because our focus is on the mobility of retailers, not of individuals, we focus on socioeconomic characteristics in our clusters rather than measures of individual mobility such as commuting patterns. We do so because corporate actors typically make store siting decisions based on readily available demographic data through tools such as ArcGIS Business Analyst (Wylie, 2015; NAVTEQ, 2011; ESRI, 2018). To measure the racial and economic composition of census tracts, we obtained data from the U.S. Census American Community Survey (United States Census Bureau, 2017). For racial composition, we calculate population rates for African Americans, Asian Americans, and Hispanic/Latinx. For economic composition, we measure percent of households in poverty and those with yearly incomes above $150,000. As a control variable, we also calculate population density for each tract.

At the tract level, ACS data on race and economic variables are pooled into five-year samples. For example, our first dataset is constructed based on sample responses each year between 2006 and 2010. We match these estimates to our retailer data based on the midpoint of the five-year sample, meaning that the 2006-2010 ACS data are matched to retailer distance data from 2008. This allows us to track change in our demographic variables throughout the study period.

In many cases, tracts may be too small to assess the association between changes in retailer proximity and demographic composition. For example, the median distance between tract centroids in Atlanta is only 1.1 miles, but prior research has found that the median distance SNAP clients travel to shop at a supermarket is 4.9 miles (USDA Economic Research Service, 2009). As a result, chains may make siting decisions not just based on demographic shifts in a single census tract but also by those of its neighbors. To address this issue, we use hierarchical cluster analysis to group tracts into six demographically similar groups using the "hca" function in the R software package. These clusters are determined through analysis of averaged variables for race and income across our study period. This approach allows us to create demographic clusters within the urbanized area. Analyzing tracts within these clusters allows us to identify broad trends and differences in retailer proximity within and between these areas.

2.4 SNAP enrollment

The Georgia Department of Family and Children Services (DFCS) provided us with data on SNAP enrollment at zip code level for each year of our study period, which we subsequently transform to census tract estimates. The U.S. Department of Housing and Urban Development provides crosswalk tables between zip codes and census tracts, listing the proportion of each zip code's population that lives within a respective tract. We multiplied the count of SNAP clients in each zip code by these rates and then summed them to create tract level counts.

2.5 Analysis

Our analysis uses both descriptive statistics and statistical modeling to understand changes in proximity to our twenty chains in the years following the recession. In our descriptive analysis, we use exploratory visualization to identify both the geographic patterns in our variables of interest and changes in their spatial distribution during our period within each demographic cluster. To analyze retailer distribution, we visualize the distribution of distance to the third closest retailer within each demographic cluster.

For each chain, we use simple OLS regression to create tract-level trend lines through our study period, using retailer distance and year as our dependent and independent variables. Model coefficients indicate if retailer distance was increasing (positive) or decreasing (negative) during the period. Visualizing these coefficients shows changes in retailer proximity for each chain during our study period.

Lastly, we use descriptive statistics and fixed effects modeling to assess the association between retailer proximity, demographic variables, and SNAP enrollment. Fixed effects models control for unobserved characteristics unique to each individual observation through use of panel data, allowing analysts to use each observation as its own control (Allison, 2009). For example, the economic recession broadly affected our study area, and this general effect would show up in the coefficient for specific years in a fixed effects model. Our independent variables capture local variation. For these variables, we calculate the mean of each variable across years and use Spearman's rank-order correlation to identify the relationship between our independent variables and retailer proximity. We then use a fixed effects linear model to assess the relationship between our variables over time, lagging all independent variables by one year to account for a delay in chains' responses to demographic shifts and/or changing SNAP enrollment. As our dependent variable was positively skewed, we use logged values within our models. We used the plm package in R for our analysis.

3. Results

3.1 Defining the demographic clusters

Using hierarchical cluster analysis, we identify six distinct regions within our study area, shown in figure 1. These clusters are largely contiguous, extending across county boundaries, but in some cases, such as clusters 4 or 5, they are made up of smaller geographic clusters of tracts scattered across the study area.

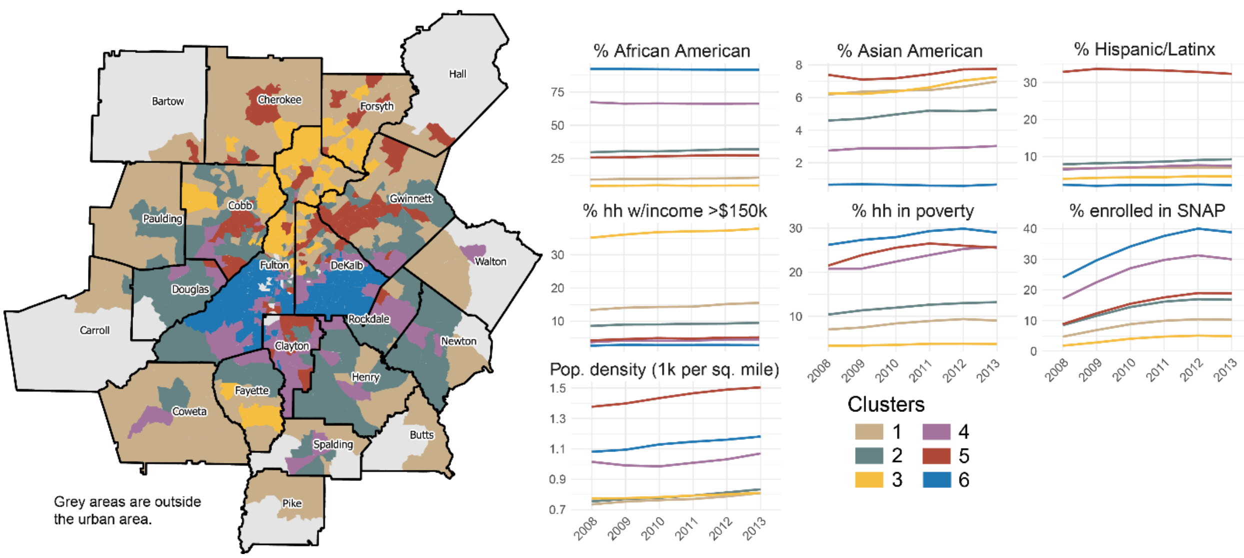

Figure 1: Demographic clusters within the Atlanta urban area

These clusters identify tracts with similar demographic characteristics for both race and income. The values for all independent variables in our analysis are shown on the right side of Figure 1. Based on these characteristics, we describe each cluster in the following way, using mean values of rates across all years:

- Cluster 1: Exurban communities with low rates of non-White populations (23%) and comprised of largely middle class households.
- Cluster 2: Suburban communities similar to cluster 1, but with higher rates of African Americans (31%) and poverty (12%).
- Cluster 3: Primarily located in the north metro, these communities have many high-income households (37%) and low rates of non-White populations (16%).
- Cluster 4: Proximate to the urban core, these inner suburbs are majority African American (66%) and have high rates of poverty (23%).
- Cluster 5: Scattered throughout the urban area, these diverse communities include many Hispanic/Latinx households (33%) as well as African Americans (27%) and high rates of poverty (25%).
- Cluster 6: Located primarily in southern Fulton (Atlanta) and DeKalb counties, these communities are almost exclusively African American (92%) and have high rates of poverty (29%).

These clusters share some commonalities. Clusters 1 and 2, for example, are both found on the outer edges of the urban area and have similar economic and racial characteristics. Clusters 4 and 6 are both heavily African American, though cluster 4 has lower rates of poverty and more individuals who identify with other races.

As Figure 1 shows, the racial composition of these clusters was largely unchanged over the study period. Poverty rates increased modestly, with clusters 4 and 6 seeing the most significant increase. SNAP enrollment had the most significant change, with rates of participation increasing to 40% for cluster 6 in

2012 and small increases even in high income cluster 3 (from 2% to 5%). Population density also increased throughout this time period in all clusters.

3.2 Retailer density and distance

Figure 2 is a small multiples map showing the location of authorized SNAP retailers for each store chain and changes in location during the study period. The grey dots show retail locations that were SNAP authorized in all years of the study period. Red dots show retailers who exited SNAP, while green dots became SNAP authorized during the study period. Orange dots entered and exited the program during the study period.

These maps demonstrate that most large retailers—Aldi, Kroger, Publix, Target, and Walmart—were concentrated in the northern and eastern sections of the study area. Food Depot and Ingles, two smaller regional chains, were concentrated in the south and east. While Target and Walmart were both most concentrated in the north, Walmart had noticeably more stores in southern sections of the county than its big box rival. Compared to convenience and combination stores, there was little volatility among large retailers. However, Publix and Ingles both lost locations in the eastern half of the study area during this time, while Aldi, Kroger, and Walmart added several locations in the northern half.

Among convenience stores, the most notable trend is the high rate of volatility during the study period. The large number of orange dots demonstrates that, with the exception of QuickTrip, which mostly added retail locations, a large number of locations entered and exited SNAP during the study period. While almost all chains are concentrated in the central section of the study area, they vary in the breadth of their coverage. Chevron, Citgo, and Shell cover most of the area. Exxon and Quick Stop are located in narrow bands near the city of Atlanta, and QuickTrip has the largest concentration in the northeast.

Combination stores vary noticeably in their geographic distribution. CVS locations are present throughout the study area, but both RiteAid and Walgreens are most concentrated in the north and east. Among dollar stores, Family Dollar is located primarily in the city of Atlanta and inner suburbs, while both Dollar Tree and Dollar General form a ring around the central city. Almost every chain expanded locations during the study period with the exception of RiteAid. For CVS, Dollar Tree, and Walgreens, this expansion happened primarily in the northern suburbs, while Family Dollar expanded to the east and south.

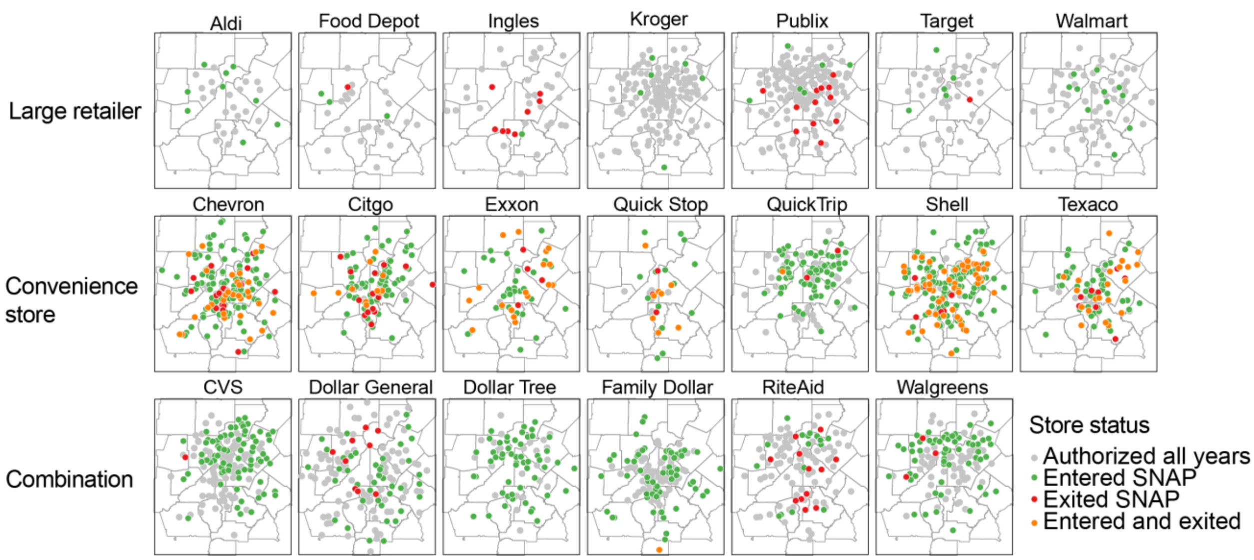

Figure 2: Locations of retailers in the 2008-2013 study period, including stores entering and/or exiting SNAP

Figure 3 shows the distribution of our main outcome variable—a census tract's distance to the third closest retail location—broken down by store chain and demographic cluster at the start of our study period, 2008. The bars used in Figure 3 represent the range for the middle 50% of data, similar to a box plot. Several trends are noticeable, with variations by both chain and cluster.

For large retailers, Kroger and Publix consistently have the closest proximity, not just among these large stores but among almost all chains we analyzed (Family Dollar being the only exception). This is not surprising given that these two stores along with Walmart are the dominant chains in the city. For both these chains, the closest locations are in cluster 3 (high income) and cluster 5 (diverse and lower income). Clusters 1 and 2 (outer suburbs) and clusters 4 and 6 (African-American, lower income) have higher distances. Target is also closest in clusters 3 and 5, while Walmart has similar ranges across all clusters. For smaller chains—Aldi, Food Depot, and Ingles—the smallest distances are in clusters 4, 5, and 6, lower income tracts in the central city or inner suburbs. Locations for these chains have higher distances in wealthy tracts (cluster 3) and the urban fringe (cluster 1).

Among convenience stores, the pattern generally follows the urban gradient, similar to Aldi or Ingles. The largest distances are present in the outer suburbs (clusters 1 and 2) as well as the higher income cluster 3. Distances are uniformly lower in clusters 4, 5, and 6—lower income tracts. Combination stores follow a roughly similar pattern, especially pronounced in the case of Family Dollar, which is concentrated in and around the city of Atlanta.

Across clusters and stores types, this visualization shows that cluster 3 has the lowest distances to major supermarkets but higher distances to other SNAP-authorized chains—smaller grocery stores as well as non-groceries. Clusters 4, 5, and 6 have lower distances to convenience and combination stores, as well as small groceries. The outer suburbs, clusters 1 and 2, have the largest distances overall, which is unsurprising given their lower population density.

We also calculated correlations between each of our variables of interest and our outcome variable, with results reported in Appendix A. We highlight all correlation coefficients with a magnitude of 0.2 or higher. Results correspond with the patterns described above. Among large stores, distances to Publix and Target are negatively correlated with the percentage of higher income households, meaning stores are generally closer in high-income tracts. Distances to Aldi, Food Depot, and Family Dollar—along with most convenience and combination stores—are negatively correlated with higher rates of poverty and percentage African-American, meaning that these stores are more proximate to these tracts. Distances to Walmart, QuikTrip, RiteAid, Walgreens and Dollar Tree are negatively correlated with percent Asian-American and Hispanic but no other variables.

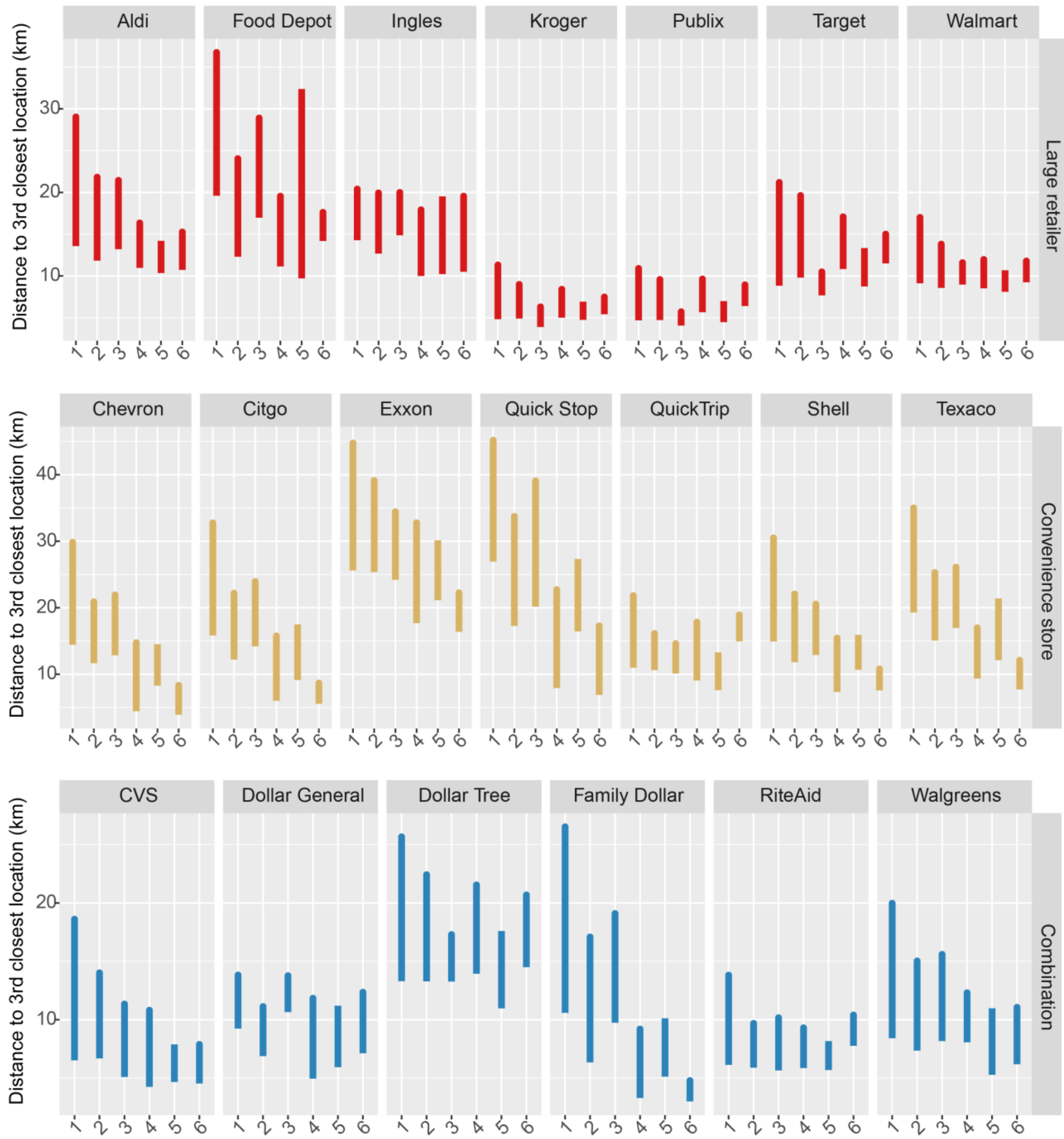

Figure 3: Range of mean distances in to third closest retailer location for the middle 50% of census tracts in 2008

We also applied a Kruskal-Wallis test to retailer distance across clusters. Similar to ANOVA, but suitable for non-parametric data, Kruksal-Wallis identifies significant differences between three or more groups, though it does not specify where those differences occur. Our analysis confirmed the presence of statistically significant differences between clusters for each chain.

3.3 Changing retailer proximity

To identify trends in retailer proximity throughout the study period, we used simple linear models to create trend lines for retailer distance each tract. We then calculated the percentage of tracts in each cluster with positive and negative coefficients. In tracts with a positive coefficient for these models, shown in red in Figure 4, the distance to the third closest location increased. For tracts with a negative coefficient, shown in green, that distance decreased.

Figure 4: Percentage of tracts in each cluster with increased or decreased distance to third closest location over the study period

In most parts of the study area, proximity to convenience and combination stores improved over the study period, but this trend was less prevalent among large retailers. Distance to Walmart locations decreased uniformly across clusters. Distance also decreased for Aldi, but primarily in the outer suburbs (clusters 1 and 2) and affluent inner suburbs (cluster 3). Many tracts had increased distances to Ingles, Kroger, and Publix, and for the last of these, these increases were most common in the lowest income areas (clusters 4, 5, and 6). Distance to Target locations also increased most noticeably in predominantly African-American areas (clusters 4 and 6).

Among convenience and combination stores, almost every chain saw uniform decreases in retailer distance, with three notable exceptions. A small percentage of tracts in low-income African American neighborhoods (clusters 4 and 6) had increased distances to Quick Stop during the study period, and a larger number had increased distances to RiteAid. In cluster 3, however, distances to RiteAid decreased in many tracts and many had increased distances to Dollar General.

The trends identified in Figure 4 show changing proximity to SNAP authorized retailers. Trends varied most noticeably among large retailers, with near uniform decreases in retailer distance for smaller chains. Many of these small retailers were physically present prior to the recession based on the limited matches we were able to make with InfoUSA data. For most chains, the growth in SNAP authorized retailers was mainly based on actual store expansions. However, approximately half of new Chevron and Shell locations were present prior to the recession (57% and 49% respectively). CVS (27%) and Family Dollar (13%) had lower but still notable rates. These figures are only suggestive, as we had low rates of correspondence between USDA and InfoUSA data. Still, these data suggest that for many of these chains, increases in geographic proximity were partially the result of increased rates of SNAP authorization.

3.4 Statistical models

The descriptive statistics above highlight several notable differences in the spatial distribution of retail chains within our study area. Statistical models found similarly divergent patterns among chains. Our models vary in overall strength. We tested models with five different dependent variables, distance to the first through the fifth closest location. The resulting R^2 values are shown in Figure 5 with the dependent variables labeled D1 to D5 respectively. In many cases, model strength improved with higher order distance measures, suggesting that our independent variables are better at predicting changing store participation in SNAP at a larger scale. For simplicity of presentation, we base our models on the middle variable—distance to the third closest location, as beta coefficients remained consistent across scale.

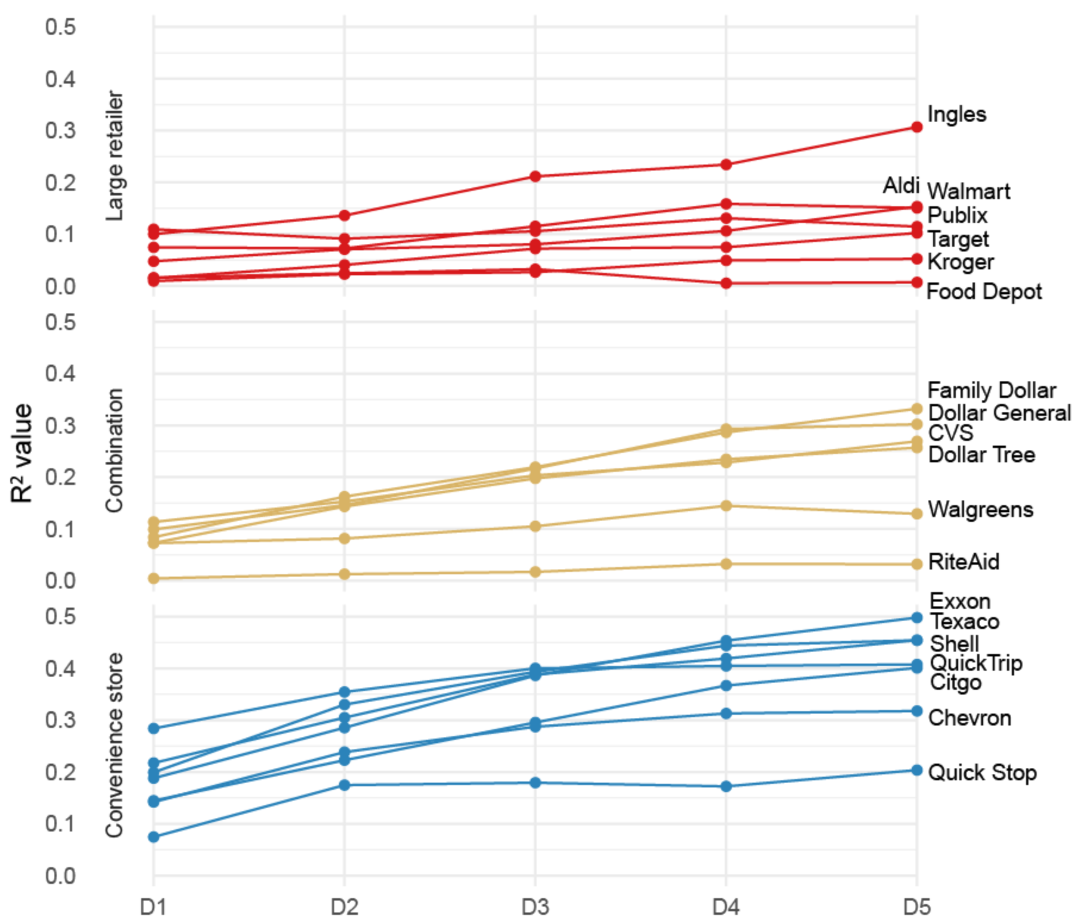

Figure 5: R2 values for the fixed effects models

For distance to the third closest store, the R^2 values ranged from 0.02 (RiteAid) to 0.40 (QuickTrip). Seven chains have R^2 values below 0.15: RiteAid, Kroger, Food Depot, Target, Aldi, Walgreens, and Walmart. Of these, five are large retailers. Many tracts experienced no change in proximity to these chains, as shown in Figure 4, which likely limits the power of these models. Future research with data for a longer study period may find more variation in proximity and thus improve model strength. The six chains with the highest R^2 values are all convenience stores, which as shown in figure 2 had the clearest pattern of growth during the study period.

Because of the large number of models, we visualized model coefficients and their associated confidence intervals in the main text (Figure 6). This figure shows only significant coefficients ($p < 0.05$). The black vertical line is placed at zero. Dots to the left of this line are negative coefficients, meaning that an increase in the independent variable was associated with decreased distances to retailers. Dots to the right of the line mean that an increased in the variable was associated with increased retailer distance. A table of model results for all models is available in Appendix B.

This figure shows that demographic variables had small, negative, and significant coefficients in models for most convenience and combination chains. In the case of CVS, for example, the coefficient for percentage African-American was -0.01. Since the dependent variable is logged distance, this coefficient indicates that a 1% increase in the African-American population was associated with a 1% decrease in distance to the third closest CVS location. While this number is small, its effect is still notable for some tracts. Of our 855 tracts, 41 had a decline of 10% or more in percentage African American during this time, and 63 tracts had an increase of 10% or more (Table 1). In the latter case, the model predicts that distance to the closest SNAP authorized Shell retailer—the chain whose negative coefficient had the greatest magnitude—dropped 13% or more in these tracts. For large retailers, while most model coefficients related to race and income are not significant, those that are significant are quite small in magnitude, ranging from -0.003 to 0.003.

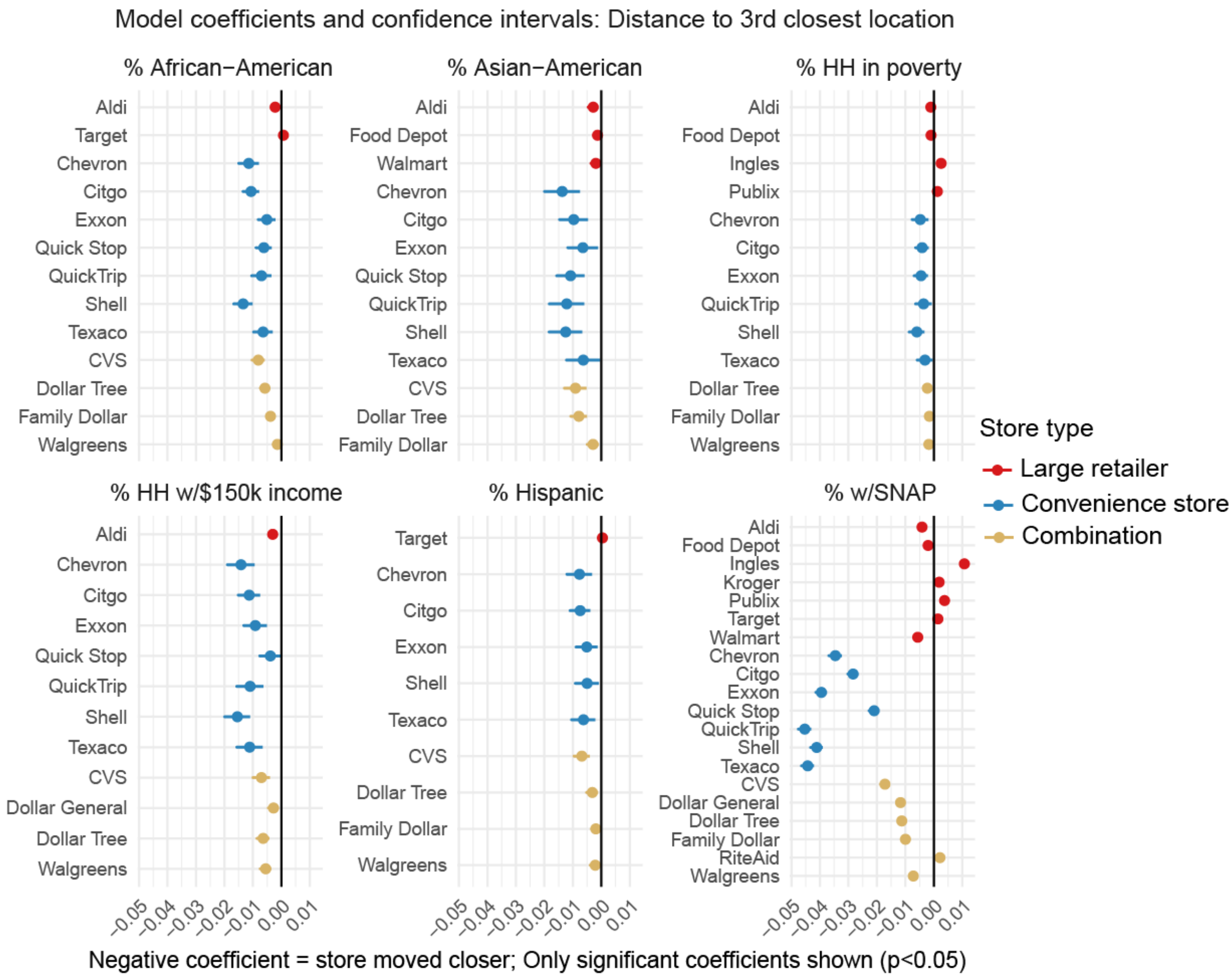

Figure 6: Beta coefficients and confidence intervals for the fixed effects models

Figure 6 illustrates much stronger association between SNAP enrollment and store proximity, with significant coefficients for every chain. For half of large retailers—Ingles, Publix, Kroger, and Target—these coefficients are positive (0.001 to 0.011). For Aldi, Food Depot, and Walmart, coefficients are negative (-0.002 to -0.006). Changes to SNAP enrollment thus had contrasting and small effects in the proximity of these stores in our study area. SNAP enrollment increased by 10% or more in 286 tracts (Table 1). In these tracts, distance to the third nearest Publix is predicted to increase 4% or more, but distance to the third nearest Walmart would decrease by 5% or more. As in other parts of our analysis, large supermarkets and Target contrast with low price chains such as Aldi and Walmart, with the latter becoming more proximate to tracts with increasing rates of SNAP participation.

For convenience stores, the coefficients are uniformly negative and several times larger in magnitude compared to large retailers (-0.02 to -0.045). This demonstrates a strong, consistent statistical association between increased SNAP participation and proximity to these chains. For tracts with a 10% or greater increase in SNAP participation, distance to the third closest QuickTrip is predicted to decrease by more than 45%, a stark contrast to the 4% increase in distance to the third closest Publix.

	Count of census tracts with change in the indicated range between 2008 and 2013		
	10% or more decrease	**10% decline - 10% increase**	**10% or more increase**
Percent African American	41	750	63
Percent Asian American	6	832	16
Percent Hispanic/Latinx	30	793	31
Percent of Households in Poverty	39	680	135
Percent of Households >$150,000	11	804	39
Percent SNAP participants	2	566	286

Table 1: Count of tracts with categorized rates of change in selected model variables between 2008 and 2013

Among combination stores, coefficients are also mostly negative for SNAP enrollment rates, but smaller in magnitude than convenience stores (-0.02 to 0.002). Still, these coefficients are notable, as a 10% increase in SNAP participation would be associated with a 17% lower distance to the third nearest CVS and a 12% lower distance to the third nearest Dollar General. RiteAid is the only store in this category with a positive coefficient in our models. As is apparent in Figure 2, this chain closed several locations in the core urban area during the study period while opening others in the far northern (and more affluent) suburbs, which may explain these results.

4. Discussion

Our analysis shows significant disparities in proximity to SNAP retailers by chain across the study area. Among the demographic clusters we identify, those with the lowest income and highest non-white populations have higher distances to chain supermarkets and lower distances to SNAP authorized small retailers when compared to high-income tracts. In our fixed effects models, for most small retailers, increases in non-white populations and higher rates of poverty are associated with a decrease in distance to closest retailer, while large retailers have small and mixed coefficients. Our use of fixed effects models and of temporally lagged independent variables suggest a causal relationship between these demographic factors and the proximity of SNAP authorized retailers.

Most notably, while increased enrollment in SNAP is associated with decreased distance to authorized small retailers, it predicts increased distance to most large retailers, a finding that supports previous research ([citation withheld for review]). In addition, our study shows that increased SNAP enrollment in a census tract may lead to increased distance to many major grocers. Large retailers do benefit financially from growth in SNAP clients. Based on data provided to us by USDA, authorized supermarkets and super stores in Georgia received $194 million in SNAP redemptions in June 2014, more than double the $94 million they received in in June 2008 (USDA benefits redemption division, personal communication, June 22, 2015). Yet for many chains, these benefits do not translate into new stores and improved access for SNAP clients in areas with increasing rates of SNAP participation.

The reasons for this increase in distance to many large retailers are not clear from our data. For large retailers, the economic stimulus provided by SNAP benefits may not be sufficient to counteract larger social and economic shifts within communities. Alternatively, chain managers may simply choose not to invest resources in stores with fewer middle and high-income consumers. Supermarkets have historically been designed for middle and upper class suburban communities (Deutsch, 2010), and our analysis shows that these chains continue to grow in these areas. While large retailers may benefit from SNAP's economic stimulus, economic decline of surrounding commercial centers may drive potential customers elsewhere. Lastly, given that SNAP enrollment is the most temporally precise variable in our model, it may also be acting as a proxy for other economic factors that are smoothed across years within our census data. If this is the case, the increased distance to large retailers may be due to generally decreased household incomes rather than SNAP participation specifically. Whatever the cause, these data indicate that the short-term economic stimulus provided by SNAP benefits is not a sufficient incentive to significantly affect the siting decisions of large supermarkets.

Our analysis is also unique in focusing on retail chains to identify how market segmentation may affect neighborhood food environments. Among large retailers, both Walmart and Publix have an extensive network of locations within the Atlanta urban area, and many areas have low distances to both stores. Yet our analysis demonstrates that Publix is most concentrated in high-income areas of the city, with models suggesting that increased SNAP enrollment predicts increased distance to the closest locations. Walmart also lacks locations near the lowest income neighborhoods within the city (demographic cluster 6). However, it is geographically more concentrated in middle to low income neighborhoods than any other large store chain, and models predict that increased SNAP enrollment predicts lower distances to nearby stores. This identified difference between these two chains highlights the value of chain-based approach.

Our analysis also finds differences among smaller retailers. SNAP authorized Dollar General and Family Dollar locations have distinctly different geographic distributions. The former is located primarily in middle-income inner suburbs while the latter is concentrated in the urban core. During our study period, proximity to the closest Dollar General increased in many sections of the city outside of the highest income areas, but for Family Dollar, store proximity increased most notably in the outer suburbs. Models showed that distance to Family Dollar decreased when rates of African-American, Hispanic, and high poverty populations increased, while greater proximity to Dollar General was only associated with rising rates of high-income households among our demographic variables. Yet both had similar responses to increased SNAP enrollment. Our models also show greater sensitivity to increased SNAP enrollment for convenience stores--gas stations and corner stores—when compared to combination stores—dollar stores and pharmacies.

Our results have several implications for policies promoting more equitable food access. First, programs such as the Healthy Food Financing Initiative have provided policy solutions for improving food accessibility by providing tax incentives for supermarket chains and leading to a broad range of projects

(Chrisinger, 2016; Office of Community Services, 2011). Though less direct in its mechanism, SNAP benefits provide another financial stimulus that can shape neighborhood food environments (Chrisinger, 2014). However, this effect may be problematic from a public health perspective. While increased SNAP benefits may spur either new retail locations or retailer participation in the SNAP program, this is true primarily for small stores who may provide only limited access to fresh, healthy foods (Cavanaugh, Mallya, Brensinger, Tierney, & Glanz, 2013; Racine, Wang, Laditka, Johnson, & Mignery, 2013).

One clear implication of this study is the need for public health professionals to work proactively with small retail chains that are most highly concentrated in low-income neighborhoods. Such work has traditionally been done at the store level (Martin et al., 2012), but this research suggests the potential power of engaging with store chains more broadly. A corporate or regional partnership with Family Dollar, for example, could result in broad improvements in healthy food access. Future research can also more closely examine the reasons for existing small retailers to become authorized for SNAP benefits and the spatial pattern of these stores compared to newly opened ones.

In addition, several large retail chains show a clear preference for middle and high-income census tracts, and this casts doubt on their ability (or willingness) to effectively provide access to healthy foods for low-income neighborhoods. Previous research has suggested that supermarket locations in low-income neighborhoods may have higher prices than locations in middle class communities ([citation removed for review]) and that new supermarkets do not necessarily result in beneficial dietary changes (Cummins et al., 2014). It may be that the disparities in store proximity linked to economic and racial characteristics are simply a consequence of the economic logic undergirding large supermarkets, which have traditionally favored middle class and often mostly white suburbs (Deutsch, 2010). Work on alternative food systems (*e.g.*, urban agriculture, food cooperatives) in the context of food justice provides possible alternative models (Alkon & Agyeman, 2011; Gottlieb & Joshi, 2010).

Nutrition education programs such as SNAP-Ed also are increasingly developing health promotion interventions with retail partners such as in-store advertising, a strategy thus far used primarily with small retailers (Gittelsohn, Rowan, & Gadhoke, 2012). Changes to the USDA stocking previsions for SNAP authorized retailers may also improve the uniformity of healthy food options across retail chains, similar to improvements seen in the past for WIC retailers (Cobb et al., 2015). Our research suggests that depending on both geographic context and audience, some chain retailers may be better suited to these initiatives than others.

Our findings have several limitations. First, our study is set in a single urban area, limiting the generalizability of the findings. Second, further comparative research using longitudinal store data is needed. We examine store change over a relatively short period. The location decisions of large retailers in particular may play out over decades rather than a few years. A longer study period would also allow us to capture greater demographic shifts within our study area, improving the strength of these variables in our models and addressing the limitations of pooled ACS data. Third, in focusing on only the most common retail chains, our analysis does not include independently owned stores. Independent supermarkets can fill in gaps left by larger chains. Future work on independent and chain retailers could assess this issue. Finally, future research could incorporate commuting data or GPS tracks to examine the intersection of retailer and individual mobilities.

5. Conclusion

The recent focus on the mobility of individuals in food shopping how shown how food accessibility can exhibit significant spatiotemporal variability. Yet as our analysis shows, food consumers are not the only mobile elements of the urban food system. Retailers are also mobile, changing locations based on changing socioeconomic landscapes and policy environments. Our analysis reveals ongoing disparities in food environments within a major American city during a period including the Great Recession. While SNAP benefits provided a valuable support to many households during this time, the stimulative effects of these benefits on the surrounding food environment is linked to deepening socioeconomic and racial inequities: increased proximity to small retailers and similar or decreased proximity to many large ones. By better understanding the factors shaping retailer mobility, policy makers and public health advocates may be better equipped to develop partnerships ensuring healthier and more equitable urban food systems.

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