Searching For Food Access Policies To Reduce Food Insecurity

Jeffrey H. Dorfman, Jared D. Grant, and Craig Gundersen
University of Georgia, The Ohio State University and Baylor University

May 2023

Abstract

We examine a variety of measures hypothesized to have impacts on food security, utilizing them to develop insight into which food initiatives and related policies are most likely to reduce food insecurity. We find empirical evidence that focusing on store openings is likely to be less impactful of food insecurity than improving transit options to reach nearby stores and designing/retrofitting neighborhoods so that walking or driving to a food retailer is easier.

Selected Paper prepared for presentation at the 2023 Agricultural & Applied Economics Association Annual Meeting, Washington DC; July 23-25, 2023

Searching For Food Access Policies To Reduce Food Insecurity

INTRODUCTION

Food insecurity has become a leading, if not the leading, indicator of well-being for vulnerable persons in the U.S. In 2021, almost 34 million people were food insecure (Coleman-Jensen et el., 2022). While down from highs of over 50 million a decade ago, this means one-in-ten Americans are food insecure. The proportion of the population that experiences food insecurity makes this a leading policy issue as do the extensive negative health outcomes associated with food insecurity (for a review see Gundersen and Ziliak, 2015) with corresponding increases in health care costs (Berkowitz et al., 2018) and mortality (Walker et al., 2019).

An extensive literature has examined the determinants of food insecurity at the household level (for a review, see Gundersen and Ziliak, 2018). Alongside this research on household-level determinants, there has been some work on the impacts of broader community level factors. For example, research has examined the impacts of food prices (Bronchetti et al., 2019; Gregory and Coleman-Jensen, 2013), food taxes (Zheng et al., 2021), and the role of large-scale supermarket expansion (Courtemanche et al., 2019) on food insecurity. Despite its prominent role in many discussions about the food economy in the U.S., "food deserts" has received surprisingly little attention in the food insecurity literature.

A food desert has been defined in a variety of ways, but generally along the lines of a neighborhood where healthy foods are either unavailable or unaffordable to purchase. The USDA Economic Service (ERS) created a Food Access Research Atlas that flags low-income census tracts as low food access if they are beyond either 1/2 mile (or 1 mile) from a supermarket. These measures can also be specified to measure the share of a census tract's population that is beyond

1/2 mile (1 mile) from a supermarket. Two problems with this measure are that while it is on the census tract level, it doesn't include every census tract within the United States and it is difficult to determine if census tracts that are classified as low food access are comparable or equal. Consequently, it cannot properly explain variation in food access with the precision needed for better analysis of the role food access plays in public health and food insecurity; thus, a more continuous, more nuanced measure would be preferred.

This paper begins a journey toward a policymaking-centric, customizable, continuous food access measure. We build on previous work in this area and the USDA binary food desert variables to produce several continuous food access measures that can be computed for all U.S. census tracts. Beyond distance to a food store, we add information on access to transportation, neighborhood walkability, and store reliability. We aim to show that food access measures can be constructed which incorporate much more information than simply distance to a store selling affordable, healthy food and that such measures can provide useful information to policy makers through examining the marginal effect of different components on desired policy outcomes such as lower food insecurity rates.

One previous approach to constructing a continuous measure of food access is found in Armin et al. (2021). Their measure, called mRFEI, provides a continuous measure of food access defined as the percentage of healthy food retailers in a census tract; that is simply (# stores selling healthy food)/(# of stores selling food). While this measure provides more information than the ERS binary measure, the reality of food access in an area will differ depending on things income, walkability, store access, and vehicle access. This paper builds on Armin et al. by adding to their healthy food retailers percentage a suite of census tract level information on transportation access, walkability, and store turnover. This yields a continuous measure at the census tract level. We then use our new measure to examine which of the components shows the most promise at reducing food insecurity, providing policy makers with information on which policies promise the most bang for the buck.

The rest of the paper is organized as follows. We present a set of component variables we believe should be included in the process of building a continuous food access measure. Then the data details are discussed. We then present both correlations between the component measures and census tract-level food insecurity rates and estimation results for a translog model combining all the components to explain variation in the census tract-level food insecurity rates. Finally, we use the estimated translog model to present estimates of the marginal impact of improvements in our component measures on food insecurity rates, providing policy makers with some empirical evidence on where they could do the most good in attacking food insecurity

FOOD ACCESS MEASUREMENT COMPONENTS

As the basic building block to create a more comprehensive measure of food access we begin with what we call the Healthy Environmental Access Tract (HEAT) Score. Similar to the mRFEI measure of Armin et al. (2021), the HEAT Score is a ratio of weighted SNAP eligible stores to the number of SNAP eligible stores by census tract. We differ from Armin et al. (2021) by weighting by each store type's share of total SNAP spending to account for the differential impact on food access between, for example, a corner convenience store and a big box supercenter retailer. The second component constructed is the percent of people in each census tract that regularly use public transit or drive a car. This measures the ability of people to access food from neighboring areas. Third, the walkability score of the census tract is included in our more comprehensive approach, to account for the actual ease of access to a store. This differs from other measures which use the direct distance to a store rather than the distance after taking into consideration things such as the construction of intersections. Fourth, we include ERS' binary food desert measure, with the one-mile radius. Finally, we add information on the cumulative rate of turnover among food stores in a census tract with the idea that when store ownership changes more frequently and stores do not remain in operation for very long, consumers are less likely to trust those retailers and, thus, effective food access may be lower than it would appear just from store counts and locations.

To describe these components in detail, we employ the USDA Food and Nutrition Service (FNS) Snap Retailer Locator Dataset and the US Census Bureau 2020 Tiger FGDB to build a database of every food retailer that accepts SNAP in every census tract. To qualify as a SNAP retailer, the store must stock a minimum amount of healthy foods, so this seems the appropriate universe of food stores to measure food access. All stores in the USDA-FNS database are categorized by type (convenience store, small grocery store, supercenter, etc.). Each store was given a weight based on the share of SNAP dollars spent at stores in that category. This ensures that the HEAT Score increases more if a Walmart or full-size supermarket opens in your census tract than if a bakery or a butcher's shop opens in the same location.[1] These weighted stores were then summed up for each census tract and then divided by the total (unweighted) number of SNAP-accepting food retailers in that census tract. This is the HEAT Score, depicted mathematically as

$$HEAT = \frac{Weighted\ Sum\ of\ Total\ SNAP\ Retailers}{Unweighted\ Sum\ of\ Total\ SNAP\ Retailers}.$$

However, while the ideal measure of food access is local, a census tract is a pretty small area in many cases. Many people shop for food in a different census tract than the one they live in.

[1] For the weights equal to the share of SNAP dollars spent at each category of stores, see Data Appendix Table 2.

To account for other shopping opportunities in the neighborhood around each person's home census tract, we did the following. First, we computed the percent of people in each census tract that have access to a car plus the percent of residents who used public transportation to commute to work (both measures come from the American Community Survey). This gives us the share of people who can most easily shop outside their home census tract. Second, we multiplied each commute percentage by the census tract average HEAT Score from neighboring census tracts. This was done to show a census tract with high vehicle access or public transportation is important if its neighboring census tract has a high a high HEAT Score. We believe it makes more sense to use this information than to simply measure distance from residence to a store.

To further incorporate information on the ease or difficulty of reaching nearby stores, we also add to our measure the walkability index of each census tract, using the measure from the Smart Location Database (US EPA, 2023). Walkability measures how easily a person can walk from point A to point B within a neighborhood and the diversity of land uses within walking distance; thus, an area with regular street grids gets a high walkability score while cul-de-sacs and other barriers (such as a highway dividing a neighborhood) cause an area to get a low walkability score. Importantly, an area with residential and retail locations within walking distance of each other will get a better walkability score than a purely residential neighborhood.

The USDA's Economic Research Service (ERS) produces several binary food access (food desert) measures. We incorporate one that reports the percent of each census tract's residences that are within one mile of a food retailer. Unfortunately, ERS does not have values for their measures for all census tracts, so this component is included in the subset of census tracts for which it exists, and results are reported for that set of census tracts and for measures without the ERS component for all census tracts.

The final piece of information to add to our new continuous food access measure is a measure of store reliability. If most food retailers in a neighborhood are new, residents may not trust them enough to shop there regularly yet. If stores close frequently, residents similarly may chose to buy their food at a store they can rely on, even if it is farther away. People don't want to adapt to a new grocery store all the time as the search and adjustment costs can be quite high. To include a proxy for trust, a store turnover rate was crafted from the FNS Historical SNAP Retailer Locator dataset. To measure store turnover, the stores in the dataset were grouped by street address and summed over time to measure how many stores were operated at a location from 2002 to December 2022. The variable we create to measure the trust in and reliability of food retailers within a census tract combines the relative age of food retailers in a census tract compared to the national average multiplied by the census tract's average store turnover rate compared to the national average store turnover rate. Mathematically,

$$Store\ Location\ History\ =\ \left(\frac{Years\ Open\ (National\ Average)}{Years\ Open\ (Census\ Tract\ Average)}\right)\left(\frac{Store\ Turnover\ Rate\ (Census\ Tract\ Average)}{Store\ Turnover\ Rate\ (National\ Average)}\right).$$

A census tract with stores that have been operating in the same location for longer or have turned over less frequently (meaning a new store in the same location as a now-closed food retailer) will have lower scores, so on this measure lower scores are better. Thus, instead of adding this one to the previous components, we subtract the store location history measure for each census tract. A store that has a store turnover of 1 means that one store has operated at that specific location for 20 years. The rationale was if a location has a high store turnover rate, the community might have little trust in a future grocery store staying open in that location and will not frequent it in future.

The correlations of these component measures with food insecurity rates are presented in the empirical results section below.

To investigate the impact of each of these measure on food insecurity, we construct a translog regression-based measure for which we use all the components discussed above (HEAT score, transportation access, walkability, ERS binary measure, and store turnover history) as regressors in a translog functional form with the (log of) estimated census tract food insecurity rates as the dependent variable. The predicted values of this regression can give us, in a sense, a continuous food access measure that by construction is designed to correlate well with estimated census tract-level food insecurity. Importantly, this measure also lets us compute the elasticity of census tract-level food insecurity rates with respect to each of the components of our measure. These elasticities allow us to offer forecasts of the likely impact on food insecurity of policies to address each component in our measure. Thus, policy makers can get some idea of how much food insecurity could be affected by, for example, opening a new store in a low food access neighborhood or improving transit access. These provide some real-world, policy-relevant empirical results on which food access policies might provide the most bang for the buck.

DATA DETAILS

To validate our continuous food access measure, we need something to compare it to. Since there is no agreed upon measure (or even definition) of food access, we have to compare it to something it should be expected to be correlated with; for this we choose food security. After all, the main reason people care about measuring food access is because of the assumed impact it has on food insecurity. If healthy, affordable food is not easy to purchase close to home, it makes sense that people are more likely to have difficulty affording and procuring a reliable, food supply. **Appendix 1** shows a lookup table with for all the measures used with their sources.

The U.S. government does not have a measure of food insecurity that is available at the census tract or even county level. In response, we use data from Feeding America’s Map the Meal

Gap (MMG) project which provides interpolated data for counties and census tracts based on official 2020 food security rates at the state level. (For more details about Map the Meal Gap see https://map.feedingamerica.org/ and for uses of MMG in other studies see, e.g., Gundersen et al., 2017 and Berkowitz et al., 2019.)

The USDA Food and Nutrition Service (FNS) SNAP Retailer Locator Dataset, which contains street addresses for food retailers across the United States from 1930-2022, was used to create several variables used in this research. Each store type was assigned a weight based on the 2021 FNS fiscal year end summary of SNAP spending by store type (USDA-FNS) as show in **Appendix 2.** These weights were used to calculate a food access measure between 0 and 1 by dividing the weighted sum of SNAP eligible food retailers in a census tract by the unweighted total number of SNAP eligible food retailers in the census tract. Such a measure favors supermarkets and supercenters over convenience stores and small, specialty grocery stores.

The Census Bureau American Community Survey (ACS) contains census tract level data from surveys conducted nationally. The ACS variables used to include public transportation and vehicle access on the census tract level and their codes are shown **Appendix 1**. The United States Environmental Protection Agency (EPA) Smart Location Database was the source for neighborhood walkability, on a Census Block level (Environmental Protection Agency). The share of residents living within one mile of a food store from the USDA ERS Food Access Atlas was also included (USDA-ERS). **Table 1** shows the summary statistics table for each food access measure.

Table 1. Summary Statistics for Food Access Measures and their Components

Variable	Min	Q1	Median	Mean	Q3	Max
Food Insecurity Rates (FI)	0.000	0.065	0.098	0.109	0.141	0.816
Walkability Score (WALK)	0.050	0.317	0.475	0.492	0.672	1.000
Transportation (TRAN)	0.000	0.042	0.058	0.062	0.077	0.371
ERS Population Share Rates (ERS)	0.000	0.050	0.460	0.460	0.840	1.000
Store History (STH)	0.000	0.000	0.000	0.003	0.000	1.000
HEAT Score (HEAT)	0.000	0.035	0.051	0.080	0.106	0.529

EVALUATING THE NEW FOOD ACCESS MEASURE

To provide some evidence for why these component variables should be included in a measure of food access, we calculated correlations between these components and the food insecurity rates estimated by Feeding America. Using ArcGIS Pro, we merged all data sources by their census tract FIPS code. Because the component measures are designed to be between 0 and 1 with higher values meaning better food access and we correlate them with food insecurity rates (where higher values are bad), the expected correlations are negative. Larger correlations suggest a component will be a better predictor of food insecurity rates.

Correlations between the component variables we constructed and the Feeding America interpolated food insecurity rates by census tract are shown below in **Table 2**. The table shows moderate correlations between the components and the estimated food insecurity rates. Thanks to the large number of census tracts, these correlations are all statistically significantly different from zero. However, this doesn’t tell us how effective changing any of these variables would be at reducing food insecurity.

Table 2: Correlation with Food Insecurity Rates

Measure	Correlation with Food Insecurity	
	ERS Tracts Only	All Census Tracts
HEAT	-0.0469	-0.0488
Transportation	-0.1500	-0.1574
Walk Score	0.0743	0.1161
ERS	0.0868	-
History	0.035	0.0261

The correlation results suggest that walkability is worth investigating as a food security-enhancing policy measure and combined with the correlation on transportation suggests a much greater focus on mobility in general. When people can more easily walk, drive, or take public transit to a store, the actual physical distance to the closest store becomes less important in determining food access and food security. The correlation between the HEAT score and food insecurity rates suggests that local stores do matter and larger stores matter more.

To see visually why a more comprehensive approach might be worthwhile, how the existing and new measure vary, Figures 1, 2, and 3 compare the ERS binary food desert measure, the Feeding America estimates of food insecurity rates and the HEAT Score by census tract, making clear how much more information can be conveyed by allowing for continuous, rather than binary, measures. Figures showing the geographic diversity in the component measures are included in the Appendix.

POLICY PRIORITY INSIGHTS

To implement the translog regression, all variables were rescaled so that they range from 0 to 100 instead of 0 to 1. Then we added one to each observation so as to avoid zeroes which cannot be logged. The results of the translog regression are shown in **Appendix 3**. Because the translog is nonlinear in the regressors (having logs, logs squared, and interaction terms), the elasticities vary with the levels of the variables. Thus, we present estimated elasticities for each variable at its 25th, 50th, and 75th percentile, while all other variables are set at their average value. For the store turnover history, the value is the same for about 90 percent of the observations (no turnover), so just for store turnover we use the 90th, 95th, and 99th percentiles are our low, medium, and high settings.

The results show walkability has a large, pretty constant, elasticity estimate, suggesting that improving walkability scores either through better street layouts, avoiding pedestrian divides (such as uncrossable highways), or encouraging more mixed land uses could have a large impact in lowering food insecurity rates. Improving access to transportation when adjacent census tracts have food stores located within them also helps lower food insecurity, with the magnitude of the effect increasing as the level of transportation access or number of stores nearby improves. Thus, this suggests that providing poor bus service would do little to help food security, but a high-quality bus line might pay off. Encouraging store openings, especially of supermarkets or supercenters (to boost the heat score) does help, but the magnitudes of those elasticities are smaller and matter more when a neighborhood moves from medium to high levels of store availability. Thus, spending a lot of money to open a single, small food store in a "food desert" may not have much impact on food security.

Table 3. Elasticities of Food Insecurity Rates by Quartile

Measure	25th Percentile	Median	75th Percentile	At the means
HEAT score	0.068	0.006	-0.124	-0.073
Transportation	-0.097	-0.192	-0.288	-0.218
Walkability	-3.945	-3.976	-4.002	-3.978
ERS measure	-0.766	-0.792	-0.799	-0.792
Store history	-0.803	-0.769	-0.710	-0.792

Note: In columns 2 through 4, the elasticities are evaluated at the 25th, 50th, or 75th percentile of the variable named in that row while all other variables are set to their means. For store history, we use the 90th, 95th, and 99th percentile because the variable value is the same for about 90 percent of observations.

CONCLUSIONS

This is an unusual paper. Most of the time we ask a research question and go about answering it. In this paper we have in mind a destination, a desired new data product, and we then present some initial steps to improve upon the currently available measures of food access.

Our measures include information on being within a mile of a food retailer, the share of local food retailers who sell food, the reliability of local stores, and the ease with which residents' can shop at those stores by examining a neighborhood's walkability score and residents' access to cars and public transit. The composite measure proposed here provides good correlation with food insecurity rates, suggesting that our measure could be useful in designing policies to improve food security. In particular, the elasticities show which policy levers are most likely to produce significant improvement in food insecurity and account for different levels of those variables in different locations. For example, improving walkability has a large effect on reducing food insecurity rates while improvements in access to transportation have a much larger effect on food insecurity when the transportation access is quite high, it provides access to adjacent neighborhoods with high-quality food retailers, or both. Thus, spending money for low-quality public transit is likely to be wasted but going from average to high-quality transit could make a significant difference in food security.

Importantly, this research direction is by no means complete. We do not claim to have built a better measure than the binary food desert measure nor the Armin et al. (2019) measure, only that we are exploring a measure that may allow us to see other aspects of the landscape of food access in the U.S. Future improvements could involve better measures of mobility (an easy walk to the store is not quite the same as an easy drive), more nuanced scoring of specialty shops, particularly ethnic grocery stores (e.g., a Korean grocery store may provide greater food access for those who enjoy eating Korean food), and the presence and affordability of food delivery services (I don't need transportation if the groceries come to me).

Further, we focused her specifically on food insecurity rates but not all food-related policies are designed to impact food insecurity. If policymakers were striving to design a policy to increase healthy eating, then a food access measure that is customized to best correlate with healthy eating would be more appropriate. Thus, we believe that food policy studies need a variety of measures that are multifaceted in terms of the information they incorporate and more customized in the sense of being built specifically for the policy application at hand. Food access measures are not an end in and of themselves, but rather a means to understand a specific problem (e.g., food insecurity, social inequalities, poor diet quality). Because of that, they should differ depending on the problem to be addressed. Luckily, increasing access to geographically-localized data should make such improvements in information content and customization relative to planned usage easier to accomplish in the future. In the age of ever-growing big data sets, the research presented here should be just one step toward a future of better food access measures and better food related policies.

REFERENCES

Amin, Modhurima Dey, Syed Badruddoza, and Jill J. McCluskey. “Predicting access to healthful food retailers with machine learning.” *Food Policy* 99 (2021): 101985.

Balcombe, Kelvin, et al. "Information customization and food choice." *American Journal of Agricultural Economics* 98.1 (2016): 54-73.

Berkowitz, Seth, Sanjay Basu, Craig Gundersen, and Hilary Seligman. “State-level and county-level estimates of health care costs associated with food insecurity.” Preventing Chronic Disease 16 (2019):180549.

Berkowitz, Seth, Hilary Seligman, James Meigs, and Sanjay Basu. “Food insecurity healthcare utilization and high cost: A longitudinal cohort study.” *The American Journal of Managed Care* 24.9 (2018): 399-404.

Brinkley, Catherine, et al. “‘If you build it with them, they will come’: What makes a supermarket intervention successful in a food desert?” *Journal of Public Affairs*. 19.3 (2019),.

Bronchetti, Erin, Garret Christensen, Hilary Hoynes. “Local food prices, SNAP purchasing power, and child health.” *Journal of Health Economics* 68 (2019): 102231.

Burchi, Francesco, and Pasquale De Muro. “From food availability to nutritional capabilities: Advancing food security analysis.” *Food Policy* 60 (2016): 10-19.

Coleman-Jensen, Alisha, Matthew Rabbitt, Christian Gregory, and Anita Singh. *Household Food Security in the United States in 2021*. Economic Research Report No. (ERR-309). 2022.

Courtemanche, Charles, Art Carden, Xilin Zhou, and Murugi Ndirangu. "Do Walmart Supercenters improve food security?" *Applied Economic Perspectives and Policy* 41.2 (2019): 177–198.

Downs, Julie S., George Loewenstein, and Jessica Wisdom. "Strategies for promoting healthier food choices." *American Economic Review* 99.2 (2009): 159-64.

Dubowitz, Tamara, et al. "Diet and perceptions change with supermarket introduction in a food desert, but not because of supermarket use." *Health Affairs* 34.11 (2015): 1858-1868.

Feeding America, "Map the Meal Gap." *Feeding America*, 2022. Available online at https://www.feedingamerica.org/research/map-the-meal-gap/how-we-got-the-map-data.

"Food Access Research Atlas." *USDA ERS - Food Access Research Atlas*, https://www.ers.usda.gov/data-products/food-access-research-atlas.

"FNS Nutrition Programs." *Food and Nutrition Service U.S. Department of Agriculture*, https://www.fns.usda.gov/programs.

Gregory, Christian and Alisha Coleman-Jensen. "Do high food prices increase food insecurity in the United States?" *Applied Economic Perspectives and Policy* 35 (2013): 679-707.

Gundersen, Craig, and James P. Ziliak. "Food insecurity research in the United States: Where we have been and where we need to go." *Applied Economic Perspectives and Policy* 40.1 (2018): 119-135.

Gundersen, Craig, and James P. Ziliak. "Food Insecurity and Health Outcomes." *Health Affairs* 34.11 (2015): 1830-1839.

Gundersen, Craig, Adam Dewey, Monica Hake, Emily Engelhard, and Amy Crumbaugh. "Food Insecurity Across the Rural/Urban Divide: Are Counties in Need Being Reached by Charitable Food Assistance?" *The ANNALS of the American Academy of Political and Social Science* 672.1 (2017):217-236.

U.S. Environmental Protection Agency. National Walkability Index User Guide and Methodology. Accessed May 3, 2023 at https://www.epa.gov/smartgrowth/national-walkability-index-user-guide-and-methodology

Ver Ploeg, Michele, and Parke E. Wilde. "How do food retail choices vary within and between food retail environments?" *Food Policy*79 (2018): 300–308.

Ware, Brandon O., Modhurima Dey Amin, Eric L. Jessup, and Jill J. McCluskey. "Neighborhood racial composition, income, and distance to grocery retailers in Seattle." *Agricultural and Resource Economics Review* (2021): 1-21.

Walker, Rebekah, Ajay Chawla, Emma Garacci, Joni Williams, Carlos Mendez, Mukuso Ozieh, and Leonard Egede. "Assessing the relationship between food insecurity and mortality among U.S. adults." Annals of Epidemiology 32 (2019); 43-48.

Zheng, Yuqing, Jianqiang Zhao, Steven Buck, Shaheer Burney, Harry M. Kaiser, and Norbert L. Wilson. "Putting grocery food taxes on the table: Evidence for food security policy-makers." *Food Policy* 101 (2021): 102098.

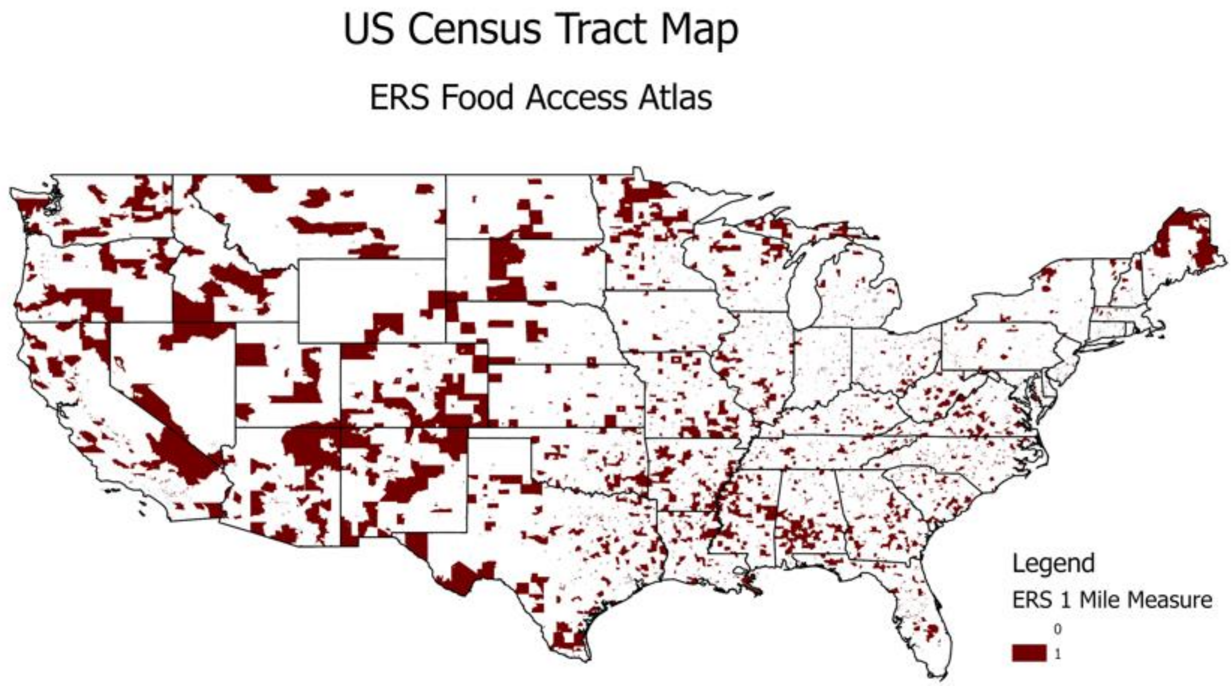


Figure 1. ERS Binary Food Desert Variable

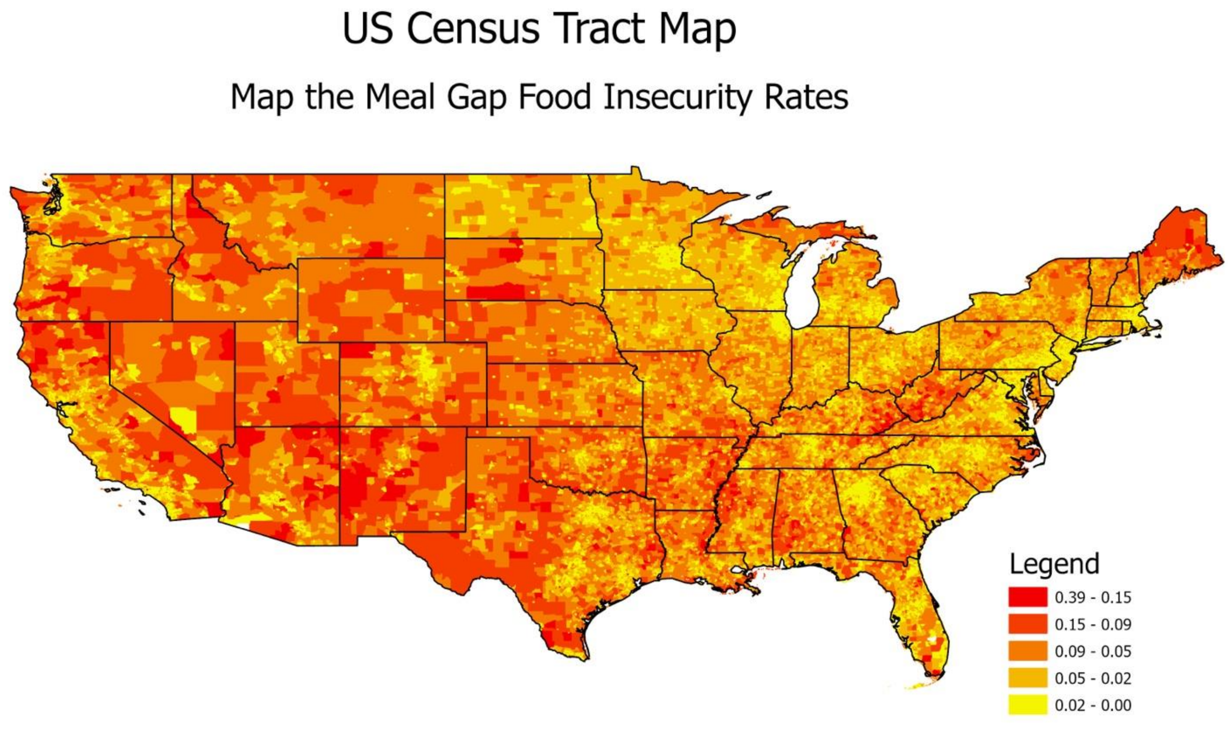


Figure 2: 2020 Map the Meal Gap Food Insecurity Rates

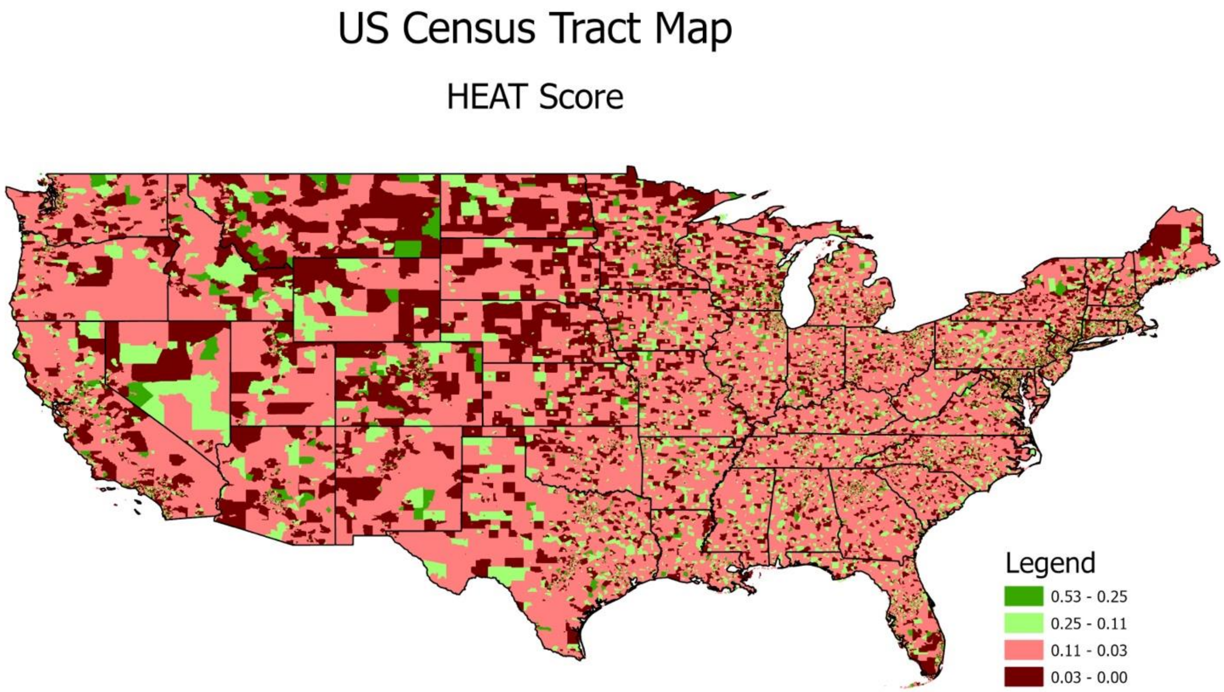


Figure 3. Heat Score

Appendix

Appendix Table 1

Measure	Source
Map of US by Census tracts and States	US Census Bureau 2020 Tiger FGDB (National Sub-State)
Food Insecurity Rates for 2020	Feeding America: Map the Meal Gap 2022 (2020 Data)
Total number of SNAP Allowable Retailer	Food and Nutrition Service (FNS) Snap Retailer Locator Dataset
The Walkability Score	Smart Location Database
Percent per census tract that have Vehicle Access (B08301_calc_pctDroveAloneE)	American Community Survey (ACS) Workers mode of commute
Percent per census tract that use public transportation to work (B08301_calc_pctPublicE)	
Store History (Trust Measure)	Food and Nutrition Service (FNS) Snap Retailer Locator Dataset
USDA Measure of population that are beyond 1 mile from supermarket	ERS Food Access Research Atlas

Appendix Table 2

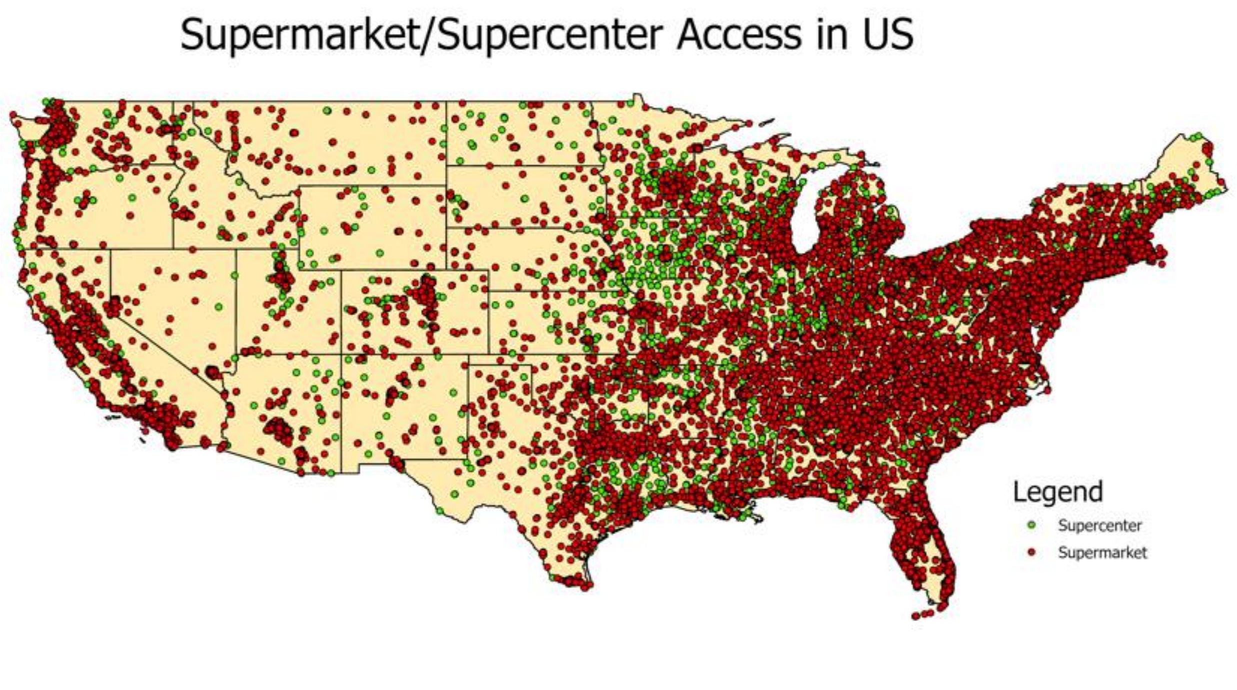
Fiscal Year 2021 Year End Summary		
Firm Type	Redemption Amount	Percent of Total
Bakery Specialty	$174,302,051	0.14%
Combination Grocery/Other	$6,692,641,091	5.33%
Convenience Store	$6,382,363,373	5.08%
Delivery Route	$93,691,427	0.07%
Direct Marketing Farmer	$25,114,636	0.02%
Farmers Market	$33,594,519	0.03%
Fruits/Veg Specialty	$68,714,717	0.05%
Internet Retailer	$4,963,714,985	3.95%
Large Grocery Store	$1,983,780,228	1.58%
Meat/Poultry Specialty	$513,130,557	0.41%
Medium Grocery Store	$2,614,812,666	2.08%
Military Commissary	$64,651,295	0.05%
Non-profit Food Buying Co-op	$10,011,651	0.01%
Seafood Specialty	$400,962,011	0.32%
Small Grocery Store	$840,723,897	0.67%
Super Store	$66,419,389,719	52.91%
Supermarket	$33,899,251,209	27.01%
Total	$125,180,850,033	99.73%

Note: the percent of total was used as weights for the HEAT Score Measure

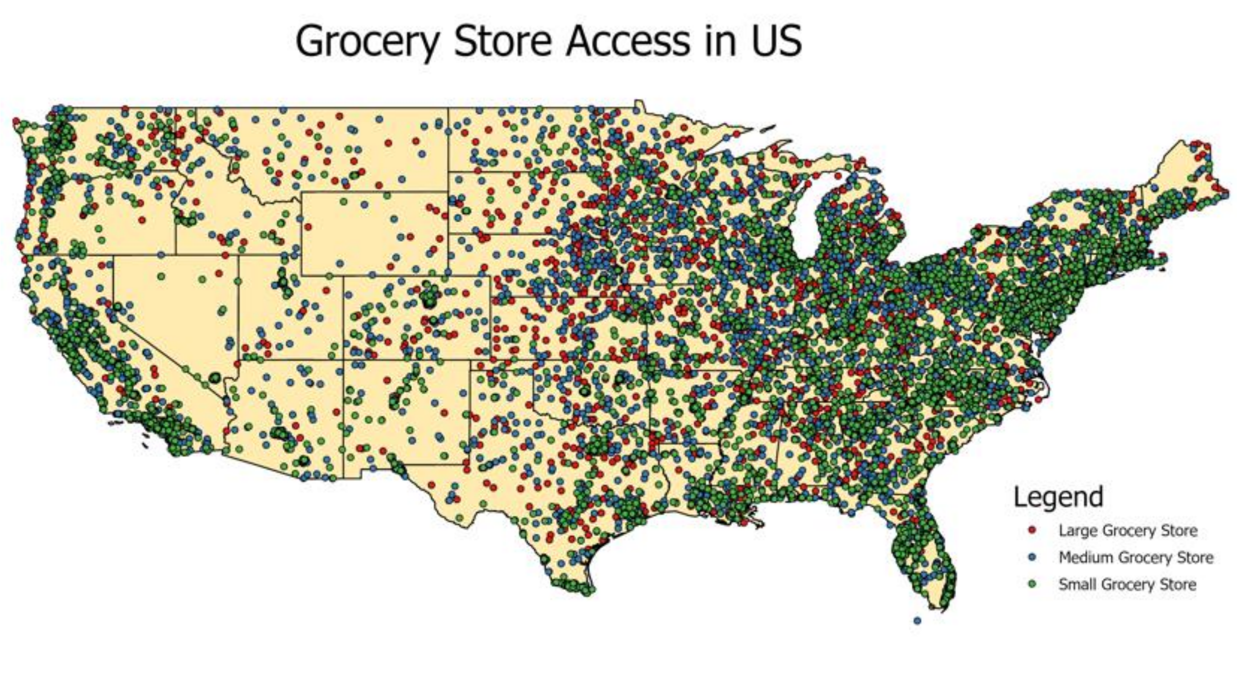
Appendix Table 3: Food Insecurity Translog Regression

Independent Variables	Coefficient Estimate	Std Error
Intercept	6.446***	0.192
HEAT	0.343***	0.028
ERS	0.211***	0.021
Transportaton	0.785***	0.072
Walk	-2.975***	0.102
History	0.417***	0.093
HEAT Squared	-0.200***	0.005
ERS Squared	0.071***	0.003
Transportation Squared	-0.374***	0.021
Walk Squared	0.924***	0.030
History Squared	-0.110***	0.019
HEAT*ERS	0.009***	0.002
HEAT*Transportation	0.032***	0.007
HEAT*Walk	-0.016*	0.008
HEAT*History	-0.047***	0.010
ERS*Transportion	-0.012*	0.005
ERS*Walk	-0.091***	0.006
ERS*History	-0.017*	0.008
Transportation*Walk	-0.076***	0.019
Transportation*History	0.047	0.024
Walk*History	-0.043	0.245
Obs.	42,874	
R-squared	0.1249	

Note: Less than .001% Significance *** Less than .01% Significance **
Less than .05% Significance *

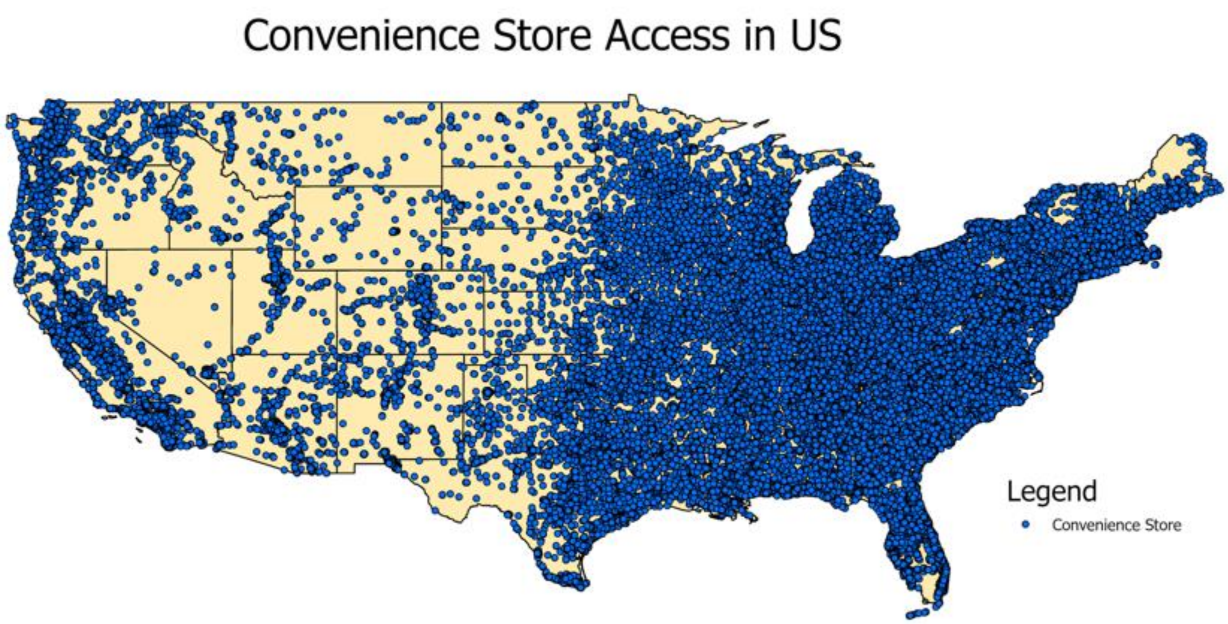


Appendix Figure 1

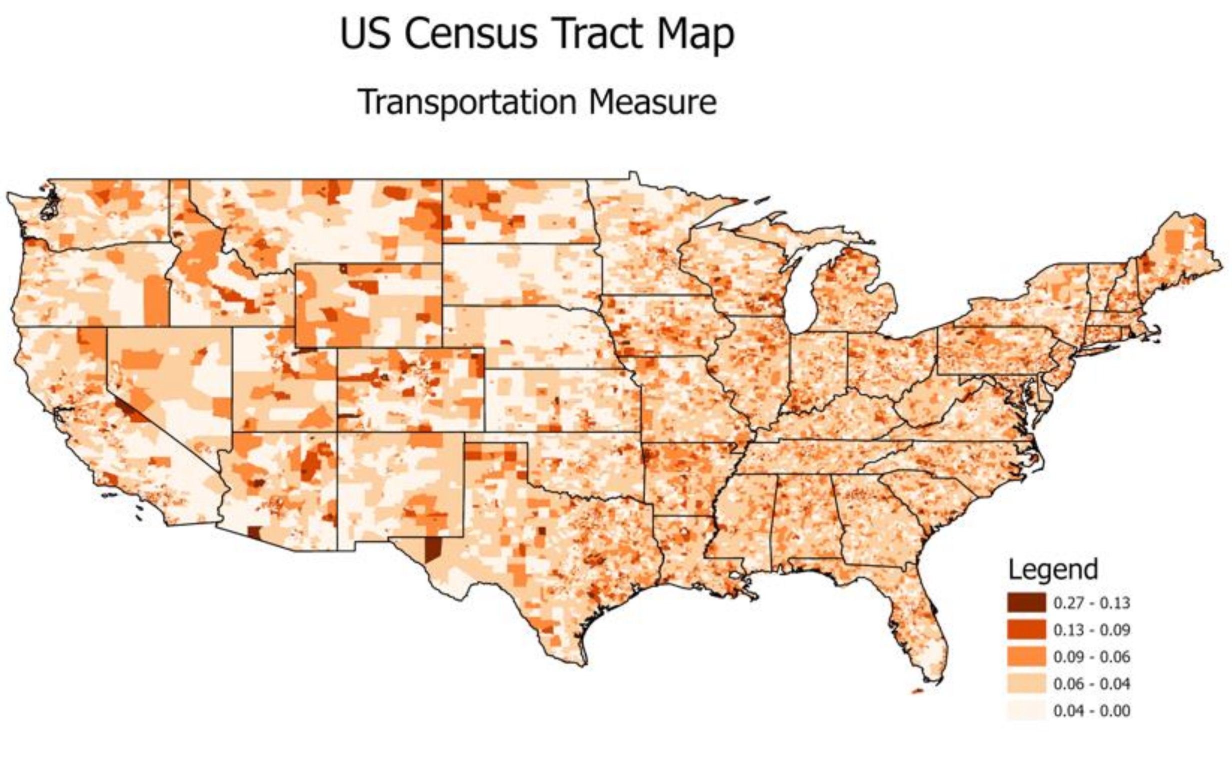


Appendix Figure 2

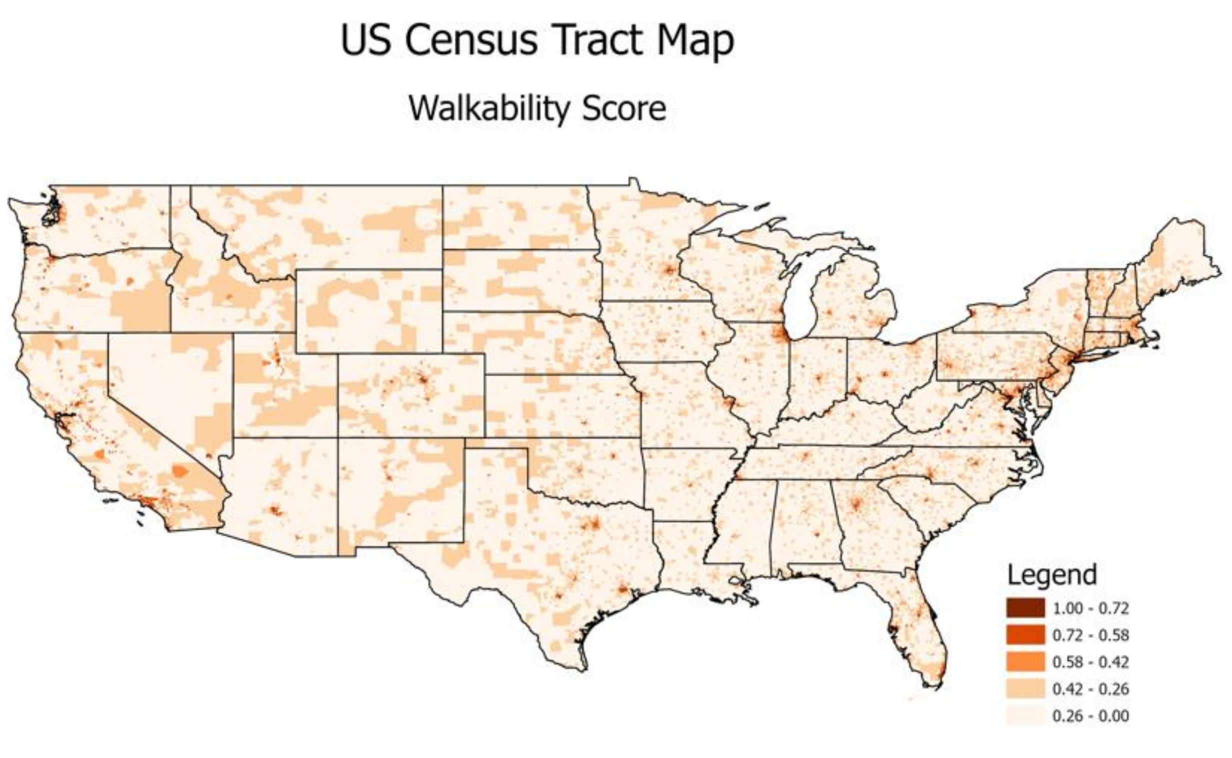
Appendix Figure 3



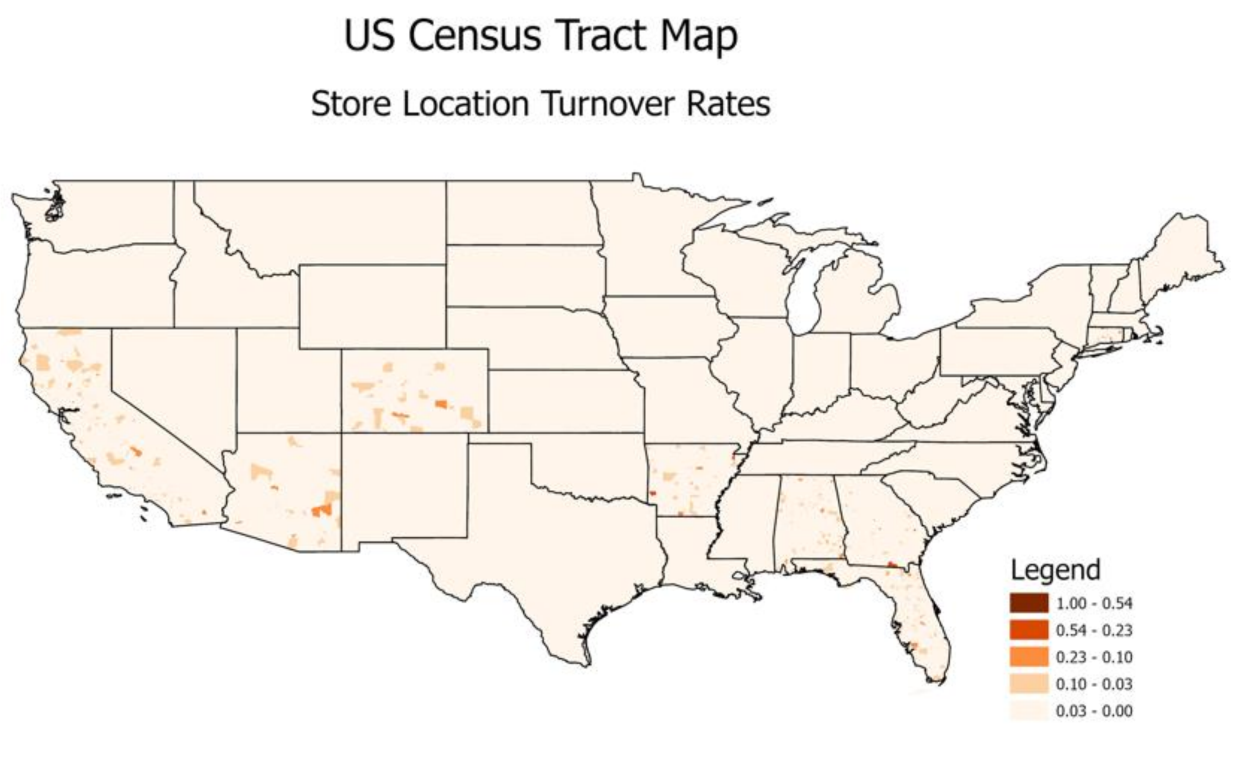
Appendix Figure 4



Appendix Figure 5



Appendix Figure 6



Appendix Figure 7