The Consumer Welfare Impact of Expanding Access to Fruits and Vegetables in Food Deserts

Linlin Fan[**]

May 2017

Abstract

Low access to healthy retailers is considered to cause unhealthy eating and obesity. Various policies seek to expand access to fruits and vegetables in these food deserts. I use detailed store sales and consumer demographics data to (*1*) estimate a discrete choice demand system for food stores with consumer heterogeneity, (*2*) quantify the welfare impact of expanding access to fruits and vegetables in food deserts, and (*3*) simulate the counterfactual welfare change from a food desert household facing non-food-desert levels of prices and store characteristics, and vice-versa. First, I find prices are more important to consumers than the availability of fruits and vegetables and store proximity. Second, expanding the availability of fruits and vegetables in the nearest stores of food deserts does not greatly change consumers' store choices or improve consumer welfare. Third, consumers' low demand for better access to fruits and vegetables may be the reason why food deserts exist.

Keywords: Discrete choice models, spatial differentiation, food deserts, food access, fruits and vegetables, consumer welfare

[*] I gratefully acknowledge financial support through Cooperative Agreement No. 58-5000-1-0051 between the University of Illinois and the Economic Research Service (ERS) of the U.S. Department of Agriculture (USDA). I would like to thank my dissertation committee members (Kathy Baylis, Guillermo Marshall, Craig Gundersen, Brenna Ellison), Alessandro Bonanno for helpful comments. I acknowledge the help of Director Lynda Perez from the U.S. Department of Health and Human Services (HHS) to allow me to attend the HHS Community Economic Development Grantee Conference. I appreciate the real-world experience and valuable feedbacks from Federal Healthy Food Financing Initiatives (HFFI) project managers: Dana Harvey from Mandela Marketplace in Oakland CA, Ener Chiu from East Bay Asian Local Development in Oakland CA, Neelam Sharma from Community Services Unlimited Inc in Los Angeles CA, Jose Villalobos from the East Los Angeles Community Union in Los Angeles CA, Mark Johnson from Community Ventures Corporation in Lexington KY, Jeff Epstein from MidTown Cleveland in Cleveland, OH, Howard Snyder from Northwest Side Community in Milwaukee WI and Lee Jaffe from Cypress Hills Local Development in New York, NY. The views expressed are those of the author and should not be attributed the USDA, the HHS, IRI or any of the HHFI grantees.
[**]Department of Agricultural and Consumer Economics, University of Illinois Urbana-Champaign, 402 Mumford Hall, 1301 W. Gregory Dr., Urbana, IL 61801, U.S.A. Email: lfan3@illinois.edu.

The public health literature and public policy debate have given substantial attention to the hypothesis that low access to healthful foods in low-income neighborhoods contributes to poor diets and leads to higher levels of obesity and other diet-related disease, such as diabetes and heart disease (Ahern, Brown and Duka 2011; Morland, Wing and Diet-Roux 2002; Bodor et al. 2008). A number of policies are built around this hypothesis: for example, the US Healthy Food Financing Initiative authorized by 2014 Farm Bill allocates $125 million annually in grants, loan subsidies, and technical assistance for healthy food retailers in food deserts, defined as geographic areas with low-income and low food access (Aussenberg 2014). Furthermore, projects aimed at "eliminating food deserts" are eligible for the $100 million in Community Transformation Grants under the Affordable Care Act (HHS 2011). Former First Lady Michelle Obama's signature initiative *Let's Move* features building healthy communities and targets eliminating food deserts in the U.S. in seven years.

Although various policy interventions have been implemented to eradicate food deserts, it is unclear whether such policies change store choices and improve household welfare. Evaluating the welfare impact of such policy interventions is challenging. The interventions are not randomly assigned or exogenously determined. Thus it is hard to separate the effect of improving food access from other unobserved socioeconomic factors. Existing literature on the effect of food access on food purchases largely infer the role of food environment from a cross-sectional correlation between store density and food purchases in a single city or a single urban food desert (Cummins et al. 2005, Bodor et al. 2008, Sharkey et al. 2010). More recently, Handbury, Rahkovsky and Schnell (2016) use household fixed effects to control for time-invariant demand factors that may affect store access. They find that spatial disparities in access play a limited role in generating socioeconomic disparities in nutritional consumption. However, store entry and product offerings decisions may be correlated with time-varying demand factors even after controlling for household fixed effects and thus yield biased estimates of the access effect. Allcott, Diamond and Dube (2016) use a structural demand model for food categories and micronutrients jointly, which is similar to the work of Dubois, Griffith, and Nevo (2014), to study why nutrition-income disparities exist. They find that prices explain 30% and preferences explain around 70% of nutrition-income disparities. However, they do not evaluate the direct impact of improving access on consumer welfare or explore why food deserts exist.

In this article, I use a discrete choice model to estimate structural consumer demand for different types of food stores and identify the welfare impact of improving access to fruits and vegetables in food deserts. I explicitly model consumer demand with heterogeneous preferences and spatial differentiation of stores. If the existence of food deserts is caused by lower demand for access to healthy foods, then improving food access alone will not be effective. Thus it is important to allow consumers in food deserts and non-food deserts to have different demand for store access among other characteristics. With specific knowledge of consumers' demand and preferences, a counterfactual analysis is performed to study the impact of intervention policies in food deserts on consumer welfare *ex ante*. Although the direct health effects of such an intervention cannot be measured, consumer welfare analysis provides an important perspective in evaluating the effectiveness of the policy. This approach strengthens the identification of welfare impact by holding other unobserved factors equal.

I use a three-dimensional panel of quantities and prices for 174 food stores from 11 counties over a period of 16 quarters (2009-2012), collected using scanning devices from Information Resources Inc. (IRI). Store characteristics come from TDLinx store directory data and census-tract level socio-demographics from 2008-2012 American Community Survey (ACS). The census-tract level food deserts indicators are from 2010 USDA Food Access Research Altas (FARA, USDA 2013).

A random-coefficient discrete choice model (Berry, Levinsohn, and Pakes or BLP 1995; Nevo 2001) is used to estimate consumers' demand for a food store in each census tract in a county. The indirect utility of the consumer is a function of store prices, store characteristics, heterogeneous consumer preferences, and unknown parameters. The store characteristics include the number of fruits and vegetables offered, store square footage, store chain dummies and the distance to consumer's home. The BLP model allows the consumer's valuation of store's proximity to home to vary with whether the consumer owns a car and unobserved consumer characteristics. Furthermore, this model allows consumers with different income to have differential preferences towards store characteristics and prices. The correlation between prices, availability of fruits and vegetables and unobserved demand shocks, which are included in the econometric error term, makes prices and availability of fruits and vegetables potentially endogenous in the demand estimation. To address this concern, I use observed variation in store-specific cost shifters such as the store's distance to the nearest distribution center and quarterly regional fruits wholesale prices as the instrumental variables for store prices and number of fruits and vegetables.

After obtaining the demand parameters, two counterfactual analyses are conducted. First, I simulate the effect of increasing the number of fruits and vegetables to levels as Family Dollar (50), Kmart (100), CVS Pharmacy (250)[1], Fred Meyer (350) and Safeway (1,200), in the nearest store of each food desert census tract and measure the impact on consumer welfare. Second, I simulate the welfare change from the scenario of a food desert (non-food desert) household facing the prices and store characteristics in a non-food desert (food desert) to study the extent to which demand explains the existence of food deserts.

My central findings are as follows. First, among store attributes, price is the most important factor that affects consumers' choice of stores. Consumers prefer stores with lower prices much more than the availability of fruits and vegetables and store proximity. Second, expanding access to fruits and vegetables in food deserts increases total consumer welfare in an average county by $1,475,443 to $25,428,399 in 2015 CPI-adjusted dollars, depending on the number of fruits and vegetables increased, over 20 years of operation with discounting. The estimated benefit is less than the cost of the policy intervention when the increase in fruits and vegetables is small, which is explained by food deserts residents' low preference for proximity to fruits and vegetables. If the policy intervention focuses on expanding access to just a few fruits and vegetables without lowering prices in a store or changing households' preferences, consumers, especially poor price-sensitive consumers in food deserts, would not go there to shop or buy more healthy foods. Last, I find that even when a food desert household faced the exactly same store attributes and prices as a non-food desert household, their welfare increased by a modest amount (9.9%) on average. In contrast, a household who moved from a non-food desert to a food desert would experience a three times bigger impact, a sharp decrease of 31.5% in their welfare. In short, a food desert household has lower demand for good access to fruits and vegetables (FV) compared to a non-food desert one, which may be the reason why supermarkets do not locate in food deserts.

This article is related to several strands in the literature. The first is the literature that studies the welfare implications of improving food access. Empirical studies include Anderson and

[1] The fruits and vegetables provided in CVS Pharmacy are mostly different sizes of canned fruits and vegetables.

Matsa (2011), Currie et al. (2010), Davis and Carpenter (2009) and Dunn (2010) who find that access to fast food restaurants has small causal effect on food consumption and obesity. The results are qualitatively consistent with their work and complement theirs by explicitly studying food at home. Recent studies have mixed findings. On one hand, some studies find that limited food access is associated with increased incidence of obesity, less healthy grocery purchases (Caillavet et al. 2015; Thomsen et al. 2015) and lower food security (Bonnano and Li 2015). Other work finds that the expansion of supercenters such as Wal-Mart lower the prices of unhealthy foods more than healthy foods, thus reducing rather than improving the healthfulness of food purchases and increasing obesity (Courtemanche and Carden 2011; Volpe, Okrent and Leibtag 2013). Recent work finds that supermarket entry has limited effects on the healthfulness of food purchases or dietary choices (Cummins, Flint and Matthews 2014; Handbury, Rahkovsky, and Schnell 2016). Prices and preferences explain about 30% and 70% of the relationship (Allcott, Diamond, and Dube 2016). Fan et al. (2017) suggest that living in a food desert is unlikely to influence food insecurity to a great extent, given the difference in the variety-adjusted price index found between food deserts and non-food deserts is small. This article distinguishes the roles of preferences, store attributes and prices play in consumers' store choices, and thus identifying why and how improving access to fruits and vegetables in food deserts affects welfare. To the best of our knowledge, this paper conducts the first welfare impact evaluation of intervention programs to eliminate food deserts.

Second, this paper contributes to the literature on food store choice. Existing literature (e.g. Arnold, Oum, and Tigert 1983; Smith 2004; Smith 2006; Hausman and Leibtag 2007; Marshall and Pires 2017; Chenarides and Jaenicke 2017) have identified that consumers choose food stores based on a variety of factors including overall prices, product variety, store type, location, convenience, courteous services and the degree of competition. Taylor and Villas-Boas (2016) estimate consumer food outlet choices as a function of outlet type, store distances to home and household attributes. They find heterogeneous willingness to pay (WTP) for distances to different types of stores. My paper complements Taylor and Villas-Boas (2016) by quantifying the welfare impact of policy interventions aimed at improving FV access by reducing the distance to stores with plenty of FV.

This paper has important policy implications. Given the small benefits to the community, the policy aimed at increasing the availability of just a few FV in food deserts alone may not be as effective as is expected to be. Price is the most important factor when consumers decide where to shop and thus policies impacting prices could be more effective. Furthermore, the results inform the question of why food deserts exist and I find that low demand for proximity to FV may explain the existence of food deserts. Thus policies affecting preferences could perhaps impact consumer store choices and welfare, such as restaurant calorie labels (Ellison, Lusk and Davis 2014) and healthy eating education classes.

Discrete Choice Demand

This section presents a standard BLP model of discrete choice demand with heterogeneous customers. The preferences for store attributes and prices are allowed to differ at the consumer level. Thus the existence of food deserts could be caused by the heterogeneity in preferences.

The model allows for several sources of consumer heterogeneity. First, consumers with different income levels could have different price sensitivity and valuation of FV availability. Second, vehicle access affects consumers' preferences for store proximity. Third, unobserved consumer characteristics are allowed to influence valuation of all store attributes and prices.

Demand can be summarized as follows: consumer[2] in census tract i (called consumer i hereafter) derives indirect utility from buying food in store j at time t (a quarter-county combination):

$$u_{ijt} = \delta_{jt} + \mu_{ijt} + \varepsilon_{ijt}$$

The first component, δ_{jt}, is a store-time specific utility term common to all consumers. The μ_{ijt} term captures heterogeneity in consumer tastes for observed store characteristics. The term ε_{ijt} is a taste terms that is assumed to be independent and identically distributed across both stores and consumers. Consumer i is assumed to choose the store j that gives maximum utility, and market shares yield from aggregating over consumers.

Specifically, the utility component common to all consumers, δ_{jt} and the consumer varying

---

[2] In this article, a consumer is a household. Consumer and household are used interchangeably throughout the article.

utility term μ_{ijt} are given as

$$\delta_{jt} = x_{jt}\beta + \alpha p_{jt} + \xi_{jt}$$

$$\mu_{ijt} = x_{jt}\left(\Pi_1 D_i + \Sigma_1 v_i\right) + p_{jt}\left(\Pi_2 D_i + \Sigma_2 v_i\right) + d_{ij}\left(\gamma + \Pi_3 D_i + \Sigma_3 v_i\right)$$

This Lancasterian approach makes the payoff of a consumer depend on store, consumer characteristics and model parameters. Consumer's indirect utility depends on a vector of K observable store characteristics x_{jt}, store price p_{jt}, distance from the store to the consumer i's home d_{ij}, and unobserved (by the econometrician) store characteristics ξ_j[3]. The coefficients β, α, γ are consumer's mean valuation of various store attributes. In addition, consumer's valuation of store attributes is affected by observed consumer demographics D_i and unobserved consumer characteristics v_i, distributed i.i.d. standard normals. Π is a matrix of coefficients that measures the effect of demographics on the consumer valuation of store characteristics while Σ measures the covariance in unobserved preferences across characteristics.

After integrating over ε_{ijt} which is assumed to have a type 1 extreme value distribution, D_i and v_i which are observable and unobservable attributes for consumer i, the model prediction of market share for store j at time t is given by:

$$s_{jt} = \sum_{i \in I_t} w_i \int_{v_i}\int_{D_t} \frac{\exp\left(\delta_{jt} + \mu_{ijt}(v_i, D_i)\right)}{1 + \sum_{k \in J_t} \exp\left(\delta_{jk} + \mu_{ikt}(v_i, D_i)\right)} dP(D_i)\, dP(v_i) \qquad (1)$$

Each census tract is weighted by w_i, the population share of the census tract i in the market. S_{0t} denotes the market share of the outside option.

For the analysis below, the inclusive value (or expected maximized utility) is used as the measure of consumer welfare. This measure is defined as

$$E\left[\max_{j \in J_t} u_{ijt}\right] = \log\left(1 + \sum_{k \in J_t} \exp(\alpha_i p_{jt} + x_{jt}\beta_i + d_{ij}\gamma_i + \xi_{jt})\right)$$

where the measure is expressed in "utils" (McFadden 1973; McFadden 1976; Small and Rosen

[3] This specification assumes that the unobserved components are common to all consumers. An alternative is to model the distribution of valuation of the unobserved characteristics, as in Das, Olley, and Pakes (1994).

1981). The price coefficient α_i is the negative marginal utility of income in the indirect utility function. To express this measure of consumer welfare in "dollars", I divide (7) by $-\alpha_i$. Then a monetary measure of how consumer i's welfare is affected by a change from x_{jt} to x_{jt}' is defined as

$$\Delta W_{it} = \frac{1}{\alpha_i} \log\left(1 + \sum_{j \in J_t} \exp(\alpha_i p_{jt} + x_{jt}\beta_i + d_{ij}\gamma_i + \xi_{jt})\right) - \frac{1}{\alpha_i} \log\left(1 + \sum_{j \in J_t} \exp(\alpha_i p_{jt} + x_{jt}'\beta_i + d_{ij}\gamma_i + \xi_{jt})\right) \qquad (2)$$

where ΔW_{it} is the change in consumer surplus or compensating variation (CV), the amount that a household needs to be compensated/pay when x_{jt} is changed into x_{jt}' while keeping their utility intact.

The consumer i's WTP for store attribute x_{jt} is captured by the change in consumer welfare by a marginal change in x_{jt}:

$$\frac{\partial W_{it}}{\partial x_{jt}} = S_{ijt}' \frac{\beta_i}{\alpha_i} \qquad (3)$$

where S'_{ijt} is the new probability of consumer i visiting store j at time t when x_{jt} is changed into x'_{jt}. In contrast to previous literature on estimating WTP based on discrete choice models, the true WTP should take both the extensive (S'_{ijt}) and intensive margin effects ($\frac{\beta_i}{\alpha_i}$) into account. Thus changing a store attribute affects consumer welfare both through new valuations of the store attribute conditional on visiting the store ($\frac{\beta_i}{\alpha_i}$) and different likelihood of visiting the store (S'_{ijt}).

Estimation

My estimation strategy closely resembles the generalized method of moments (GMM) approach taken by BLP (1995) and Nevo (2001). One might describe the BLP approach as two parts. The first part matches the model's share predictions, $s_j(\delta(\theta),\theta)$, to those in the data, s_j, or

$$s_j(\delta(\theta),\theta) - s_j = 0, \qquad j = 0,1,...,J_t \qquad (4)$$

where θ are demand parameters. Subscript t for notation simplicity is omitted in the following text. This part is equivalent to solving for the vector $\delta(\theta)$ that matches the predicted to the observed market shares, which Berry (1994) shows exists and is unique under mild regularity conditions on the distribution of consumer tastes.

The second part matches moments related to the market-level disturbances ξ_j. Except for price and number of fruits and vegetables, the unobserved demand disturbances for any store j are assumed to be uncorrelated with observed demand and cost-side variables of the store in that county-quarter, or

$$E\left[Z' \cdot \xi_j\left(\theta\right)\right] = 0 \qquad Z = X, W \qquad (5)$$

where θ is the true value of parameters in the demand model. For prices and number of fruits and vegetables, two sets of instruments (Z) are available. First, store j's characteristics (X) are valid instruments for the stores. The second set are cost-side variables (W) that are excluded from the demand equation. The GMM estimate is

$$\widehat{\theta} = \arg\min \xi(\theta)' Z (Z'Z)^{-1} Z' \xi(\theta)$$

Asymptotically robust standard errors for the estimates above are computed using the standard formulas (Hansen 1982; Newey and MacFadden 1994).

Instruments

The key identifying assumption in the estimation is the population moment condition, which requires a set of exogenous instrumental variables. By the standard oligopoly price competition model, prices are a function of marginal costs and a markup term. Players in the industry set prices after accounting for store characteristics or demand shocks, either of which may be unobserved by the econometrician. Similarly, the number of fruits and vegetables offered in the store may react to local demand shocks and thus are endogenous. Thus the non-linear least squares regressions will give biased estimates of price sensitivity, α and the coefficient on the number of fruits and vegetables.

To address the endogeneity, I use store characteristics and cost shifters as instruments following much of the previous work (Nevo 2001; Petrin 2002). The store characteristics include store footage. Specifically, four cost shifters are used (a) the distance to the nearest distribution center, which picks up transportation costs (b) the quarterly regional wholesale prices of bananas interacted with distance to the nearest distribution center, which is a proxy for wholesale cost of fruits[4] (c) population density and (d) average housing value per square feet in the store census tract as a proxy for the cost of space and land.[5]

In addition to the endogeneity of prices and number of fruits and vegetables, distances to stores may also be correlated with unobserved local demand. Store location is a choice. Retailers take into account local demand to choose where to locate and households consider retail amenities in deciding where to live (Ver Ploeg, Mancino and Todd 2015). However, the coefficients on distances in the utility model are not estimated based on the orthogonality condition between the demand error term and distance (equation 5). Rather it is estimated through matching predicted and observed market shares (equation 4) and thus the estimates of preferences towards distances still satisfy the moment conditions and thus are unbiased.

Furthermore, I strengthen the identification strategy by exploiting the panel structure of the data. Store chain fixed effects are used to control for any store chain quality that does not vary by market. For example, store chain specific characteristics such as the existence of a deli department and whether there is a parking lot outside the store could be fully controlled for by using the chain fixed effects. Therefore, the correlation between prices and the unobserved store chain quality is fully accounted for and does not require an instrument. Additionally, county fixed effects are included to capture time-invariant county-level unobservables such as regional tastes. For example west coast counties may prefer stores with more fruits and vegetables while counties in Texas may prefer stores with better beef. Lastly quarter fixed effects are used to control for national temporal and seasonal shocks.

Data

The data required to estimate the model consist of four sets of variables: store attributes and

---

[4] I also choose quarterly regional wholesale prices of oranges and apples interacted with distances to the nearest distribution centers as IVs, and the results do not change substantially. If one is still concerned about the power of the IVs for the number of fruits and vegetables, I treat the number of FV as exogenous and find the demand estimates do not change much.

[5] One may be concerned that population density and average housing value per square feet also reflect local demand that is embedded in the error term of the utility model. I test the robustness of our results by excluding those two as IVs and results do not change substantially.

prices in a market (in this article a county-quarter combination), consumer characteristics, food deserts indicators, and instrumental variables.

Spatial differentiation will play a significant role in market structure only if population, or available demand, is sufficiently large and geographically spread out for firms to exploit. According to the 2012 USDA Food Acquisition and Purchases Survey (FoodAPS), the average customer travels only 3.3 miles for a one-way trip to the primary food store. The markets used in this study are selected, therefore, to provide adequate scope for spatial differentiation by firms, while not being so large that distant competitors would rarely, if ever, compete with each other for customers. To facilitate the identification of competitors operating within the market as well as potential customers in the market, I focus on 11 randomly selected well-delimited and medium-sized counties including only urban census tracts across the United States. Rural census tracts are excluded because they are very large in space and are likely self-contained markets. The population of these counties ranges from 50,000 to 500,000, with two counties in the Northeast, two in the Midwest, four in the South, and three in the West. Furthermore, food desert is a prominent problem in these counties, where the portion of people and the poor live in food deserts are on average 27% and 34% respectively.

Prices and quantities come from Information Resources, Inc. (IRI) retailer scanner data (IRI InfoScan). The IRI InfoScan data provide weekly sales, quantities, brand and the product description of each food item[6] at the barcode level at each store or regional market area (RMA)[7].[8] The data contains 174 stores from the first quarter of 2009 to the last quarter of 2012 in the sample counties. As a result, there are 2,668 observations (store-quarters). The store price is calculated by multiplying the average price of an item by the average number of items (i.e. 20, estimated from the FoodAPS) per shopping trip to one of the store types covered by the IRI. The average price of an item is calculated as dividing the total sales by the total units sold of the item. It is essentially a quantity weighted average price where the items more frequently purchased are

[6] The data include both random-weight food items (usually fresh produce) that have a pseudo UPC and non-random-weight food items (fixed weight food items) that have a unique UPC.

[7] Some store chains only provide weekly sales datasets at the RMA level. The RMAs of a store chain are aggregate geographical areas defined by the retailer and usually include several stores. Thus the individual prices paid for a UPC cannot be identified at each store within a RMA. Therefore, I use the average price for the whole RMA to impute for each store and assume that if a UPC is sold in the RMA, then all stores in the RMA also sell that UPC at the same price.

[8] The covered stores include stores of various types, i.e. mass merchandises, drug stores, convenience stores, dollar stores, grocery stores and club stores.

put on more weight. All prices are adjusted by 2015 Consumer Price Index (CPI).

This measure of price is chosen for two reasons. First, constructing a cost of a basket of food such as Thrifty Food Plan (TFP, CNPP 2007) for each food store is not feasible because many convenience and drug stores do not sell any vegetables or meat. Missing prices of those food categories pose a challenging problem to construct the cost of a TFP basket for each store. Second, I do not use the variety-adjusted price index that address both product heterogeneity and variety bias such as Handbury and Weinstein (2014) and Fan et al. (2017) because the price index cannot be easily adapted to calculate the welfare change of policy interventions in dollar value like equation (2). However, I do test the robustness of demand estimates when the variety-adjusted price index and the cost of a basket of commonly available foods across stores are used instead. The results are qualitatively similar (presented in Appendix Table A1 and A2). The number of fruits and vegetables Universal Product Codes (UPCs) sold is used as the availability of fruits and vegetables in each store-quarter.[9],[10]

Market shares are calculated by dividing food sales of each store by the total food sales of all TDLinx stores in a market. TDLinx is the most complete list of geocoded food stores in the U.S. that varies annually and is widely used by the industry to analyze the regional retail market. The TDLinx contains the names, characteristics, annual sales and geo-coded locations of 594 stores in sample counties.[11] Furthermore, the store size measured in 1000 square feet is also from TDLinx data. The distance from each IRI store to a consumer's home is evaluated as the distance from the store to the population weighted centroid of consumer's resident census tract. Thus all households are assumed to locate in the population-weighted centroid of census tract.[12]

The distribution of consumer attributes for each census tract, i.e. income and vehicle access comes from 2008-2012 ACS and thus doesn't vary across years. Although this may not be

[9] It is possible that the number of FV items sold is not equal to what's available in the store. However, I obtain the availability measure by summing over all 13 weeks in a given quarter, which lowers the likelihood that an item available in the store is never sold once in a quarter.

[10] I do not distinguish canned, frozen and fresh fruits and vegetables here because existing research hasn't reached consensus on which form of fruits and vegetables is more healthful or nutritious. The nutrition value of each type of fruits and vegetables may depend on the way of transportation, processing and storage (Rickman, Barrett and Bruhn 2007)

[11] I also use 2012 Economic Census of Retail Trade data to define the total sales in a market. Although the sales in the Economic Census do not change over time from 2009 to 2012, this is the most complete list of stores to date. The results do not change much when using the Economic Census to calculate market shares.

[12] I also assume consumers live in block group (BG) population weighted centroid (a smaller area than census tract) and measure the distance from the BG population weighted centroid to stores as a robustness check. The results are qualitatively identical.

exactly true, it seems like a reasonable first approximation. I sample 250 draws for each census tract.[13]

Food deserts indicators are from 2010 FARA and are defined as low-income low-access census tracts. A low-income census tract is one with either a poverty rate of 20 percent or higher, or a median family income at or below 80 percent of the area's median family income. A low-access census is one where at least 500 people and/or 33 percent of the population residing more than one mile from a supermarket[14] in urban areas. This definition of food deserts is commonly used in the literature (e.g. Thomsen et al. 2015) and had direct policy implications. For example, federal Healthy Food Financing Initiative (HFFI) uses this definition to qualify projects expanding access to nutritious food in a food desert. There are 323 urban census tracts in the data, 70 of which are food deserts by this definition.[15]

Finally, the instrumental variables are constructed using four data sources. The average housing value per square feet in each census tract is from the 2008-2012 ACS and the census-tract population density is from 2010 Census. The distance from the store to the nearest distribution center is looked up and calculated by the author based on information from stores' official websites, annual reports and news. The regional quarterly prices of bananas are from the USDA commodity price data (USDA 2016).

Descriptive Statistics

Table 1 presents the average census tract characteristics by food deserts and non-food deserts. There are fewer households and people living in food deserts. Not surprisingly, households in food deserts earn less income, by almost $20,000 than households in non-food deserts. Furthermore, households in food deserts are less likely to have access to vehicles. The constraint of income and vehicle access for food deserts households to buy healthy foods is further

---

[13] The ACS provides the share of households in eight income categories with cut-off points of $12,500, $30,000, $42,500, $62,500, $87,500, $125,000 and $175,000. Multinomial distribution is used to draw samples from the eight income categories, i.e. the probability of being in one category is the share of households in the tract that belong to the category. The midpoint of each income category is selected afterwards. Two hundred and fifty households are randomly selected in a census tract from a Bernoulli distribution where share of households with access to car in the census tract is used as the probability of success.

[14] A supermarket is a store that has over 2 million annual sales and has all major food departments including fresh produce, fresh meat and poultry, dairy, dry and packaged foods and frozen foods.

[15] The definition of food deserts is hotly debated in the literature. Thus I use vehicle access as an alternative definition of food deserts in the robustness test. By 2010 FARA, a low-access census tract is a food desert if at least 100 households are more than 0.5 mile away from the nearest supermarket and have no access to vehicle; or at least 500 people or 33 percent of the population live more than 20 miles away from the nearest supermarket, regardless of the vehicle access. The results do not change substantially when this alternative measure is used.

complicated by the lower availability of fruits and vegetables and higher prices in food deserts. Food deserts are also farther away from supermarkets than non-food deserts.

Figure 1 is a map of census tracts in one of the sample counties, Macon, IL with store locations. I find that first, all food deserts are urban census tracts. Second, many stores are clustered at the same location, implying the economies of agglomeration. Third, the nearest stores of food deserts are mostly drug, dollar and convenience stores while non-food deserts are more likely to have a grocery store nearby. The other ten counties in the sample represent similar geographic characteristics as Macon county.

The summary statistics of store characteristics is reported in table 2. The average food store has a market share of 2.5%, sells 427 fruits and vegetables items and costs \$46.9 per household per grocery shopping trip. The average store size is 27,000 square feet. The most common types of food stores are grocery (32%), drug (31%), convenience stores (17%), where the type of stores are defined by the IRI. The average distance to the nearest distribution center is modest, amounting to 156.4 miles because most of the nearest distribution centers are within the state.

Results

A simplifying assumption commonly made to solve the integral given in equation (1) is that consumer heterogeneity enters the model only through the separable additive random shocks, ε_{ijt}, (i.e. μ_{ijt} does not exist) and that these shocks are distributed i.i.d. with Type I extreme-value distribution. This assumption reduces the model to the well-known Logit model, which is appealing due to its tractability. However, the Logit model yields restrictive and unrealistic substitution patterns, i.e. Independence of Irrelevant Alternatives (IIA). The restrictions on the cross-price elasticities, which the Logit assumptions imply are a function only of market shares and prices, are crucial to the counterfactual analysis. This implies that if, for example, CVS Pharmacy and Kroger have similar market shares and price levels, then the substitution from Walgreen's Pharmacy toward either of them will be the same, while CVS Pharmacy and Walgreen's Pharmacy are of the same store type and expected to be more substitutable towards each other than Kroger. Therefore Logit model may be inadequate to conduct counterfactual analysis. Nevertheless, due to its computational simplicity it is a useful tool in getting a feel for the data. I use the Logit model to examine (a) the importance of instrumenting for prices and number of fruits and vegetables in the store; (b) the value of including proximity to stores into the demand estimation.

Column (1) and (2) in table 3 display the results obtained by regressing ln(s_{jt})-ln(s_{0t}) on prices, number of fruits and vegetables, store size, county, quarter and retail chain fixed effects. Column (1) reports the results of ordinary least squares regressions. The coefficient on price is positive but close to zero. Column (2) in table 3 use instrumental variables in two-stage least squares regressions like much of the previous work. Indeed, compared to column (1) the price coefficient becomes negative. Thus the instrument is correcting a positive missing variable bias in the OLS estimate, where there are factors unobserved by the econometrician for why a household dose not go to the cheapest store. For instance, the store may be close to the workplace of the consumer. Column (3) incorporates the distance from each store to consumer's home in the demand model. The coefficient on distance to stores is statistically significant and the price sensitivity increases by almost five times. It demonstrates the value of including distances to stores and thus spatial differentiation of stores in the demand estimation.

The estimates of the full model are based on equation (1) and were computed using the procedure described in the estimation section. Predicted market shares are computed using equation (1) and are based on the empirical distribution of demographics (as sampled according to 2012 ACS), independent normal distributions (for v), and Type I extreme value distribution (for ε). The IV's are store characteristics and cost shifters discussed in the instruments section. The results from the preferred specification are presented in table 4. The means of the distribution of marginal utilities, $\beta's$, are presented in the first column. Basically all coefficients are statistically significant and of the expected sign.

Estimates of heterogeneity around these means are presented in the next few columns. Taste parameters standard deviations estimates ($\sigma's$) are insignificant at conventional significance levels, which suggests that unobserved consumer characteristics such as household size and education, do not affect consumers' valuation of fruits and vegetables availability, proximity and prices of stores. As expected, households with higher income are less price sensitive and prefer more fruits and vegetables offered in a store.[16] Furthermore, households with access to vehicles value distance to stores in a less negative way but richer households who are more time-

[16] I do not find that access to vehicle significantly affects preferences for FV offerings in the store directly. The results are presented in appendix table A3.

constraint prefer closer stores for grocery shopping.

To compare the relative importance of store prices and attributes in consumers' store choices, the elasticities of store prices and attributes with respect to market shares are presented in table 5.[17] The results demonstrate that price is the most important factor in determining consumers' choice of stores and is much more important than the availability of FV and store proximity. Table 5 reports the change in the market shares with respect to 1% increase in price, the number of FV and the distance to store in miles. I calculate the elasticities at the average based on demand estimates in table 4. I find that price has a much larger elasticity than FV availability and store proximity. Furthermore, households with access to vehicles value FV availability much more than distance to stores. This suggests that even a store that is far away from the household expands its selection of FV, as long as the household has access to vehicle, it will also greatly benefit the household. This is demonstrated in the counterfactual analysis.

Additionally, there is substantial heterogeneity in consumers' preferences towards prices and store attributes. Specifically, higher income households have lower price sensitivity, prefer better access to FV and closer stores. An average household with annual household income of $12,500 is almost three times more price sensitive than one that earns $200,000 per year. Similarly, the elasticity of availability of FV and distance to store increases by almost four times (column 2-4) when the households' annual income rises from $12,500 to $200,000. In addition to income, access to vehicles plays a big role in consumers' valuation of store proximity. The elasticities of market shares with respect to distances to store for households without access to vehicles are 23%-46% higher than households with access. Lastly, I find that food deserts households are 20% more price sensitive than non-food deserts households. In summary, price is the most important factor when consumers decide where to shop, particularly for food deserts households.

Table 6 presents the WTP for 10% increase in the number of FV (an average increase of 43 UPCs) and one mile increase in the distance to stores to quantify the monetary value of different store attributes. The WTP per shopping trip is calculated based on equation (3) where both change in the likelihood of patronizing a store (extensive margin effects) and the value of a store attribute conditional on patronizing the store (intensive margin effects) are accounted for. Then the WTP per trip is multiplied by the annual average number of grocery shopping trips (104) based on the FoodAPS, where households pay two grocery shopping trips per week on average.

[17] The estimates with standard errors for table 5-13 except for table 11 are presented in appendix B.

The WTP demonstrates the monetary values of different store attributes and thus forecasts the impact of policy interventions aimed at changing store attributes.

There are three central findings. First, the WTP for FV access and store proximity per year is small in magnitude, regardless of household income and vehicle access. Specifically, in table 6, both the WTP for FV availability and distance to store are less than $10 per year. It is due to the fact that an average store has a small market share (2.5%) and it suggests that due to the competition effects, even if a store's offerings of FV and distance to consumers' home are improved, given that consumers have many other store choices that have already provided a good selection of FV items and are close, changing the availability of FV and store proximity will not divert a lot of market shares from the competitors into the store. The importance of competition effects and hence extensive margin effects has crucial welfare implications, which will be discussed in the counterfactual analysis.

Second, there is substantive consumer heterogeneity in the WTP for availability of FV and store proximity. A household with $200,000 annual income but no access to vehicles is willing to pay $6.4 per year to have a store one mile closer to home, more than doubling the WTP of a similar household with the lowest income level ($2.9). Besides, having access to vehicles does not completely remove the utility from having closer stores. Time cost is still very important, in spite of access to vehicles, especially for high-income households. For instance, both with access to vehicles, a household with $200,000 annual income is willing to pay over two times higher than a $12,500 income counterpart for a store to come one mile closer ($5.0 vs. $2.2). Importantly, a household with $200,000 annual income is willing to pay over two times more for a ten percent increase in the number of FV than the household with annual income of $12,500 ($4.8 vs. $2.2). High-income households' stronger preference for good access to FV suggests that they may benefit more than low-income households from policies that expand access to FV.

Third, non-food deserts (NFD) households, who are richer than food deserts (FD) households on average, are willing to pay more money for both closer stores and more FV in a store than NFD households. Specifically, NFD households are willing to pay $3.3 for 10% increase in FV offerings compared to $3.0 for FD households. Additionally, a NFD household is willing to pay $3.4 for a store to locate one mile closer compared to $3.1 for a FD household. In short, FD households have lower preferences towards good access to FV than NFD households, which supports the argument that large grocery stores do not locate in food deserts because of lower demand. The difference in revealed preferences towards stores also affects the distributional effects of expanding access to FV in food deserts, which is discussed in the next section.

Table 7 shows the WTP for a similar increase in the number of FV and distance to stores but only accounts for intensive margin effects. I find that the intensive margin effects are $2.25-4.89 *per week* for households without vehicle access and $1.66-3.81 for those with vehicle access as distance to stores increase by one mile. My estimates are of similar magnitude as Taylor and Villas-Boas (2016) who find that households are willing to pay $2-5 and $1-6 per week to have a Superstore and a Supermarket 1 mile closer to their home, respectively. This result again highlights the importance of incorporating extensive margin effects when quantifying the benefits of policy interventions.

Counterfactual Analysis

In this section, I first focus on a specific policy intervention that increased the offerings of FV in the nearest store of each food desert. Change in consumer welfare is calculated and compared with the cost of intervention to assess the effectiveness of the policy. Next, I explore why food deserts exist by moving a FD household to a NFD, holding preferences constant while changing store characteristics and prices the FD household faced, and vice versa. By comparing the changes in consumer welfare in these two scenarios, one can infer whether preferences explain, at least in part, why supermarkets do not locate in food deserts.

Table 8 presents results on how consumer welfare changed once the nearest store of each food deserts census tract increased its offerings of FV by different levels. The total welfare changes per county over 10 and 20 years are shown. The counterfactual changes are simulated by setting the number of UPCs in the intervene stores to 50, 100, 250 (approximately median, 95th percentile and maximum number of FV UPCs among the nearest non-grocery stores of food deserts), 350 and 1,200 (about the minimum and median number of FV UPCs in a grocery store), if the intervene store had fewer FV than the counterfactual amount. The counterfactual numbers of FV are similar as Family Dollar (50), Kmart (100), CVS Pharmacy (250), Fred Meyer (350) and Safeway (1,200). The annual welfare change is calculated based on equation (2).

According to the Department of Treasury New Markets Tax Credits Programs for financing supermarkets in food deserts, industry investors desire an annual yield in the neighborhood of 4.2% (U.S. Treasury 2011). Thus I use 4.2% to discount the changes in consumer welfare (compensating variation or CV). Additionally, the total CV over 10 and 20 years is calculated to fully capture the total welfare impact of the policies.[18] The cost of the different policy interventions is calculated by multiplying the average cost of expanding the selection of FV in existing stores funded by the Department of Health and Human Services (HHS) HFFI with the number of intervene stores, where the average cost is $1,127,900 (HHS 2015). I recognize the fact that the stores funded by the HHS HFFI are small independent stores rather than big chain stores, thus the actual costs for policy interventions aimed at increasing the number of FV UPCs to levels of large grocery stores, i.e. UPC=350 and 1,200 are probably larger than the costs provided in table 7. The nearest stores of FD census tracts are mostly established drug and convenience retail chains, i.e. Family Dollar and Circle K, which may need to invest much more than $1,127,900 to have as many FV items as in Fred Meyer (UPC=350) and Safeway (UPC=1200). Thus the estimated net benefits of these two policy interventions are upper bounds.

There are four central findings from this counterfactual analysis. First, consumers benefit from this policy intervention, and the total welfare gain ranges from $1,475,443 to $25,428,399 over 20 years (table 8). Second, after isolating the effect of population, I find in table 9 that an average FD household gained $2.8 (0.4%) to $96.0 (13.1%) whereas an average NFD household gained $4.2 (0.6%) to $ 112.3 (15.3%) per year. So even just the nearest stores of *FD* were intervened to provide more FV, *NFD* households would also benefit because NFD households prefer better access to FV than FD households (as shown in table 6) and a store being far away doesn't bother them much compared to being able to shop more FV in the store (as shown in table 5).

Third, such a policy expanding access to FV may not generate enough benefits to cover the cost of the policy intervention especially when the number of FV is increased to a limited amount (i.e. 50 and 100). Furthermore, the impact on the healthfulness of food purchases is limited. As a back-of-envelope calculation, I assumed the increased market shares of intervene stores all go to FV while the decreased market shares of non-intervene stores are all from decreased purchases of non-FV. No substitution effects between FV and non-FV are accounted for and thus this calculation provides the upper bound of effects on the healthfulness of food purchases. Appendix table A4 shows that after such a policy intervention, the average change in

[18] According to industry standards, the average period before a food store has a major renovation is 7-10 years. I also present results with 20 years as an upper bound of the benefits of the policy interventions.

county-level store sales shares from FV only increased 0.08-0.13 percentage points. Thus the policy interventions aimed at increasing the number of FV in food desert stores have limited effects on both consumer welfare and healthfulness of food purchases.

Fourth, the small benefit from increasing a limited amount of FV in existing stores is caused by both small extensive and intensive margin effects. First, the existing grocery stores in the market already provide cheap and wide selection of FV to FD consumer, which is supported by the fact that over 90% of FD households have access to vehicles and choose a supermarket for their primary grocery shopping regardless of their distances according to the FoodAPS data. Having access to vehicle moderates the effects of local neighborhood supply conditions on constraining the choice set. This is further supported by the small changes in market shares between intervene and non-intervene stores in each policy scenario in table 10. Second, consumers do not value proximity to FV much compared to price (table 7). Therefore, improved availability of FV would not attract more low-income consumers to visit the stores if the prices are not lowered and low-income households' preferences are unchanged.

I demonstrate how consumer heterogeneity affects the welfare changes or CV from each policy scenario. In table 11, log of CV for each household-quarter is regressed against log income, log distance, log distance interacted with vehicle access, as well as county and quarter fixed effects. I find that within the same county and quarter, richer households benefit more from expanding access to FV in food deserts, and the benefit is larger when more FV UPCs were included in food deserts stores. Households who live further away from the intervene store and do not have vehicle access benefit less from the policy. But for the households with access to vehicle, distance to the intervene stores does not matter at all in determining how much they benefit from the policy. This explains the reason why NFD households on average benefit more from expanding FV in FD, i.e. NFD households are richer and have better access to vehicles.

If the policies that only increase the number of FV are not effective, what policies might help mitigate the problem of food deserts? Because price is more important in changing households' store choice, reducing FV prices in food deserts may be more useful. Appendix table A5 presents the welfare impact when the FV prices in the nearest non-grocery store of food deserts were lowered by 1%, 5%, 10%, 20% and 30%. The cost of each policy intervention is calculated by multiplying the price difference with FV quantities sold to assume that government subsidize every FV item sold in the nearest non-grocery store of food deserts.[19] On all counterfactual levels, the benefits were greater than cost of the interventions. Notably, decreasing FV prices by 5% and 10% generates similar benefits as increasing the number of FV items to the levels of Fred Meyer (350) and Safeway (1200). Contrary to the FV selection interventions analyzed above, the price reduction policy is more beneficial for FD households (appendix table A6). This result suggests that price reduction policies may be more cost-effective and have better distributional effects (i.e. benefit the FD households the policy is intended to help).

I also explore the regional heterogeneity in the counterfactual analysis to see if the results vary by different regions of the country. Appendix table A7 presents the demand estimates by region. The results suggest that Northeasterners and Westerners prefer more FV and closer stores, while Midwest and Southerners are more price sensitive. This has direct welfare implications. Because FV selection and store proximity are more important for Northeasterners and Westerners, policies aimed at increasing the number of FV in food deserts stores are more effective in Northeast and West than other regions (as shown in appendix table A8). In contrast, because households from Midwest and South are more price sensitive, policies targeted at reducing FV prices are more effective (as shown in appendix table A9). Nevertheless, the welfare impact of price reduction policy is larger for all regions compared to that of FV increase intervention. In the Northeast and West, 10% FV price reduction is similar to increasing FV UPCs to 1,200 while in the Midwest and South, the FV price reduction that generates similar welfare impact is 5%. Lastly, similar to the main results, FV price reduction policy benefits FD households more and thus has better distributional effects than FV increase interventions. This analysis highlights the importance of regional heterogeneity and suggests that HFFI should be designed to fit the local demand and supply conditions in each low-income, low-access area in question.

The second set of counterfactual analysis relates to why food deserts exist. Specifically, are food deserts caused by lower demand? Table 5 and 6 have demonstrated that FD households have lower preferences to FV availability and store proximity, and are more price sensitive than NFD households. However, it is unclear whether local neighborhood supply conditions, i.e. store

[19] I first calculate the increased FV quantities sold due to price reduction based on the price elasticity of FV demand estimated in the literature (Andreyeva, Long and Brownell 2010). Then the increased FV quantities sold is added to the baseline FV quantities to obtain the new total FV quantities sold after price reduction.

attributes are even more important than the preferences in determining where consumers shop. To tackle this, I simulate the welfare change of a household from a FD census tract if faced with store attributes from a NFD census tract. I start by examining the behavior of the average FD household. The simulation can be viewed as moving a FD household to a NFD census tract, changing only its shopping environment, namely the store attributes and prices, and asking how would their welfare change. In particular, household's income and access to vehicle are envisioned as staying constant. Then consumers' welfare in these counterfactuals are then compared to actual welfare of the average consumer in the FD.

In defining preferences I always use the estimated random coefficients $\alpha_i, \beta_i, \gamma_i$ in table 4 from the home FD census tract. In the counterfactual, preferences are those of average household in a FD, but store attributes are in a NFD. In this analysis, the store attribute is the distance to store d_{ij}. The welfare change between the counterfactual (consumer i in NFD s) and the average consumer i in the FD i is defined as

$$\Delta W_{it} = \frac{1}{\alpha_i} \log\left(1 + \sum_{j \in J_t} \exp(\alpha_i p_{jt} + x_{jt}\beta_i + d_{sj}\gamma_i + \xi_{jt})\right) - \frac{1}{\alpha_i} \log\left(1 + \sum_{j \in J_t} \exp(\alpha_i p_{jt} + x_{jt}\beta_i + d_{ij}\gamma_i + \xi_{jt})\right)$$

which captures the effect of store access on consumer welfare.

Table 12 presents the results that consumers are better off with closer access to FV. But the benefit was \$72.17 for an average household in FD, which is only about 9.9% increase in the household's annual welfare from grocery shopping. In table 13, I reverse the counterfactual analysis and move the NFD household to a FD instead. As a result, the NFD household experienced a big drop in their welfare by 31.5% or \$230.34. Both results indicate that FD households may not value proximity to FV as much as a NFD household and changing the store distances does not alter FD households' shopping behavior a lot. Thus local food retailers in food deserts may lack incentives to improve the availability of FV. Additionally, supermarkets may have already learnt that FD households have insufficient demand for closer access to FV and thus are reluctant to enter food deserts. In conclusion, lower demand of closer access to FV in food deserts seems to explain why food deserts exist.

Conclusion

This article uses a random coefficients discrete choice (mixed Logit) model to estimate a store-level demand system for the food retail industry. Parameter identification is based on an independent assumption of demand shocks with cost shifters. The estimated parameters are used to compute the welfare impact of subsidizing the number of fruits and vegetables in the nearest stores of food deserts. Furthermore, the welfare change of a food desert (non-food desert) household moving to a non-food desert (food deserts census tract is evaluated to explore why food deserts exist.

I find that first, price is the most important factor when consumers decide where to shop and is much more important than availability of fruits and vegetables and store proximity. Second, the consumer's welfare rise by little when the number of fruits and vegetables are increased by a small amount in each nearest store of food deserts. It is due to the fact that consumers do not value availability of fruits and vegetables as much as prices, and most consumers have access to vehicles and are thus less constrained by store distances to shop in the nearest supermarkets. Third, food deserts households' demand for better access to fruits and vegetables is low and may explain why food deserts exist.

The results have three important policy implications. First, expanding availability of fruits and vegetables without changing prices or consumers preferences has limited effect on increasing consumers' welfare. Second, since price is the most important factor in poor households' store choices, policies impacting prices could impact store choices and benefit food deserts households more than non-food deserts counterparts. Third, preferences for store attributes such as selection of fruits and vegetables matter a lot in store choices and explain why food deserts exist. Therefore, policies addressing underlying factors driving preferences could be more effective in improving welfare.

There are two areas for future research. First, although the measure of consumer welfare is theoretically founded and useful for benefit-cost analysis of policy intervention, direct health benefits may not be fully incorporated into consumer welfare. Thus future research on direct impact of food deserts policies on nutrition and health will complement the study. Second, in this article I focus on the demand side and consumer welfare. While providing a useful benchmark for evaluating policies targeted at food deserts, the demand model can be combined with different models of supply conduct. In doing so one can evaluate how equilibrium prices change in response to different policy interventions and incorporate the producer surplus into the welfare analysis.

Table 1. Average Census Tract Characteristics

	Food Deserts	Non-Food Deserts
Number of census tracts	70	253
Number of households	1686	1690
Population	4471	4470
Tract Family Median Income ($)	43,819	63,035
Access to vehicles	0.90	0.94
Number of fruits and vegetables UPCs in the nearest store	345	488
Price of the nearest store (2015 $)	51.32	44.83
Distance to the nearest supermarket (miles)	3.87	3.25

Table 2. Summary Statistics of Store Characteristics

	Mean (Std)
Market shares (%)	2.5
	(4.5)
Number of fruits and vegetables UPCs	427.4
	(609.4)
Prices (2015 $)	46.9
	(12.8)
Store size (1000 square feet)	27.0
	(30.0)
Grocery stores	0.32
	(0.47)
Club stores	0.01
	(0.11)
Mass merchandiser	0.06
	(0.24)
Drug stores	0.31
	(0.46)
Convenience stores	0.17
	(0.37)
Dollar Stores	0.13
	(0.34)
Distance to the nearest distribution center (miles)	156.4
	(271.4)
Number of observations	2,888

Table 3. Demand Estimates

Variables	OLS Logit (1)	IV Logit (2)	Random Coefficients (3)
Price	0.006***	-0.086***	-0.419***
	(0.002)	(0.031)	(0.175)
Log count of fruits and vegetables UPCs	0.033***	-0.0007	0.628***
	(0.006)	(0.206)	(0.465)
Store size	0.004***	0.004**	0.010**
	(0.001)	(0.001)	(0.005)
Log distance to store			-1.129***
			(0.035)
No. of Observations	2,668	2,668	2,668

Notes: *,**,*** denote significance levels at 0.1, 0.05 and 0.01 respectively. Asymptotically robust s.e. are reported in the parentheses. All regressions include quarter, chain and county fixed effects. The instrumental variables are the distance from the store to the nearest distribution center, distance to the nearest distribution center interacted with quarterly regional banana prices, housing value per square feet and population density of the store census tract.

Table 4. Results from Full Model

Variables	Means ($\beta's$)	Standard Deviations ($\sigma's$)	Interaction with Demographic Variables: Vehicle Access	Interaction with Demographic Variables: Log Income
Price	-0.433***	0.589		0.028***
	(0.022)	(0.101)		(0.007)
Log count of fruits and vegetables UPCs	0.585***	0.263		0.089**
	(0.145)	(0.560)		(0.016)
Store size	0.008***			
	(0.003)			
Log distance to store	-0.498***	0.713	0.321***	-0.078***
	(0.053)	(0.578)	(0.076)	(0.002)

Notes: *,**,*** denote significance levels at 0.1, 0.05 and 0.01 respectively. Asymptotically robust s.e. are reported in the parentheses. All regressions include quarter, chain and county fixed effects.

Table 5. Elasticities of Market Shares

Income Category	Price	FV	Distance (With Vehicle)	Distance (Without Vehicle)	Distance (Average Vehicle Access)
	(1)	(2)	(3)	(4)	(5)
$12,500	-12.32	0.112	-0.078	-0.081	-0.079
$30,000	-11.92	0.182	-0.102	-0.135	-0.114
$42,500	-10.21	0.201	-0.123	-0.159	-0.131
$62,500	-9.45	0.276	-0.154	-0.211	-0.158
$87,500	-8.93	0.311	-0.179	-0.234	-0.184
$125,000	-7.72	0.378	-0.213	-0.265	-0.221
$175,000	-6.19	0.421	-0.236	-0.299	-0.241
$200,000	-4.92	0.480	-0.278	-0.346	-0.284
Food Access Category					
Food Deserts	-9.32	0.212	-0.146	-0.213	-0.154
Non-Food Deserts	-8.11	0.352	-0.183	-0.273	-0.194

Notes: All elasticities correspond to 1% increase in price, number of FV UPCs and distance in miles.

Table 6. Annual Household Willingness to Pay for Store Attributes (Intensive and Extensive Margins)

Income Category	FV	Distance (With Vehicle)	Distance (Without Vehicle)	Distance (Average Vehicle Access)
	(1)	(2)	(3)	(4)
$12,500	$2.2	-$2.2	-$2.9	-$2.2
$30,000	$2.7	-$2.7	-$3.6	-$2.8
$42,500	$3.0	-$3.0	-$4.0	-$3.1
$62,500	$3.3	-$3.4	-$4.4	-$3.4
$87,500	$3.6	-$3.7	-$4.8	-$3.8
$125,000	$4.1	-$4.2	-$5.4	-$4.3
$175,000	$4.5	-$4.7	-$6.1	-$4.8
$200,000	$4.8	-$5.0	-$6.4	-$5.0
Food Access Category				
Food Deserts	$3.0	-$3.0	-$4.0	-$3.1
Non-Food Deserts	$3.3	-$3.4	-$4.4	-$3.4

Notes: The WTP has accounted for the change in the probability of a household shopping in the store (extensive margin effects). Column (1) corresponds to the WTP for 10% increase in the number of fruits and vegetables in a store on average. Column (2)-(4) denote the WTP for one mile increase in the distance to the store. Average vehicle access uses the average census tract share of vehicle access in each income category.

Table 7. Annual Household Willingness to Pay for Store Attributes (Intensive Margin)

Income Category	FV	Distance (With Vehicle)	Distance (Without Vehicle)	Distance (Average Vehicle Access)
	(1)	(2)	(3)	(4)
\$12,500	\$87.7	-\$86.5	-\$116.9	-\$88.6
\$30,000	\$108.3	-\$108.7	-\$144.3	-\$111.2
\$42,500	\$118.5	-\$119.9	-\$158.0	-\$122.5
\$62,500	\$131.7	-\$134.2	-\$175.7	-\$137.1
\$87,500	\$145.3	-\$148.9	-\$193.8	-\$152.1
\$125,000	\$162.3	-\$167.4	-\$216.6	-\$170.9
\$175,000	\$181.7	-\$188.5	-\$242.5	-\$192.3
\$200,000	\$190.5	-\$198.0	-\$254.3	-\$202.0
Food Access Category				
Food Deserts	\$119.5	-\$120.9	-\$159.3	-\$124.7
Non-Food Deserts	\$132.0	-\$134.5	-\$176.1	-\$137.0

Notes: The WTP has NOT accounted for the change in the probability of a household shopping in the store (extensive margin effects). Column (1) corresponds to the WTP for 10% increase in the number of fruits and vegetables in a store on average. Column (2)-(4) denote the WTP for one mile increase in the distance to the store. Average vehicle access uses the average census tract share of vehicle access in each income category.

Table 8. Average Change in Consumer Welfare Per County

No. of FV UPCs	Compensating Variation (10 years)	Compensating Variation (20 years)	Cost
50	\$886,968	\$1,475,443	\$3,383,700
100	\$2,117,851	\$3,528,592	\$3,383,700
250	\$4,939,857	\$8,215,586	\$3,383,700
350	\$6,270,647	\$10,446,241	\$4,511,600
1200	\$18,256,178	\$25,428,399	\$4,511,600

Notes: Computations were done using 2015 CPI-adjusted dollars. The counterfactual policy is to increase the number of fruits and vegetables in the nearest store of each food deserts census tract to different levels as indicated by the No. of FV UPCs.

Table 9. Change in Household-Level Consumer Welfare Per Year from Increasing the Number of Fruits and Vegetables in the Nearest Store of Each Food Deserts Census Tract

Scenario	Total	Food Deserts	Non-Food Deserts	Total	Food Deserts	Non-Food Deserts
UPC=50	$3.6	$2.8	$4.2	0.5%	0.4%	0.6%
UPC=100	$8.6	$7.5	$13.3	1.2%	1.0%	1.8%
UPC=250	$32.1	$29.5	$38.1	4.4%	4.0%	5.2%
UPC=350	$45.5	$41.6	$49.6	6.2%	5.7%	6.8%
UPC=1200	$101.5	$96.0	$112.3	13.9%	13.1%	15.3%

Notes: Computations were done using 2015 CPI-adjusted dollars.

Table 10. Average Changes in Store Market Shares

No. of FV UPCs	Intervene Stores	Non-Intervene Stores
50	1.3 pp	-0.64 pp
100	1.7 pp	-0.79 pp
250	1.9 pp	-0.88 pp
350	1.9 pp	-0.91 pp
1200	2.2 pp	-1.10 pp

Notes: pp stands for percentage points. The counterfactual policy is to increase the number of fruits and vegetables in the nearest store of each food deserts census tract to different levels as indicated by the No. of FV UPCs.

Table 11. Effects of Income and Distance on Log Compensating Variation (CV)

Variable	UPC=50	UPC=100	UPC=250	UPC=350	UPC=1200
Log income	0.141**	0.148**	0.181**	0.209***	0.284***
	(0.073)	(0.066)	(0.087)	(0.067)	(0.062)
Log distance	-1.761***	-1.784***	-1.680***	-1.785***	-1.761***
	(0.312)	(0.301)	(0.473)	(0.262)	(0.638)
Log distance X	1.859***	1.684***	1.789***	1.779***	1.782***
vehicle access	(0.438)	(0.451)	(0.599)	(0.671)	(0.421)
County FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes

Notes: *,**,*** denote significance levels at 0.1, 0.05 and 0.01 respectively. Standard errors are clustered at the county level. The unit of observation is a household-quarter. Distance is measured from the census tract centroid to nearest intervene store within the same county.

Table 12. Annual Consumer Welfare Impact of a Food Deserts Household Moving to a Non-Food Desert

Statistic	Compared to an Average Household in the Food Desert	Percentage Change
Mean	$72.17	9.9%
Median	$45.91	6.3%
Min	-$31.62	-4.3%
Max	$752.81	102.9%
% Change>0	95.12	

Notes: Computations were done using 2015 CPI-adjusted dollars.

Table 13. Annual Consumer Welfare Impact of a Non-Food Deserts Household Moving to a Food Desert

Statistic	Compared to an Average Household in the Food Desert	Percentage Change
Mean	-$230.34	-31.5%
Median	-$169.21	-23.1%
Min	-$6,565.32	-896.6%
Max	$0	0.0%
% Change>0	100	

Notes: Computations were done using 2015 CPI-adjusted dollars.

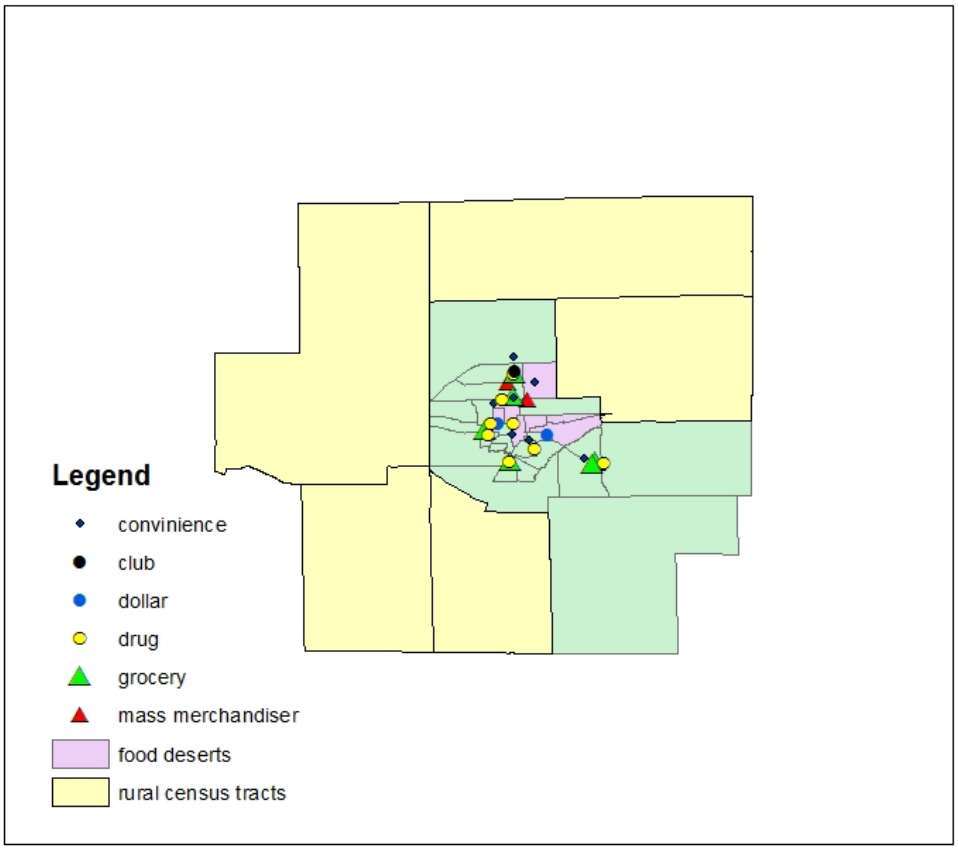

Figure 1. Stores in Macon County

References

Ahern M, C. Brown and S. Dukas. 2011. “A National Study of the Association Between Food Environments and County-Level Health Outcomes.” *The Journal of Rural Health* 27: 367-379.

Allcott H., R. Diamond and J. Dube. 2016. “The Geography of Poverty and Nutrition: Food Deserts and Food Choices Across the United States.” NBER Working Paper.

Anderson, M., and D. Matsa. 2011. “Are Restaurants Really Supersizing America?" *American Economic Journal: Applied Economics*, 3 (1): 152-188.

Andreyeva T., M. W. Long, and K. D. Brownell. 2010. “The Impact of Food Prices on Consumption: A Systematic Review of Research on the Price Elasticity of Demand for Food.” *American Journal of Public Health* 100(2): 216-222.

Arnold, S., T. Oum, and D. Tigert. 1983. “Determinant Attributes in Retail Patronage: Seasonal, Temporal, Regional, and International Comparisons.” *Journal of Marketing Research* 20(2): 149-157.

Aussenberg, R.A., “SNAP and related nutrition provisions of the 2014 Farm Bill (P.L. 113-79),” Congressional Research Service Report, 2014.

Berry, S. 1994. "Estimating Discrete-Choice Models of Product Differentiation," *Rand Journal of Economics* 25: 242-262.

Berry, S., J. Levinsohn, and A. Pakes. 1995. “Automobile Price in Market Equilibrium." *Econometrica* 63: 841-90.

Bodor. N., D. Rose, T.A. Farley, C. Swalm, and S.K. Scott. 2008. “Neighbourhood Fruit and Vegetable Availability and Consumption: the Role of Small Food Stores in an Urban Environment.” *Public Health Nutrition* 11(4): 413-420.

Bonanno, A. and J. Li. 2015. “Food Insecurity and Food Access in U.S. Metropolitan Areas.” *Applied Economic Perspectives and Policy* 37(2): 177-204.

Cailiavet, F., G. Kyureghian, R. M. Nayga, C. Ferrant, and P. Chauvin. “Does Healthy Food Access Matter in a French Urban Setting?” *American Journal of Agricultural Economics* 97(5): 1400-1416.

Center for Nutrition Policy and Promotion (CNPP), U.S. Department of Agriculture. 2007. *Thrifty Food Plan, 2006*. Washington D.C.

Chenarides, L. and E. C. Jaenicke. “Store Choice and Consumer Behavior in Food Deserts: An

Empirical Application of the Distance Metric Method." Department of Agricultural Economics, Sociology, and Education, Penn State University, Working Paper.

Cummins, S., A. Findlay, M. Petticrew, and L. Sparks. 2005. "Healthy Cities: The Impact of Food Retail-led Regeneration on Food Access, Choice, and Retail Structure." *Built Environment*, 31(4): 288-301.

Cummins, S., E. Flint and S. A. Matthews. 2014. "New Neighborhood Grocery Store Increased Awareness of Food Access but Did Not Alter Dietary Habits or Obesity" *Health Affairs* 33(2): 283-291.

Currie, J., S. DellaVigna, E. Moretti, and V. Pathania. 2010. "The Effect of Fast Food Restaurants on Obesity and Weight Gain." *American Economic Journal: Economic Policy*, 2 (3): 32-63.

Das, S., S. Olley and A. Pakes. 1994. "Evolution of Brand Qualities of Consumer Electronics in the U.S.," mimeo.

Davis, B., and C. Carpenter. 2009. "Proximity of Fast-Food Restaurants to Schools and Adolescent Obesity." *American Journal of Public Health*, 99 (3): 505-510.

Dubois, P., R. Griffith, and A. Nevo. 2014. "Do Prices and Attributes Explain International Differences in Food Purchases?" *American Economic Review*, 104 (3): 832-867.

Dunn, R. A. 2010. "The Effect of Fast-Food Availability on Obesity: An Analysis by Gender, Race, and Residential Location." *American Journal of Agricultural Economics*, 92 (4): 1149-1164.

Ellison, B., J. L. Lusk and D. Davis. 2014. "The Impact of Restaurant Calorie Labels on Food Choices: Results from a Field Experiment." Economic Inquiry 52(2): 666-681.

Fan, L., K. Baylis, C. Gundersen, and M. Ver Ploeg. 2016. "Does a Nutritious Diet Cost More in Food Deserts?" Department of Agricultural and Consumer Economics, University of Illinois Urbana-Champaign, Working Paper.

Handbury, J., I. Rahkovsky, and M. Schnell. 2016. "hat Drives Nutritional Disparities? Retail Access and Food Purchases across the Socioeconomic Spectrum." National Bureau of Economic Research Working Paper 21126.

Handbury, J., and Weinstein, D. E., 2014. "Goods Prices and Availability in Cities." *The Review of Economic Studies* 81(4): 1-39.

Hansen, L. 1982. "Large Sample Properties of Generalized Method of Moments Estimators."

Econometrica 50: 1029-1054.

Hausman, J. and E. Leibtag. 2007. “Consumer Benefits from Increased Competition in Shopping Outlets: Measuring the Effect of Wal-Mart.” Journal of Applied Econometrics 22(7): 1157-1177.

Hendel, I. 1999. "Estimating Multiple Discrete Choice Models: An Application to Computerization Returns," Review of Economic Studies, 66: 423-446.

HHS (U.S. Department of Health and Human Services). 2011. “$100 million in Affordable Care Act grants to help create healthier U.S. communities." Access via http://www.epa.gov/care/documents/A_ordableCareActGrants.pdf

Marshall, G. and T. Pires. 2017. “Measuring the Impact of Travel Costs on Grocery Shopping.” Department of Economics, University of Illinois at Urbana-Champaign, Working Paper.

McFadden, Daniel L 1973. “Conditional Logit Analysis of Qualitative Choice Behavior," *Frontiers in Econometrics*, 105-142.

McFadden, D.1976. “Quantal Choice Analysis: A Survey," in *Annals of Economic and Social Measurement, Volume 5, number 4*: NBER, 363-390.

Morland K, S. Wing and A. Diez-Roux A. 2002. “The Contextual Effect of the Local Food Environment on Residents’ Diets: The Atherosclerosis Risk in Communities Study.” *American Journal of Public Health* 92(11):1761-1767.

Nevo, A. 2001. "Measuring Market Power in the Ready-to-Eat Cereal Industry." *Econometrica* 69(2): 307-342.

Newey, W. and D. Mcfadden. 1994: "Estimation in Large Samples," in *The Handbook of Econometrics*, Vol. 4, ed. by D. McFadden and R. Engle. Amsterdam: North-Holland.

Petrin A.2002. “Quantifying the Benefits of New Products: The Case of Minivan.” *Journal of Political Economy* 110(4): 705-729.

Rickman J. C., D. M. Barrett, and C. M. Bruhn. “Nutritional Comparison of Fresh, Frozen and Canned Fruits and Vegetables. Part 1. Vitamins C and B and Phenolic Compounds.” *Journal of the Science of Food and Agriculture*. 87(6): 930-944.

Sharkey, J. R., S. Horel, and W. R. Dean. 2010. “Neighborhood Deprivation, Vehicle Ownership, and Potential Spatial Access to a Variety of Fruits and Vegetables in a Large Rural Area in Texas." *International Journal of Health Geographics*, 9 (26): 1-27.

Small, K. A and H. S. Rosen. 1981. “Applied Welfare Economics with Discrete Choice Models," *Econometrica*: *Journal of the Econometric Society*, 105-130.

Smith, H. 2004. "Supermarket Choice and Supermarket Competition in Market Equilibrium." *Review of Economic Studies* 71:235-263.

Smith, H. 2006. "Store Characteristics in Retail Oligopoly." The RAND Journal of Economics 37(2): 416-430.

Taylor, R., and S. B. Villas-Boas. "Food Store Choices of Poor Households: A Discrete Choice Analysis of the National Household Food Acquisition and Purchases Survey (FoodAPS)." *American Journal of Agricultural Economics* 98(2): 513-532.

The Reinvestment Fund. 2011. "New Markets Tax Credits and Urban Supermarkets." Financing Healthy Food Options: Implementation Handbook.

Thomassen, O., H. Smith, S. Siler, and P. Schiraldi. 2017. "Multi-Category Competition and Market Power: A Model of Supermarket Pricing." American Economic Review (In Press).

Thomsen, M. R., R.M. Nayga, P. A. Alviola and H. L. Rouse. 2015. "The Effect of Food Deserts on The Body Mass Index of Elementary School Children." *American Journal of Agricultural Economics* 98(1): 1-18.

U.S. Department of Agriculture. 2013. Economic Research Service. Food Access Research Atlas, http://www.ers.usda.gov/data-products/food-access-research-atlas.aspx. (Accessed on May 15, 2017).

U.S. Department of Agriculture. 2016. Agricultural Marketing Services. Specialty Crops Custom Reports. https://www.marketnews.usda.gov/mnp/fv-nav-byCom?navClass=FRUITS&navType=byComm. (Accessed on April 20, 2016)

Ver Ploeg, M., P. Dutko, and V. Breneman. 2015. "Measuring Food Access and Food Deserts for Policy Purposes." *Applied Economic Perspectives and Policy* 37 (2): 205–25.

Ver Ploeg, M., L. Mancino, and J. Todd. 2015. "Where Do Americans Usually Shop for Food and How Do They Travel to Get There? Initial Findings from the National Food Acquisition and Purchase Survey." Washington DC: U.S. Department of Agriculture, Economic Research Service, Economic Information Bulletin No. 138.

Online Appendix: Not For Publication

The Consumer Welfare Impact of Expanding Access to Fruits and Vegetables in Food Deserts

Linlin Fan

Department of Agricultural and Consumer Economics

University of Illinois Urbana-Champaign

lfan3@illinois.edu

APPENDIX A Robustness Tests

Table A1. Results from Full Model—Using Prices of A Basket of Commonly Available Food

Variables	**Means** ($\beta's$)	**Standard Deviations** ($\sigma's$)	**Interaction with Demographic Variables**	
			Vehicle Access	**Log Income**
Price	-2.186***	0.014		0.059***
	(0.219)	(0.021)		(0.006)
Log count of fruits and vegetables UPCs	1.014***	0.005		0.051***
	(0.122)	(1.306)		(0.007)
Store size	0.008***			
	(0.003)			
Log distance to store	-0.598**	0.009	0.139***	-0.056***
	(0.292)	(0.146)	(0.052)	(0.017)

Notes: *,**,*** denote significance levels at 0.1, 0.05 and 0.01 respectively. Asymptotically robust s.e. are reported in the parentheses. All regressions include quarter, chain and county fixed effects.

Table A2. Results from Full Model—Using Variety-Adjusted Price Index

Variables	**Means** ($\beta's$)	**Standard Deviations** ($\sigma's$)	**Interaction with Demographic Variables**	
			Vehicle Access	**Log Income**
Price	-1.254***	0.253		0.132*
	(0.360)	(0.288)		(0.087)
Log count of fruits and vegetables UPCs	1.451***	0.304		0.442***
	(0.219)	(1.012)		(0.115)
Store size	-0.001			
	(0.003)			
Log distance to store	-0.116**	0.166	0.123***	-0.150***
	(0.050)	(1.253)	(0.034)	(0.046)

Notes: *,**,*** denote significance levels at 0.1, 0.05 and 0.01 respectively. Asymptotically robust s.e. are reported in the parentheses. All regressions include quarter, chain and county fixed effects.

Table A3. Results from Full Model—Interacting Vehicle Access with Count of FV UPCs

Variables	Means (β's)	Standard Deviations (σ's)	Interaction with Demographic Variables	
			Vehicle Access	Log Income
Price	-0.192***	0.014		-0.070
	(0.025)	(0.025)		(0.062)
Log count of fruits and vegetables UPCs	0.200	0.322***	-0.208	0.076
	(0.159)	(0.077)	(0.154)	(0.212)
Store size	0.008***			
	(0.003)			
Log distance to store	0.154	0.271	0.504***	-0.382
	(0.466)	(1.341)	(0.186)	(0.456)

Notes: *,**,*** denote significance levels at 0.1, 0.05 and 0.01 respectively. Asymptotically robust s.e. are reported in the parentheses. All regressions include quarter, chain and county fixed effects.

Table A4. Average Changes in Fruit and Vegetables Sales Shares

No. of FV UPCs	Change in Sales Shares
50	0.08 pp
100	0.09 pp
250	0.10 pp
350	0.10 pp
1200	0.13 pp

Notes: pp stands for percentage points. The counterfactual policy is to increase the number of fruits and vegetables in the nearest store of each food deserts census tract to different levels as indicated in the No. of FV UPCs. The calculation is based on the assumption that all increased market shares in intervene stores go to fruits and vegetables (FV) while all decreased market shares go to non-FV, without any substitution effects between FV and non-FV.

Table A5. Average Change in Consumer Welfare Per County

Price Reduction	Compensating Variation (10 years)	Cost (10 years)	Compensating Variation (20 years)	Cost (20 years)
1%	$1,223,406	$733,953	$2,034,168	$1,467,906
5%	$8,286,025	$3,762,195	$13,777,247	$7,524,390
10%	$13,164,336	$5,755,471	$21,888,458	$11,510,942
20%	$25,192,795	$10,435,266	$41,888,285	$20,870,532
30%	$72,783,200	$26,039,387	$101,267,635	$52,078,774

Notes: Computations were done using 2015 CPI-adjusted dollars. The counterfactual policy is to decrease prices in the nearest store of each food deserts census tract by different percentages as indicated in the No. of FV UPCs.

Table A6. Change in Household-Level Consumer Welfare Per Year from Decreasing Fruits and Vegetables Prices in the Nearest Store of Each Food Deserts Census Tract

Scenario	Total	Food Deserts	Non-Food Deserts	Total	Food Deserts	Non-Food Deserts
1%	$3.49	$4.03	$3.06	0.48%	0.55%	0.42%
5%	$25.60	$26.99	$20.59	3.50%	3.69%	2.81%
10%	$50.68	$52.48	$41.37	6.92%	7.17%	5.65%
20%	$78.19	$82.37	$63.31	10.68%	11.25%	8.65%
30%	$137.37	$143.00	$115.15	18.77%	19.53%	15.73%

Notes: Computations were done using 2015 CPI-adjusted dollars. Compensating variation over 20 years is used.

Table A7. Regional Heterogeneity in Demand Estimation

Variables	Means ($\beta's$)	Standard Deviations ($\sigma's$)	Interaction with Demographic Variables	
			Vehicle Access	Log Income
Northeast				
Price	-0.212***	0.005		0.042***
	(0.007)	(0.023)		(0.009)
Log count of fruits	1.681***	0.044		0.268***
and vegetables UPCs	(0.076)	(0.156)		(0.058)
Store size	0.008			
	(0.011)			
Log distance to store	-0.264**	0.245**	0.049	-0.053
	(0.104)	(0.124)	(0.115)	(0.170)
Midwest				
Price	-0.563***	0.017		0.052
	(0.099)	(0.176)		(0.052)
Log count of fruits	0.543***	0.128		0.185**
and vegetables UPCs	(0.369)	(0.919)		(0.090)
Store size	-0.002			
	(0.005)			
Log distance to store	-0.089	0.176	0.071	-0.097
	(0.231)	(0.553)	(0.661)	(0.409)
South				
Price	-0.382***	0.077		0.064**
	(0.066)	(0.163)		(0.067)
Log count of fruits	1.516***	0.096		0.005
and vegetables UPCs	(0.534)	(1.792)		(0.222)
Store size	0.018**			
	(0.008)			
Log distance to store	-0.004	0.092	0.064	-0.112**
	(1.398)	(0.998)	(0.332)	(0.547)
West				
Price	-0.204	0.009		0.013
	(0.221)	(0.030)		(0.009)
Log count of fruits	1.077***	0.594		0.342***
and vegetables UPCs	(0.014)	(0.454)		(0.044)
Store size	0.007			
	(0.067)			
Log distance to store	-0.148	0.372**	0.038***	-0.089
	(0.104)	(0.177)	(0.067)	(0.085)

Notes: *,**,*** denote significance levels at 0.1, 0.05 and 0.01 respectively. Asymptotically robust s.e. are reported in the parentheses. All regressions include quarter, chain and county fixed effects.

Table A8. Regional Heterogeneity in Average Change in County Level Consumer Welfare

Region	No. of FV UPCs	Compensating Variation (10 years)	Compensating Variation (20 years)	Cost
Northeast	50	$1,555,366	$2,586,121	$3,383,700
	100	$4,233,721	$6,982,327	$3,383,700
	250	$4,782,581	$8,009,160	$3,383,700
	350	$7,127,677	$11,744,973	$4,511,600
	1200	$9,929,800	$13,655,557	$4,511,600
Midwest	50	$806,661	$1,341,243	$3,383,700
	100	$928,243	$1,496,220	$3,383,700
	250	$1,381,577	$2,344,337	$3,383,700
	350	$1,493,275	$2,482,882	$4,511,600
	1200	$5,773,610	$8,033,170	$4,511,600
South	50	$1,310,796	$2,074,615	$3,383,700
	100	$1,966,784	$3,007,804	$3,383,700
	250	$2,318,378	$3,959,644	$3,383,700
	350	$4,441,735	$7,643,530	$4,511,600
	1200	$5,836,500	$8,114,384	$4,511,600
West	50	$1,940,128	$3,225,868	$3,383,700
	100	$2,709,234	$4,504,667	$3,383,700
	250	$4,120,251	$6,850,778	$3,383,700
	350	$6,606,310	$10,984,370	$4,511,600
	1200	$9,750,000	$13,565,760	$4,511,600

Notes: Computations were done using 2015 CPI-adjusted dollars. The counterfactual policy is to increase the number of fruits and vegetables in the nearest store of each food deserts census tract.

Table A9. Regional Heterogeneity in Average Change in County Level Consumer Welfare

Region	Price Reduction	Compensating Variation (10 years)	Cost (10 years)	Compensating Variation (20 years)	Cost (20 years)
Northeast	1%	$1,749,762	$1,034,528	$2,567,283	$2,069,056
	5%	$6,002,029	$5,872,238	$11,483,249	$11,744,476
	10%	$9,387,070	$6,897,246	$14,783,767	$13,794,492
	20%	$20,859,237	$12,672,344	$32,872,095	$25,344,688
	30%	$48,726,915	$30,783,372	$89,872,983	$61,566,744
Midwest	1%	$2,552,749	$578,634	$3,493,926	$1,157,268
	5%	$9,458,876	$2,003,478	$18,784,410	$4,006,956
	10%	$15,764,876	$4,234,663	$26,986,698	$8,469,326
	20%	$30,242,925	$8,678,332	$43,926,457	$17,356,664
	30%	$81,283,050	$24,653,127	$109,180,386	$49,306,254
South	1%	$1,786,326	$663,556	$4,008,784	$1,327,112
	5%	$9,098,769	$2,764,334	$16,897,437	$5,528,668
	10%	$14,879,084	$5,003,672	$24,669,594	$10,007,344
	20%	$28,897,487	$9,778,335	$42,789,378	$19,556,670
	30%	$78,783,456	$25,622,109	$107,874,569	$51,244,218
West	1%	$1,237,879	$893,378	$2,008,231	$1,786,756
	5%	$4,897,783	$3,347,347	$7,342,779	$6,694,694
	10%	$8,767,896	$5,567,338	$13,623,145	$11,134,676
	20%	$18,678,749	$11,678,376	$30,221,467	$23,356,752
	30%	$45,768,923	$28,376,228	$86,673,541	$56,752,456

Notes: Computations were done using 2015 CPI-adjusted dollars. The counterfactual policy is to increase the number of fruits and vegetables in the nearest store of each food deserts census tract.

Table A10. Regional Heterogeneity in Consumer Welfare Per Household Per Year

Region	Price Reduction	Total	Food Deserts	Non-Food Deserts	Total	Food Deserts	Non-Food Deserts
Northeast	1%	$2.46	$3.15	$2.13	0.33%	0.42%	0.28%
	5%	$23.87	$25.64	$19.76	3.18%	3.42%	2.63%
	10%	$43.65	$50.83	$39.62	5.82%	6.78%	5.26%
	20%	$68.57	$78.67	$60.99	9.14%	10.50%	8.10%
	30%	$120.96	$135.79	$112.60	16.13%	18.12%	14.96%
Midwest	1%	$3.81	$5.11	$3.54	0.54%	0.72%	0.50%
	5%	$27.57	$30.38	$26.20	3.88%	4.29%	3.68%
	10%	$57.19	$65.09	$54.25	8.05%	9.18%	7.61%
	20%	$84.16	$90.68	$80.48	11.84%	12.79%	11.29%
	30%	$147.28	$167.91	$140.37	20.72%	23.69%	19.69%
South	1%	$3.66	$4.98	$3.42	0.52%	0.70%	0.48%
	5%	$26.92	$29.79	$25.99	3.80%	4.20%	3.65%
	10%	$55.72	$59.25	$52.37	7.86%	8.36%	7.36%
	20%	$82.38	$87.23	$79.35	11.62%	12.31%	11.15%
	30%	$142.73	$162.87	$138.38	20.13%	22.98%	19.44%
West	1%	$2.23	$2.98	$2.03	0.30%	0.41%	0.28%
	5%	$20.75	$23.63	$18.29	2.82%	3.21%	2.48%
	10%	$41.87	$48.24	$36.60	5.69%	6.56%	4.97%
	20%	$65.78	$74.67	$58.21	8.94%	10.16%	7.91%
	30%	$117.67	132.65	$110.32	15.99%	18.04%	14.99%

Appendix B Estimates with Standard Errors

Table B1. Elasticities of Market Shares

Income Category	Price	FV	Distance (With Vehicle)	Distance (Without Vehicle)	Distance (Average Vehicle Access)
	(1)	(2)	(3)	(4)	(5)
	-12.32	0.112	-0.078	-0.081	-0.079
$12,500	(3.76)	(0.153)	(0.021)	(0.023)	(0.026)
	-11.92	0.182	-0.102	-0.135	-0.114
$30,000	(1.88)	(0.114)	(0.018)	(0.019)	(0.018)
	-10.21	0.201	-0.123	-0.159	-0.131
$42,500	(1.38)	(0.109)	(0.012)	(0.016)	(0.017)
	-9.45	0.276	-0.154	-0.211	-0.158
$62,500	(1.68)	(0.102)	(0.012)	(0.017)	(0.014)
	-8.93	0.311	-0.179	-0.234	-0.184
$87,500	(1.33)	(0.112)	(0.009)	(0.013)	(0.013)
	-7.72	0.378	-0.213	-0.265	-0.221
$125,000	(1.99)	(0.099)	(0.015)	(0.015)	(0.014)
	-6.19	0.421	-0.236	-0.299	-0.241
$175,000	(2.22)	(0.135)	(0.018)	(0.018)	(0.020)
	-4.92	0.480	-0.278	-0.346	-0.284
$200,000	(2.01)	(0.187)	(0.019)	(0.020)	(0.021)
Food Access Category					
	-9.32	0.212	-0.146	-0.213	-0.154
Food Deserts	(1.44)	(0.104)	(0.014)	(0.016)	(0.018)
	-8.11	0.352	-0.183	-0.273	-0.194
Non-Food Deserts	(1.48)	(0.109)	(0.018)	(0.019)	(0.020)

Table B2. Annual Household Willingness to Pay for Store Attributes (Intensive and Extensive Margins)

Income Category	FV	Distance (With Vehicle)	Distance (Without Vehicle)	Distance (Average Vehicle Access)
	(1)	(2)	(3)	(4)
	$2.2	-$2.2	-$2.9	-$2.2
$12,500	(1.31)	(1.11)	(1.20)	(1.22)
	$2.7	-$2.7	-$3.6	-$2.8
$30,000	(1.32)	(1.02)	(1.14)	(1.19)
	$3.0	-$3.0	-$4.0	-$3.1
$42,500	(1.30)	(1.12)	(1.12)	(1.18)
$62,500	$3.3	-$3.4	-$4.4	-$3.4

	(1.29)	(1.09)	(1.13)	(1.19)
	$3.6	-$3.7	-$4.8	-$3.8
$87,500	(1.34)	(1.04)	(1.14)	(1.17)
	$4.1	-$4.2	-$5.4	-$4.3
$125,000	(1.35)	(1.11)	(1.15)	(1.16)
	$4.5	-$4.7	-$6.1	-$4.8
$175,000	(1.30)	(1.13)	(1.16)	(1.18)
	$4.8	-$5.0	-$6.4	-$5.0
$200,000	(1.33)	(1.14)	(1.18)	(1.21)
Food Access Category				
	$3.0	-$3.0	-$4.0	-$3.1
Food Deserts	(1.32)	(1.15)	(1.17)	(1.16)
	$3.3	-$3.4	-$4.4	-$3.4
Non-Food Deserts	(1.35)	(1.17)	(1.16)	(1.18)

Notes: The WTP has accounted for the change in the probability of a household shopping in the store (extensive margin effects). Column (1) corresponds to the WTP for 10% increase in the number of fruits and vegetables in a store on average. Column (2)-(4) denote the WTP for one mile increase in the distance to the store. Average vehicle access uses the average census tract share of vehicle access in each category.

Table B3. Annual Household Willingness to Pay for Store Attributes (Intensive Margins)

Income Category	FV	Distance (With Vehicle)	Distance (Without Vehicle)	Distance (Average Vehicle Access)
	(1)	**(2)**	**(3)**	**(4)**
	$87.7	-$86.5	-$116.9	-$88.6
$12,500	(45.34)	(45.44)	(47.87)	(45.89)
	$108.3	-$108.7	-$144.3	-$111.2
$30,000	(52.23)	(47.88)	(50.12)	(48.39)
	$118.5	-$119.9	-$158.0	-$122.5
$42,500	(53.11)	(48.98)	(52.28)	(51.23)
	$131.7	-$134.2	-$175.7	-$137.1
$62,500	(54.02)	(53.33)	(53.45)	(54.89)
	$145.3	-$148.9	-$193.8	-$152.1
$87,500	(53.23)	(54.39)	(55.45)	(57.63)
	$162.3	-$167.4	-$216.6	-$170.9
$125,000	(52.44)	(55.34)	(57.87)	(60.83)
	$181.7	-$188.5	-$242.5	-$192.3
$175,000	(55.23)	(56.38)	(58.34)	(62.98)
	$190.5	-$198.0	-$254.3	-$202.0
$200,000	(61.67)	(59.88)	(61.22)	(63.77)
Food Access Category				
	$119.5	-$120.9	-$159.3	-$124.7
Food Deserts	(52.21)	(54.23)	(56.78)	(55.68)

	$132.0	-$134.5	-$176.1	-$137.0
Non-Food Deserts	(53.33)	(56.89)	(58.89)	(60.19)

Notes: The WTP has NOT accounted for the change in the probability of a household shopping in the store (extensive marginal effects). Column (1) corresponds to the WTP for 10% increase in the number of fruits and vegetables in a store on average. Column (2)-(4) denote the WTP for one mile increase in the distance to the store. Average vehicle access uses the average census tract share of vehicle access in each category.

Table B4. Average Change in Consumer Welfare Per County

No. of FV UPCs	Compensating Variation (10 years)	Compensating Variation (20 years)	Cost
50	$886,968 (432,768)	$1,475,443 (673,241)	$3,383,700
100	$2,117,85 (873,789)	$3,528,592 (1,023,889)	$3,383,700
250	$4,939,857 (1,008,893)	$8,215,586 (2,340,782)	$3,383,700
350	$6,270,647 (1,768,938)	$10,446,241 (3,487,982)	$4,511,600
1200	$18,256,178 (3,478,234)	$25,428,399 (5,678,213)	$4,511,600

Notes: Computations were done using 2015 CPI-adjusted dollars. The counterfactual policy is to increase the number of fruits and vegetables in the nearest store of each food deserts census tract to different levels as indicated in the No. of FV UPCs.

Table B5. Change in Consumer Welfare Per Household Per Year from Increasing the Number of Fruits and Vegetables in the Nearest Store of Each Food Deserts Census Tract

Scenario	Total	Food Deserts	Non-Food Deserts	Total	Food Deserts	Non-Food Deserts
UPC=50	$3.6 (1.03)	$2.8 (1.05)	$4.2 (1.08)	0.5% (0.11%)	0.4% (0.14%)	0.6% (0.13%)
UPC=100	$8.6 (3.11)	$7.5 (3.41)	$13.3 (3.56)	1.2% (0.41%)	1.0% (0.43)	1.8% (0.44%)
UPC=250	$32.1 (5.12)	$29.5 (5.56)	$38.1 (5.98)	4.4% (1.34%)	4.0% (1.39%)	5.2% (1.35%)
UPC=350	$45.5 (6.34)	$41.6 (6.88)	$49.6 (6.98)	6.2% (2.52%)	5.7% (2.58%)	6.8% (2.60%)
UPC=1200	$101.5 (10.98)	$96.0 (10.12)	$112.3 (10.01)	13.9% (3.03%)	13.1% (3.11%)	15.3% (3.15%)

Notes: Computations were done using 2015 CPI-adjusted dollars.

Table B6. Average Changes in Store Market Shares

No. of FV UPCs	Intervene Stores	Non-Intervene Stores
50	1.3 pp (0.21)	-0.64 pp (0.14)
100	1.7 pp (0.23)	-0.79 pp (0.11)
250	1.9 pp (0.24)	-0.88 pp (0.15)
350	1.9 pp (0.21)	-0.91 pp (0.16)
1200	2.2 pp (0.26)	-1.10 pp (0.18)

Notes: pp stands for percentage points. The counterfactual policy is to increase the number of fruits and vegetables in the nearest store of each food deserts census tract to different levels as indicated in the No. of FV UPCs.

Table B7. Annual Consumer Welfare Impact of a Food Deserts Household Moving to a Non-Food Desert

Statistic	Value	Percentage Change
Mean	\$72.17	9.9%
	(10.89)	(1.43%)
Median	\$45.91	6.3%
	(13.45)	(2.23%)
Min	-\$31.62	-4.3%
	(12.32)	(2.12%)
Max	\$752.81	102.9%
	(102.78)	(18.12%)
% Change>0	94.78	

Notes: Computations were done using 2015 CPI-adjusted dollars.

Table B8. Annual Consumer Welfare Impact of a Non-Food Deserts Household Moving to a Food Desert

Statistic	Value	Percentage Change
Mean	-$230.34	-31.5%
	(53.28)	(7.78%)
Median	-$169.21	-23.1%
	(34.87)	(4.44%)
Min	-$6,565.32	-896.6%
	(231.39)	(58.3%)
Max	$0	0.0%
	(10.21)	(5.88%)
% Change>0	100	

Notes: Computations were done using 2015 CPI-adjusted dollars.