FOOD STORE CHOICES OF POOR HOUSEHOLDS: A DISCRETE CHOICE ANALYSIS OF THE NATIONAL HOUSEHOLD FOOD ACQUISITION AND PURCHASE SURVEY (FOODAPS)

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Policymakers are pursing initiatives to increase food access for low-income households. However, due in part to previous data deficiencies, there is still little evidence supporting the assumption that improved food store access will alter dietary habits, especially for the poorest of U.S. households. This article uses the new National Household Food Acquisition and Purchase Survey (FoodAPS) to estimate consumer food outlet choices as a function of outlet type and household attributes in a multinomial mixed logit model. In particular, we allow for the composition of the local retail food environment to play a role in explaining household store choice decisions and food acquisition patterns. We find that households are willing to pay more per week in distance traveled to shop at superstores, supermarkets, and fast food outlets than at farmers markets and smaller grocery stores, and that willingness to pay is heterogeneous across income group, Supplemental Nutrition Assistance Program participation, and other household and food environment characteristics. Our results imply that policymakers should consider incentivizing the building of certain outlet types over others, and that Healthy Food Financing Initiatives should be designed to fit the sociodemographic composition of each identified low-income, low-access area in question.

Key words: Discrete choice model, food access, FoodAPS, store choice, Supplemental Nutrition Assistance Program.

JEL codes: C25, D12, I38.

The 2014 Farm Bill allocated $125 million to the USDA for a national Healthy Food Financing Initiative (HFFI)—an initiative to eliminate food deserts by incentivizing retailers to do business in these areas. As Rep. Schwartz (PA-13) summarizes the goal of this legislation, "[b]y establishing healthier food options in underserved areas, millions of Americans will have the opportunity to live longer, healthier lives, saving billions in health care costs."[1] Financing for the HFFI was granted after numerous studies indicated a link between disparities in access to healthy foods and poor health outcomes.[2] However, despite the growing body of research on food

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[1] Official press release from the Office of Rep. Allyson Schwartz (PA-13). November 30, 2011. Available at: https://www.legistorm.com/stormfeed/view_rss/273550/member/465.html.

[2] For a comprehensive review of the literature on food access and health outcomes, see Caswell and Yaktine (2013). Recent studies have found that (i) elderly residents living in food deserts who do not own a vehicle are more likely than those with a vehicle to report food insufficiency (Fitzpatrick, Greenhalgh-Stanley, and Ver Ploeg 2016); (ii) exposure to food deserts is correlated with higher body mass index scores among elementary schoolchildren (Thomsen et al. 2016); and (iii) increased access to large supermarkets, grocery stores, and convenience stores in metropolitan

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deserts and health outcomes, there is limited evidence supporting the assumption that improved access will alter eating patterns (Kyureghian and Nayga 2013). In fact, Cummins, Flint, and Matthews (2014) evaluate the impact of opening a new supermarket in a food desert and find that while the intervention increased residents' awareness of food accessibility, it did not lead to changes in dietary habits over the four years of the study.

While programs under the HFFI address the supply of retail food stores, both supply *and* demand forces (e.g., consumer preferences, population and income growth, adoption of the Supplemental Nutrition Assistance Program (SNAP) and other income support programs) determine the number and types of food stores to which consumers have access (Bonanno 2012). In light of these dual forces, it is important to understand the current determinants of store choice among low-income households before implementing policies that incentivize retailers to do business in food deserts. With this objective in mind, our research asks (1) which types of food-at-home (FAH) and food-away-from-home (FAFH) outlets do households prefer, (2) how much are households willing to pay in distance traveled to shop at various outlet types, and (3) how do these revealed preferences vary among SNAP-participating and non-participating low-income households?

To answer these questions, we employ a multinomial mixed logit demand model, which is common in the discrete choice literature, and data from the USDA's new *National Household Food Acquisition and Purchase Survey* (FoodAPS). The unique FoodAPS datasets contain detailed information about the foods purchased or otherwise acquired by surveyed households for at-home and away-from-home consumption. These data allow us to address holes in the existing literature that are vital to understanding store choice and to implementing policies to improve food access.

This article builds upon a long body of literature examining food store choices. An early study by Arnold, Oum, and Tigert (1983) finds that the determinants of store choice among FAH shoppers include lowest overall prices, location, convenience, courteous service, the variety of merchandise, fast checkout, and quality of meat and produce. Store patronage is also influenced by household characteristics such as demographics and past purchase history (Staus 2009), and by characteristics of the entire local food market such as the physical availability of different types of retail stores (Feather 2003; Kyureghian and Nayga 2013; Kyureghian, Nayga, and Bhattacharya 2013), the degree of competition between food stores (Hausman and Leibtag 2007), and prices offered by various outlet types (Broda, Leibtag, and Weinstein 2009).

However, we identify three gaps in the store choice literature that the FoodAPS data allow us to fill. First, data constraints have restricted the ability of previous studies to focus on the store choices of target populations, such as low-income and SNAP-participating households (Kyureghian et al. 2013). Unlike other datasets in the store choice literature, the FoodAPS data are designed to be nationally representative of SNAP households and non-participant households in three income groups: (1) incomes below 100% of the Federal Poverty Line (FPL); (2) incomes between 100 and 185% of FPL; and (3) incomes at or above 185% of FPL. With food purchase and acquisition data for 1,483 SNAP-participating households, 1,353 eligible but non-participating households, and 1,825 non-eligible non-participating households, the FoodAPS data allow us to focus our analysis on the very households for which HFFI policies are most concerned.

Second, no study to our knowledge has examined store choice across both FAH and FAFH outlets. Staus (2009); Kyureghian and Nayga (2013), and Kyureghian, Nayga, and Bhattacharya (2013) examine store choice among FAH stores using multinomial logit models and household home-scan data—data from a panel of households supplied with handheld scanners to scan the universal product codes of all purchases made for at-home consumption.[3] While home-scan datasets contain rich information on households and their FAH purchases over time, they do not include FAFH purchases. Given that Americans spend nearly half of their food dollars away from home—at restaurants, hotels,

areas can mitigate the likelihood of adults experiencing food insecurity (Bonnano and Li 2015).

[3] Staus (2009) uses GfK ConsumerScan data while Kyureghian and Nayga (2013), Kyureghian, Nayga, and Bhattacharya (2013), and Broda, Leibtag, and Weinstein (2009) use Nielsen HomeScan data.

and schools (Stewart et al. 2004)—this is an important data limitation. With the FoodAPS datasets we are able to address this previous data limitation and examine low-income households' store choices both among and between various FAFH and FAH outlet types.

The third important attribute of the FoodAPS data for our empirical strategy is its geographic component, which enables us to construct detailed pictures of the individual retail environments in which the sampled households live. Previous studies have needed to rely on broad area-based measures of food access instead of individual-level measures (VerPloeg, Dutko, and Breneman 2015a). Area-based measures include supermarket density within Metropolitan Statistical Areas or Census Blocks. Conversely, the FoodAPS geographic component includes data on the precise distance between retail food outlets visited and each household's residence, as well as the number and types of outlets in proximity to each household. We hypothesize that distance from home plays a significant role in explaining store choice decisions and purchasing patterns for both FAH and FAFH consumption.

Using a discrete choice structural model of consumer behavior (McFadden 1973; Berry 1994; McFadden and Train 2000), we specify that a consumer has several food outlet alternatives where he or she can acquire food, and those alternatives are defined as a bundle of perceived attributes—namely, outlet type and distance from home. This provides the framework to compute consumers' willingness to pay for outlet attributes in a straightforward way and offers flexibility in incorporating heterogeneity with regard to household types. In our model, households have nine discrete outlet categories from which to choose. For FAFH outlets we consider (1) fast food and (2) full-service restaurants. For FAH outlets we consider (3) supermarkets, (4) superstores, (5) grocery stores, (6) combination retailers, (7) convenience stores, and (8) farmers markets. Lastly, for the outside option we consider (9) other category, which includes all remaining means of acquiring food. We will estimate the choice model, first, for the entire FoodAPS sample, and second, for subsamples of households—based on SNAP participation, income, measures of food access, and stated preferences—in order to capture heterogeneity by household type.

To preview our results, we find that households have the highest willingness to pay for superstores, supermarkets, and fast food, at approximately $15 per week in distance traveled. Equating these estimates to dollars per mile, FoodAPS households are willing to pay $2.50 per week to have a superstore or supermarket one mile closer to their home, and $2 per week for a fast food outlet to be one mile closer to home. Conversely, households would need to be compensated, on average, to shop at the remaining four FAH outlets. These willingness to pay estimates are heterogeneous across SNAP participation, income, and outlet accessibility. As a comparison, Feather (2003) finds that improving store access by creating supermarkets that are close to SNAP recipients results in a gain in welfare ranging from $2 to $8 per month. However, Feather's (2003) data include only SNAP recipients in one city, and his welfare estimates consider only the benefits of building a supermarket closer to recipients, and not the benefits from other outlet types. Our results imply that policymakers should consider incentivizing the building of certain outlet types over others, and that Healthy Food Financing Initiative incentives should be designed to fit the sociodemographic composition of each identified low-income, low-access area in question.

FoodAPS Data

We use the unique food acquisition data obtained from the USDA's *National Household Food Acquisition and Purchase Survey* (FoodAPS).[4] A total of 4,826 households completed the survey between April 2012 and January 2013. The FoodAPS survey collected detailed information about all foods purchased or otherwise acquired, from all food sources and by all household members, over the course of seven days. The primary respondent (PR) for each household—that is, the main food shopper or meal planner—provided information about the household

[4] This article uses the FoodAPS data as of September 25, 2015. For more information about FoodAPS, please see the USDA, ERS website at: http://www.ers.usda.gov/data-products/foodaps-national-household-food-acquisition-and-purchase-survey.aspx.

and individuals in the household through two in-person interviews. These interviews collected household demographics and information about the household related to food purchases, intake, and diet/health. In addition to the in-person interviews, households were asked to scan barcodes on food, save their receipts from stores and restaurants, and record information in provided food books. Three phone calls with the primary respondent (PR) occurred over the week to collect additional information. Together, these records describe 15,999 FAH acquisition events and 38,869 FAFH acquisition events.

Crucial to our research question and empirical design, the FoodAPS datasets contain a geographic component. After the interviews, data on the distances to food outlets from each household's residence (or from the center of the household's census block group) were collected and processed. The geographic component not only includes distance measures for the food outlets actually visited by the household during the week (i.e., each food event recorded has a distance-from-home measure), it also contains distance measures for the food outlets that each household could have visited within their Primary Sampling Unit or within adjacent PSUs.[5] Having information on stores in adjacent PSUs means that access to food outlets is measured without border constraints for all households. In particular, for six FAH outlet categories and two FAFH outlet categories, we have the distance from each household's residence to the closest outlet of each category, as well as the number of outlets of each category within a one-mile radius. With these data we are able to construct comprehensive pictures of the local food environments in which the surveyed households live.[6] Previous studies, which were constrained by limited geographic data, were forced to examine retail environments at a much broader level. For instance, Kyureghian and Nayga (2013), in one of the studies most similar to this article, use county business pattern data on the number of establishments in 100 square miles.

Another unique feature of the FoodAPS data is that the survey was designed to be representative of SNAP households and nonparticipant households in three income groups: those with incomes below 100% of the Federal Poverty Line (FPL), between 100 and 185% of the FPL, and above 185% of the FPL.[7] The SNAP and low-income non-participant groups were oversampled to allow analysis of food spending and shopping patterns specifically for these groups, which has not always been possible with other surveys or data collection efforts. We will often refer to non-SNAP participating households with incomes below 185% as "eligible non-SNAP" and with incomes above 185% as "non-eligible non-SNAP."[8] Tables 1, 2, and 3 present weighted summary statistics of the FoodAPS households, for both the full sample of respondents and for mutually exclusive subgroups based on income and SNAP participation. Means in all three tables are weighted using household weights to account for oversampling and the complex survey design of FoodAPS. Bold text in columns 3–5 indicates the estimate is statistically different from the reference group–SNAP households (column 2)–at the 5% significance level. While 4,826 households completed the survey, we restrict our analysis to 4,661 households that report food acquisition events as well as interview data.

Table 1 describes the weekly food store choices made by the households, with food events divided into nine mutually exclusive outlet types: 1) Superstore, 2) Supermarket, 3) Grocery, 4) Combo Retail, 5) Convenience, 6) Farmers Market, 7) Restaurant,

[5] Primary Sampling Units (PSUs) are defined as counties or groups of contiguous counties.

[6] For all outlet categories except Farmers Markets, distances are measured from each household's home. For Farmers Markets, distances are measured from the centroid of each household's census block group. We use the "straight-line distance" for all distance measures, calculated by SAS version 9.3 GeoDist function. We drop 282 food acquisition events where the straight-line distance between the respondent's home and the acquisition place exceeded 200 miles, as it seemed likely that any acquisition with a distance greater than 200 miles occurred while respondents were traveling for work or vacation, rather than originating from the respondent's home. For distance measures of the food outlets each household visited, the FoodAPS data also contain the "driving distance," calculated by Google maps. Our results in the latter sections of this article are robust to using the driving distance instead of the straight-line distance.

[7] During the initial interview, households were asked if anyone in the household receives SNAP benefits and if so, when SNAP was last received. After the survey was completed, consenting FoodAPS households were matched to state agency SNAP administrative files to confirm SNAP participation. Monthly income information for the household was reported by the PR during the final interview.

[8] We use 100% and 185% of FPL as group thresholds following VerPloeg, Mancino, and Todd (2015b). While 185% of FPL is an approximation for SNAP eligibility, the ERS has also developed model-based predictions of SNAP eligibility for the FoodAPS households, which we plan to investigate in future work.

Table 1. Summary Statistics: Weekly Food Store Choices

			Non-SNAP		
Variable	Overall (1)	SNAP (2)	Income ≤ 100% FPL (3)	Income 101 - 185% FPL (4)	Income > 185% FPL (5)
Expenditure ($)					
Superstore	56.78, (3.61)	53.33, (4.12)	44.51, (4.86)	**41.52**, (2.45)	62.30, (4.55)
Supermarket	39.58, (3.69)	38.61, (4.39)	33.30, (4.94)	**24.63**, (2.98)	43.51, (4.63)
Grocery Store	2.42, (0.32)	3.77, (0.75)	**1.73**, (0.42)	2.43, (0.47)	2.27, (0.39)
Combo Retail	5.56, (0.91)	9.37, (1.46)	**4.95**, (1.02)	**4.01**, (0.58)	**5.17**, (1.20)
Convenience	4.44, (0.46)	4.93, (0.74)	**2.72**, (0.67)	**2.44**, (0.33)	5.00, (0.68)
Farmers Market	0.79, (0.22)	0.13, (0.05)	0.16, (0.06)	0.52, (0.26)	**1.09**, (0.33)
Restaurant	26.73, (1.86)	12.06, (1.46)	19.87, (4.76)	13.13, (1.60)	**33.28**, (2.44)
Fast Food	20.10, (0.88)	15.93, (1.14)	16.49, (2.44)	14.43, (1.36)	**22.57**, (1.16)
Other Category	8.73, (0.78)	4.63, (0.48)	7.62, (2.17)	5.30, (1.06)	**10.35**, (0.99)
Number of Trips					
Superstore	1.24, (0.07)	1.38, (0.10)	1.12, (0.10)	1.14, (0.09)	1.26, (0.08)
Supermarket	1.08, (0.10)	1.08, (0.09)	1.03, (0.11)	0.89, (0.09)	1.13, (0.11)
Grocery Store	0.13, (0.01)	0.23, (0.04)	**0.12**, (0.02)	0.18, (0.04)	**0.10**, (0.01)
Combo Retail	0.36, (0.03)	0.61, (0.06)	**0.35**, (0.05)	**0.41**, (0.05)	**0.30**, (0.04)
Convenience	0.59, (0.04)	0.76, (0.07)	**0.34**, (0.07)	**0.43**, (0.06)	0.62, (0.06)
Farmers Market	0.05, (0.01)	0.02, (0.01)	0.02, (0.01)	0.05, (0.03)	**0.06**, (0.01)
Restaurant	1.37, (0.06)	0.77, (0.06)	0.97, (0.14)	0.89, (0.09)	**1.65**, (0.07)
Fast Food	2.32, (0.10)	2.00, (0.12)	1.77, (0.22)	1.85, (0.15)	**2.57**, (0.12)
Other Category	3.22, (0.14)	3.57, (0.21)	**2.47**, (0.24)	**2.78**, (0.20)	3.36, (0.18)
Average Distance Traveled (miles)					
Super Store	6.89, (1.00)	5.58, (0.87)	5.19, (0.71)	5.78, (0.91)	7.61, (1.22)
Supermarket	4.73, (0.53)	3.81, (0.55)	4.27, (0.89)	4.13, (0.64)	5.07, (0.68)
Grocery Store	5.10, (0.85)	3.68, (0.95)	7.32, (3.26)	3.06, (0.65)	5.59, (1.07)
Combo Retail	5.24, (0.74)	3.17, (0.50)	3.43, (0.74)	4.89, (1.24)	**6.35**, (1.16)
Convenience	9.56, (1.01)	6.20, (1.09)	10.01, (2.70)	5.98, (0.93)	**10.71**, (1.33)
Farmers Market	5.15, (1.84)	8.72, (1.90)	37.68, (32.65)	5.34, (1.90)	**3.95**, (1.10)
Restaurant	12.73, (1.25)	7.72, (1.04)	10.10, (1.27)	10.67, (2.17)	**13.77**, (1.51)
Fast Food	10.13, (0.96)	5.22, (0.53)	7.91, (1.34)	7.08, (0.92)	**11.72**, (1.27)
N Households	4661	1483	570	783	1825
Share of Households	—	0.32	0.12	0.17	0.39

Note: Weighted means reported. Standard errors are in parentheses. Bold text in columns 3-5 indicates the estimate is statistically different from the reference group—SNAP households (column 2)—with a p-value ≤0.05.

8) Fast Food, and 9) Other Category.[9] *Superstore* includes large retail establishments that combine a supermarket and department store under one roof; they are considered a one-stop shop for all of the customer's needs. *Supermarket* includes large grocery stores that offer customers a variety of food items and non-food household supplies, generally related to food items, such as garbage bags and storage containers. *Grocery Store* includes establishments that are smaller than Supermarkets and sell primarily, or exclusively, food items. *Combo Retail* includes dollar stores, pharmacies, express grocery stores, and small grocery stores combined with a restaurant. *Convenience* includes establishments with extended hours, in convenient locations, stocking a limited range of household goods and groceries. *Restaurant* includes full-service restaurants, where customers are seated at tables while servers take their full order. *Fast Food* includes quick-service restaurants, which capitalize on speed of service and convenience, and typically have a service counter with cashiers working to take orders. Finally, *Other Category* includes all remaining locations to obtain food, such as meals at work and at school, meals at a friend or family member's home, and food from vending machines, places of worship, clubs, and food pantries.

In table 1 we see that the average household in our overall sample (column 1) spends

[9] Outlets in the FoodAPS data were coded into types based on information in Store Tracking and Redemption System (STARS), InfoUSA, Google, and keywords in the reported place names.

Table 2. Summary Statistics: Retail Food Environment

			Non-SNAP		
Variable	Overall (1)	SNAP (2)	Income ≤ 100% FPL (3)	Income 101 - 185% FPL (4)	Income > 185% FPL (5)
Number of stores in a 1-mile radius					
Superstore	0.68, (0.09)	0.84, (0.12)	1.00, (0.22)	0.79, (0.13)	0.58, (0.07)
Supermarket	0.80, (0.12)	1.06, (0.14)	1.13, (0.22)	0.82, (0.13)	**0.69**, (0.11)
Grocery Store	1.07, (0.32)	1.50, (0.39)	2.20, (0.80)	1.61, (0.59)	0.70, (0.20)
Combo Retail	1.93, (0.23)	2.56, (0.27)	2.29, (0.35)	2.19, (0.36)	**1.70**, (0.21)
Convenience	3.85, (0.66)	5.93, (0.84)	6.42, (1.72)	5.11, (1.15)	**2.77**, (0.43)
Farmers Market	0.25, (0.04)	0.27, (0.06)	0.37, (0.10)	0.20, (0.05)	0.23, (0.05)
Restaurant	25.39, (4.45)	28.63, (5.09)	37.98, (9.81)	27.41, (6.53)	22.20, (3.88)
Fast Food	5.27, (0.62)	6.25, (0.62)	6.41, (1.00)	5.50, (0.80)	4.84, (0.63)
Distance to closest store (miles)					
Superstore	3.23, (0.53)	3.28, (0.65)	2.55, (0.35)	3.39, (0.76)	3.30, (0.54)
Supermarket	3.10, (0.71)	2.69, (0.72)	2.51, (0.54)	3.54, (1.13)	3.21, (0.72)
Grocery Store	4.61, (0.57)	3.97, (0.71)	4.35, (0.59)	4.43, (0.65)	4.81, (0.59)
Combo Retail	1.87, (0.37)	1.43, (0.26)	1.44, (0.22)	2.02, (0.55)	2.01, (0.41)
Convenience	1.66, (0.24)	1.16, (0.18)	1.32, (0.19)	1.53, (0.33)	**1.85**, (0.28)
Farmers Market	12.25, (1.35)	13.24, (2.09)	10.70, (1.55)	14.47, (2.14)	11.93, (1.20)
Restaurant	0.98, (0.14)	0.85, (0.17)	0.74, (0.11)	1.07, (0.18)	1.04, (0.15)
Fast Food	2.28, (0.49)	2.35, (0.60)	1.55, (0.29)	2.51, (0.75)	2.35, (0.49)
Population density	5013, (862)	6580, (1173)	8577, (2018)	6027, (1561)	**3903**, (602)
Rural (share)	0.33, (0.05)	0.26, (0.05)	0.26, (0.05)	0.35, (0.07)	0.36, (0.05)
Food Desert (share)	0.05, (0.01)	0.09, (0.02)	0.05, (0.01)	0.08, (0.03)	**0.03**, (0.01)
No car access (share)	0.05, (0.01)	0.15, (0.02)	0.12, (0.03)	**0.07**, (0.01)	**0.02**, (0.00)
N Households	4661	1483	570	783	1825
Share of Households	—	0.32	0.12	0.17	0.39

Note: Weighted means reported. Standard errors in parentheses. Bold text in columns 3–5 indicates the estimate is statistically different from the reference group—SNAP households (column 2)—with a p-value ≤0.05.

the most per week at Superstore outlets ($56.78), followed by Supermarkets ($39.58), Restaurants ($26.73), and Fast Food ($20.10). The average household also makes approximately one trip per week to Superstore, Supermarket, and Restaurant outlets, and two trips per week to Fast Food.[10] The average distance from home to FAH stores visited over the week is between 4–10 miles, while the average distance from home to FAFH stores visited is between 10–13 miles.[11]

In comparing SNAP and non-SNAP households, non-eligible non-SNAP households (column 5) spend significantly more at Farmers Market, Restaurant, and Fast Food outlets than all SNAP-eligible households (columns 2–4). Non-eligible households also spend more at Superstores and Supermarkets than eligible non-SNAP households (columns 3–4); however, their spending at these outlets is statistically indistinguishable from SNAP households (column 2). SNAP households make more trips per week to Combo Retail, Convenience, and Other Category outlets than eligible non-SNAP households, and they make fewer trips to Restaurant and Fast Food outlets than non-eligible non-SNAP households. The average distance SNAP households travel to food outlets is not statistically different than eligible non-SNAP households. However, in comparison to non-eligible non-SNAP households, SNAP households travel shorter distances to Fast Food, Restaurant, Convenience, and Combo Retail outlets, and they travel farther to Farmers Markets.

It is important to note here that expenditures for SNAP households include the SNAP benefits they spend, and that SNAP

[10] We also calculate the share of households that never visit a particular outlet type during the sample week: Superstores, Supermarkets, and Restaurants are never visited by roughly 40% of FoodAPS households; Combo Retail, Convenience, and the Other Category are never visited by 70%; Farmers Markets and Grocery Stores are never visited by 95%; and Fast Food is never visited by 30%.

[11] Distance measures do not represent the actual distance traveled by households, as each food event does not necessarily originate from home.

Table 3. Summary Statistics: Household and Primary Respondent Characteristics

Variable	Overall (1)	SNAP (2)	Non-SNAP Income ≤ 100% FPL (3)	Non-SNAP Income 101 - 185% FPL (4)	Non-SNAP Income > 185% FPL (5)
Household (HH) Characteristics					
HH size (mean)	2.44, (0.05)	3.11, (0.10)	**2.20**, (0.12)	**2.24**, (0.11)	**2.38**, (0.05)
White (share)	0.80, (0.02)	0.63, (0.05)	0.73, (0.04)	**0.77**, (0.04)	**0.86**, (0.02)
Black (share)	0.13, (0.02)	0.28, (0.05)	**0.16**, (0.03)	0.18, (0.04)	**0.09**, (0.02)
Asian (share)	0.02, (0.01)	0.01, (0.00)	**0.03**, (0.01)	0.02, (0.01)	**0.03**, (0.01)
Hispanic (share)	0.13, (0.02)	0.25, (0.04)	0.19, (0.04)	0.16, (0.03)	**0.09**, (0.02)
Non-U.S. citizen (share)	0.04, (0.01)	0.04, (0.01)	0.08, (0.02)	0.06, (0.02)	0.03, (0.01)
Children age <18 (share)	0.33, (0.01)	0.51, (0.02)	**0.30**, (0.03)	**0.26**, (0.02)	**0.31**, (0.02)
Elderly age >65 (share)	0.25, (0.01)	0.17, (0.02)	**0.29**, (0.03)	**0.35**, (0.03)	**0.25**, (0.02)
Food Secure (share)	0.85, (0.01)	0.57, (0.02)	**0.72**, (0.03)	**0.75**, (0.02)	**0.94**, (0.01)
WIC HH (share)	0.04, (0.00)	0.14, (0.01)	**0.04**, (0.01)	**0.06**, (0.01)	**0.02**, (0.00)
Primary Respondent (PR) Characteristics					
Age (mean)	49.74, (0.62)	44.47, (0.94)	**51.22**, (1.27)	**52.54**, (1.35)	**50.05**, (0.70)
Female (share)	0.67, (0.01)	0.73, (0.02)	0.72, (0.03)	0.66, (0.04)	**0.66**, (0.02)
Less than high school (share)	0.10, (0.01)	0.25, (0.02)	0.20, (0.03)	**0.13**, (0.02)	**0.04**, (0.01)
High school or GED (share)	0.25, (0.02)	0.36, (0.03)	**0.20**, (0.02)	0.33, (0.03)	**0.23**, (0.02)
Some college education (share)	0.33, (0.01)	0.31, (0.02)	0.32, (0.04)	0.33, (0.03)	0.34, (0.02)
Bachelor's degree or more (share)	0.32, (0.02)	0.08, (0.01)	**0.28**, (0.05)	**0.20**, (0.03)	**0.39**, (0.02)
Reason for shopping at primary store (share)					
Prices/Value	0.53, (0.02)	0.61, (0.02)	**0.50**, (0.03)	**0.52**, (0.03)	**0.51**, (0.03)
Good Produce	0.17, (0.01)	0.12, (0.02)	0.14, (0.02)	0.14, (0.03)	**0.19**, (0.02)
Good Meat	0.12, (0.01)	0.13, (0.02)	0.12, (0.02)	0.15, (0.02)	0.12, (0.01)
Variety	0.24, (0.02)	0.19, (0.02)	0.21, (0.03)	0.23, (0.04)	**0.26**, (0.02)
Specialty Foods	0.07, (0.01)	0.06, (0.01)	0.09, (0.02)	0.07, (0.02)	0.07, (0.01)
Close to home	0.53, (0.02)	0.47, (0.03)	0.50, (0.04)	0.46, (0.04)	**0.56**, (0.02)
Loyalty program	0.11, (0.02)	0.09, (0.02)	0.09, (0.02)	0.08, (0.02)	0.12, (0.02)
N Households	4661	1483	570	783	1825
Share of Households	—	0.32	0.12	0.17	0.39

Note: Weighted means reported. Standard errors are in parentheses. Bold text in columns 3–5 indicates the estimate is statistically different from the reference group—SNAP households (column 2)—with a p-value ≤0.05.

benefits cannot be used at all outlet types equally. For instance, SNAP benefits cannot be used to purchase non-food items, alcoholic beverages, tobacco products, any foods that will be eaten in-store, or any foods marketed as heated in-store.[12] Therefore, SNAP benefits cannot be used at Restaurant and Fast Food outlets. Castner and Henke (2011) find that approximately 64% of Electronic Benefit Transfer (EBT) purchases in 2009 were made at Supermarkets and Superstores, 15% were made at Convenience stores, and 12% were made at Groceries. In the FoodAPS data, we find that approximately 95% of Superstores and Supermarkets visited are authorized to accept SNAP benefits, 91% of Combo Retail, 76% of Grocery Stores, 46% of Convenience, 16% of Farmers Markets, 1% of the Other Category, and as we would expect, 0% of Fast Food and Restaurants.

Table 2 describes the retail food environment in which the FoodAPS households live, again employing the nine mutually exclusive outlet categories.[13] In looking at the

[12] "Supplemental Nutrition Assistance Program: Using SNAP Benefits." USDA Food and Nutrition Service. Available at: http://www.fns.usda.gov/snap/using-snap-benefits.

[13] The retail food environment measures for FAH outlets are constructed using the nationwide STARS datasets that include all retailers authorized to receive SNAP benefits as of June 2012. The locations of FAFH outlets came from InfoUSA, which is a private company that develops databases of business addresses. The InfoUSA data is from January 2012.

number of outlets within one mile of each household's residence, we find that households in the overall sample (column 1) have approximately one Superstore and Supermarket, four Convenience, five Fast Food, and 25 Restaurant outlets within a mile of their home. Correspondingly, the average distance from each household's residence to the closest Superstore and Supermarket is 3 miles, to the closest Fast Food, Convenience, and Combo Retail outlet is 2 miles, and to the closest Restaurant is 1 mile. The average distance to the closest Farmers Market is 12 miles, making it the farthest outlet category from home, on average.

We examine four additional measures of the food environment and food access—population density of the FoodAPS households' census block group, share of households living in rural census tracts, share of households living in a census block groups identified as a food desert, and share of households without car access. We use the USDA's definition of a food desert.[14] A census block group is identified as a food desert if: (1) it qualifies as a "low-income community" based on having a poverty rate of 20% or greater; and (2) it qualifies as a "low-access community" based on the determination that at least 33% of the population live more than 1 mile from a supermarket or large grocery store (or 10 miles in the case of rural census block groups). Car access is based on survey questions about whether the household owns or leases a vehicle and whether the household receives rides from others or has access to a vehicle. For the overall sample, the average population density is 5,013 persons per square mile, 33% of households live in rural areas, 5% live in a food desert, and 5% do not have access to a vehicle.

Once again comparing SNAP and non-SNAP households, we find little statistically significant difference in the retail food environments of SNAP and eligible non-SNAP households. However, SNAP households have more Supermarket, Combo Retail, and Convenience outlets in a 1-mile radius of their homes than non-eligible non-SNAP households. The population density around SNAP households is also higher than non-eligible non-SNAP households, and SNAP households are more likely to live in a food desert (9%) and to report not having car access (15%) than non-eligible non-SNAP households.

Finally, table 3 presents household (HH) and PR characteristics. On average, SNAP households are larger than non-SNAP households, are more likely to have children, are less likely to have elderly members, and are less likely to report being food secure.[15] The PR of SNAP households are younger, more likely to be female, and less likely to have a Bachelor's degree. During the initial interview, the PR was asked to state their primary food store and their reason for shopping at this store. With respect to reasons for shopping at primary stores, the question had eight pre-coded responses (including "other"), and a respondent could select more than one response. Prices and closeness to home are the top two reasons stated across all respondents. SNAP and eligible non-SNAP households state similar preferences, with the exception that SNAP households are more likely to care about prices. Finally, non-eligible non-SNAP households care more about good produce, variety, and closeness-to-home than all other households.

The Choice Model

We model household food store choices with a random utility discrete choice structural model using a multinomial mixed logit (McFadden 1973; Berry 1994; McFadden and Train 2000; Nevo 2000; Kyureghian and Nayga 2013). We specify that a household has several outlet alternatives for acquiring food, and those alternatives are defined as a bundle of perceived attributes, namely outlet type and distance from home. This modeling approach, combined with the representative sampling design in the FoodAPS data, allows the estimation of household utility for outlet characteristics among SNAP and non-SNAP households. It also provides a framework to compute household willingness to pay in distance traveled for each of the outlet categories.

[14] Food Access Research Atlas. *United States Department of Agriculture, Economic Research Service.* Available at: http://www.ers.usda.gov/data-products/food-access-research-atlas/documentation.aspx#definitions.

[15] Food security status is based on the 10 questions used to assess household food security status in the USDA's 30-day Adult Food Security Scale.

We allow households to choose between nine outlet categories for purchasing food-at-home and food-away-from-home. For FAFH we consider Fast Food (FF) and Restaurant (R) outlets; for FAH we consider Superstore (SS), Supermarket (SM), Grocery Store (GS), Combo Retail (CR), Convenience (C), and Farmers Market (FM) outlets, and for the outside option we consider Other Category (OC) outlets.[16]

The indirect utility of choosing alternative $j = FF, R, SS, SM, GS, CR, C, FM, OC$ at period t by household i is given by:

$$(1) \qquad U_{ijt} = \alpha_t + \alpha_j + \boldsymbol{X_{ijt}\beta_i} + \varepsilon_{ijt} + \epsilon_{ijt}.$$

Outlet type dummies, α_j, capture any differences between outlets that are time invariant, and time dummies, α_t, control for changes over time (i.e., holidays and seasons) common to all outlet types. The matrix $\boldsymbol{X_{ijt}}$ contains the attributes of outlet type j at time t (i.e., distance from home), while the vector $\boldsymbol{\beta_i}$ represents the marginal utility placed on each of the $\boldsymbol{X}$ attributes. The error term ε_{ijt} captures the determinants of household marginal utility that are unobserved by the econometrician, but seen by the household when making choices, while $\boldsymbol{\epsilon}_{ijt}$ captures all remaining (unobserved to all) determinants of utility.

Distributional assumptions about $\boldsymbol{\beta_i}$ and $\boldsymbol{\epsilon}_{ijt}$ drive the econometric model choice. If we assume that $\boldsymbol{\epsilon}_{ijt}$ are independently and identically distributed extreme value (type I), then we have a logit choice model. If we specify that $\boldsymbol{\beta_i} = \beta + \boldsymbol{Z_i}\sigma_z$, then we have a mixed logit. The mixed logit store choice model captures preference heterogeneity by estimating an average (among the households) marginal utility with respect to the observed attributes, β, and also estimates a standard deviation from that mean marginal utility, σ_z, given $\boldsymbol{Z_i}$ household observable attributes.

We normalize the mean utility of the outside option, Other Category (OC), to zero, such that the indirect utility from the outside option only is given by the idiosyncratic error term, that is, $U_{iOCt} = \epsilon_{iOCt}$. Assuming that households visit the alternative j at a certain time t that maximizes their indirect utility, then the probability that alternative $j = FF, R, SS, SM, GS, CR, C, FM, OC$ is chosen is the probability that $U_{ijt} > U_{ikt}\ \forall k$ which has the following form:

$$(2) \qquad pr_{ijt} = \frac{e^{\alpha_j + \alpha_t + \boldsymbol{X_{ijt}\beta_i} + \varepsilon_{ijt}}}{1 + \sum_{k=1}^{8} e^{\alpha_k + \alpha_t + \boldsymbol{X_{ikt}\beta_i} + \varepsilon_{ikt}}}.$$

We estimate the multinomial mixed logit model using the Berry (1994) approach to linearize the choice model equation. Taking the log of the probability of an alternative j and subtracting the log of the probability of the outside option yields a linear equation to which we can apply ordinary least squares (OLS):

$$(3) \qquad ln(pr_{ijt}) - ln(pr_{iOCt}) = \alpha_j + \alpha_t + \boldsymbol{X_{ijt}\beta_i} + \varepsilon_{ijt}.$$

As the empirical analogue of probabilities, we will use the household share of expenditures spent by outlet type, such that we estimate:

$$(4) \qquad ln(s_{ijt}) - ln(s_{iOCt}) = \alpha_j + \alpha_t + \boldsymbol{X_{ijt}\beta_i} + \varepsilon_{ijt}$$

where s_{ijt} is household i's share of expenditures made at outlet type j during the seven days of the survey $\left(\text{i.e., } pr_{ijt} = s_{ijt} = \frac{expend_{ijt}}{\sum_{k=1}^{9} expend_{ikt}}\right)$. Thus the outlet choice model is obtained by regressing the log difference of eight observed outlet expenditure shares relative to the outside option on the variables entering the mean utility.

Estimation Concerns

Before discussing the results of the outlet choice model, there are four estimation concerns to address: (1) zero weight on free food events; (2) omitted outlet-level price data; (3) unobserved outlet attributes correlated with distance; and (4) location endogeneity.

First, an issue with using expenditure shares as the empirical analogue of choice probabilities is that it does not account for food events that were "free" or without expenditures. This happens, for instance, when eating at a friend's house or at a place of worship. By using expenditure shares, our model ignores free-food events by giving them zero weight. Since we categorize free-food events into the outside option, Other

[16] The "outside option" captures that fact that households may decide not to acquire food at any of the "inside options." The Other Category is the designated outside option for our analysis because, unlike the other eight outlet categories, we do not have distance measures for most of the Other Category food events, and consequently we cannot estimate the Other Category mean utility directly.

Category, our model may underestimate the mean utility of the Other Category relative to the remaining eight outlet categories. However, importantly, the mean utility estimates of the remaining eight categories relative to one another are unaffected by the omission of free-food events.

Second, prices—while an important outlet type attribute—are omitted from the model. Once price data are available in the FoodAPS geographic component, future work will include measures of food prices by outlet type and food category in the bundle of outlet type attributes. However, as long as outlet type *j* always has higher prices than outlet type *k*, the time-invariant differences in prices will be captured by the outlet type fixed effects.

The third estimation concern relates to omitted variable bias due to unobserved outlet attributes correlated with distance. The coefficient $\beta_i^{distance}$ represents the marginal utility that household *i* places on distance. We hypothesize that $\beta_i^{distance}$ will be negative, as greater distance from home brings disutility to households. However, there may be reasons, known to the household yet unseen by the econometrician, for why a household does not go to the closest outlet to their home of a given outlet type. For instance, a particular outlet may be chosen because it is on the way to another destination, or because it is running a promotion that week. If not all of the outlet characteristics are observed and these unobserved attributes are correlated with the observed distance chosen, then we are faced with endogeneity due to these missing attributes. To address this potential missing variable bias, we instrument the distance chosen by the household to a given outlet type with a characteristic of the food environment that generates variation in distance yet is predetermined to the household's week-to-week store choices—namely, the distance from home to the closest outlet of the given type. This instrumental variable (IV) strategy rests on the assumption that the instrument is uncorrelated with the unobserved outlet attributes and demand shocks. Since distance from home to the closest outlet of the given type is predetermined to the household's week-to-week store choices, and thus cannot react to demand shocks, we argue that our instrument is exogenous to the omitted reasons that households choose one outlet over another during the sample week, and consequently addresses the omitted variable bias. However, it is important to note that if the presence of outlets close to where households live impacts store choice not only through distance traveled, the validity of the exclusion assumption would be impaired.

A final estimation concern, widely acknowledged in the store choice literature, is that household locations and store locations are endogenous. Retailers consider population characteristics in deciding where to locate, and households consider retail amenities in deciding of where to live (VerPloeg, Mancino, and Todd 2015b). Kyureghian and Nayga (2013) address the potential endogeneity of retail environment variables with store choice by using lagged values of the retail environment. Alternatively, Currie et al. (2010) rely on the geographic detail of their data to defend their identification, finding no evidence of endogenous store placement when examining small distances and in the presence of a large array of household controls. While we do not have lagged values of our distance measures, we have remarkably rich household and food environment data in FoodAPS. Thus, we will follow Currie et al. (2010) and present a specification of the model controlling for a wide assortment of household and local food environment characteristics.

Results

The results are presented as follows. Table 4 reports the mean utility estimates for the outlet choice model, comparing OLS and IV specifications and the inclusion of various controls. Table 5 reports the mean utility estimates of the preferred specification for the entire sample of households, as well as for subsamples of households by SNAP participation and income group. Finally, table 6 reports heterogeneity in the mean utility estimates with respect to car access and food desert status, urban/rural status, and the stated reasons for primary store choice.

Mean Utility Estimates for the Food Outlet Choice Model

The first column in table 4 contains an OLS specification and has as independent variables the average distance from home traveled to each of the outlet categories, outlet category dummies, and a constant term referring to the omitted outlet category

Table 4. Mean Utility Estimates for the Outlet Choice Model

	OLS (1)	IV (2)	IV (3)	IV (4)
Distance	0.0768***	−0.0556***	−0.0585***	−0.0590***
	(0.0042)	(0.0071)	(0.0065)	(0.0065)
Superstore	1.326***	1.410***	1.415***	1.416***
	(0.172)	(0.173)	(0.176)	(0.176)
Grocery Store	−5.724***	−5.663***	−5.654***	−5.651***
	(0.153)	(0.153)	(0.158)	(0.158)
Combo Retail	−3.839***	−4.057***	−4.051***	−4.053***
	(0.161)	(0.163)	(0.168)	(0.168)
Convenience	−3.859***	−3.984***	−3.959***	−3.959***
	(0.160)	(0.162)	(0.166)	(0.167)
Farmers Market	−7.288***	−6.252***	−6.223***	−6.220***
	(0.150)	(0.156)	(0.159)	(0.160)
Restaurant	−1.758***	−1.554***	−1.387***	−1.389***
	(0.174)	(0.179)	(0.173)	(0.173)
Fast Food	0.899***	1.186***	1.211***	1.209***
	(0.166)	(0.168)	(0.171)	(0.172)
Constant	2.906***	3.341***	2.245***	3.070***
	(0.276)	(0.280)	(0.210)	(0.130)
Week Fixed Effects	YES	YES	YES	NO
HH Characteristics[a]	YES	YES	NO	NO
N	36226	36226	36226	36226
R-sq	0.179	—	—	—
1st-stage R-sq	—	0.342	0.334	0.334
1st-stage F-Test	—	25837	32984	33470
1st-stage IV Coef	—	0.978***	1.012***	1.013***

Note: Robust standard errors are in parentheses. The dependent variable is the Log Expenditure Share of one of eight Food Outlets minus the Log Expenditure Share of the Outside Option. The constant term refers to the omitted outlet category, Supermarket. In the IV columns, distance traveled is instrumented with the distance to closest outlet of the given outlet type. Significance indicated by + $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; and *** $p < 0.001$. Superscript [a]indicates that household control variables include state of residence, household size, race, presence of children under 18, presence of elderly over 65, income group and SNAP participation, car access, food desert status, living in a rural census tract, number of outlets in a one-mile radius, population density, and the age, gender, and education of the primary respondent.

(Supermarket).[17] It also includes week-in-year fixed effects to control for seasonality and a rich set of controls for household characteristics.[18,19] Column 2 contains the IV specification of column 1, where we instrument the average distance to an outlet category chosen with the predetermined distance to the closest outlet of that category. If households choose the closest outlet of a particular type most often, then the OLS estimates in column 1 will be very similar to the IV estimates in column 2. Column 3 repeats the IV specification in column 2 without the household characteristics, and column 4 further removes the week-in-year fixed effects.

In the OLS specification (column 1), an increase in the distance from home of an outlet type is correlated with an increase in mean utility. However, when we instrument for distance (column 2), the point estimate for distance becomes negative, now indicating that an increase in distance from home leads to a decrease in mean utility. Thus, the instrument is correcting a positive missing variable bias in the OLS estimate, where there are factors unseen by the econometrician for why a household does not go to the closest outlet to their home of a given outlet type. However, while the point estimate switching from positive to negative is reassuring, bias may persist if either the instrument

[17] For households that never frequent a particular outlet category, we use the distance to the closest outlet of that category.

[18] Week-in-year fixed effects also allow us to control for the SNAP benefits cycle—the issuance of SNAP benefits during the first week of the month. In future work we will examine how outlet choices change for SNAP households over the course of the month.

[19] Household control variables include state of residence, household size, race, presence of children under 18, presence of elderly over 65, income group and SNAP participation, car access, food desert status, living in a rural census tract, number of outlets in a one mile radius, population density, and the age, gender, and education of the PR.

Table 5. Mean Utility Estimates, by SNAP Participation and Income Group

			Non-SNAP		
	Overall (1)	SNAP (2)	Income ≤ 100% FPL (3)	Income 101 - 185% FPL (4)	Income > 185% FPL (5)
Distance	−0.0556***	−0.0429***	−0.0575**	−0.0478**	−0.0633***
	(0.0071)	(0.0107)	(0.0201)	(0.0147)	(0.0136)
Superstore	1.410***	1.250***	1.339**	1.845***	1.378***
	(0.173)	(0.295)	(0.482)	(0.411)	(0.278)
Grocery Store	−5.663***	−5.684***	−5.417***	−5.134***	−5.953***
	(0.153)	(0.266)	(0.420)	(0.357)	(0.246)
Combo Retail	−4.057***	−3.617***	−3.876***	−3.632***	−4.639***
	(0.163)	(0.284)	(0.448)	(0.388)	(0.258)
Convenience	−3.984***	−3.635***	−4.498***	−3.886***	−4.140***
	(0.162)	(0.284)	(0.441)	(0.373)	(0.261)
Farmers Market	−6.252***	−6.550***	−6.031***	−5.912***	−6.291***
	(0.156)	(0.264)	(0.429)	(0.365)	(0.254)
Restaurant	−1.554***	−3.682***	−2.005***	−1.684***	0.392
	(0.179)	(0.298)	(0.493)	(0.428)	(0.293)
Fast Food	1.186***	0.139	0.634	1.413***	2.106***
	(0.168)	(0.291)	(0.477)	(0.394)	(0.270)
Constant	3.341***	4.551***	1.686*	4.018***	4.303***
	(0.280)	(0.525)	(0.796)	(0.693)	(0.427)
Week Fixed Effects	YES	YES	YES	YES	YES
HH Characteristics[a]	YES	YES	YES	YES	YES
N	36226	11482	4424	6115	14205

Note: Robust standard errors appear in parentheses. The dependent variable is the Log Expenditure Share of one of eight Food Outlets minus the Log Expenditure Share of the Outside Option. The constant term refers to the omitted outlet category, Supermarket. In all columns, distance traveled is instrumented with the distance to closest outlet of the given outlet type. Each column uses the same model specification, but on different samples of FoodAPS households. Column (1) includes the entire sample. Column (2) includes only SNAP participating households. Columns (3)–(5) include non-SNAP participating households within three separate income groups: incomes below or equal to 100% of the Federal Poverty Line (FPL), between 101–185% FPL, and above 185% FPL. Significance indicated by $+p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$. Superscript[a] indicates that household control variables include state of residence, household size, race, presence of children under 18, presence of elderly over 65, income group and SNAP participation, car access, food desert status, living in a rural census tract, number of outlets in a one-mile radius, population density, and the age, gender, and education of the primary respondent.

impacts store choice not only though distance traveled, or there are shocks common to some stores, such as a gasoline price shock. A gasoline price shock would affect the choice of going to stores close to one another, which would not be corrected with our distance to other store instrument. At the bottom of table 4 we report the first-stage R-squared, the first-stage F-Test, and the first-stage coefficient for the instrument. The first-stage R-squared and F-statistic in all IV regressions are high, suggesting that the instrumental variable has power. Also, as we would expect, a one-mile increase in the distance to the closest outlet of a given type corresponds to a one-mile increase in the average distance traveled to the given outlet type.

Across all specifications we find that households in this sample place a positive mean utility on Supermarkets relative to the outside option, given the positive estimates of the constant term. The point estimates for Superstore are positive and significant, indicating that households prefer Superstores to Supermarkets. Households also prefer shopping at Superstores relative to the outside option, with the coefficient of the mean utility of Superstores obtained by adding the constant and the coefficient in the Superstore row (e.g., in column 2 the mean utility of Superstores relative to the outside option is $3.341 + 1.410 = 4.751$).

Comparing the mean utility estimates across outlet type reveals the following preference ranking, from highest to lowest utility: (1st) Superstore; (2nd) Fast Food; (3rd) Supermarket; (4th) Restaurant; (5th) Other Category; (6th) Convenience; (7th) Combo Retail; (8th) Grocery Store; and (9th) Farmers Market. Omitting household characteristic control variables (column 3) and time fixed effects (column 4) does not alter

Table 6. Mean Utility Estimates, by Car Access and Food Desert Status, Urban and Rural Status, and Rationale for Primary Store Choice

	No Car, Food Desert (1)	Car, Food Desert (2)	No Car, Not Food Desert (3)	Car, Not Food Desert (4)	Urban (5)	Rural (6)	Shop for Prices (7)	Shop for closeness (8)
Distance	−0.0501	−0.0223	−0.1410*	−0.0602***	−0.0304***	−0.0966***	−0.0314**	−0.0825***
	(0.0394)	(0.0157)	(0.0578)	(0.0079)	(0.0081)	(0.0129)	(0.0116)	(0.0113)
Superstore	4.085+	0.708	1.491+	1.458***	1.329***	1.630***	1.974***	0.893***
	(2.385)	(0.588)	(0.765)	(0.184)	(0.201)	(0.333)	(0.289)	(0.245)
Grocery Store	−3.554+	−6.041***	−2.990***	−5.767***	−5.799***	−5.319***	−5.448***	−5.819***
	(2.151)	(0.524)	(0.662)	(0.163)	(0.179)	(0.291)	(0.261)	(0.214)
Combo Retail	−3.752+	−3.757***	−2.383***	−4.170***	−4.241***	−3.650***	−3.981***	−4.137***
	(1.981)	(0.564)	(0.724)	(0.173)	(0.188)	(0.318)	(0.273)	(0.230)
Convenience	0.430	−3.307***	−2.652***	−4.121***	−4.159***	−3.660***	−3.615***	−4.193***
	(2.472)	(0.563)	(0.728)	(0.172)	(0.189)	(0.314)	(0.273)	(0.228)
Farmers Market	−5.020**	−6.595***	−4.479***	−6.294***	−6.532***	−5.718***	−6.341***	−6.164***
	(1.879)	(0.541)	(0.663)	(0.166)	(0.184)	(0.290)	(0.264)	(0.220)
Restaurant	−4.068+	−2.511***	−2.827***	−1.432***	−1.569***	−1.815***	−1.849***	−1.248***
	(2.300)	(0.657)	(0.827)	(0.190)	(0.211)	(0.346)	(0.307)	(0.255)
Fast Food	−1.353	0.686	0.398	1.268***	1.223***	0.933**	1.196***	1.266***
	(2.369)	(0.588)	(0.740)	(0.179)	(0.196)	(0.326)	(0.285)	(0.237)
Constant	3.570+	6.760***	0.852	3.463***	3.076***	8.471***	2.635***	4.058***
	(1.960)	(1.271)	(1.714)	(0.297)	(0.319)	(1.561)	(0.450)	(0.414)
Week Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
HH Characteristics[a]	YES	YES	YES	YES	YES	YES	YES	YES
N	95	2509	1536	32086	26395	9831	12712	18056

Note: Robust standard errors appear in parentheses. The dependent variable is the Log Expenditure Share of one of eight Food Outlets minus the Log Expenditure Share of the Outside Option. The constant term refers to the omitted outlet category, Supermarket. In all columns, distance traveled is instrumented with the distance to closest outlet of the given outlet type. Each column uses the same model specification, but on a different sample of FoodAPS households. Columns (1) to (4) divide households by whether they report having car access, and by whether they live in a food desert designated census block group. Columns (5) and (6) divide households by whether they live in a urban or rural census tract. Column (7) divides households by whether they state prices or closeness-to-home (and not prices) as their reason for shopping at their primary food store. Significance indicated by $+p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$. Superscript [a]indicates that household control variables include state of residence, household size, race, presence of children under 18, presence of elderly over 65, income group and SNAP participation, car access, food desert status, living in a rural census tract, number of outlets in one mile radius, population density, and the age, gender, and education of the primary respondent.

the revealed preference ranking.[20] To save space, we do not include the estimates for the household characteristic control variables. However, the interested reader can find them in a supplementary appendix online. The coefficient on distance is also consistent across all three IV specifications. For the remainder of the article we will use the full IV specification in column 2.

Heterogeneity by SNAP Participation and Income

Table 5 reports heterogeneity in the choice model mean utility estimates with respect to SNAP participation and income group, using the preferred specification in table 4. The columns of table 5 are organized as follows. Column 1 provides estimates for the entire sample. Column 2 provides estimates for the 1,483 SNAP participating households. Column 3 reports the estimates for the 570 non-SNAP households with income less than 100% of FPL (i.e., lowest-income non-SNAP), column 4 reports estimates for the 783 non-SNAP households with income between 101–185% of FPL (i.e., mid-income non-SNAP), and finally, column 5 provides estimates for the 1,825 non-SNAP households with income greater than 185% of FPL (i.e., non-eligible non-SNAP).

The results presented in table 5 show that when breaking up the sample, the distance point estimates are negative and statistically different from zero for both SNAP and non-SNAP households. Breaking up the sample also yields interesting patterns for the utility estimates by outlet category. First, we find that Supermarkets are preferred to the outside option across all household groups, given the positive and statistically significant point estimate of the constant term in each column. Second, Superstores are found to be the most preferred outlet across all household groups except non-eligible non-SNAP households, who prefer Fast Food first and Superstores second. Third, for SNAP and the lowest-income non-SNAP households, the utility estimates for Fast Food are not statistically different from those of Supermarkets, and for non-eligible non-SNAP households, the utility estimates for Restaurants are not statistically different from those of Supermarkets. Lastly, Farmers Markets and Grocery Stores have the most negative and significant mean utility estimates of all outlet alternatives, and are therefore revealed to be the least-preferred alternatives available to the households in the sample, regardless of SNAP participation and income level. Given that prices are not included in the bundle of outlet attributes, the low preferences for Farmers Markets and Grocery Stores may be picking up the consistently higher prices offered at these outlets compared to their larger counterparts (i.e., Supermarkets and Superstores).

Heterogeneity by Food Outlet Accessibility and Store Choice Rationale

Table 6 reports heterogeneity in the mean utility estimates by household food desert status and reported car access, by household rural/urban status, and by households citing either price alone or closeness to home as the reason for choosing their primary store.

In columns 1–4 we divide the households by the food desert status of the census block group in which they live, and by self-reported vehicle access. In the FoodAPS sample, 1% of the households report no car access and live in a food desert, 4% report car access and live in a food desert, 3% report no car access and do not live in a food desert, and 93% report car access and do not live in a food desert. We posit that the households in column 1 have the lowest food store access, while those in column 4 have the highest.

A result that stands out is that the distance point estimate for households without car access and not living in a food desert (column 3) is more than double the magnitude of what we find for households with car access not living in a food desert (column 4). For households living in food deserts (columns 1 and 2), the point estimates for distance are negative, but not statistically different from zero. This non-significance may be due to small sample problems, given that only 5% of households live in food deserts. With respect to revealed preference ranking, only households with the highest food store access (column 4) value shopping at Fast Food significantly more than at Supermarkets. Interestingly, households with the least food store access (column 1) place a higher value on Convenience stores than households with greater access.

[20] With the inclusion of household characteristic control variables, the constant term corresponds to the utility placed on Supermarket consumption relative to the outside option for the omitted reference group of households.

Next, in columns 5 and 6 we divide the households by whether they live in an urban or rural census tract. The point estimate for distance is greater in magnitude for households living in rural areas than for those in urban areas, and this difference is statistically significant at the 1% significance level. Thus, households that live remotely place higher disutility on having to travel one mile farther to get food than those in more populated areas. The revealed preference rankings for outlet types are similar for both urban and rural households.

In the final two columns, households are classified into groups depending on whether they stated either prices (alone) or closeness-to-home as the reason for choosing their primary food store during the initial interview. As discussed in the FoodAPS data section above, the bottom rows of table 3 report the share of households choosing each of the pre-coded reasons for primary store choice, where respondents could select more than one response. Roughly 35% of households cite prices as a reason for primary store choice without selecting closeness-to-home, while half list closeness-to-home, with or without selecting prices. The point estimates of mean utility for these two mutually exclusive groups are reported in columns 7 and 8, respectively. We find that distance has a negative point estimate for both household groups, and, as we would expect, the point estimate is greater in magnitude for the households that list closeness as their reason for store choice. Furthermore, households that list prices value Superstores more than Fast Food, whereas the reverse is true for those that state closeness-to-home. It is reassuring that our revealed preference estimates from our discrete choice model match the stated preferences of the households.

In summary, our results consistently emphasize that households obtain disutility from traveling farther to food outlets and positive utility from acquiring food at Superstores, Fast Food, and Supermarkets compared to the Other Category, Grocery Stores, and Farmers Markets.[21] We find slight variations depending on which household groups we include in the sample. For mean utility estimates along additional dimensions of household heterogeneity, the interested reader can find result tables—by household composition and size, by race and ethnicity, and by gender, age, and education of the PR—in the supplementary appendix online.

Inferring Willingness to Pay

Based on the estimates of mean utilities reported in the previous tables, we can infer the willingness to pay (WTP) in distance traveled to shop at each outlet category. The approach has two steps. First, by dividing the marginal utility parameter of outlet type, α_j, by the absolute value of the marginal utility for distance from home, $\beta_{distance}$, we obtain a willingness to pay in miles to acquire food at outlet type *j*, given by

$$(5) \qquad WTP_{miles} = \frac{\alpha_j}{|\beta_{distance}|}.$$

This marginal utility ratio tells us the number of miles per week that would yield the same household utility as shopping at a particular outlet type.

Second, to obtain the (easier to interpret) dollar equivalent, we convert miles into dollars by multiplying by the average amount an American spends in operating costs to drive one mile, which is approximately 20 cents per mile (AAA 2013).[22] Other studies in the store choice literature use similar travel costs. For instance, using self-reported travel data, Feather (2003) reports that the weighted average out-of-pocket expense for getting a ride, driving one's own car, or driving a borrowed car is 23 cents per mile. Yet importantly, while we believe 20 cents per

[21] As mentioned above, a concern with using expenditure shares as the empirical analogue of choice probabilities is that by placing zero weight on the free-food events in the Other Category, our model may underestimate the mean utility of the Other Category relative to the remaining eight outlet categories. To explore the extent to which this is an issue, we estimate the model using an alternative measure of choice probabilities: the share of trips made to each outlet type. Importantly, trip shares weight all food events equally, regardless of expenditures (i.e., free food events are given equal weight as paid food events). Supplementary appendix table 5 replicates table 5 using trip shares, rather than expenditure shares, to create the dependent variable. Reassuringly, we find broadly similar patterns in the preference rankings for outlet types in both tables. For both trip shares and expenditure shares, the FoodAPS households are revealed to prefer Supermarkets, Superstores, and Fast Food above Restaurant, Combo Retail, and Convenience outlets, and they prefer Grocery Stores and Farmers Markets the least. The main difference in using trip shares is that the Other Category moves up one spot in the preference ranking, making it preferred to Supermarkets.

[22] The operating cost includes gas, maintenance, and tires. It does not include the ownership cost of insurance, license, registration, taxes, and depreciation.

Table 7. Willingness to Pay in Distance Traveled, by SNAP Participation and Income Group

			Non-SNAP		
	Overall (1)	SNAP (2)	Income ≤ 100% FPL (3)	Income 101 - 185% FPL (4)	Income > 185% FPL (5)
WTP (miles)					
Superstore	85.450***	135.221***	52.609*	122.657**	89.747***
	(12.401)	(36.531)	(24.432)	(41.316)	(21.002)
Supermarket	60.090***	106.084***	29.322	84.059+	67.978***
	(12.567)	(31.252)	(25.068)	(47.247)	(16.193)
Grocery Store	−41.763***	−26.410+	−64.887*	−23.347	−26.066**
	(7.829)	(15.029)	(27.272)	(17.704)	(9.522)
Combo Retail	−12.878	21.772	−38.087	8.075	−5.308
	(8.063)	(15.579)	(28.183)	(18.325)	(9.868)
Convenience	−11.565+	21.352	−48.904*	2.762	2.575
	(6.045)	(14.856)	(20.903)	(16.566)	(8.004)
Farmers Market	−52.356***	−46.597**	−75.565***	−39.623*	−31.406***
	(5.693)	(15.391)	(21.371)	(16.540)	(7.966)
Restaurant	32.140***	20.256	−5.548	48.828*	74.171***
	(8.770)	(18.389)	(30.735)	(21.031)	(10.074)
Fast Food	81.421***	109.324***	40.348*	113.619***	101.248***
	(7.305)	(14.950)	(16.151)	(22.631)	(18.535)
WTP ($)					
Superstore	17.167***	27.166***	10.569*	24.642**	18.030***
	(2.491)	(7.339)	(4.908)	(8.300)	(4.219)
Supermarket	12.072***	21.312***	5.891	16.887+	13.657***
	(2.525)	(6.278)	(5.036)	(9.492)	(3.253)
Grocery Store	−8.390***	−5.306+	−13.036*	−4.690	−5.237**
	(1.573)	(3.019)	(5.479)	(3.557)	(1.913)
Combo Retail	−2.587	4.374	−7.652	1.622	−1.066
	(1.620)	(3.130)	(5.662)	(3.681)	(1.983)
Convenience	−2.323+	4.290	−9.825*	0.555	0.517
	(1.215)	(2.985)	(4.199)	(3.328)	(1.608)
Farmers Market	−10.518***	−9.361***	−15.181***	−7.960*	−6.309***
	(1.144)	(3.092)	(4.293)	(3.323)	(1.600)
Restaurant	6.457***	4.070	−1.115	9.810*	14.901***
	(1.762)	(3.694)	(6.175)	(4.225)	(2.024)
Fast Food	16.357***	21.963***	8.106*	22.826***	20.341***
	(1.468)	(3.003)	(3.245)	(4.547)	(3.724)

Note: Robust standard errors appear in parentheses. Significance indicated by $+p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$. We obtain average and heterogeneous willingness to pay estimates in terms of miles traveled: $WTP_{miles} = \frac{\alpha_j}{|\beta_{distance}|}$. To convert those into dollars, we use the fact that Americans spend, on average, 20 cents per mile in car operating costs (AAA 2013).

mile is a reasonable cost estimate, we will put more weight on the relative size of the WTP estimates across outlet types, which is not affected by the size of the scalar used.[23]

The WTP estimates for the outlet choice model are reported in table 7, for the entire sample and by SNAP participation and income group. In the top panel we report the weekly WTP in miles, and in the bottom panel we report the same WTP estimates converted to dollars. Focusing on the bottom panel, in column 1 we find that the WTP for Superstores and Fast Food are the two highest among the alternatives, at $17.17 and $16.36, respectively. The options that are revealed to be the least preferred are Farmers Markets and Grocery Stores, which have WTP estimates of −$10.52 and −$8.39. These estimates mean that, on average, a household in this sample would need to be compensated with 8–10 dollars a week to attend a Farmers Market or a smaller Grocery Store.

SNAP households (column 2) are willing to pay more to shop at Superstores and Supermarkets than the other household groups. Given that SNAP households can

[23] If one used a lower (higher) travel cost estimate, then the WTP estimates would be scaled down (up).

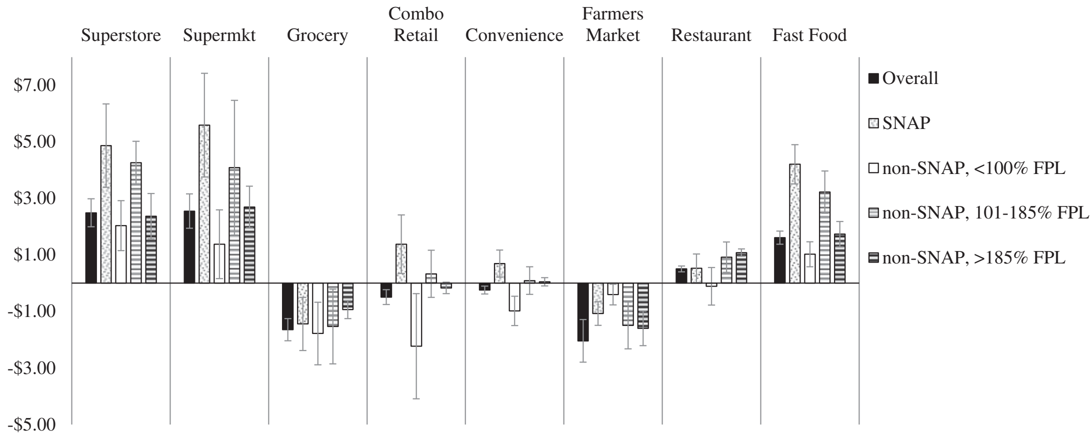

Figure 1. Weekly willingness to pay for an outlet type to be located one mile closer to home

Note: This figure uses the WTP estimates from the bottom panel of table 7, as well as the average distances traveled by each of the household groups to each of the outlet categories from table 1, in order to calculate the average weekly WTP for an outlet type to be one mile closer to home.

only redeem their SNAP benefits at FAH outlets, this is perhaps not surprising. SNAP households are also willing to pay $21.96 for Fast Food, which is similar in magnitude to what the non-eligible non-SNAP households are willing to pay for Fast Food. This is consistent with SNAP households being infra-marginal—where SNAP benefits expand the budget set so that households can buy more of all goods.

The lowest-income non-SNAP households (column 3) are willing to pay less than all other households groups (columns 2, 4, and 5) across all outlet categories, but have the same relative rankings, namely, they are willing to pay the most for Superstores ($10.57) and Fast Food ($8.11), and need to be compensated to go to Grocery Stores and Farmers Markets. The non-eligible non-SNAP households (column 5) are willing to pay slightly more for Fast Food ($20.34) than for Superstores ($18.03), though the difference is not statistically significant. Non-eligible, non-SNAP households also have the highest WTP for Restaurants ($14.90).

While we examine the utility estimates separately for SNAP and non-SNAP households, we stress that these estimates are not designed to measure the causal effects of SNAP participation on WTP for outlet types. Take, for example, the results that mid-income non-SNAP households (column 4) are willing to pay $5 more for Restaurants than SNAP households (column 1). This relationship could be explained with two opposing arguments. Perhaps eligible non-SNAP households do not participate in SNAP because they value Restaurants, or perhaps eligible non-SNAP households value Restaurants more than SNAP households because they are not restricted to use SNAP benefits at FAH outlets.

We can also estimate how much households are willing to pay to have each of the outlet types 1 mile closer to their home. Figure 1 uses the WTP estimates from the bottom panel of table 7—as well as the average distances traveled by each of the household groups to each of the outlet categories in table 1—in a back-of-the-envelope calculation of the average weekly WTP for an outlet type to be located 1 mile closer to home. We find that households are willing to pay $2–5 per week to have a Superstore 1 mile closer to their home, $1–4 for a Fast Food restaurant to be 1 mile closer to home, and $1–6 for a Supermarket to be 1 mile closer to home. Once again, households would pay very little, or need to be compensated, on average, for the remaining four FAH outlet categories to be 1 mile closer to home.

In summary, households are willing to pay the most for the two largest FAH options (Superstores and Supermarkets) and for Fast Food. Interestingly, even the lowest-income non-SNAP households are willing to pay a positive and significant amount for Superstores and Fast Food. Thus, contrary to the hypothesis that eligible non-SNAP households do not participate in SNAP because they do not value FAH stores, we find that having a Superstore closer to home would be valued by these households. Given that prices are not included in the bundle of outlet attributes, the revealed preferences for Superstores and Fast Food may be picking up a preference for the consistently lower prices offered at these outlets.

Conclusions

Using detailed household-level food acquisition data, we estimate a model of store choice, not only as a function of household characteristics but also as a function of attributes of the households' local food environment. By analyzing actual consumer decisions we estimate directly revealed preferences and willingness to pay for outlet types. We find that FoodAPS households are willing to pay between \$12 and \$17 per week in distance traveled for Superstores, Supermarkets, and Fast Food, while they are willing to pay significantly less for the remaining outlets. To put this in perspective, a WTP of \$15 represents 9.6% of the weekly food expenditures of the average household in the FoodAPS sample.[24]

The results of this research have large policy implications regarding the improvement of food access for low-income households, and provide policymakers with important information on the determinants and correlates of consumer preferences towards retail food outlets. In particular, our results imply that low-income households would be receptive to policymakers promoting the building of certain types of food stores (Superstores) over other types (Convenience and smaller Grocery Stores). Furthermore, across heterogeneous household characteristics, the households in this sample have low WTP for Farmers Markets to be closer to home, and high WTP to pay for Fast Food to be closer to home. This implies that simply building Farmers Markets will not induce households to shop there. Instead, low-income households may need to be compensated to shop at Farmers Markets.[25] Interestingly, the WTP for Fast Food is almost as high as the WTP for Superstores. This is true for all household types, and not just those with the lowest incomes.

While we find broadly similar patterns of preferences across heterogeneous household groups, we do identify some differences. SNAP households are willing to pay more than non-SNAP households to have FAH outlets closer to their home. Our estimates also vary by food desert status and car access, by urban/rural status, and by stated price/distance sensitivity. In particular, we find that households (a) without car access and not living in a food desert, (b) situated in a rural area, or (c) that state closeness-to-home as their reason for primary store choice, receive greater disutility from distance than their counterparts. Because of this, incentives such as the Healthy Food Financing Initiative potentially should be designed to fit the sociodemographic composition of each identified low-income, low-access neighborhood in question.

We discuss four estimation concerns that could limit the validity of our results: (1) zero weight on free food events; (2) omitted outlet-level price data; (3) unobserved outlet attributes correlated with distance; and (4) location endogeneity. We address the last two issues, which are of particular concern, by instrumenting the chosen distance to each outlet type with the predetermined distance to the closest outlet of each type, and by employing the FoodAPS datasets' rich assortment of household and local food environment characteristics in our model. While it is reassuring to find that our instrument corrects the positive bias with which we are concerned, it is important to note that bias may persist if the presence of outlets close to where households live impacts store choice not only through distance traveled.

In future work we plan to extend the structural choice model in this article to perform simulations of counterfactual changes to the households' choice set. In particular, we will estimate how households alter their shopping habits when faced with changes in the distance from home to each of the outlet types, and consequently, examine what one could expect from policies designed to increase the availability of food stores in underserved areas.

[24] The average household in the FoodAPS sample spends \$157 per week on food.

[25] Programs that compensate SNAP households to shop at Farmers Markets and buy fruits and vegetables already exist and are growing in size and number, such as Michigan's "Double Up Food Bucks." For more information on "Double Up Food Bucks," see http://www.doubleupfoodbucks.org/.

In conclusion, while we present utility estimates separately for SNAP and non-SNAP households, we stress that these estimates are not designed to measure the causal effects of SNAP participation on WTP for outlet type. Moreover, while we find that all households value Superstores, Supermarkets, and Fast Food more than other food outlets, the building of these preferred outlets is not a silver bullet for improved dietary outcomes. Changing consumers' diets involves both advancing the retail food environment and working with consumers. This article provides a necessary step in understanding where low-income households want to purchase food. The next step is to explore how these revealed preferences can be leveraged, when working with both retailers and consumers, to promote healthier eating.

Supplementary Material

Supplementary material is available at http://oxfordjournals.org/our_journals/ajae/online.

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