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Food Security and Geographic Factors in Food Purchase and Acquisition Decisions: A Compilation of Research Conducted under USDA Cooperative Agreements 58-5000-1-0050 and 58-5000-3-0066

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I. Introduction

In April 2012 the Economic Research Service (ERS) and the Food and Nutrition Service (FNS) in the U.S. Department of Agriculture embarked on an ambitious new data collection enterprise known as the National Household Food Acquisition and Purchase Survey (FoodAPS). FoodAPS is innovative in that it is the first nationally representative household survey to collect comprehensive data on household food expenditures and acquisitions, including those obtained using benefits from food assistance programs. The survey includes data from 4,826 households, including Supplemental Nutrition Assistance Program (SNAP) households, low-income eligible households not participating in SNAP, and higher income households. FoodAPS is specifically well suited to address factors affecting food demand, including access to food stores, as well as the pressing public health threat posed by food insecurity and how well America's food and nutrition assistance programs serve to alleviate that threat.[1]

The data in FoodAPS were collected for all sample household members over a seven-day period between April 2012 and January 2013. The total survey period for the typical household was nine days, with the initial and final days consisting of in-person interviews (training on the first visit and reviewing documents on the last visit), and the seven days in between consisting of recording food acquisitions and meals and snacks eaten supplemented by phone calls to the survey research firm (Mathematica Policy Research) on days 2, 5, and 7. The food acquired was delineated into food at home (FAH) and food away from home (FAFH), and detailed information on quantities and prices, product descriptions, and geographic location of the sample household was

[1] Discussion papers of these research projects are available at http://www.ukcpr.org/research/discussion-papers

recorded. The survey also collected information on non-food spending, the demographic composition of the household, income, food security, health status, diet and nutrition knowledge, program participation (e.g., in SNAP, National School Lunch Program), and food access such as distance to food stores and restaurants. FoodAPS survey data are linked with information created from a nationally representative geographic sample from Information Resources, Inc. (IRI) on the local food environment of the sampled households that contains information about the prices of food at retail outlets. In addition, there is information from other sources associated with FoodAPS on the nutrient content of food acquisitions based on scanner barcodes; access to farmers' market and food pantries; area-level socio-economic characteristics; and some food policy information, such as state and local tax policies.

To foster new research utilizing this extensive data resource, ERS and FNS commissioned the University of Kentucky Center for Poverty Research and the University of Illinois to sponsor a competitive grants program. In response to the 2014 Request for Proposals, 60 completed applications were submitted, and after a rigorous external review process, 12 were selected for funding. Final reports were submitted in the summer of 2016, and below we provide a summary of the research results. Appendix 1 contains a complete listing of the final reports and electronic copies of the final reports can be found at http://www.ukcpr.org/research/food-assistance/foodaps .

II. Household Food Behaviors and SNAP

A. How do food prices across geographic space affect food insecurity and the sufficiency of SNAP benefits?

SNAP is the cornerstone of the food assistance system in the United States, and the consequences and implications of participation in SNAP have been widely examined (Bartfeld et al. 2015). A large literature demonstrates that SNAP decreases food insecurity and improves health for recipients (Hoynes et al. 2016; Gregory et al. 2015; Hoynes and Schanzenbach 2016; Gundersen and Ziliak 2014, 2015). SNAP benefits are based on an assessment of need that takes into account household size, income, adjustments to income, and the cost of a nutritious diet. While SNAP benefits are set nationally, local prices, household characteristics outside of benefit calculation, and the timing of benefits can potentially affect the behavior of recipients and the effectiveness of SNAP. However, data quality is often an issue that prevents researchers and policy makers from understanding what individuals receiving SNAP and those at risk for food insecurity purchase, the nutritional quality of purchases, and shopping habits.

The detailed FoodAPS data permit researchers to examine the sufficiency of SNAP benefits in achieving nutrition policy goals. SNAP benefits are designed to provide sufficient funds for households to adhere to the Thrifty Food Plan (TFP), a food plan constructed by the USDA that outlines a nutritious diet at minimal cost to households. For example, the TFP suggests a two parent family with two children aged 2-5 should be able to afford a nutritious diet for $128.80 per week (Ziliak 2016). Heterogeneity of prices across geographic space may be important to the feasibility of meeting dietary needs through the TFP. These differences in food prices across the U.S. could generate substantial differences in the real value of SNAP benefits, since benefits are only indexed to regional food prices in Alaska and Hawaii.

In a study conducted for this project, Bronchetti et al. (2016) examine the adequacy of SNAP benefits in meeting the TFP while taking into account the regional variation in food pricing. The authors calculate the percentage of SNAP recipients and SNAP-eligible households for whom SNAP benefits are adequate to purchase the TFP. They simulate potential SNAP benefits based on household income, family size, expenses, and composition. Results suggest that 20 to 30 percent of SNAP recipient households face TFP prices that are too high to be purchased with SNAP benefits plus 30 percent of net income.

They also find that, although many SNAP recipient households are struggling to afford the TFP, the proportion of SNAP recipients affording the TFP increases if the distance the household is assumed to shop in is expanded. For those households who cannot afford the TFP, average dollar shortfalls are around $150 per month. One interpretation of these results is that SNAP benefit levels should be more closely linked to local area food prices as is done in Alaska and Hawaii.

Regional price variation is not limited to food. Many studies (Berkowitz et al. 2014; Bhattacharya et al. 2003) document that a substantial trade off exists among many low income households between necessities such as food, rent, medical care, and other basic household needs. Basu et al. (2016) examine how cost of living, inclusive of food, impacts the healthfulness of food acquisitions. They also examine if SNAP participation is associated with living in lower cost of living areas, and if SNAP recipients purchase more healthful food.

Using an endogenous treatment effects model, and estimating cost of living through Bureau of Economic Analysis and the Census Bureau regional price indices, the authors find that higher area-level cost of living is associated with less healthful food acquisition. The authors also found that SNAP recipients were no more likely to live in low cost of living areas, nor were they more likely to purchase more healthful food. If SNAP recipients are unable to purchase the TFP, and are likely to live in high cost of living areas where nutritious diets are harder to obtain, directed increases in SNAP benefits may be worth considering.

B. Do local food prices impact diet quality among SNAP participants and nonparticipants?

Lyford et al. (2016) explore how SNAP beneficiaries navigate food consumption in an attempt to understand the impact of regional food price differences. The authors utilize the detailed geographic and consumption data present in FoodAPS to control for local market structure and the market for food items, as well as controlling for demographic characteristics. The authors also address the endogeneity of SNAP participation with an instrumental variables approach. They find that on average, although an index of food prices paid by SNAP recipients was 0.09 points lower than the index of non-participants, SNAP recipients are not systematically disadvantaged, and that budgeting plays a crucial role in the affordability of food for individuals receiving SNAP.

Chang et al. (2016) also note the importance of budgeting, examining how cost and financial literacy impact diet quality and sufficiency. Similar to Lyford, et al. (2016), they examine various measures of consumer competency, including how households handle bills, whether the household receives payday loans or cash advances, and whether or not the household employs store savings methods such as coupons or loyalty benefits. To identify the causal impact of SNAP on consumer competency, state policy and administrative indicators are used as instrumental variables for SNAP participation.

The authors find somewhat mixed results, with prices negatively associated with financial management practices such as coupon use, using nutrition facts, and using a grocery list, but positively associated with loyalty programs and other store specific savings. However, SNAP participation improved financial management practices. These findings suggest that low income individuals struggle implementing many competent consumption strategies.

These results compliment those found in Lyford et al. (2016), who suggest that SNAP recipients are better at budgeting, that budgeting improves food consumption, and that more education could improve food choices. Chang et al. (2016) find that, while SNAP recipients are better able to employ competent consumer strategies, these strategies are far from ubiquitous. Thus, these results taken together suggest that broad financial education could play an important role in the effectiveness of the SNAP program in helping recipients afford plentiful and healthful food. Existing work through the USDA's SNAP-Ed program has focused efforts in this budgeting and financial management, and these results, along with those in the recent randomized control trial in Indiana funded by UKCPR and FNS (Rivera et al. 2016), suggest that education in budgeting should continue, and perhaps be expanded. This information would allow SNAP recipients means to better afford a healthful diet by paying comparatively lower food prices.

C. What is the importance of the SNAP benefit cycle and consumer competency for food consumption?

For SNAP beneficiaries, financial management is complicated by distribution rules. Not only do recipients have to make income stretch between pay periods, they also have to allot SNAP dollars across the benefit month. The benefit month is the period between which benefits are distributed. For example, in Alaska, benefits are made available at the beginning of every month, while benefits in Kentucky are randomly distributed based on a household's case number. Many households have a large spike in food consumption and expenditure when benefits arrive, only for this consumption to taper off at the end of the benefit month. Kuhn (2016) and Berning et al. (2016) examine the consequences and causes of these SNAP cycles. Kuhn (2016) finds strong evidence of this cycle, with expenditure decays of roughly 4% per day over the course of the benefit month, and a loss of up to 12 meals per month. However, Kuhn notes that the correlation between expenditure and consumption cycles is weaker than expected, and that children are insulated from these cycles (especially young children), due to parental oversight and food provided at school. Kuhn also notes that diet quality decreases over the benefit month, and that travel time to grocery stores is not predictive of more severe expenditure cycles.

Berning et al. (2016) examine two behavioral responses of SNAP participants associated with the SNAP benefit cycle—short run impatience and the degree of substitutability between SNAP dollars and cash. The authors find strong evidence of time inconsistent spending, with households spending much more on food the day that benefits are issued. The authors also find that spending falls significantly in the days following benefit distribution, similar to Kuhn (2016). Berning et al. also find that households purchase more healthful foods and that perishable foods and FAH in general decline over the benefit cycle.

The research by Seligman et al. (2012) suggests that this benefit cycle may be associated with diabetes and acute onset of hypoglycemia and hospital admissions. The evidence suggests that the SNAP benefit may be inadequate to meet the needs across the month, which is likely tied to the TFP being too low (Caswell and Yaktine 2013; Ziliak 2016).

D. How does food access across geographic location influence prices and shopping habits?

Hillier et al. (2016) also examine the cyclicality of SNAP benefits, but in relation to the spatial distribution of stores and the nutritional content of meals, analyzing the role of these mechanisms in determining food shopping decisions in time and space. The authors first determine a choice set of stores where households could shop. They find that SNAP participants' store choices are influenced by demographic characteristics and, in the main, this leads them to shop at large supermarkets. They find, similar to studies mentioned above, that the nutritional quality of food at home choices decreases over the benefit cycle, and that purchases at natural/gourmet and limited assortment stores were more healthful than those purchased at large supermarkets, perhaps reflecting the different set of products available at those stores. However, the authors also find that the health quality of purchases by SNAP households were not significantly different than those by households which were not SNAP eligible, but that purchases by SNAP eligible non-recipients were of lower health quality than those of SNAP recipient households. These results show how diet quality is a complex web of benefits, timing, location, and individual preferences, but they offer some insight on the relationship between store choice and SNAP policy.

IV: The Role of the Local Food Environment on Food Purchases

A. What is the role of the local food environment and food prices on food

security?

When investigating the impact of food environments, it is crucial to account for household characteristics as well as the local prices that each household faces. Few data sources have the necessary links between local food retailers and pricing, household food purchases, food insecurity, and their spatial relation. With the FoodAPS, however, researchers can more fully investigate the role of food deserts and food prices via the merging of FoodAPS with information created from IRI data. Evidence from the FoodAPS suggests that the conventional wisdom surrounding food deserts (areas with low food access) may be misguided and that local prices play a larger role than proximity to food retailers.

In a study conducted for this project, Downing and Laraia (2016) use the FoodAPS to examine the impact of food prices and food deserts on food security and health. The average household in the dataset lives between 3-5 miles from the nearest supermarket. Food insecure households live slightly closer to supermarkets (2.5 miles) and shop closer to home (3.8 miles) than food secure households. They find that living in a food desert is not associated with being food insecure, which is consistent with, e.g. Bitler and Haider (2011). Food deserts may not have large impacts on health as well. They find that there is no difference in obesity by food environment.

Using the FoodAPS, Allard and Ruggles (2016) indicate that many population sub-groups identified in the literature as being vulnerable to low food resource access, such as households headed by a black person and low-income households, actually have greater or comparable spatial access to several different types of food resources compared to less vulnerable population sub-groups. Over 90 percent of poor and non-poor households report using supermarkets or superstores as their primary food shopping venue. Additionally, black and Hispanic households are much closer to the nearest SNAP supermarket or superstore than white households. Black and Hispanic households also are within 1 mile of about 0.5 more supermarkets and superstores than white households. There is also no significant difference in supermarket access between SNAP participants and eligible non-participants. However, urban households are much closer to SNAP retailers and concentrations of SNAP retailers than households in suburban and rural areas. So while there are not differences in food access by income or participation, there are significant differences between urban and suburban/rural locations.

Given the consistent findings of minimal differences in food access, perhaps more important are the local food prices faced by each household. As discussed above, large heterogeneity in food prices across the U.S. can generate substantial differences in the real value of SNAP benefits and their potential impact. Though food deserts themselves are not associated with food insecurity, akin to the findings of Gregory and Coleman-Jensen (2013), Downing and Laraia (2016) find that food insecurity is linked with presence of high cost supermarkets, but not with the absence of supermarkets, in high poverty neighborhoods. Indeed, they find that 13 percent of food insecure households lived in high poverty areas with higher than average supermarket prices, compared with only 5 percent of food secure households. Additionally, households who select their supermarket based on low prices compared to other reasons such as variety or produce selection are 5-7% more likely to be food insecure.

B. How does food retail environment affect food purchases?

A unique feature of FoodAPS is that it allows research to construct a precise food environment for every individual in the dataset, for both FAH and FAFH purchases. This depth, combined with the rich geographic information on the precise distance between retail food outlets visited and each household's residence, as well the number and types of outlets in proximity to each household, allows researchers to construct detailed pictures of household's retail environments. Previous studies have needed to rely on broad area-based measures of access instead of individual level measures.

Gustafson and Allen (2016) use a fractional multinomial logit analysis to examine all FAH and FAFH venues a household faces and find that close proximity to superstores or supermarkets increases the share of weekly food purchases made there, and that car access increases the share of FAFH purchases and decreases the share of FAH purchases other than superstores or supermarket.

The structural model of Taylor and Villas-Boas (2016) is able to translate these preferences into a consumer's willingness to pay (WTP). That is, how much would a consumer be willing to pay per week for a particular food environment. Using a discrete choice model, Taylor and Villas-Boas find that households have the highest willingness to pay for superstores, supermarkets, and fast food, at approximately $15 per week in distance traveled. To put this in perspective, a WTP of $15 represents 9.6% of the weekly food expenditures of the average household in FoodAPS. Equating these estimates to dollars per mile, FoodAPS households are willing to pay $2-$5 per week to have a superstore 1 mile closer to their home, $1-$4 per week for a fast food restaurant to be 1 mile closer to home, and $1-$6 per week for a supermarket to be 1 mile closer to home. Furthermore, across heterogeneous household characteristics, the households in this sample have low WTP for farmers' markets to be closer to home. This implies that simply building farmers markets will not induce households to shop there.

Both studies find that SNAP participation plays a role in food venue choice. SNAP participation increases the share of purchases at superstores and decreases the share spent at FAFH venues, on average. SNAP households are also willing to pay more than non-SNAP households to have FAH outlets closer to their home. Regarding household income, Taylor and Villas-Boas argue that low-income households would be receptive to policymakers promoting the building of certain types of food stores (i.e., superstores) over other types (i.e., convenience and smaller grocery stores). Additionally, households either without car access and not living in a food desert, living in a rural area, or that state closeness-to-home as their reason for primary store choice, receive greater disutility from distance than their counterparts. Taken together, these findings suggest that food-access incentives potentially should be designed to fit the sociodemographic composition of each identified low-income, low-access neighborhood in question.

C. How does food environment affect health?

If policy makers want to encourage the building of supermarkets and supercenters in low-access neighborhoods, it is also important to consider what food the households will purchase and what the health consequences may be. Gustafson and Allen (2016) examine this question specifically and find that shopping at these types of stores influences what is purchased. At supermarkets, SNAP households tend to purchase lower calorie beverages and fruits and vegetables. Whereas at supercenters, SNAP households purchase healthier food items, but they also purchase sugar-sweetened beverages, snacks, and higher calorie items.

Bowen et al. (2016) expand on this result by providing a more comprehensive measure of healthy eating by using a Healthy Eating Index that incorporates dollars spent and amount of food (measured by weight) in several categories: fruit, vegetables, snacks, and sweetened beverages. They employ multilevel models with neighborhood and state effects to analyze the associations between household characteristics, neighborhood characteristics, regional attributes, and dietary quality. The authors find that the number of large food stores in the neighborhood is significantly and positively associated with dietary quality, while other neighborhood characteristics such as neighborhood deprivation is not significantly associated with dietary quality. Importantly, Bowen et al. also incorporate household finances and regional prices to give a more complete picture of determinants of a household's food purchases. Their model shows that at the household level, financial condition and home ownership are significantly and positively related to dietary quality; highlighting the importance of financial security, while U.S. citizenship status and living in a rural area were negatively associated with dietary quality. Interestingly, their measure of a regional food price index was not significant while the neighborhood random effects were significant, stressing the importance of using local food prices as done by Downing and Laraia (2016).

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List of FY 2014 Grantee Final Reports

"The Spatial Context of Food Shopping: Understanding How Local Food Retailer Access and Pricing Affect Household Behavior"
Scott W. Allard, University of Washington; and Patricia Ruggles, NORC at the University of Chicago *Paper to be released January 2017*

"Cost of Living, Healthy Food Acquisition, and the Supplemental Nutrition Assistance Program"
Sanjay Basu, Stanford University; Christopher Wimer, Columbia University; and Hilary Seligman, University of California at San Francisco

> Published as Basu, S., Wimer, C., & Seligman, H. (2016, Nov.). Moderation of the relation of county-level cost of living to nutrition by the Supplemental Nutrition Assistance Program. *American Journal of Public Health, 106 (11)*, 2064-2070.

"The Effects of Benefit Timing and Income Fungibility on Food Purchasing Decisions among SNAP Households"
Joshua P. Berning, University of Georgia; Gregory Colson, University of Georgia; Jeffery H. Dorfman, University of Georgia; Travis A. Smith, University of Georgia; and Xiaosi Yang, University of Georgia

> Published as Smith, T., Berning, J., Yang, X., Colson, G., & Dorfman, J. (2016). The effects of benefit timing and income fungibility on food purchasing decisions among SNAP households. *American Journal of Agricultural Economics, 98(2),* 564-580.

"Contextualizing Family Food Decisions: The Role of Household Characteristics, Neighborhood Deprivation, and Local Food Environments"
Sarah Bowen, North Carolina State University; Richelle Winkler, Michigan Technological University; J. Dara Bloom, North Carolina state University; and Lillian MacNell, North Carolina State University

"Variation in Food Pricing and SNAP Adequacy for Purchasing the Thrifty Food Plan"
Erin Bronchetti, Swarthmore College; Garret Christensen, University of California-Berkeley; and Benjamin Hansen, University of Oregon

"The Effect of Food Price on Food Insecurity and Diet Quality: Exploring Potential Moderating Roles of SNAP and Consumer Competency"
Yunhee Chang, University of Mississippi; Jinhee Kim, University of Maryland; and Swarn Chatterjee, University of Georgia

"Supermarket Proximity and Price: Food Insecurity and Obesity in the United States"

Janelle Downing, University of California-Berkeley; and Barbara Laraia, University of California-Berkeley

"The Relationship between Neighborhood Food Environment and Food Store Choice on the Purchasing Habits among Supplemental Nutrition Assistance Program (SNAP) Participants and Lower-Income Households"
Alison Gustafson, University of Kentucky; James Allen IV, University of Kentucky; Nancy Schoenberg, University of Kentucky; and Mark Swanson, University of Kentucky

"Influence of SNAP Participation and Food Environment on Nutritional Quality of Food at Home Purchases"
Amy Hillier, University of Pennsylvania; Benjamin Chrisinger, Stanford University; Tony E. Smith, University of Pennsylvania; Eliza Whiteman, University of Pennsylvania; and Michael Kallan, University of Pennsylvania

"Causes and Consequences of the Calorie Crunch"
Michael Kuhn, University of Oregon

"Do SNAP Recipients Get the Best Prices?"
Conrad Lyford, Texas Tech University; Carlos Carpio, Texas Tech University; Tullaya Boonsaeng, Texas Tech University; and Raymond March, Texas Tech University

"Food Store Choices of Poor Households: A Discrete Choice Analysis of the National Household Food Acquisition and Purchase Survey"
Rebecca Taylor, University of California-Berkeley; Sofia Berto Villas-Boas, University of California-Berkeley

> Published as Taylor, R., and S. B. Villas-Boas, 2016. "Food Store Choices of Poor Households: A Discrete Choice Analysis of the National Household Food Acquisition and Purchase Survey (FoodAPS)," *American Journal of Agricultural Economics*, 98(2), 513-532.

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Variation in Food Prices and SNAP Adequacy for Purchasing the Thrifty Food Plan

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Abstract

Whether Supplemental Nutrition Assistance Program (SNAP) benefits are adequate to provide food security for eligible households is an important and timely policy question. While the nominal value of SNAP benefits is fixed across states (except for Hawaii and Alaska), variation in food prices across geographic areas is dramatic, and the real value of SNAP benefits varies widely across the U.S. Our research provides new evidence on geographic variation in the adequacy of SNAP benefits to purchase the Thrifty Food Plan (TFP). Using multiple methods to estimate the cost of the Thrifty Food Plan (TFP) faced by households across the nation, and several measures of the SNAP benefits available to them, we consistently find that a substantial fraction of SNAP-recipient households receive benefits that are insufficient to purchase the TFP. Our primary estimates indicate that SNAP benefits (plus 30 percent of income) are insufficient for approximately 20-30 percent of households to purchase the TFP. Sufficiency rates increase monotonically as we expand the distance within which the household is assumed to be able to shop. For households who are unable to afford the TFP, average dollar shortfalls between the cost of the TFP and SNAP benefits (plus 30 percent of income) are often as large as $150 per month. When shoppers are assumed to be able to purchase the TFP at the minimum-cost store in the area, SNAP benefits are sufficient for over 90 percent of households. However, this assumption seems unlikely to hold for many SNAP households.

Executive summary

Objectives

Our research provides new evidence on the adequacy of SNAP benefits, taking into account geographic variation in local food prices across the U.S. Because SNAP benefits are not indexed to local food prices (except for in Alaska and Hawaii), the real value of SNAP benefits differs widely. In some areas, SNAP benefits may be insufficient to purchase the Thrifty Food Plan (TFP), the USDA's low-cost, nutritious food plan that is the basis for legislated SNAP benefit levels. Using multiple measures of the local TFP cost faced by households in FoodAPS, we calculate the percentage of SNAP recipients and SNAP-eligible households for whom SNAP benefits are adequate to purchase the TFP.

Methods

Using FoodAPS and FoodAPS-GC data, along with food basket costs estimated by Gundersen et al. from store-level IRI data to approximate the TFP, we calculate the respondent's cost of food in several ways:

- basket cost at the primary store at which the respondent reports shopping
- basket cost at the alternate store at which the respondent reports shopping
- the mean, median, and minimum basket cost in the respondent's county
- the mean, median, and minimum basket cost at stores within an X-mile radius of the respondent's census block centroid (where X = 20, 10, 5, 3.4, 2.5)
- the mean, median, and minimum basket cost at the X stores nearest to the respondent's census block centroid (where X = 5, 2, 1)

Our primary estimates compute the fraction of SNAP-recipient households for whom self-reported SNAP benefits received (plus 30 percent of income) are sufficient to purchase the TFP. For SNAP-eligible households, we compute sufficiency rates by simulating the potential SNAP benefit to which the household is entitled, using information on household income, expenses, family size and composition. We also calculate the average dollar shortfall (i.e., the gap between TFP cost and benefits plus 30 percent of income) for households for whom SNAP is insufficient.

Results and policy implications

Our evidence indicates that geographical variation in food prices may render SNAP benefit levels inadequate for a sizeable fraction of households to purchase the TFP, despite the fact that this bundle of foods provides the basis for legislated SNAP benefit levels. Using fairly conservative assumptions about where households are able to shop, our estimates suggest this fraction may be on the order of 20-30 percent. An open question is whether SNAP benefits are also overly *generous* in areas with relatively low food prices. If so, one interpretation of our results would be that SNAP benefit levels should be more directly indexed to local food prices.

Introduction

The Supplemental Nutritional Assistance Program (SNAP, or formerly, Food Stamps), is one of the largest forms of government assistance in the United States. Both caseloads and program costs peaked at the time of our study (2012-2013), with more than 1 in every 7 Americans participating the program, and annual program costs exceeded 80 billion dollars (Bartfeld et al. 2015). A substantial body of literature has demonstrated that SNAP significantly reduces food insecurity in recipient households (Yen et al. 2008; Nord and Golla 2009; Mykerezi and Mills 2010), and leads to short- and long-run improvements in outcomes like health, education, and economic self-sufficiency, particularly for those who receive benefits as children.[1] Despite the program's successes, food insecurity remains a problem for more than one-fifth of households with children in the U.S. Even among SNAP-recipient households, the rate of food insecurity remains quite high, at over fifty percent (Coleman-Jensen et al., 2014).

Dramatic differences in local food prices across the country can generate wide variation in the *real* value of SNAP benefits, since benefit levels are legislated nationally and are not separately indexed to the regional price of food (except for in Alaska and Hawaii). Data from the Quarterly Food at Home Price Database (QFAHPD) show that regional food prices vary from 70-90 percent of the national average at the low end to 120-140 percent at the high end (Todd et al. 2010; Todd, Leibtag, and Penberthy 2011). Not surprisingly, households in market areas with higher food prices are more likely to be food insecure (Gregory and Coleman-Jensen, 2013).

This study explores the degree to which SNAP benefits are adequate for households to

[1] See Hoynes and Schanzenbach (2015) for a review of SNAP and other food assistance programs and their impacts.

purchase the Thrifty Food Plan (TFP). The TFP is a food plan constructed by the USDA to represent a nutritious diet at a minimal cost and is used as the basis for legislated maximum SNAP benefit levels. Whether SNAP benefits are sufficient to purchase the TFP in a SNAP recipient's area will depend on the food prices the individual faces. Using new data from the FoodAPS and FoodAPS-Geography Component data sets, we are able to account for variation in local food prices at a much tighter geographical level than has been possible in prior research. Rather than rely on regional food price indices, we use multiple methods to estimate the cost of the TFP faced by SNAP-recipient households and SNAP-eligible households at the stores where they are likely able to shop, as well as at the stores where they report shopping.

We then use information on households' SNAP benefits to determine the fraction of households for whom benefits (plus 30 percent of income) are sufficient to purchase the TFP.[2] For households for whom benefits are found to be insufficient, we also compute the average dollar shortfall between the cost of the TFP and SNAP benefits (plus 30 percent of income).

Methods and data

Our samples include (1) FoodAPS respondent households who report receiving SNAP benefits in the past month[3] ("SNAP recipients"), and (2) FoodAPS households who are simulated to be eligible for SNAP, according to models constructed by USDA-ERS ("SNAP eligibles"). The first goal of our research is to link each respondent in these samples to information on what

[2] For SNAP recipients, we use both self-reported benefit levels plus 30 percent of income (separately for gross and net income, calculated using family size and potential deductions) and maximum benefit entitlements (calculated using only family size). For SNAP-eligible households who do not take up benefits, we use simulated levels of benefits, as well as maximum benefit for family size.

[3] See section 2.3.4 of the data documentation at http://www.ers.usda.gov/datafiles/FoodAPS_National_Household_Food_Acquisition_and_Purchase_Survey/In_person_interviews/Initialcodebook.pdf, May 26, 2016 version, as the SNAP recipient variable (SNAPNOWHH) includes a correction for matching self-reports to state administrative data.

it would cost the household to purchase the TFP from local stores. We use store-level "basket prices," calculated by the teams at the University of Illinois and the University of Florida from IRI scanner data, and link these to FoodAPS respondents using the FoodAPS-GC data. Throughout, we use the Illinois/Florida team's variable, *low_basket_price* as our measure of TFP cost.[4] In some ways, this is a conservative approach, in that it assumes that within each TFP food category, SNAP households purchase low-priced items. Additionally, the basket prices may include "variety bias" in that stores that do not sell particular items included in the Thrifty Food Plan do not include a price estimate for that item, thus under-estimating the true cost of the TFP at that store. To the extent this is true, it would bias our estimates towards finding high rates of SNAP sufficiency.

We create multiple measures of TFP cost faced by the respondent, each of which involve different assumptions about how and where respondents shop. Specifically, we analyze the adequacy of SNAP benefits to purchase the TFP, using the following measures of TFP cost:

- basket cost at the primary store at which the respondent reports shopping
- basket cost at the alternate store at which the respondent reports shopping
- the average of the basket costs at the primary and alternate store
- the mean, median, and minimum basket cost in the respondent's county

[4] The basket price data specifically does not refer to its basket prices as the "Thrifty Food Plan." The prices are calculated using all items in a food category from a store, including high-price items and thus may not be representative of the purchases made by low-income SNAP households. However, the Illinois/Florida team has constructed two TFP-cost variables, *basket_price* and *low_basket_price*. The first takes the median price-per-pound for each TFP category, multiples that price by the quantity (in pounds) prescribed for the TFP, and sums across TFP categories. The latter makes the same calculation, but calculates the median price-per-pound only among items in the <u>lowest quintile</u> of prices for that TFP category. We employ the latter measure throughout our analysis, both because the assumption that SNAP households buy low-priced items seems reasonable, and because it would tend to bias us away from finding SNAP benefits to be insufficient to purchase the TFP.

- the mean, median, and minimum basket cost at stores within an X-mile radius of the respondent's census block centroid (where X = 20, 10, 5, 3.4, 2.5)
- the mean, median, and minimum basket cost at the X stores nearest to the respondent's census block centroid (where X = 5, 2, 1)

Once we have estimated the cost of the TFP for each respondent using the several definitions above, we compare these to the household's resources, using two different measures of the resources available for purchasing food: (1) SNAP benefits plus 30 percent of net income, and (2) Maximum legislated SNAP benefits for household size.[5] Sufficiency rates are calculated simply as the fraction of households for which the measure of resources exceeds the TFP cost measure, given the household's size.

We use 30 percent of income because SNAP benefit amounts are designed with the assumption that recipient households spend 30 percent of their income on food. Additionally, SNAP benefits are calculated by subtracting 30 percent of net income from the maximum legislated benefit, where net income is calculated by adjusting gross income according to deductions for costs associated with housing, earnings, dependent care, medical expenses, child support payments, and other transfer program deductions. We use household-level and person-level data to estimate the amount of these deductions and impute the household's net income. Given the statutory definition of benefit levels, these two estimates would be identical with perfect reporting, but in practice they are not.

After determining the fraction of SNAP households for whom SNAP benefits (plus 30

[5] For completeness, sufficiency levels (as well as dollar amount of the shortfall) have also been calculated using 30% of gross income in lieu of net income. Results are available upon request. Sufficiency rates are higher using gross income, though this is more than households are expected to contribute under current law.

percent of income) are insufficient to purchase the TFP, we present a measure of the extent of insufficiency for these households. Specifically, we compute the average dollar shortfall between the cost of the TFP and the household's benefits (plus 30 percent of income). Finally, we compare the average characteristics of households for whom SNAP is and is not sufficient to purchase the TFP.

Results

For the purposes of this report, we have condensed our main results into three tables. Table 1 displays SNAP sufficiency rates for SNAP-recipient and SNAP-eligible households for different measures of the TFP cost faced by the household. Sufficiency rates are somewhat low for households to purchase the TFP at the stores at which they report shopping. SNAP benefits allow 63-76 percent of households to afford the TFP at their primary stores (i.e., the store at which they report doing the most shopping). Households could do slightly better purchasing the TFP at their alternate store or the store nearest their census block centroid, with sufficiency rates around 70-80 percent and 69-78 percent, respectively. We note that these estimates ought to be viewed cautiously, as the sample sizes decrease substantially when we employ these TFP cost measures. This is because, for example, of the 1444 FoodAPS households who receive SNAP benefits, only 719 of them list a primary store that is also observed in the IRI data from which TFP cost measures are constructed.

On the other hand, essentially all FoodAPS respondent households are able to be linked to a store in their counties, so we view the estimates that rely on county-level TFP-cost measures as fairly robust. It is reassuring that these sufficiency rate estimates are of similar magnitude to the others we calculate. These estimates indicate that SNAP benefits are likely to be insufficient for about 20 to 30 percent of relevant households to purchase the TFP. When we examine SNAP sufficiency rates by varying the *distance* within which we assume assuming that households can shop to purchase the TFP, sufficiency rates are of similar magnitudes and monotonically increase with the distance the household is assumed to be able to travel to shop. For example, assuming households face the mean TFP cost within a 3.4-mile radius of their census block centroid (the mean distance households report traveling to shop), we find that SNAP is sufficient for 63 to 75 percent of recipient households to purchase the TFP. When that radius is extended to 20 miles, sufficiency rates for recipient households range from 71 to 78 percent.

Sufficiency rates are, of course, highest when we allow shoppers to purchase the TFP at the *minimum*-cost store within a given distance. While sufficiency rates often exceed 90 percent when shoppers are assumed to purchase the TFP at the lowest-cost store in their area, we note that it is unlikely that most shoppers are actually able to identify and travel to such a store.[6]

Finally, comparing sufficiency rates based on maximum SNAP benefit levels for households SNAP-recipient and SNAP-eligible households, we find that sufficiency rates are somewhat lower among SNAP-eligibles. A puzzling result is that the difference in sufficiency rates between net income and maximum benefits seems to be larger for eligible households than for recipient households. It is hard to know whether this is due to a characteristic of eligible households, or is merely an artifact of the simulation of benefits and eligibility.

Next, Table 2 contains estimates of the average dollar shortfall for both recipient and eligible households for whom SNAP is found to be insufficient. This is calculated using the difference

[6] Also recall that we are already imposing the assumption that within any given store, shoppers purchase TFP items with prices in the lowest quintile of prices for that TFP category.

between the benefits plus (30 percent of) income and the cost of the TFP, or between maximum SNAP benefits and the cost of the TFP.[7] We discussed previously that the sufficiency rates exhibit largely the expected pattern of decreasing as the shopping region gets smaller and smaller around the household. The size of the gaps sometimes exhibit a similar pattern, though the rule holds much less tightly. This is not surprising given that the size of the gap is an average only for the households who cannot afford the TFP (i.e., excluding households with surplus benefits or exactly equal to TFP cost), and the number of these households changes with each calculation.

For example, when we compute TFP cost as the mean among stores within certain mile radii, the average gap (using SNAP plus 30 percent of net income) goes from $159 at 20 miles to $153 at 3.4 miles, but then back down to $155 for a 2.5-mile radius. (As expected, the number of households for whom there is a gap decreases monotonically from 318 to 292.) Using maximum benefits yields a different story: the average dollar shortfall estimates are much smaller, and bounce around between $34 and $40. Shopping at the minimum-cost store within radii exhibits a monotonic increase in the size of the dollar shortfall, from $84 in a 20-mile radius to $103 in a 2.5-mile radius (using SNAP plus 30 percent of net income).

One pattern that does seem to hold strongly is that gaps for eligible household are significantly lower than for recipient households, especially when using SNAP plus net income as opposed to maximum benefits. While recipient households have gaps in the range of $150 using net income, eligible households have gaps less than half that size. This could be a result of using a simulated measure of SNAP benefits, however. When comparing gaps using maximum

[7] These gaps, in addition to the sufficiency rates shown previously, are estimated using the nationally representative survey design, but the large majority of mean estimates of gaps contain singleton observations within strata, so standard errors cannot be calculated.

benefits across the board, recipient and eligible households for whom SNAP is insufficient to afford the TFP have rather similar average dollar shortfalls.

While the absolute dollar amounts we have calculated may be of importance to policy makers, the size of these gaps relative to household's income and benefits is likely what is important to the households themselves. For the sake of illustration, consider SNAP-recipient households who cannot afford the TFP at mean area prices and face an average dollar shortfall of around $150. These households generally receive $200 to $250 in SNAP benefits per month, and report earned income of $800 to $1200 and total income of $1400 to $2100. Thus, the shortfalls are greater than half of the amount of benefits received, or over 10% of earned income and perhaps 5-10% of total income.

Lastly, Table 3 compares the characteristics of recipient and eligible households, across households for whom SNAP benefits are sufficient versus insufficient to purchase the TFP. Not surprisingly, SNAP-recipient households with benefits insufficient to purchase the TFP are significantly more likely to live in high food price areas and more likely to reside in metropolitan areas. In the case of SNAP-eligible households, they are also more likely to be low food security households, and appear to have larger families (p=0.11). Households with insufficient benefits are generally no more likely to have earned income, face trouble paying bills, contain elderly family members, or reside in specific census regions.

Discussion and conclusions

This study provides new descriptive evidence on the adequacy of SNAP benefits to purchase a low-cost, nutritious diet as specified by the Thrifty Food Plan, which is the basis for legislated SNAP benefit levels. Acknowledging that a given amount of SNAP benefits will buy less food in areas with high food prices, we estimate the fraction of SNAP households that are able to purchase the TFP at *local* prices. Using newly available FoodAPS data to answer this question, we account for geographic variation in local food prices in much finer detail than has previously been possible.

At present we use the cost of the food basket ignoring the specific week in which the basket cost was calculated and the week in which the respondent was surveyed. We are also only able to link respondents to basket prices from stores in the IRI data, which in some cases makes for small sample sizes. Further work with the local basket price data may provide additional insights and change our estimates slightly, especially for estimates based on proximity to census block group centroid.

Our main findings indicate that a substantial share (on the order of 20 to 30 percent) of SNAP-recipient households face TFP prices that are too high to be purchased with SNAP benefits plus 30 percent of income. Sufficiency rates increase monotonically as we expand the distance within which the household is assumed to be able to shop. For households who are unable to afford the TFP, average dollar shortfalls between the cost of the TFP and SNAP benefits (plus 30 percent of income) are often as large as $150 per month.

On the other hand, when shoppers are assumed to be able to purchase the TFP at the *minimum*-cost store in a 20-mile radius, SNAP benefits are sufficient for nearly all recipient households to do so. Whether it is reasonable to assume that households are able to identify and travel to the minimum TFP-cost store in their areas is an open question.

A related question that we have not yet explored is whether SNAP benefits are also overly *generous* in areas with relatively low food prices. If so, one interpretation of our results would be that SNAP benefit levels should be more directly indexed to local food prices. Even without directly tying benefit levels to local food prices, policy makers could better adjust SNAP benefits for local food prices by increasing the generosity of existing deductions for costs associated with housing, earnings, child care, and medical care, all of which are likely to correlate positively with local food price.

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Table 1
Sufficiency Rates of SNAP to Purchase the Thrifty Food Plan (TFP)

	SNAP Recipient Households		**SNAP Eligible Households**	
TFP Cost Calculation	*SNAP plus 0.30*Net Income*	*SNAP Max Benefit*	*Simulated SNAP plus 0.30*Net Income*	*SNAP Maximum Benefit*
Primary Store (N=719, 1220)	0.76	0.63	0.91	0.57
Alternate Store (N=549, 850)	0.80	0.70	0.92	0.65
Avg. of Primary and Alternate (N=981, 1641)	0.77	0.69	0.92	0.63
Nearest store (N=853, 1313)	0.78	0.69	0.92	0.62
Mean				
County (N=1431)	0.77	0.76	0.97	0.67
20-mile radius (N=1325, 2221)	0.78	0.71	0.91	0.68
10-mile radius (N=1275, 2140)	0.78	0.71	0.92	0.67
5-mile radius (N=1186, 1990)	0.76	0.67	0.90	0.60
3.4-mile radius (N=1140, 1920)	0.75	0.63	0.89	0.58
2.5 mile radius (N=1094, 1841)	0.75	0.58	0.88	0.54
5 nearest stores (N=1265, 2101)	0.74	0.62	0.90	0.59
2 nearest stores (N=1069, 1777)	0.76	0.64	0.90	0.58
Median				
County (N=1431)	0.79	0.74	0.98	0.70
20-mile radius (N=1325, 2221)	0.77	0.64	0.91	0.64
10-mile radius (N=1275, 2140)	0.76	0.65	0.91	0.61
5-mile radius (N=1186, 1990)	0.75	0.64	0.90	0.56
3.4-mile radius (N=1140, 1920)	0.75	0.65	0.90	0.58
2.5 mile radius (N=1094, 1841)	0.75	0.61	0.89	0.54
5 nearest stores (N=1265, 2101)	0.76	0.64	0.90	0.60
2 nearest stores (N=1069, 1777)	--	--	--	--
Minimum				
County (N=1431)	0.94	1.00	1.00	0.71
20-mile radius (N=1325, 2221)	0.95	1.00	1.00	1.00
10-mile radius (N=1275, 2140)	0.94	0.99	0.99	1.00
5-mile radius (N=1186, 1990)	0.92	0.99	0.99	0.99
3.4-mile radius (N=1140, 1920)	0.91	0.99	0.99	0.99
2.5 mile radius (N=1094, 1841)	0.89	0.99	0.99	0.98
5 nearest stores (N=1265, 2101)	0.89	0.97	0.98	0.95
2 nearest stores (N=1069, 1777)	0.86	0.92	0.97	0.88

Note: Table contains sufficiency rate for SNAP benefits to purchase TFP for SNAP-recipient and SNAP-eligible households. Benefits are self-reported for SNAP-recipient households. Benefits are imputed for SNAP-eligibles using using gross and net income and maximum benefit for family size. All estimates are population weighted.

Table 2
Average Dollar Shortfalls between SNAP (plus 30% of income) and Cost of the Thrifty Food Plan (TFP)
(Sample: Households for whom SNAP is insufficient to purchase TFP)

	SNAP Recipient Households				SNAP Eligible Households			
TFP Calculation	*SNAP plus 0.30*Net Income*	*# of Households*	*SNAP Max Benefit*	*# of Households*	*Simulated SNAP plus 0.30*Net Income*	*# of Households*	*SNAP Maximum Benefit*	*# of Households*
Primary Store	$118	173	$41	255	$60	127	$41	430
Alternate Store	$155	106	$49	157	$48	87	$45	282
Avg. of Primary and Alternate	$127	224	$42	282	$51	151	$40	495
Nearest store	$150	199	$56	261	$61	130	$41	473
Mean: County	$151	367	$51	414	$73	240	$34	704
Mean: 20-mile radius	$159	318	$34	402	$44	226	$26	648
Mean: 10-mile radius	$158	313	$40	389	$56	201	$32	613
Mean: 5-mile radius	$155	309	$38	403	$58	209	$31	657
Mean: 3.4-mile radius	$153	306	$40	431	$63	212	$35	717
Mean: 2.5-mile radius	$155	292	$40	444	$61	227	$36	709
Mean: 5 nearest stores	$146	326	$47	488	$57	247	$36	759
Mean: 2 nearest stores	$142	268	$53	386	$60	207	$42	681
Median: County	$143	337	$19	380	$32	197	$17	649
Median: 20-mile radius	$139	332	$18	453	$29	223	$20	743
Median: 10-mile radius	$140	316	$20	463	$34	212	$23	755
Median: 5-mile radius	$144	307	$23	445	$42	203	$27	762
Median: 3.4-mile radius	$145	289	$26	387	$43	200	$29	675
Median: 2.5-mile radius	$149	281	$29	431	$47	218	$31	741
Median: 5 nearest stores	$144	310	$33	444	$48	229	$31	768
Median: 2 nearest stores	--	--	--	--	--	--	--	--
Minimum: County	$78	68	$135	6	$103	9	$109	4
Minimum: 20-mile radius	$84	66	--	0	$70	4	--	0
Minimum: 10-mile radius	$91	82	$11	5	$48	8	$12	6
Minimum: 5-mile radius	$101	94	$11	5	$42	9	$11	7
Minimum: 3.4-mile radius	$103	104	$11	5	$46	12	$30	12
Minimum: 2.5-mile radius	$103	115	$22	7	$44	15	$36	17
Minimum: 5 nearest stores	$112	144	$25	39	$52	33	$31	85
Minimum: 2 nearest stores	$105	162	$30	100	$52	52	$33	175

Note: Table contains average dollar shortfalls for households that for whom SNAP (plus 30 percent of income) or maximum SNAP benefit is insufficient to purchase the TFP. Benefits are self-reported for SNAP-recipient households. Benefits are imputed for SNAP-eligibles using using gross and net income and maximum benefit for family size. All estimates are population weighted.

Table 3
Average Characteristics of Households by SNAP Sufficiency

	SNAP Recipient Households			**SNAP Eligible Households**		
	No	Yes	p-value	No	Yes	p-value
Family Size	2.78	2.64	0.41	2.52	2.21	0.11
Household has earned income	0.50	0.53	0.60	0.60	0.55	0.20
Household has elderly	0.30	0.27	0.40	0.38	0.37	0.83
Nonmetro area	0.03	0.17	0.01	0.03	0.17	0.02
Metro area	0.97	0.83	0.01	0.97	0.83	0.02
High food security household	0.34	0.32	0.50	0.45	0.50	0.45
Marginal food security household	0.25	0.21	0.25	0.23	0.19	0.14
Low food security household	0.24	0.26	0.59	0.21	0.16	0.08
Very low food security household	0.18	0.21	0.39	0.11	0.16	0.02
Trouble paying bills	0.30	0.28	0.49	0.18	0.17	0.83
High price area	0.88	0.00	0.00	0.90	0.00	0.00
Northeast	0.22	0.09	0.25	0.29	0.09	0.13
Midwest	0.24	0.34	0.33	0.16	0.35	0.05
South	0.33	0.43	0.25	0.32	0.42	0.34
West	0.21	0.14	0.49	0.22	0.14	0.40

Note: Table contains characteristics of households by SNAP sufficiency and a p-value of the test of the difference, separately for SNAP recipients and SNAP eligible HH. Benefits are all calculated using maximum benefit for family size. Eligibility is estimated using model 4. All estimates are population weighted.

Cost of living, healthy food acquisition, and the Supplemental Nutrition Assistance Program

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Abstract

We tested the hypothesis that high costs of living, such as from high housing rents, reduce the healthfulness of food acquisitions. Using the National Household Food Acquisition and Purchase Survey (2012-13), we examined the relationships between cost of living and food acquisition patterns among both SNAP participants and non-participants (N = 5,414 individuals from households participating in SNAP, 3,863 individuals from non-participating households <185% of the federal poverty threshold, and 5,036 individuals from non-participating households ≥185% of the federal poverty threshold). Indices for cost of living included county-level Regional Price Parities for major classes of expenditures and the geographic adjustment to the Supplemental Poverty Measure, which is based on rent prices. We regressed the cost of living indices against measures of food acquisitions per person per day in each of several standard food categories, controlling for individual-, household-, and county-level characteristics. Using endogenous treatment effects models to potentially address unmeasured confounders influencing both the propensity to live in high-cost areas and patterns of food acquisition, we observed that higher area-level costs of living were associated with less healthy food acquisitions, including significantly fewer acquisitions of vegetables, fruits, and whole grains, and significantly greater acquisitions of refined grains, fats and oils, and added sugars. Overall, living in a high-cost area was associated with an 11% reduction in the Healthy Eating Index—a composite nutritional index previously associated with obesity, type II diabetes, and all-cause mortality. Additionally, we found that SNAP participation was associated with a significantly improvement in the healthfulness of food acquisitions among persons living in high-cost counties.

Executive Summary

A recent Institute of Medicine report raised the question of whether Supplemental Nutrition Assistance Program (SNAP) benefits should be adjusted for geographic variations in the cost of living, including variations in the cost of food, to promote nutrition among low-income Americans (1). Substantial existing literature in the fields of sociology, economics, and epidemiology has highlighted the trade-offs that low-income Americans face when attempting to pay for foods, such as having to sacrifice food budgets to pay for heating bills or medical care costs (2, 3).

Here, we sought to test the following three key hypotheses relating the cost of living to the healthfulness of food acquisitions: (i) first, a higher area-level cost of living is associated with less healthy food acquisitions (which we define as lower Healthy Eating Index [HEI] scores, particularly from lower acquisition of fruits and vegetables and higher acquisition of refined grains and added sugars); (ii) second, SNAP participation is associated with living in a lower-cost area after accounting for other observed and unobserved covariates related to both SNAP and area of living (because the value of a SNAP dollar would be more in a lower-cost area, thus incentivizing enrollment); and (iii) third, any association between SNAP participation and the healthfulness of food acquisitions (i.e., HEI scores) is moderated by area-level cost of living (i.e., SNAP would have differential benefits to nutrition among areas with different costs of living).

To test these hypotheses, we utilized data from the National Household Food Acquisition and Purchase Survey (2012-13; *N* = 5,414 SNAP participants, 3,863 SNAP-eligible non-participants <185% of the federal poverty threshold, and 5,036 ineligible non-participants

≥185% of the federal poverty threshold), which we linked to data on the cost of living computed by the Bureau of Economic Analysis (Regional Price Parities for major classes of expenditures) and by the U.S. Census Bureau (geographic adjustments to the Supplemental Poverty Measure). These indices of cost of living were chosen because they are routinely updated and therefore theoretically available to agencies that wish to regularly adjust benefit allotments from safety net programs for area cost of living; we studied these cost indices at the county-level, as the county area typically includes the primary food store of purchasing for most FoodAPS participants (4), unlike smaller areas of analysis, and has readily available social and economic covariate statistics that capture important area-level variations in food availability, unlike larger areas of analysis.

Because there are potentially several unobserved or unmeasured confounders that may relate to SNAP participation, the propensity to live in a higher- or lower-cost area, and the healthfulness of food acquisitions, we used endogenous treatment effects models to test our hypotheses. These models utilize a control function approach to minimize the influence of endogeneity on estimates of the effects of an exposure on an outcome, such as the effect of living in a high-cost area on the HEI score.

We found evidence consistent with our first hypothesis—that higher area-level cost of living was associated with less healthy food acquisitions. We defined a high cost of living area as being more than one standard deviation above the mean cost measured by either a regional price parity or the geographic adjustment to the Supplemental Poverty Measure. We found that living in a high-cost of living area was associated with significantly fewer acquisitions of vegetables, fruits, and whole grains, and was associated with significantly greater acquisitions of refined grains, dairy products, protein, fats and oils, and added sugars. This finding was observed no matter which metric we chose for the area-level cost of living: overall regional price parity, rent/housing cost regional price parity, food regional price parity, regional price parities for goods or for services, or the geographic adjustment to the Supplemental Poverty Measure. Having controlled for individual-level factors such as education level, household-level factors such as income, and county-level factors such as food availability, the estimated effect of living in a high-cost county reduced the overall HEI score by approximately 11%. Clinically-speaking, this observed decrease in HEI is larger than those associated with a significantly increased risk of cardiovascular disease, type II diabetes, and all-cause mortality. Hence, we would expect such effects to be meaningful to public health.

Importantly, we observed that the cost of living metric for food was not necessarily the most predictive of changes in the healthfulness of food acquisitions, perhaps because significant expenditures in other domains of life greatly influence the food budget. For the overall nutritional metric of HEI score, higher rent costs were more strongly associated with reduced healthiness of food acquisitions than higher food indices. This is an important result for policymakers who may need to choose metric of overall cost of living rather than only food costs when considering whether SNAP benefits should be adjusted for local-area cost of living.

Our further subgroup analyses examining the relationships between area-level cost of living and food acquisitions revealed that low-income (<185% of the federal poverty threshold) SNAP non-participants were more sensitive to overall cost of living metrics than SNAP participants net of other individual-, household- and county-level covariates, consistent with the idea that SNAP participation itself buffers the negative impact of high living costs on nutrition. In our analytical sample, low-income non-participants had lower income than SNAP participants, contrary to the idea that eligible non-participants are those who would typically receive the least SNAP benefits. This indicates that encouraging SNAP participation among eligible non-participants may be particularly beneficial to buffering low-income populations from negative nutritional effects of living in high-cost areas.

We rejected our second hypothesis that SNAP would be associated with living in a lower-cost area. Rather, receiving SNAP was associated with a significantly increased probability of living in a high-cost area. One theory is that SNAP participation, by increasing economic mobility, may permit low-income households to live in environments where they would otherwise be "priced out". Alternatively, the association may be indicative of reverse causality: that living in a high-cost area induces eligible populations to enroll in SNAP because the additional SNAP dollars are vital to survival.

In testing our third hypotheses, we found that SNAP was associated with no significant on the healthfulness of food acquisitions in lower-cost areas, because increased fruit and vegetable acquisitions and lower refined grain acquisitions attributable to SNAP participation were counterbalanced by increased acquisitions of fats and oils as well as added sugars. Overall, SNAP increased calories but did not disproportionately increase "unhealthy" calories; hence, SNAP had a statistically-neutral impact on HEI scores in lower-cost areas. By contrast, while individuals had a worse dietary profile in higher-cost areas, as discussed above, SNAP was associated with improved nutrition in such areas—permitting greater acquisitions of vegetables and fewer refined grains, with fewer adverse compensation from increased fat and oil or added sugar acquisitions. One theory to explain these findings may be that in a higher-cost environment, SNAP dollars are used disproportionately to assist households in acquiring those foods that are most out of reach due to high perceived or real prices. This finding may also be a commentary on the nature of the food acquisition environment in lower-cost counties; if lower-cost counties indeed have environments saturated with less-healthy foods, as suggested in the public health literature, SNAP participation may have limited effects on the healthfulness of food acquisitions because the unhealthy food environment overwhelms any potentially beneficial effects of SNAP.

Our findings do not necessarily imply that a cost of living adjustment using currently available county-level cost of living metrics would improve the healthfulness of food acquisitions among SNAP participants currently living in lower-cost areas. However, our findings imply that SNAP participation is associated with living in a higher-cost area, and that SNAP participation is associated with improved nutrition in those areas. If SNAP participation is associated with living in higher-cost areas because SNAP increases economic mobility, then additional benefits might accrue to low-income populations given a cost-of-living adjustment. The existing sociology literature suggests that higher-cost areas that are typically lower in poverty may have substantial health benefits for low-income individuals who move to such areas. However, if SNAP benefits are reduced by cost of living adjustments among those populations living in lower-cost areas, it is possible that SNAP participation would be discouraged, or that SNAP would no longer have a neutral association with nutrition, but have rather a negative association, especially, if such benefits become disproportionately used on fats and oils or added sugars. A direct experiment or pilot study involving cost-adjusted SNAP benefits would help shed light on the effects of benefit modification on living costs and healthy food acquisitions.

Introduction

Food insecurity among low-income Americans has been associated with poor nutrition, an increased risk of major nutrition-related chronic diseases, and poor clinical outcomes for patients with chronic diseases such as hypertension and type II diabetes (5–8). It is believed that low-income Americans faced with food insecurity often engage in economic trade-offs—sacrificing their food budgets to pay for major living expenditures, such as rent or other housing costs, or medical bills (2,3). Potentially as a result of such trade-offs, foods purchased by low-income Americans tend to be of lower nutrition value, in part because perceived or real prices of healthier food items such as fruits and vegetables are often higher than those of calorie-dense, nutrient-poor food items, which primarily contain refined grains and added sugars (9). Furthermore, in the context of rising economic inequality, many low-income Americans live in areas where neighborhood living costs are driven higher by inflated housing and food prices, even as real wages have lagged behind (10). As a result, neighborhood-level cost of living has increased for many low-income American households (particularly as housing costs have increased as a proportion of income (11)) potentially putting further pressure on food budgets among the lowest-income households (12).

Extensive prior studies have associated local-area food availability and food costs with poor nutrition and nutrition-related health outcomes (for recent systematic reviews of this very large literature, see (13,14)). To assist in improving nutrition among the food insecure, the nation's largest nutritional assistance program—the Supplemental Nutrition Assistance Program (SNAP)—currently provides assistance to nearly 1 in 7 Americans (15). SNAP has been extensively studied for its effects on nutritional purchasing and nutrition-related health outcomes, with variable results. Some highly publicized prior research studies have associated SNAP participation with obesity and poor nutritional metrics (16,17), although these findings have not been consistently robust to alternative statistical specifications—particularly when unmeasured confounders (i.e., unobserved factors that may be correlated to both SNAP participation and poor nutrition) are considered (18,19). Area-level cost of living is among one of the key correlates of food insecurity for which data have been previously very limited, and to our knowledge the relationships between overall area-level cost of living, SNAP participation, and the healthfulness of food acquisitions have not been studied.

The relationships between these factors are of particular interest because SNAP benefits are currently set based on a national estimate of the cost of living (rather than local-area costs). SNAP benefits are calculated by subtracting from a maximum monthly benefit, which is based on household size and fixed across the contiguous 48 states and the District of Columbia (while set to slightly higher levels in Alaska and Hawaii), from which 30% of net income is subtracted to determine an individual participant's benefit (20). The maximum monthly benefit is given by the cost of the Thrifty Food Plan (TFP), which is a model-based estimate of the average national cost of a market basket of low-cost foods that would permit participants to achieve some components of national dietary guidelines on a limited budget. Net income is based on gross income (most private income and some transfer income) minus deductions based on national thresholds for major living costs including official child support payments, a standard deduction based on household size, a high-cost shelter deduction, and an out-of-pocket medical cost deduction for the elderly and disabled. Some prior adjustments to SNAP benefits have occurred, as legislation in 1988 increased the TFP by 3% to reflect time-lags in how quickly the national cost of living adjustment was implemented between its calculation and its reflection in actual payments to beneficiaries; the 3% increase was later eliminated (21). More recently, as part of the post-recession American Recovery and Reinvestment Act of 2009, a 13.6% increase was added to the TFP for most households, which expired in 2013 (22). To our knowledge, studies of the 1988 adjustment on food security or nutritional outcomes are unavailable, but a study of the more recent 2009 increase reported that "the food security of low-income households (those with incomes in the eligible range for SNAP) improved from 2008 to 2009, and a substantial share of that improvement may be due to the increase in SNAP benefits implemented under ARRA" (23). Early studies of this change suggest that Medicaid costs in Massachusetts reduced during the ARRA stimulus (24), potentially as fewer low-income households experienced the complications of chronic disease associated with food insecurity (e.g., hypoglycemia among people with diabetes (25)).

In considering the relationships between cost of living and SNAP benefits, it is noteworthy to understand prior assumptions and data availability concerning living costs. The maximum SNAP benefit is adjusted each year in October based on Consumer Price Indices (CPIs) for 29 food categories included in the TFP that have a CPI for each age- and sex-group in the country (26). To disaggregate costs of living or food to local areas would require further sub-national data. Yet, the Bureau of Labor Statistics that produces CPIs does not provide an official CPI measure or measures for the TFP for different areas of the country at a sufficient scale. Monthly CPIs are available for only three large metro areas, bimonthly CPIs for 14 metro areas, semiannual CPIs for 26 metro areas, and CPIs for 362 metropolitan statistical areas have annual data (27). Hence large areas of the contiguous U.S. states may substantially differ in their costs of living, or at least in food costs, to warrant a nationally-based cost input to the TFP, but CPI data area unavailable for them. This dilemma was addressed when the U.S. Department of Agriculture produced the Quarterly Food-at-home Price Database in 2011, which provided retrospective estimates of prices in 26 metropolitan and 9 nonmetropolitan areas from 1999. The Quarterly Food-at-home Price Database required extensive matching and reconstruction of variables from corporate databases obtained from consumer purchasers (e.g., the Nielsen Homescan Data) to translate prices into standard comparable quantities, forbidding the effort from becoming a routine annual exercise from which to adjust the TFP (28). We discuss this limitation and a potential strategy to overcome it below, where we discuss the recent availability of Regional Price Parity (RPP) statistics from the Bureau of Economic Analysis.

Nevertheless, the Quarterly Food-at-home Price Database and its underlying Nielsen Homescan Data do reveal substantial geographic variations in food prices across the nation, as detailed in several papers from the USDA's Economic Research Service (29–31). One study by Todd and colleagues found that although healthy foods were not universally more expensive than less healthy foods, there was great variation in healthy food prices across the country (30). For example, whole grains were almost always more expensive than refined grains across the country; but the price variation ranged from 23% higher in San Francisco to >60% higher in nonmetropolitan Pennsylvania and New York. Similarly, fresh and frozen dark green vegetables were more expensive than starchy vegetables across the country, but prices varied from 20% higher to 80% higher. Furthermore, Gregory and Coleman-Jensen observed that the variations in food price related to variations in food security, such that one standard deviation increase in food prices was associated with a 5.0% increase in the prevalence of adult food insecurity (32).

These variations are unlikely to be sufficiently accounted for by the existing TFP formula. Prior studies in Boston and Philadelphia suggest that the TFP is unlikely to provide sufficient benefits to meet the intended nutritional standards in some urban areas. For example, a study in 2008 based on surveys of TFP-based food lists reported that a family of four receiving its maximum SNAP benefit would require an additional $2,520 in metropolitan Boston and $3,165 in metropolitan Philadelphia each year to purchase foods that meet the TFP's nutrition goals; these quantities are approximately 40% to 50% greater than the maximum annual benefit as of 2008 (33). Notably, many of the TFP food items (16-38%) were also unavailable at surveyed stores.

Despite the fact that the national standard for cost of living adjustment may not account for such food price differences and food availability differences, there are some implicit area-level adjustments in the SNAP benefit formula. Two major deductions available to working SNAP participants include a 20% deduction of earnings from gross income, which implicitly accounts for wage variation across local labor markets (34), and a dependent care deduction which permits direct costs of dependent care including transportation and copayments for fees to be deducted, implicitly accounting for childcare cost variations across geographic areas (35). For the elderly and disabled, out-of-pocket medical cost deductions may additionally alter the impact of regional medical spending variations (36). The deduction for child support payments may account for state differences in child support awards (37). Finally, the inclusion of income from other safety net programs (such as Temporary Assistance for Needy Families, or TANF) may adjust benefits in the opposite direction, by reducing the size of the SNAP benefit. Because TANF is larger in higher-cost states (e.g., California, New York), adjustment for TANF benefits may effectively “tax” SNAP benefits for those living in high-cost states.

In reviewing this information, an Institute of Medicine Panel assembled in 2013 to assess the adequacy of SNAP benefits concluded: “Because most of the geographic differences in cost of living in the SNAP benefit formula are implicit rather than explicit, the question arises of whether making the adjustment more direct would facilitate definition of the benefit’s adequacy…The challenge of implementing geographic cost-of-living adjustments is that at present, BLS [the Bureau of Labor Statistics] does not produce a regional price index…adjusting the maximum benefit geographically for differences in cost of living (or even food) is likely to be infeasible until further progress is made on regional price indices” (1).

Since the publication of the Institute of Medicine panel report, regional price indices have been produced and disseminated by the Bureau of Economic Analysis (BEA) and the U.S. Census, to assist in meeting the challenge of defining small area-level cost of living indices that can be routinely updated to adjust benefit formulas such as the TFP. The BEA has constructed regional price parities (RPPs), which are price indices measuring the price level differences across regions for a given time period by dividing the average price of goods or services in an area (typically a metropolitan statistical area, county, or state) by the national average price across all areas (38,39). The national average is set to a value of 100 such that an area’s RPP can be interpreted as a percent of the national average, e.g., all goods and services in New York State are 14.1% higher than the national average, so New York State has an RPP of 114.1. To derive the RPP index, the BEA obtained price and expenditure levels of individual goods and services in 16 expenditure classes (apparel, rents, and a goods class and a services class in each of the categories of: education, food, housing excluding rents, medical, recreation, transportation, and other), which are further subdivided into strata (e.g., “major appliances”, under “goods”) and elementary level items (e.g., “refrigerators and freezers”, under “major appliances”), and clusters (e.g., “refrigerators”, under “refrigerators and freezers”). The prices for rents are obtained from the American Community Survey, while the prices for other goods and services are estimated from expanded BLS data obtained from product sellers, as is done to construct CPIs. The individual price observations (~1 million observations per year) include hundreds of consumer goods and services, often including multiple quotes for the same product from multiple sellers. The geometric average of the prices for each type of good, specific to outlet type and unique product, is then taken and linked to expenditure weights designed to reflect the distribution of personal consumption expenditures in a geographic area (40). Expenditures for rents account for the largest weighted share of expenditures (~43% of total expenditures), and variation in rents are greater than that of any other expenditure class nationally. The data are then allocated to counties, such that the RPP methodology implicitly ignores within-county variations in price; for goods and services other than rents, the methodology effectively ignores variations across counties within a BLS index area from which BLS consumer purchasing datasets are not further disaggregated (e.g., RPPs in Jefferson county (WV), in Prince George’s county (MD), and in Alexandria City (VA), are effectively assumed to be the same as the average in the entire Washington-DC-MD-VA-WV area, because this region is a single BLS area). Finally, the data are subjected to hedonic regressions, which attempt to account for variations in characteristics of goods and services provided, including differences in packaging, unit size, and type of outlet from which they are sold, to assemble an aggregate index of cost in each item stratum. Hedonic regressions take into account consumer preference variations by area (e.g., apples may be a preferred fruit in one county, and oranges in another, so food regional price parities will account for variations in fruit preferences by location, rather than only comparing apple prices across all areas). An outlier analysis is performed to exclude extreme values, and missing data are imputed in some locations with limited input data. Estimation details have been extensively catalogued previously (38,39).

While the RPPs produced by the BEA have been newly constructed, the U.S. Census Bureau had previously assembled another metric of area cost of living: the geographic adjustment to the Supplemental Poverty Measure (41). In 1990, Congress appropriated a budget for an independent scientific study of the measurement and data for a poverty measure, with which the National Academy of Sciences established the Panel on Poverty and Family Assistance (42). Though the Panel released a report in 1995 discussing the need for a new measure to supplement the official poverty measure and account for a broad array of challenges faced by households in poverty, it was not until 2010 that the Interagency Technical Working Group on Developing a Supplemental Poverty Measure provided further details sufficient to incorporate a new measure into the Current Population Survey (CPS) to both produce a Supplemental Poverty Measure that captures a broad array of improvements to the poverty measure, including geographic adjustment of poverty thresholds for cost of living (43). The latter improvements are based on geographic differences in rental costs in the American Community Survey (ACS). The ACS now provides sufficient information on differences in rental prices across geographic areas, based on 5-year estimates of median gross rents for two-bedroom apartments with complete kitchen and plumbing facilities. Hence, this "geographic adjustment to the Supplemental Poverty Measure" is less comprehensive than the BEA's RPPs and is primarily reliant on housing costs, which are generally the largest expenditure for low-income households (11). Separate medians are estimated for each of 271 metropolitan statistical areas large enough to be identified on the public-use version of the CPS data file. For each state, a median is estimated for all nonmetropolitan areas and for a combination of all smaller metropolitan areas, producing 385 adjustment factors (41).

Given the availability of both RPPs and the geographic adjustment to the Supplemental Poverty Measure, we sought to test three key hypotheses relating the cost of living to the healthfulness of food acquisitions. Our *first hypothesis* was that a higher area-level cost of living would be associated with less healthy food acquisitions (which we define as lower Healthy Eating Index-2010 [HEI] scores, particularly from lower acquisition of fruits and vegetables and higher acquisition of refined grains and added sugars). The rationale for this first hypothesis was that higher cost of living would induce individuals to sacrifice food budgets for other costs such as rent, and that in many areas the perceived or real costs of healthier food items would be higher than those of less healthy items, such that lower overall food budgets would induce less healthy food acquisitions. Our *second hypothesis* was that SNAP participation would be associated with living in a lower-cost area after accounting for other observed and unobserved covariates related to both SNAP and area of living. The rationale for this second hypothesis was that SNAP benefits are adjusted based on national average cost of living indices, not local data, so the purchasing power of a SNAP dollar would be higher in lower food-cost areas, where overall cost of living is typically lower as well. Our *third hypothesis* was that any association between SNAP participation and the healthfulness of food acquisitions (i.e., HEI scores) would be partially moderated by area-level cost of living. The rationale for this third hypothesis is that SNAP participation itself may lead to changes in the healthfulness of food acquisitions (e.g., SNAP benefits may lead to the ability to purchase more fruits and vegetables, which are generally thought to be more expensive products), but the degree to which SNAP dollars affect the healthfulness of food acquisitions may be influenced both by food costs in the area, and by costs of living including expenditures that compete with the food budget (e.g., rent) and affect how much SNAP users are able to supplement their SNAP allotments with other sources of income.

All three of our hypotheses have genuine scientific equipoise, as reasonable alternative hypotheses are available for each. Specifically, an arguable alternative to our first hypothesis is that a higher area-level cost of living will be associated with more healthy food acquisitions, due to self-selection of highly health-conscious persons to live in more costly areas that have real or perceived increased availability of healthier foods, and real or perceived social norms favoring healthier food consumption. Similarly, an alternative to our second hypothesis is that higher-cost areas would be associated with greater SNAP participation because people in such areas would be more desperate for funds to supplement their budgets. Finally, an alternative to our third hypothesis is that any association between SNAP participation and the healthfulness of food acquisitions is not significantly moderated by area-level cost of living, as the latter may be irrelevant or have only a weak effect if SNAP participants compartmentalize their food budget from other budgets.

Methods

We tested our hypotheses using newly-available data from the National Household Food Acquisition and Purchase Survey (2012-13) made available by the U.S. Department of Agriculture, which is the first nationally representative survey of American households to collect comprehensive data about household food purchases and acquisitions (44).

Details on the data source

The National Household Food Acquisition and Purchase Survey, or FoodAPS, is a unique household-level food survey that details food-at-home (FAH) and food-away-from-home (FAFH) purchases and acquisitions among a national sample of households, each surveyed for one week during the period April 2012 to January 2013. Households were defined as all persons who live together and share food and who expect to be present at the sampled address during at least part of the data collection week. The survey design attempts to be representative of non-institutionalized households nationally, as well as representative of four subgroups: SNAP participants, and nonparticipant households in three income groups (income below the federal poverty threshold for household size; incomes equal to or greater than 100 percent of the federal poverty threshold but less than 185 percent; and income greater than or equal to 185 percent of the federal poverty threshold). The sample of households was selected through a multi-stage sample design limited to the contiguous United States, with oversampling of SNAP-participating and other low-income households. Within a stratified sample of 50 counties or groups of contiguous counties selected as Primary Sampling Units through probability proportional to size selection, eight secondary sampling units of a census block group or group of contiguous block groups were selected. Among these secondary sampling units, households were screened for eligibility, and a total of 4,826 households containing 14,317 individuals participated in the survey.

During screening for participation, a primary respondent in each household was identified as the main food shopper or meal planner, and was asked to complete two in-person interviews and to call the study's telephone center for three brief telephone interviews regarding food acquisition events over the course of one week. In addition, each household member 11 years or older was asked to track and report all food acquisitions during the week in specially-prepared booklets distinguishing between food and drink brought home and used to prepare meals for consumption at home or elsewhere (e.g., sandwich made at home and brought to work), which constituted FAH, and food and drink obtained and consumed away from home, and prepared foods brought home or delivered (e.g., pizza), which constituted FAFH. The booklets also enabled participants to enter detailed information about food acquisition "events", including location, date, and payment types. Households scanned barcodes on packaged foods and submitted receipts from stores and restaurants, which enabled independent confirmation of reports. Variable-weight items (e.g., a head of lettuce or individual apples) and other items without a barcode were also included by enabling respondents to scan barcodes from a standardized food barcode book or write item details of foods not coded. Post-collection processing included resolution of inconsistencies through receipts and imputation where possible, as detailed elsewhere (45). To enable nutritional analyses, individual food items were matched to items in the USDA Food and Nutrient Database for Dietary Studies or the USDA National Nutrient Database for Standard Reference (46,47).

Additional data collection in FoodAPS included detailed demographic, socioeconomic and nutrition-related information about each household. This information included SNAP participation status in the prior 30 days, determined by both participant self-report and matches to USDA administrative records for confirmation of SNAP participation or non-participation among the 97.5% of respondents who consented to the administrative match. When administrative match was not consented to or no match was found, participant self-report of SNAP participation status was taken at face value. Of note, FoodAPS identified households in which anyone received SNAP, but did not try to identify who within each household received SNAP, under the premise that household members would typically share SNAP benefits.

In addition to SNAP participation, FoodAPS data collection included self-reported information about the primary store at which the household did most of its food shopping, the typical mode of transportation used to get to that store, and type of store (e.g., supercenter, grocery store, convenience store). Locations of SNAP-authorized stores were geocoded and distances from the households to the nearest SNAP supermarket or supercenter, as well as distances to the primary food store were recorded. Euclidean distance (straight line) estimates were our primary distance metric, as these are more standardized than driving and walking route estimates. Additional self-reported WIC participation by any member of the household and food security status based on the 10 questions used to assess household food security status in USDA's 30-day Adult Food Security Scale were also asked, as were standard Census-type questions regarding participant demographics and socioeconomic characteristics including education and employment (48).

Each household was given a sampling weight, based on reported SNAP participation status revised per the administrative data match, to make the sample nationally representative of all non-institutionalized households in the contiguous United States and account for differential probability of selection and nonresponse. Weights were stratified to replicate 2013 Current Population Survey Annual Social and Economic Supplement estimates of the number of households in the United States and the distribution by demographic and economic characteristics using iterative proportional fitting for Hispanic status, race, annual income, receipt of SNAP, poverty status, household size, number of children in the household, and presence of least one person age 60 or older in the household. Weights were trimmed to reduce design effect.

Data organization, variable construction, and choice of outcome metrics.

To perform our assessment, we first constructed estimates of household-level food acquisition, expressed in both kilocalories (kcals) and in food pattern equivalents units (ounce-equivalents, oz-eq, or cup-equivalents, cup-eq) per household per day. Specifically, we used estimates of the kilocalories per 100 grams and food pattern equivalents per 100 grams contained in each food product, provided in the FoodAPS, which were estimated by the USDA by matching individual food items to records in the Food Patterns Equivalents Database (2011-2012) and Food Patterns Ingredients Database, supplemented by the School Nutrition Dietary Assessment Study for foods obtained from reimbursable school lunch and breakfast meals (49,50). We multiplied kilocalories per 100 grams or food pattern equivalents per 100 grams by the estimated volume (in 100-grams, unrounded to include exact decimals) of each product, also estimated by the USDA and provided in FoodAPS for both at-home and away-from-home food acquisition events based on participant-reported descriptions of food and/or product database estimates of the edible portion of each scanned food item. We summed the total kilocalories and total food pattern equivalents acquired per household across all events over the entire 7-day survey period, then computed the average total kilocalories as well as the food pattern equivalents per household member per day in the eight food categories assembled from the classification system in the National Food and Nutrient Database for Dietary Studies, version 5.0 (2012): (i) vegetables (total dark green, red and orange, starchy vegetables, and legumes counted as vegetables); (ii) whole fruits and 100% fruit juices; (iii) whole grains; (iv) refined grains; (v) dairy products (milk, yogurt, cheese, and whey); (vi) proteins (meat, poultry, seafood, eggs, soy, nuts, seeds, and legumes counted as protein); (vii) solid fats and oils; and (viii) added sugars. Individual-level estimates accounted for the number of household members and non-household guests among whom the food item was reported to be shared; however, the FoodAPS survey only contained information on acquisitions, not on consumption (i.e., the data are not dietary recalls), hence we cannot account for intra-household variations in consumption, food preparation, or food waste.

As an overall dietary quality metric, we computed a Healthy Eating Index (HEI, version 2010) for each individual. The HEI is a widely-used metric of overall dietary quality, which has been correlated to cardiovascular disease and cancer risk in longitudinal cohort studies of diet and health. A key advantage of HEI is that it is constructed to assess dietary quality through universal standards and a density approach (e.g., nutrients per 1000 calories) that can be applied and compared at all levels of the food system—from farm to supermarket to individual—and at all levels of production or consumption—from manufacturer to neighborhood availability to food acquisition to dietary intake. Hence, the Index has been applied, for example, to assess the dietary quality of neighborhood food environments, individual restaurant menus, supermarket sales circulars, and food purchases among food assistance program participants (51–57). At the time of this writing, the HEI-2010 was the most recently-available year of the Index, corresponding to the Dietary Guidelines for Americans, 2010 (58). The more recent Guidelines (released 2016, but recommended for years 2015-2020) are mostly concordant with the 2010 Guidelines, but additionally recommend reducing meat intake among adult males, and limiting intake of added sugars (59). The HEI-2010 is a composite score from 0 to 100 indicating the concordance of, in our case, food acquisitions per person per day, to the 2010 Dietary Guidelines for Americans; a score of 50 would indicate that the quality of an individual's food acquisitions are only half as high as recommended. The score is constructed from 12 food categories and nutrient components by adding points for foods considered health-promoting per the 2010 Guidelines (total fruit, whole fruit, total vegetables, greens and beans, whole grains, dairy, total protein foods, seafood and plant proteins, and poly- and mono-unsaturated fatty acids), and for low intake of foods considered potentially harmful to health (refined grains, sodium, and empty calories, referring to calories from solid fats, added sugars and alcohol). Macro- and micro-nutrient components such as sodium and fatty acids were available per food item in FoodAPS, calculated by the USDA by matching foods to the Food and Nutrient Database for Dietary Studies (2011-2012), and its underlying National Nutrient Database for Standard Reference (46,47), as well as to the School Nutrition Dietary Assessment Study (50) for foods obtained from reimbursable school lunch and breakfast meals. The HEI-2010 for each individual was then calculated from the density ratios of each food category and nutrient component, using standardized software code assembled by the National Cancer Institute, available online (60). For reference, a recent assessment of the 2010 U.S. food supply based on national food availability data estimated an overall HEI-2010 score of 55 for the nation (54); a recent assessment of U.S. national food consumption patterns based on dietary recall data in the National Health and Nutrition Examination Survey (2009-2010, N = 9,522) also reported a mean HEI-2010 score of

55 (51).

Hypothesis 1: Relationships between cost of living and healthy food acquisition

To test hypothesis (i), that a higher area-level cost of living is associated with less healthy food acquisition, we regressed daily per person food acquisition in each food category and, separately, the HEI measure of food acquisition quality, against metrics of the cost of living (regional price parities or the geographic adjustment to the supplemental poverty measure). We performed separate regressions for each food category and for the HEI score, and separate regressions for each metric of living cost (overall regional price parity; regional price parities for rent, food, all goods and all services; and the geographic adjustment to the supplemental poverty measure). Among the regional price parities, we specifically focused on the rent regional price parity (generally the largest share of overall household expenditure among low-income consumers) and food regional price parity (39). The regional price parities and geographic adjustments to the supplemental poverty measures were available at the Metropolitan Statistical Area (MSA) level, and included an average for non-MSA areas in each state. The BEA lacks regularly-updated data for geocoded areas smaller than the MSA level, hence it is likely that if SNAP were to be adjusted for local area-level cost of living, the MSA level would be the smallest local area for which such costs would be routinely available from the BEA. By comparison, the USDA's Quarterly Food-at-home Price Database, the previously most-comprehensive public source for food price data nationally, was aggregated to much larger food purchasing metropolitan market groups, which are more aggregate than the level of MSA (i.e., there are 99 food purchasing market groups, instead of the 388 MSAs). We linked the MSA-level data to county geocodes in the FoodAPS dataset, as MSAs are defined by one or more counties, and county geocodes were available in the FoodAPS.

In our regressions, we included individual-, household-, and area-level covariates that we theorized to be potentially of pertinence to the relationship between area-level cost of living and food acquisitions. We chose the county as the area level of interest, as significant data were available at the county level to describe pertinent aspects of the food environment and living environment that were unavailable at smaller geocoded units, as detailed further below. Additionally, recent studies including those conducted on FoodAPS have revealed that SNAP participant households as well as non-participant households tend to travel outside of their immediate census block or census tract when acquiring food, but the primary food store remains typically within their county of residence (61–64). Hence, too small of a geographical area may not capture pertinent covariates of interest. At the individual level, covariates in our regressions included age (in years), age-squared, sex, race (White, Black, or other), ethnicity (Hispanic or not), education (high school or less, or more than high school), and employment status (currently employed or not). At the household level, covariates in our regressions included household size (number of non-guest residents in the home), income (annual, as a percent of the federal poverty threshold adjusted for household size), distance to primary food store (Euclidean distance, which per a prior USDA assessment was thought to provide more standardized estimates than distances based on driving or walking routes (4) (65), rural residence, food security status (low or very low food security of the primary adult respondent on the USDA 30-day adult food security scale) (48), WIC participation (current self-reported participation of any household member), and SNAP participation (current SNAP participation of any household member, either administratively-confirmed or based on self-report for participants not consenting to administrative confirmation or for whom administrative data were not available for confirmation). At the county level, covariates in our regressions included density of supermarkets (stores per 1,000 population), density of non-supermarket food-selling stores (per 1,000), density of full-service restaurants ("sit down" restaurants, per 1,000), density of limited-service restaurants ("order at the counter" restaurants, often referred to as "fast food" establishments, per 1,000), poverty rate (% of population below federal poverty threshold), area-level household income (median annual in 2012 inflation-adjusted U.S. Dollars), education (% of population 25 years or older with at least high school education), access to kitchens (% of occupied housing units with complete kitchen facilities available), and vehicle density (% of occupied housing units with at least one vehicle available).

Despite the extensive data available on pertinent covariates at multiple levels, additional unobserved factors could influence individuals to both live in a high-cost or a low-cost area, and affect the healthfulness of their food acquisition patterns (e.g., preferences for organic foods might influence individuals towards living in higher-cost areas and towards having higher HEI scores). Hence, our regressions were performed using an endogenous treatment effects model, which attempts to control for the endogeneity of treatment assignment (whether one lives in a high-cost or lower-cost area) by including residuals from a model of treatment assignment as a regressor in the models for the potential outcomes (i.e., a control function approach) (66) . The endogenous treatment effects approach has the following functional form:

[1] $$y_{i0} = E(y_{i0}|\boldsymbol{x}_i) + \epsilon_{i0}$$

[2] $$y_{i1} = E(y_{i1}|\boldsymbol{x}_i) + \epsilon_{i1}$$

[3] $$t_i = E(t_i|\boldsymbol{z}_i) + v_i$$

[4] $y_i = t_i y_{i1} + (1 - t_i) y_{i0}$

[5] $E(\epsilon_{ij} | \boldsymbol{x}_i \boldsymbol{z}_i) = E(\epsilon_{ij} | \boldsymbol{z}_i) = E(\epsilon_{ij} | \boldsymbol{x}_i) = 0$ for $j \in \{0, 1\}$

[6] $E(\epsilon_{ij} | t) \neq 0$ for $j \in \{0, 1\}$

where individuals *i* experience potential outcomes (food pattern equivalents, or HEI scores) y_{i1} when living in a high-cost area, or y_{i0} when living in a lower-cost area. The variable t_i designates the observed treatment and y_i the observed outcome. Each of the potential outcomes *y* is estimated from its expected value conditional on observed covariates $\boldsymbol{x}_i$ and an unobserved random component ϵ_{ij} for $j \in \{0, 1\}$. The treatment *t* (whether one lives in a high- or lower-cost area) is also estimated from its expected value conditional on regressors $\boldsymbol{z}_i$ (which, importantly, do not need to differ from $\boldsymbol{x}_i$), and from an unobserved component v_i. While equations 1 through 4 specify the treatment effects model, equation 5 specifies that unobserved factors in the potential outcome are independent from the observed regressors $\boldsymbol{z}_i$, and equation 6 specifies the endogeneous nature of treatment, indicating that unobserved factors in the outcomes equations are potentially correlated to the treatment. Equation 5 restricts the correlation between t_i and unobserved factors to be equivalent to the correlation between ϵ_{ij} and v_i, which means that:

[7] $E(\epsilon_{ij} | t) = E(\epsilon_{ij} | E(t | \boldsymbol{z}_i) + v_i) = E(\epsilon_{ij} | v_i) = v_i \beta_{2j}$

To estimate the model, equation 3 is fit using a probit estimator, which produces the statistic $\widehat{v_i}$ for the difference between the treatment and the estimated $E(t_i | \boldsymbol{z}_i)$; this statistic, given equation 7, allows us to compute an estimate of $E(y_{ij} | \boldsymbol{x}_i, v_i, t_i)$:

[8] $E(y_{ij} | \boldsymbol{x}_i, v_i, t_i = j) = \boldsymbol{x}_i' \beta_{1j} + v_i \beta_{2j}$ for $j \in \{0, 1\}$.

We estimate the effect of living in a high- versus lower-cost area (the treatment) on the outcome of food pattern equivalents acquired in each food category and, separately, on the outcome of HEI score. The average treatment effect of living in a high- versus lost-cost area, $[E(y_{ij}|\boldsymbol{x}_i, v_i, t_i = 1) - E(y_{ij}|\boldsymbol{x}_i, v_i, t_i = 0)]$, is estimated by the generalized methods of moments using the Stata module eteffects (67). We included all individual-, household-, and county-level covariates as both regressors $\boldsymbol{x}_i$ and $\boldsymbol{z}_i$. As the endogenous treatment effects estimation approach requires a binary treatment, we constructed a cut-point for values of each regional price parity and for the geographic adjustment to the supplemental poverty measure, above which area cost of living was defined as "high" (and, conversely, below which cost of living was defined as "lower"). The cut-point for each regional price parity (overall, and for each good or service regional price parity) and for the geographic adjustment to the supplemental poverty measure was defined as one standard deviation above the mean. For comparison, we performed ordinarily least squares (OLS) regressions of the food pattern equivalents acquired and of HEI score against the metrics of cost of living and the above-noted covariates, although the effect size estimates from such regressions would be expected to be biased by failing to account for potential unobserved factors influencing both the area of living and healthfulness of food acquisitions. Our rationale for performing OLS regressions was to explore whether older studies using OLS estimates (e.g., correlating SNAP participation to worse nutrition (17)) would be consistent with the endogenous treatment effects model. The Stata survey (svy) module was utilized to adjust regression estimates for stratification and clustering, and to apply survey sample weights to account for differential sampling and nonresponse. Missing data was not imputed, as food acquisition data cannot be determined to be missing (i.e., a failure to scan or report a food cannot be identified), and minimal data were missing for HEI score calculations or for covariates in the regressions (<7% missing for any single variable).

Hypothesis 2: SNAP participation and cost of living

To test hypothesis (ii), that SNAP participation is associated with living in a lower-cost area, we repeated the above endogenous treatment effects model, but labeled SNAP participation as the treatment *t* and the probability of living in an area with higher cost of living as the outcome *y* estimated using a probit model. The relationship between SNAP participation and cost of living can be conceived of as endogenous both because of the potential for reverse causality (e.g., living in a higher-cost area may induce a person to sign up for SNAP benefits to afford more or better quality foods, or alternatively receiving SNAP may lead a person to select a low-cost area in which to live, to make dollars go further), and because of unobserved factors (e.g., persistent economic deprivation may lead to both SNAP participation for poverty relief and selecting a lower cost of living area to reduce housing costs).

In regressing cost of living against SNAP participation, we included all of the individual-, household-, and county-level covariates as in our test of hypothesis (i), but we additionally included more regressors among $\boldsymbol{z}_i$—specifically, state variations in SNAP administration policy that may serve as instrumental variables potentially inducing or discouraging SNAP administration. We tested several available instrumental variables describing state-level SNAP administrative policies that were included in FoodAPS, imported from the SNAP Policy Database: (i) whether the state uses broad-based categorical eligibility to increase or eliminate the asset test and/or to increase the gross income limit for virtually all SNAP applicants (true for 73% of the unweighted FoodAPS participant sample); (ii) whether the state operates call centers, and whether or not call centers service the entire State or select regions within the State (74%);

(iii) whether the state operates a Combined Application Project for recipients of Supplemental Security Income (SSI), so that SSI recipients are able to use a streamlined SNAP application process (66%); (iv) whether the state disqualifies SNAP applicants or recipients who fail to perform actions required by other means-tested programs, primarily Temporary Assistance for Needy Families (TANF) (41%); (v) whether the state has been granted a waiver to use a telephone interview in lieu of a face-to-face interview at initial certification, without having to document household hardship (77%); (vi) whether the state has been granted a waiver to use a telephone interview in lieu of a face-to- face interview at recertification, without having to document household hardship (90%); (vii) whether the state requires fingerprinting of SNAP applicants (34%); (viii) whether all legal noncitizen adults (age 18-64) who satisfy other SNAP eligibility requirements such as income and asset limits are eligible for Federal SNAP benefits or State-funded food assistance (22%); (ix) whether the state allows households to submit a SNAP application online (74%); (x) the sum of Federal, State, and grant outreach spending in nominal dollars ($1,000s) (83% non-zero); (xi) for households with earnings, whether the state uses the simplified reporting option that reduces requirements for reporting changes in household circumstances (88%); (xii) whether the state excludes all vehicles in the household from the SNAP asset test (83%); (xiii) whether the state exempts an amount higher than the SNAP standard auto exemption from the fair market value to determine the countable resource value of a vehicle (14%); and (xiv) whether the state excludes at least one, but not all, vehicles in the household from the SNAP asset test (3%). Other policies listed in the SNAP Policy Database had no variation (i.e., all states had the same policy), for example in eligibility towards noncitizen children, or had complete overlap with one of the above instruments in terms of which states implemented the policy. To select the strongest instruments for inclusion among regressors $\boldsymbol{z}_i$ in the endogenous treatment effects model, we performed a two-stage least-squares regression of overall cost of living against the individual-, household-, and county-level covariates and SNAP participation, where the latter was instrumented by each eligible instrument in turn; we then included the subset of instruments with a significant (p<0.05) first-stage F-test>10, which were instruments (ii) call centers (F=76.0), (iii) combined application project for SSSI recipients (F =699.2), (iv) disqualification for failing to perform TANF requirements (F =279.3), (vi) waiver for telephone interview (F =204.9), (vii) fingerprinting (F =526.8), (viii) eligibility for noncitizen adults (F =259.7), (ix) online application (F =160.7), (x) outreach spending (F =14.4), and (xi) simplified reporting (F =249.8) in the above list.

We isolated our test of hypothesis (ii) to only the subset of participants in SNAP and non-participants with household income less than 185% of the federal poverty threshold level, because our question was applicable only to the subset of the population theoretically eligible for SNAP participation and 185% of the federal poverty threshold is used as a cut-point for eligibility. We estimated both the average treatment effect (ATE, or the generalizable effect of participating in SNAP on whether a person lives in a low- or higher-cost area), and the average treatment effect on the treated (ATET, or the specific effect of participating in SNAP among those observed to be participants), using the Stata eteffects module (67). As in our testing of hypothesis (i), missing data were not imputed prior to estimation of the treatment effects in our regressions testing hypothesis (ii).

Hypothesis 3: Whether SNAP effects on healthy food acquisition are moderated by cost of living

Finally, we tested hypothesis (iii) that any association between SNAP participation and the healthfulness of food acquisitions (i.e., HEI scores) is partially moderated by area-level cost of living. To test this hypothesis, we repeated the endogenous treatment effects model, first labeling SNAP participation as the treatment *t* and food pattern equivalents acquired and, separately, overall HEI score as the outcome *y*, to assess the association between SNAP and the healthfulness of food acquisitions, then repeating the analysis with the interaction between SNAP participation and the area cost of living as the treatment, to determine the significance of the interaction term defining how the SNAP-food acquisition relationship was moderated by cost of living.

As with hypothesis (ii), we isolated our test of hypothesis (iii) to only the subset of participants in SNAP and non-participants with household income less than 185% of the federal poverty threshold level, because our question was applicable only to the subset of the population theoretically eligible for SNAP participation. We estimated both the average treatment effect (ATE, or the generalizable effect of participating in SNAP on whether a person lives in a low- or higher-cost area), and the average treatment effect on the treated (ATET, or the specific effect of participating in SNAP among those observed to be participants), using the Stata eteffects module. As in our testing of the other two hypotheses, missing data were not imputed prior to estimation of the treatment effects in our regressions testing hypothesis (ii).

All estimates were performed using Stata version MP/14 (StataCorp, College Station, Texas).

Results

Descriptive statistics on the analytical sample

Table 1 provides summary statistics on the analytical sample. The sample included 1,581

SNAP participant households (*N*=5,414 individuals), 1,391 non-participant households <185% of the federal poverty threshold (*N*=3,863 individuals), and 1,852 non-participant households >=185% of the federal poverty threshold (*N*=5,036 individuals). As shown in the Table, the average age of the SNAP participants in the sample (30 years of age) was eight to nine years younger than non-participants; only 6% of the SNAP participant sample were above the age of 65, as compared to 16% of non-participants <185% of the federal poverty threshold and 13% of non-participants >=185% of the federal poverty threshold. The SNAP participants in the sample had a similar proportion of females (54%), as compared to 54% and 51% of non-participants below and at/above 185% of the federal poverty threshold, respectively. Fewer SNAP participants in the sample were White (63%, versus 75% and 83% of non-participants below and at/above 185% of the federal poverty threshold, respectively), and more were Black (27% versus 15% and 10%, respectively) and Hispanic (31%, versus 28% and 12%, respectively). Fewer SNAP participants in the sample had completed high school (48%, versus 59% and 73% of non-participants below and at/above 185% of the federal poverty threshold, respectively) and fewer were employed (29%, versus 34% and 56%, respectively).

At a household level, the SNAP participant sample had larger household sizes (4.2 members, versus 3.6 and 3.1 among non-participants below and above 185% of the federal poverty threshold, respectively). SNAP participant households in the sample also had higher mean income than non-participants less than 185% of the federal poverty threshold, with SNAP households having an income of 138.6% of the federal poverty threshold for household size, versus 100.8% for non-participants less than 185% of the federal poverty threshold. This finding is contradictory to the perception that non-participants are those who are likely to get smaller

SNAP benefits and therefore fail to enroll. SNAP participants in the sample also faced lower housing costs ($577 of monthly rent or mortgage expenses, versus $721 and $1,014 among non-participants below and at/above 185% of the federal poverty threshold, respectively), and were closer to their primary food store in Euclidean miles (3.1, versus 3.6 and 3.9, respectively), though both housing costs and distances to stores varied widely among all sample subgroups, as shown in **Table 1**. SNAP participants in the sample tended to be less rural than the other groups (23% in a rural residence, versus 28% and 35% among non-participants below and at/above 185% of the federal poverty threshold, respectively). SNAP participants in the sample were also more likely to have low or very low food security (43%, versus 32% and 7% among non-participants below and at/above 185% of the federal poverty threshold, respectively) and to participate in WIC (22%, versus 14% and 3%, respectively).

At the county level, SNAP participants in the sample had a similar density of supermarkets as non-participants (12 per 1,000 people), and slightly more non-supermarket food retailers (28 per 1,000, versus 26 and 23 among non-participants below and at/above 185% of the federal poverty threshold, respectively). SNAP participants in the sample also had fewer full-service restaurants (74 per 1,000 versus 79 and 82 among non-participants below and at/above 185% of the federal poverty threshold, respectively), but a similar density of limited-service "fast food" restaurants (at 69 per 1,000 among all subgroups). The poverty rate in the counties in which the SNAP participant sample lived was equivalent to that of the non-participant sample less than 185% of the federal poverty threshold (at 16%), and only slightly lower than among the non-participant sample ≥185% of the federal poverty threshold (at 14%). County-level median household incomes were more graded, with the SNAP participant sample living in counties with an area median income of $50,400, versus $52,800 and $55,400 among non-participants below and at/above 185% of the federal poverty threshold, respectively. County-level high school educational attainment among persons at least 25 years old was similar across subgroups (85% among the SNAP participant sample, versus 84% and 87% among non-participants below and at/above 185% of the federal poverty threshold, respectively). Vehicle density and kitchen availability was high and did not differ among the subgroup samples of SNAP participants and non-participants below and at/above 185% of the federal poverty threshold.

The cost of living metrics were generally only minimally lower among the SNAP participant sample, on average, than among the non-participant samples—but the distributions of the cost of living metrics were largely overlapping among all three subgroup samples. The overall regional price parity averaged 98% among the SNAP participant sample versus 100% and 99% among non-participants below and above 185% of the federal poverty threshold, respectively. The rent regional price parity was more substantially lower on average for the SNAP participant sample, at 96%, versus 104% and 102% among non-participants below and at/above 185% of the federal poverty threshold, respectively. The food regional price parity was minimally lower on average for the SNAP participant sample, at 99%, versus 100% and 100% among non-participants below and at/above 185% of the federal poverty threshold, respectively. The regional price parity for goods was at 99% for all subgroup samples, and for services was slightly lower at 98% for the SNAP participant sample, versus 100% and 99% among non-participants below and at/above 185% of the federal poverty threshold, respectively. The geographic adjustment to the Supplemental Poverty Measure differed more between SNAP participants and non-participants, at 99% for the SNAP participant sample, versus 105% and

104%, respectively, among non-participants below and at/above 185% of the federal poverty threshold.

To further characterize overall cost of living among the studied populations, we plotted the distribution of the overall regional price parity among each subgroup sample (**Figure 1**). As shown in the Figure, all three population subgroups largely spanned the same spectrum of possible cost of living levels, and the overall regional price parity was multi-modal, with a larger population living below the national average cost (more common for SNAP participants than non-participants), a second group living near the national average (also more common for SNAP participants than non-participants), a third group living around 7% above the national average cost (more common for the non-participants at/above 185% of the federal poverty threshold) and a fourth group living around 25% above the national average cost (interestingly, most common for the non-participants below 185% of the federal poverty threshold).

Food acquisition patterns in the analytical sample

Table 2 summarizes the food acquisition patterns, at the household and at the individual level, among SNAP participants and non-participants below and at/above 185% of the federal poverty threshold in our analytical sample. As shown in **Table 2**, food acquisition patterns did not differ significantly among the three subgroup samples, except in the food category of added sugars. Among all groups, added sugars constituted the most acquired food category by grams, with SNAP participants having significantly (at the $p<0.05$ level) higher acquisition (941 grams/person/day, SE: 48) than non-participants below 185% of the federal poverty threshold (749, SE: 35), though not significantly differing from non-participants at/above 185% of the federal poverty threshold (884, SE: 45). Fats and oils constituted the second largest group of acquisitions by grams, followed by dairy products, refined grains, then vegetables and fruits, and last whole grains. The subgroups did not significantly differ in their acquisitions in these categories, and overall kilocalories acquired did not significantly differ among the groups (ranging from a low of 2,336 kcals/person/day on average the SNAP non-participant sample below 185% of the federal poverty threshold, SE: 114, to a high of 2,588 kcals/person/day on average among the SNAP participant sample, SE: 122).

To provide reference ranges and context to the food acquisition values, **Table 3** compares the estimated food acquisitions per person per day in our analytical sample to the reported food consumption (estimated via 24-hour dietary recalls) among participants in the National Health and Nutrition Examination Survey (NHANES) (68), and to current National Dietary Guidelines (69). As shown in the Table, the food acquired among all three subgroup samples was generally consistent with the food consumed by nationally-representative participants in the NHANES survey, although the standard errors around the food acquired estimates were larger than the standard errors around consumption in NHANES. The notable exceptions were in added sugars, fats and soils, and refined grains, where estimates of food acquired were 86%, 27%, and 29% higher, respectively, in our FoodAPS food acquisition estimates than in the NHANES food consumption estimates. This may be because acquisition (FoodAPS) differs profoundly from consumption (NHANES) for these items, particularly because these products have longer shelf-lives and potentially are more commonly wasted or shelved rather than consumed; alternatively, it may suggest population sampling differences, as the most acquisition in all three categories was among the SNAP participant sample, whereas NHANES is a nationally-representative sample. Alternatively, the stigma associated with consuming these foods may mean that their consumption is underreported in NHANES dietary recalls. Consistent with the average HEI-2010 score of 55.4 (SE: 0.7) among NHANES participants, the average HEI-2010 score among all subgroup samples in FoodAPS was 54.4 and 54.7 (among SNAP participants and non-participants below 185% of the federal poverty threshold, respectively, SE 0.2) or 55.0 (among non-participants at/above 185% of the federal poverty threshold, SE 0.1). Also consistent with NHANES, the food acquisition patterns in FoodAPS were highly discordant from federal nutrition guidelines, with all groups acquiring or consuming few fewer vegetables, fruits, whole grains or dairy products than recommended, and far more refined grains, fats and oils, and added sugars than recommended.

Hypothesis 1: is a higher area-level cost of living associated with less healthy food acquisition?

Table 4 summarizes the estimated average relationship between living in a high-cost county and patterns of food acquisition in the overall FoodAPS analytical sample. The coefficients and standard errors displayed in the Table are estimates from the endogenous treatment effects model in which county-level cost of living is regressed against food acquisitions in each food category, after controlling for the individual-, household-, and county-level covariates listed in **Table 1**. In **Table 4**, the rows display the metric of cost of living being used as an independent variable (e.g., overall regional price parity, regional price parity for rent, etc.); the columns display the outcome measure of foods acquired in each food category (e.g., vegetables, fruits, etc.) in food pattern equivalents (e.g., cup-equivalents, ounce-equivalents) specific to that food category, per person per day. For reference, the mean levels of food acquired in food pattern equivalent units, per person per day, is provided in **Table 2**.

As shown in **Table 4**, no matter which metric we used as a measure of cost of living (overall regional price parity, category-specific regional price parity, or the geographic adjustment to the Supplemental Poverty Measure), living in a higher cost of living county was associated with significantly fewer acquisitions of vegetables, fruits, and whole grains, and was associated with significantly greater acquisitions of refined grains, dairy products, protein, fats and oils, and added sugars. Having controlled for individual-level factors such as education level, household-level factors such as income, and county-level factors such as food availability, living in a high-cost county, as measured by the overall regional price parity, was associated with a decline in vegetable acquisition by about 0.65 cup-equivalents per person per day (SE: 0.04, $p<0.001$), which is approximately a 37% decline relative to estimated mean acquisition for that food category among equivalent persons living in a low-cost county. Living in a higher-cost county (measured by the overall regional price parity) was also associated with 0.14 cup-equivalents lower fruit acquisitions (16%), and 0.11 ounce-equivalents lower whole grain acquisitions (11%). By contrast, living in a high-cost county, as measured by the overall regional price parity, was associated with an increase in refined grain acquisition by about 2.35 ounce-equivalents per person per day (SE: 0.12, $p<0.001$), which is approximately a 34% increase relative to mean acquisitions for that food category among equivalent persons living in a low-cost county. Living in a higher-cost county (measured by the overall regional price parity) was also associated with increased fat and oil acquisitions of 36.63 grams (52%), and increased added sugar acquisitions of 9.40 teaspoon-equivalents (35%). Living in a high-cost county was associated with a higher caloric intake by approximately 550 kcals/person/day when using the overall regional price parity as the metric of cost of living. Overall, living in a high-cost county, as measured by the overall regional price parity, was associated with a 6.0 point lower HEI-2010 score (SE: 0.09, p<0.001), a 11% decrease relative to the mean among equivalent persons living in a low-cost county.

Different subcategories of costs of living (rent, food, all goods, or all services) were most strongly associated with changes in different food categories. As shown in **Table 4**, reduced acquisition of vegetables was more strongly associated with an increase in rent regional price parity than with an increase in the food regional price parity. Acquisitions in the food categories of whole grains, protein, and fats and oils, as well as the overall HEI score, were also most sensitive to the rent regional price parity as compared to any other subcategory of cost of living. The food regional price parity was more strongly correlated to acquisitions of fruits, refined grains, dairy products and added sugars than any other regional price parity. The geographic adjustment to the Supplemental Poverty Measure was, however, more strongly related to acquisitions of food in all of those categories, and to overall HEI-2010 score, than was the food regional price parity (**Table 4**). Overall, living in a high cost of living area as defined by the geographic adjustment to the Supplemental Poverty Measure was associated with a 2.1 point decline in HEI-2010 score, SE 0.9, p<0.05), whereas living in a high cost of living area as defined by the food regional price parity was associated with a 1.4 point decline (SE 1.0, p>0.05), and living in a high cost of living area as defined by the rent regional price parity was associated with 6.0 point decline (SE 0.9, p<0.001).

Figure 2 provides a subgroup analysis of the relationship between living in a high-cost county and patterns of food acquisition, stratified by the three subgroup samples of SNAP participants, non-participants below 185% of the federal poverty threshold, and non-participants at/above 185% of the federal poverty threshold. The Figure displays the coefficients and 95%

confidence intervals around the coefficients from endogenous treatment effects models regressing county-level cost of living against HEI-2010 scores, after controlling for the individual-, household-, and county-level covariates listed in **Table 1**. Changes in individual food categories were consistent across all sample subgroups. As shown in **Figure 2**, however, SNAP non-participants below 185% of the federal poverty threshold were most sensitive to changes in the cost of living as measured by the regional price parity, while the non-participants at/above 185% of the federal poverty threshold were the least sensitive. Living in a high cost of living area, as measured by the overall regional price parity, was associated with 5.8 points lower HEI-2010 scores among SNAP participants (SE: 0.9, $p<0.001$), 7.0 points lower HEI-2010 scores among SNAP non-participants below 185% of the federal poverty threshold (SE: 1.0, $p<0.001$), and 4.0 points lower HEI-2010 scores among SNAP non-participants at/above 185% of the federal poverty threshold (SE: 0.6, $p<0.001$). Consistent with the overall results, the subcategory of cost of living that was associated with the greatest decline in the HEI-2010 score among all subgroup populations was the rent regional price parity; by contrast, the food regional price parity was not significantly associated with changes in HEI scores due to large standard errors around the treatment effects model coefficient.

Hypothesis 2: is SNAP participation associated with living in a lower-cost area?

Table 5 summarizes the estimated average relationship between SNAP participation and the probability of living in a higher-cost area in the overall FoodAPS analytical sample. The coefficients and standard errors displayed in the Table are estimates from the endogenous treatment effects model in which county-level cost of living is regressed against food acquisitions in each food category, after controlling for the individual-, household-, and county-level covariates listed in **Table 1**, and additionally including instrumental variables that capture differences between states in how they execute SNAP enrollment (see **Methods**). In **Table 5**, the two columns display the change in the probability of living in a higher-cost county given SNAP participation, either among the overall eligible population (average treatment effect) or among those who are observed to be SNAP participants (average treatment effect on the treated). Each row lists a different metric for the cost of living, ranging from the overall regional price parity to various subcategories of regional price parities (rent, food, all goods, all services) to the geographic adjustment to the Supplemental Poverty Measure.

As shown in **Table 5**, SNAP participation was associated with a higher probability of living in a high-cost county, no matter which metric we chose to define cost of living, after controlling for relevant individual-, household-, and county-level confounding variables. In addition, as shown in the Table, the estimated association between SNAP and the probability of living in a high-cost county was smaller for a theoretically eligible person (the average treatment effect) than for a person observed to participate in SNAP (average treatment effect on the treated). The average treatment effect was that SNAP participation was associated with a higher probability of living in a high-cost area, as measured by the overall regional price parity, from 0.20 to 0.64 (an increase of 0.44, SE: 0.01, $p<0.001$); the average treatment effect on the treated was that SNAP participation was associated with a higher probability of living in a high-cost area from <0.01 to 0.22 (an increase of 0.22, SE: <0.01, $p<0.001$). Notably, the biggest treatment effect on the treated was observed for the food regional price parity (SNAP participation was associated with a higher probability of living in a high-food-cost area by 0.24, SE 0.01, $p<0.001$). Since the directionality of the treatment-effects model is uncertain, this implies either that living in a high-cost county induces SNAP participation, or that SNAP participation induces living in a higher-cost area (e.g., SNAP permits individuals or their households to afford living in an area with more expensive food costs).

Hypothesis 3: does cost of living moderate the SNAP-food acquisition relationship?

Figure 3 displays the interactions between SNAP participation and cost of living when the outcome of interest is HEI-2010 score. As shown in the Figure, living in a high-cost area is associated with a lower HEI score, consistent with our results summarized above, but SNAP participation improved the low HEI score among those persons who lived in high-cost areas (from a score of 41 to a score of 61, based on the average treatment effect from the model). Yet the benefits of SNAP in changing the HEI-2010 score were not significant in lower-cost areas.

Table 6 provides a breakdown of how much SNAP participation and its interaction with cost of living is associated with food acquisitions in each of the studied food categories, based on endogenous treatment effects models. As shown in the Table, in both low- and high-cost areas SNAP participation was associated with increased fruit and vegetable acquisition. In lower cost areas, SNAP was also associated with increased acquisition of fats and oils and sugars, which offset the HEI improvements, which would have been observed from the increased fruit and vegetable acquisition. Hence, SNAP participation was associated with an insignificant change in HEI score in low-cost areas, but a significantly improved HEI score in high-cost areas.

OLS results

In addition to testing the endogenous treatment effects model, we performed tests of endogeneity (estimating the significance of the correlation between unobservables that affect treatment and outcome in the control function equations specified above, which should be zero if there is no endogeneity). All of these tests rejected the null hypothesis of no endogeneity for all of our regressions—justifying our use of the endogenous treatment effects modeling approach. As a result, we would expect that ordinary least squares (OLS) regressions would be biased in their estimates due for example to omitted variables. We nevertheless present them here to understand how the endogenous treatment effects model differs from what would be observed in OLS regressions, and to understand how key covariates included as control variables in the regressions also relate to the outcomes of interest. We also show these OLS regressions because they are the classical strategy for relating SNAP to food acquisition outcomes, and we wish to understand how much this classical inference method differs from our endogenous treatment effects model.

Table 7 presents the OLS regressions revealing the associations between cost of living metrics and food acquisition in each food category, as well as the overall HEI score. A higher cost of living was associated with less acquisition of vegetables and more acquisition of refined grains, dairy products, fats and oils, and added sugars. The associations between cost of living metrics and acquisitions in the other food categories were generally insignificant due to large standard errors around the estimates, or inconsistent in having some positive associations but not a robust association across all metrics of cost of living, as shown in the Table. A lower cost of living was generally associated with a lower HEI score, although this was not true of the food regional price parity; in OLS regressions, this association may reflect other unmeasured endogenous factors such as frugality, which may lead individuals towards less expensive cost of living areas and less-healthy cheaper foods. Notably, as shown in **Table 7**, older age, female sex, Black race or Hispanic ethnicity, greater education, employment, and income were associated with higher HEI scores after controlling for cost of living and other household- and county-level covariates. Housing costs, longer distance to a primary food store, and low or very low food security were associated with lower HEI scores. At a county level, rural residence was associated with a higher HEI score, as was having fewer supermarkets or full-service restaurants, having more limited-service restaurants, and having less kitchen availability. These results are counter-intuitive and we suspect that factors producing endogeneity between cost of living and healthfulness of food acquisitions may also be driving these estimates, such as the fact that rural areas that have all of the above features tend to have lower refined grain availability and greater fruit and vegetable availability, which are two food categories heavily weighted in the HEI metric. SNAP participation was associated with a lower HEI score, also contrary to the endogenous treatment effects model; this indicates that associations between SNAP and less healthy food acquisitions may be due to other factors not observed or controlled for, justifying our use of an endogenous treatment effects model in our main analysis.

Table 8 presents the OLS regressions revealing the associations between SNAP participation and county-level cost of living. SNAP participation was generally associated with living in a lower-cost county in these OLS models, subject to endogenous unobserved covariates such as frugality. Living in a lower-cost county is also associated with older age, male sex, Black race, Hispanic ethnicity, and being unemployed. Living in a higher-cost county was associated with having lower income, driving a farther distance to a primary food store, being less rural, having better food security, and having more availability of supermarkets, non-supermarkets, and full-service restaurants. Interestingly, a higher county-level cost of living was associated with WIC participation and a higher poverty rate and lower area-level prevalence of high school graduation, which may reflect high inequality in high-cost counties. High-cost counties also had greater vehicle density and lower kitchen availability.

Table 9 presents the OLS regressions revealing associations between the interaction of SNAP participation and living in a high cost of living county. The interaction terms were negative for vegetables and protein, positive for fruits, grains, dairy, fats and oils, and added sugars. Negative interaction terms imply less food acquisition in that food category if a person is both on SNAP and lives in a high-cost county. The interaction term had a positive coefficient when regressed against overall HEI score, suggesting that SNAP would improve HEI scores more in a high-cost than in a lower-cost county, consistent with the endogenous treatment effects model result.

Discussion

Major findings

As poverty and economic inequality have been recognized as major social determinants of health, epidemiologists have increasingly sought to understand which social programs might best reduce these burdens. The Supplemental Nutrition Assistance Program (SNAP) remains one of the largest “safety nets” for low-income populations in the United States, and is well recognized for its role in reducing poverty and food insecurity (70). Yet some literature has also correlated SNAP participation to worse nutrition-related outcomes such as obesity. Such correlative findings may suffer from substantial methodological problems such as the failure to control for unobserved confounders that influence both participation in SNAP and nutritional quality, and misreporting of SNAP participation status in common nutritional datasets (19). In a recent Institute of Medicine review, an expert panel reviewing the SNAP program suggested that further research should use improved methods and datasets to examine how SNAP currently affects nutritional quality and how it modifies the relationship between local food prices and nutritional quality; furthermore, the Institute of Medicine panel suggested that studies should evaluate how SNAP might be further improved to enhance its benefits to nutrition among low-income Americans. One of these potential improvements is to adjust SNAP benefits for local food prices or cost of living, as it is believed that high local food prices and/or high costs of living (i.e., competing expenses such as rents) may exacerbate challenges in affording high nutrient-dense foods for low-income populations. SNAP benefits are not currently adjusted for local food prices or costs of living in the continental U.S.

A practical limitation has prevented pursuit of the IOM panel's suggested research objectives: the largest, nationally-representative dataset on food acquisition and nutrition quality (the National Health and Nutrition Examination Survey, NHANES) lacks reliable data on SNAP participation, and is not sufficiently geographically distributed to facilitate assessments of how variations in cost of living relate to the healthfulness of food acquisitions. The new National Household Food Acquisition and Purchase Survey (FoodAPS, 2012-2013) resolves these deficits, and facilitates inferences around the impact of SNAP on food acquisitions by sampling a nationally-representative group of administratively-confirmed SNAP participants, income-eligible non-participants, and higher-income SNAP-ineligible non-participants. Here, we studied the FoodAPS dataset to understand how cost of living relates to the healthfulness of food acquisitions, how SNAP participation is related to cost of living, and the degree to which SNAP benefits have different relationships to nutritional quality in geographic areas with varying costs-of-living, including varying food prices. We specifically measured cost of living using indices that might be used in the future to adjust SNAP benefits for local food and living costs, including county-level regional price parities assembled by the U.S. Bureau of Economic Analysis, and county-level geographic adjustments to the Supplemental Poverty Threshold, assembled by the U.S. Census Bureau.

Using data on food equivalents acquired by food category, and a common metric of overall healthfulness of food acquisitions (the Healthy Eating Index, HEI, 2010 edition), we explored three key hypotheses relating the cost of living to the healthfulness of food acquisitions: (i) that a higher area-level cost of living would be associated with less healthy food acquisitions; (ii) that SNAP participation would be associated with living in a lower-cost area after accounting for other observed and unobserved covariates related to both SNAP and area of living; and (iii) that associations between SNAP participation and the healthfulness of food acquisitions would be moderated by area-level cost of living. We envisioned that higher cost of living would induce individuals to sacrifice food budgets for other costs such as rent, inducing less healthy food acquisitions. We also envisioned that because SNAP benefits are adjusted based on national average cost of living indices, the purchasing power of a SNAP dollar would be higher in a lower food-cost area and thereby induce living in lower-cost areas. Finally, we envisioned that the marginal impact of each dollar of SNAP benefits would be affected by area cost of living.

Hypothesis 1: Cost of living and the healthfulness of food acquisitions

We found evidence consistent with our first hypothesis—that higher area-level cost of living was associated with less healthy food acquisitions. In particular, when we defined a high cost of living area as being more than one standard deviation above the mean cost measured by either a regional price parity or the geographic adjustment to the Supplemental Poverty Measure, we found that living in a higher cost of living county was associated with significantly fewer acquisitions of vegetables, fruits, and whole grains, and was associated with significantly greater acquisitions of refined grains, dairy products, protein, fats and oils, and added sugars. This finding was consistent no matter which metric we chose for the area-level cost of living. Having controlled for individual-level factors such as education level, household-level factors such as income, and county-level factors such as food availability, the estimated effect of living in a high-cost county reduced the overall HEI score by approximately 11%. Clinically-speaking, the observed decrease in HEI is larger than reductions in HEI associated with a significant increase in the risk of cardiovascular disease, type II diabetes, and all-cause mortality. Hence, we would expect such effects are meaningful to public health.

Importantly, we observed that the cost of living metric for food was not the most predictive of changes in the healthfulness of food acquisitions, perhaps because expenditures in other domains of the budget so substantially impact the food budget. For the overall nutritional metric of HEI score, higher rent costs were more strongly associated with reduced healthiness of food acquisitions than higher food costs when measured by county-level cost of living indices. As the food regional price parity was not significantly associated with a reduction in HEI score (because of the wide standard errors around the estimate), the food regional price parity may not capture whatever economic forces are leading to less healthy food acquisitions as well as the rent regional price parity or overall regional price parity. This is an important result for policymakers who may need to choose what metric of cost of living would be utilized if SNAP or related benefits were adjusted for cost of living. An increasing literature suggest that when rent prices are too high, very few funds remain available to low-income households to augment their SNAP budget, and families become reliant on emergency food aid (11); hence, food prices are less useful as an indicator of food purchasing desperation when essentially no food can be purchased, and high rent prices may constitute the largest expenditure away from the food budget of the most vulnerable low-income households.

Our further subgroup analyses examining the relationships between area-level cost of living and food acquisitions revealed that low-income (<185% of the federal poverty threshold) SNAP non-participants were the most sensitive subgroup affected by overall cost of living metrics, followed by SNAP participants and lastly by higher-income SNAP non-participants. This gradient across the three groups may suggest that greater income mitigates the relationship between area cost of living and the healthfulness of food acquisitions. The finding also suggests that SNAP may be effectively buffering individuals from the negative impacts of higher area-level cost of living—a theory we return to when exploring the results of hypothesis 3, below.

Hypothesis 2: SNAP and area-level cost of living

We rejected our second hypothesis that SNAP would be associated with living in a lower-cost area. While the ordinarily least squares regressions of SNAP against area-level cost of living revealed that SNAP participation was correlated to living in a lower-cost area, our main analysis employed endogeneous treatment effects models that attempted to estimate the effects of SNAP participation while reducing or eliminating unobserved or unmeasured confounders that produce endogeneity between SNAP and area-level cost of living. In these endogenous treatment effects models, we observed SNAP was associated with a higher probability of living in a high-cost county. One potential explanation for the finding is that SNAP participation increases economic mobility—by relieving budgets enough to allow low-income households to live in environments where they would otherwise be "priced out" (11). Alternatively, the association may be due to reverse causality: that high-cost areas more quickly drain monthly budgets, increasing need for SNAP participation in order to make ends meet, such that SNAP participation is associated with living in high-cost areas. In exploring this hypothesis, it was notable that among the different measures of cost of living, the biggest treatment effect on the treated (estimated effect among those who were observed to be SNAP participants in the data) was from the food regional price parity. This finding is consistent with either explanatory mechanism, but further suggests that self-selection into SNAP enrollment is appropriately selecting households facing the greatest need from a food cost perspective, in that SNAP dollars are most likely to be spent in areas where they are most needed to afford food.

Hypothesis 3: cost of living as a moderator of SNAP's relationship to food acquisition

Our testing of our third hypothesis revealed that indeed county-level cost of living did moderate the relationship between SNAP and the healthiness of food acquisitions, but not in the expected direction. We anticipated that SNAP would be most beneficial to those living in lower-cost areas, as each program dollar would be able to purchase more food in those areas, particularly foods that were of perceived or real higher costs (e.g., fruits and vegetables). Yet in fact SNAP had a neutral impact on the healthfulness of food acquisitions in lower-cost areas, because increased fruit and vegetable acquisitions and lower refined grain acquisitions, attributable to SNAP participation, were counterbalanced by increased acquisitions of fats and oils as well as added sugars. Overall, SNAP increased calories but did not disproportionately increase "healthy" calories; hence, SNAP had a statistically-neutral impact on HEI scores in lower-cost areas.

By contrast, while individuals had a worse dietary profile in higher-cost areas, as discussed above, SNAP made a greater positive impact in such areas, by permitting greater acquisitions of vegetables and fewer refined grains, with less adverse compensation from increased fat and oil or added sugar acquisitions. One theory to explain these findings may be that in a higher-cost environment, SNAP dollars are used disproportionately to assist households in acquiring those foods that are most out of reach due to high perceived or real prices. The finding may also be a commentary on the nature of the food acquisition environment in lower-cost counties; if lower-cost counties indeed have environments saturated with less-healthy foods as suggested in the public health literature (71), SNAP participation may have limited effects on the healthfulness of food acquisitions because the food environment dominates the purchasing patterns of participants, whereas higher-cost areas may have somewhat healthier food availability. We discuss further assessments of this theory in our discussion of future research studies, below.

Contribution to the existing literature

Substantial existing literature in the fields of sociology, economics, and epidemiology has highlighted the trade-offs that low-income Americans face when attempting to pay for foods. While prior literature has documented trade-offs between energy costs, rent costs, medical care costs and food (2,3,72), our study adds the additional dimension of assessing how costs-of-living among low-income Americans relate to the healthfulness of food acquisitions, and the impact of the largest nutritional assistance program in the country. To our knowledge, this is the first assessment to use nationally-representative survey data to understand how broad costs of living across the country relate to the healthfulness of food acquisitions nationally. Other surveys, such as NHANES, have not collected or provided access to sufficient geocoded information for such analyses. Our analysis provides the important insight that lower-income populations may be particularly vulnerable to less healthy food acquisitions when they face high costs-of-living, at least when they are not enrolled in SNAP. Furthermore, costs of food in a county are not the only—or even the best—metric of which costs-of-living are associated with less healthy food acquisitions. Rather, rent and other housing costs appear to be a particularly influential factor in influencing the healthfulness of food acquisitions, concordant with literature suggesting that housing-related costs are a major source of stress and financial constraint among low-income households. Interestingly, there was only a 65% correlation between the rent regional price parity and the food regional price parity among all counties in the sample.

It is notable that in our study of the FoodAPS dataset, the analytical sample of low-income non-participants who are theoretically eligible for the SNAP program had a lower income that did SNAP participants. This finding is contrary to the idea that eligible persons who fail to participate in SNAP are those who are minimally-qualified based on income, and who would receive the fewest benefits (i.e., rendering them less motivated to receive benefits, since the burden of enrollment exceeds the benefits of enrollment). By contrast, our findings suggest that eligible non-participants may include the extreme poor, and more rural, White, low-salaried employed persons, whose food acquisitions are disproportionately less healthy in higher cost of living areas. Notably, extensive emerging public health literature indicates that this demographic group has experienced declines in life expectancy associated with numerous financial and social hardships, and associated chronic diseases that include nutritional and psychiatric conditions related to food insecurity and chronic deprivation. Hence, our findings may indicate that outreach to eligible but un-enrolled participations, to buffer them from the adverse nutritional effects of living in higher cost of living areas.

Furthermore, our study is unique in utilizing the FoodAPS dataset, which offers the opportunity to identify SNAP participants who are administratively-confirmed participants in the program. Other surveys such as NHANES are known to mis-identify such participants (19), likely due to the stigma of identification and confusion or lack of awareness of benefits received by an individual or other household members, which prevents accurate assessments of program impact. Our findings reveal that SNAP participation may serve as a buffer from the adverse effects of high cost of living on healthful food acquisitions, being particularly beneficial to those individuals who live in high-cost counties. A large literature in the sociology discipline has pointed to the benefits of living in lower-poverty areas that typically have higher area-level cost of living. Mostly commonly cited is the Moving to Opportunity Study, in which households randomized to a voucher program permitting movement to a lower-poverty neighborhood experienced subsequent clinically-meaningful reductions in the risk of obesity and type II diabetes as well as some associated mental health benefits (73,74). Given the rich literature supporting the poverty-reducing effects of SNAP, our results suggesting that SNAP's effects include improving the ability to live in—and consume healthier foods in—higher-cost areas may be part of the pathway by which SNAP improves both economic and health mobility.

Another key contribution to the literature from our study is the finding that SNAP may be associated, in ordinarily least square regressions, with poorer nutrition, but endogenous treatment effects models to detect the effects of SNAP while reducing or eliminating the impact of omitted variable bias did not reveal a negative impact of SNAP on nutrition in lower-cost areas and revealed a positive impact of SNAP on nutrition in high-cost areas. This finding suggests that standard regressions and prior literature relying on such regressions to link SNAP participation to adverse nutritional outcomes such as obesity may be confounded by omitted variables that influence both SNAP participation and the likelihood of living in low-quality food environments or being predisposed to acquire less healthy foods.

Limitations

Several notable limitations in our analysis are important to highlight. First, our data are from catalogued food acquisitions, not 24-hour dietary recalls. Food acquisitions may not reflect food consumption due to food wastage, which is particularly likely for foods that have very short shelf lives, such as vegetables and fruits, or those that have very long shelf lives and are consumed well after they are acquired or are stored rather than consumed, such as canned goods, solid fats and oils, or foods containing a high content of added sugars. Related to the issue of having food acquisitions catalogued rather than true food intake is the potential for missing data. We did not impute missing data as a low proportion of survey-based variables were missing; it is not possible to impute missing food acquisition data, since there is no strategy we are aware of to determine whether a respondent has failed to report a food acquisition. The data are also subject to observational effects in that a participating individual may have changed their food acquisition patterns due to participation in the study.

A further limitation of our analysis is the assumption that household members consume an equal portion of the food acquired at the household level, which is particularly unlikely for households with children. We computed average food acquisitions per person per day from seven-day food diaries catalogued among all respondents in a household. We chose to perform our regressions on individual-level food acquisitions both to assess the face validity of our statistics—which were highly concordant to estimates of food consumption in NHANES, despite FoodAPS being a record of food acquisition rather than consumption—and to provide interpretable regression coefficients that are comparable to the broader nutrition epidemiology literature, which catalogues consumption of food at an individual level. Nevertheless, dividing total household acquisitions among those persons who participated in a given food acquisition "event" (e.g., a meal) will not capture important within-household inequalities in food acquisition, which may be particularly important for understanding differences in the healthfulness of food acquisitions between children and adults.

An additional limitation is that we utilized data on costs geocoded to the county level, not individual, household or local neighborhood-area levels. Our choice of this geographic level was dictated by the availability of cost of living metrics that are routinely updated and would be the most likely indices for adjustment of SNAP benefits in the future if such adjustments were to be instituted. We also controlled for county-level covariates because this was the smallest area level for which we possessed numerous variables of interest concerning the neighborhood environment and population. Furthermore, recent data including data from FoodAPS reveal that Americans typically travel significant distances to their primary food store, even among the lowest-income populations (4); hence, local neighborhood-area prices may be from areas that are not sufficiently wide to account for the distribution of prices for goods and services faced by most households.

Implications for future research

Our findings and the limitations of our current analysis prompt several future research pathways. First, understanding the mechanisms behind some of our findings will be important, as our findings were not concordant with many of our *a priori* hypotheses. In particular, understanding the mechanisms by which SNAP participation is associated with living in a higher-cost area would be important to understanding the economic mobility implications of the program. Furthermore, why SNAP participation was associated with healthier food acquisitions in higher-cost counties will be important to explain to understand how individuals and household choose to utilize nutrition assistance benefits. This may require further analysis of local and store-specific prices and availability of food products. At the time of this writing, FoodAPS developers are still building linkages between the dataset and external data from geocoded store datasets to assemble store-level and neighborhood-level food basket costs, which may be more refined than our county-level price indices in defining local prices, and should be paired with indices of food availability to understand how consumers make food acquisitions choices in different environments.

Given that our endogenous treatment effects models did not find adverse effects of SNAP on nutritional indicators, older studies using standard regressions to link SNAP to adverse chronic disease outcomes such as obesity should be revisited. Our findings indicate that the links between SNAP and adverse health conditions may have been driven by endogeneity from omitted variable bias, which has important implications for program evaluation and to understanding what mechanisms may be best for improving the nutritional benefits of SNAP and related food assistance programs. Our findings suggest that the program benefits themselves may be less related to unhealthy food acquisitions than the food environment in which participants live.

Implications for policy

Our study intended to shed light on the issue of whether SNAP benefits could improve the healthfulness of food acquisitions if they were adjusted using locally-based (county-level) indices of cost of living, rather than national average living cost data. Our study would have provided a clearer indication that such adjustments would be beneficial if our findings had been consistent with our hypothesis that SNAP benefits to nutritional metrics were larger in lower-cost areas than in higher-cost areas. Yet our findings were contrary to this hypothesis. We found that SNAP was associated with improved nutrition more in higher-cost counties than in lower-cost counties, with our leading theory for this finding being that food environments in lower-cost counties permitted greater acquisition of fats and oils and added sugars with SNAP benefits. Hence, our findings do not necessarily imply that a cost of living adjustment using currently available county-level cost of living metrics would improve the healthfulness of food acquisitions among SNAP participants currently living in lower-cost areas. However, our findings do imply that SNAP participation itself is associated with a higher probability of living in a higher-cost area, and improves nutrition in those areas; hence, via this more circuitous pathway, it is possible that adjusting SNAP benefits for county-level cost of living may improve nutrition. The sociology literature in particular suggests that higher-cost areas that are typically lower in poverty may have substantial health benefits for low-income individuals who move to such areas. Hence, any economic mobility benefits of SNAP might be enhanced though cost of living adjustments; conversely, however, if SNAP benefits are reduced by cost of living adjustments among those populations living in lower-cost areas, it is possible that SNAP participation would no longer have a neutral impact, but have a negative impact, if such benefits become disproportionately used on fats and oils or added sugars, for example. A direct experiment or pilot study involving cost-adjusted SNAP benefits may be the most definitive strategy for identifying the effects of benefit modification for living costs.

Regardless of whether benefits are adjusted, we found that it was unlikely for food cost metrics alone to sufficiently capture the key cost of living factors that drive the relationship between area cost of living and the healthfulness of food acquisitions among low-income Americans. Rather, we found that overall cost of living indices, and particularly indices strongly driven by rent and housing costs, were often more significantly related to the healthfulness of food acquisitions than were food cost indices. Hence, the economic trade-offs taking place within low-income households that affect the healthfulness of what the food budget is spent on may be critically driven by large expenditures such as housing. This finding calls for an expansion of what data are utilized to consider the value of benefits and the influences of economic factors on the benefits of nutrition assistance programs and other safety nets targeting low-income Americans.

Conclusions

By linking data from the National Household Food Acquisition and Purchase Survey (FoodAPS) to data on county-level cost of living, we found that higher area-level cost of living was associated with less healthy food acquisitions. Additionally, we found that SNAP participation was associated with a higher probability of living in a high-cost county, net of individual, household, and county-level covariates; SNAP participation was also associated with a significant improvement in the healthfulness of food acquisitions in high-cost counties, but had a neutral impact in lower-cost counties.

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Figures and Tables

Table 1: Descriptive statistics of participants in the National Household Food Acquisition and Purchase Survey (2012-2013) by Supplemental Nutrition Assistance Program (SNAP) participation status and income level. The Stata commands svy, subpop were applied to data from each subpopulation (SNAP participants, non-participants <185% of the federal poverty level, and non-participants >=185% of the federal poverty level) to adjust estimates for stratification and clustering, and to apply sample weights. 95% confidence intervals are provided in parentheses for continuous variables. FPL: federal poverty threshold level.

Characteristic	**Definition/units**	**SNAP participants**	**Non-participants <185% FPL**	**Non-participants >=185% FPL**
Household sample size	Number of households	1,581	1,391	1,852
Individual sample size	Number of individuals	5,414	3,863	5,036
Weighted individual sample size	Population represented	51,642,828	61,670,710	186,959,075
Age	Years	30.0 (2.0-67.0)	37.5 (4.0-78.0)	38.9 (4.0-72.0)
Older adults	% Age >=65 years	5.9	15.9	13.0
Sex	% Female	53.6	53.7	51.3
White race	% White	63.0	75.4	83.3
Black race	% Black	26.7	15.3	9.8
Hispanic ethnicity	% Hispanic	31.2	27.8	12.2
Education	% Completed high-school	47.5	58.9	73.3
Employment	% Employed (1=yes)	28.9	34.3	55.9
Household size	Number of non-guest residents	4.2 (1.0-9.0)	3.6 (1.0-8.0)	3.1 (1.0-6.0)
Income	Total income as % of federal poverty threshold for household size	138.6 (0.0-357.0)	100.8 (0.0-180.0)	503.9 (206.0-1048.0)
Housing cost	Household's monthly rent/mortgage expense, $	577.1 (0.0-1500.0)	720.6 (0.0-2000.0)	1,014 (0.0-2400.0)
Distance to primary food store	Miles, Euclidean distance	3.1 (0.2-13.3)	3.5 (0.2-14.3)	3.9 (0.4-14.1)

Rural residence residence	% Rural residence	22.7	27.5	35.4
Food security status	% low or very low food security on USDA 30-day Adult Food Security Scale	42.7	31.9	6.9
WIC	% households with a member participating in the Women, Infants and Children program	22.4	14.1	3.0
Supermarkets	Per 1,000 people, in county of residence	12.0 (6.1-21.4)	11.8 (6.4-21.4)	12.1 (6.7-21.7)
Non-supermarkets (non-supermarket food retailer)	Per 1,000 people, in county of residence	28.4 (13.3-52.8)	25.8 (9.7-51.5)	23.4 (7.1-44.0)
Full-service restaurants ("sit down" table service)	Per 1,000 people, in county of residence	74.0 (42.1-111.0)	78.6 (41.2-142.4)	82.1 (45.3-142.4)
Limited-service restaurants ("fast food")	Per 1,000 people, in county of residence	69.2 (34.8-88.4)	69.4 (42.1-91.0)	69.6 (42.1-91.0)
Poverty rate	% of people below poverty threshold, in county of residence	16.2 (9.6-25.8)	15.6 (7.7-23.6)	13.8 (6.6-21.8)
Area-level household income	Median, in county of residence (2012 inflation-adj $)	50,360 (32,960-78,187)	52,825 (35,093-81,093)	55,405 (36,875-87,751)
Area-level educational attainment	% of population 25+ years old with high school education	84.7 (73.9-92.6)	84.0 (75.6-92.8)	87.0 (75.4-94.5)
Vehicle density	% of occupied housing units with at least one vehicle available	91.6 (82.3-95.8)	92.1 (82.3-96.8)	93.0 (86.4-97.1)
Kitchen availability	% of occupied housing units with complete kitchen facilities available	99.1 (98.3-99.6)	99.0 (98.3-99.7)	99.1 (98.3-99.6)

Regional price parity, overall	Overall cost of living, relative to national average (100% = average)	97.6 (89.6-1.21)	100.4 (89.6-122.2)	99.3 (89.6-121.4)
Regional price parity, rents	Rent/mortgage costs, relative to national average (100% = average)	95.8 (65.4-156.7)	103.8 (70.6-181.3)	102.4 (70.6-181.3)
Regional price parity, food	Food costs, relative to national average (100% = average)	98.7 (94.9-112.3)	100.1 (94.9-112.3)	100.0 (84.8-112.3)
Regional price parity, all goods	Cost of goods, relative to national average (100% = average)	98.8 (95.0-108.9)	99.8 (95.0-108.9)	99.3 (92.6-108.9)
Regional price parity, all services	Cost of services, relative to national average (100% = average)	98.1 (88.4-119.0)	100.2 (88.4-119.0)	98.7 (88.4-119.0)
Geographic adjustment to Supplemental Poverty Measure	Gross rents for two-bedroom apartments with complete Kitchen availability and plumbing, relative to national average (100% = average)	98.6 (75.3-155.9)	104.6 (75.6-166.9)	103.8 (75.6-166.9)

Table 2: Food acquired at home and away from home among participants in the National Household Food Acquisition and Purchase Survey (2012-2013) by Supplemental Nutrition Assistance Program (SNAP) participation status and income level. The Stata commands svy linearized, subpop were applied to data from each subpopulation (SNAP participants, non-participants <=185% of the federal poverty level, and non-participants >185% of the federal poverty level) to adjust estimates for stratification and clustering, and to apply sample weights. Acquisitions are expressed both in grams per household per week in each food category and food pattern equivalents (e.g., cup-equivalents, ounce-equivalents) per household per week. Acquisitions per person per day were calculated by dividing the amount of food acquired by each respondent by the reported number of persons among whom that food was shared. Standard errors are provided in parentheses. FPL: federal poverty threshold level. FPE: food pattern equivalents.

Food category	**Household level food acquisitions**						**Person level food acquisitions**						**FPE units**
	in grams/week			in FPE/week			in grams/day			in FPE/day			
	SNAP participants	Non-participants <=185% FPL	Non-participants >185% FPL	SNAP participants	Non-participants <=185% FPL	Non-participants >185% FPL	SNAP participants	Non-participants <=185% FPL	Non-participants >185% FPL	SNAP participants	Non-participants <=185% FPL	Non-participants >185% FPL	
Vegetables	7800 (351)	6628 (317)	7371 (239)	35.1 (2.0)	29.8 (1.4)	34.4 (1.4)	334 (19)	389 (19)	414 (13)	1.5 (0.1)	1.8 (0.1)	2.0 (0.1)	Cup-eq
Fruits	7014 (573)	4722 (365)	5078 (255)	18.9 (1.3)	15.6 (1.2)	17.0 (0.9)	290 (24)	256 (20)	282 (16)	0.8 (0.1)	0.9 (0.1)	0.9 (0.1)	Cup-eq
Whole grains	1690 (168)	1178 (105)	1247 (58)	24.9 (6.0)	15.6 (1.5)	20.4 (2.0)	66 (5)	62 (6)	68 (4)	0.9 (0.1)	0.9 (0.1)	1.2 (0.1)	Oz-eq
Refined grains	8536 (484)	6228 (348)	6854 (243)	170.3 (11.9)	121.9 (8.5)	128.2 (4.9)	361 (20)	335 (16)	370 (15)	7.1 (0.4)	6.5 (0.3)	7.0 (0.4)	Oz-eq
Dairy	10377 (398)	8082 (472)	8966 (357)	42.4 (2.2)	33.4 (1.9)	38.3 (2.1)	439 (21)	436 (22)	485 (18)	1.8 (0.1)	1.9 (0.1)	2.0 (0.1)	Cup-eq
Protein	8529 (463)	5858 (256)	6774 (233)	121.8 (6.3)	81.7 (3.8)	97.2 (3.9)	369 (20)	337 (19)	381 (13)	5.5 (0.3)	4.8 (0.2)	5.6 (0.3)	Oz-eq
Fats and oils	18089 (624)	13113 (626)	14580 (417)	1664 (97)	1102 (60)	1266 (57)	780 (39)	747 (36)	804 (26)	72.1 (4.4)	67.0 (4.7)	71.1 (4.0)	Grams
Added sugars	21550 (1054)	14212 (817)	15983 (764)	747 (58)	432 (32)	480 (35)	941 (48)	749 (35)	884 (45)	31.4 (2.4)	23.0 (1.4)	25.9 (1.9)	Tsp-eq
Total kcals/person/day	-	-	-	-	-	-	-	-	-	2588 (122)	2336 (114)	2567 (105)	Kcals

Table 3: Comparison of food acquisition estimates from the National Household Food Acquisition and Purchase Survey (2012-2013) by Supplemental Nutrition Assistance Program (SNAP) participation status and income level to independent estimates of food consumption from the National Health and Nutrition Examination Survey (2007-2010) and U.S. National Dietary Guidelines (2015-2020). The Stata commands svy linearized, subpop were applied to data from each subpopulation (SNAP participants, non-participants <=185% of the federal poverty level, and non-participants >185% of the federal poverty level) to adjust estimates for stratification and clustering, and to apply sample weights. FPE: food pattern equivalents. Standard errors in parentheses. HEI: Healthy Eating Index, 2010.

Food category	Acquisitions in food pattern equivalents/day, National Food Acquisition and Purchasing Survey (2012-2013)			Consumption in food pattern equivalents/day, National Health and Nutrition Examination Survey (2007-2010)	National Dietary Guidelines (2015-2020), for sedentary persons Age 40 yrs w/ a mean recommended caloric intake (2,200 kcal/day)	FPE units
	SNAP participants	Non-participants <=185% FPL	Non-participants >185% FPL	All persons	All persons	
Vegetables	1.5 (0.1)	1.8 (0.1)	2.0 (0.1)	1.5 (0.02)	3.0	Cup-eq
Fruits	0.8 (0.1)	0.9 (0.1)	0.9 (0.1)	1.1 (0.03)	2.0	Cup-eq
Whole grains	0.9 (0.1)	0.9 (0.1)	1.2 (0.1)	0.8 (0.02)	3.5	Oz-eq
Refined grains	7.1 (0.4)	6.5 (0.3)	7.0 (0.4)	5.5 (0.06)	3.5	Oz-eq
Dairy	1.8 (0.1)	1.9 (0.1)	2.0 (0.1)	1.8 (0.03)	3.0	Cup-eq
Protein	5.5 (0.3)	4.8 (0.2)	5.6 (0.3)	5.7 (0.07)	6.0	Oz-eq
Fats and oils	72.1 (4.4)	67.0 (4.7)	71.1 (4.0)	56.8 (0.7)	29.0	Grams
Added sugars	31.4 (2.4)	23.0 (1.4)	25.9 (1.9)	16.8 (0.3)	13.8	Tsp-eq
HEI score	54.4 (0.2)	54.7 (0.2)	55.0 (0.1)	55.4 (0.7)	100	Scale 0 (worst) to 100 (best)

Table 4: Average effect of living in a high-cost area (at least one standard deviation above the mean national cost) on food acquisitions and overall Healthy Eating Index (HEI) scores. Cost of living is measured by regional price parities (RPPs), either overall, or by category of expenditure (rent, food, all goods, or all services); the geographic adjustment to the Supplemental Poverty Measure is provided as an alternative cost-of-living metric. Estimates of average effect are based on an endogenous treatment effects model applied to data from participants in the National Household Food Acquisition and Purchase Survey (2012-2013). All regressions control for individual-, household-, and county-level factors detailed in the text. Standard errors in parentheses. FPE: food pattern equivalents. RPP: regional price parity.

Metric of cost-of-living	Food category								Calories	HEI score
	Vegetables	Fruits	Whole grains	Refined grains	Dairy	Protein	Fats and oils	Added sugars		
		Units								
	Cup-eq	Cup-eq	Oz-eq	Oz-eq	Cup-eq	Oz-eq	Grams	Tsp-eq	Kcals /person/day	Scale from 0 (worst) to 100 (best)
Overall cost of living (RPP)	-0.65 (0.04)***	-0.14 (0.02)***	-0.11 (0.03)**	2.35 (0.12)***	0.28 (0.04)***	0.86 (0.11)***	36.63 (1.89)***	9.40 (0.84)***	542.92 (45.60)***	-6.0 (0.9)***
Rent cost (RPP)	-0.65 (0.04)***	-0.14 (0.02)***	-0.11 (0.03)**	2.35 (0.12)***	0.28 (0.04)***	0.86 (0.11)***	36.63 (1.89)***	9.40 (0.84)***	542.92 (45.60)***	-6.0 (0.9)***
Food cost (RPP)	-0.41 (0.04)***	-0.17 (0.02)***	-0.06 (0.04)	2.68 (0.13)***	0.33 (0.04)***	0.64 (0.12)***	31.74 (1.40)***	9.63 (0.66)***	471.50 (40.91)***	-1.4 (1.0)
All goods (RPP)	-0.34 (0.03)****	-0.10 (0.01)***	0.38 (0.04)***	2.67 (0.11)***	0.24 (0.03)***	1.38 (0.10)***	43.45 (1.97)***	11.54 (0.82)***	884.54 (66.84)***	-4.5 (0.8)***
All services (RPP)	-0.35 (0.03)***	-0.11 (0.02)***	0.36 (0.04)***	2.80 (0.12)***	0.34 (0.04)***	1.10 (0.10)***	45.07 (2.46)***	16.15 (1.05)***	869.22 (73.18)***	-4.1 (0.8)***
Geographic adjustment to Supplemental Poverty Measure	-0.67 (0.04)***	-0.18 (0.02)***	-0.05 (0.04)	3.05 (0.13)***	0.36 (0.04)***	1.35 (0.11)***	47.71 (2.11)***	12.57 (0.92)***	766.35 (52.10)***	-2.1 (0.9)*

* = p<0.05; ** = p<0.01; *** = p<0.001

Table 5: Average treatment effect of SNAP participation on the probability of living in a high-cost area (at least one standard deviation above the mean national cost). Cost of living is measured by regional price parities (RPPs), either overall, or by category of expenditure (rent, food, all goods, or all services); the geographic adjustment to the Supplemental Poverty Measure is provided as an alternative cost-of-living metric. Estimates of average effect are based on an endogenous treatment effects model applied to data from participants in the National Household Food Acquisition and Purchase Survey (2012-2013). All regressions control for individual-, household-, and county-level factors detailed in the text. Standard errors in parentheses. FPE: food pattern equivalents.

Cost-of-living metric	Average treatment effect		Average treatment effect on the treated	
	Probability of living in high-cost county given non-participant in SNAP	Increased probability given SNAP participation	Probability of living in high-cost county given non-participant in SNAP	Increased probability given SNAP participation
Overall regional price parity	0.20 (0.01)***	0.44 (0.01)***	0.00 (0.00)***	0.22 (0.00)***
Rent regional price parity	0.20 (0.01)***	0.44 (0.01)***	0.00 (0.00)***	0.22 (0.00)***
Food regional price parity	0.27 (0.02)***	0.39 (0.02)***	0.00 (0.01)	0.24 (0.01)***
Goods regional price parity	0.26 (0.02)***	0.40 (0.02)***	0.01 (0.00)*	0.22 (0.00)***
Services regional price parity	0.20 (0.01)***	0.43 (0.01)***	0.00 (0.00)***	0.22 (0.00)***
Geographic adjustment to the Supplemental Poverty Measure	0.27 (0.02)***	0.36 (0.02)***	0.08 (0.03)**	0.17 (0.02)***

*=p<0.05, **=p<0.01, ***=p<0.001

Table 6. Interactions between SNAP participation, cost of living, and food acquisitions. Coefficients for each food category are in units of food pattern equivalents (e.g., cup-equivalents, ounce-equivalents) as detailed in Table 2, whereas the Healthy Eating Index (HEI) is on a scale from 0 (worst) to 100 (best).

(A) Average treatment effect

Food category	Low-cost area (Overall regional price parity)		High-cost area (Overall regional price parity)	
	Acquisition if not participating in SNAP	Change in acquisition if participating in SNAP	Acquisition if not participating in SNAP	Change in acquisition if participating in SNAP
Vegetables	1.98 (0.22)***	0.73 (0.01)***	0.75 (0.01)***	0.09 (0.01)***
Fruits	0.63 (0.07)***	0.31 (0.00)***	0.17 (0.09)	0.01 (0.90)
Whole grains	0.60 (0.10)***	0.60 (0.01)***	0.27 (0.23)	-0.03 (0.02)
Refined grains	9.54 (1.33)***	-4.54 (1.33)**	2.86 (0.07)***	-1.49 (0.08)***
Dairy	2.41 (0.23)***	0.90 (0.06)***	0.92 (0.08)***	0.13 (0.08)
Protein	4.27 (0.53)***	2.71 (0.17)***	1.80 (0.01)***	1.12 (0.03)***
Fats and oils	124.1 (15.4)***	28.95 (0.83)***	32.88 (2.92)***	9.53 (2.95)**
Added sugars	9.76 (0.08)***	9.29 (0.39)***	9.35 (0.10)***	7.14 (0.18)***
Kcals/person/day	1232.30 (49.27)***	1167.4 (90.45)***	958.58 (12.47)***	517.83 (17.23)***
HEI score	54.48 (0.74)***	-0.51 (0.76)	40.67 (1.04)***	19.77 (1.68)***

*=p<0.05, **=p<0.01, ***=p<0.001

(B) Average treatment effect on the treated

Food category	Low-cost area (Overall regional price parity)		High-cost area (Overall regional price parity)	
	Acquisition if not participating in SNAP	Change in acquisition if participating in SNAP	Acquisition if not participating in SNAP	Change in acquisition if participating in SNAP
Vegetables	1.32 (0.02)***	0.05 (0.02)**	1.48 (0.02)***	0.05 (0.02)**
Fruits	0.67 (0.01)***	0.03 (0.00)***	0.03 (0.02)	0.00 (0.01)
Whole grains	0.10 (0.29)	0.01 (0.03)	0.49 (0.42)	-0.05 (0.04)
Refined grains	11.63 (2.24)***	-4.81 (2.24)*	7.61 (0.12)***	0.26 (0.13)
Dairy	1.49 (0.10)***	0.32 (0.10)**	1.59 (0.14)***	0.31 (0.14)*
Protein	3.51 (0.28)***	1.51 (0.28)***	5.27 (0.04)***	0.01 (0.00)**
Fats and oils	63.44 (1.40)***	6.62 (1.35)***	65.05 (5.13)***	11.63 (5.81)
Added sugars	26.07 (0.16)***	0.45 (0.08)***	29.80 (0.23)***	0.00 (0.01)
Kcals/person/day	1833.17 (82.95)***	560.44 (82.36)***	2626.21 (23.15)***	31.35 (16.31)
HEI score	54.44 (1.25)***	-0.32 (1.25)	29.43 (1.88)***	25.13 (0.02)***

*=p<0.05, **=p<0.01, ***=p<0.001

Table 7: Ordinary least squares regressions testing hypothesis 1: that increased cost of living is associated with less healthy food acquisitions. Subtables (A)-(H) correspond to food pattern equivalents of food categories 1 through 8 (vegetables through added sugars) as the outcome (in food patterns equivalent units), while subtable (I) corresponds to kilocalories per person per day as the outcome and (J) corresponds to the Healthy Eating Index as the outcome. All regressions include survey sample weights to account for differential sampling and response. * = p<0.05; ** = p<0.01; *** = p<0.001

(A)

Covariate	Change in acquisition of vegetables					
Cost of living metric	Overall RPP	Rent RPP	Food RPP	Good RPP	Services RPP	Geographic adjustment to the Supplemental Poverty Measure
Cost of living	-0.1097 (0.0117)***	-0.1097 (0.0117)***	-0.0727 (0.0102)***	-0.0698 (0.0112)***	-0.0765 (0.0113)***	-0.069 (0.0114)***
Age	0.0288 (0.001)***	0.0288 (0.001)***	0.0289 (0.001)***	0.0289 (0.001)***	0.0289 (0.001)***	0.0289 (0.001)***
Age squared	-0.0002 (0)***	-0.0002 (0)***	-0.0002 (0)***	-0.0002 (0)***	-0.0002 (0)***	-0.0002 (0)***
Sex (1=female)	0.1343 (0.0085)***	0.1343 (0.0085)***	0.1343 (0.0085)***	0.1341 (0.0085)***	0.1341 (0.0085)***	0.1342 (0.0085)***
White race	0.1015 (0.0123)***	0.1015 (0.0123)***	0.1055 (0.0123)***	0.1037 (0.0123)***	0.1034 (0.0123)***	0.1023 (0.0123)***
Black race	-0.1575 (0.0158)***	-0.1575 (0.0158)***	-0.1506 (0.0158)***	-0.1522 (0.0157)***	-0.1532 (0.0157)***	-0.1562 (0.0158)***
Hispanic	-0.1757 (0.012)***	-0.1757 (0.012)***	-0.1652 (0.0119)***	-0.1712 (0.012)***	-0.1711 (0.012)***	-0.1722 (0.012)***
Education >= high school	-0.1819 (0.0111)***	-0.1819 (0.0111)***	-0.1826 (0.0111)***	-0.183 (0.0111)***	-0.1832 (0.0111)***	-0.1826 (0.0111)***
Employed (1=yes)	-0.0409 (0.009)***	-0.0409 (0.009)***	-0.0413 (0.009)***	-0.0406 (0.009)***	-0.0409 (0.009)***	-0.0407 (0.009)***
Household size	-0.1872 (0.0024)***	-0.1872 (0.0024)***	-0.1876 (0.0024)***	-0.1871 (0.0024)***	-0.1873 (0.0024)***	-0.187 (0.0024)***

Income ($/10^4)	0.326 (0.151)*	0.326 (0.151)*	0.4 (0.151)*	0.399 (0.151)**	0.392 (0.151)**	0.34 (0.151)*
Housing cost ($/10^4)	0.717 (0.036)***	0.717 ().036)***	0.725 (0.0361)****	0.716 (0.036)***	0.718 (0.036)***	0.714 (0.036)***
Distance to primary food store	0.0086 (0.001)***	0.0086 (0.001)***	0.0085 (0.001)***	0.0087 (0.001)***	0.0087 (0.001)***	0.0088 (0.001)***
Rural residence	0.1408 (0.0115)***	0.1408 (0.0115)***	0.136 (0.0115)***	0.136 (0.0115)***	0.1382 (0.0116)***	0.1333 (0.0115)***
Food security status	-0.0788 (0.0092)***	-0.0788 (0.0092)***	-0.0802 (0.0092)***	-0.079 (0.0092)***	-0.0786 (0.0092)***	-0.0794 (0.0092)***
WIC	0.0405 (0.0127)**	0.0405 (0.0127)**	0.0383 (0.0127)**	0.0383 (0.0127)**	0.039 (0.0127)**	0.0385 (0.0127)**
Supermarkets	0.4258 (0.1166)***	0.4258 (0.1166)***	0.3119 (0.1154)**	0.366 (0.1167)**	0.3676 (0.1165)**	0.3232 (0.1158)**
Non-supermarkets	-0.6554 (0.0446)***	-0.6554 (0.0446)***	-0.6812 (0.0444)***	-0.676 (0.0445)***	-0.666 (0.0447)***	-0.6839 (0.0444)***
Full-service restaurants	-0.0424 (0.0174)*	-0.0424 (0.0174)*	-0.0474 (0.0175)**	-0.0557 (0.0173)**	-0.0523 (0.0174)**	-0.0512 (0.0175)**
Limited-service restaurants	-0.1355 (0.0348)***	-0.1355 (0.0348)***	-0.11 (0.0347)**	-0.0945 (0.0344)**	-0.104 (0.0346)**	-0.107 (0.035)**
Poverty rate	1.7455 (0.1879)***	1.7455 (0.1879)***	1.5159 (0.188)***	1.64 (0.1875)***	1.6397 (0.1874)***	1.6662 (0.1876)***
Area-level household income	0 (0)***	0 (0)***	0 (0)**	0 (0)**	0 (0)***	0 (0)**
Area-level educational attainment	-1.1778 (0.1094)***	-1.1778 (0.1094)***	-1.096 (0.1092)***	-1.0815 (0.11)***	-1.1001 (0.1099)***	-1.0663 (0.1096)***
Vehicle density	0.7893 (0.1587)***	0.7893 (0.1587)***	0.6746 (0.1582)***	0.7238 (0.1584)***	0.744 (0.1585)***	0.75 (0.1587)***
Kitchen availability	7.1063 (1.2728)***	7.1063 (1.2728)***	8.9548 (1.2373)***	9.0047 (1.2451)***	8.5776 (1.2548)***	8.4611 (1.2731)***

SNAP participation	-0.0574 (0.0093)***	-0.0574 (0.0093)***	-0.0574 (0.0093)***	-0.058 (0.0093)***	-0.0577 (0.0093)***	-0.0578 (0.0093)***
Intercept	-5.4052 (1.2176)***	-5.4052 (1.2176)***	-7.207 (1.1815)***	-7.324 (1.1889)***	-6.9144 (1.1984)***	-6.8099 (1.2191)***
Observations	230,323	230,323	230,323	230,323	230,323	230,323
R-squared	0.0698	0.0698	0.0696	0.0696	0.0696	0.0696

(B)

Covariates	Change in acquisition of fruits					
Cost of living metric	Overall RPP	Rent RPP	Food RPP	Good RPP	Services RPP	Geographic adjustment to the Supplemental Poverty Measure
Cost of living	0.0074 (0.0052)	0.0074 (0.0052)	0.0463 (0.0045)***	0.0314 (0.005)***	0.0186 (0.005)***	0.0265 (0.0051)***
Age	0.0017 (0.0004)***	0.0017 (0.0004)***	0.0017 (0.0004)***	0.0017 (0.0004)***	0.0017 (0.0004)***	0.0017 (0.0004)***
Age squared	0 (0)***	0 (0)***	0 (0)***	0 (0)***	0 (0)***	0 (0)***
Sex (1=female)	0.0702 (0.0038)***	0.0702 (0.0038)***	0.0698 (0.0038)***	0.0701 (0.0038)***	0.0701 (0.0038)***	0.07 (0.0038)***
White race	0.0166 (0.0055)**	0.0166 (0.0055)**	0.0155 (0.0055)**	0.0166 (0.0055)**	0.0166 (0.0055)**	0.0171 (0.0055)**
Black race	-0.0155 (0.007)*	-0.0155 (0.007)*	-0.0175 (0.007)*	-0.0163 (0.007)*	-0.0158 (0.007)*	-0.0147 (0.007)*
Hispanic	0.1373 (0.0053)***	0.1373 (0.0053)***	0.1381 (0.0053)***	0.1403 (0.0053)***	0.1385 (0.0053)***	0.1401 (0.0054)***
Education >= high school	0.0741 (0.005)***	0.0741 (0.005)***	0.0738 (0.005)***	0.0741 (0.005)***	0.0742 (0.005)***	0.074 (0.005)***
Employed (1=yes)	-0.0835 (0.004)***	-0.0835 (0.004)***	-0.0825 (0.004)***	-0.0831 (0.004)***	-0.0833 (0.004)***	-0.0832 (0.004)***
Household size	-0.0641 (0.0011)***	-0.0641 (0.0011)***	-0.0636 (0.0011)***	-0.064 (0.0011)***	-0.064 (0.0011)***	-0.064 (0.0011)***
Income ($/10^4)	1.842 (0.0672)***	1.852 (0.0672)***	1.814 (0.0672)***	1.822 (0.0672)***	1.832 (0.0672)***	1.847 (0.0671)***
Housing cost ($/10^4)	0.369 (0.0161)***	0.369 (0.0161)***	0.361 (0.0161)***	0.368 (0.0161)***	0.368 (0.0161)***	0.368 (0.0161)***
Distance to primary food store	0.0141 (0.0004)***	0.0141 (0.0004)***	0.0143 (0.0004)***	0.0141 (0.0004)***	0.0141 (0.0004)***	0.0141 (0.0004)***
Rural residence	-0.0718 (0.0051)***	-0.0718 (0.0051)***	-0.0789 (0.0051)***	-0.0764 (0.0051)***	-0.0743 (0.0052)***	-0.0745 (0.0051)***
Food security status	-0.1194 (0.0041)***	-0.1194 (0.0041)***	-0.119 (0.0041)***	-0.1197 (0.0041)***	-0.1196 (0.0041)***	-0.1194 (0.0041)***
WIC	0.1215 (0.0057)***	0.1215 (0.0057)***	0.1204 (0.0057)***	0.1208 (0.0057)***	0.1211 (0.0057)***	0.1209 (0.0057)***
Supermarkets	0.2295 (0.052)***	0.2295 (0.052)***	0.1963 (0.0514)***	0.1854 (0.052)***	0.211 (0.0519)***	0.2102 (0.0516)***
Non-supermarkets	0.0529 (0.0199)**	0.0529 (0.0199)**	0.0376 (0.0198)	0.0409 (0.0198)*	0.0457 (0.0199)*	0.0462 (0.0198)*
Full-service restaurants	-0.0379 (0.0078)***	-0.0379 (0.0078)***	-0.0513 (0.0078)***	-0.043 (0.0077)***	-0.0406 (0.0077)***	-0.0437 (0.0078)***
Limited-service restaurants	0.0576 (0.0155)***	0.0576 (0.0155)***	0.0926 (0.0154)***	0.0736 (0.0153)***	0.0658 (0.0154)***	0.0751 (0.0156)***
Poverty rate	0.6329 (0.0837)***	0.6329 (0.0837)***	0.7065 (0.0837)***	0.6315 (0.0835)***	0.6362 (0.0835)***	0.6229 (0.0836)***

Area-level household income	0 (0)***	0 (0)***	0 (0)***	0 (0)***	0 (0)***	0 (0)***
Area-level educational attainment	0.4898 (0.0487)***	0.4898 (0.0487)***	0.6222 (0.0486)***	0.5702 (0.049)***	0.5278 (0.049)***	0.5494 (0.0488)***
Vehicle density	0.2604 (0.0707)***	0.2604 (0.0707)***	0.2666 (0.0705)***	0.2449 (0.0706)**	0.2508 (0.0706)***	0.2383 (0.0707)**
Kitchen availability	-4.7157 (0.5673)***	-4.7157 (0.5673)***	-3.7175 (0.5513)***	-4.1097 (0.5548)***	-4.402 (0.5591)***	-4.0275 (0.5673)***
SNAP participation	0.0711 (0.0041)***	0.0711 (0.0041)***	0.0708 (0.0041)***	0.0711 (0.0041)***	0.071 (0.0041)***	0.0711 (0.0041)***
Intercept	4.6897 (0.5427)***	4.6897 (0.5427)***	3.5488 (0.5264)***	4.017 (0.5298)***	4.3503 (0.534)***	3.9579 (0.5432)***
Observations	230,323	230,323	230,323	230,323	230,323	230,323
R-squared	0.0637	0.0637	0.0642	0.0639	0.0638	0.0639

(C)

Covariates	Change in acquisition of whole grains					
Cost of living metric	Overall RPP	Rent RPP	Food RPP	Good RPP	Services RPP	Geographic adjustment to the Supplemental Poverty Measure
Cost of living	0.1023 (0.0152)***	0.1023 (0.0152)***	-0.025 (0.0132)	0.0143 (0.0146)	0.0271 (0.0146)	0.1105 (0.0148)***
Age	0.01 (0.0013)***	0.01 (0.0013)***	0.0099 (0.0013)***	0.0099 (0.0013)***	0.0099 (0.0013)***	0.01 (0.0013)***
Age squared	-0.0001 (0)***	-0.0001 (0)***	-0.0001 (0)***	-0.0001 (0)***	-0.0001 (0)***	-0.0001 (0)***
Sex (1=female)	0.1478 (0.011)***	0.1478 (0.011)***	0.1485 (0.011)***	0.1482 (0.011)***	0.1482 (0.011)***	0.1477 (0.011)***
White race	-0.248 (0.016)***	-0.248 (0.016)***	-0.25 (0.016)***	-0.2504 (0.016)***	-0.2502 (0.016)***	-0.2475 (0.016)***
Black race	-0.4635 (0.0205)***	-0.4635 (0.0205)***	-0.4664 (0.0205)***	-0.4675 (0.0205)***	-0.4674 (0.0205)***	-0.4627 (0.0205)***
Hispanic	-0.3772 (0.0156)***	-0.3772 (0.0156)***	-0.3903 (0.0155)***	-0.3876 (0.0156)***	-0.3864 (0.0156)***	-0.374 (0.0156)***
Education >= high school	0.2145 (0.0145)***	0.2145 (0.0145)***	0.216 (0.0145)***	0.2157 (0.0145)***	0.2157 (0.0145)***	0.2147 (0.0145)***
Employed (1=yes)	-0.2536 (0.0117)***	-0.2536 (0.0117)***	-0.2555 (0.0117)***	-0.2546 (0.0117)***	-0.2544 (0.0117)***	-0.2531 (0.0117)***
Household size	-0.0572 (0.0031)***	-0.0572 (0.0031)***	-0.0577 (0.0031)***	-0.0575 (0.0031)***	-0.0574 (0.0031)***	-0.0574 (0.0031)***
Income ($/10^4)	0.212 (0.196)	0.212 (0.196)	0.193 (0.196)	0.172 (0.196)	0.169 (0.196)	0.213 (0.196)
Housing cost ($/10^4)	-0.0259 (0.0469)	-0.0259 (0.0469)	-0.0163 (0.0469)	-0.0218 (0.0469)	-0.0241 (0.0469)	-0.0254 (0.0468)
Distance to primary food store	0.011 (0.0013)***	0.011 (0.0013)***	0.0105 (0.0013)***	0.0107 (0.0013)***	0.0108 (0.0013)***	0.011 (0.0013)***
Rural residence	-0.1037 (0.015)***	-0.1037 (0.015)***	-0.0826 (0.0149)***	-0.0898 (0.015)***	-0.0925 (0.015)***	-0.1037 (0.0149)***
Food security status	-0.1999 (0.012)***	-0.1999 (0.012)***	-0.1992 (0.012)***	-0.1992 (0.012)***	-0.1995 (0.012)***	-0.1996 (0.012)***
WIC	0.0789 (0.0166)***	0.0789 (0.0166)***	0.0838 (0.0166)***	0.0826 (0.0166)***	0.082 (0.0166)***	0.0792 (0.0166)***
Supermarkets	-0.1158 (0.1517)	-0.1158 (0.1517)	0.0819 (0.1501)	0.0315 (0.1518)	0.0122 (0.1515)	-0.0755 (0.1506)
Non-supermarkets	0.1554 (0.0579)**	0.1554 (0.0579)**	0.2175 (0.0577)***	0.2001 (0.0579)**	0.1913 (0.0581)**	0.1639 (0.0577)**
Full-service restaurants	0.522 (0.0227)***	0.522 (0.0227)***	0.5575 (0.0227)***	0.5459 (0.0226)***	0.5423 (0.0226)***	0.5167 (0.0227)***
Limited-service restaurants	-0.9248 (0.0453)***	-0.9248 (0.0453)***	-1.0308 (0.0451)***	-0.9986 (0.0447)***	-0.9879 (0.045)***	-0.9103 (0.0455)***

Poverty rate	3.2654 (0.2443)***	3.2654 (0.2443)***	3.3496 (0.2444)***	3.38 (0.2438)***	3.3768 (0.2438)***	3.3069 (0.2439)***
Area-level household income	0 (0)***	0 (0)***	0 (0)***	0 (0)***	0 (0)***	0 (0)***
Area-level educational attainment	1.2371 (0.1422)***	1.2371 (0.1422)***	0.8522 (0.142)***	0.9819 (0.1431)***	1.0223 (0.143)***	1.2745 (0.1424)***
Vehicle density	-3.6996 (0.2063)***	-3.6996 (0.2063)***	-3.5892 (0.2057)***	-3.6008 (0.206)***	-3.6156 (0.2062)***	-3.7151 (0.2064)***
Kitchen availability	6.5199 (1.6552)***	6.5199 (1.6552)***	2.2837 (1.6091)	3.3536 (1.6191)*	3.7907 (1.6317)*	6.8999 (1.6553)***
SNAP participation	0.0689 (0.0121)***	0.0689 (0.0121)***	0.0696 (0.0121)***	0.0694 (0.0121)***	0.0693 (0.0121)***	0.0692 (0.0121)***
Intercept	-5.6066 (1.5834)***	-5.6066 (1.5834)***	-1.1017 (1.5364)	-2.2921 (1.5461)	-2.7493 (1.5584)	-6.0388 (1.5851)***
Observations	230,323	230,323	230,323	230,323	230,323	230,323
R-squared	0.0273	0.0273	0.0271	0.0271	0.0271	0.0273

(D)

Covariates	Change in acquisition of refined grains					
Cost of living metric	Overall RPP	Rent RPP	Food RPP	Good RPP	Services RPP	Geographic adjustment to the Supplemental Poverty Measure
Cost of living	0.5461 (0.0368)***	0.5461 (0.0368)***	0.1898 (0.0321)***	0.4626 (0.0354)***	0.4985 (0.0355)***	0.7781 (0.036)***
Age	0.1048 (0.0032)***	0.1048 (0.0032)***	0.1042 (0.0032)***	0.1046 (0.0032)***	0.1047 (0.0032)***	0.1047 (0.0032)***
Age squared	-0.0012 (0)***	-0.0012 (0)***	-0.0011 (0)***	-0.0012 (0)***	-0.0011 (0)***	-0.0012 (0)***
Sex (1=female)	0.3501 (0.0267)***	0.3501 (0.0267)***	0.3513 (0.0267)***	0.3508 (0.0267)***	0.3507 (0.0267)***	0.3484 (0.0267)***
White race	0.2966 (0.0387)***	0.2966 (0.0387)***	0.2799 (0.0387)***	0.2862 (0.0387)***	0.2881 (0.0387)***	0.3042 (0.0387)***
Black race	-0.2097 (0.0497)***	-0.2097 (0.0497)***	-0.2374 (0.0497)***	-0.2377 (0.0497)***	-0.2315 (0.0497)***	-0.1978 (0.0497)***
Hispanic	-0.3439 (0.0378)***	-0.3439 (0.0378)***	-0.4025 (0.0376)***	-0.3523 (0.0378)***	-0.3538 (0.0378)***	-0.3011 (0.0379)***
Education >= high school	-0.234 (0.0352)***	-0.234 (0.0352)***	-0.229 (0.0352)***	-0.2289 (0.0352)***	-0.2281 (0.0352)***	-0.2352 (0.0351)***
Employed (1=yes)	-0.271 (0.0284)***	-0.271 (0.0284)***	-0.2732 (0.0284)***	-0.2708 (0.0284)***	-0.2689 (0.0284)***	-0.2652 (0.0284)***
Household size	-0.4373 (0.0075)***	-0.4373 (0.0075)***	-0.437 (0.0075)***	-0.4376 (0.0075)***	-0.4366 (0.0075)***	-0.438 (0.0075)***
Income ($/10^4)	-7.91 (0.475)***	-7.91 (0.475)***	-8.182 (0.476)***	-8.332 (0.476)***	-8.281 (0.476)***	-7.845 (0.475)***
Housing cost ($/10^4)	2.862 (0.114)***	2.862 (0.114)***	2.854 (0.114)***	2.861 (0.114)***	2.849 (0.114)****	2.847 (0.114)***
Distance to primary food store	0.0766 (0.0031)***	0.0766 (0.0031)***	0.076 (0.0031)***	0.0766 (0.0031)***	0.0768 (0.0031)***	0.0772 (0.0031)***
Rural residence	-0.0346 (0.0363)	-0.0346 (0.0363)	0.0199 (0.0363)	-0.0324 (0.0364)	-0.045 (0.0365)	-0.0625 (0.0362)
Food security status	-0.2168 (0.0292)***	-0.2168 (0.0292)***	-0.2112 (0.0292)***	-0.2174 (0.0292)***	-0.2196 (0.0292)***	-0.2163 (0.0292)***
WIC	0.0249 (0.0402)	0.0249 (0.0402)	0.0411 (0.0402)	0.0321 (0.0402)	0.0282 (0.0402)	0.0197 (0.0401)
Supermarkets	-4.0753 (0.3681)***	-4.0753 (0.3681)***	-3.3387 (0.3643)***	-3.9846 (0.3684)***	-3.9813 (0.3676)***	-4.0863 (0.3651)***
Non-supermarkets	0.9861 (0.1406)***	0.9861 (0.1406)***	1.1854 (0.14)***	1.031 (0.1405)***	0.9701 (0.1409)***	0.9575 (0.14)***
Full-service restaurants	-0.1728 (0.055)**	-0.1728 (0.055)**	-0.091 (0.0552)	-0.1325 (0.0547)*	-0.1534 (0.0549)**	-0.2567 (0.0551)***
Limited-service restaurants	-0.1194 (0.1099)	-0.1194 (0.1099)	-0.3986 (0.1094)***	-0.2425 (0.1085)*	-0.186 (0.1091)	0.1257 (0.1103)

Poverty rate	0.0452 (0.5929)	0.0452 (0.5929)	0.9477 (0.5933)	0.5339 (0.5915)	0.5383 (0.5914)	0.1346 (0.5915)
Area-level household income	0 (0)***	0 (0)***	0 (0)***	0 (0)***	0 (0)***	0 (0)***
Area-level educational attainment	-0.3482 (0.3451)	-0.3482 (0.3451)	-1.3275 (0.3446)***	-0.4541 (0.3472)	-0.3576 (0.3469)	0.4301 (0.3455)
Vehicle density	1.0595 (0.5006)*	1.0595 (0.5006)*	1.6372 (0.4993)**	1.3001 (0.4998)**	1.1746 (0.5002)*	0.7635 (0.5004)
Kitchen availability	76.3886 (4.0164)***	76.3886 (4.0164)***	62.5276 (3.9055)***	70.0939 (3.9288)***	72.6686 (3.9591)***	85.1344 (4.0145)***
SNAP participation	1.0151 (0.0293)***	1.0151 (0.0293)***	1.0164 (0.0293)***	1.0185 (0.0293)***	1.0163 (0.0293)***	1.0166 (0.0293)***
Intercept	-71.8519 (3.8421)***	-71.8519 (3.8421)***	-57.6445 (3.7292)***	-65.7481 (3.7515)***	-68.1891 (3.7812)***	-81.281 (3.8441)***
Observations	230,323	230,323	230,323	230,323	230,323	230,323
R-squared	0.0445	0.0445	0.0437	0.0443	0.0444	0.0455

(E)

Covariates	Change in acquisition of dairy					
Cost of living metric	Overall RPP	Rent RPP	Food RPP	Good RPP	Services RPP	Geographic adjustment to the Supplemental Poverty Measure
Cost of living	0.1297 (0.01)***	0.1297 (0.01)***	0.0031 (0.0087)	0.0911 (0.0096)***	0.0878 (0.0096)***	0.1851 (0.0097)***
Age	0.0126 (0.0009)***	0.0126 (0.0009)***	0.0124 (0.0009)***	0.0125 (0.0009)***	0.0125 (0.0009)***	0.0125 (0.0009)***
Age squared	-0.0002 (0)***	-0.0002 (0)***	-0.0002 (0)***	-0.0002 (0)***	-0.0002 (0)***	-0.0002 (0)***
Sex (1=female)	0.0624 (0.0072)***	0.0624 (0.0072)***	0.063 (0.0072)***	0.0627 (0.0072)***	0.0627 (0.0072)***	0.062 (0.0072)***
White race	0.3358 (0.0105)***	0.3358 (0.0105)***	0.3327 (0.0105)***	0.3333 (0.0105)***	0.3336 (0.0105)***	0.3377 (0.0105)***
Black race	-0.1957 (0.0134)***	-0.1957 (0.0134)***	-0.2007 (0.0134)***	-0.2021 (0.0134)***	-0.2008 (0.0134)***	-0.1929 (0.0134)***
Hispanic	-0.1114 (0.0102)***	-0.1114 (0.0102)***	-0.1268 (0.0102)***	-0.1157 (0.0102)***	-0.1172 (0.0102)***	-0.1012 (0.0102)***
Education >= high school	0.0717 (0.0095)***	0.0717 (0.0095)***	0.0732 (0.0095)***	0.0729 (0.0095)***	0.0731 (0.0095)***	0.0714 (0.0095)***
Employed (1=yes)	-0.0906 (0.0077)***	-0.0906 (0.0077)***	-0.0921 (0.0077)***	-0.0908 (0.0077)***	-0.0906 (0.0077)***	-0.0892 (0.0077)***
Household size	-0.1131 (0.002)***	-0.1131 (0.002)***	-0.1134 (0.002)***	-0.1132 (0.002)***	-0.113 (0.002)***	-0.1132 (0.002)***
Income ($/10^4)	-0.495 (0.128)***	-0.495 (0.128)***	-0.537 (0.128)***	-0.585 (0.128)***	-0.571 (0.128)***	-0.479 (0.128)***
Housing cost ($/10^4)	0.712 (0.0307)***	0.712 (0.0307)***	0.718 (0.0307)***	0.713 (0.0307)***	0.711 (0.0307)***	0.711 (0.0307)***
Distance to primary food store	0.0276 (0.0008)***	0.0276 (0.0008)***	0.0272 (0.0008)***	0.0275 (0.0008)***	0.0275 (0.0008)***	0.0277 (0.0008)***
Rural residence	-0.0027 (0.0098)	-0.0027 (0.0098)	0.0178 (0.0098)	0.0013 (0.0098)	0.0009 (0.0099)	-0.0094 (0.0098)
Food security status	-0.0686 (0.0079)***	-0.0686 (0.0079)***	-0.0675 (0.0079)***	-0.0685 (0.0079)***	-0.0688 (0.0079)***	-0.0685 (0.0079)***
WIC	0.0389 (0.0108)***	0.0389 (0.0108)***	0.044 (0.0108)***	0.0412 (0.0108)***	0.0408 (0.0108)***	0.0376 (0.0108)**
Supermarkets	-0.9916 (0.0994)***	-0.9916 (0.0994)***	-0.7753 (0.0984)***	-0.9364 (0.0995)***	-0.9184 (0.0993)***	-0.9947 (0.0986)***
Non-supermarkets	0.1549 (0.038)***	0.1549 (0.038)***	0.2194 (0.0378)***	0.1749 (0.0379)***	0.169 (0.0381)***	0.1479 (0.0378)***
Full-service restaurants	-0.1434 (0.0149)***	-0.1434 (0.0149)***	-0.11 (0.0149)***	-0.1296 (0.0148)***	-0.1311 (0.0148)***	-0.1634 (0.0149)***
Limited-service restaurants	-0.126 (0.0297)***	-0.126 (0.0297)***	-0.2295 (0.0296)***	-0.1683 (0.0293)***	-0.1652 (0.0295)***	-0.0675 (0.0298)*

Poverty rate	-0.2466 (0.1601)	-0.2466 (0.1601)	-0.0911 (0.1602)	-0.1246 (0.1598)	-0.1207 (0.1597)	-0.2256 (0.1598)
Area-level household income	0 (0)***	0 (0)***	0 (0)***	0 (0)***	0 (0)***	0 (0)***
Area-level educational attainment	2.2235 (0.0932)***	2.2235 (0.0932)***	1.8513 (0.0931)***	2.1376 (0.0938)***	2.1231 (0.0937)***	2.4094 (0.0933)***
Vehicle density	0.6727 (0.1352)***	0.6727 (0.1352)***	0.8114 (0.1348)***	0.7438 (0.135)***	0.7288 (0.1351)***	0.6021 (0.1352)***
Kitchen availability	10.3971 (1.0847)***	10.3971 (1.0847)***	5.9681 (1.0547)***	8.3891 (1.0611)***	8.5766 (1.0694)***	12.4861 (1.0843)***
SNAP participation	0.1941 (0.0079)***	0.1941 (0.0079)***	0.1947 (0.0079)***	0.1949 (0.0079)***	0.1945 (0.0079)***	0.1944 (0.0079)***
Intercept	-10.1894 (1.0376)***	-10.1894 (1.0376)***	-5.5367 (1.0071)***	-8.1792 (1.0132)***	-8.3186 (1.0213)***	-12.4413 (1.0383)***
Observations	230,323	230,323	230,323	230,323	230,323	230,323
R-squared	0.0665	0.0665	0.0658	0.0662	0.0661	0.0673

(F)

Covariates	Change in acquisition of protein					
Cost of living metric	Overall RPP	Rent RPP	Food RPP	Good RPP	Services RPP	Geographic adjustment to the Supplemental Poverty Measure
Cost of living	0.0424 (0.0322)	0.0424 (0.0322)	-0.0992 (0.028)***	0.1121 (0.0309)***	0.0295 (0.031)	0.1579 (0.0314)***
Age	0.1064 (0.0028)***	0.1064 (0.0028)***	0.1063 (0.0028)***	0.1065 (0.0028)***	0.1064 (0.0028)***	0.1065 (0.0028)***
Age squared	-0.001 (0)***	-0.001 (0)***	-0.001 (0)***	-0.001 (0)***	-0.001 (0)***	-0.001 (0)***
Sex (1=female)	-0.1212 (0.0233)***	-0.1212 (0.0233)***	-0.1202 (0.0233)***	-0.1215 (0.0233)***	-0.1211 (0.0233)***	-0.1219 (0.0233)***
White race	0.3126 (0.0338)***	0.3126 (0.0338)***	0.3136 (0.0338)***	0.3123 (0.0338)***	0.3119 (0.0338)***	0.3158 (0.0338)***
Black race	0.2695 (0.0434)***	0.2695 (0.0434)***	0.2716 (0.0434)***	0.2661 (0.0434)***	0.2678 (0.0434)***	0.2745 (0.0434)***
Hispanic	-0.2019 (0.033)***	-0.2019 (0.033)***	-0.2105 (0.0328)***	-0.1931 (0.033)***	-0.2037 (0.033)***	-0.185 (0.0331)***
Education >= high school	-0.0853 (0.0307)**	-0.0853 (0.0307)**	-0.0839 (0.0307)**	-0.0851 (0.0307)**	-0.0848 (0.0307)**	-0.0863 (0.0307)**
Employed (1=yes)	-0.5655 (0.0248)***	-0.5655 (0.0248)***	-0.5684 (0.0248)***	-0.5644 (0.0248)***	-0.5655 (0.0248)***	-0.5635 (0.0248)***
Household size	-0.5957 (0.0066)***	-0.5957 (0.0066)***	-0.5968 (0.0066)***	-0.5956 (0.0066)***	-0.5957 (0.0066)***	-0.5957 (0.0066)***
Income ($/10^4)	2.908 (0.415)***	2.908 (0.415)***	2.949 (0.415)***	2.834 (0.415)***	2.883 (0.415)***	2.943 (0.415)***
Housing cost ($/10^4)	1.693 (0.0992)***	1.693 (0.0992)***	1.714 (0.0994)***	1.689 (0.0992)***	1.693 (0.00993)***	1.689 (0.0992)***
Distance to primary food store	0.0238 (0.0027)***	0.0238 (0.0027)***	0.023 (0.0027)***	0.0241 (0.0027)***	0.0238 (0.0027)***	0.0241 (0.0027)***
Rural residence	0.1947 (0.0317)***	0.1947 (0.0317)***	0.2194 (0.0316)***	0.1806 (0.0318)***	0.1957 (0.0318)***	0.1779 (0.0316)***
Food security status	-0.0461 (0.0255)	-0.0461 (0.0255)	-0.0464 (0.0255)	-0.047 (0.0255)	-0.0462 (0.0255)	-0.0466 (0.0255)
WIC	0.1369 (0.0351)***	0.1369 (0.0351)***	0.1415 (0.0351)***	0.135 (0.0351)***	0.1375 (0.0351)***	0.1331 (0.0351)***
Supermarkets	2.1521 (0.3213)***	2.1521 (0.3213)***	2.3217 (0.3178)***	2.022 (0.3215)***	2.1747 (0.3208)***	2.0341 (0.3189)***
Non-supermarkets	-0.8158 (0.1227)***	-0.8158 (0.1227)***	-0.7536 (0.1222)***	-0.8505 (0.1226)***	-0.8116 (0.123)***	-0.8563 (0.1223)***
Full-service restaurants	0.4039 (0.048)***	0.4039 (0.048)***	0.4482 (0.0482)***	0.3898 (0.0478)***	0.4077 (0.0479)***	0.3687 (0.0481)***
Limited-service restaurants	-0.6727 (0.0959)***	-0.6727 (0.0959)***	-0.7954 (0.0955)***	-0.6289 (0.0947)***	-0.6849 (0.0952)***	-0.5669 (0.0964)***
Poverty rate	11.4431 (0.5175)***	11.4431 (0.5175)***	11.3535 (0.5176)***	11.4567 (0.5163)***	11.484 (0.5162)***	11.3815 (0.5166)***

Area-level household income	0 (0)*	0 (0)*	0 (0)***	0 (0)	0 (0)*	0 (0)
Area-level educational attainment	1.7041 (0.3012)***	1.7041 (0.3012)***	1.2488 (0.3007)***	1.9436 (0.303)***	1.6737 (0.3028)***	2.0637 (0.3017)***
Vehicle density	0.0875 (0.437)	0.0875 (0.437)	0.1366 (0.4356)	0.0496 (0.4362)	0.1051 (0.4366)	-0.0457 (0.4371)
Kitchen availability	37.302 (3.5059)***	37.302 (3.5059)***	33.1374 (3.4077)***	38.905 (3.429)***	36.7303 (3.4558)***	41.4561 (3.506)***
SNAP participation	0.8834 (0.0256)***	0.8834 (0.0256)***	0.8844 (0.0256)***	0.8838 (0.0256)***	0.8836 (0.0256)***	0.8834 (0.0256)***
Intercept	-38.0579 (3.3538)***	-38.0579 (3.3538)***	-33.4826 (3.2538)***	-39.8694 (3.2743)***	-37.4713 (3.3005)***	-42.4741 (3.3572)***
Observations	230,323	230,323	230,323	230,323	230,323	230,323
R-squared	0.0774	0.0774	0.0774	0.0774	0.0774	0.0775

(G)

Covariates	Change in acquisition of fats and oils					
Cost of living metric	Overall RPP	Rent RPP	Food RPP	Good RPP	Services RPP	Geographic adjustment to the Supplemental Poverty Measure
Cost of living	9.5756 (0.8897)***	9.5756 (0.8897)***	3.4126 (0.7739)***	10.6087 (0.8543)***	8.5808 (0.8578)***	10.5073 (0.8686)***
Age	1.0868 (0.0764)***	1.0868 (0.0764)***	1.0758 (0.0764)***	1.0858 (0.0764)***	1.0834 (0.0764)***	1.0816 (0.0764)***
Age squared	-0.0109 (0.0009)***	-0.0109 (0.0009)***	-0.0108 (0.0009)***	-0.0109 (0.0009)***	-0.0108 (0.0009)***	-0.0108 (0.0009)***
Sex (1=female)	10.5683 (0.6444)***	10.5683 (0.6444)***	10.5884 (0.6446)***	10.5685 (0.6444)***	10.5786 (0.6444)***	10.5561 (0.6444)***
White race	-8.5168 (0.9352)***	-8.5168 (0.9352)***	-8.8103 (0.9352)***	-8.6852 (0.9349)***	-8.6675 (0.935)***	-8.4664 (0.9351)***
Black race	-8.524 (1.2001)***	-8.524 (1.2001)***	-9.0121 (1.2003)***	-9.0558 (1.1997)***	-8.9061 (1.1997)***	-8.4459 (1.2001)***
Hispanic	-17.1172 (0.9138)***	-17.1172 (0.9138)***	-18.1412 (0.9081)***	-16.9564 (0.9135)***	-17.3082 (0.9126)***	-16.803 (0.9155)***
Education >= high school	1.1326 (0.8488)	1.1326 (0.8488)	1.2192 (0.8489)	1.2139 (0.8486)	1.2364 (0.8487)	1.1431 (0.8487)
Employed (1=yes)	-2.7595 (0.6855)***	-2.7595 (0.6855)***	-2.7953 (0.6858)***	-2.719 (0.6854)***	-2.7253 (0.6856)***	-2.7073 (0.6855)***
Household size	-6.802 (0.1819)***	-6.802 (0.1819)***	-6.7954 (0.1821)***	-6.8011 (0.1819)***	-6.7903 (0.182)***	-6.8171 (0.1819)***
Income ($/10^4)	-28.96 (11.48)*	-28.96 (11.48)*	-33.788 (11.487)**	-37.734 (11.485)	-35.411 (11.482)**	-28.774 (11.479)*
Housing cost ($/10^4)	22.285 (2.745)***	22.285 (2.745)***	22.133 (2.749)***	22.116 (2.745)***	22.06 (2.746)***	22.33 (2.745)***
Distance to primary food store	1.4371 (0.0749)***	1.4371 (0.0749)***	1.4285 (0.075)***	1.4471 (0.0749)***	1.4398 (0.0749)***	1.4387 (0.0749)***
Rural residence	0.5389 (0.8762)	0.5389 (0.8762)	1.48 (0.8755)	0.1123 (0.8787)	0.389 (0.8808)	0.5202 (0.8738)
Food security status	-5.0586 (0.7046)***	-5.0586 (0.7046)***	-4.959 (0.7047)***	-5.0972 (0.7046)***	-5.1061 (0.7047)***	-5.0337 (0.7045)***
WIC	0.0331 (0.97)	0.0331 (0.97)	0.316 (0.9698)	0.08 (0.9696)	0.0968 (0.9699)	0.0518 (0.9697)
Supermarkets	-8.4219 (8.8875)	-8.4219 (8.8875)	4.4086 (8.7942)	-11.3325 (8.8925)	-6.5077 (8.875)	-4.8496 (8.8205)
Non-supermarkets	9.8983 (3.3949)**	9.8983 (3.3949)**	13.3578 (3.3804)***	9.4298 (3.3917)**	9.7119 (3.4024)**	10.6286 (3.3818)**
Full-service restaurants	-2.6647 (1.3283)*	-2.6647 (1.3283)*	-1.2571 (1.3325)	-2.523 (1.3213)	-2.2832 (1.3249)	-3.2124 (1.3318)*
Limited-service restaurants	5.5755 (2.6529)*	5.5755 (2.6529)*	0.7551 (2.642)	5.1688 (2.62)*	4.2847 (2.6337)	7.0821 (2.6652)**

Poverty rate	-3.7636 (14.3157)	-3.7636 (14.3157)	12.1787 (14.3222)	4.0067 (14.2795)	4.9281 (14.2807)	0.0086 (14.2902)
Area-level household income	0 (0.0001)	0 (0.0001)	0.0001 (0.0001)**	0 (0.0001)	0 (0.0001)	0 (0.0001)
Area-level educational attainment	-12.2337 (8.3324)	-12.2337 (8.3324)	-29.1211 (8.3186)***	-5.9621 (8.3819)	-12.9118 (8.3749)	-8.2134 (8.3455)
Vehicle density	21.8935 (12.0877)	21.8935 (12.0877)	32.0187 (12.0527)**	24.2531 (12.0659)*	24.0615 (12.0776)*	20.2523 (12.0894)
Kitchen availability	274.7445 (96.978)**	274.7445 (96.978)**	34.0148 (94.2843)	233.0091 (94.8457)*	204.6176 (95.5951)*	316.2784 (96.9787)**
SNAP participation	16.9698 (0.708)***	16.9698 (0.708)***	16.9921 (0.7081)***	17.0326 (0.7079)***	16.9903 (0.708)***	17.0007 (0.7079)***
Intercept	-259.1367 (92.7704)**	-259.1367 (92.7704)**	-12.6172 (90.0269)	-227.1002 (90.5659)*	-189.6767 (91.2993)*	-305.9259 (92.8629)**
Observations	230,323	230,323	230,323	230,323	230,323	230,323
R-squared	0.0211	0.0211	0.0207	0.0213	0.021	0.0212

(H)

Covariates	Change in acquisition of added sugars					
Cost of living metric	Overall RPP	Rent RPP	Food RPP	Good RPP	Services RPP	Geographic adjustment to the Supplemental Poverty Measure
Cost of living	3.6312 (0.3617)***	3.6312 (0.3617)***	1.9743 (0.3146)***	3.1593 (0.3474)***	3.0432 (0.3487)***	4.6085 (0.3531)***
Age	0.3847 (0.0311)***	0.3847 (0.0311)***	0.3808 (0.0311)***	0.3833 (0.0311)***	0.3832 (0.0311)***	0.3831 (0.0311)***
Age squared	-0.0048 (0.0004)***	-0.0048 (0.0004)***	-0.0048 (0.0004)***	-0.0048 (0.0004)***	-0.0048 (0.0004)***	-0.0048 (0.0004)***
Sex (1=female)	3.6572 (0.262)***	3.6572 (0.262)***	3.6596 (0.262)***	3.661 (0.262)***	3.662 (0.262)***	3.6491 (0.262)***
White race	-1.4637 (0.3802)***	-1.4637 (0.3802)***	-1.5882 (0.3802)***	-1.5323 (0.3801)***	-1.5227 (0.3801)***	-1.4281 (0.3802)***
Black race	-1.7413 (0.4879)***	-1.7413 (0.4879)***	-1.9519 (0.488)***	-1.929 (0.4878)***	-1.8857 (0.4878)***	-1.6857 (0.4879)**
Hispanic	-6.5238 (0.3715)***	-6.5238 (0.3715)***	-6.8876 (0.3692)***	-6.5693 (0.3715)***	-6.6197 (0.371)***	-6.3179 (0.3722)***
Education >= high school	0.8895 (0.3451)*	0.8895 (0.3451)*	0.9163 (0.3451)**	0.9231 (0.3451)**	0.9291 (0.3451)**	0.8871 (0.345)*
Employed (1=yes)	-1.6052 (0.2787)***	-1.6052 (0.2787)***	-1.6026 (0.2788)***	-1.6026 (0.2787)***	-1.5959 (0.2787)***	-1.5753 (0.2787)***
Household size	-1.4898 (0.074)***	-1.4898 (0.074)***	-1.481 (0.074)***	-1.4916 (0.074)***	-1.4863 (0.074)***	-1.4949 (0.074)***
Income ($/10^4)	-27.615 (4.667)***	-27.615 (4.667)***	-29.814 (4.67)***	-30.471 (4.67)***	-29.976 (4.668)***	-27.357 (4.667)***
Housing cost ($/10^4)	2.005 (1.116)	2.005 (1.116)	1.823 (1.118)	1.993 (1.116)	1.937 (1.116)	1.996 (1.116)
Distance to primary food store	0.6096 (0.0304)***	0.6096 (0.0304)***	0.6105 (0.0305)***	0.6101 (0.0305)***	0.6098 (0.0305)***	0.612 (0.0304)***
Rural residence	0.6868 (0.3562)	0.6868 (0.3562)	0.9215 (0.3559)*	0.6863 (0.3573)	0.6718 (0.3581)	0.5863 (0.3552)
Food security status	-1.321 (0.2865)***	-1.321 (0.2865)***	-1.2789 (0.2865)***	-1.3262 (0.2865)***	-1.3359 (0.2865)***	-1.3147 (0.2864)***
WIC	-3.4429 (0.3944)***	-3.4429 (0.3944)***	-3.3559 (0.3943)***	-3.3976 (0.3943)***	-3.4109 (0.3943)***	-3.4576 (0.3942)***
Supermarkets	0.9239 (3.6134)	0.9239 (3.6134)	5.1184 (3.5752)	1.3758 (3.6159)	2.0007 (3.6084)	1.5289 (3.5858)
Non-supermarkets	5.0193 (1.3803)***	5.0193 (1.3803)***	6.0523 (1.3743)***	5.2753 (1.3791)***	5.0726 (1.3834)***	5.0511 (1.3748)***
Full-service restaurants	-6.25 (0.5401)***	-6.25 (0.5401)***	-5.9424 (0.5417)***	-6.0008 (0.5373)***	-6.0523 (0.5387)***	-6.6412 (0.5414)***
Limited-service restaurants	2.4217 (1.0786)*	2.4217 (1.0786)*	1.197 (1.0741)	1.6618 (1.0653)	1.7712 (1.0708)	3.5485 (1.0835)**

Poverty rate	2.2486 (5.8203)	2.2486 (5.8203)	9.2471 (5.8225)	5.4713 (5.8063)	5.6053 (5.8062)	3.2403 (5.8095)
Area-level household income	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Area-level educational attainment	-7.2344 (3.3877)*	-7.2344 (3.3877)*	-11.375 (3.3818)**	-7.6659 (3.4082)*	-8.1687 (3.405)*	-3.7939 (3.3928)
Vehicle density	11.304 (4.9145)*	11.304 (4.9145)*	15.1185 (4.8999)**	12.8414 (4.9062)**	12.3248 (4.9105)*	9.9755 (4.9147)*
Kitchen availability	63.0633 (39.4282)	63.0633 (39.4282)	-9.7941 (38.3301)	23.5079 (38.566)	30.0069 (38.8667)	101.0661 (39.4252)*
SNAP participation	5.5688 (0.2878)***	5.5688 (0.2878)***	5.5721 (0.2879)***	5.5914 (0.2878)***	5.5772 (0.2879)***	5.5795 (0.2878)***
Intercept	-58.8376 (37.7175)	-58.8376 (37.7175)	13.9249 (36.5993)	-20.7638 (36.8257)	-25.5933 (37.1201)	-100.1715 (37.7519)**
Observations	230,323	230,323	230,323	230,323	230,323	230,323
R-squared	0.016	0.016	0.0157	0.0159	0.0159	0.0163

(I)

Covariates	Change in acquisition of kcals/person/day					
Cost of living metric	All	Rent	Food	Good	Service	Geo
Cost of living	213.6908 (17.4955)***	213.6908 (17.4955)***	100.7439 (15.4089)***	198.7354 (16.7829)***	180.5345 (16.9247)***	271.9475 (17.0996)***
Age	33.6024 (1.5269)***	33.6024 (1.5269)***	33.3127 (1.527)***	33.5386 (1.5269)***	33.4989 (1.5269)***	33.5307 (1.5264)***
Age squared	-0.3549 (0.0176)***	-0.3549 (0.0176)***	-0.3519 (0.0176)***	-0.3546 (0.0176)***	-0.3538 (0.0176)***	-0.3541 (0.0176)***
Sex (1=female)	207.3737 (12.8789)***	207.3737 (12.8789)***	207.4339 (12.8822)***	207.5431 (12.8791)***	207.5899 (12.8799)***	206.96 (12.8761)***
White race	-29.7101 (18.6833)	-29.7101 (18.6833)	-37.7365 (18.6818)*	-33.6793 (18.6774)	-33.4675 (18.679)	-27.2528 (18.6801)
Black race	-175.4031 (23.8863)***	-175.4031 (23.8863)***	-191.0138 (23.8704)***	-186.6609 (23.863)***	-185.0327 (23.8661)***	-170.8012 (23.8827)***
Hispanic	-401.8737 (18.1745)***	-401.8737 (18.1745)***	-421.5158 (18.0905)***	-402.9677 (18.1714)***	-406.664 (18.1583)***	-390.4421 (18.2023)***
Education >= high school	40.6816 (16.9642)*	40.6816 (16.9642)*	42.5034 (16.9673)*	42.6204 (16.9632)*	43.045 (16.9641)*	40.5004 (16.9599)*
Employed (1=yes)	-133.7668 (13.6947)***	-133.7668 (13.6947)***	-133.4033 (13.7011)***	-133.4263 (13.6954)***	-133.023 (13.697)***	-132.1955 (13.6925)***
Household size	-200.0934 (3.6364)***	-200.0934 (3.6364)***	-199.7431 (3.6398)***	-200.1667 (3.6364)***	-199.8874 (3.6371)***	-200.3827 (3.6353)***
Income	-0.0835 (0.0229)***	-0.0835 (0.0229)***	-0.0964 (0.023)***	-0.101 (0.0229)***	-0.0977 (0.0229)***	-0.0817 (0.0229)***
Housing cost	0.0743 (0.0055)***	0.0743 (0.0055)***	0.0737 (0.0055)***	0.0742 (0.0055)***	0.074 (0.0055)***	0.0742 (0.0055)***
Distance to primary food store	34.6677 (1.4968)***	34.6677 (1.4968)***	34.6459 (1.4992)***	34.7478 (1.4971)***	34.6918 (1.4973)***	34.8112 (1.4963)***
Rural residence	-3.4757 (17.4462)	-3.4757 (17.4462)	16.4352 (17.4042)	-5.8944 (17.5052)	-3.6526 (17.5425)	-10.6362 (17.3907)
Food security status	-127.332 (14.0753)***	-127.332 (14.0753)***	-124.1741 (14.0768)***	-127.776 (14.0764)***	-127.9995 (14.0783)***	-127.2321 (14.0713)***
WIC	-22.4535 (19.3852)	-22.4535 (19.3852)	-16.3039 (19.3807)	-20.1978 (19.3797)	-20.4531 (19.3838)	-23.5373 (19.3768)
Supermarkets	-121.7797 (176.7616)	-121.7797 (176.7616)	120.3072 (175.2386)	-118.2932 (176.8537)	-66.7768 (176.5952)	-80.2491 (175.5576)
Non-supermarkets	339.6398 (66.3065)***	339.6398 (66.3065)***	385.7711 (66.2006)***	348.2456 (66.2584)***	335.6688 (66.4553)***	348.3814 (66.1193)***
Full-service restaurants	-210.3131 (25.1438)***	-210.3131 (25.1438)***	-171.7034 (25.0527)***	-198.5301 (24.9553)***	-194.4596 (25.0089)***	-238.8015 (25.2208)***
Limited-service restaurants	97.7063 (50.6484)	97.7063 (50.6484)	-18.0903 (49.8796)	61.9368 (49.8432)	51.5819 (50.0645)	174.925 (50.9076)**
Poverty rate	267.1659 (273.8725)	267.1659 (273.8725)	799.4013 (271.8986)**	452.8953 (272.3408)	506.6017 (272.1586)	276.5304 (272.7734)
Area-level household income	-0.0043 (0.001)***	-0.0043 (0.001)***	-0.001 (0.0009)	-0.0041 (0.001)***	-0.0037 (0.001)***	-0.0049 (0.001)***

Area-level educational attainment	95.709 (165.9443)	95.709 (165.9443)	-191.6975 (166.0107)	112.0125 (166.8807)	47.6546 (166.8517)	297.8486 (166.1989)
Vehicle density	1837.181 (126.0363)***	1837.181 (126.0363)***	1729.557 (125.9621)***	1917.709 (127.3076)***	1796.765 (125.8842)***	1871.693 (125.7321)***
Kitchen availability	14961.37 (1936.219)***	14961.37 (1936.219)***	9927.348 (1877.159)***	12985.27 (1892.467)***	12962.7 (1907.152)***	17336.27 (1935.719)***
SNAP participation	425.0196 (14.1497)***	425.0196 (14.1497)***	425.5168 (14.1531)***	426.369 (14.1496)***	425.5673 (14.1506)***	425.5873 (14.1462)***
Intercept	-14301.97 (1850.147)***	-14301.97 (1850.147)***	-9158.007 (1788.17)***	-12445.57 (1804.575)***	-12276.34 (1818.698)***	-16896.19 (1851.454)***
	0 (0)***	0 (0)***	0 (0)***	0 (0)***	0 (0)***	0 (0)***
Observations	230,323	230,323	230,323	230,323	230,323	230,323
R-squared	0.0388	0.0388	0.0383	0.0387	0.0386	0.0392

(J)

Covariates	Change in HEI score					
Cost of living metric	Overall RPP	Rent RPP	Food RPP	Good RPP	Services RPP	Geographic adjustment to the Supplemental Poverty Measure
Cost of living	0.1507 (0.0278)***	0.1507 (0.0278)***	0.0424 (0.0242)	0.1705 (0.0267)***	0.1703 (0.0268)***	0.1945 (0.0272)***
Age	0.2863 (0.0024)***	0.2863 (0.0024)***	0.2862 (0.0024)***	0.2863 (0.0024)***	0.2863 (0.0024)***	0.2863 (0.0024)***
Age squared	-0.0027 (0)***	-0.0027 (0)***	-0.0027 (0)***	-0.0027 (0)***	-0.0027 (0)***	-0.0027 (0)***
Sex (1=female)	0.8019 (0.0201)***	0.8019 (0.0201)***	0.8023 (0.0201)***	0.8019 (0.0201)***	0.8019 (0.0201)***	0.8016 (0.0201)***
White race	-0.6794 (0.0292)***	-0.6794 (0.0292)***	-0.6838 (0.0292)***	-0.682 (0.0292)***	-0.6815 (0.0292)***	-0.6778 (0.0292)***
Black race	0.0839 (0.0375)*	0.0839 (0.0375)*	0.0766 (0.0375)*	0.0755 (0.0375)*	0.0778 (0.0375)*	0.0863 (0.0375)*
Hispanic	0.2705 (0.0286)***	0.2705 (0.0286)***	0.2539 (0.0284)***	0.2734 (0.0286)***	0.2714 (0.0285)***	0.2794 (0.0286)***
Education >= high school	0.3887 (0.0265)***	0.3887 (0.0265)***	0.3902 (0.0265)***	0.39 (0.0265)***	0.3903 (0.0265)***	0.3886 (0.0265)***
Employed (1=yes)	0.1422 (0.0214)***	0.1422 (0.0214)***	0.1414 (0.0214)***	0.1429 (0.0214)***	0.1434 (0.0214)***	0.1435 (0.0214)***
Household size	-0.0524 (0.0057)***	-0.0524 (0.0057)***	-0.0524 (0.0057)***	-0.0524 (0.0057)***	-0.0521 (0.0057)***	-0.0526 (0.0057)***
Income ($/10^4)	1.09 (0.359)**	1.09 (0.359)**	1.02 (0.359)	0.95 (0.359)**	0.975 (0.359)**	1.102 (0.359)**
Housing cost ($/10^4)	-0.367 (0.0858)***	-0.367 (0.0858)***	-0.357 (0.0859)***	-0.37 (0.0858)***	-0.373 (0.0858)***	-0.357 (0.0858)***
Distance to primary food store	-0.0176 (0.0023)***	-0.0176 (0.0023)***	-0.0178 (0.0023)***	-0.0175 (0.0023)***	-0.0174 (0.0023)***	-0.0175 (0.0023)***
Rural residence	0.2329 (0.0274)***	0.2329 (0.0274)***	0.2497 (0.0274)***	0.2255 (0.0275)***	0.2235 (0.0275)***	0.2282 (0.0273)***
Food security status	-0.1016 (0.022)***	-0.1016 (0.022)***	-0.1001 (0.022)***	-0.1022 (0.022)***	-0.1028 (0.022)***	-0.1013 (0.022)***
WIC	0.5077 (0.0303)***	0.5077 (0.0303)***	0.5125 (0.0303)***	0.5083 (0.0303)***	0.5074 (0.0303)***	0.507 (0.0303)***
Supermarkets	-1.5117 (0.2778)***	-1.5117 (0.2778)***	-1.2986 (0.2749)***	-1.5638 (0.278)***	-1.5403 (0.2774)***	-1.4904 (0.2758)***
Non-supermarkets	-0.1971 (0.1061)	-0.1971 (0.1061)	-0.138 (0.1057)	-0.2062 (0.106)	-0.2207 (0.1064)*	-0.197 (0.1057)
Full-service restaurants	-0.3059 (0.0415)***	-0.3059 (0.0415)***	-0.28 (0.0417)***	-0.3045 (0.0413)***	-0.3088 (0.0414)***	-0.3231 (0.0416)***
Limited-service restaurants	0.9541 (0.0829)***	0.9541 (0.0829)***	0.8682 (0.0826)***	0.9501 (0.0819)***	0.9607 (0.0823)***	1.0037 (0.0833)***

Poverty rate	0.3167 (0.4476)	0.3167 (0.4476)	0.5518 (0.4477)	0.4379 (0.4464)	0.4434 (0.4464)	0.3556 (0.4468)
Area-level household income	0 (0)***	0 (0)***	0 (0)***	0 (0)***	0 (0)***	0 (0)***
Area-level educational attainment	-1.8695 (0.2605)***	-1.8695 (0.2605)***	-2.1729 (0.26)***	-1.7595 (0.2621)***	-1.7669 (0.2618)***	-1.7169 (0.2609)***
Vehicle density	2.2086 (0.3779)***	2.2086 (0.3779)***	2.3684 (0.3767)***	2.2432 (0.3772)***	2.2095 (0.3776)***	2.1498 (0.378)***
Kitchen availability	-10.5467 (3.0318)**	-10.5467 (3.0318)**	-14.6418 (2.9472)***	-11.1081 (2.9653)***	-10.5699 (2.9884)***	-8.8552 (3.0319)**
SNAP participation	-0.0697 (0.0221)**	-0.0697 (0.0221)**	-0.0693 (0.0221)**	-0.0688 (0.0221)**	-0.0695 (0.0221)**	-0.0693 (0.0221)**
Intercept	56.5581 (2.9003)***	56.5581 (2.9003)***	60.7823 (2.8141)***	56.9579 (2.8315)***	56.4971 (2.8541)***	54.7214 (2.9032)***
Observations	230,323	230,323	230,323	230,323	230,323	230,323
R-squared	0.1487	0.1487	0.1486	0.1487	0.1487	0.1488

-: Ordinary least squares regressions testing hypothesis 2: that SNAP participation is associated with living in a lower cost of living area. Regressions include survey sample weights to account for differential sampling and response. * = p<0.05; ** = p<0.01; *** = p<0.001

	Change in probability of living in a high-cost area					
Cost of living metric for outcome	Overall RPP	Rent RPP	Food RPP	Good RPP	Services RPP	Geographic adjustment to the Supplemental Poverty Measure
Covariates						
Age	-0.0007 (0.0002)**	-0.0007 (0.0002)**	0.0001 (0.0002)	-0.0001 (0.0002)	-0.0002 (0.0002)	-0.0002 (0.0002)
Age squared	0 (0)**	0 (0)**	0 (0)	0 (0)	0 (0)	0 (0)
Sex (1=female)	0.0115 (0.0021)***	0.0115 (0.0021)***	0.0117 (0.0023)***	0.0068 (0.0021)**	0.009 (0.0021)***	0.0138 (0.0021)***
White race	-0.0054 (0.0029)	-0.0054 (0.0029)	0.0205 (0.0032)***	0.0046 (0.0029)	-0.0002 (0.0029)	-0.0119 (0.0029)***
Black race	-0.0165 (0.0036)***	-0.0165 (0.0036)***	0.0093 (0.004)*	0.0101 (0.0037)**	-0.0101 (0.0037)**	-0.02 (0.0036)***
Hispanic	-0.1165 (0.0028)***	-0.1165 (0.0028)***	-0.0608 (0.0031)***	-0.135 (0.0028)***	-0.1253 (0.0028)***	-0.1271 (0.0028)***
Education >= high school	0.0004 (0.0024)	0.0004 (0.0024)	0.0062 (0.0026)*	0.0014 (0.0024)	-0.0021 (0.0024)	-0.002 (0.0024)
Employed (1=yes)	-0.0058 (0.0021)**	-0.0058 (0.0021)**	-0.0123 (0.0024)***	-0.0077 (0.0022)***	-0.0085 (0.0022)***	-0.0089 (0.0022)***
Household size	0.0033 (0.0005)***	0.0033 (0.0005)***	-0.005 (0.0006)***	0.0029 (0.0005)***	0.0019 (0.0005)***	0.0042 (0.0005)***
Income ($/10^4)	-0.62 (0.0747)***	-0.62 (0.0747)***	-0.322 (0.0825)**	-0.496 (0.076)***	-0.46 (0.0758)***	-0.581 (0.0753)***
Housing cost ($/10^4)	0.0498 (0.0075)***	0.0498 (0.0075)***	0.101 (0.0082)***	0.0491 (0.0076)***	0.0521 (0.0076)***	0.0412 (0.0075)***
Distance to primary food store	-0.0017 (0.0002)***	-0.0017 (0.0002)***	-0.0046 (0.0003)***	-0.0018 (0.0003)***	-0.0019 (0.0002)***	-0.001 (0.0002)***
Rural residence	-0.1829 (0.0028)***	-0.1829 (0.0028)***	-0.1703 (0.0031)***	-0.1712 (0.0029)***	-0.1787 (0.0029)***	-0.1884 (0.0029)***
Food security status	0.009 (0.0019)***	0.009 (0.0019)***	-0.0109 (0.0021)***	0.0083 (0.002)***	0.0101 (0.002)***	0.0083 (0.002)***
WIC	0.0275 (0.0026)***	0.0275 (0.0026)***	0.0252 (0.0028)***	0.0152 (0.0026)***	0.0274 (0.0026)***	0.0301 (0.0026)***
Supermarkets	2.0403 (0.0282)***	2.0403 (0.0282)***	1.4664 (0.0311)***	2.1276 (0.0287)***	2.0222 (0.0286)***	1.7591 (0.0284)***
Non-supermarkets	0.4815 (0.0103)***	0.4815 (0.0103)***	0.3486 (0.0114)***	0.448 (0.0105)***	0.5125 (0.0104)***	0.3087 (0.0104)***
Full-service restaurants	0.25 (0.0045)***	0.25 (0.0045)***	0.3368 (0.005)***	0.2189 (0.0046)***	0.2502 (0.0046)***	0.276 (0.0046)***
Limited-service restaurants	-0.9057 (0.0084)***	-0.9057 (0.0084)***	-1.0491 (0.0093)***	-0.8327 (0.0086)***	-0.9014 (0.0085)***	-1.0018 (0.0085)***

Poverty rate	1.365 (0.045)***	1.365 (0.045)***	-0.5246 (0.0497)***	1.0621 (0.0458)***	1.0474 (0.0457)***	1.505 (0.0454)***
Area-level household income	0 (0)***	0 (0)***	0 (0)***	0 (0)***	0 (0)***	0 (0)***
Area-level educational attainment	-2.4975 (0.0246)***	-2.4975 (0.0246)***	-2.7909 (0.0271)***	-2.6542 (0.025)***	-2.6466 (0.0249)***	-2.4548 (0.0248)***
Vehicle density	0.8337 (0.0385)***	0.8337 (0.0385)***	-0.1663 (0.0425)***	0.7765 (0.0392)***	0.7916 (0.039)***	0.6883 (0.0388)***
Kitchen availability	-33.5129 (0.2834)***	-33.5129 (0.2834)***	-29.0668 (0.3131)***	-29.4001 (0.2885)***	-31.774 (0.2876)***	-34.0333 (0.2857)***
SNAP (1=participant)	-0.0049 (0.002)*	-0.0049 (0.002)*	0.0012 (0.0022)	-0.0118 (0.002)***	-0.0071 (0.002)***	-0.0034 (0.002)
Intercept	35.1516 (0.2676)***	35.1516 (0.2676)***	32.0741 (0.2957)***	31.4474 (0.2724)***	33.5628 (0.2716)***	35.8165 (0.2698)***
Observations	135,627	135,627	135,627	135,627	135,627	135,627
R-squared	0.5176	0.5176	0.4279	0.5073	0.5058	0.5127

Table 9: Ordinary least squares regressions testing hypothesis 3: that the relationship between SNAP participation and food acquisition is moderated by area cost of living. Subtables (A)-(H) correspond to food pattern equivalents of food categories 1 through 8 (vegetables through added sugars) as the outcome (in food pattern equivalents units), while subtable (I) corresponds to kilocalories per person per day as the outcome and (J) corresponds to the Healthy Eating Index as the outcome. Each table includes an interaction term for participation in SNAP interacted with living in a high-cost area, either by overall regional price parity as the metric of cost of living, or by food regional price parity as the metric of cost of living. All regressions include survey sample weights to account for differential sampling and response. * = p<0.05; ** = p<0.01; *** = p<0.001

(A)

Covariate	Change in acquisition of vegetables	
Cost of living metric	Overall RPP	Food RPP
Age	0.0267 (0.0013)***	0.0268 (0.0013)***
Age squared	-0.0002 (0)***	-0.0002 (0)***
Sex (1=female)	0.1063 (0.012)***	0.1054 (0.012)***
White race	0.0553 (0.0166)**	0.0559 (0.0166)**
Black race	-0.204 (0.0208)***	-0.2028 (0.0208)***
Hispanic	-0.2501 (0.0161)***	-0.2431 (0.0161)***
Education >= high school	-0.163 (0.0137)***	-0.1623 (0.0137)***
Employed (1=yes)	-0.0954 (0.0124)***	-0.0956 (0.0124)***
Household size	-0.188 (0.003)***	-0.1884 (0.003)***
Income ($/10^4)	1.249 (0.432)**	1.272 (0.432)**
Housing cost ($/10^4)	0.911 (0.0431)***	0.913 (0.0431)***
Distance to primary food store	0.0072 (0.0014)***	0.0072 (0.0014)***
Rural residence	0.2179 (0.0166)***	0.2096 (0.0165)***
Food security status	-0.0834 (0.0112)***	-0.0841 (0.0112)***

WIC	0.0588 (0.0149)***	0.0577 (0.0149)***
Supermarkets	-0.598 (0.1657)***	-0.7098 (0.1644)***
Non-supermarkets	-0.441 (0.0597)***	-0.4596 (0.0596)***
Full-service restaurants	-0.2206 (0.0266)***	-0.2314 (0.0267)***
Limited-service restaurants	0.1457 (0.0505)**	0.1856 (0.0507)***
Poverty rate	2.7404 (0.2614)***	2.6084 (0.2605)***
Area-level household income	0 (0)***	0 (0)***
Area-level educational attainment	-1.5401 (0.1463)***	-1.435 (0.1465)***
Vehicle density	0.3844 (0.2227)	0.321 (0.2226)
Kitchen availability	8.0199 (1.7048)***	9.6985 (1.6803)***
snap	-0.1352 (0.0121)***	-0.1233 (0.0121)***
SNAP-cost interaction	-0.0545 (0.0098)***	-0.0226 (0.0091)*
Intercept	-6.0353 (1.6247)***	-7.7546 (1.6012)***
Observations	135,627	135,627
R-squared	0.0684	0.0683

(B)

Covariate	Change in acquisition of fruits	
Cost of living metric	Overall RPP	Food RPP
Age	0.003 (0.0005)***	0.0029 (0.0005)***
Age squared	0 (0)	0 (0)
Sex (1=female)	0.0439 (0.005)***	0.0436 (0.005)***
White race	0.0373 (0.0069)***	0.0346 (0.0069)***
Black race	0.003 (0.0086)	0.0009 (0.0086)
Hispanic	0.1704 (0.0067)***	0.1684 (0.0067)***
Education >= high school	0.0786 (0.0057)***	0.0787 (0.0057)***
Employed (1=yes)	-0.064 (0.0051)***	-0.0636 (0.0051)***
Household size	-0.069 (0.0013)***	-0.0686 (0.0013)***
Income ($/10^4)	-022 (0.179)	-0.223 (0.179)
Housing cost ($/10^4)	0.454 (0.0179)***	0.451 (0.0179)
Distance to primary food store	0.0204 (0.0006)***	0.0206 (0.0006)***
Rural residence	-0.0877 (0.0069)***	-0.0903 (0.0068)***
Food security status	-0.1225 (0.0047)***	-0.1214 (0.0047)***
WIC	0.146 (0.0062)***	0.1458 (0.0062)***
Supermarkets	-0.5423 (0.0687)***	-0.5581 (0.0682)***
Non-supermarkets	0.2485 (0.0247)***	0.2481 (0.0247)***
Full-service restaurants	-0.0603 (0.011)***	-0.0714 (0.0111)***
Limited-service restaurants	0.0646 (0.0209)**	0.0939 (0.021)***
Poverty rate	1.2914 (0.1084)***	1.3705 (0.108)***
Area-level household income	0 (0)***	0 (0)***

Area-level educational attainment	0.4424 (0.0607)***	0.5121 (0.0607)***
Vehicle density	-0.2659 (0.0924)**	-0.2231 (0.0923)*
Kitchen availability	-5.4358 (0.7071)***	-5.0195 (0.6966)***
snap	0.0773 (0.005)***	0.0848 (0.005)***
SNAP-cost interaction	0.0279 (0.0041)***	0.043 (0.0038)***
Intercept	4.9826 (0.6739)***	4.4475 (0.6638)***
Observations	135,627	135,627
R-squared	0.0757	0.0763

(C)

Covariate	Change in acquisition of whole grains	
Cost of living metric	Overall RPP	Food RPP
Age	0.0108 (0.0019)***	0.0105 (0.0019)***
Age squared	-0.0001 (0)**	-0.0001 (0)**
Sex (1=female)	0.1643 (0.0174)***	0.1652 (0.0174)***
White race	-0.5929 (0.024)***	-0.5968 (0.0241)***
Black race	-0.7991 (0.0302)***	-0.8032 (0.0302)***
Hispanic	-0.623 (0.0234)***	-0.6351 (0.0233)***
Education >= high school	0.2685 (0.0199)***	0.2677 (0.0199)***
Employed (1=yes)	-0.3386 (0.018)***	-0.338 (0.018)***
Household size	-0.037 (0.0044)***	-0.036 (0.0044)***
Income ($/10^4)	7.213 (0.627)***	7.177 (0.627)***
Housing cost ($/10^4)	0.178 (0.0626)**	0.178 1 (0.0626)**
Distance to primary food store	0.0116 (0.0021)***	0.0119 (0.0021)***
Rural residence	-0.1123 (0.024)***	-0.1036 (0.024)***
Food security status	-0.2399 (0.0163)***	-0.2378 (0.0163)***
WIC	0.0626 (0.0216)**	0.064 (0.0216)**
Supermarkets	-1.6465 (0.2404)***	-1.5067 (0.2386)***
Non-supermarkets	0.8362 (0.0866)***	0.8619 (0.0864)***
Full-service restaurants	0.293 (0.0386)***	0.2958 (0.0388)***
Limited-service restaurants	-0.8946 (0.0733)***	-0.9181 (0.0736)***
Poverty rate	4.3844 (0.3792)***	4.6584 (0.3779)***
Area-level household income	0 (0)***	0 (0)***

Area-level educational attainment	0.8057 (0.2122)***	0.7355 (0.2125)**
Vehicle density	-5.044 (0.3231)***	-4.9071 (0.3229)***
drive	2.8652 (0.2106)***	2.7291 (0.2089)***
Kitchen availability	4.5716 (2.4731)	2.6744 (2.4376)
snap	0.0329 (0.0175)	0.0245 (0.0175)
SNAP-cost interaction	0.1078 (0.0142)***	0.0798 (0.0132)***
Intercept	-3.8055 (2.357)	-1.9835 (2.3228)
Observations	135,627	135,627
R-squared	0.0323	0.0321

(D)

Covariate	Change in acquisition of refined grains	
Cost of living metric	Overall RPP	Food RPP
Age	0.0922 (0.0041)***	0.0918 (0.0041)***
Age squared	-0.0009 (0)***	-0.0009 (0)***
Sex (1=female)	0.4 (0.0378)***	0.4058 (0.0378)***
White race	-0.0397 (0.0523)	-0.0359 (0.0524)
Black race	-0.2025 (0.0657)**	-0.2035 (0.0658)**
Hispanic	-0.7198 (0.0509)***	-0.7518 (0.0507)***
Education >= high school	-0.2587 (0.0434)***	-0.2628 (0.0434)***
Employed (1=yes)	-0.2832 (0.0392)***	-0.2835 (0.0392)***
Household size	-0.4309 (0.0096)***	-0.4298 (0.0096)***
Income ($/10^4)	-12.997 (1.364)***	-13.112 (1.365)***
Housing cost ($/10^4)	3.595 (0.136)***	3.593 (0.136)***
Distance to primary food store	0.1326 (0.0045)***	0.1323 (0.0045)***
Rural residence	-0.0337 (0.0523)	0.0181 (0.0522)
Food security status	-0.2878 (0.0355)***	-0.2869 (0.0355)***
WIC	0.1512 (0.0471)**	0.158 (0.0471)**
Supermarkets	-5.8804 (0.5234)***	-5.2388 (0.5194)***
Non-supermarkets	2.2466 (0.1884)***	2.3469 (0.1881)***
Full-service restaurants	0.0246 (0.0841)	0.1123 (0.0845)
Limited-service restaurants	0.1256 (0.1595)	-0.1678 (0.1601)
Poverty rate	7.5429 (0.8254)***	8.0345 (0.8226)***
Area-level household income	0 (0)***	0 (0)***
Area-level educational attainment	-0.4576 (0.4619)	-1.2093 (0.4626)**

Vehicle density	-1.0346 (0.7034)	-0.8112 (0.7029)
Kitchen availability	61.8326 (5.3835)***	51.7184 (5.3067)***
snap	1.1929 (0.0381)***	1.1084 (0.0381)***
SNAP-cost interaction	0.2157 (0.031)***	0.0041 (0.0287)
Intercept	-59.9126 (5.1306)***	-49.2575 (5.0566)***
Observations	135,627	135,627
R-squared	0.0501	0.0498

(E)

Covariate	Change in acquisition of dairy	
Cost of living metric	Overall RPP	Food RPP
Age	0.0118 (0.001)***	0.0116 (0.001)***
Age squared	-0.0001 (0)***	-0.0001 (0)***
Sex (1=female)	0.0136 (0.0095)	0.0152 (0.0095)
White race	0.2361 (0.0131)***	0.2332 (0.0131)***
Black race	-0.1962 (0.0164)***	-0.2001 (0.0164)***
Hispanic	-0.1595 (0.0127)***	-0.1744 (0.0127)***
Education >= high school	0.0963 (0.0108)***	0.0949 (0.0108)***
Employed (1=yes)	-0.1848 (0.0098)***	-0.1843 (0.0098)***
Household size	-0.1419 (0.0024)***	-0.1408 (0.0024)***
Income ($/10^4)	-2.288 (0.341)***	-2.334 (0.341)***
Housing cost ($/10^4)	0.937 (0.034)***	0.931 (0.034)***
Distance to primary food store	0.0324 (0.0011)***	0.0326 (0.0011)***
Rural residence	0.0255 (0.0131)	0.0399 (0.013)**
Food security status	-0.0841 (0.0089)***	-0.082 (0.0089)***
WIC	0.0891 (0.0118)***	0.0912 (0.0118)***
Supermarkets	-1.4844 (0.1307)***	-1.2773 (0.1298)***
Non-supermarkets	0.3349 (0.0471)***	0.3707 (0.047)***
Full-service restaurants	-0.2546 (0.021)***	-0.2409 (0.0211)***
Limited-service restaurants	0.1634 (0.0398)***	0.105 (0.04)**
Poverty rate	0.3703 (0.2062)	0.6787 (0.2056)**
Area-level household income	0 (0)***	0 (0)***

Area-level educational attainment	2.3557 (0.1154)***	2.1971 (0.1156)***
Vehicle density	1.5702 (0.1757)***	1.7215 (0.1756)***
Kitchen availability	18.4356 (1.3447)***	15.4456 (1.326)***
snap	0.2523 (0.0095)***	0.234 (0.0095)***
SNAP-cost interaction	0.1242 (0.0077)***	0.0722 (0.0072)***
Intercept	-18.6849 (1.2816)***	-15.6937 (1.2636)***
Observations	135,627	135,627
R-squared	0.0857	0.0846

(F)

Covariate	Change in acquisition of protein	
Cost of living metric	Overall RPP	Food RPP
Age	0.1251 (0.0036)***	0.1252 (0.0036)***
Age squared	-0.0012 (0)***	-0.0012 (0)***
Sex (1=female)	-0.1747 (0.0336)***	-0.1754 (0.0336)***
White race	-0.0035 (0.0465)	-0.0004 (0.0465)
Black race	0.3895 (0.0584)***	0.3927 (0.0584)***
Hispanic	-0.3263 (0.0452)***	-0.3177 (0.0451)***
Education >= high school	-0.0518 (0.0386)	-0.0513 (0.0386)
Employed (1=yes)	-0.9609 (0.0348)***	-0.9614 (0.0349)***
Household size	-0.5795 (0.0085)***	-0.5803 (0.0085)***
Income ($/10^4)	-3.287 (1.213)**	-3.262 (1.213)**
Housing cost ($/10^4)	2.005 (0.121)***	2.01 (0.121)***
Distance to primary food store	0.0312 (0.004)***	0.0309 (0.004)***
Rural residence	0.4975 (0.0465)***	0.4919 (0.0464)***
Food security status	0.0134 (0.0315)	0.0117 (0.0315)
WIC	0.1583 (0.0419)***	0.1574 (0.0419)***
Supermarkets	3.0403 (0.4652)***	2.9468 (0.4615)***
Non-supermarkets	-0.6213 (0.1675)***	-0.6389 (0.1671)***
Full-service restaurants	0.5449 (0.0747)***	0.545 (0.0751)***
Limited-service restaurants	-0.257 (0.1417)	-0.2462 (0.1423)
Poverty rate	16.5517 (0.7337)***	16.3483 (0.731)***
Area-level household income	0 (0)***	0 (0)***

Area-level educational attainment	2.3642 (0.4106)***	2.3998 (0.4111)***
Vehicle density	-0.6527 (0.6252)	-0.755 (0.6246)
drive	1.9179 (0.4075)***	2.0132 (0.4042)***
Kitchen availability	34.3474 (4.7849)***	35.5805 (4.7158)***
snap	0.9302 (0.0338)***	0.9347 (0.0338)***
SNAP-cost interaction	-0.0795 (0.0276)**	-0.0629 (0.0255)*
Intercept	-36.5534 (4.5602)***	-37.7128 (4.4936)***
Observations	135,627	135,627
R-squared	0.0861	0.0861

(G)

Covariate	Change in acquisition of fats and oils	
Cost of living metric	Overall RPP	Food RPP
Age	1.2836 (0.0483)***	1.2793 (0.0483)***
Age squared	-0.0116 (0.0006)***	-0.0115 (0.0006)***
Sex (1=female)	8.5377 (0.4471)***	8.5813 (0.4472)***
White race	0.6779 (0.6185)	0.658 (0.619)
Black race	8.0296 (0.7769)***	7.9796 (0.7771)***
Hispanic	-12.2177 (0.6013)***	-12.5304 (0.5991)***
Education >= high school	2.731 (0.5128)***	2.6981 (0.5128)***
Employed (1=yes)	-8.4309 (0.4634)***	-8.4263 (0.4634)***
Household size	-6.0662 (0.1134)***	-6.049 (0.1134)***
Income ($/10^4)	64.691 (16.125)***	63.65 (16.126)***
Housing cost ($/10^4)	36.18 (1.609)***	36.10 (1.61)***
Distance to primary food store	1.6262 (0.053)***	1.6277 (0.0531)***
Rural residence	2.4528 (0.6183)***	2.8424 (0.6164)***
Food security status	-3.5758 (0.4193)***	-3.5475 (0.4194)***
WIC	0.5354 (0.5569)	0.5891 (0.5569)
Supermarkets	-26.4108 (6.1854)***	-21.2379 (6.1372)**
Non-supermarkets	17.4438 (2.2265)***	18.2934 (2.2226)***
Full-service restaurants	0.882 (0.9937)	1.4132 (0.9982)
Limited-service restaurants	-9.7655 (1.8845)***	-11.695 (1.8922)***
Poverty rate	100.6032 (9.7546)***	106.3655 (9.7211)***
Area-level household income	0.0003 (0)***	0.0004 (0)***
Area-level educational attainment	47.6844 (5.4591)***	42.6326 (5.466)***
Vehicle density	-19.2996 (8.3124)*	-16.5467 (8.3057)*
Kitchen availability	389.0452 (63.6202)***	310.7975 (62.7095)***
snap	15.6823 (0.4499)***	15.1086 (0.4501)***

SNAP-cost interaction	2.3946 (0.3664)***	0.8837 (0.3387)**
Intercept	-417.3511 (60.6323)***	-336.8238 (59.7551)***
Observations	135,627	135,627
R-squared	0.0881	0.0879

(H)

Covariate	Change in acquisition of added sugars	
Cost of living metric	Overall RPP	Food RPP
Age	0.5216 (0.0183)***	0.5206 (0.0183)***
Age squared	-0.0058 (0.0002)***	-0.0058 (0.0002)***
Sex (1=female)	2.7438 (0.1693)***	2.7491 (0.1693)***
White race	3.0518 (0.2342)***	3.0349 (0.2344)***
Black race	4.8005 (0.2942)***	4.7817 (0.2942)***
Hispanic	-3.876 (0.2277)***	-3.936 (0.2268)***
Education >= high school	0.0915 (0.1942)	0.0868 (0.1941)
Employed (1=yes)	-3.1789 (0.1754)***	-3.1762 (0.1755)***
Household size	-1.4775 (0.0429)***	-1.4726 (0.0429)***
Income ($/10^4)	-25.384 (6.106)***	-25.565 (6.105)***
Housing cost ($/10^4)	6.475 (0.609)***	6.456 (0.609)***
Distance to primary food store	0.5469 (0.0201)***	0.5482 (0.0201)***
Rural residence	1.7875 (0.2341)***	1.8355 (0.2334)***
Food security status	-1.5852 (0.1588)***	-1.5753 (0.1588)***
WIC	-3.0214 (0.2109)***	-3.014 (0.2108)***
Supermarkets	5.7006 (2.3421)*	6.4404 (2.3236)**
Non-supermarkets	8.0486 (0.843)***	8.1813 (0.8415)***
Full-service restaurants	-4.3931 (0.3763)***	-4.366 (0.3779)***
Limited-service restaurants	-3.2527 (0.7136)***	-3.4074 (0.7164)***
Poverty rate	31.4413 (3.6935)***	32.7657 (3.6804)***
Area-level household income	0 (0)***	0.0001 (0)***
Area-level educational attainment	8.1859 (2.067)***	7.7441 (2.0694)***
Vehicle density	-8.2539 (3.1474)**	-7.5955 (3.1445)*
Kitchen availability	107.9243 (24.0892)***	97.6518 (23.7418)***
snap	5.6182 (0.1703)***	5.566 (0.1704)***

SNAP-cost interaction	0.5247 (0.1388)***	0.363 (0.1282)**
Intercept	-110.3159 (22.9579)***	-100.2963 (22.6232)***
Observations	135,627	135,627
R-squared	0.0758	0.0758

(I)

Covariate	Change in kilocalories/person/day	
Cost of living metric	Overall RPP	Food RPP
Age	37.4988 (1.2033)***	37.3395 (1.2033)***
Age squared	-0.3656 (0.0142)***	-0.3639 (0.0142)***
Sex (1=female)	164.001 (11.1319)***	164.9818 (11.132)***
White race	80.5028 (15.3961)***	78.3529 (15.4092)***
Black race	104.6139 (19.2504)***	100.8695 (19.2516)***
Hispanic	-349.8915 (14.9167)***	-357.3436 (14.8752)***
Education >= high school	53.8587 (12.7669)***	53.2153 (12.768)***
Employed (1=yes)	-262.3515 (11.5309)***	-261.7551 (11.5323)***
Household size	-187.9727 (2.8225)***	-187.3265 (2.823)***
Income	-0.0343 (0.0401)	-0.0365 (0.0401)
Housing cost	0.1066 (0.004)***	0.1064 (0.004)***
Distance to primary food store	42.0453 (1.3207)***	42.1828 (1.3216)***
Rural residence	68.3213 (15.319)***	77.076 (15.2507)***
Food security status	-125.2916 (10.4339)***	-123.7915 (10.436)***
WIC	5.3686 (13.8621)	6.7269 (13.8617)
Supermarkets	-461.4209 (151.9407)**	-368.0763 (151.0981)*
Non-supermarkets	701.3832 (54.6747)***	714.1627 (54.6359)***
Full-service restaurants	-213.851 (22.6361)***	-200.1242 (22.6236)***
Limited-service restaurants	-49.6616 (43.7776)	-91.0862 (43.5921)*
Poverty rate	3186.945 (237.0871)***	3404.771 (235.3594)***
Area-level household income	0.0074 (0.0009)***	0.0086 (0.0008)***
Area-level educational attainment	1180.219 (135.8952)***	1102.95 (136.0946)***
Vehicle density	619.1396 (99.3471)***	571.6953 (99.2529)***

Kitchen availability	16412.4 (1578.274)***	14713.96 (1551.604)***
snap	431.6374 (11.1895)***	422.7793 (11.2035)***
Snap-cost interaction	70.4185 (9.024)***	44.5117 (8.4075)***
Intercept	-16838.61 (1499.23)***	-15121.55 (1471.873)***
Observations	135,627	135,627
R-squared	0.1077	0.1075

(J)

Covariate	Change in HEI score	
Cost of living metric	Overall RPP	Food RPP
Age	0.3021 (0.003)***	0.302 (0.003)***
Age squared	-0.0029 (0)***	-0.0029 (0)***
Sex (1=female)	0.956 (0.0278)***	0.9566 (0.0278)***
White race	-0.6208 (0.0384)***	-0.6222 (0.0384)***
Black race	0.2403 (0.0482)***	0.2387 (0.0482)***
Hispanic	0.3151 (0.0373)***	0.3093 (0.0372)***
Education >= high school	0.1632 (0.0318)***	0.1627 (0.0318)***
Employed (1=yes)	0.3715 (0.0288)***	0.3717 (0.0288)***
Household size	-0.0166 (0.007)*	-0.0161 (0.007)*
Income ($/10^4)	-1.545 (1.001)	-1.562 (1.001)
Housing cost ($/10^4)	-0.399 (0.0999)***	-0.402 (0.0999)***
Distance to primary food store	-0.0137 (0.0033)***	-0.0136 (0.0033)***
Rural residence	0.1918 (0.0384)***	0.1968 (0.0383)***
Food security status	-0.1168 (0.026)***	-0.1159 (0.026)***
WIC	0.4287 (0.0346)***	0.4295 (0.0346)***
Supermarkets	-2.0617 (0.3839)***	-1.986 (0.3809)***
Non-supermarkets	-0.4681 (0.1382)**	-0.4547 (0.1379)**
Full-service restaurants	-0.3384 (0.0617)***	-0.3345 (0.0619)***
Limited-service restaurants	0.8095 (0.117)***	0.7909 (0.1174)***
Poverty rate	-3.4832 (0.6055)***	-3.3591 (0.6033)***
Area-level household income	0 (0)*	0 (0)*

Area-level educational attainment	-1.7552 (0.3388)***	-1.8067 (0.3392)***
Vehicle density	0.6007 (0.5159)	0.662 (0.5155)
Kitchen availability	-27.8803 (3.9488)***	-28.9513 (3.8918)***
snap	-0.118 (0.0279)***	-0.124 (0.0279)***
Snap-cost interaction	0.0495 (0.0227)*	0.0318 (0.021)
Intercept	75.3744 (3.7634)***	76.4328 (3.7085)***
Observations	135,627	135,627
R-squared	0.1645	0.1644

Figure 1: Distributions of the cost of living, as measured by overall regional price parities for the year 2012, among participants in the National Household Food Acquisition and Purchase Survey (2012-2013), by Supplemental Nutrition Assistance Program (SNAP) participation status and income level. Legend: SNAP = SNAP participants, Lo-inc non-SNAP = non-participants <185% of the federal poverty level, and Hi-inc non-SNAP = non-participants >=185% of the federal poverty level.

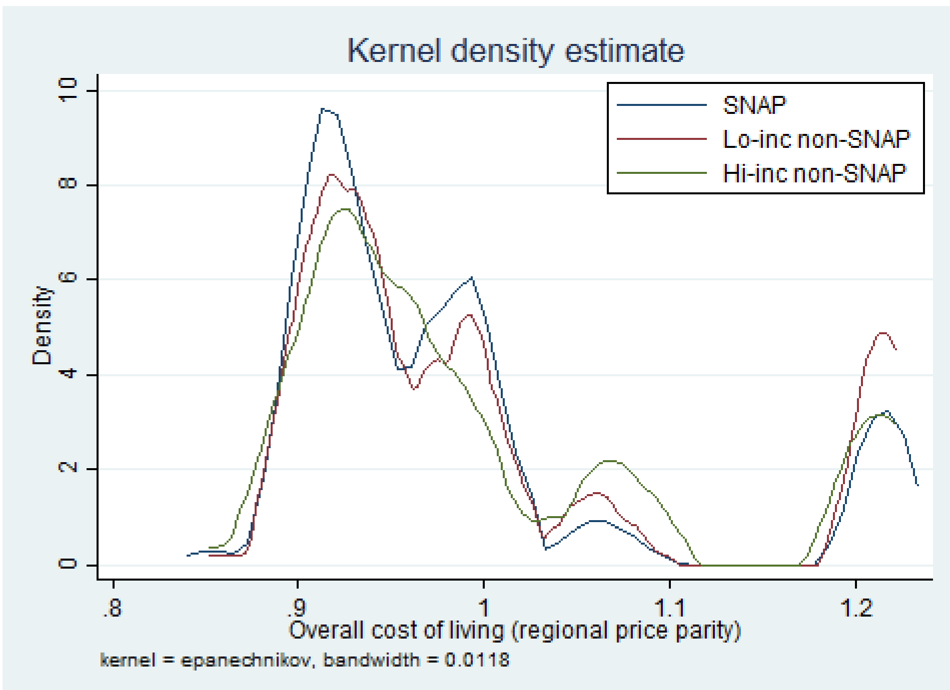


Figure 2: Subgroup analyses of the association between living in a high cost-of-living area (as defined by the overall regional price parity) and change in the Healthy Eating Index (HEI) 2010 score among SNAP participants, non-participants below 185% of the federal poverty threshold, and non-participants above 185% of the federal poverty threshold. A decline in HEI score indicates a worse nutrition profile; the mean HEI score in the analytical sample was 55, and the range of possible HEI scores is 0 (worst) to 100 (best). Legend: RPP = regional price parity; Geoadj SPM = geographical adjustment to the Supplemental Poverty Measure.

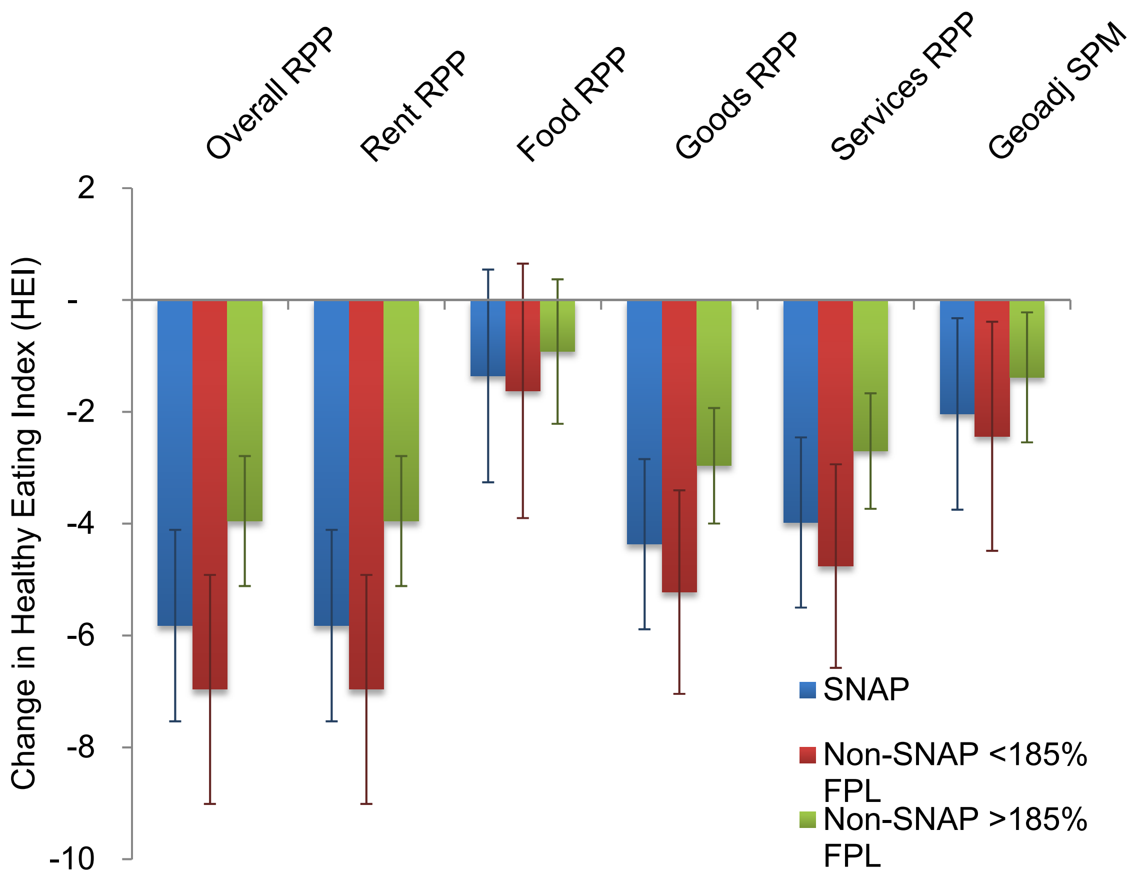
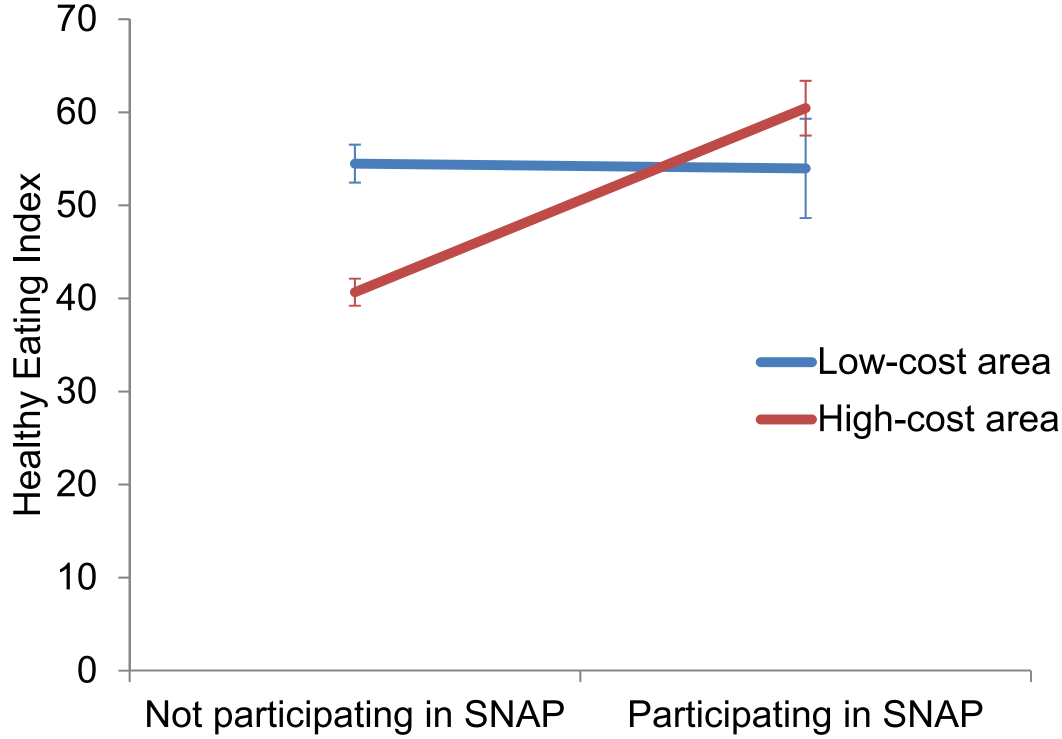


Figure 3: Interactions between SNAP participation and cost of living when the outcome of interest is the Healthy Eating Index-2010 score. Estimates are from an endogenous treatment effects parameter, estimating the average treatment effect of SNAP. Cost of living at the area (county) level is defined by the overall regional price parity, where high-cost is one standard deviation above the mean.



Supermarket Proximity and Price: Food Insecurity and Obesity in the United States

By

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Introduction

Where we live matters for our health. The social, economic, and physical features of neighborhoods can play a powerful role in health and longevity. Neighborhood concentration of poverty and poor health have been shown to be linked (1). Residing in low-income neighborhoods has been associated with diet related chronic diseases such as obesity and diabetes (2).

One in seven American households, mostly those living at or below the poverty line, were considered food insecure in 2014, which means they were without access to enough food to lead a healthy life (3). Those who report being food insecure are at greater risk for poor mental health, obesity, and chronic disease (4). Food insecure households face several barriers to accessing food including: 1) living geographically too far from supermarkets or other venues selling healthy foods, and, 2) the cost of purchasing healthy foods is higher than households can afford. We refer to these barriers as the "distance problem" and the "food price problem" respectively.

Policy interventions, such as the Health Food Financing Initiative, were designed to target the first barrier of reducing food deserts through incentivizing healthy food retailers to open in low-income neighborhoods. Despite the intent of these initiatives, there has been little evidence to show that reducing the "distance problem" through building supermarkets in low-income communities has pushed the needle on changing health outcomes (5-7) or food consumption behavior (8, 9).

The second barrier, the "food price problem," may exacerbate the lived experience of household food insecurity if food prices (and cost of living) are high and wages are low. The Supplemental Nutrition Assistance Program (SNAP), formerly known as the Food Stamp Program since the 1960s, is an in-kind transfer program to help families improve their ability to purchase foods through normal channels of commerce and provided food-purchasing assistance for some 46.5 million low-income U.S. households in 2014. The amount of the assistance is a function of household net income, deductions, the Thrifty Food Plan (TFP), and the maximum benefit for each household size. The TFP represents the price of a nutritionally adequate monthly basket of food based on family composition, and is calculated based on national food prices. However, supermarket prices vary between market areas. This means that if food costs are too high within a given food shopping area, even participation in SNAP may not be enough to alleviate household food insecurity.

Despite the efforts to understand how the distance and food price problems have led to food insecurity and poor health, inconsistency of findings among these relationships remain in part because we knew very little about how household preferences played a role in the food purchasing decisions of households. Households might select to shop at a supermarket based on perception of food prices, proximity to the home, or some combination of these factors. Little is known about how perception of these factors maps with objective measures of food prices and distance.

Two cross-sectional studies found that participants were more likely to be obese who shopped at stores where (actual) prices were lower (10, 11). This is likely because obese participants were also likely to be lower socioeconomic status, and thus sought lower priced stores. If food insecurity is associated with obesity among U.S. adults, as one study showed (12), we anticipate that there will be an association between households preferences to shop at stores with low prices and food insecurity.

Our research aims to address understand how both the subjective experience and objective measures of the “distance problem” and “food price problem” are associated with household food insecurity and obesity. First, we estimate the association of perceived distance and low prices with food insecurity and obesity. Next, we estimate how objectively measured access to supermarkets – based on presence of supermarkets and prices – relate to food insecurity and obesity. Specifically, our research questions are as follows:

1. Are individuals who select their primary supermarket based on perceived price or proximity more likely to live in a food insecure household and be obese, compared to those who select their primary supermarket based on <u>both</u> low prices and perceived proximity?
2. Are individuals who reside in a food desert more likely to be a part of a food insecure household and be obese, compared to those who do not live in a food desert?
3. Are individuals who reside in a high poverty area with higher than average supermarket prices are more likely to be a part of a food insecure household and be obese, compared to those who live in areas with low or average supermarket prices?

Conceptual Model of Food Insecurity

Drawing from Barrett (2002), the lack of access to goods market can be viewed as one of several structural characteristics of households that increases risk of food insecurity (13). Residing at a great distance from a food retailer is expected to increase food insecurity by a lower access to the goods market by way of increasing travel costs (13, 14). Also, the combination of living in a high poverty neighborhood located at a great distance from food retailers (e.g., food desert) is expected to increase food insecurity by limiting access to the labor market (15). Finally, those with very low-incomes who live far from stores with affordably priced foods might experience a greater risk of food insecurity if they have low purchase power in their local market. Becker's human capital theory (1975) and theory for demand for children (1991) suggest that food insecurity is directly related to household composition, income, and transfers. We expect that additional children in the household will increase food insecurity and additional adults will decrease food insecurity through household labor supply. Age, race, and sex are expected to impact household food insecurity through wage rate.

Methods

Study Design and Subjects

This study uses data collected by the Economic Research Service of the United States Department of Agriculture, the National Household Food Acquisition and Purchase Survey (FoodAPS), from April 2012 to January 2013. This includes nationally representative data from 4,826 households on household food shopping and purchasing behaviors. There were 2,015 households (SNAP participants and non-participants) with household income below the federal poverty threshold. For this analysis, we included the full sample, not restricted to SNAP participants or low-income households.

We also used data from the 2010 U.S. Census, which provides detailed counts and characteristics of the US population, and the American Community Survey, which includes demographic, housing, social, and economic information from the 5-year average data from 2008 to 2012. In addition, we used data from Nielsen TDLinx, FNS Store Tracking and Redemption System (STARS) sources, and Information Resources, Inc (IRI) which includes information on the location and type of food retailers in 2012.

Outcomes

The primary outcome of interest, food security, is measured at the household level and takes into account whether households have enough food to eat and are able to afford balanced meals in the last month. This was assessed using the 10-item U.S. Adult Food Security Survey Module with a reference to the prior month (16). We created a binary variable of food secure (1/0) that was turned on if a household gave 2 or fewer responses in the affirmative. As a sensitivity analysis we also created an ordered outcome: *very low* (6-10), *low* (3-5), *marginal* (1-2), and *high* (0) answers in the affirmative.

The secondary outcome of interest, obesity, is based on a self reported measure for each primary respondent adult, and is a binary indicator that is turned on if the individual has a body mass index (BMI) of 30 kg/m^2 or greater. As a sensitivity analysis, we also used the natural log of BMI as a continuous measure.

Exposures

Subjective Measure of Food Access: Determinants of Store Choice

Primary respondents were asked to indicate all of the main reasons for shopping at the store where most of the household shopping was done including options such as low prices, produce selection, meat department, variety of foods, variety of special foods, close to home, and loyalty/frequent shopper program. We created a variable that was coded 1 if the primary respondent selected "low prices", 2 for "close to home" or both "low price" and "close to home" (0). Respondents who did not select any of these items were set as missing for purposes of this analysis.

Objective Measure of Food Access

Two approaches were used to measure food access within the household's "neighborhood." First, we created a measure of a *food desert* which was defined as having a poverty rate of 20 percent or greater (or the BG median income is less than or equal to 80 percent of the Metropolitan area median family income) and the closest supermarket is more than one mile away from the census block centroid (10 miles, for non-metropolitan block groups). 90% of all census block groups in 2010 had less than 2 square miles of land area, and the median block group was 0.2

square miles.

Next, we create a similar measure at the census tract level for purposes of comparability with other studies. Also the census tract is the geographical unit that best represents the average size of a shopping area; nationwide the mean area of a census tract is 13.7 square miles and three-quarters of all census tracts located within metropolitan statistical areas (MSAs) are less than 4.5 square miles (17). The indicator is turned on when a participant lives in a low income census tract (defined by Department of Treasury's New Markets Tax Credit program where the tract has a poverty rate 20 percent or greater or the tract's median income is less than or equal to 80 percent of the Metropolitan area median family income) and at least 500 persons or at least 33% of the census tract's population live more than one mile from a supermarket or large grocery store (10 miles, for non-metropolitan census tracts).

The second measure, *food tundra*[1], builds upon the food desert measure and reflects that proximity to supermarket is only a relevant criterion to characterize food access if store prices are not too high. First, we create two measures for each block group that reflect the weekly median and low cost of the Thrifty Food Plan (TFP) for a family of 4 of all store chains within three buffers (3, 5, 10 miles) of the block group centroid during the study period. These distances were selected based on our descriptive estimates from Table 3. The average distance traveled to closest supermarket (3 miles) and primary supermarket (5 miles). Less than 1 percent of all block groups did not have a supermarket within 10 miles from its centroid.

The TFP was created by the USDA's Center for Nutrition Policy and Promotion and includes quantities of 29 categories of food types based on age and sex (18). The median cost measure was derived using the median costs per pound (after removing outliers) and the low cost

[1] A tundra is a frozen, treeless plain that makes it difficult for plants and animals to survive.

measure uses the per pound price at the 10th percentile. The data was obtained from the Information Resources, Inc (IRI), a private company that provides retail store scanner data. Some store chains such as Target, Safeway, and Kroger do not report item-level prices for private label items, and are thus not included. More information on the specifics of the construction of this measure and its limitations have been published elsewhere (19). We use the median costs of only stores with all TFP categories. To account for missingness of categories that preclude a store's inclusion in the analysis, as a sensitivity analysis we construct an alternate measure which uses the median cost of each category in each block group and multiplies that by the number of pounds to get a price measure.

To create the measure of *food tundra*, which is defined having poverty rate of 20 percent or greater (or the BG median income is less than or equal to 80 percent of the Metropolitan area median family income), and having a median weekly TFP cost that is in the top quintile of all block groups. As an alternate measure, we substitute low cost for median cost.

Covariates

Several variables were constructed that were hypothesized to influence both household food security and food access. This includes primary respondent characteristics such as sex (female =1, male =0), age at time of survey, marital status (currently married = 1, prior/never married = 0), race/ethnicity (0 = non-Hispanic White, 1 = Black, 2 = Hispanic, 3 = Asian), citizenship status (1=U.S. citizen, 0 = not U.S. Citizen), highest educational attainment (0 = bachelors degree+, 1= some college, 2 = high school degree, 3 = some high school), and employment status (1= employed in the prior month, 0= not employed), as well as household-characteristics such as monthly income (in $US), home ownership (1= owns home, 2= renter or other), number of children, number of disabled members, and number of adults.

Statistical Methods

The relationship between store determinant choice or food access and food insecurity or obesity is specified with the general form of the model as follows:

$$Y_{ij} = \beta_{oj} + \beta_1 A_{ij} + \beta_2 X_{ij} + \beta_3 W_{ij} + \varepsilon_{ij}$$

where Y_{ij} is a measure of food insecurity or obesity in household *i* in census block *j*; β_{oj} is the census block-specific intercept; A_{ij} is a measure of store determinant choice or food access of household *i* in in census tract; X_{ij} is a vector of primary-respondent characteristics of household *i* in census tract *j*; W_{ij} is a vector of household-characteristics of household *i* in census tract *j*; and ε_{ij} is the error term.

A_j = selection of primary supermarket based on perceived price (1), distance (2), or both price & distance (0) <u>or</u> residence in a food desert (1/0) <u>or</u> residence in a food tundra (1/0)

X_{ij} = *female, age, race/ethnicity, US citizen, marital status, education, employment status*

W_{ij} = *log of income, home ownership, car ownership, number of children, number of adults, number of disabled*

We fit a series of logit and multinomial logit models to estimate the log odds of household food insecurity or adult obesity as a function of the above variables.

Sensitivity Analyses

We measured food security as both as a binary and ordinal outcome. Additionally, we measured obesity as a binary outcome and used log of BMI as an alternate measure. For comparability to prior research, we also estimated the effect of residing in a food desert at the census tract level in addition to the census block level. Next, as we were concerned with the robustness of the supermarket price variable, we created an alternate measure of low cost TFP in addition to the median cost TFP we used in our main model. In addition, as we were concerned with potential bias introduced by missing stores, we created another alternate measure of the median cost TFP by taking the median cost of each of the 29 categories of the TFP. Finally, our measure of food tundra was assessed at 3 distances from the block group centroid (3, 5, and 10 miles).

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Table 1: Primary respondent and household characteristics

	All	Food Insecure	Poor (<=FPL)
Female	67.4%	69.2%	71.1%
Age			
18 to 24	5.1%	8.1%	8.8%
25 to 34	16.9%	20.3%	15.3%
35 to 44	16.7%	20.6%	15.7%
45 to 54	19.8%	22.4%	20.1%
55 to 65	21.1%	16.6%	20.9%
65+	20.2%	12.0%	19.0%
Marital Status			
Currently Married	44.1%	28.1%	25.8%
Previously Married	33.5%	41.7%	41.8%
Never Married	22.3%	30.2%	32.4%
Race			
Black	13.3%	23.2%	23.1%
White	80.1%	68.5%	67.9%
U.S. Citizen	57.8%	47.6%	52.1%
Educational Attainment			
Some High School	9.9%	23.6%	24.2%
High School Diploma	25.6%	32.1%	27.1%
Some College	33.1%	32.3%	27.8%
Bachelor’s Degree +	31.4%	11.9%	19.7%
Worked in Prior Week	55.6%	43.2%	30.3%
Obesity (BMI>30)	32.0%	40.8%	34.0%
Poor Health	17.8%	36.2%	27.9%
SNAP Participation	13.6%	37.7%	39.5%
Mean Monthly Household Income	$5,074.63	$2,344.12	$646.76
Owns/Leases Car	89.5%	64.3%	69.0%
Homeowner	61.6%	30.2%	42.6%
Moved in Past Year	10.9%	18.5%	15.2%
Household Size			
1	33.9%	37.4%	45.8%
2	27.4%	19.0%	15.9%
3	16.5%	15.0%	12.0%
4	13.5%	14.9%	13.7%
5 +	8.6%	13.7%	12.6%

Note: Survey weights applied

Table 2. Block Group Supermarket Price Environment (n = 748 block groups)

	Distance from Block Group Centroid		
	3 miles	5 miles	10 miles
Number of Block Groups without any Stores	146	86	30
Number of Block Groups with Median Price	416	462	511
Mean (Standard Deviation) of Basket Cost - Median	360.97 (59.09)	367.02 (62.39)	362.65 (57.54)
Mean (Standard Deviation) of Basket Cost - Low	157.24 (23.41)	158.89 (24.62)	158.11 (21.26)

Table 3: Food Environment Household Characteristics, by Food Security and Obesity

	All	Food Insecure	Food Secure	Obese	Non-Obese
Household characteristics					
Miles to closest supermarket	3.08 (0.36)	2.49 (0.35)	3.18 (0.36)	3.42 (0.43)	2.93 (0.35)
Driving distance (miles) to primary supermarket	5.11 (0.62)	3.82 (0.38)	5.36 (0.67)	5.59 (0.59)	4.89 (0.67
# supermarkets within 1 mile of BG centroid	1.34 (0.17)	1.73 (0.24)	1.27 (0.16)	1.21 (0.14)	1.39 (0.19)
Residence in Block Group Food Desert (%)	4.30 (1.11)	6.56 (1.92)	3.87 (1.02)	5.62 (1.72)	3.70 (1.02)
Residence in Census Tract Food Desert (%)	13.82 (2.05)	18.81 (2.61)	12.87 (2.09)	17.16 (2.09)	12.19 (2.33)
Residence in Food Tundra[a] (%)	6.29 (1.83)	12.95 (4.93)	4.93 (1.51)	6.49 (1.93)	6.16 (2.04)
Residence in top fifth most expensive environment [a] (%)	21.16 (4.62)	25.02 (5.09)	20.37 (4.76)	17.69 (4.17)	22.93 (5.09)
Median cost of TFP ($)	363.28 (6.07)	368.10 (6.65)	362.30 (6.30)	359.04 (5.61)	365.44 (6.76)
Low cost of TFP ($)	158.18 (2.44)	157.36 (3.07)	158.34 (2.46)	155.92 (2.49)	159.37 (2.57)
Determinants of Primary Store Choice (%)					
Low Prices	30.1 (1.8)	40.0 (3.0)	28.2 (1.8)	32.9 (2.3)	28.5 (1.9)
Close	30.3 (1.3)	26.6 (2.1)	31.0 (1.3)	30.0 (2.3)	30.3 (1.6)
Both Low Prices and Close	22.7 (1.9)	18.9 (2.2)	23.4 (2.0)	21.7 (2.5)	23.5 (2.1)
Note: Standard errors are in parentheses					

(a) Estimates from 3 miles from Block Group Centroid. N= 3,484; excludes those with no stores or missing store price data. For 5 and 10 miles, estimates are similar.

Table 4: Marginal Effects of Food Environment on Food Security

	M1, Predictor: Tundra		M2, Predictor: Desert		M3, Predictor: Both	
	dy/dx	**SE**	**dy/dx**	**SE**	**dy/dx**	**SE**
Tundra (3mi)	0.070***	0.027			0.069***	0.028
Food Desert			0.013	0.023	0.007	0.023
Female	0.012	0.014	0.012	0.015	0.012	0.014
Age	-0.001	0.001	0.001	0.001	-0.001	0.001
White	ref		ref		ref	
Black	-0.023	0.019	-0.021	0.019	-0.023	0.019
Hispanic	0.029	0.025	0.035	0.025	0.030	0.025
Other	0.039*	0.02	0.039	0.020	0.040	0.020
US Citizen	0.009	0.029	0.011	0.029	0.009	0.029
Married	-0.063***	0.013	-0.063***	0.013	-0.063***	0.013
< HS	ref		ref		ref	
High School	-0.081***	0.017	-0.081***	0.0169	0.081***	0.017
Some College	-0.099***	0.018	-0.099***	0.0176	-0.100***	0.017
Bachelors +	-0.238***	0.022	-0.238***	0.022	-0.237***	0.022
Owns Car	-0.036**	0.017	-0.041**	0.017	-0.036**	0.018
Renter	0.137***	0.015	0.139***	0.015	0.137***	0.0159
Unemployed	0.059***	0.019	0.061***	0.019	0.0591***	0.019
Income (log)	-0.017***	0.003	-0.017***	0.002	-0.017***	0.003
# Adults	0.027***	0.006	0.028***	0.006	0.027***	0.006
# Children	0.012***	0.006	0.012**	0.006	0.012**	0.006
# Disabled	0.159***	0.013	0.159***	0.014	0.159***	0.014

Note: *p<0.1, **p<0.05, ***p<0.01. All models included robust standard errors clustered at the Census Block Group. Models fit with logit produced similar results to probit estimates. Number of Households is 4,826. Missing-Indicator approach was used. Results were nearly identical with complete case analysis, including sampling weights, and adjusting for region.

Figure 1: Proportion of Block Groups in each Geographic Region, by Food Price Environment

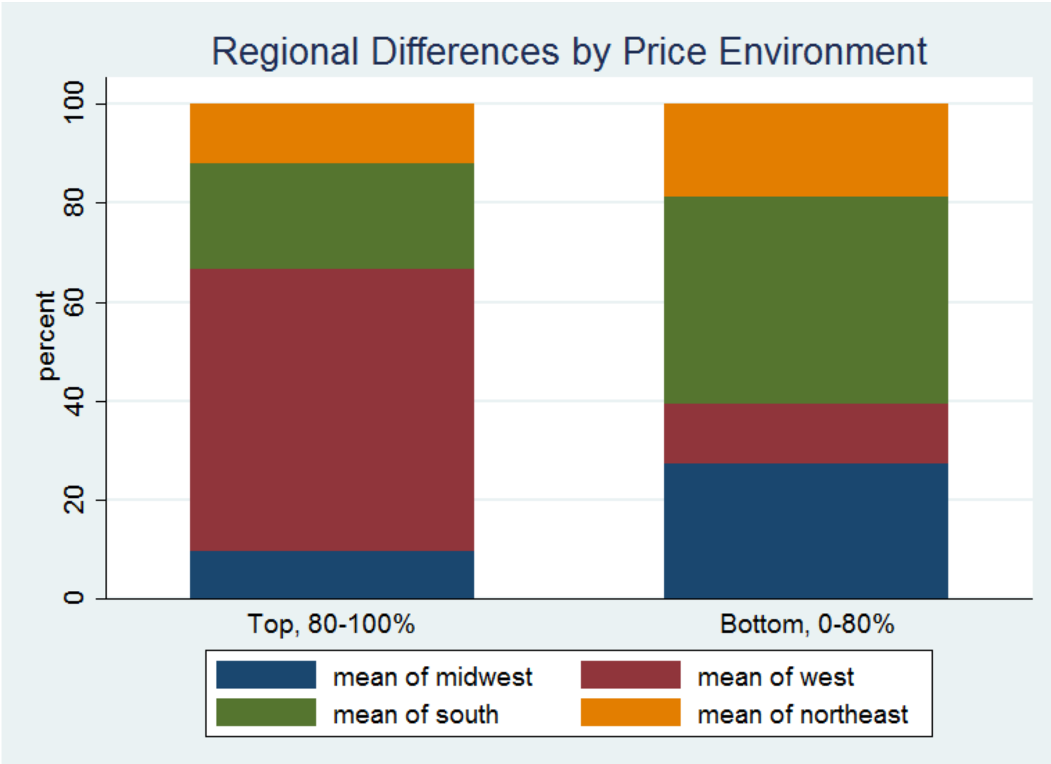


Figure 2: Proportion of Rural and Urban Block Groups in High (Top 5th) Food Price Environment

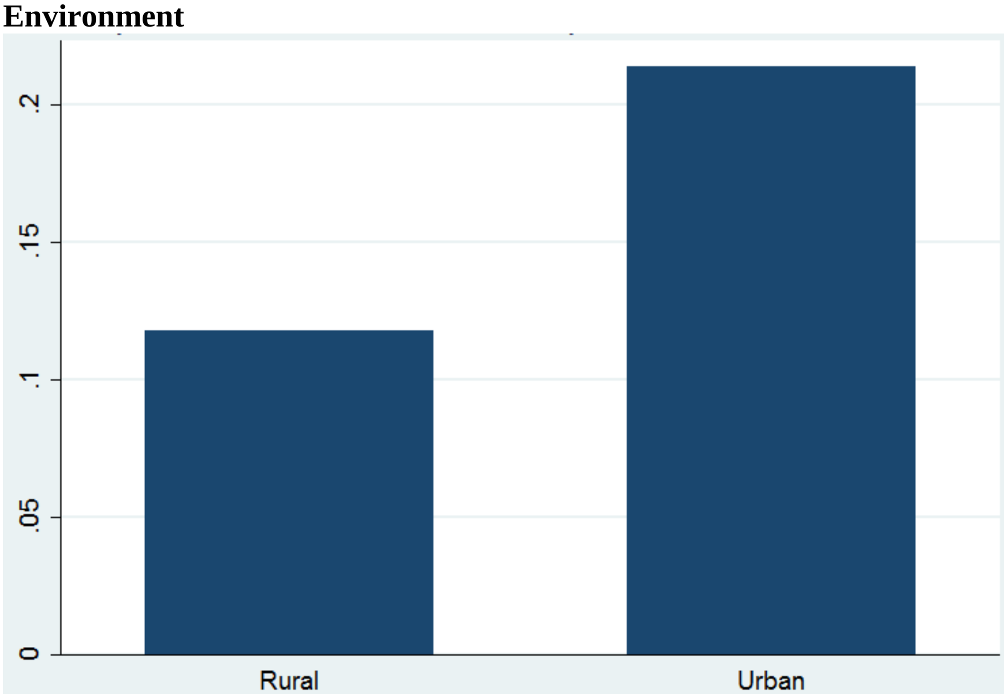


Figure 3: Proportion of Income on Housing, by Price Environment

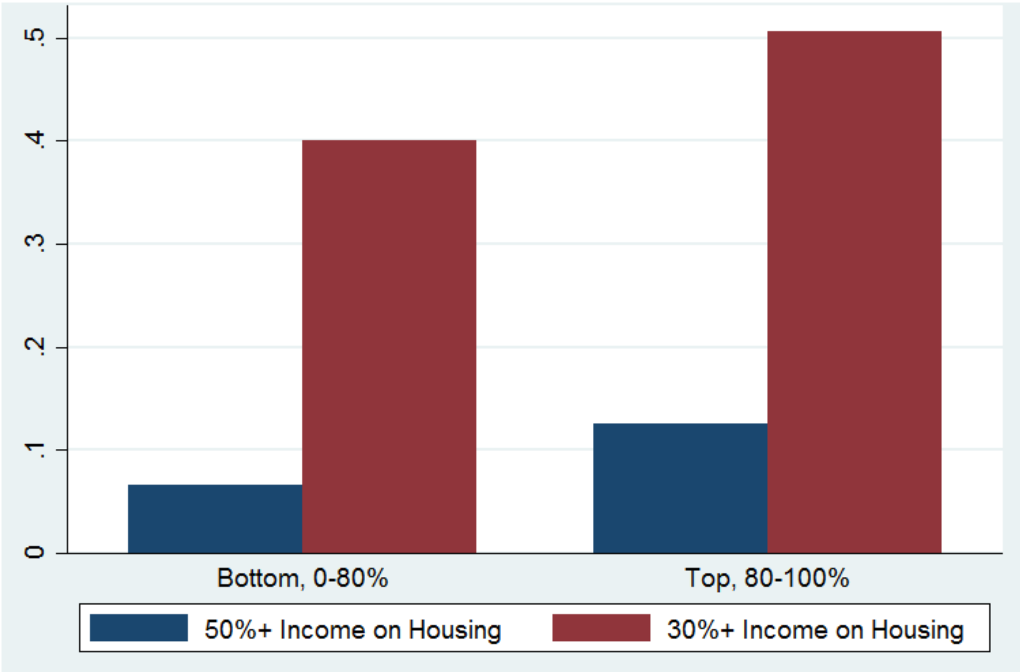


Figure 4: Household Reasons for Selecting Primary Supermarket, by Food Security and Obesity

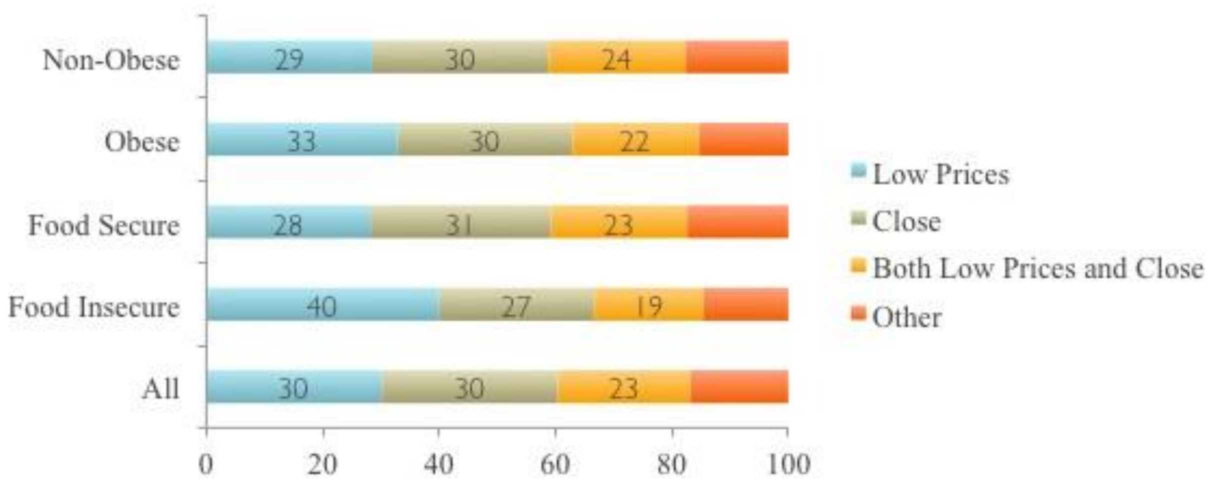


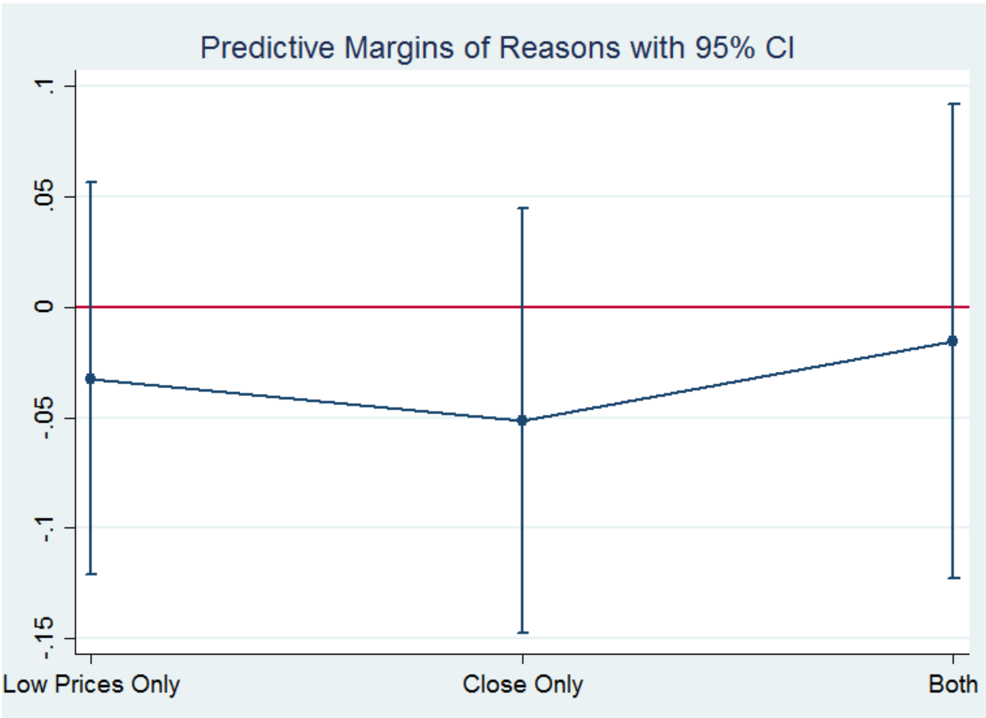
Figure 5: Predictive Margins of Food Insecurity (Binary) with 95% CI, by Reasons for Shopping at Primary Store

Note: Reference group (not shown) is "other" reasons for selecting primary store. Graph shows the marginal effects
after a logit model adjusted for full set of covariates, with robust standard errors clustered at the block group. 95% confidence intervals that cross zero are not statistically significant.

Figure 6: Predictive Margins of Food Insecurity (Binary) with 95% CI, by Shopping at Primary Store for Low Prices

Note: Reference group (not shown) is not selecting "low prices" are reason for shopping at primary store. Graph shows the marginal effects after a logit model adjusted for full set of covariates, with robust standard errors clustered at the block group. 95% confidence intervals that cross zero are not statistically significant.

Figure 7: Predictive Margins of Obesity (Binary) with 95% CI, by Reasons for Shopping at Primary Store

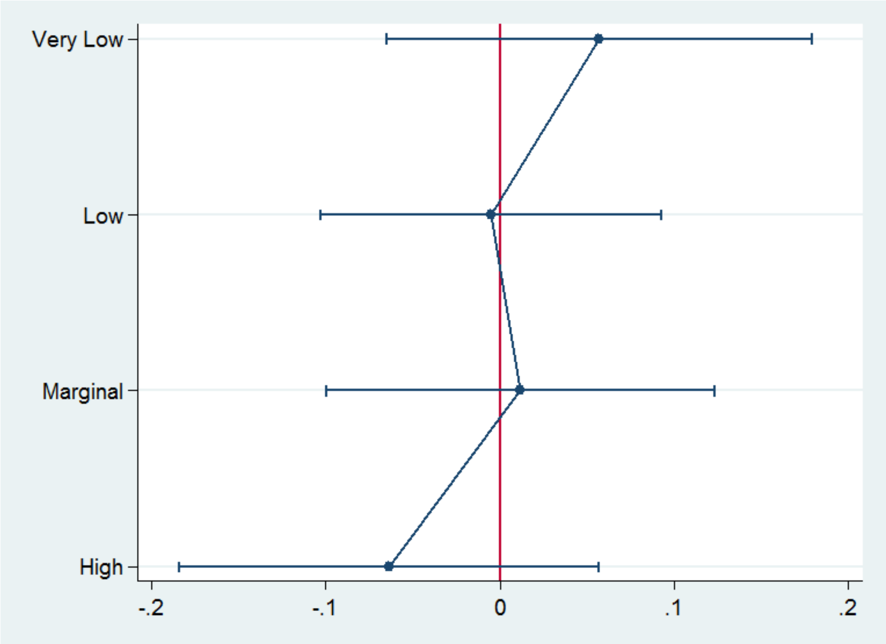


Note: Reference group (not shown) is "other" reasons for selecting primary store. Graph shows the marginal effects after a logit model adjusted for full set of covariates, with robust standard errors clustered at the block group. 95% confidence intervals that cross zero are not statistically significant.

Figure 8: Predictive Margins of Obesity (Binary) with 95% CI, by Shopping at Primary Store for Low Prices

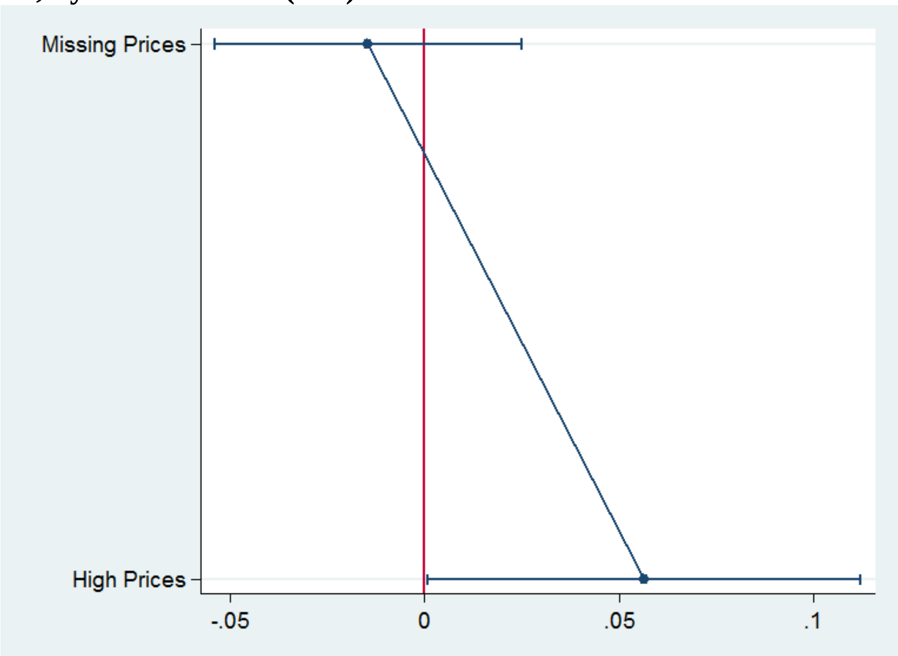
Note: Reference group (not shown) is not selecting "low prices" are reason for shopping at primary store. Graph shows the marginal effects after a logit model adjusted for full set of covariates, with robust standard errors clustered at the block group. 95% confidence intervals that cross zero are not statistically significant.

Figure 9: Predictive Margins of Food Security (Ordinal) with 95% CI, by Food Desert (Block Group)



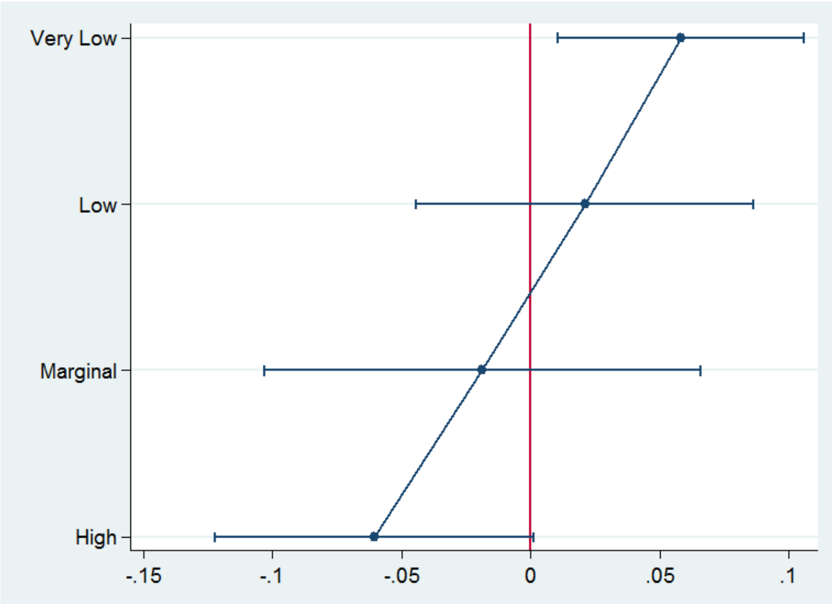
Note: Graph shows the marginal effects of living in a food desert on high, marginal, low, and very low food security after a multinomial logit model adjusted for full set of covariates, with robust standard errors clustered at the block group. 95% confidence intervals that cross zero are not statistically significant.

Figure 10: Predictive Margins of Food Insecurity (Binary) in Poor Block Groups with 95% CI, by Food Tundra (3mi)



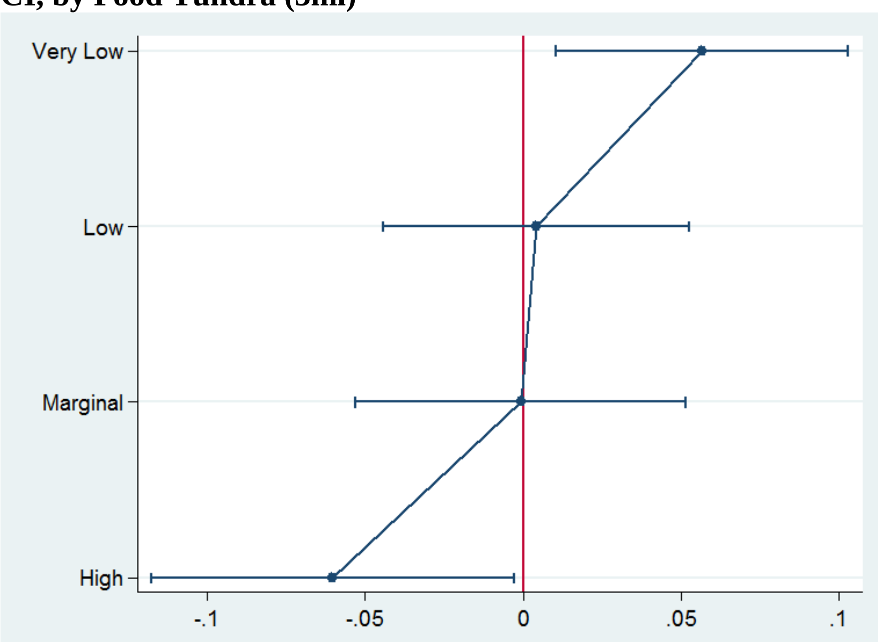
Note: Reference group (not shown) is not residing in a block group with food prices in top 5th. Graph shows the marginal effects of food insecurity after a logit model adjusted for full set of covariates, with robust standard errors clustered at the block group. 95% confidence intervals that cross zero are not statistically significant.

Figure 11: Predictive Margins of Food Security (Ordinal) with 95% CI, by Food Tundra (3mi)



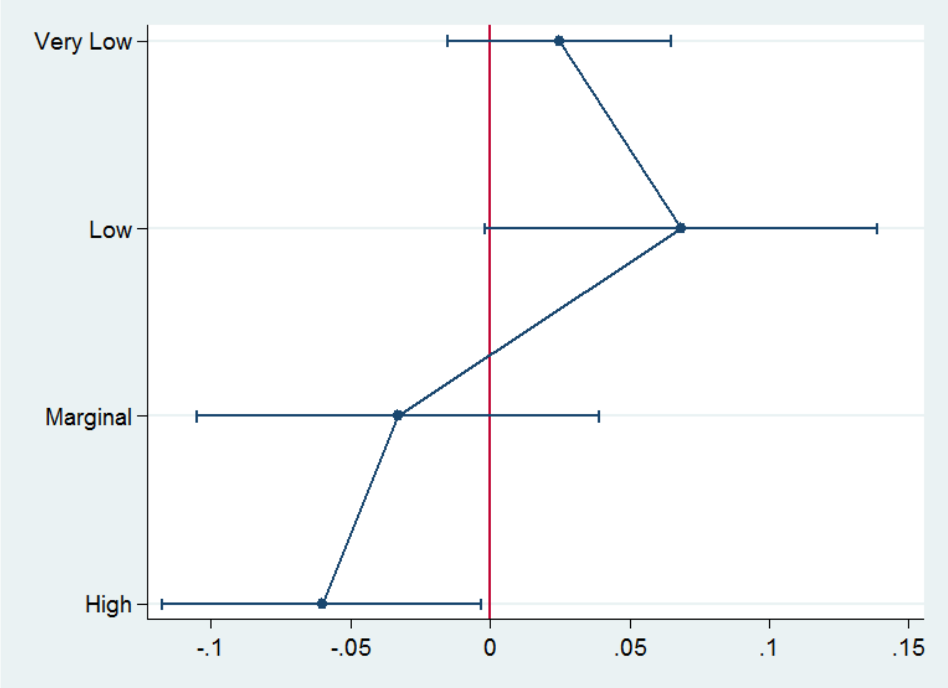
Note: Graph shows the marginal effects of residing in a food tundra (3mi) on high, marginal, low, and very low food security after a multinomial logit model adjusted for full set of covariates, with robust standard errors clustered at the block group. 95% confidence intervals that cross zero are not statistically significant.

Figure 12: Predictive Margins of Food Security (Ordinal) in Poor Block Groups with 95% CI, by Food Tundra (3mi)



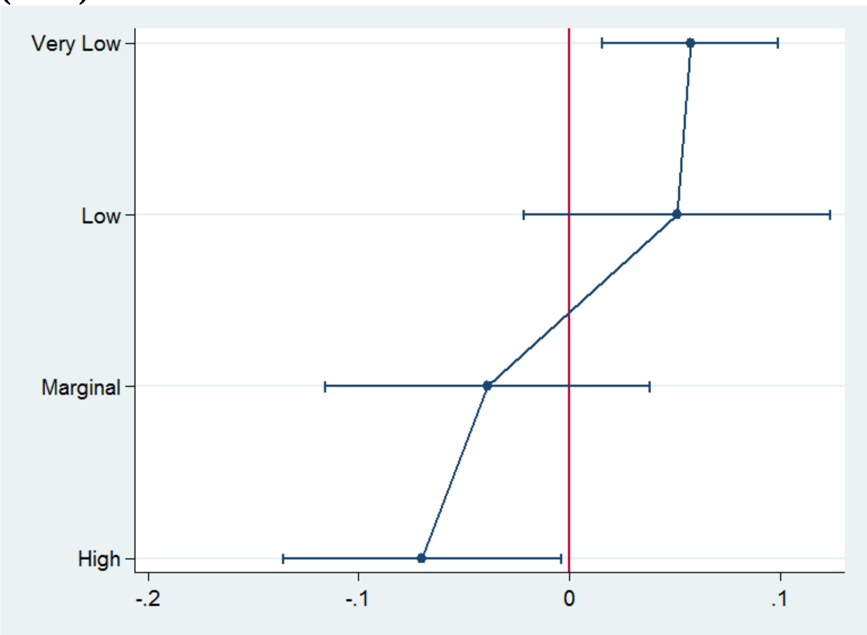
Note: Graph shows the marginal effects of residing in a food tundra on high, marginal, low, and very low food security among residents of poor block groups after a multinomial logit model adjusted for full set of covariates, with robust standard errors clustered at the block group. 95% confidence intervals that cross zero are not statistically significant.

Figure 13: Predictive Margins of Food Security (Ordinal) with 95% CI, by Food Tundra (5mi)



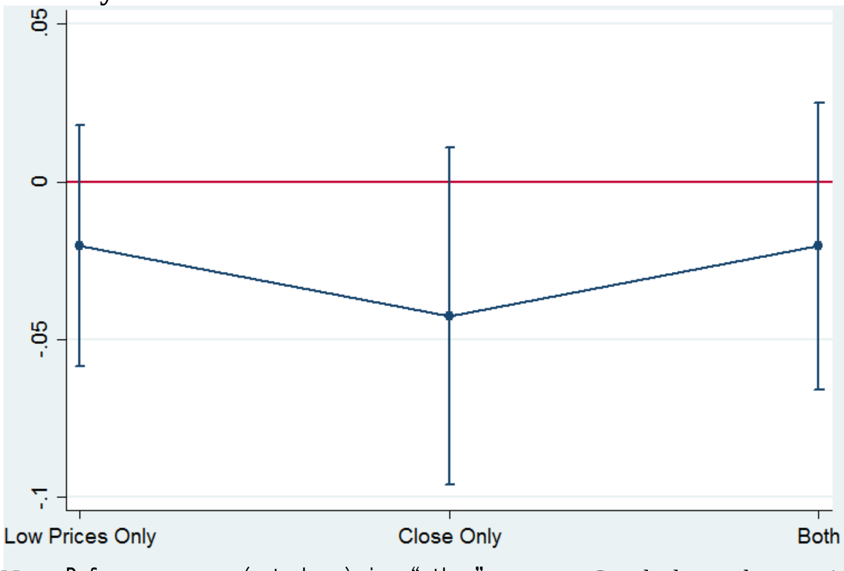
Note: Graph shows the marginal effects of residing in a food tundra (5mi) on high, marginal, low, and very low food security after a multinomial logit model adjusted for full set of covariates, with robust standard errors clustered at the block group. 95% confidence intervals that cross zero are not statistically significant.

Figure 14: Predictive Margins of Food Security (Ordinal) with 95% CI, by Food Tundra (10mi)



Note: Graph shows the marginal effects of residing in a food tundra (10mi) on high, marginal, low, and very low food security after a multinomial logit model adjusted for full set of covariates, with robust standard errors clustered at the block group. 95% confidence intervals that cross zero are not statistically significant.

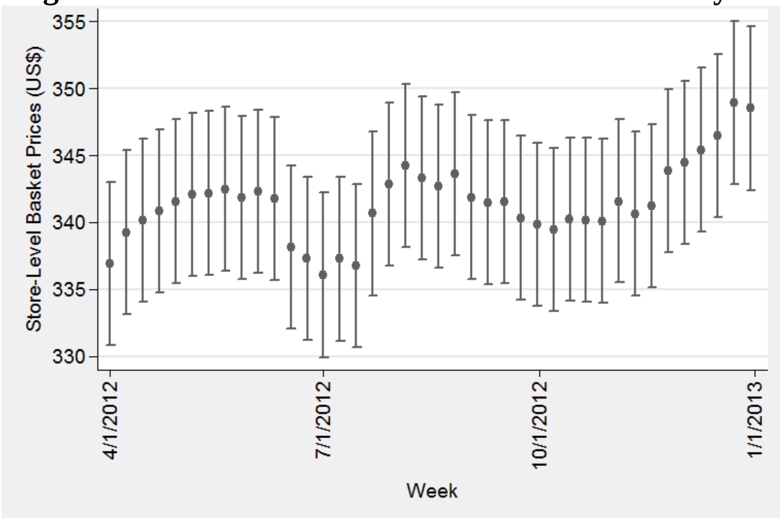
Figure 15: Predictive Margins of BMI (log) with 95% CI, by Reasons for Shopping at Primary Store



Note: Reference group (not shown) is "other" reason. Graph shows the marginal effects of shopping at a primary store on the log of BMI after a linear model adjusted for full set of covariates, with robust standard errors clustered at the block group. 95% confidence intervals that cross zero are not statistically significant.

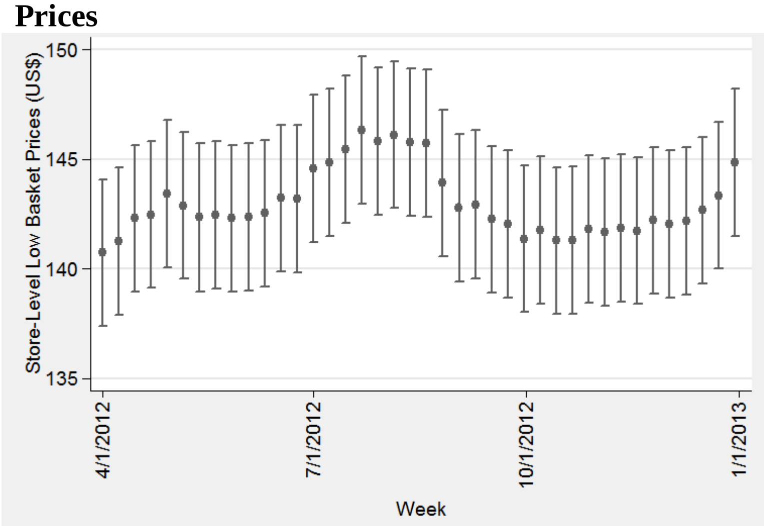
Appendix

Figure A1: Mean and Standard Deviation of County Weekly Store-Level Basket Prices



Note: The weekly Thrifty Food Plan (TFP) store-level basket prices were created from IRI store sales data using both the Universal Product Code (UPC) and random-weight purchases. For stores that do not report store-level sales, data from aggregate sales at a Regional Market Area (RMA) level was used. The median price was weighted by the TFP category weights for a family of four (male 19 to 50, female 19 to 50, child age 6 to 8, child age 9 to 11) for each TFP category.

Figure A2: Mean and Standard Deviation of County Weekly Low Store-Level Basket Prices



Note: The weekly Thrifty Food Plan (TFP) store-level basket prices were created from IRI store sales data using both the Universal Product Code (UPC) and random-weight purchases. For stores that do not report store-level sales, data from aggregate sales at a Regional Market Area (RMA) level was used. To create the "low-cost food basket" measure, the 10th percentile of price for each category was adjusted by the TFP category weights for a family of four (male 19 to 50, female 19 to 50, child age 6 to 8, child age 9 to 11)

The Effect of Food Price on Food Insecurity and Diet Quality: Exploring Potential Moderating Roles of SNAP and Consumer Competency

By
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Abstract

Higher food prices may aggravate household food insecurity and hurt diet quality. Using a sample of low-income households from the National Household Food Acquisition and Purchase Survey (FoodAPS), this study examines whether local food prices affect food insecurity and nutritional quality of foods acquired, and how households use competent consumer behaviors to mitigate any adverse effects of price. Financial management practices, nutrition literacy, and conscientious food shopping practices were considered for consumer competency. Our findings indicate that low-income households in higher-cost areas, regardless of whether they participate in SNAP or not, are more likely to adopt loyalty or other store savings programs than those in areas where food cost is relatively lower. Also, controlling for local food cost and various household characteristics, SNAP participants are more likely to use loyalty programs or other store savings, and are more likely to be aware of the dietary guidelines than nonparticipants. Our findings suggest that, although theoretically households could benefit from various consumer competencies and skills especially when the food cost is high, taking advantage of competent consumption strategies may be out of reach for many low-income consumers dealing with high food cost. Further, policies that incentivize competent or conscientious consumption among program participants might decrease food insecurity but likely at the expense of lowered nutritional quality of acquired foods, as long as less healthy food choices are also less expensive.

Executive summary

Introduction: Households living in high food price areas are more likely to suffer food insecurity (Gregory & Coleman-Jensen, 2013) and may also be priced out of healthy food options. This study takes advantage of detailed food acquisition and purchase records and geographic indicators in the FoodAPS data to explore whether local food price affects low-income households' risk of food insecurity as well as nutritional quality of foods acquired, and how households that are faced with high food cost in the area use competent consumption behaviors to maintain food security and diet quality.

Methods: To assess whether low-income households in high food price areas are more likely to display competent consumption behaviors, dichotomous variables of behaviors representing consumer competency are regressed over the local-level food price, along with various household characteristics as controls. Because price varies across the year and was measured for the given time period during which each household's food acquisition was recorded, time-specific fixed effect term is included. To see if SNAP participants and nonparticipants respond differently to high cost of food, an interaction term is included. Logit models were estimated. To examine whether consumer competency alleviates the adverse effect of high food cost on nutritional outcomes, food insecurity and diet quality variables were each regressed over local basket price, consumer competency indicators, SNAP participation, household characteristics, and week fixed effects.

Data: The study uses data from the USDA's National Household Food Acquisition and Purchase Survey (FoodAPS). A sample of 1,908 households, who had incomes below 185% of the federal poverty level and reported at least one event of grocery shopping during the seven-day reporting period were used for analysis. The food insecurity status was determined based on the 30-day adult food security survey module. A series of nutritional quality measures were computed by aggregating food component and nutrient information of all food items acquired by the household during the seven-day reporting period. Indicators for three areas of consumer competency pertinent to food purchase, including financial competency, nutrition literacy, and conscientious buying, were constructed based on survey responses as well as records of food acquisition events. Four alternate measures of local cost of aggregate food categories comprising Thrifty Food Plan (TFP) were obtained from the geographic component (FoodAPS-GC) and matched to household level data based on location of the household and the timing (week) of the survey.

Results: The results indicate that basket price were negatively associated with financial management practices, shopping with a grocery list, coupon use, and using nutrition facts labels, after controlling for the household characteristics, food environment, and the weekly fixed effects. On the other hand, high food cost in the area was strongly correlated with households' increased use of loyalty programs or other store savings. While we suspect the disturbing negative associations largely reflect endogeneity or reverse causality, we find that these negative associations between food cost and consumer competency were not as pronounced among SNAP participants as they were with nonparticipants. Controlling for consumer competency, we find little evidence that food cost affects the risk of food insecurity. local food cost lowers the whole-grain content of the acquired foods, but it also significantly lowers sodium density of acquired foods.

Discussion: Our findings indicate that low-income households in higher-cost areas, regardless of whether they participate in SNAP or not, are more likely to adopt loyalty or other store savings programs than those in areas where food cost is relatively lower. Also, controlling for local food cost and various household characteristics, SNAP participants are more likely to use loyalty programs or other store savings, and are more likely to be aware of the dietary guidelines than nonparticipants.

Conclusion: Our findings suggest that, although theoretically households could benefit from various consumer competencies and skills especially when the food cost is high, taking advantage of competent consumption strategies may be out of reach for many low-income consumers dealing with high food cost. Further, policies that incentivize competent or conscientious consumption among program participants might decrease food insecurity but likely at the expense of lowered nutritional quality of acquired foods, as long as less healthy food choices are also less expensive.

Introduction

Households living in high food price areas are more likely to suffer food insecurity (Gregory & Coleman-Jensen, 2013) and may also be priced out of healthy food options. This study takes advantage of detailed food acquisition and purchase records and geographic indicators in the FoodAPS data to explore whether local food price affects low-income households' risk of food insecurity as well as nutritional quality of foods acquired, and how households that are faced with high food cost in the area use competent consumption behaviors to maintain food security and diet quality.

Millions of Americans are challenged with food insecurity -- a condition of insufficient access to food due to resource constraint. In 2014, 14% of U.S. households (17.4 million households) were food insecure (Coleman-Jensen, Rabbitt, Gregory, & Singh, 2015). Whereas recent studies found that SNAP participation decreases food insecurity (Borjas, 2004; Li, Mills, Davis, & Mykerezi, 2014; Nord & Golla, 2009; Shaefer & Gutierrez, 2013), the rate of food insecurity among SNAP participants is still high (Nord, Coleman-Jensen, Andrews, & Carlson, 2010). Although food insecurity is a condition strongly associated with poverty and income volatility (Loopstra & Tarasuk, 2013), income alone may be an imperfect predictor of food insecurity. Research has found that households' competency as consumers may help them avoid food insecurity. Low-to-moderate-income households who had better financial management practices or greater financial literacy were less likely to be food insecure than others (Gaines, Robb, Knol, & Sickler, 2014; Gundersen & Garasky, 2012; Millimet, McDonough, & Fomby, 2015). Other skills and behaviors such as food budgeting, food shopping, and food resource management have also been linked to adequate food access (Kaiser et al., 2015; Lohse, Belue, Smith, Wamboldt, & Cunningham-Sabo, 2015).

Besides food insecurity, improving the dietary quality of low-income population is another goal of food assistance programs such as SNAP (Bitler, 2014). Poor diet quality is often associated with food insecurity; however, food insecurity may not directly determine poor diet quality (Bhattacharya, Currie, & Haider, 2004). Faced with high food price, households with limited resources may use various coping strategies to acquire healthful foods. Existing literature identified various consumer competencies that relate to improved dietary intake. Not only that eating competence, nutrition knowledge, and health literacy were associated with dietary intake (Lohse, Bailey, Krall, Wall, & Mitchell, 2012; Spronk, Kullen, Burdon, & O'Connor, 2014; Wardle, Parmenter, & Waller, 2000; Zoellner et al., 2011), perceived consumer effectiveness and food shopping practices such as label use or shopping with a grocery list have been found to predict better dietary quality especially among low-income individuals (Dubowitz, Cohen, Huang, Beckman, & Collins, 2015; Hersey et al., 2001; Kim, Nayga, & Capps, 2000; Vermeir & Verbeke, 2006; Wiig & Smith, 2009).

Although many research findings provided evidence that consumer competency is an important determinant of food security and diet quality and implied an argument for incorporating resource management skills in the nutrition education curricula for program participants such as SNAP-ED, more knowledge of the role of consumer competency in improving food insecurity and nutrition among limited-resource households is desired for at least two reasons. First, current understanding of the role of consumer competency is based on studies that each investigated the relationship between a particular aspect of consumer competency and its targeted nutritional outcome. Little is known about how consumer strategies to secure a sufficient *quantity* of foods (e.g., money-saving, budget-stretching techniques) are associated with the nutritional *quality* of foods consumed, or how households' abilities and efforts to acquire and consume healthful foods may affect their food insecurity. Second, the vast majority of existing research regarding consumer competency and shopping behaviors relied on local data or limited geographic scope and therefore lacked the ability to observe whether households in high cost areas are more likely to display competent consumer behaviors than those in low cost areas. More needs to be known regarding how the cost of food affects nutritional quality of foods consumed by low-income households, and how this potential effect of food cost interacts with consumer competency. If households use coping strategies such as competent consumer behavior in response to high food cost, a crude estimate of the effect of food cost on food security and nutritional outcomes or the effects of consumer competency might be an underestimation.

This study extends the literature by considering a wide array of consumer competencies and explores how they are associated with both food security and nutritional quality of foods that low-income households buy. It also examines whether low-income households in higher-cost areas are more likely to engage in competent consumer behaviors to counteract the price disadvantage. This study also examines whether SNAP participants are different from nonparticipants in terms of consumer competency. If SNAP participants are less competent, it should be examined whether SNAP replaces desirable behaviors or it's just that different people choose different strategies – between program reliance and consumer competency.

Consumer Competency

Consumers' skills and abilities in managing resources can avoid food insecurity. These include financial management, food resource management, and nutrition literacy. A few recent studies argue that nutrition education for low-income audience should incorporate food resource management (e.g., food budgeting and food shopping), to help them best manage their food dollars to afford healthy food (Kaiser et al., 2015; Lohse et al., 2015; Wiig & Smith, 2008).

Improving food resource management skills through effective nutrition education programs could enhance food security of low-income households (Kaiser et al. 2015; Lohse et al., 2015). Additionally, nutrition literacy, "the degree to which individuals have the capacity to obtain, process, and understand nutrition information and skills needed to make appropriate nutrition decisions" has been linked to nutrition outcomes such as diet quality (Zoellner, Connell, Bounds, et al., 2009). Health literacy is associated with healthy eating as well as sugar-sweetened beverage intake (Zoellner et al., 2011). While nutrition is a key part of health literacy, other studies examined nutrition knowledge and its relationship with diet quality (Spronk et al., 2014). With the comprehensive literature review, Spronk et al. found the association between nutrition knowledge and dietary intake most often a higher intake of fruit and vegetables. However, they noted the heterogeneity in assessing nutrition knowledge and dietary quality (Spronk et al., 2014). Additionally, food shopping practice has been associated with dietary quality of low income women (Hersey et al., 2001). Worrying about money for food is negatively associated with eating competence (Lohse, et al., 2012). Therefore, nutrition education for low-income individuals often includes food shopping and food resource management in order to enhance the nutrition quality.

A substantial number of low-income families already engage in various thrifty food shopping practices (Dachner, Ricciuto, Kirpatrick, & Tarasuk, 2010; Hersey, et al., 2001). However, despite the efforts to maximize food dollars, many households could not afford to purchase enough healthy diet (Dachner et al., 2010). Moreover, Kaiser et al. (2015) found that improvement in resource management skills was associated with reduced food insecurity only among participants who received SNAP benefits. They suggest that both SNAP participation and education on food resource management are needed to reduce food insecurity (Kaiser et al., 2015). The effects of consumer competency may vary by the resources, including SNAP, which low-income households may have access to. The results will provide policy implications with more complete knowledge of how "consumer competency" serves as tools for low-income households in dealing with food insecurity and diet quality.

Utilizing the data from the newly available USDA's National Household Food Acquisition and Purchase Survey (FoodAPS), this study examines the roles of SNAP and consumer competency such as financial management, nutrition literacy, and conscientious food shopping in household food insecurity and nutritional quality of acquired foods.

SNAP

Estimating the impacts of SNAP in addressing food insecurity has been challenged with endogeneity or selection bias (Gundersen et al., 2011; Li, Mills, Davis, & Mykerezi, 2014; Shafer & Gutierrez, 2013). With attempts to address this issue, However, unobserved differences between food insecure and food secure households have been noted. Further the impact of SNAP on nutrition quality has been more complicated. Low-income families are faced with overwhelming challenge feeding the family at low cost. Low-cost energy dense foods are often one strategy to choose and prepare food family to ensure no one in family goes hungry (Basiotis, Kramer-LeBlan, & Kennedy, 1998; Drewnowski, 2004). Evidence of how SNAP affects diet quality has been mixed.

Estimated effects range from modest improvement in healthy food consumption to contributing to unhealthy diet and obesity (Bitler, 2014; DeBono, Ross, Berrang-Ford, 2012; Gregory, Ver Ploeg, Andrews, & Coleman-Jensen, 2012; Whitmore, 2002; Zagorsky & Smith, 2009). Overall, research on the nutrition effects of SNAP has been challenged with selection bias.

Other Factors

Food insecurity is a public concern due to adverse health outcomes. Food insecurity has been associated with race/ethnicity, marital status, education, age, home ownership, presence of children, income, asset ownership, and others (Gundersen, Kreider & Pepper, 2011). Individuals' health and diet conditions have bidirectional relationship with food insecurity. Furthermore, food access and food environment has been considered as a causal factor of behaviors related to nutrition and health (McKinnon et al., 2009). Participation in other assistance programs such as WIC or National School Lunch Program was also found to ameliorate food insecurity.

Methods

To assess whether low-income households in high food price areas are more likely to display competent consumption behaviors, dichotomous variables of behaviors representing consumer competency are regressed over the local-level food price, along with various household characteristics as controls. That is,

$$\boldsymbol{C}^*_{\boldsymbol{ij}} = \alpha_1 Price_{jt} + \alpha_2 SNAP_{ij} + \boldsymbol{X_{ij}}'\boldsymbol{\alpha_3} + \boldsymbol{\gamma_t}$$

where $\boldsymbol{C}^*$ is the latent values of consumer competency, *Price* is the local average cost of a standard food basket in US dollars, SNAP is a dichotomous variable for the household's SNAP participation, $\boldsymbol{X}$ is a vector of household characteristics, and *i*, *j*, and *t* index households, geographic location, and time, respectively. Because price varies across the year and was measured for the given time period during which each household's food acquisition was recorded, time-specific fixed effect term is included. The regression coefficients $\alpha_{1...3}$ are estimated in Logit models. If high food price makes households use more competent consumption behaviors, α_1 will be positive. We also estimate this with state policy and administrative indicators as instrumental variables for *SNAP* to assess the causal effect of SNAP participation on consumer competency.

To see if SNAP participants and nonparticipants respond differently to high cost of food, the above equation is modified to include an interaction term:

$$\boldsymbol{C}_{\boldsymbol{ij}}^{*} = \alpha_1 Price_{jt} + \alpha_2 SNAP_{ij} + \alpha_3 SNAP_{ij} * Price_j + \boldsymbol{X}_{\boldsymbol{ij}}{}' \boldsymbol{\alpha}_{\boldsymbol{4}} + \boldsymbol{\gamma}_{\boldsymbol{t}}.$$

The coefficient α_3 is expected be negative if SNAP participants are less likely than nonparticipants to respond to high cost of food.

Our main research objectives include whether consumer competency alleviates the adverse effect of high food cost on nutritional outcomes, namely food security and nutritional quality of acquired food. We first estimate the relationship between food cost and the outcome measures:

$$\boldsymbol{Y}_{\boldsymbol{ij}}^{*} = \beta_1 Price_{jt} + \boldsymbol{C}_{\boldsymbol{ij}}' \boldsymbol{\beta}_{\boldsymbol{2}} + \beta_3 SNAP_{ij} + \boldsymbol{X}_{\boldsymbol{ij}}' \boldsymbol{\beta}_{\boldsymbol{4}} + \boldsymbol{\gamma}_{\boldsymbol{t}}$$

For the food insecurity equation, $\boldsymbol{Y}^{*}$ denotes the latent variable of food insecurity, so that $Y=1$ if $Y^{*}>0$, and $Y=0$ otherwise; and the coefficients are estimated with Logit models. For the outcome of nutritional quality, this equation is estimated in linear regressions. The coefficient $\boldsymbol{\beta}_{\boldsymbol{2}}$ denotes the association between consumer competency and the outcome measures. We estimate this regression model with and without the consumer competency term, so that the change in the coefficient β_1 would assess the mediating role of competency.

Data

The study uses data from the USDA's National Household Food Acquisition and Purchase Survey (FoodAPS). The FoodAPS is a survey of a nationally representative sample of households on their food acquisition. The data contain detailed records of the participating households' food acquisition activities during the seven-day reporting period including groceries as well as foods eaten outside the home by household members. The data also include in-depth interviews of households' main food shoppers or meal planners about on usual food acquisition behavior, places of food acquisition, expenditures, food security status, nutrition knowledge, program participation, and socio-demographic information. Based on the seven-day food acquisition record, the amount and types of foods and nutrients acquired were also computed. Among household main data files, we use the household file, individual file, food-at-home event file, and food-at-home nutrient file. The FoodAPS files store some of this information at levels as specific as food acquisition event or individual food item, which we summarize at the household level before merging. We also extract food price and other relevant food environmental information from the FoodAPS's Geography Component data files. These geographic files are merged to household main data using the household geocodes data file.

Of 4,826 participating households, we excluded 581 households that did not report any grocery shopping during the seven-day reporting period or reported buying only one food item of zero calorie. Additional 122 households had missing values in key variables and 216 households had no price data, and had to be dropped. The sample was further reduced to those with incomes below 185% of the federal poverty level (FPL). After dropping these observations, a total of 1,908 households comprised our final sample for analysis. Sampling weights were applied to represent the given population.

Variables

Food Insecurity

The food insecurity status was determined by the interview data using the 30-day adult food security module developed by the USDA's Economic Research Service. Following the USDA definition, households were classified into four categories: food security, marginal food security, low food security, and very low food security based on the number of affirmative responses. This study defines the dichotomous variable of food insecurity as belonging to either low or very low food security. We also use the dichotomous variable of very low food security as an additional outcome measure. The FoodAPS did not measure child food insecurity, but given not all households have children, adult food insecurity may be a fair and comparable measure for the entire sample.

Nutritional Quality of Acquired Foods

We construct a series of nutritional quality measures at the household level by aggregating food component and nutrient information of all food items acquired by the household during the seven-day reporting period. The quality of acquired food used as a proxy for diet quality is justified by the literature that found *home availability* is among the strongest correlates of food intake (Neumark-Stzainer et al, 2003; Story et al, 2008). However, compared to food-intake diaries, food acquisition records may have three or more limitations in representing one's diet quality. First, acquisition is at the household-level, thus individual-level food consumption is unknown. Despite our control for household size and composition, intra-household distribution of foods and nutrients remains unknown. Second, it is uncertain to the researchers over what period the acquired food was consumed (e.g., a box of dry pasta might be consumed over several months in one household and in one night in another household). Without knowing each household's frequency of food acquisition, we attempt to maximize accuracy by controlling for household size, usual dine-out frequency, and presence of recent meal guests. We also believe that the items that are consumed over a longer period are purchased less frequently, and therefore averages may still be accurate. Third, the portion of the acquired foods that gets consumed or if the food is consumed at all is also unknown (e.g., a half bag of fresh vegetable might be thrown away uneaten). Lack of information for food waste introduces a potential bias because food acquisition data will likely overstate consumption of perishable fresh foods more than consumption of nonperishable processed foods. One shortcoming of this study is we only analyze foods to be consumed at home because food-away-from-home nutrient data are unavailable at this point.

SNAP

Participation in SNAP is coded as 1 if anyone in the household currently receives SNAP benefits, and 0 otherwise. In the FoodAPS, this variable was created based on survey responses and confirmed by the system match to the SNAP administrative database.

Consumer Competency

This study investigates three competency areas pertinent to food purchase, including financial competency, nutrition literacy, and conscientious buying.

Three variables of financial competency were created. First, *Financial Management* is a continuous variable, which is a mean of responses to four questions: “how often household reviews bills for accuracy”, “how often household pays bills on time”, “how often household pays more than minimum payment”, and household’s reported financial condition. Each of these was recorded on a 5-point scale, with greater values meaning better management. Second, *No Default* is a dichotomous variable indicating the respondent disagreed to all three statements: “could not pay rent/mortgage, utility, or important medical bill within last 6 months”, “evicted for not paying rent/mortgage within last 6 months”, and “could not pay full amount of utility bills within last 6 months”. If the household experienced any of these within the last 6 months of the survey, the variable was coded 0. Third, *No Loan* variable is a dichotomous measure indicating the household has not taken any credit card cash advance or payday-like loans within last 6 months. Defaulting payments or taking out short-term loans can signify unsound financial practices, or it can simply be a reflection of hardship. Therefore, we also estimate models with the financial management variable only, without these two variables.

Several survey questions were combined to create three dichotomous variables indicating nutrition literacy. They are: respondent has heard of dietary guidelines, such as MyPlate or MyPyramid (*Know Guideline*); respondent attempts to follow MyPlate or MyPyramid recommendations (*Follow Guideline*); and respondent uses the nutrition facts panel on food product packaging most of the time or always (*Use Panel*).

In addition to financial literacy and nutrition literacy, conscientious or frugal buying behavior can imply competency in consumption. In this study we use three indicators: whether they shop with a grocery list at least most of the time (*Grocery List*), whether they used any coupons (*Coupons*), and whether they used any other types of store savings (*Store Savings*). Whereas *Grocery List* was based on a questionnaire item about usual behavior, the variables *Coupons* and *Store Savings* were based on actual use reported or observed in the food acquisition events during the seven-day reporting period.

Food Cost

Local cost of aggregate food categories comprising Thrifty Food Plan (TFP) was obtained from the geographic component (FoodAPS-GC) and matched to household level data based on location of the household and the timing (week) of the survey. Cost of food was measured at two different geographic levels – (i) average market basket price of participating retailers in the given county, and (ii) average market basket price of participating retailers that are within 20 miles of the Census block group centroid. Also, the cost was assessed as average of the *median* basket price at each of the stores, and an average of the *low-cost* basket price.

Results

Descriptive Statistics

The descriptive statistics from table 1 indicate that a significantly higher portion of respondents who reported being food insecure (49%) and very food insecure (22%) were SNAP participants as compared to those who were food insecure (28%) and very food insecure (13%) but did not participate in SNAP. A significantly higher percentage of respondents who consumed 'solid fats, alcohol, and added sugar' (SoFAAS) also reported being SNAP (40%) when compared to those who did not participate in SNAP (36%). Additionally, a higher percentage of individuals who reported good financial management practices were SNAP participants. Among those respondents who shopped with a grocery list 49% were not SNAP participants while 39% were SNAP participants.

The additional summary statistics are shown in table 2. The SNAP participants on average are younger in age (46) than the non-SNAP participants (54). Among all participants under 185% of FPL, a higher percentage among the Black (26%) and Hispanic (23%) respondents were SNAP participants as compared to the Black (14%) and Hispanic (19%) respondents who were not SNAP participants. Among respondents with educational attainment of high school or lower a higher percentage were SNAP participants, while for respondents with educational attainment of higher than high school a higher percentage were non-SNAP participants. Similarly, higher percentages among respondents who were single or never married, or were divorced were SNAP participants, whereas a higher percentage among respondents who were either married or widowed was non-SNAP participants. Among respondents with a child in school 40% were SNAP participants, whereas 25% were non-SNAP participants. A higher percentage of homeowners and vehicle owners were non-SNAP participants, while a lower percentage of homeowners and vehicle owners were SNAP participants. Among those who reported poor health approximately 50% were SNAP participants while 31% were non-SNAP participants.

Financial Management Practices: Implications for Food Price

Table 3A shows the results of the logistic regression analysis with the different financial management variables assigned as the dependent variables. The results indicate that county average median basket price and block group average median basket price were negatively associated with the likelihood of paying bills on time after controlling for the household characteristics, food environment, and the weekly fixed effects. Similarly block group average median basket price was also positively associated with the participants' likelihood of making more than minimum payments on revolving debt both before and after controlling for the household characteristics, food environment, and the weekly fixed effects.

Conscientious Buying and Nutrition Literacy: Implications of Food Price

Table 3B shows the results of the logistic regression analysis with the different conscientious shopping practices assigned as dependent variables. The results indicate that county average median and low cost basket price variables, and the block group average median and block group average low cost basket variables were negatively associated with shopping using a grocery list both before and after controlling for the household characteristics, food environment, and the weekly fixed effects. Similarly, the county average median and low cost basket prices were negatively associated with the participants' use of coupons when shopping for food when the household characteristics, food environment, and the weekly fixed effects were included in the model. Interestingly, the county average median and low cost basket price variables, and the block group average median and block group average low cost basket variables were positively associated with consumers' using loyalty or other stores savings cards both before and after controlling for the household characteristics, food environment, and the weekly fixed effects. Conversely, the county average median basket price was negatively associated with the use of nutrition facts labels by the respondents.

Financial Management Practices: Implications of Food Price and SNAP

Table 4A shows the results of the logistic regression analyses for the various financial management practices after controlling for the SNAP participation. The model also controls for the county and block level average median and low cost basket variables, the household characteristics, food environment, and the weekly fixed effects. The results indicate that when the model includes SNAP participation and the county level average median variable and the interaction of the two, SNAP participation is negatively associated with being in good financial condition, but the significance of this variable goes away once the household characteristics, food environment, and the weekly fixed effects are included in the model. Similarly, the county average median basket and SNAP participation was negatively associated with reviewing the bill once a purchase has been done. The SNAP variable, however, was not significant once the household characteristics, food environment, and the weekly fixed effects were included in the model. Similarly, SNAP participation was also negatively associated with the other desirable financial management practices such as paying bills on time, paying more than the minimum requirement on revolving credit, and non-participation in payday loans. The block group average median basket was negatively associated with being in good financial condition, reviewing bills, paying bills on time, and not participating in payday loans. However, these differences went away once the household characteristics, food environment, and the weekly fixed effects were included in the model. The interaction of SNAP participation and block group average median price was positively associated with reviewing bills and non-participation in the payday loan markets.

Conscientious Buying and Nutrition Literacy: Implications of Food Price and SNAP

Tables 4B shows the results of the logistic regression analyses for the various conscientious buying practices and SNAP participation. The model also controls for the county and block level average median and low cost basket variables, the household characteristics, food environment, and the weekly fixed effects. The results indicate that when the model includes SNAP participation and the county level average median basket price variable and the interaction of the two, SNAP participation is negatively associated in shopping with a grocery list, the county level average median basket price is also significant and negatively associated with shopping with a grocery list. However, the interaction term of SNAP participation and county average median basket price was positively associated with having a grocery list when shopping even after controlling for the household characteristics, food environment, and weekly fixed effects in the model, and for following guideline when the household characteristics, food environment, and weekly fixed effects were not included in the model. Similarly, the county average median basket was negatively associated with using coupons, but positively associated with loyalty programs or store savings when the household characteristics, food environment, and weekly fixed effects were not included in the model.

Similarly, in the logistic regression models un with county average low-cost basket, SNAP, and the interaction term of these two variables, the results indicate that the county average low-cost basket variable was negatively associated with having a grocery list when shopping across both the models that separately controlled for the weekly trend, and household characteristics, food environment, and weekly fixed effects. The use of loyalty or other store savings was negatively associated with the county average low-cost basket variable only when the household characteristics, food environment, and weekly fixed effects variables were included in the model. Conversely, the county average low-cost basket variable was positively associated with the use of loyalty or store savings, and guideline knowledge. SNAP participation was also negatively associated with having a grocery list when shopping, but positively associated with the use of loyalty or other store savings, and guideline knowledge. However, the interaction term of these two variables was positively associated with having a grocery list when shopping, and negatively associated with knowledge of nutrition guidelines. The interaction variable of SNAP participation and country average low cost basket was also negatively associated with use of loyalty or other savings when household characteristics, food environment, and weekly fixed effects were not included in the model.

The logistic regression models run with Block group level average median basket, SNAP participation, and the interaction of these two variables show that Block group average median basket price and SNAP participation were negatively associated with having a grocery list when shopping, but positively associated with the use of loyalty or other store savings. The SNAP participation variable was also negatively associated with the use of nutrition fact labels when shopping when household characteristics, food environment, and weekly fixed effects were not included in the model. The interaction term of SNAP participation and Block group median average basket was positively associated with having a grocery list when shopping, and negatively associated with the use of loyalty discounts or other store savings.

Correspondingly, the logistic regression models that included Block group level low-cost basket, SNAP participation, and the interaction of these two variables show that Block group average low-cost basket was negatively associated with having a grocery list when shopping in the model when shopping when household characteristics, food environment, and weekly fixed effects were not included in the model. But it was positively associated with the use of loyalty or other store savings. The SNAP participation variable was also positively associated with the use of loyalty discounts or other stores savings, and the knowledge of nutrition guideline. The interaction term of SNAP participation and Block group low-cost basket average was negatively associated with the use of loyalty discounts or other store savings and knowledge of the guideline.

Food Insecurity: Implications of Food Price and Consumer Competency

The logistic regression results examining the association for the county and block level food basket prices, and consumer competency related factors on food insecurity after controlling for the household level characteristics, food environment, and weekly fixed effects is shown in table 5. The results indicate that participants who perceived being in good financial condition were less likely to be food insecure. Similarly, paying bills on time, making more than minimum payments on revolving debt, and not defaulting on loans were negatively associated with food insecurity after controlling for factors related to household characteristics, food environment, and the weekly fixed effects.

Nutrition Quality of Acquired food: Implications of Food Price and Consumer Competency

The linear regression results for the association between nutrition quality factors such as energy density, fruit density, whole fruit density, and whole grain density are shown in table 6A. The independent variables include county average median basket and the consumer competency variables. The model also controls for household characteristics, food environment, and the weekly fixed effects. The results indicate that perception of being in good financial condition was positively associated with consumption of foods that have high energy density and whole grain density. County average median basket price was negatively associated with the intake of foods with whole grain density. Use of loyalty discounts or other store savings and the use of nutrition facts labels were also positively associated with the intake of food with higher whole grain density.

The linear regression results for the nutrition quality variables: vegetable density, sodium density, and SoFAAS density are shown in table 6B. The results indicate that respondents who did not participate in cash advance or payday loans were positively associated with the consumption of food with greater vegetable density. Conversely, the use of loyalty or store savings discounts was negatively associated with the consumption of meals high in vegetable density. County average median price basket and paying more than minimum on revolving debt, and use of nutrition labels when shopping were negatively associated with the amount of sodium density consumed in meals. The perception of being in good financial condition and not defaulting on debt were negatively associated with the consumption of the percentage of SoFAAS consumed in meals.

Discussion

Our findings show that high food cost is negatively associated with certain behaviors indicating consumer competency in low-income households. Households living in the areas with higher local food cost, regardless of the four different methods chosen to define high cost, were less likely to engage in review bills regularly, pay bills on time, use grocery list, use coupons, or use nutrition facts labels. However, high food cost in the area was strongly correlated with households' increased use of loyalty programs or other store savings.

While we suspect the disturbing negative associations largely reflect endogeneity or reverse causality, we find that these negative associations between food cost and consumer competency were not as pronounced among SNAP participants compared to nonparticipants. For example, SNAP participants in high cost areas were more likely than nonparticipants or participants in low cost areas to review bills regularly, avoid high-interest financial services such as cash advance or payday loans, shop with a grocery list, and follow dietary guidelines when faced with higher food cost. It is also noteworthy that, controlling for local food cost, SNAP participants were more likely to use loyalty programs or other store savings, and more likely to be aware of the dietary guidelines than nonparticipants.

Controlling for consumer competency, other household characteristics, and food environment of the community, we find little evidence that food cost affects the risk of food insecurity. Controlling for various household and community characteristics, households that engage in better financial management practices were less likely to be food insecure. Again, we are not sure how much of it is due to causal effects and how much is due to endogeneity. Households' use of other competent behaviors such as nutrition literacy or thrifty food shopping was not significantly associated with the risk of food insecurity.

Controlling for consumer competency, household characteristics, and food environment of the community, local food cost lowers the whole-grain content of the acquired foods, but it also significantly lowers sodium density of acquired foods.

Certain consumer competency items were associated with higher nutritional quality of acquired foods. Avoiding cash advance or payday loans was associated with greater vegetable density, paying bills more than the required minimum was associated with lower sodium and empty calorie densities. Use of loyalty or other store savings was positively associated with whole grain density, but negatively associated with buying vegetables. Those who frequently use nutrition facts labels acquired foods with greater whole grain contents, and foods with less with sodium or empty calorie.

Conclusion

Our findings indicate that the relationship between food price and nutritional outcomes can be complex. Although at least theoretically households could benefit from various consumer competencies and skills especially when the food cost is high, taking advantage of competent consumption strategies may be out of reach for many low-income consumers dealing with high food cost. One thrifty shopping strategy we find low-income consumers diligently use in coping with high cost of food is participation in loyalty programs or other store savings. Low-income households in higher-cost areas, SNAP participants and nonparticipants alike, are more likely to adopt loyalty or other store savings programs than those in areas where food cost is relatively lower.

Our findings also suggest different areas of consumer competency have different roles in relation to food security and nutritional quality of acquired foods. Financial management was found to be associated with low food insecurity but its correlation with nutritional quality is weak and mixed. On the other hand, nutrition literacy was significantly associated with positive nutritional quality of acquired foods but not with food insecurity. For low-income households, purchasing enough food to avoid hunger and acquiring nutritious foods may be competing needs, especially when healthful foods cost more than unhealthy ones. We find that, although conscientious shopping strategies were actively used among low-income households to stretch food dollars to purchase enough food for the family, they did not necessarily translate into improved nutritional quality of acquired foods, and sometimes rather decreased nutritional quality. This may indicate that those who are more strained for resources may be more likely to utilize conscientious shopping strategies than others. Their priorities may be to avoid their family from going hungry, meaning purchasing low-cost, energy-dense food.

Our current study has several limitations. First, the local food cost is likely to be correlated with cost of living in general, which our model did not consider. Second, food away from home was not included in our measures of nutritional quality of acquired foods. Third, the relationships between food price, consumer competency, and nutrition outcomes we measure are based on correlations and cannot be interpreted as cause-and-effect.

Policy focus on consumer competency programs in SNAP might help achieving program goals at the margin but the effect may be modest due to the economic strain challenging many consumption categories for low-income households. Our findings suggest policies that incentivize competent or conscientious consumption among program participants might decrease food insecurity but likely at the expense of lowered nutritional quality, as long as less healthy food choices are also less expensive.

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Table 1

Summary Statistics: Key Variables

	All <185% (N=1,923)	SNAP (N=1,011)	Non-SNAP (N=912)	t
Food Insecurity[A]	.360 (.481)	.491 (.500)	.279 (.449)	7.04***
Very Low Food Security[A]	.166 (.372)	.224 (.417)	.131 (.337)	4.27***
Fruit density	.346 (.744)	.317 (.769)	.364 (.729)	-1.00
Whole fruit density	.285 (.728)	.256 (.751)	.303 (.713)	-0.96
Whole grain density	.424 (.932)	.357 (.642)	.465 (1.070)	-1.36
Vegetable density	.574 (1.581)	.494 (1.446)	.623 (1.657)	-1.10
Energy density	1.414 (.821)	1.336 (.764)	1.461 (.852)	-1.87†
Sodium density	1840 (6945)	1815 (7625)	1856 (6497)	-0.12
SoFAAS percent	37.5 (21.9)	40.4 (21.9)	35.8 (21.8)	3.60***
Financial Management				
In good financial condition[A]	.320 (.466)	.186 (.390)	.403 (.491)	−7.50***
Review bills usually[A]	.685 (.464)	.641 (.480)	.713 (.453)	−2.91**
Pay bills on time usually[A]	.803 (.398)	.687 (.464)	.874 (.332)	−8.45***
Pay more than minimum usually[A]	.265 (.441)	.127 (.333)	.350 (.477)	−5.71***
No financial delinquency[A]	.693 (.461)	.543 (.498)	.786 (.411)	−9.32***
No cash advance or payday loan[A]	.921 (.269)	.899 (.302)	.936 (.246)	−2.19*
Conscientious Consumption				
Shop with grocery list usually[A]	.451 (.498)	.387 (.487)	.490 (.500)	−2.48*
Use coupons[A]	.225 (.418)	.216 (.412)	.230 (.421)	−0.58
Use loyalty or other store savings[A]	.552 (.497)	.566 (.496)	.543 (.498)	0.71
Nutrition Literacy				
Guideline knowledge[A]	.551 (.498)	.581 (.494)	.532 (.499)	1.06
Follow guideline[A]	.212 (.409)	.243 (.429)	.192 (.394)	1.37
Use nutrition facts labels usually[A]	.323 (.468)	.301 (.459)	.337 (.473)	−1.33
Basket Price				
County average median basket price	281.2 (39.0)	278.4 (36.5)	282.9 (40.4)	−1.54
County average low-cost basket price	149.0 (20.4)	147.7 (18.7)	149.8 (21.4)	−1.17
Block group average median basket price	280.3 (44.9)	280.4 (44.5)	280.3 (45.2)	0.06
Block group average low-cost basket price	148.4 (21.5)	148.4 (22.2)	148.4 (21.0)	0.02

Notes: Means and standard deviations adjusted for survey weights. [A] dichotomous variables. † p<.10, * p<.05, ** p<.01, *** p<.001

Table 2

Summary Statistics: Demographic, Program Participation, Dietary Needs, and Environmental Variables

	All <185% (N=1,923)	SNAP (N=1,011)	Non-SNAP (N=912)
Age	51.2 (17.8)	46.3 (15.8)	54.2 (18.3)
Gender [A]	.443 (.497)	.476 (.500)	.423 (.494)
Race: White[A]	.693 (.461)	.605 (.489)	.748 (.434)
Race: Black[A]	.186 (.389)	.256 (.437)	.143 (.351)
Race: Asian[A]	--- (---)	--- (---)	--- (---)
Race: Other[A]	.100 (.300)	.132 (.338)	.081 (.273)
Hispanic[A]	.204 (.403)	.232 (.422)	.186 (.390)
Education: Less than HS[A]	.227 (.419)	.293 (.455)	.186 (.389)
Education: High school[A]	.353 (.478)	.358 (.480)	.349 (.477)
Education: Some college[A]	.202 (.402)	.189 (.391)	.211 (.408)
Education: Bachelors[A]	.083 (.276)	.061 (.239)	.097 (.296)
Education: Postgraduate[A]	--- (---)	--- (---)	--- (---)
Marital: Married[A]	.280 (.449)	.208 (.406)	.324 (.468)
Marital: Widowed[A]	.137 (.344)	.094 (.292)	.164 (.370)
Marital: Divorced or separated[A]	.315 (.464)	.341 (.474)	.298 (.459)
Marital: Never married[A]	.269 (.443)	.357 (.479)	.214 (.411)
Child in school[A]	.305 (.461)	.402 (.490)	.246 (.431)
Household size	2.5 (1.8)	2.8 (1.9)	2.3 (1.8)
Employed[A]	.384 (.486)	.347 (.476)	.406 (.491)
Income ($/m)	1552.3 (985.9)	1310.0 (975.1)	1701.5 (963.0)
Home tenure	12.4 (14.5)	9.5 (12.7)	14.2 (15.2)
Home ownership[A]	.417 (.493)	.271 (.444)	.507 (.500)
Vehicle ownership[A]	.746 (.435)	.649 (.478)	.806 (.396)
WIC[A]	.082 (.275)	.141 (.348)	.046 (.210)
NSLP/NSBP[A]	.248 (.432)	.361 (.481)	.178 (.382)
Special dietary needs[A]	.531 (.499)	.558 (.497)	.514 (.500)
Poor health[A]	.382 (.486)	.498 (.500)	.310 (.463)
#Dinners out per week[A]	1.2 (1.3)	1.1 (1.2)	1.2 (1.3)
Urban tract[A]	.682 (.466)	.720 (.449)	.659 (.474)
Miles to nearest supermarket from BG center	2.5 (3.5)	2.2 (3.3)	2.6 (3.7)
Low access tract (1 mile for urban, 20 miles for rural) [A]	.259 (.438)	.261 (.440)	.257 (.437)
Food exempt from state sales tax[A]	.929 (.256)	.956 (.204)	.913 (.282)
State food tax rate (%)	.476 (1.328)	.333 (1.085)	.564 (1.451)

Notes: Means and standard deviations adjusted for survey weights. [A] dichotomous variables.

Table 3A

Logit Regressions of Financial Management Practices: Implications of Food Price (N=1,923)

	In good financial condition		Review bills		Pay bills on time		Pay more than minimum		No defaulting		No cash advance or payday loan	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
County average median basket price	-.0011 (.0032)	-.0037 (.0031)	-.0023 (.0014)	-.0003 (.0015)	-.0045 (.0033)	-.0081* (.0038)	.0042 (.0027)	.0028 (.0023)	-.0020 (.0027)	-.0028 (.0031)	-.0033 (.0030)	-.0035 (.0034)
County average low-cost basket price	.0029 (.0035)	.0010 (.0036)	-.0032 (.0024)	-.0013 (.0025)	.0012 (.0047)	-.0018 (.0065)	.0005 (.0054)	.0005 (.0032)	-.0003 (.0043)	-.0007 (.0054)	-.0046 (.0055)	-.0047 (.0063)
Block group average median basket price	-.0001 (.0017)	-.0010 (.0024)	-.0019 (.0016)	-.0005 (.0015)	-.0032 (.0024)	-.0042† (.0024)	.0057** (.0018)	.0054* (.0020)	.0010 (.0015)	.0011 (.0019)	-.0009 (.0024)	-.0011 (.0025)
Block group average low-cost basket price	.0005 (.0030)	.0007 (.0044)	-.0045 (.0035)	-.0022 (.0036)	-.0022 (.0046)	.0024 (.0054)	.0029 (.0042)	.0043 (.0034)	.0012 (.0030)	.0034 (.0034)	-.0029 (.0040)	-.0014 (.0044)
Weekly trend	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Household characteristics	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Food environment	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Weekly fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Weighted Logit regression coefficients and linearized standard errors. Each of the four price measures was estimated in separate regressions. † p<.10, * p<.05, ** p<.01, *** p<.001

Table 3B

Logit Regressions of Conscientious Buying and Nutrition Literacy: Implications of Food Price (N=1,923)

	Shop with grocery list		Use coupons		Use loyalty or other store savings		Guideline knowledge		Follow guideline		Use nutrition facts labels	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
County average median basket price	-.0041* (.0017)	-.0046* (.0017)	-.0015 (.0025)	-.0045† (.0024)	.0092*** (.0023)	.0110*** (.0019)	.0013 (.0020)	-.0015 (.0026)	-.0014 (.0020)	-.0018 (.0023)	-.0007 (.0022)	-.0037† (.0021)
County average low-cost basket price	-.0089** (.0029)	-.0117** (.0030)	-.0019 (.0032)	-.0062† (.0036)	0172** (.0053)	.0186** (.0055)	.0056 (.0038)	.0002 (.0039)	-.0014 (.0034)	-.0021 (.0046)	.0002 (.0038)	-.0024 (.0041)
Block group average median basket price	-.0038* (.0015)	-.0029† (.0014)	-.0001 (.0020)	-.0020 (.0023)	.0063*** (.0016)	.0078** (.0021)	.0013 (.0015)	-.0018 (.0013)	.0007 (.0017)	-.0005 (.0021)	.0002 (.0013)	-.0005 (.0016)
Block group average low-cost basket price	-.0084* (.0031)	-.0072** (.0023)	.0025 (.0035)	-.0017 (.0039)	.0125** (.0042)	.0140** (.0042)	.0043 (.0037)	-.0024 (.0028)	.0002 (.0035)	-.0022 (.0040)	.0010 (.0027)	.0002 (.0032)
Weekly trend	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Household characteristics	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Food environment	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Weekly fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Weighted Logit regression coefficients and linearized standard errors. Each of the four price measures was estimated in separate regressions. † p<.10, * p<.05, ** p<.01, *** p<.001

Table 4A

Logit Regressions of Financial Management Practices: Implications of Food Price and SNAP

	In good financial condition		Review bills		Pay bills on time		Pay more than minimum		No defaulting		No cash advance or payday loan	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
County average median basket	-.002	-.004	-.005**	-.004†	-.007	-.008	.003	.002	-.003	-.003	-.008	-.007
	(.003)	(.003)	(.002)	(.002)	(.005)	(.005)	(.003)	(.003)	(.003)	(.004)	(.005)	(.005)
SNAP*County median basket	.003	.003	.006	.005	.004	.001	.006	.005	.000	.001	.010	.009
	(.003)	(.003)	(.004)	(.004)	(.004)	(.004)	(.005)	(.004)	(.003)	(.004)	(.007)	(.007)
SNAP	-1.839†	-1.572	-1.907†	-1.322	-2.247*	-1.137	-3.261*	-2.286†	-1.236	-.944	-3.283†	-2.659
	(.977)	(.965)	(1.064)	(1.055)	(1.052)	(1.016)	(1.392)	(1.179)	(.862)	(1.093)	(1.871)	(1.878)
County average low-cost basket	.003	.003	-.005	-.003	-.002	-.001	-.003	-.001	-.002	-.001	-.005	-.003
	(.005)	(.005)	(.004)	(.004)	(.006)	(.008)	(.006)	(.004)	(.006)	(.007)	(.009)	(.010)
SNAP*County low cost basket	-.007	-.007	.004	.003	.003	-.001	.008	.006	.002	.001	-.001	-.001
	(.006)	(.008)	(.005)	(.006)	(.006)	(.005)	(.010)	(.010)	(.006)	(.005)	(.010)	(.011)
SNAP	-.155	.383	-.923	-.337	-1.661†	-.679	-2.627†	-1.849	-1.420	-.887	-.463	-.014
	(.934)	(1.075)	(.740)	(.913)	(.856)	(.780)	(1.505)	(1.469)	(.906)	(.827)	(1.523)	(1.665)
Block group average median basket	-.003*	-.003	-.005**	-.003	-.006†	-.005	.002	.003	-.003	-.002	-.009*	-.006
	(.002)	(.002)	(.002)	(.002)	(.003)	(.003)	(.002)	(.002)	(.002)	(.002)	(.004)	(.004)
SNAP*Block group median	.002	.002	.006*	.005†	.001	-.001	-.000	-.001	.002	.004	.011*	.011†
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.004)	(.004)	(.003)	(.004)	(.005)	(.006)
SNAP	-1.611*	-1.251	-1.966*	-1.353†	-1.597†	-.535	-1.339	-.850	-1.825*	-1.715	-3.577*	-3.319†
	(.748)	(.823)	(.750)	(.709)	(.865)	(.818)	(1.205)	(1.134)	(.851)	(1.092)	(1.398)	(1.648)
Block group average low-cost basket	-.004	-.002	-.006	.001	-.006	-.000	-.002	.001	-.005	-.001	-.009	-.004
	(.005)	(.006)	(.004)	(.004)	(.006)	(.006)	(.006)	(.005)	(.004)	(.005)	(.008)	(.009)
SNAP*block group low cost basket	-.004	-.003	.005	.004	.000	-.005	-.002	-.000	.004	.005	.002	.001
	(.008)	(.008)	(.005)	(.006)	(.005)	(.006)	(.011)	(.010)	(.006)	(.006)	(.010)	(.012)
SNAP	-.575	-.325	-1.101	-.467	-1.232	-.076	-1.093	-1.001	-1.709*	-1.351	-.902	-.431
	(1.176)	(1.099)	(.803)	(.946)	(.837)	(.896)	(1.763)	(1.559)	(.834)	(1.109)	(1.491)	(1.766)

Notes: Weighted Logit regression coefficients and linearized standard errors. Each of the four price measures was estimated in separate regressions. † p<.10, * p<.05, ** p<.01, *** p<.001

Table 4B

Logit Regressions of Conscientious Buying and Nutrition Literacy: Implications of Food Price and SNAP

	Shop with grocery list		Use coupons		Use loyalty or other store savings		Guideline knowledge		Follow guideline		Use nutrition facts labels	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
County average median basket	-.009** (.003)	-.010*** (.002)	-.004 (.003)	-.007* (.003)	.011*** (.003)	.012 (.002)	.002 (.003)	-.000 (.003)	-.004 (.004)	-.004 (.003)	-.001 (.003)	-.004 (.003)
SNAP*County median basket	.012** (.004)	.013** (.004)	.005 (.005)	.006 (.005)	-.004 (.004)	-.004 (.003)	.001 (.005)	-.001 (.005)	.008† (.005)	.006 (.005)	.001 (.004)	-.000 (.004)
SNAP	-3.668** (1.114)	-3.753** (1.205)	-1.430 (1.608)	-1.639 (1.634)	1.351 (1.083)	1.647 (.985)	-.100 (1.378)	.480 (1.283)	-2.042 (1.261)	-1.503 (1.366)	-.372 (1.050)	-.050 (1.228)
County average low-cost basket	-.015*** (.004)	-.018*** (.004)	-.005 (.005)	-.010† (.005)	.021*** (.005)	.022*** (.006)	.012* (.005)	.008* (.004)	-.003 (.006)	-.003 (.007)	-.002 (.005)	-.003 (.005)
SNAP*County low cost basket	.016** (.005)	.019** (.006)	.009 (.008)	.009 (.009)	-.010* (.005)	-.009 (.006)	-.015** (.005)	-.018** (.005)	.009 (.010)	.007 (.012)	.001 (.007)	-.001 (.008)
SNAP	-2.826** (.823)	-2.986** (.923)	-1.409 (1.363)	-1.277 (1.462)	1.562* (.682)	1.772† (.890)	2.469** (.745)	2.916*** (.735)	-1.120 (1.537)	-.722 (1.774)	-.406 (1.072)	.091 (1.203)
Block group average median basket	-.006* (.002)	-.005* (.002)	-.001 (.002)	-.003 (.003)	.007** (.002)	.009*** (.002)	.003 (.003)	.001 (.002)	-.002 (.002)	-.003 (.003)	-.002 (.002)	-.002 (.002)
SNAP*Block group median	.006† (.003)	.006† (.003)	.000 (.004)	.002 (.004)	-.005† (.003)	-.006* (.003)	-.002 (.003)	-.004 (.003)	.006† (.003)	.006 (.004)	.005 (.003)	.004 (.003)
SNAP	-2.054* (.953)	-1.902* (.917)	-.221 (1.216)	-.549 (1.265)	1.475* (.724)	2.084** (.755)	.722 (.994)	1.352 (.910)	-1.462 (.949)	-1.394 (1.217)	-1.500† (.874)	-1.273 (.921)
Block group average low-cost basket	-.008† (.004)	-.005 (.003)	.001 (.004)	-.004 (.005)	.016*** (.005)	.020*** (.004)	.010 (.006)	.004 (.005)	-.003 (.006)	-.004 (.007)	-.006 (.005)	-.006 (.004)
SNAP*block group low cost basket	.002 (.005)	.003 (.005)	-.001 (.007)	.004 (.008)	-.012* (.005)	-.013* (.006)	-.015† (.008)	-.018* (.008)	.007 (.010)	.008 (.011)	.009 (.008)	.008 (.009)
SNAP	-.645 (.808)	-.661 (.762)	.072 (1.181)	-.518 (1.235)	1.812* (.790)	2.259** (.828)	2.352* (1.130)	2.798* (1.138)	-.743 (1.554)	-.942 (1.688)	-1.477 (1.211)	-1.307 (1.260)

Notes: Weighted Logit regression coefficients and linearized standard errors. Each of the four price measures was estimated in separate regressions. † p<.10, * p<.05, ** p<.01, *** p<.001

Table 5

Logit regressions of food insecurity: Implications of food price and consumer competency

	Food insecurity	Food insecurity	Food insecurity	Food insecurity
County average median basket	-.001 (.003)			
County average low-cost basket		.001 (.004)		
Block group average median basket			-.001 (.002)	
Block group average low-cost basket				.000 (.004)
In good financial condition	-1.844 (.286)***	-1.841 (.290)***	-1.850 (.284)***	-1.840 (.289)***
Review bills	.143 (.161)	.148 (.163)	.147 (.162)	.147 (.164)
Pay bills on time	-.686 (.201)*	-.673 (.205)**	-.686 (.203)**	-.672 (.204)**
Pay more than minimum	-.684 (.256)*	-.697 (.252)**	-.682 (.253)*	-.697 (.252)**
No defaulting	-1.001 (.201)***	-1.003 (.199)***	-.997 (.202)***	-1.003 (.201)***
No cash advance or payday loan	-.202 (.264)	-.195 (.262)	-.198 (.262)	-.196 (.262)
Shop with grocery list	-.064 (.192)	.068 (.190)	.063 (.190)	.067 (.190)
Use coupons	.055 (.195)	.074 (.191)	.059 (.191)	.072 (.191)
Use loyalty or other store savings	-.115 (.186)	-.142 (.181)	-.120 (.178)	-.139 (.179)
Guideline knowledge	-.309 (.188)	-.311 (.187)	-.309 (.189)	-.310 (.188)
Follow guideline	-.029 (.207)	-.036 (.210)	-.029 (.208)	-.35 (.210)
Use nutrition facts labels	-.120 (.219)	-.116 (.220)	-.115 (.219)	-.116 (.220)
Household characteristics	Yes	Yes	Yes	Yes
Food environment	Yes	Yes	Yes	Yes
Weekly fixed effect	Yes	Yes	Yes	Yes

Notes: Weighted Logit regression coefficients and linearized standard errors. * p<.05, ** p<.01, *** p<.001

Table 6A

Linear regressions of nutritional quality of acquired food: Implications of food price and consumer competency

	Fruit density	Whole fruit density	Whole grain density	Vegetable density
County average median basket	.001 (.001)	.000 (.001)	-.002 (.001)†	-.001 (.001)
In good financial condition	-.038 (.066)	-.056 (.066)	.146 (.075)†	-.213 (.140)
Review bills	-.048 (.065)	-.050 (.068)	.020 (.054)	-.028 (.097)
Pay bills on time	-.006 (.060)	-.006 (.058)	-.095 (.066)	-.026 (.137)
Pay more than minimum	-.000 (.046)	-.011 (.044)	-.089 (.093)	.080 (.123)
No defaulting	-.017 (.072)	.016 (.068)	-.063 (.072)	.104 (.115)
No cash advance or payday loan	.027 (.074)	.026 (.067)	-.134 (.0864)	.223 (.109)*
Shop with grocery list	.015 (.043)	-.007 (.044)	-.119 (.078)	.062 (.076)
Use coupons	-.068 (.059)	-.069 (.055)	-.090 (.084)	.117 (.133)
Use loyalty or other store savings	-.084 (.060)	-.091 (.059)	.169 (.076)*	-.291 (.143)*
Guideline knowledge	.074 (.050)	.065 (.052)	-.014 (.066)	.127 (.088)
Follow guideline	.077 (.091)	.070 (.090)	.006 (.078)	.003 (.093)
Use nutrition facts labels	.052 (.057)	.052 (.059)	.183 (.085)*	-.011 (.138)
Household characteristics	Yes	Yes	Yes	Yes
Food environment	Yes	Yes	Yes	Yes
Weekly fixed effect	Yes	Yes	Yes	Yes

Notes: Weighted Logit regression coefficients and linearized standard errors. † p<.10, * p<.05, ** p<.01

Table 6B

Linear regressions of nutritional quality of acquired food: Implications of food price and consumer competency

	Energy density	Sodium density	SoFAAS percent
County average median basket	-.000 (.001)	-5.0 (2.1)*	.019 (.019)
In good financial condition	.228 (.069)**	-567.8 (418.9)	-3.654 (1.610)*
Review bills	-.036 (.061)	-232.6 (378.9)	2.079 (1.514)
Pay bills on time	-.081 (.058)	329.7 (210.2)	.542 (1.648)
Pay more than minimum	-.044 (.064)	-485.8 (221.7)*	-3.823 (1.808)*
No defaulting	-.089 (.075)	589.4 (397.4)	1.618 (1.989)
No cash advance or payday loan	.141 (.094)	-392.9 (455.4)	-.767 (2.247)
Shop with grocery list	.040 (.061)	-455.8 (303.5)	1.706 (1.710)
Use coupons	-.011 (.070)	-489.0 (355.3)	2.581 (1.456)†
Use loyalty or other store savings	.051 (.045)	271.2 (376.0)	.245 (1.482)
Guideline knowledge	-.002 (.047)	-240.7 (379.7)	-1.234 (1.692)
Follow guideline	-.044 (.061)	738.1 (674.7)	.576 (1.751)
Use nutrition facts labels	-.059 (.055)	-664.5 (366.2)†	-2.570 (1.509)†
Household characteristics	Yes	Yes	Yes
Food environment	Yes	Yes	Yes
Weekly fixed effect	Yes	Yes	Yes

Notes: Weighted Logit regression coefficients and linearized standard errors. † p<.10, * p<.05

Do SNAP Recipients Get the Best Prices?

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Abstract

This paper examines the relationship between SNAP participation and prices paid for food items. To test this relationship, we develop an expensiveness index following the method of Aguiar and Hurst (2007) and use the FoodAPS data set. Using both the ordinary least squares method and controlling for endogeneity using an instrumental variables approach, we found SNAP participation did not hold a statistically significant relationship with the prices paid for food items when we controlled for consumer behavior and food market variables. This suggests that SNAP participants are not systematically disadvantaged in their food purchases. Additional efforts to further educate SNAP participants of effective shopping and budgeting habits may be fruitful in helping households pay comparatively lower food prices.

Executive summary

The main focus of the research was to estimate the effect of SNAP participation on the prices paid for food products. The key consideration is whether SNAP participants were disadvantaged systematically in the cost of food purchases in the US food system. Efficiency in the provision of SNAP benefits to recipients is the considerations here as even a small difference would be important in enhancing food security for the US population. The recent USDA innovation in developing the FoodAPS data set provides a unique opportunity to evaluate this question directly as this data set more fully identifies often under-reported SNAP participation.

This research uses statistical analysis that showed that SNAP participants are not disadvantaged in their food purchases in the US food system. This statistical analysis controlled for the significant effects of market structure (e.g. number of competitors in the market), individual characteristics (e.g. education, age, number of children) and food shopping behavior (e.g. use of budgeting). Furthermore, the endogeneity of SNAP participation was controlled for using modern econometric techniques.

An interesting issue that was explored in the analysis was the role of food shopping behavior, and it was found that using budgeting resulted in paying less for food purchases. This is a traditional area where SNAP-Ed has focused efforts. The results show that budgeting enables less expensive food purchases and suggests that SNAP-Ed efforts in this area should be continued and perhaps expanded.

Our variables controlling for the local market for food items indicates both concentration of non-supermarket stores and closer proximity to SNAP authorized retailers were associated with comparatively lower prices paid for food items. Although smaller (non-supermarket) stores are typically associated comparatively higher prices than larger (supermarket) stores, it is possible higher competition for consumer patronage drives down prices. Both these findings demonstrate if the consumer is knowledgeable of potential bargains or saving opportunities in their local food market, they will be better able to attain comparatively lower food costs. This could also be further emphasized in SNAP-Ed efforts.

It is recommended for the future development of the FoodAPS data set that several critical areas are focused on. First, because many SNAP participants are disabled with associated special needs, a direct measure of disability in the data set would better help us understand their food behavior along with specific efforts to facilitate their food security. Second, while the data set does report on use of private food charities, this use is not full identified and is almost certainly underreported. Given the importance of private food charities and their interactions with SNAP benefits, more fully identifying food charity provision would be particularly useful in enhancing the joint effectiveness of private food charities and SNAP in food security. Third, direct questions about SNAP-Ed educational efforts can be put in the data set to determine the effectiveness of these education efforts in enhancing food security including addressing obesity reduction and other desired policy and health outcomes.

As the ability to effectively use SNAP to lower food costs is jointly related to the participating households' local food market and their specific consumer behaviors, it may be fruitful for researchers and policy makers to further examine these relationships specifically. It may be particularly fruitful to provide households participating in SNAP with additional information or educational materials on effective budgeting, financial planning, and shopping strategies for their local market environment. This would provide households with both the means and knowledge to pay comparatively lower food prices. The continued development and availability of FoodAPS data should be important in achieving these outcomes.

Introduction

One of the key challenges when purchasing food is the ability to consider relative prices in a particular food environment. Within a food environment, a consumer can act to make “smart decisions” and purchase relatively less expensive items with the goal of obtaining desired food outcomes in a thrifty manner. Lower income households arguably have the strongest incentives to purchase food in the thriftiest way possible because the tradeoffs of not optimizing on price and nutritional value are comparatively higher than the tradeoffs faced by higher income households (Ghez and Becker 1975).

The Supplemental Nutrition Assistance Program (SNAP) is the US government’s main effort towards improving food security of low income individuals in the United States. In 2015, the US government spent approximately $74 billion on SNAP with nearly 46 million participants (USDA 2016)[a]. An important question for the efficiency of this program is whether participants pay prices that are consistent with non-recipients. Small improvements in the efficiency of participant usage could have large effects upon the impact of the program. In fact, educational efforts have also been provided to SNAP participants to improve their food purchasing decisions (USDA 2016)[b].

The main focus of this study is the analysis of factors affecting food prices paid by low income households. Of special interest, is the question of whether low income households which participate in SNAP obtain lower food prices relative to nonparticipants. To answer our research questions, we make use of the FoodAPS data set. The FoodAPS dataset is the first nationally representative survey of US household’s food purchases including SNAP participants and non-participants. FoodAPS data contains information on prices paid for food items by 4046 families in conjunction with detailed information pertaining to household socio-demographic characteristics as well as information about the local food environment and competitive food market structure. Thus, the FoodAPS database provides a unique opportunity to consider the ability of low income households to achieve improved purchasing decisions, while controlling for the number and quality of food providers in their food market as well as individual capability. The proposed analysis is not achievable with existing data sets such as the National Health and Nutrition Survey (NHANES) or the Behavioral Risk Factor Surveillance System (BRFSS). Specifically, the NHANES and BRFSS do not contain information regarding local food market factors or variables measuring behaviors of consumers when making purchase decisions for food items.

Our analysis generates valuable information for policy makers and those involved in SNAP-Ed efforts because it specifically examines the prices SNAP participants paid when purchasing food items and provides a more thorough analysis than previously conducted by incorporating household sociodemographic and shopping behaviors, and market characteristics. By using the FoodAPS dataset, we are better able to determine the effectiveness of the SNAP program to provide lower income households with the ability and knowledge to obtain nutritional food at comparatively lower costs. We also provide a more robust analysis of the impact of food retailer market structure and socio-economic factors on food prices a household faces.

Literature review

Food prices faced by households are the result of economic, demographic, and geographic factors. Household characteristics including size, race, income, and educational level may contribute to the prices paid by for food items by affecting the quantity or type of food purchased. Similarly, the specific shopping behaviors and habits of the food purchasers in a household in conjunction with the food market they make purchases in can impact the ability to achieve lower food prices.

Although a few studies have evaluated the effect of store type and socio-demographic characteristics on food prices in the United States, they have been limited to specific geographic areas (Aguiar and Hurst 2007; Musgrove and Galindo 1988; Rao 2000), specific food products (Bekesi, Loy, and Weiss 2013), or have used a limited set of explanatory variables (Stewart and Dong 2011). In this section, we summarize the main findings from this literature.

Several studies have explored the relationship between household income and food prices. A common finding among of these studies is the inverse relationship between income and prices paid. Several explanations have been provided to explain this result. At the aggregate level, higher food prices for higher income consumers may be the result of food quality (Aguiar and Hurst 2007). For example, Kyureghian, Nayga, and Bhattacharya (2013) found that income had a significantly positive relationship with the purchase of fruits and vegetables and that these items are a relatively more expensive purchase then many sugary and starchy products. Lower income consumers purchase food items with higher energy density and higher fat content (Drewnowski and Specter 2004; Morland et al 2001).

Lower income households may also face higher food costs because they are unable to afford larger quantities of food which can be purchased at lower per unit costs. This is referred to in the literature as the "size effect" (Mendoza 2011). In a case study of 3 villages in India, Rao (2000) found families from lower income villages frequently paid higher unit costs for food items because lower income families did not take advantage of bulk discount opportunities. Kunreuther (1973) found similar evidence from households in the United States where households did not purchase bundles of food products at the lowest per unit costs because some households faced lower storage capacity and tighter budgets.

It is important to distinguish the knowledge of how to take advantage of bulk discounts from the inability to take advantage of bulk discounts due to income constraints. Beatty (2010) found that lower income households in the United Kingdom were able to pay comparatively lower costs on average by spending a larger share of income on food items with quantity discounts. Varying consumer knowledge of lower prices in conjunction with effective educational policy could explain these findings.

Alternatively, in some situations, higher income households may pay higher prices for food items because higher incomes imply higher tradeoffs for time spent searching for lower prices (Becker 1965). For example, Cronovich, Daneshvary, and Schwer (1997) found that households earning over $75,000 were less likely to use coupons. They also found that households that thought that their income was inadequate were more likely to use coupons (p. 1639)[1].

The composition of a household has also been shown to affect buying patterns which affect food prices paid. Bekesi, Loy, and Weiss (2013) found that households with children are less likely to form specific buying habits than single adult households with no children due to the frequently changing tastes of children. Cronovich, Daneshvary, and Schwer (1997) found that families with a child between 1 and 5 years old were less likely to utilize coupons when purchasing food; however, the authors found that as the number of adults per household increased, households were more likely to use coupons. As food purchases become a larger portion of household expenses, it becomes more important for households to minimize costs. The literature has also found households with older adults were more likely to base their purchasing decision on past choices (Bekesi, Loy and Weiss 2013), more likely to use coupons (Cronovich, Daneshvary, and Schwer 1997), and were willing to go shopping more frequently to obtain lower prices (Anguiar and Hurst 2007). Households with older adults have also been associated with stronger preferences for nutritious foods than single person households and comparatively younger households (Blanciforti, Green, and Lane 1981). Race has also been associated with variation in food prices paid by households.

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[1] Adequacy was determined by a households who were asked, “How adequate do you consider your income?” (Cronovich, Daneshvary, and Schwer 1997, p. 1663). Responses were recorded as values between 1 (very adequate) to 5 (inadequate).

Black and Hispanic households are significantly less likely to use coupons than other racial groups (Cronovich, Daneshvary, and Schwer 1997).

Geographical proximity to food providers, in many cases related to the racial makeup of neighborhoods, has also been shown to affect the food prices households pay. Cummings and Mcintyre (2005) found that predominantly African-American neighborhoods are more likely to be located further to food access than neighborhoods of other racial composition. Zenk et al. (2005) also found that supermarkets were an average of 1.15 miles farther away from predominantly black neighborhoods than predominantly white neighborhoods. According to Kunreuther (1973), "*They [referring to lower income families] are thus more likely to patronize the neighborhood store than to travel some distance to chain store*" (p. 373-374). This limited travel choice could result in higher food costs. Hoch et al. (1995) found, "*isolated stores display less price sensitivity than stores close to their competitors*" (p.28). This lack of access to chain stores may lead to more income allocation to food (Chung and Myers 1999; Moreland et al. 2001).

In addition to distance from chain stores, households which do not own a means of transportation may also have limited ability to access stores with comparatively lower food prices. Andrews, Bhatta, and Ver Ploeg (2012) found that citizens of New Orleans who did not own their own mode of transportation paid additional travel costs of approximately $11 more per month than those with their own vehicle[2]. For low income families, these costs can be significant barriers to obtaining food items at lower prices.

Education level may also have an effect on purchasing decisions. In theory, individuals with more education may be more likely to understand and implement cost saving strategies, such as using coupons, to pay lower prices for food (Narashman 1984). In contrast to this theory, Cronovich, Daneshvary, and Schwer (1997) did not find a statistically significant relationship

[2]The cost was approximately 12 times more if the shopper used a taxi service.

between coupon usage and college education. However, the authors did find a statistically significant relationship between, households with at least one full time college student and coupon usage. This is likely explained by the differences in incomes between college graduates and college students.

Employment status may also affect the purchasing decisions a household makes. Previous research has shown that adults who work full time and part time are less likely to pursue efforts which could food costs (Cronovich, Daneshvary, and Schwer 1997). Sheethan, Ainslie, and Chintagunta (1999) found no statistically significant relationship between previous buying patterns and purchases made by retired, unemployed, and single mother households. This is likely indicative of high price sensitivity due to income constrains.

Each of the factors or conditions examined in the previous literature can play important roles in household food purchase decisions and can impact prices paid. Our analysis builds on this literature incorporating all of the previously examined variables into a single analysis. We also use the FoodAPS dataset which has not been used to assess the impact of SNAP on price paid for food items[3]. Additionally, our analysis specifically examines the food prices paid by SNAP participants relative to nonparticipants. This has not been examined in the previous literature.

Data

The FoodAPS dataset contains information from a nationally representative survey of United States household food purchases collected from April 2012 to January 2013. FoodAPS is composed of individual, household, events, items, places, and geodata datasets. These subsets of the FoodAPS dataset contain data on individual characteristics, household characteristics, food acquisition (both away and at home), food items purchased, location where the food item was purchased, and

[3] Taylor and Villas-Boas (2016) used the FoodAPS dataset to examine the effects of SNAP participation on store selection but do not extend their analysis to include prices.

geographical and local food market information relevant to the location of the household, respectively. The FoodAPS database contains 55,307 observations of 4,826 families selecting from 208 different food items in total. A complete list of the food items used in the FoodAPS dataset is provided in Table 1.

The FoodAPS dataset was collected using a multi-stage sampling design. The first stage selected a stratified sample of 50 primary sampling units (these units are based on metropolitan statistical areas defined by the US office of Management and Budget) with each unit being a composite reflecting overall sample targets and estimated population of each primary sampling unit. The second stages consisted of data collection all food purchases made by members of each household.

Each household was asked to report all food purchases over a 7-day period. Households were also instructed to distinguish between food items purchased for the purpose of being consumed in the home and food items purchased to be consumed outside the home. The primary food shopper was identified as the primary respondent for each household. The primary food shopper was responsible for recording all food item purchases made, the weight of each item purchased, where the purchases were made, and if the household made use of SNAP benefits when making these purchases. Adults and youths were also given food books and asked to record all purchases made following the same guidelines as the primary food buyer. Adults were defined as those 19 years old and older. Youths were defined as those 18 and under. Food purchases were recorded in food books which were collected after the sampling period.

Interviews were conducted before and after food purchases during the data collection period. The first interview was conducted to determine household eligibility for the FoodAPS survey and to categorize the household into SNAP or non-SNAP recipient categories[4]. The information collected during the second interview included the primary food buyer's socio demographic characteristics including age, sex, race[5], marital status and highest level of schooling completed. Information regarding household characteristics (size, income, etc.) was also collected during the second interview.

Households which reported receiving SNAP benefits were then matched by ERS staff the administrative records to verify both accuracy of their participation and the last date the household received SNAP benefits. Administrative confirmation the household received SNAP benefits were based on records obtained from the caseload and Anti-fraud Locator using EBT Retailer Transactions (ALERT) data. SNAP participants were also asked when they last received SNAP benefits and what amount they received.

Food access and food market information was compiled in the FoodAPS Retail Environment Study Data. The food access data is composed of 3 levels of food geographic aggregation: county-level, tract-level, and main block group-level. County-level aggregation includes information on the total population-normalized count of food retailers. Tract-level aggregation includes information of food retailers in and around each primary sampling unit. Main block group-level aggregation is the lowest level of aggregation and includes information on the availability of food retailers in and around block groups of each primary sample unit. Group blocks are distinguished by population count and socioeconomic indicators within a population sample unit.

Information regarding food retailers are also broken into four categories: supermarket, non-supermarket, farmers market, and farmers markets accepting SNAP. Supermarkets are categorized

[4] Verification requirements included the household was within the scope of the dataset, data was obtained from the household's primary residence (as opposed to a vacation home).
[5]Racial composition includes the categories: White, Black or African American, Hispanic or Spanish or Latino, American Indian or Alaskan Native, Asian, Hawaiian or Pacific Islander, and other.

as food retailers with annual sales greater than $2 million. The non-supermarket category includes smaller grocery stores with annual sales less than $2 million. The non-supermarket category also includes convenience stores, pharmacies, gas stations, dollars stores, and specialties stores such as bakeries. Farmers markets are categorized as "*two or more farm vendors selling at a common direct retail outlet and the same physical location on a recurring basis*" (Wilde and Llobrera, 2014; p. 8).

Data on the local food environment for the market component of our empirical analysis is found in the geography component of the FoodAPS database. In the geography component retailers which are SNAP-authorized and not SNAP-authorized are categorized as either super store, supermarket, a combination of grocery/other store, convenience store, medium and large grocery store, or Wal-Mart. Each category of SNAP-approved retailer is further categorized on the number of each type of food retailer within 0.25, 0.5, 1, 2, 5, 10, 15, or 30 miles from the household. Summary statistics for the data set used is provided in Table 2.

Methods

Given that households buy a variety of different goods during each shopping trip, the first step of the analysis involved the calculation of a price index—also called expensiveness index (Beatty, 2010; Aguiar and Hurst, 2007)[6]. The second step of the analysis involved regressing the expensiveness index on a set of explanatory variables.

The Expensiveness Index

This index compares the cost of a household's food basket at average prices paid by all households in the sample to the cost actually paid by the household. The price index construction follows the method used by Aguiar and Hurst (2007). First, we calculated total expenditures for

[6] We use the household as our unit of measurement for the food basket instead of family size because the primary food purchaser reports the items purchased for all household members including residents which are not related to the primary food purchaser.

household j in period m are (X_m^j)

$$(1)\ X_m^j = \sum_{i \in I, t \in m} p_{i,t}^j q_{i,t}^j, = \sum_{i \in I, t \in m} X_{i,t}^j,$$

where $p_{i,t}^j$denotes the price per ounce paid, $q_{i,t}^j$ denotes the quantity of ounces purchased, $X_{i,t}^j$denotes expenditures on good i and shopping trip (date) t. Another element needed for the calculation of the price index is the average price paid for product i by all households in period m $(\bar{p}_{\mathrm{i},m})$:

$$(2)\ \bar{p}_{\mathrm{i},m} = \sum_{j \epsilon J, t \epsilon m} \left(\frac{X_{i,t}^j}{\bar{q}_{i,m}}\right),$$

where $\bar{q}_{i,m} = \sum_{j \epsilon J, t \epsilon m} q_{i,t}^j$ is the total quantity of food item i purchased by all households during period m. Thus, the cost of household j food basket at average prices is:

$$(3)\ \tilde{X}_j = \sum_{i \epsilon I} \bar{p}_{\mathrm{i},m} q_{i,t}^j.$$

Finally, the price (expensiveness) index, where I represents the set of all goods, for household j is (I^j):

$$(4)\ I^j = \frac{X_j}{\tilde{X}_j}.$$

We normalized the price index around one by dividing by dividing the average expensiveness index for each household by the average price index. An expensiveness index above 1 indicates that a household spent more than average in acquiring their food basket and a value below 1 indicates the household spent less than average on their food basket. Equations (1) and (2) consider the entire period of observation (8 months) as only one period (m=1).

Regression Analysis

The model we use is:

$I^j = \alpha + \beta_{SNAP}\text{SNAP}_j + \beta'_{X^H} X_j^H + \beta'_{X^C} X_j^C + \beta'_{X^M} X_j^M + e_j$, where I^j represents our expensiveness index developed above. The expensiveness index is regressed against the X^H, X^C, and X^M vectors which consist of our household, shopping behavior and habits, and food market variables, respectively and e_j is a random error (see Table 3).

SNAP, our primary interest, is a binary variable which indicates if the household received SNAP benefits. We only include households which have been confirmed by administrative match to be receiving SNAP benefits instead of measuring receiving SNAP benefits by households which indicated they have received SNAP benefits[7]. We use this approach to avoid misreporting participation which could bias our results (Almada, McCarthy, and Tchernis 2015).

Our vector controlling for household related variables includes the logarithm of the yearly household income[8] and the logarithm of the household size. To determine the effects of the household composition on prices paid for food items we also include variables of the percentage of household members over 60 years, between the ages of 5 and 17, and less than 5 years old[9]. We also use binary variables indicating the household is composed of a Single Person and if the primary food purchaser is male. Our Age variable represents the age of the primary food purchaser.

To account for education level, we use 5 binary variables which hold a value of 1 if the primary food purchaser has earned their GED or equivalence, received some college education but has not received a college degree received an associate's degree, received a bachelor's degree or has

[7]The difference between the reported and confirmed amount was 145 household or approximately 10% of all households who responded they were receiving SNAP benefits.
[8] We calculate this by taking the logarithm of the reported monthly income of the household multiplied by 12 because yearly income was not recorded during the interview process.
[9] We use the same age distinctions as Beatty (2010).

received a Master's degree or above. We also use binary variables to represent if the primary food purchaser is Black, Asian or Hispanic and if the household owns their place of residence or their car.

In the vector controlling for consumer behavior variables, we measure the household's financial capacity as a binary variable which holds a value of 1 if the household has $2,000 or more in liquid assets. Our budgeting variable is a binary and holds a value of 1 if the household reported previously skipped meals because of budgeting problems. The Grocery List variable is binary and holds a value of 1 if the respondent "almost always" or "most of the time" shops with a grocery store list according to their survey. Health Interest is a binary variable and holds a value of 1 if the household tried to follow the recommendations of the MyPryamid plan.

In our vector controlling for the food market structure, rural is a binary variable with a value of one if the household lives in a rural census tract according to the US Census Bureau. DistNearSNAP represents the closest distance to the nearest retailer accepting SNAP benefits. TotalSuperMarket represents the county total number of supermarkets, superstores, and large grocery stores. TotalNonSuperMarket represents the county total for non-supermarkets. DensitySuperMarket represents the number of supermarkets per 1000 people at the county level. DensityNonSuperMarket represents the number of non-supermarkets per 1000 people at the county level.

To account for different food prices in different geographical regions, we also include binary variables indicating the household is located in either the South, West, or Midwest region of the US. We follow the US Census Bureau's regional distinctions. A complete list of all variables used and how they are measured is provided in Table 3.

For our regression analysis we first used the ordinary least squares approach (OLS) with different groups of control variables. We first estimated a model including only SNAP participation (Model 1), followed by a model with SNAP participation and household socio-demographic control variables (Model 2), a model with the same variables as Model 2 and consumer behavior variables (Model 3), and finally a model with the same variable as Model 3 plus the food market variables (Model 4). To account for potential endogeneity of the SNAP variable, we then used a method developed by Lewbel (2012) with the same models described above. In this method identification is achieved by having regressors that are uncorrelated with the product of heteroskedastic errors. This technique is especially helpful where instrumental variables are not available (Lewbel 2012; Lewbel 2007; Gregory et al. 2013; Almada and Tchernis 2015; Baum 2011).

Results

As noted in Table 3, the values for our expensiveness index range from 0.04 to 7.84 or approximately from 4% of the average value to nearly 800% of the average vale. This indicates a wide range of amount spent on food items. Similarly, the summary statistics indicate a wide range of household sizes where the logarithm of the household size range from 0 (1 person) to 2.64 (14 people). Supermarket and non-supermarket densities range from zero per county capita to 0.5 and 1 per county capita. The majority of the other variables used in this analysis are binary.

All the coefficient estimates in Tables 4 and 5 represent the effect of SNAP participation on the expenditure index. Using the OLS method, we received mixed results regarding the significance of SNAP participation on the index representing the prices paid for food products by a household. Without controlling for household, consumer, or market variables, SNAP participants were found to have an expensiveness index that was 0.09 points lower (i.e., 9%) than SNAP nonparticipants. When we controlled for household variables, the effect of SNAP participation was still statistically significant and negative but the magnitude (in absolute value) of the difference relative to SNAP nonparticipants was lower (0.05 points lower). When controlling for consumer and market variables, we found the effect SNAP participation was no longer statistically significantly. The magnitude of the change in the SNAP effect as more variables are added to the model is indicative of the relative importance of the control variables explaining the raw difference in expensiveness index values in Model 1 (Altonji et al. 2005). Thus, these results indicate shopping behavior and habits and the local food market structure, but particularly shopping behavior and habits, have a larger impact on the average prices a consumer pays for food products than the socio-demographic factors.

The regressions also showed a consistent negative statistically significant relationship between household size and our expensiveness index where each additional household member decreases the expensiveness index between 0.02 and 0.03 points. Age was also consistently found to hold a negative statistically significant relationship to the average prices paid for food items where a one-year increase in the age of the primary food purchaser decreases the expensiveness index by 0.002 points. Similar to findings in the previous literature, higher amounts of education were consistently associated with a higher expensiveness index where attainment of an associate, bachelor's, and master's degree or above were found to have a positive effect to the expensiveness index. Our findings indicate higher levels of education were found to have an expensiveness index that was between 0.08 and 0.07 points higher (i.e., 7-8%) for primary food purchasers with associate degrees, between 0.08 and 0.11 points higher (i.e., 8-11%) for primary food purchasers with a bachelor's degree, and between 0.18 and 0.2 points higher (i.e., 11-20%) higher if the primary food purchaser obtained a master's degree or above.

The financial capability variable demonstrated a consistent positive statistically significant relationship with the expensiveness index where a household with $2000 or above in liquid assets was found to have an expensiveness index a 0.07 higher that households with less than $2,000 in liquid assets. Interestingly, using budgeting resulted in 0.07 and 0.08 lower amounts spent. In the regression including the market variables, we found a statistically significant negative effect of the number of non-supermarket stores per 1000 county citizens on the expensiveness index. We also found a negative statistically negative effect of distance to the nearest SNAP-authorized retailer and the expensiveness index. We also found households located in the South, West, and Midwest regions of the US paid comparatively lower food prices relative to households located in the NorthEast region. This indicates geographical location may have a significant impact on prices paid for food items. Detailed results of our findings using the OLS approach are reported in Table 4.

Our next of regressions, shown in Table 5, use the instrumental variable approach to account for endogeneity in the SNAP participation using Lewbel's (2012) method. Over identification restrictions tests (Hansen J-statistic) fail to reject the null hypothesis that the moment conditions implied by the approach were valid, which provides some evidence about the validity of the approach used. Overall, we found little difference in the quantitative impacts and similar statistically significant relationships from our OLS estimations. We again found no statistically significant relationship between participation in SNAP and our expensiveness index when we controlled for consumer and market variables. The similarity of our results indicates robustness of the effects of SNAP participation on the expensiveness index[10].

Discussion and conclusion

The main focus of the research was to estimate the effect of SNAP participation on the prices paid for food products. The key consideration is whether SNAP participants were disadvantaged systematically in the cost of food purchases in the US food system. Efficiency in

[10] To account for price fluctuations for food items only available during certain seasons, we also add binary variables to indicated households made purchases during summer, autumn, and winter. These variables did not add additional explanatory power to our analysis.

the provision of SNAP benefits to recipients is the considerations here as even a small difference would be important in enhancing food security for the US population. Although, on average, the expensiveness index of SNAP was found to be 0.09 points lower than the index of non-participants, when we control for the food market structure and consumer shopping behaviors and habits, participation in SNAP does not have a statistically significant impact on the prices households pay for food items. This likely indicates shopping behavior and habits and the food market structure play a comparatively more significant role in determining food prices paid for by families than participation in SNAP. This also yields the important conclusion that SNAP participants do not seem to be systematically disadvantaged in food purchases.

This research showed that SNAP participants are not disadvantaged in their food purchases in the US food system, while controlling for effects that have not been possible in prior data sets. The analysis controlled for the significant effects of market structure (e.g. number of competitors in the market), individual characteristics (e.g. education, age, number of children) and food shopping behavior and habits (e.g. use of budgeting). Of a particular relevance for SNAP, the data set establishes whether respondents are actually SNAP participants by checking with the list of actual enrollees. This deals with the substantial under-reporting of SNAP participation in other data sets. Furthermore, the endogeneity of SNAP participation was controlled for using an instrumental variables method.

An interesting issue that was explored in the analysis was the role of food shopping behavior, and it was found that using budgeting resulted in paying less for food purchases. This is a traditional area where SNAP-Ed has focused efforts. The results show that budgeting enables less expensive food purchases and suggests that SNAP-Ed efforts in this area should be continued and perhaps expanded.

Financial capacity, which held a positive statistically significant relationship to our expensiveness index, indicates households who are able to attain savings are more likely to pay higher prices for food items. Our variables controlling for the local market for food items indicates both concentration of non-supermarket stores and closer proximity to SNAP authorized retailers were associated with comparatively lower prices paid for food items. Although smaller (non-supermarket) stores are typically associated with comparatively higher prices than larger (supermarket) stores, it is possible higher competition for consumer patronage drives down prices. Both these findings demonstrate if the consumer is knowledgeable of potential bargains or saving opportunities in their local food market, they will be better able to attain comparatively lower food costs.

As the ability to effectively use SNAP to lower food costs is jointly related to the participating households' local food market and their specific consumer behaviors, it may be fruitful for researchers and policy makers to further examine these relationships specifically. It may be particularly fruitful to provide households participating in SNAP with additional information or educational materials on effective budgeting, financial planning, and shopping strategies for their local market environment. This would provide households with both the means and knowledge to pay comparatively lower food prices.

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Table 1: Food Items Surveyed*

Aloe Vera and Juices	Coffee cappuccino drinks	Flour/ meal	Mexican food	Potatoes/ onions (FRZ)	Spreads (RFG)	UWF radish
Appetizers/ Snack rolls	Coffee creamer	Frankfurters	Mexican sauce	Poultry/ poultry substitutes	Steak/ Worcestershire sauce	UWF Spinach
Aseptic juices	Cold cereal	Fresh bread and rolls	Microwave package/ dinner entry	Poultry (FRZ/RFG)	Stuffing mixes	UWF Sprouts
Asian food	Cookies	Fresh eggs	Milk	Powdered Milk	Sugar	UWF Tomato
Baby food	Corn on the cob	Frosting	Milk flavoring/ cocoa mixes	Premixed cocktails/ coolers	Sugar substitutes	UWF Yams
Baby formula/ electrolytes	Cottage cheese	Frozen meat (not poultry)	Mustard and ketchup	Prepared deli/ gourmet food (RFG)	Syrup	UWF Tofu/ soybean
Baked beans/Canned bread	Crackers	Fruit and vegetable preservative	Natural cheese	Prepared vegetables (frozen)	Tea bags/ loose	UWF Vegetables
Baked goods	Cream cheese/ Cream cheese spread	Fruit	Noncarbonated water (including flavored)	Processed cheese	Tea instant mix	Vinegar
Bakery snacks	Creams/ creamers	Gelatin/pudding product/ mixes	Non fruit drinks	Processed poultry (FRZ/RFG)	Tea/ coffee ready to drink	Vitamins
Baking mixes	Dessert toppings	Glazed fruit	Non chocolate candy	Rice	Tea/ coffee refrigerated	Weight control/ nutritional liquid
Baking needs	Desserts	Grated cheese	Novelties	Rice/ popcorn	Tarts/ toaster pastries	Weight control/ protein supplement
Baking nuts	Desserts/ toppings	Gravy/ sauce mix	Other breakfast food	Salad dressing (RFG)	Tomato products	Whipped Toppings (RFG)
Baking syrup/ Molasses	Dinner sausage	Gum	Other condiments	Salad dressing	Tortillas/ eggrolls/ wanton wrap (refrigerated)	Wine
Barbeque sauce	Dinners	Ham	Other foods	Salad toppings	Uncooked meats (RFG)	Yogurt
Beer/Ale/Alcoholic cider	Dinners/ entrees	Hot cereal	Other salty snacks (not nuts)	Salad/ coleslaw (RFG)	UWF beans	
Bottled juices	Dip/dip mixes	Ice cream cones/ mixes	Other sauces	Salty snacks	UWF broccoli	
Bottled water	Dips	Ice cream/ sherbet	Other snacks	Seafood (FRZ)	UWF cabbage	
Bread/ dough	Dough/ biscuit dough	Instant potatoes	Pancake mixes	Seafood (RFG)	UWF carrots	
Bread crumbs/ Batter	Dried fruit	Jellies/ jam/ honey	Pasta	Seafood	UWF cauliflower	
Breakfast foods	Dried meat snacks	Juice/drink concentrate	Pasta (FRZ)	Shortening and oil	UWF Celery	
Breakfast meats	Drink mixes	Juices	Pasta (RFG)	Side dishes (RFG)	UWF cucumber	
Breath fresheners	Dry beans/ vegetables	Juices/ drinks	Pastry/ donuts	Snack bars/ granola bars	UWF grapefruit	
Butter	Dry dinner mix (add meat)	Lunch meat	Peanut butter	Snack nuts/ seeds /corn nuts	UWF lettuce	
Cake (not snack)/ Coffee cake	Dry fruit snacks	Luncheon meats	Pickles/ relish (RFG)	Soup	UWF mixed vegetables	
Canned juices	Dry packaged dinner mixes	Lunches	Pickles/ relish/ olives	Soup/sides/ other (FRZ)	UWF mushrooms	

Canned/bottled fruit	Energy drinks	Margarine/ spreads/butters	Pies and cakes	Sour cream	UWF onions
Canned/prepared tea	English muffins	Marshmallows	Pies (FRZ)	Spaghetti/ Italian sauce	UWF oranges
Carbonated beverages	Entrees	Mutzod food	Pizza (FRZ)	Specialty nut butter	UWF other fruit
Cheesecakes	Evaporated/ condensed milk	Mayonnaise	Pizza (RFG)	Spices/ seasonings (not salt or pepper)	UWF other vegetables
Chocolate candy	Fish/ seafood FRZ	Meat (FRZ)	Pizza products	Spices/ seasonings	UWF peas
Cocktail mixes	Fish/seafood	Meat (RFG)	Plain vegetables	Spirits/ liquors	UWF peppers
Coffee	Eggnog/ buttermilk/ flavored milk	Meat	Popcorn/ popcorn oil	Sports drinks	UWF potato

*Where RFG refers to refrigerated items, FRZ to frozen items, and UWF represents uniform weight fresh items

Table 2 Summary Statistics

Variable	Obs	Mean	Std. Dev.
ExpensivenessIndex	3601	1.00	0.40
SNAP	3601	0.28	0.44
ln(Income)	3601	9.33	3.13
ln(HhSize)	3601	0.94	0.59
CompElder	3600	0.21	0.37
CompChild	3600	0.14	0.21
CompSmallChild	3600	0.08	0.15
SinglePerson	3600	0.19	0.39
Age	3597	46.05	16.07
Male	3601	0.25	0.43
GED	3601	0.29	0.45
SomeCollege	3601	0.27	0.45
AssociateDegree	3601	0.12	0.32
BachelorsDegree	3601	0.15	0.36
MastersorAbove	3601	0.07	0.26
AutoOwn	3601	0.83	0.37
HouseOwn	3601	0.50	0.50
Rural	3601	0.29	0.45
Black	3601	0.11	0.32
Asian	3601	0.04	0.20
Hispanic	3601	0.18	0.39
FinancialCapacity	3601	0.35	0.47
Budgeting	3601	0.08	0.27
List	2951	0.40	0.49
HealthInterest	3601	0.17	0.37
DistNearSNAP	3601	0.90	1.39
TotalSuperMarket	3601	130.73	235.70
TotalNonSuperMarket	3601	239.47	370.68
DensitySuperMarket	3601	0.12	0.04
DensityNonSuperMarket	3601	0.26	0.12
West	3601	0.22	0.42
South	3601	0.36	0.48
MidWest	3601	0.25	0.43

Table 3 Variable Categories and Explanations

Category	Variable	Definition
	Expensiveness Index (I^j)	Calculated as the sum of the cost of a household's food basket divided by the average cost of a food basket paid by other households
	SNAP	Binary variable indicating administrative match household received SNAP benefits
Household Vector (X^H)	ln(Income)	Represents the logarithm household's income per year
	Ln(HhSize)	Represents the logarithm of household size
	CompElder	Represents percentage of household size composed of members over 60 years old
	CompChild	Represents percentage of household size composed of members between the ages of 5 and 17
	CompSmallChild	Represents percentage of household size composed of members less than 5 years old
	SinglePerson	Binary variable indicating household is composed of one individual
	Male	Binary variable representing the primary food purchaser is male
	GED	Binary variable representing food purchaser has received a high school diploma or equivalence
	SomeCollege	Binary variable representing primary food purchaser has received some college education but has not received a college degree
	AssociatesDegree	Binary variable representing primary food purchaser holds an associate's degree
	BachelorsDegree	Binary variable representing primary food purchaser holds a bachelors degree
	MastersorAbove	Binary variable representing primary food purchaser holds a masters degree or a higher degree
	AutoOwn	Binary variable representing the household owns a vehicle
	HouseOwn	Binary variable representing the household owns their place of residency
	Black	Binary variable representing the primary food purchaser is Black

	Asian	Binary variable representing the primary food purchaser is Asian
	Hispanic	binary variable which holds a value of 1 if the primary food purchaser is Hispanic
Consumer Behavior Vector (X^C)	FinancialCapacity	Binary variable representing the household has $2,000 or more in liquid assets
	Budgeting	Binary variable representing the household has ever skipped meals because of budgeting problems
	List	Binary variable representingprimary food purchaser "almost always" or "most of the time" shops with a grocery store
	HealthInterest	Binary variable representing household tried to follow the recommendations of the MyPryamid plain
	Rural	Binary variable representing household lives in a rural census tract according to the US Census Bureau
Market Variables Vector (X^M)	DistNearSNAP	Represents distance to nearest retailer accepting SNAP benefits
	TotalSuperMarket	Represents county total number of supermarkets, superstores, and large grocery stores
	TotalNonSuperMarket	Represents the county total number of nonsupermarkets
	DensitySuperMarket	Represents the number of supermarkets per 1000 people at the county level
	DensityNonSuperMarket	Represents the number of nonsupermarkets per 1000 people at the county level
	West	Binary variable representing household is located in the West region of the United States
	South	Binary variable representing household is located in the South region of the United States
	MidWest	Binary variable representing household is located in the Mid-West region of the United States

Table 4 OLS Results

	Model 1	Model 2	Model 3	Model 4
SNAP	-0.09 (-6.73)***	-0.05(-3.36)***	-0.02 (-1.35)	-0.02 (-1.27)
Log Annual Income Log		0.00 (1.22)	0.00(0.54)	0.00 (0.59)
Household Size Percent		-0.08 (-5.21)***	-0.06 (-3.73)***	-0.06 (-3.68)***
Elderly Members		0.03 (0.77)	-0.01 (-0.67)	-0.02 (-0.76)
Percent Children		0.00 (0.06)	-0.01 (-0.31)	-0.01 (-0.42)
Percent Small Children		0.02 (0.90)	0.01 (0.54)	0.01 (0.34)
Single Person		-0.06 (-2.40)**	-0.04 (-1.47)	-0.03 (-1.32)
Age		-0.00 (-3.81)***	-0.00 (-3.10)***	-0.00 (-3.26)***
Male		-0.03 (-2.15)**	-0.03 (-2.03)**	-0.03 (-1.84)*
GED		0.01 (0.47)	-0.00 (-0.12)	-0.01 (-0.41)
Some College		0.03 (1.90)*	0.00 (1.19)	0.02 (1.15)
Associate Degree		0.08 (3.08)***	0.06 (2.42)**	0.06 (2.26)**
Bachelor's		0.11 (5.09)***	0.09 (3.98)***	0.07 (3.68)***
Degree Master's		0.20 (6.64)***	0.20 (5.57)***	0.19 (5.26)***
or Above Owns		-0.04 (-1.70)**	-0.03 (-1.42)	-0.03 (-1.28)
Car		0.03 (1.89)*	0.001 (0.41)	0.08 (0.54)
Owns House		-0.05 (-3.77)***	-0.05 (-3.02)***	-0.03 (-1.60)
Rural Location		-0.05 (-2.15) **	-0.03 (-1.32)	-0.02 (-0.98)
Black		-0.09 (-2.23)**	-0.09 (-1.85)*	-0.07 (-1.73)*
Asian		-0.04 (-2.54)**	-0.04 (-1.92)*	-0.03 (-1.73)*
Hispanic			0.07 (4.68)***	0.07 (4.60)***
Financial Capacity			-0.05 (-1.94)*	-0.05 (-1.92)*
Budgeting			0.00 (0.13)	0.00 (0.13)
Health Interest			0.01 (0.61)	0.01 (0.64)
Distance Nearest SNAP retailer				-0.01 (-1.83)*
Total Supermarkets				0.00 (0.71)
Total NonSupermarkets				-0.00(-1.24)
Density of Supermarket				-0.03 (-0.19)
Density of NonSupermarkets				-0.15 (-2.69)**
West				-0.07 (-2.57)**
South				-0.05 (-2.23)*
MidWest				-0.09 (-4.17)***
Constant	1.02 (124.58)***	1.18 (23.88)***	1.13 (28.38)***	1.23 (27.22)***
N	3601	3597	2949	2949
F-stat	45.26	7.60	8.34	7.35
R^2	0.01	0.05	0.07	0.08

Model 1 regresses our expensiveness index on our SNAP variable. Model 2 includes SNAP and our household variables. Model 3 includes SNAP, household, and consumer behavior variables. Model 4 includes our SNAP, household, consumer behavior, and market variables. The decrease in observations for Model 3 and 4 are a result of households not reporting if they use a grocery list when making food purchasing decisions. We also tested the robustness of our results by using the household weights provided by the FoodAPS dataset sampling system. When we used these weights, our results remained largely the same. t statistics in parentheses where * p<0.1 ** p<0.05 *** p<0.01, Regressions reported with robust standard errors.

Table 5 IV Using the Lewbel Method

	Model 1	Model 2	Model 3
SNAP	-0.003 (-0.10)	0.03 (1.15)	0.03 (1.21)
Log Annual Income Log	0.00 (1.52)	0.00 (0.63)	0.00 (0.64)
Household Size Percent	-0.08 (-5.68)***	-0.07 (-5.22)***	-0.07 (-5.23)***
Elderly Members Percent	0.03 (1.10)	-0.01 (-0.28)	-0.01 (-0.29)
Children	-0.00 (-0.08)	-0.00 (-0.01)	-0.01 (-0.48)
Percent Small Children	0.02 (1.02)	0.02 (1.26)	0.02 (1.15)
Single Person	-0.07 (-3.36)***	-0.05 (-0.20)	-0.04 (-0.18)
Age	-0.00 (-3.76)***	-0.00 (-3.41)***	-0.00 (-3.84)***
Male	-0.02 (-1.53)	-0.03 (-1.80)*	-0.02 (1.65)*
GED	0.00 (0.15)	0.02 (1.13)	0.00 (0.03)
Some College	0.03 (1.96)*	0.01 (0.55)	0.02 (1.22)
Associate Degree	0.06 (2.55)***	0.05 (2.33)**	0.05 (2.41)**
Bachelors Degree	0.11 (5.49)***	0.11 (4.92)***	0.10 (4.77)***
Masters or Above	0.21 (6.89)***	0.21 (5.95)***	0.20 (5.75)***
Owns Car	-0.01 (-0.63)*	-0.01 (-0.61)	-0.01 (-0.54)
Owns House	0.03 (2.68)**	0.02 (1.64)	0.02 (1.72)*
Rural Location	-0.06 (-4.38)***	-0.05 (-3.53)***	-0.04 (-2.54)**
Black	-0.05 (-2.57)***	-0.04 (-2.09)**	-0.04 (-1.85)*
Asian	-0.08 (-2.07)**	-0.08 (-1.92)*	-0.08 (-2.03)**
Hispanic	-0.05 (-2.84)**	-0.04 (-1.90)**	-0.04 (-1.73)*
Financial Capacity		0.08 (5.32)***	0.08 (5.31)***
Budgeting		-0.07 (-2.87)***	-0.08 (-3.53)***
Uses Grocery List		-0.00 (-0.28)	0.00 (0.11)
Health Interest		0.00 (0.00)	0.00 (0.09)
Distance Nearest SNAP retailer			-0.01 (-1.44)
Total Supermarkets			0.00 (0.33)
Total NonSupermarkets			-0.00 (-0.88)
Density of Supermarket			0.01 (0.68)
Density of NonSupermarkets			-0.17 (-3.05)***
West			-0.07 (-2.84)***
South			-0.04 (-2.26)**
MidWest			-0.09 (-4.13)***
Constant	1.11 (28.67)***	1.14 (28.44)***	1.18 (27.39)***
N	3597	2949	2949
F-stat	8.67	9.18	8.35
Centered R^2	0.05	0.06	0.07
Hansen J-Stat	25.34	24.32	36.65

Model 1 includes SNAP and our household variables. Model 2 includes SNAP, household, and consumer behavior variables. Model 3 includes our SNAP, household, consumer behavior, and market variables. We do not include a regression of our expensiveness index and our SNAP variable only because the method cannot be used with a single regressor. Z score in parentheses. Where * p<0.1 ** p<0.05 *** p<0.01, Regressions reported with robust standard errors

Contextualizing Family Food Decisions: The Role of Household Characteristics, Neighborhood Deprivation, and Local Food Environments

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Abstract

We employ multilevel models with neighborhood and state effects (fixed effects and random effects) to analyze the associations between household characteristics, neighborhood characteristics, regional attributes and dietary quality. We use data from the USDA National Household Food Acquisition and Purchase Survey. Our dependent variable is a Healthy Eating Index that incorporates dollars spent and amount of food in several categories. Key explanatory variables at the household level include variables household financial condition, housing burden, home ownership, car access, household size. We include a variable for the number of large food stores in the neighborhood, a neighborhood deprivation index, and a regional food price index, along with neighborhood and state random effects. Our model shows that at the household level, financial condition and home ownership are significantly and positively related to dietary quality, while U.S. citizenship status and living in a rural area were negatively associated with dietary quality. The number of large food stores in the neighborhood is significantly and positively associated with dietary quality. Neighborhood deprivation is not significantly associated with dietary quality, nor is the regional food price index. However, the neighborhood and state random effects variables were both significant, and the neighborhood variable explains close to half of the variation in household dietary quality. Our results highlight the complexity of understanding factors at different spatial scales that influence dietary quality. Food environments are important in shaping household food decisions, as are household finances. Future research should work on untangling additional neighborhood-level factors that matter for dietary quality.

Executive summary

A growing body of literature focuses on disparities in access to healthy foods and on the relationships between local food environments and outcomes related to diet and health. This work has had direct policy implications, as evidenced by healthier food retail legislation at the state and federal levels. At the same time, recent research also suggests that the food environment-diet relationship is far from straightforward, and that household finances, not proximity to stores, may be more important. These studies suggest that the local food environment interacts in critical ways with issues related to poverty and household resources. In this analysis, we employ multilevel models with neighborhood and state effects (fixed effects and random effects) to analyze the associations between household characteristics, neighborhood characteristics, regional attributes and dietary quality. We use data from the USDA National Household Food Acquisition and Purchase Survey (FoodAPS). Our dependent variable is a Healthy Eating Index that incorporates dollars spent and amount of food (measured by weight) in several categories: fruit, vegetables, snacks, and sweetened beverages. Key explanatory variables at the household level include variables household financial condition, housing burden, home ownership, car access, household size. We include a variable for the number of large food stores in the neighborhood, a neighborhood deprivation index, and a regional food price index, along with neighborhood and state random effects. Our model shows that at the household level, financial condition and home ownership are significantly and positively related to dietary quality, while U.S. citizenship status and living in a rural area were negatively associated with dietary quality. The number of large food stores in the neighborhood is significantly and positively associated with dietary quality. Neighborhood deprivation is not significantly associated with dietary quality, nor is the regional food price index. However, the neighborhood and state random effects variables were both significant, and the neighborhood variable explains close to half of the variation in household dietary quality. Our results highlight the complexity of understanding factors at different spatial scales that influence dietary quality. Food environments are important in shaping household food decisions, as are household finances. Future research should work on untangling additional neighborhood-level factors that matter for dietary quality.

Introduction

An increasing number of researchers explore disparities in access to healthy foods and the relationships between local food environments and dietary outcomes[1-3]. Residents of poorer neighborhoods, neighborhoods with higher proportions of people of color, and rural areas tend to live farther away from large supermarkets or supercenters[4-6]. Though these neighborhoods may have a higher number of small grocery, corner, and convenience stores[5,7,8], scholars point that that these stores tend to carry fewer healthy foods[9,10] and have higher prices than supermarkets[11-13]. The majority of food environment research has focused on proximity-based measures of food access; for example, scholars for example, scholars have compared different types of food stores in terms of differences in price, food availability, and food quality [14-16]. However, recent studies suggest that the food environment-diet relationship is far from straightforward.

While some scholars have found a correlation between consumption of healthy foods (e.g. fresh produce) and access to large supermarkets[17,18], two recent large-scale studies found that improved access to supermarkets was generally unrelated to dietary quality[4,5]. To account for this, researchers suggest that household finances are a more critical factor in determining what people eat than proximity to food stores[6-8]. In fact, many people intentionally bypass their nearest stores altogether, preferring to incur high travel costs to reach farther food stores that offer more affordable food and more healthy options[19-23]. Most recently, a report from the large-scale, nationally representative FoodAPS project found that the average consumer's primary store is not the closest one to their home, and that they travel as much as an additional 1.5 miles to reach their preferred store[24]. This study also highlights the role that transportation can play in food purchasing decisions; fewer consumers without cars reported bypassing their nearest store to shop for food. Several other studies have similarly found that transportation can be a major barrier to food access for low-income individuals[25-27], with others finding that they often travel farther for food than wealthier individuals, suggesting higher transportation costs[28-30].

These studies suggest that the local food environment interacts in critical ways with issues related to poverty and household resources. Until now, however, we have not had representative data that would allow us to contextualize family food decisions within the complex array of factors at the household and neighborhood level. Yet, the consequences of living in an area with poor food access are likely to vary from place to place and for different types of households. For example, food access may look very different in urban and rural areas, for several reasons; these might include the availability of public transportation in urban vs. rural areas, lower cost of living in rural areas, and potentially greater access to gardens or farm produce in rural areas[31]. Race and ethnicity may also differentially affect people's experiences living in places with low food access[32]. In order to expand our understanding of issues of food access beyond proximity to different store types, a growing number of scholars call for multilevel studies that explore interactions between household variables and neighborhood variables and their varying effects on dietary outcomes[1,7,33].

Methods

This study employs multilevel models with neighborhood and state effects (fixed effects and random effects) to analyze the associations between household characteristics, neighborhood characteristics, regional attributes and dietary quality. We used the R Project for Statistical

Computing version 3.0.1 for analysis, including library packages *MASS* version 7.3 and *nlme* version 3.1. Data were imported into R from SAS and merged by each individual's household identification number (HHNUM).

At the household level (level 1), we expect that characteristics such as financial well-being, educational attainment, race/ethnicity, household structure, citizenship status, homeownership, access to a car, and the number of large stores in the neighborhood will impact dietary choices. We recognize that households located within the same census block group will not be independent from one another with regards to the number of large stores in the neighborhood. We also expect that neighborhood-level conditions could impact the local social and food environment within which household dietary decisions are made. For these reasons, we investigate effects at the neighborhood level (level 2). Here, we expect that neighborhood characteristics such as neighborhood deprivation (a fixed effect specified in the model through an index score at the block group level) will impact household dietary choices. Because other aspects of the neighborhood environment (i.e., culture, social trust) could also be important, we include a random effect at the neighborhood level as well.

Next, we are interested in the possibility that the cost of food varies across space and that these price differences impact food choices. Data on average food prices are available in the FoodAPS data at the county level and are included in our model as a fixed effect. Because the FoodAPS data are structured so that only one or a small number of usually spatially clustered counties were sampled within each state, it is difficult to separate the cost of food at the county level from other county-level social and economic conditions that might impact food choices or from state-level effects that could be related to state policy differences in providing access to food and social services. So, given county-state complications in the structure of the data, we include a random state effect that we believe captures some mix of social and economic regional effects that occur at the county or state level (level 3).

Our proposed research approach included spatial analysis to investigate the possibility that relationships between household characteristics and diet vary across space, using geographically weighted regression (GWR) at the block group level. As we explored the data, we decided that approach was not viable or appropriate to the data structure and decided to implement the multilevel approach described above to model spatial effects through neighborhood and regional effects. The FoodAPS data are structured so that the sample of 3,286 households for which relevant data are available are located within 27 states with a range of between 22 to 439 observations per state. Relatively few (n= 649 of over 200,000) block groups are represented in the sample, with a range of 1 to 38 household observations within each block group and an average of 5.1 households per block group. The sample size was not large enough within the average block group to reasonably represent the block group, nor were there enough block groups included in the dataset to distinguish spatial effects from the impacts of observable conditions, such as rurality and economic conditions. In short, GWR is an exploratory tool that works well for uncovering possible spatial variance in relationships between variables; but we feel like the multilevel modeling approach we ultimately decided to take is both better suited to the data structure and also offers more concrete and policy applicable findings.

Data

We use data from the USDA National Household Food Acquisition and Purchase Survey (FoodAPS). Our dependent variable is a Healthy Eating Index that incorporates dollars spent and amount of food (measured by weight) in several categories: fruit, vegetables, snacks, and sweetened beverages. The Healthy Eating Index was created using principal components analysis based on the following variables: dollars per person spent on fruits, dollars per person spent on vegetables, grams of fruits acquired per person, grams of vegetables acquired per person, dollars per person spent on snacks, and dollars per person spent on sweetened beverages. The components load on three factors with an eigenvalue >1. The first is essentially the "buying a lot of food" factor, which is closely related to household size. The factor of interest is the second one, the Healthy Eating Index. We scored this second factor so that fruits and vegetables contributed positively to the index, and snacks and sweetened beverages contributed negatively to the index. The third factor is of potential interest for future analysis, and is essentially those households that buy a lot of sweetened beverages but not snacks.

Table 1 outlines the variables included in the analysis. Key explanatory variables at the household level include a household financial index, based on principal component analysis that included monthly household income (positively associated with index), self-reported problems paying utility bills (negatively associated with the index), self-reported problems paying other bills (negatively associated with the index), and self-reported financial condition (negatively associated with index); this latter variable is a categorical measure of how comfortable and secure financially the head of household feels, ranging from 1, "very comfortable and secure," to 5, "in over your head". We also include a measure to capture the influence of housing circumstances[12,13]: housing burden, operationalized as shelter costs for the previous month (including rent or mortgage, insurance, property taxes, and utilities) as a proportion of the previous month's household income. In addition, we include a binary variable measuring home ownership and a binary variable measuring access to a car, which previous research indicates may affect the food environment-diet relationship[14]. We also include control variables at the household level, including household size, the number of children under age 12, whether the home is in a rural area, and the primary respondent's race/ethnicity, citizenship status, and education level.

The concept of "food access" includes a number of dimensions, including availability and affordability[3]. Our model operationalizes availability as the number of supermarkets within 1 mile of the centroid of urban block groups and within 10 miles of rural block groups[1]. We operationalize affordability using an index of food prices in the county in which participants live, which is the measure most consistently linked to dietary outcomes[3].

Finally, based on previous qualitative research conducted with low-income women in North Carolina, we hypothesized that neighborhood deprivation, previously linked to health outcomes[15-17], would also influence dietary quality. Using several variables derived from the Census 2010 and the American Community Survey (2008-2012), to represent multiple, theoretically-distinct constructs of neighborhood social disadvantage[16], we use a neighborhood deprivation index. The neighborhood deprivation index was developed using principal components analysis based on the following variables: median household income (negatively associated with index), percent homeowners (negatively associated with index), percent single parent households among households with children (positively associated with index), and percent Black race (positively associated with index). The index is calculated at the census tract level.

Results

Results are shown in Table 2, page 254.

Model 1 is a simple OLS model based on household-level variables that we expected would impact healthy eating. For this model, the Healthy Eating Index was the dependent

[1] Rural is operationalized as a sparsely populated area with fewer than 2,500 people, while urban areas have more than 2,500 people.

variable. Based on Model 1, we found that housing burden, car access, household size, the presence of children in the household, and whether the head of household was Black or Latino had no effect on healthy eating. The following variables were positively associated with dietary quality: financial condition, home ownership, education of the head of household, and whether the head of household identified her or her race as “other” (not White, Black, or Hispanic). The number of supermarkets in the neighborhood was also positively associated with dietary quality. Citizenship status and living in a rural area were negatively associated with dietary quality.

Next, we wanted to see how neighborhood conditions impacted healthy eating. Model 2 is a multilevel mixed effects model. It includes the same level 1 household characteristics as the household level OLS model, but it also includes fixed effects for neighborhood deprivation (level 2 - block group) and for the regional food price index (level 3- state/county), as well as random effects at the neighborhood and state levels. We not that we are referring to level 3 as regional effects because there are only a few counties in each state, with counties clustered together, making it difficult to separate county and state effects. The "regional effects" are thus a combination of state and county effects.

Understanding how neighborhood conditions impact dietary quality is of particular importance to our research question. Based on our hypothesis that neighborhood deprivation would have a significant effect on household food purchases and thus dietary quality, Model 2 includes an index for neighborhood deprivation. Altogether, Model 2 is specified to address four concurrent issues that can't be addressed with the OLS model: (1) to adjust for the fact that households within the same neighborhoods are not independent from one another, particularly on variables such as number of stores in the neighborhood and the neighborhood deprivation index; (2) to test for the effects of neighborhood-level impacts on household diets; (3) to test the relationship between regional food prices and dietary quality; and (4) to adjust for the fact that unspecified factors operating at the regional level (e.g., social and economic conditions, state and local policies) may impact household dietary quality.

The results for Model 2 are shown in Table 2. Most of the relationships identified as significant in Model 1 are still significant in Model 2. The only change is that the years of education of the head of household is no longer significant. The number of supermarkets in the neighborhood is still significant and positively associated with dietary quality. However, contrary to our expectations, neither the county-level food price index nor the index for neighborhood deprivation is significant. In other words, living in a deprived neighborhood or a region with higher food prices does not significantly affect healthy eating. However, neighborhood conditions do matter. Approximately 3.1% of the variation between households can be explained by unspecified random neighborhood effects, or neighborhood-level differences. This is a small relationship, but it is almost half of the overall variance explained in the model that includes multiple household level characteristics. Therefore, there are unspecified neighborhood conditions (for example, local culture, social trust, or other aspects of the food retail environment) that account for as much of the variation in household level dietary quality as a full suite of household-level variables. State effects are also statistically significant, but substantively negligible.

Discussion

Our results highlight the complexity of understanding factors at different spatial scales that influence dietary quality. Overall, our model predicted only 6.8% of the variation in household dietary quality. Dietary quality is likely affected by a wide range of factors at multiple scales, which helps explain our low adjusted R^2 value. This is further complicated by the fact that our model measures dietary quality in terms of household food purchases, as opposed to individual people's consumption patterns (as in the case of dietary recalls, for example). We note that previous versions of the model—for example, those with dependent variables comprised of just one or two dietary components, such as per person dollars spent on fruit or vegetables—had even lower R^2 values. However, as we continue to refine our model, we will work to identify additional key variables to improve our model.

Given this caveat, however, our research suggests that places matters. First, food environments do matter: the number of supermarkets in a neighborhood was significantly related to household dietary quality. Contrary to our expectations, however, the county price index was not significantly related to dietary quality when controlling for other factors.

In addition, and echoing several recent studies[6-8], our results highlight the importance of household finances in shaping food decisions and by extension, dietary quality. We found a significant relationship between household dietary quality and financial condition. Although housing burden was not significantly related to dietary quality, home ownership had a significant and positive effect on dietary quality.

In general, we found a lack of associations between the race/ethnicity of the head of household and dietary quality, with one exception. Having a household head who identified as "other" (non-White, Black, or Hispanic) was significantly and positively associated with dietary quality. This category consisted of people identifying as Asian, Native Hawaiian or Other Pacific Islander, American Indian or Alaska Native, or another race. In addition, although there was not a significant association between Hispanic heads of household and dietary quality, there was a significant negative association between U.S. citizenship and dietary quality. In other words, non-citizens had higher dietary quality. This is in keeping with research on immigrants and dietary acculturation. This literature finds that immigrants generally have healthier diets than the U.S. born population among arrival to the United States, and that that dietary quality deteriorates as immigrants adapt to U.S. culture. Among Latinos, acculturation is generally associated with less healthy diets, including lower intake of fruits and vegetables and higher consumption of fast food, junk food, and sugar-sweetened beverages.[34-37]

Although our index of neighborhood material hardship was not significantly related to dietary quality, we conclude based on our analysis that place matters. First, living in a rural area was significantly and negatively related to dietary quality. While it is often assumed that people living in rural areas will have better access to healthy food because of farming and gardening traditions, studies of food insecurity indicate that rural areas have higher food insecurity rates than urban, suburban or exurban areas, as well as higher poverty and lower educational attainment rates[38-39]. Researchers have attributed differences in food access between rural and urban areas in part to a lack of transportation infrastructure in rural areas, as well as to larger distances between supermarkets due to insufficient population bases and issues with food distribution[39-40]. Second, the random neighborhood effects variable was significant. We note that the index of neighborhood deprivation is highly negatively correlated with home ownership (-0.38); homeowners are less likely to live in deprived neighborhoods. (In addition, the index of neighborhood deprivation includes percent home ownership as one component). Because of this, neighborhood deprivation becomes significant if we take homeownership out of the model. Similarly, neighborhood deprivation is highly negatively correlated with the number of large supermarkets; more deprived neighborhoods have fewer stores. Taken together, this means that neighborhood deprivation may matter, but that is so closely linked to home ownership and the presence of supermarkets that it becomes insignificant when we include these variables.

However, our multilevel model also tests for neighborhood effects beyond what we've measured with the deprivation scale. This suggests that neighborhood does matter, even net of the effects of the number of stores in a neighborhood and presence of homeowner-occupied houses.

In subsequent analyses, we will work to try to identify additional neighborhood-level variables that could explain this variation. These could include, for example, the prevalence in the neighborhood of other types of food retail outlets besides large supermarkets: for example, farmers' markets or smaller corner or "ethnic" grocery stores, on the one hand, or fast food restaurants, on the other hand. Particularly given our finding about citizenship status, it could also include a measure of the degree to which neighborhoods are isolated immigrant enclaves, which could provide a protective effect on dietary quality by enabling immigrants to maintain food traditions that are healthier than typical U.S. diets. A study of Hispanic immigrants in New York City found that adherence to a healthier diet pattern was positively associated with both neighborhood poverty and neighborhood linguistic isolation; the authors conclude that this research supports the hypothesis that living in immigrant enclaves is associated with healthy diet patterns among Hispanics.[41]

Conclusions

Our findings demonstrate promising evidence that place matters for dietary quality. Food environments explain part, but not all, of the relationship between dietary quality and neighborhoods. Households in neighborhoods with more supermarkets had better dietary quality. Home ownership was also significantly and positively associated with dietary quality. Both of these factors are negatively correlated with neighborhood deprivation. Thus, although neighborhood deprivation is not significant in our final model, this may be in part because neighborhood deprivation predicts other factors that matter for dietary quality, such as home ownership and presence of supermarkets. Furthermore, we found a significant neighborhood effect that is still unspecified; future analyses will attempt to identify other neighborhood-level factors that could better explain variation in dietary quality.

Some variables that we predicted would be significant were not; for example, car access was not significantly related to dietary quality. However, our research does support our general expectation that the households that are worst off likely experience a cluster of factors, including low food access, high economic stress, and unstable housing (measured by a lack of home ownership).

This research challenges public health experts and practitioners to think more comprehensively about how consumers make food decisions. Our findings may suggest, for example, that while policies to increase access to retail food stores are helpful, policies to increase household financial resources and ensure access to adequate housing are also critical. Most challengingly, it suggests that the most effective promotion of healthy food decisions will require a “mainstreaming” of the issue, so that community development, regional transport, and anti-poverty programs all adopt healthy food promotion as an important planning principle.

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Table 1. Variables included in analysis.

Outcome	Prevalence/average	Notes
Healthy Eating Index		Principal components analysis based on the following variables: dollars per person spent on fruits, dollars per person spent on vegetables, grams of fruits acquired per person, grams of vegetables acquired per person, dollars per person spent on snacks, and dollars per person spent on sweetened beverages.
Exposures		
Financial condition index		Principal components analysis based on the following variables: Monthly household income, self-reported financial index (categorical variable from 1 = very comfortable and secure to 5 = in over your head), self-reported difficulty paying housing expenses in the last six months, and self-reported difficulty paying utilities in the last six months.
Housing burden	Mean = 39% SD = 28%	Monthly housing expenses (rent/mortgage, insurance, property tax, and utilities) as a proportion of monthly household income. People with zero income AND zero housing expenses were considered to have a 0% housing burden. People with zero income who do have housing expenses were considered to have 100% housing burden.
Home ownership	No = 2095 Yes = 2138	Whether or not the primary respondent owns the home in which they live.
Car access	No = 678 Yes = 3681	Whether the household has access to a car when needed.
Household size	Mean = 3.0 SD = 1.7	Total number of people (children and adults) in the household.
Young kids in household	Mean = 0.58 SD = 1.0	Number of children in the household under age 12.
Rural	No = 3159 Yes = 1208	Whether the household is in a rural census tract.
Race/ethnicity	White = 2618 Black = 559 Hispanic = 858 Other = 329	Race/ethnicity of the primary respondent. Respondents who indicated that they are both Hispanic and another race were only counted as Hispanic for this variable.
Citizenship status	No = 433 Yes = 3925	Whether the primary respondent is a U.S. citizen.
Educational attainment	Mean = 20.2 SD = 2.8	Years of education of the primary respondent.
Stores in neighborhood	Mean = 4.2 SD = 7.9	Number of large supermarkets within 1-mile of urban and 10-miles of rural homes.
Food price index	Mean = $262.50 SD = $54.90	Average food basket price for a family of four, at the county level.
Neighborhood deprivation		Principal components analysis based on the following variables: Median household income, percent homeowners, percent single-parent households (among households with children), and percent Black race, all at the census tract level.

Table 2. Household and multi-level models used in analysis.

	Model 1 Household-level OLS B		Model 2 Neighborhood & State effects B	
Financial condition	0.0786	***	0.0692	***
Housing burden	0.0229		0.0503	
Home ownership	0.2198	***	0.2112	***
Car access	0.052		0.0510	
HH size	-0.04		-0.0383	
Young kids in HH	-0.0247		-0.0360	
Rural	-0.3363	***	-0.2474	**
Black	-0.0036		-0.0094	
Hispanic	0.135		-0.0214	
Other non-White race	0.3573	***	0.2681	**
Citizenship status	-0.3445	***	-0.2961	***
Educational attainment	0.03	**	0.0219	
Stores in neighborhood	0.0104	**	0.0103	**
County food price index	--		0.0020	
Neighborhood deprivation	--		-0.0186	
N	3578		3286	
Adjusted R2	0.0483		0.0668	
Wald Chi2	--		206.6	***
State effect	--		0.0078	***
Neighborhood effect (rho)	--		0.0314	***
** = p<0.01, *** = p<0.001				

The Relationship between Neighborhood Food Environment and Food Store Choice on Purchasing Habits among SNAP and Lower Income Households, USDA FoodAPS Data

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Abstract

The objective of the study was to determine relationship between neighborhood food store availability, store choice and food purchasing habits among Supplemental Nutrition Assistance Program (SNAP) participating households. The study sample consisted of SNAP households (n=1581) and low income households participating in the USDA's National Household Food Acquisition and Purchase Survey (FoodAPS) a nationally representative cross-sectional survey of American households with household food purchases and acquisitions data. Main Outcomes: 1) Food purchasing choices (sugar-sweetened beverages, fruits and vegetables, snacks, water, and milk) obtained from store receipts over a one-week period; 2) food shopping activities was obtained from a log book of where food was purchased over a one-week period. Key findings indicated those SNAP households within 1 mile of a supermarket had higher odds of shopping at a supermarket (2.05 OR [95% CI 1.34, 3.15]) compared to those without a supermarket. Shopping at a supermarket was associated with greater odds of purchasing water and low-calorie beverages (OR 1.69 [95% CI 1.12, 2.54]) and fruits and vegetables (OR 2.50 (95% CI 1.52, 4.11]) compared to not shopping at supermarket among SNAP households. Additionally, a fractional multinomial logit analysis (n=4,664) similarly found that close proximity to superstores or supermarkets increases the share of weekly food purchases made there, and that car access increases purchases made at restaurants while decreasing purchases made at other food shopping venues. Findings suggest that policies aiming to improve food purchasing habits among SNAP need to consider how to situate stores where SNAP households will choose to shop.

Executive summary

Over the past several years, research has begun to examine various factors that may influence rates of obesity and dietary intake, especially among lower income households and those households participating in the Supplemental Nutrition Assistance Program (SNAP), formerly food stamps. Research has established key constructs related to dietary intake such as access to food stores, transportation, and socio-economic status, among many others. However, there have been mixed reviews with regard to neighborhood environmental factors with a direct correlation to dietary intake. It is not surprising the mix of results given that the construct of neighborhood environment may be a complex factor with several related variables. To these ends this project examined the construct of food store choice as a key factor in food purchases and amount spent at various food venues among SNAP households.

In Chapter 1 of this report, the project focused on the analyzing the relationship between SNAP households, food store choices, and food purchasing habits. The findings indicate that neighborhood availability of stores influences the type of stores where SNAP households choose to shop. The store choice has a subsequent effect on the types of food purchased among SNAP households. Those who live in neighborhoods with close proximity (1 mile) to supercenters or supermarkets tend to shop at those stores. Shopping at these types of stores influences what is purchased. At supermarkets SNAP households tend to purchase lower calorie beverages and fruits and vegetables. Whereas at supercenters SNAP households purchase healthier food items but at the same they purchase sugar-sweetened beverages, snacks, and higher calorie items. The findings suggest that policies aiming to improve the purchasing habits among SNAP households may consider the types of stores that are in close proximity to SNAP households.

In Chapter 2 of this report, the project aimed to identify and measure the relevance of consumer determinants of food venue choice using a fractional multinomial logit model. Using the nationally representative cross-sectional data from the USDA's National Household Food Acquisition and Purchase Survey (FoodAPS), we examined neighborhood food environment, household characteristics, and SNAP participation affected the shares of household weekly food expenditures made at different types of food venues—superstores, supermarkets, other FAH food venues, and all FAFH food venues. Using the fractional multinomial logit model enabled the analysis to consider shares of all food venue choices simultaneously and compare their relative importance for food acquisition via purchase shares.

Average marginal effects calculated from the fractional multinomial logit results estimated that close proximity to a superstore or supermarket increased the share of food purchases made at that store type. Car access increases the share of food purchases made at food-away-from-home (FAFH) venues and decreased the share of purchases made at food-at-home (FAH) venues other than a superstore or supermarket. SNAP participation also played a role, increasing the share of purchases at superstores and decreasing the share spent at FAFH venues, on average. Notably, neither income nor household size significantly impact purchase shares between the food venue categories. These findings suggest that both the neighborhood food environment, including transportation access, play a role in determining food venue choice for enough consumers for it to matter. While several localized studies have also found this to be true, this evidence is based on a nationally representative sample. In addition, SNAP participation affects food venue choice as well, though more research is needed to study the relationship between SNAP, food venue choice, food purchasing decisions and health; it may be that while SNAP participation leads to fewer purchases at FAFH venues, it may also negatively affect food purchasing decisions at FAH venues, and it is unclear whether this trade-off results in better or worse health outcomes relative to SNAP-eligible-not-receiving households.

CHAPTER 1: Logistic Analysis Relating Neighborhood Food Availability to Food Store and Purchasing Choices

Introduction

In recent years the role of the food environment has been suggested to be a key determinant in diet and obesity rates [1]. Distal determinants (upstream causes) particularly the availability of food venues (grocery stores, farmers' markets) surrounding a home [2-6] are thought to play a key role in dietary intake and obesity rates. In part due to the complexity of measuring the neighborhood food environment, studies reveal mixed results regarding the relationship between availability of food venues and diet and obesity status among various sub-populations [7-14]. One limiting factor of studies exploring availability is the lack of attention to the potentially mediating variable of store choice [15-17]. Research has suggested that the type and number of stores in a neighborhood may influence the type of stores residents choose to shop in, which in turn influence what is purchased and consumed [16,18]. In a recent study, qualitative findings point to individuals adapting their personal shopping choices to meet financial needs. Shoppers in this urban setting choose stores to avoid violence and crime, while also choosing stores based on convenience [17,19] and not necessarily closest to home [17]. Additional work has demonstrated that individuals typically choose stores which reflect their racial and economic profile [19]. While these studies provide insight into distinct urban populations, there remains limited understanding of how low income residents across the United States make food shopping choices and food purchases based on their neighborhood.

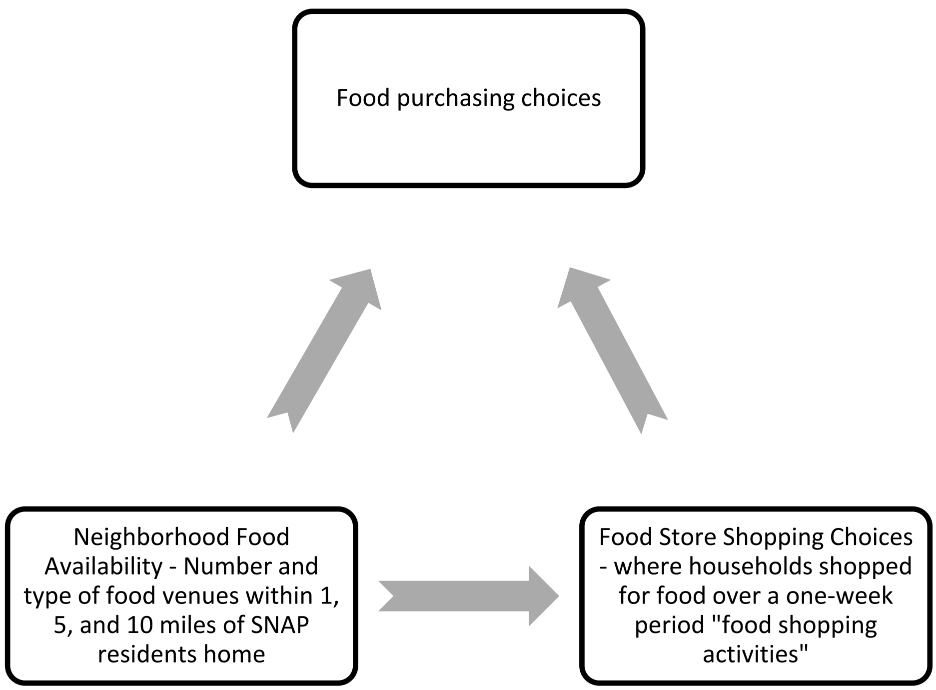
A sub population most affected by neighborhood access is lower income households are those participating in the Supplemental Nutrition Assistance Program (SNAP, formerly Food Stamps). Households participating in SNAP may be disproportionally impacted by both the neighborhood food environment and factors affecting individual store choice [20]. Several studies have reported that low-income households and those participating in SNAP have less access to grocery stores and stores selling healthier food items [20-22]. For example, households participating in SNAP often are living in neighborhoods with limited access to stores selling high quality and low priced healthy food items. SNAP households of differing racial and rural composition report residing in areas with limited access to stores accepting SNAP benefits[23]. SNAP households may live in food deserts and those that do have access to grocery stores may still choose to shop in neighborhood other than their own.

Additionally, many SNAP households are faced with challenges such as transportation and traveling to stores which accept EBT cards, posing limitations on store choice and thus purchasing habits. A recent study has pointed to SNAP households in lower income neighborhoods spending a large proportion of their benefits in medium size grocery stores [24], but several studies have also suggested that SNAP households shop outside their neighborhood for food a majority of the time [20,24,25]. The type of food venue SNAP households choose to shop in may be a reflection of their neighborhood but also the unique role that the actual SNAP benefits influences on the overall comfort that SNAP household members feel at stores [26] and acceptance of electronic benefit transfer (EBT) [27].

Existing research is limited by focusing only on food venue availability within a neighborhood and not expanding on how availability may influence store choice and purchasing habits. This study takes advantage of a unique data set, the FoodAPS data from United States Department of Agriculture(USDA), to examine multiple environmental influences of diet and obesity among SNAP participating households. The aims of the study are to determine the association between 1) neighborhood food store availability and the outcome of primary food store choice; 2) neighborhood food store availability and the outcome of types of food purchased; and 3) primary food store choice and the outcome of types of food purchase. For each of these comparisons, we examine SNAP Participating households.

Conceptual model

The figure depicts the relationship between neighborhood food availability, food store shopping choices, and food purchasing choices. Neighborhood food availability both proximally and distally (via food store shopping choices) affects food purchasing choices. The study aims to examine the relationships depicted here as a way to better understand food purchasing choices.



Data

Dataset - USDA's National Household Food Acquisition and Purchase Survey (FoodAPS) is the first nationally representative survey of American households to collect detailed and comprehensive data about household food purchases and acquisitions. Detailed information was collected about foods purchased or otherwise acquired for consumption at home and away from home. The survey includes nationally representative data from 4,826 households, including Supplemental Nutrition Assistance Program (SNAP) households, low-income households not participating in SNAP, and higher income households.

Survey - The primary respondent (PR) was identified as the primary food shopper for the household. The PR completed 2 in-person interviews and 3 brief telephone interviews. All household members were also asked to track and report food acquisitions during a 1-week period; scan barcodes on food products; save their store receipts; and write information in a food book. For a detailed description of the methods see http://www.ers.usda.gov/data-products/foodaps-national-household-food-acquisition-and-purchase-survey/documentation.aspx.

Sample - From the survey question asking "Has anyone in your household received SNAP in the past year" the SNAP variable was created with verification of date last received with state-level enrollment files for March through November 2012 (n= 1581). There may be endogeniety of those selecting into SNAP being different compared to other eligible households that select to not participate in SNAP which could influence store choice. Therefore, we tested several instrumental variables such as county level poverty index or median household income at the county level and did not find that an IV approach worked for modeling endogeneity. Thus we included covariates that conceptually would be related to selecting into SNAP and be associated with store choice.

Methods

Independent variables

Neighborhood Availability of Food Venues - The first independent variable was availability of food venues within 1 , 2, and 10 miles of the home. These distances were chosen based on the average miles from home SNAP households live from various food venues (see

Table 1). This variable was categorized as a binary variable, indicated whether each type of food store was present in the neighborhood surrounding each SNAP household for each mile buffer. The binary variable for each store type was coded as either the household did not have this store type within a 1, 2, and 10-mile radius of their homes (coded as "0") or they did have this store type within a 1,2, or 10-mile radius of their homse (coded as "1"). The following types of food venues were used: 1) supermarkets (greater than 50 employees but sells primarily food); 2) supercenters (greater than 50 employees and sells food plus a significant amount of other items such as clothes, automotive, household, furniture); 3) convenience stores; 4) combination grocery stores (i.e. food is sold as well as prepared food items and household goods); and 5) medium and large grocery stores (less than 50 employees). This information about the presence of each type of store within the geographic radius was derived from several steps, described below. First, each household was geocoded based on the latitude and longitude of FoodAPS households provided by Mathematica Policy Research. Then the USDA Economic Research Service (ERS) created point locations for the households. Block group, tract, county, and state FIPS code identifiers for both the 2000 and 2010 census geographies for the household points were obtained by using point-in-polygon geospatial analysis to identify in which 2000 and 2010 TIGER block group polygons each household was located. Data from the FoodAPS Geography component are based on 2010 census geographies. Second, the categorization of the food stores used the STARS dataset. The STARS system classifies stores into types. The types of stores are categorized based on industry standards. Place names were standardized through matching to the STARS database and then through a manual review and then a final place category and place type were assigned based on information from STARS, InfoUSA, Google, and keywords in the place names.

Dependent variables

Our first set of models examined the odds of shopping at a particular food venue during the week of data collection "food shopping activity". The second set of models assessed the relationship between neighborhood availability and store choice on foods purchased. These variables are described in detail below.

The variable "Food shopping activity" was derived from participants keeping a log of all the locations they purchased food for the home in one week. The following categories were used for the type of food venues the PR had their food shopping events at during the 1-week period: 1) supermarkets; 2) supercenters; 3) medium/large grocery stores; 4) combination grocery (grocery store plus retail such as clothing); and 5) dollar stores/convenience/gas stations labeled "convenience". These "food shopping activities" were categorized based on the type of food venue the PR purchased food from. There are 5 separate models for each type of food shopping activity. A binary variable was created to indicate if the PR shopped at this type of store (coded as "0" for not shopping at this store type and "1" for shopping at this type of store) over the one-week recorded period.

Our second set of models examines food purchases as the primary outcome. Food purchases were grouped in to the following categories_1) sugar-sweetened beverages (full calorie soda; sports drinks); 2) milk (including whole, skim, flavored); 3) low-calorie beverages and water; 4) juice including 100% fruit juice; 5) produce (fresh and frozen fruits and vegetables); 6) snacks (chocolate, candy, chips, pretzels). Cereal and breads were omitted since they could not be separated for sugar or fiber content, meats were omitted since they could not be separated for fat content. For each food category a binary variable was created if the household purchased the food category or if they did not purchase the food category during the one-week period (coded as

"0" for not purchasing the food category and "1" if they did purchase the food category). These groups are not mutually exclusive, such that a household can purchase snacks and milk in the same one-week period. There are 5 different models assessing the odds of purchasing these food categories. These food purchases for home (FAH) were collected using three methods: 1) survey booklets complemented with telephone calls, 2) hand-held scanners, and 3) post-survey processing of saved receipts. Respondents were asked to record all acquisitions on the Daily List in the Primary Respondent's Book. PRs were asked to fill out a corresponding detailed page for each acquisition on pages which asked for details such as location, date, and payment types. PRs were asked to scan items purchased using the hand-held scanner and record details about items that could not be scanned. They also were asked to attach the receipt. On days 2, 5, and 7 of the reporting week, PRs were asked to report all acquisitions that had been written on the Daily List. For FAH purchases, the telephone interviews collected information on the Daily List as well as supplementary information about any problems respondents had in using the hand-held scanner. At this time, respondents were reminded to save their receipts.

To capture each FAH purchase at the item level there was coalescing of information from the Food Books, telephone interviews, scanners, and receipts by USDA. There was matching to phone reported events through a double entry process, where a second data entry person resolved any inconsistencies. Items that were scanned or written were matched to receipts, and prices were assigned using the receipts information. In addition, item descriptions were updated using receipt information if the description from the scanned barcode or written information was limited or incomplete. Lastly, the categorization of the food purchases was matched to the isle.

Co-variates

Several key variables were collected to examine food shopping and neighborhood food venue availability. These include car ownership, primary reasons for choosing their primary store (prices of food, quality of food, location to home, good produce), household size, family size (the number of individuals who met the criteria for qualifying as being a legal relationship to the primary respondent), and household income (derived from asking the PR the household income including all assets). Additionally, distance from the respondent's home to each type of food store type (supercenter; supermarket; combination grocery; convenience; medium/large grocery) was used. Distance measures were obtained using Google Maps and the household's and place's geocoded addresses where the respondent acquired food. Lastly, to understand the differences between rural and urban counties interaction terms were tested to see if there was an effect. The interaction term was not significant but was retained in the model as cofounder, labeled as rural for census tract being in a rural area. All these covariates were included in the models below.

Analyses

To examine the association between neighborhood availability and food shopping activities a logistic model was used, controlling for car ownership, household size, distance to store type that corresponded to neighborhood availability of that store (i.e. distance to supercenter in the model examining neighborhood availability of supercenter), rural county designation, and household income. In all other analyses logistic regression was used while controlling for the same covariates in the logistic model. All models used survey commands to account for clustering of households at the neighborhood level using primary sampling units. Taylor estimation was used for robust standard errors. All analyses was done using Stata 14.0 [28].

Results

The demographic characteristics of the SNAP sample are presented in Table 1. SNAP households reported 90% as English being the primary language, 60% owning a car, and 25%

living in a rural census tract. SNAP households lived on average 3.2 miles away from a supercenter and 2.65 miles away from a supermarket, with an average travel time of 11.36 minutes to their primary food store. The distribution of stores visited during the week "food shopping activity" by SNAP participants indicates that a high percentage shop at supercenters (37%) followed by supermarkets (32%). Lastly, in regard to purchasing choices among SNAP households during a one-week period 62% bought sugar-sweetened, while 85% purchased fruits and vegetables.

Associations between food shopping events and food purchases (Table 4)

Supercenter Food Shopping - shopping at a supercenter was associated with greater odds of purchasing all food categories from any food venue over a one-week period.

Supermarket Food Shopping - shopping at a supermarket was associated with greater odds of purchasing water and low-calorie beverages (OR 1.69 [95% CI 1.12, 2.54]) and fruits and vegetables (OR 2.50 (95% CI 1.52, 4.11]). There is a similar relationship with medium/large grocery store shopping as well.

Convenience Store Food Shopping - shopping at a convenience store was associated with lower odds of purchasing any fruits and vegetables (.31 OR [95% CI .17-1.76) and water or low calorie beverage (.30 OR [95% CI .11, 1.76]) from any store type over a one-week period compared to those never shopping at a convenience store.

Discussion

This study is one of the first to utilize a comprehensive dataset examining purchasing habits at the individual level, which helps elucidate the relationship between neighborhood food availability, shopping activity, and purchasing habits. The relationships described here are meant to be descriptive only, and do not suggest that SNAP itself is driving these store choice and purchasing decisions. But rather, there are distinct behavioral choices that SNAP households make which may to a greater or lesser degree be influenced by the neighborhoods they reside in. First, neighborhood availability of stores was associated with the type of stores that SNAP household members choose to shop in over a one-week period. These data demonstrate that neighborhood availability of food stores with a supercenter have higher odds of shopping at a supercenter compared to those without a supercenter within 1 mile of their home and this food store choice is associated with higher odds of purchasing all food types. Although we find that healthy foods are being purchased at these venues, the result suggests that less healthy foods are being purchased at the same time. These results are situated within a growing body of research finding that neighborhoods with high access to supercenters is associated with higher body mass index (BMI) [29,30]. There is some suggestion that the behavior of shopping at supercenters is related to shopping once a month among SNAP household and buying foods in bulk that will last [25,31]. This type of shopping behavior and choice may lead to lower odds of purchasing healthier items such as milk and instead purchasing more shelf-stable items such as high calorie snack items [32]. The ability to make these links elucidates how neighborhood influences choice and thus what is purchased based on the type of food venue. These results are not suggesting that supercenters cause poor food purchases or obesity, but rather this result is one example of many complicated pathways which helps to explore the role of the food environment among low income and SNAP households.

A second key insight is found in the unique role that supermarket availability and shopping activity at this venue has among SNAP households. Among SNAP households, proximity to a supermarket (living within 1 mile) was associated with choosing to shop at this venue. While, living farther away from a supermarket was associated with choosing to shop at a convenience store or medium/large grocery store. Previous literature has suggested that access to supermarkets may be a piece in improving healthful diet [33] and lower odds of obesity [5,14,34]. Given, that although supermarkets carry a variety of unhealthy items they also stock a variety of healthy items at fair prices [35]. Conversely, others have found that the food available in SNAP authorized convenience store retailers carry a low variety of healthy food options [36]. Our results suggest that those choosing to shop at a supermarket or medium/large grocery store purchased fruits and vegetables and water. Since our analyses did adjust for living in a rural community the findings can suggest that regardless of rural or urban neighborhoods living farther away from stores may influence the type of store SNAP households choose to shop in and thus the types of food purchased. We are not suggesting the proximity is the only factor in store choice but rather that when policies are addressing improving food access for vulnerable populations addressing restructuring of the environment (such as moving stores where SNAP residents reside) or providing tax incentives such as transportation vouchers for those living farther away from stores [37], may be an effective strategy for improving diets [38].

Lastly, the lack of a strong direct association between neighborhood availability with food purchases among many of the food categories is similar to findings from previous studies [39,40]. This finding is not surprising given the many determinants (social, economic, physiological) along the pathway between neighborhood food store availability and purchasing habits. The lack of findings reinforces previous findings indicating the need for precise and accurate measures of the food environment, such as store choice [41,42].

There are several important limitations of this study that need to be addressed. Although the USDA FoodAPS data is the most extensive collection of food purchasing acquisitions to date, the data collection period was only over a one-week time period. While this one-week period may not reflect all the food purchases in a given month, the highly detailed data provided compensates somewhat for the limited time period covered. Extensive efforts were taken with collection of receipts however it is always possible that some food was not recorded in the food book or through the scanners. As with any self-report survey there can be over or under reporting. The neighborhood boundaries do not necessarily reflect each household's true operational neighborhood and thus these are investigator defined boundaries. While the 1, 5 and 10-mile radius was used, it does not account for ease of transport such as traffic patterns, barriers to walking, and other traffic pattern measures.

The implications of these finding points to the importance of not simply measuring the neighborhood food environment but taking a more nuanced approach to understanding the intricacies between neighborhood availability, store choice, and purchasing habits. Additionally, among lower income households those participating in SNAP may have unobserved characteristics that influence their food shopping and purchasing characteristics. Future studies among SNAP households may want to consider the in store contents of where SNAP households shop as just as vital as improving availability within neighborhoods. Lastly, policies are needed which address improving access to different food store types for SNAP households, which may help to improve health outcomes through the role of improved food purchases.

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book or through the scanners. As with any self-report survey there can be over or under reporting. The neighborhood boundaries do not necessarily reflect each household's true operational neighborhood and thus these are investigator defined boundaries. While the 1-mile radius was used, it does not account for ease of transport such as traffic patterns, barriers to walking, and other traffic pattern measures.

Conclusion

The implications of these finding points to the importance of not simply measuring the neighborhood food environment but taking a more nuanced approach to understanding the intricacies between neighborhood availability, store choice, and purchasing habits. Additionally, among lower income households those participating in SNAP may have unobserved characteristics that influence their food shopping and purchasing characteristics. Future studies among SNAP households may want to consider the in store contents of where SNAP households shop as just as vital as improving availability within neighborhoods.

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Table 1. Descriptives of neighborhood, food store choice, and purchasing habits among SNAP households, USDA FoodAps 2012 SNAP (n=1581)

	mean (SE)/percentage
Family Size	2.78 (.09)
Household Size	3.10 (.09)
English as primary language	90%
Household Receiving USDA food from local program	90%
Car Ownership	60%
Residing in rural census tract	25%
Perception of Household Diet	
Excellent	5%
Very Good	18%
Good	44%
Fair	20%
Poor	4%
Reasons for Not Buying Healthy Food (% Agree)	
Costs too much	47%
Too busy to prepare food	19%
Household doesn't think healthy food tastes good	26%
Family is eating enough healthy food	37%
Primary shopper reports eating right amount of F/V	
Eat right amount	23%
Eat More	77%
Eat Less	<1%
Reads the Nutrition Facts Panel	
Always	12%
Most of the time	15%
Sometimes	30%
Rarely	13%
Never	28%
Never seen panel	1%
Distance to Food Venues in Neighborhood (miles)	
Super Center	3.20 (.61)
Super Market	2.65 (.67)
Convenience Store	1.14 (.17)
Grocery Store	3.89 (.68)

<u>Shopping Characteristics</u>	
Travel Time to primary store self-report (minutes)	11.36 minutes
Travel Cost to store (self-report)	$2.79
<u>Neighborhood Characteristics</u>	
No SNAP retailers in .25 miles	53%
No SNAP retailers in .50 miles	30%
No SNAP retailers in 1 mile	16%
No Super Center in .5 miles	80%
No Super Center in 1 mile	55%
No Super Market in .5 mile	79%
No Super Market in 1 mile	49%
<u>Primary Store (Self-Report)</u>	
Super Center	49%
Super Market	48%
<u>Reasons for Primary Store</u>	
Low Prices	61%
Good Produce	12%
Good Quality	16%
Close to where I live	47%
<u>Shopping Choices 1-week period</u>	
Super Center	37%
Super Market	32%
Convenience	8%
Grocery	4%
Farmers Market	3%
Other (Dollar, Club)	1%
<u>Distance to Shopping Choices (1-week period)</u>	
Place distance	5.25 (.61)
Location accepted SNAP/EBT	87%
<u>Food Buying Choices (1-week period)</u>	
Sugar-sweetened beverages	62%
Milk	54%
Water/Low-Calorie Beverages	21%
Juice	23%
Fruits and Vegetable	85%
Snacks and Candy	73%

Associations between neighborhood food store availability and food shopping activities (Table 2)

Supermarket Availability **-** if a supermarket was within 1 mile of the home there was lower odds of shopping at supercenter (.36 OR [95% CI .22, .60]) compared to not having a supermarket within 1 mile. Those living within 1 mile of a supermarket had higher odds of shopping at a supermarket (2.05 OR [95% CI 1.34, 3.15]) compared to those without a supermarket within 1 mile. Of note, is that as supermarkets are farther away from a SNAP households the odds of shopping at a convenience store or combination grocery store increase. Such that, those with a supermarket 10 miles away report higher odds of shopping at a convenience store during the week (OR 3.57 [95% CI 2.24, 5.25]) and a combination store (OR 1.19 [95% CI 1.82, 2.79]).

Supercenter Availability **-** if a supercenter was within 1 mile there was higher odds of shopping at this venue (2.61 OR [95% CI 1.41, 4.79]) and less likely to shop at a supermarket (.44 OR [95% CI .26, .72])compared to those without a supercenter within 1 mile of the home. These relationships are not seen as stores are farther away from the SNAP household.

Medium/Large grocery store Availability **-** if a grocery store is within 5 miles or 10 miles there was higher odds of shopping at this venue (OR 3.97 [95% CI 1.81, 8.67]) and (OR 3.47 [95% CI 1.38, 8.74]). This result highlights the possible link between proximity of stores in a neighborhood and store choic

Table 2. Odds Ratio of food shopping activities over one-week in relation to the type of food stores within a 1, 5, and 10 mile buffer of the household among SNAP households, USDA FoodAps 2012

	Food Shopping Activities over a one-week period			
Food Venues (1 mile buffer)	Supercenter	Supermarket	Grocery	Convenience
Supermarkets	**.36 (.22, .60)***	**2.05 (1.34, 3.15)***	.77 (.50, 1.19)	1.45 (.74, 2.84)
Super Centers	**2.61 (1.41, 4.79)***	**.44 (.26, .72)***	1.53 (.81, 2.91)	.85 (.55, 1.31)
Grocery Stores	1.14 (.75, 1.75)	.64 (.42, 1.00)	1.83 (.85, 3.98)	.76 (.41, 1.43)
Convenience Stores	1.05 (.65, 1.75	.86 (.52, 1.43)	.45 (.20, 1.01)	1.33 (.54, 3.28)
Combination Grocery	.82 (.50, 1.36)	1.05 (.60, 1.87)	1.54 (.64, 3.72)	.93 (.38, 2.26)
Food Venues (5 mile buffer)				
Supermarkets	.67 (.36, 1.26)	1.97 (.96, 4.05)	.86 (.37, 1.98)	.82 (.35, 1.91)
Super Centers	1.25 (.79, 1.92)	1.56 (.81, 2.98)	.90 (.43, 1.87)	.99 (.44, 2.21)
Grocery Stores	1.17 (.76, 1.81)	1.16 (.71, 1.92)	**3.97 (1.81, 8.67)***	.76 (.47, 1.21)
Convenience Stores	1.81 (.62, 5.31)	1.03 (.28, 3.76)	.57 (.15, 2.26)	1.74 (.33, 1.92)
Combination Grocery	.75 (.35, 1.61)	1.69 (.76, 3.78)	1.65 (.31, 4.36)	1.02 (.41, 2.58)
Food Venues (10 mile buffer)				
Supermarkets	.58 (.19, 1.76)	4.30 (.97, 1.91)	.62 (.23, 1.61)	1.60 (.23, 1.32)
Super Centers	1.49 (.91, 2.45)	2.33 (.93, 5.82)	1.01 (.42, 2.43)	1.55 (.47, 5.11)
Grocery Stores	1.16 (.60, 2.22)	1.02 (.57, 1.81)	**3.47 (1.38, 8.74)***	.95 (.51, 1.79)
Convenience Stores	.25 (.02, 3.75)	**3.57 (2.24, 5.25)***	.46 (.04, 6.17)	.98 (.45, 1.32)
Combination Grocery	.34 (.05, 2.37)	**1.19 (1.82, 2.79)***	.97 (.14, 6.66)	.63 (.08, 5.29)

logistic regression model adjusted for household income, distance to store, household size, car ownership, rural census tract designation
* p<.05

Associations between neighborhood food availability and food purchases

There were no statistically significant food purchasing associations found between neighborhood food store availability and types of food purchased (Table 3).

Table 3. Odds of purchasing food categories when different types of food venues are within 1 mile of residence among SNAP participating households, USDA FoodAps 2012

	Food Category Purchases during a one-week period					
Food Venues (1 mile buffer)	SSB	Milk	Water/Low-Calorie	Juice	Fruit/Vegetable	Snack
Supermarkets	.99 (.66, 1.46)	.63 (.38, 1.03)	1.08 (.68, 1.72)	1.01 (.65, 1.60)	.79 (.50, 1.25)	.75 (.52, 1.07)
Super Centers	.89 (.59, 1.34)	.85 (.60, 1.22)	1.19 (.74, 1.92)	.99 (.66, 1.49)	.76 (.47, 1.25)	.76 (.51, 1.13)
Grocery Stores	.92 (.60, 1.42)	.95 (.64, 1.42)	.72 (.49, 1.07)	.97 (.69, 1.36)	1.45 (.85, 2.47)	.84 (.53, 1.34)
Convenience Stores	.98 (.62, 1.55)	.81 (.46, 1.42)	1.53 (.98, 2.36)	1.09 (.62, 1.92)	.76 (.40, 1.46)	.77 (.42, 1.41)
Combination Grocery	1.10 (.66, 1.83)	1.24 (.78, 1.98)	.98 (.62, 1.57)	.99 (.64, 1.53)	.81 (.45, 1.45)	.83 (.53, 1.30)

logistic model adjusted for household income, household size, car ownership, rural residence
5 separate models predicting how neighborhood availability is associated with food purchase categories
similar results were found for 5 and 10 mile buffer

Table 4. Odds of purchasing certain foods when shopping at various food venues over a 1-week period among SNAP, USDA FoodAps 2012

SNAP participating Households

Food Shopping Activities 1-week period	SSBMilk	Water/Low	Juice Calorie Beverages	Fruit/Vegetable	Snack	
Super Center	**1.60 (1.06, 2.41)***	**1.92 (1.36, 2.68)***	**2.01 (1.27, 3.16)***	**2.31 (1.24, 4.30)***	**2.11 (1.36, 3.28)***	**2.23 (1.55, 3.19)***
Super Market	1.22 (.82, 1.83)	1.30 (.84, 2.03)	**1.69 (1.12, 2.54)***	1.12 (.59, 2.12)	**2.50 (1.52, 4.11)***	1.44 (.94, 2.23)
Convenience	**1.59 (1.02, 2.49)***	.66 (.34, 1.27)	1.39 (.87, 2.22)	.57 (.31, 1.05)	**.57 (.32, 1.00)***	1.04 (.63, 1.71)
Grocery	**1.93 (1.06, 3.51)***	.71 (.32, 1.60)	.85 (.48, 1.53)	.82 (.43, 1.60)	**2.92 (1.36, 6.31)***	.77 (.38, 1.55)

logistic model adjusted for hhsize, income, distance to store, car ownership, rural designation census tract
p<.05

CHAPTER 2: Fractional Multinomial Logit Analysis on Shares of Household Weekly Food Purchases at Different Food Venues

Introduction

The Centers for Disease Control and Prevention (CDC) identifies poor nutrition as one of four health risk behaviors that cause much of the illness related to chronic diseases and conditions (e.g., obesity, diabetes, heart disease), which collectively are the leading causes of death and disability in the United States.[1] While unhealthy food consumption may directly lead to adverse health outcomes, a considerable amount of research also looks at how proximal access to food venues (i.e., the neighborhood food environment) affects food consumption, thereby indirectly affecting the impact of chronic diseases and conditions. Such research tends to focus on obesity as the primary adverse health outcome,[2-6] but findings have been mixed in regards to how the neighborhood food environment affects diet and obesity.[7-13] In fact, a systematic review of 71 studies in this literature found limited evidence for correlations between local food environments and obesity.[14] Faced with a similar task in a systematic review of local food environment interventions, one recent review starts by asking not simply what works and what does not, but rather *for whom* and *under what circumstances* does a change in food availability influence diet.[15] This framework accepts that because the role of a food environment in determining food intake is circumstantial, there may be a more generalized model to food acquisition behavior.

Taking a step back, some studies have examined the determinants and impact of food venue choice (i.e., where does a consumer choose to acquire food).[16-18] For example, a 2011 study of Kentucky adults found that food venue choice was significantly correlated with dietary intake relative to food venue availability. This paper also acknowledges that while understanding food venue exposure along regular travel patterns is important, we must also understand if and how food venue choice influences travel patterns, and moreover, if decisions to shop in a disadvantaged neighborhood may be more a function of socio-economic status and transportation than the neighborhood food environment per se.[19] This and related studies research neighborhood food environments by asking the broader questions: What factors affects food venue choice? And then, how does food venue choice affect dietary intake and health outcomes? The present research objective addresses the former question by studying the determinants of food venue choice using robust data from the United States Department of Agriculture's (USDA) National Household Food Acquisition and Purchase Survey (FoodAPS), a nationally representative survey of 4,826 American households containing detailed information on household food purchases and acquisitions. Based on a review of the literature, our conceptual model hypothesizes that food venue choice is associated with SNAP participation and eligibility, neighborhood environment, and household socioeconomic characteristics.

The challenge in modeling food venue choice is that consumers often choose more than one food venue from which to acquire their food. For example, within any given week, a household may choose to purchase half of its food from a grocery store, a quarter from a convenience store, and another quarter from fast food restaurants. Therefore, our analysis will use a fractional multinomial logit econometric model to estimate the effect of explanatory variables on shares of weekly food purchases made at several types of stores simultaneously. By modeling shares of food purchases made at store types as outcome variables, we avoid the risk of a simultaneity bias associated with including store choice as an explanatory variable. Thus, the estimates will contribute to the literature on store choice where the analytical focus on a single store type in an environment with several types of stores oversimplifies the household’s food purchasing decisions. Using the coefficients generated from the fractional multinomial logit, we will calculate average marginal effects to present how the explanatory variables affect store choices within a household.

Literature review

Where we acquire our food affects which foods we acquire; this food acquisition closely relates to which foods we consume; and food consumption impacts human health. What remains undecided is: how do consumers decide where to acquire their food? A qualitative analysis of interviews of primary household food shoppers identified four main factors: proximity to home and work, financial considerations, produce and meat availability and quality, and store characteristics.[17] The literature informs a conceptual framework used to model food venue choice.

First, as discussed in the introduction, a model of food venue choice must consider the consumer's neighborhood food environment. However, the assumption that consumers shop near their residence (i.e., their neighborhood food environment) is increasing questioned.[16] For example, a study of two low-income urban food deserts found little correlation between the nearest supermarkets and the type of store where residents chose to do their shopping. However, store choice was correlated with BMI, supporting that there is a link between store choice and human health.[20] While a model should allow for travel patterns to be influenced by food venue choice, it is also true that research on food venue exposure along normal travel routes is needed.[19] Due to these dissenting viewpoints, our model conceptualizes the neighborhood food environment via two of its components—proximity to store and access to transportation—recognizing this as a reduced characterization.

There is also a growing body of research that finds that it is not the absolute number, but the relative density (proportion) of certain food venue types in the neighborhood food environment that affects food venue choice.[21-25] For example, one study that a higher ratio of grocery stores and produce vendors relative to fast-food restaurants and convenience stores decreases the odds of obesity.[22] Additionally, a more recent study found that proximity to a high volume of fast-food restaurants had a much larger effect on body weight if they were the predominant restaurant type in the area, suggesting that consumers were impacted not so much by the absolute number of fast-food restaurants but more by the lack of alternative dining options.[21] The same may be true for food-at-home venues.

Secondly, evidence suggests that store choice is likely influenced by household characteristics, including members' income and education and overall household size and transportation options. For example, a study of rural households found that those with a grade-school education reported relatively limited access to produce and acquiring food at convenience stores and buffets more frequently, perhaps as a result of a lower income.[9] Other studies have found correlations between store choice and education[18] and income. Another study found that while distance travelled to a household's preferred food shopping venue did not significantly vary by race or socioeconomic status, socioeconomic differences did affect the mode of transportation.[16]

Third, SNAP participation may affect food venue choice. Already, evidence suggests that SNAP and non-SNAP households of similar economic backgrounds have dissimilar dietary intake; SNAP recipients are more likely to consume sugar-sweetened beverages, red meat, potatoes and less likely to consume whole grains[26-29]. One way SNAP participation may affect food venue choice stems from the fact that SNAP benefits can only be used to purchase specific items, which may be more or less available at venues. Households with time constraints may prefer larger stores where they can conveniently use all of their SNAP benefits in one trip.

Additionally, SNAP-recipient consumers may prefer food venues where electronic benefit transfer (EBT) is accepted and use of SNAP is not shunned.[30] However, there is also a possible confounding relationship between SNAP participation and the neighborhood food environment regarding their effect on food venue choice.[26] Thus, it is critical that both factors are controlled for in our analysis to tease out the different effect on food venue choice.

Conceptual Model

Based on the literature review, we hypothesize that food venue choice is a determinant of neighborhood environment, household socioeconomic characteristics, and SNAP participation, recognizing that these factors are not necessarily independent from each other.

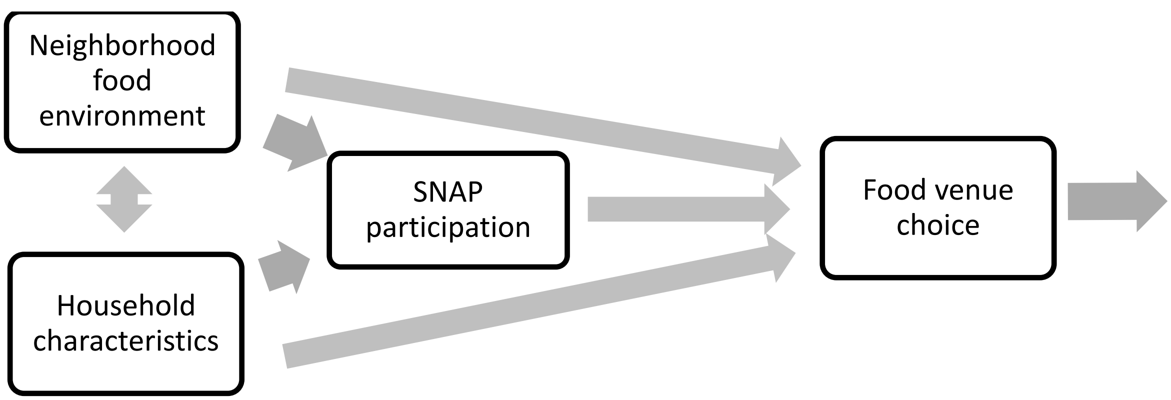

Figure 1: Consumer Determinants of Food Venue Choice

Figure 1 depicts a rudimentary illustration of the model. For any given household, the neighborhood food environment and household characteristics are related. Moreover, both factors may affect SNAP participation; certain household characteristics are required to be SNAP eligible and the neighborhood food environment (e.g., proximity to stores accepting EBT) will affect the decision to participate. All three factors help determine food venue choice. The final arrow reminds that food venue choice itself determines food acquisition and, by extension, food consumption and health outcomes, though testing this part of the theory is beyond the scope of this study.

Two factors absent from Figure 1 are those producer determinants of food venue choice. Of the four main factors identified by primary food shoppers, two were consumer determinants (proximity to home and work and financial considerations), and two were producer determinants (produce and meat availability and quality, and store characteristics).[17] Please note that our model and subsequent analysis focus on consumer determinants due to limitations posed by the econometric methodology.

Data

The data come from USDA's National Household Food Acquisition and Purchase Survey (FoodAPS), a survey of 4,826 American households containing detailed information on household food acquisitions. The stratified random sampling strategy used for FoodAPS was designed to be nationally representative for SNAP households, low-income households not participating in SNAP, and higher income households, making it ideal for exploring the relationship between SNAP participation, the neighborhood food environment and store choice.

Within each household, data were collected for foods purchased or otherwise acquired for consumption at home and away from home, including foods acquired through assistance programs. Specifically, members of participating households were asked to keep daily records of food acquisitions over a one-week period using barcodes and store receipts. For each food acquisition event, participants were asked to report where the food was purchased and the total amount paid, among other things. To improve reliability, acquisition and purchase data was relayed over the phone by the primary food shopper and then later checked using the records contained in each member’s food book. Additionally, the household’s primary food shopper completed two in-person interviews and three brief telephone interviews to gather information about household characteristics. For a more detailed description of the methods, or to learn more about other data collected, see information on USDA's FoodAPS website.[31]

Methods

Fractional Multinomial Logit Model

The fractional multinomial logit was developed in 2002,[32] and has been described and applied by a few others.[33-35] The technique combines two variations on the standard logit model: the fractional logit and the multinomial logit. The consequence is a model where the explained variable y is able to represent the different shares of various types of y, all of which sum to one, much like the various categories in a pie chart. For this reason, the model is in the family of multivariate fractional logit models, because it is measuring the changes in shares of multiple variables simultaneously as a result of some explanatory variables.[36] In other words, it allows one to ask how the slices of a pie chart change between observations as a result of differences in a certain set of related factors. In this analysis, the whole pie chart is a household's total weekly food expenditures, meaning that the fractional multinomial logit model can help to see how changes in household characteristics affect the share of weekly expenditures spent at different types of stores and locations.

Combining some main elements of the fractional logit and the multinomial logit models to come up with the fractional multinomial logit model is fairly straightforward. The fractional logit model differs from the standard logit model as it treats the dependent variable as an expected value defined by an interval rather than a response probability.[37] Similarly, the fractional multinomial logit model must ensure that the expected share of any outcome j lies between parameters A and B and that the sum of shares for all outcomes sums to unity. Mathematically,

$$A \leq E\left(S_j \middle| x\right) \leq B, \qquad j = 0, 1, 2, \ldots, J, \text{where } A = 0 \text{ and } B = 1. \tag{1}$$

$$\sum_{j=0}^{J} E\left(S_j \middle| x\right) = 1 \tag{2}$$

This technique permits the evaluation of shares of an outcome rather than the probability of whether or not the outcome occurred.

The multinomial logit describes a technique for comparing the response probabilities for several categorical variables through use of a pivot outcome, which is the difference between one and the sum of expected shares for all other outcomes. Likewise, the fractional multinomial logit model defines a pivot outcome as well, but again, its dependent variables are fractional outcomes, not response probabilities. Defining $j = 0$ as the pivot outcome, the fractional multinomial model also must establish expressions for every outcome within the logit framework.

$$E\left(S_j \middle| x\right) = G(\beta_0 + \beta_k x_k) = G(z) = e^z / (1 + \sum_{j=1}^{J} e^z), \qquad j = 1, 2, \ldots, J. \tag{3}$$

$$E(S_0 | x) = G(\beta_0 + \beta_k x_k) = G(z) = 1 / (1 + \sum_{j=1}^{J} e^z), \qquad j = 0. \tag{4}$$

Use of the pivot outcome equation (4) to estimate multiple outcomes makes it possible to evaluate the effect of explanatory variables on several variables simultaneously. Therefore, when joined together, the fractional multinomial logit model estimates coefficients which predict the expected share of several categorical outcomes within a defined interval.

By embedding the fractional logit function into the multinomial logit quasi-likelihood function, the econometric model can measure shares of outcomes—not probabilities—in what is a simplified form of the log likelihood function.[34] This new function, as a member of the linear exponential family, uses a quasi-maximum likelihood estimator (QMLE) and is efficient and consistently normally distributed provided the fractional logit function holds true.[33] The QMLE approach will maximize this new function and, with the assistance of a fractional multinomial logit Stata package,[38,39] run until it converges and is able to predict shares.

However, because the multinomial logit estimator requires some normalization, these QMLE estimates will correspond to the coefficients in the multinomial shares model.[34] Thus, it produces coefficients that may be difficult to interpret. For this reason, using the coefficients predicted from an estimation of the fractional multinomial logit model, we calculate average marginal effects (i.e., the mean of the marginal effects for all observation, as opposed to the marginal effect at the variable's mean) for every independent variable on each dependent variable.

Dependent variables

The dependent variables are the share of total weekly food expenditures made at different locations, which we are calling food venue purchase shares. Share of food expenditures made at superstores and supermarkets were large enough to comprise their own categories, but due to the high number of store types, other expenditures were aggregated. In this manuscript, we aggregated all other FAH expenditures not made at a superstore or supermarket into a third category; this includes grocery stores, convenience stores (including gas stations), and smaller venues like farmers markets. Finally, all FAFH expenditures into a fourth category, which includes all weekly expenditures made at sit-down restaurants and fast-food restaurants. The shares of a household's total food expenditures made at these four location categories are represented by *Superstore Share*, *Supermarket Share*, *FAH Other Share*, and *FAFH Share*. These are the four dependent variables—the food venue purchase shares for superstores, supermarkets, other FAH stores, and FAFH locations—the sum of which represent all weekly food expenditures made by the household.

Table 1 summarizes some basic descriptive information about the dependent variables used in the analysis. Even after group all other FAH stores, *FAH Other Share* is still the smallest category, representing about 14% of food expenditures, on average. Conversely, *FAFH Share* is the largest category at about 35%, followed by *Superstore Share* at 28%. The standard deviations reveal that these shares are heterogeneous between households, and the minimum and maximums suggest that each category is the location for both none and all of at least one household's food expenditures. These statistics suggest that there is sufficient variance between households in shares of food expenditures at these locations for the analysis.

Independent variables

The independent variables selected to predict shares of food venue purchases are intended to represent those factors which our conceptual model hypothesizes most influence shopping behavior. These variables are summarized in Table 2. First, representing the neighborhood food environment, *Mile to Superstore* and *Mile to Supermarket* are both binary variables indicating if a household's location is within a one-mile radius of a superstore or supermarket, respectively; in both cases, this applies to approximately 43% of households in the analyzed sample. Additionally, *Car* is a binary variable indicating if any household member owns or leases at least one vehicle, which is true for 84% of households in the analyzed sample.

Second, representing household characteristics, *ln(Income)* is a continuous variable derived from household income and given a log transformation to correct its skewed distribution (incomes less than one were coded as 0); as a result, it estimated coefficients should be interpreted as the marginal change resulting from one-percent increase in household income.

Moreover, *Size* is a continuous variable representing the total number of members currently living the household, which is about 3 people for the average sampled household; while it is also skewed, a log transformation was not applied as it would complicate interpretation.

Finally, *SNAP* is a binary variable indicating if any member of the household is a recipient of SNAP benefits (32% of the sample). Collectively, these variables will control for distance to major food venues, car access, income, household size, and SNAP participation in the econometric model.

Results

Drawing from 4,664 observations, the fractional multinomial model converged on a log pseudo-likelihood of -157,100,000 with a Wald chi-squared of 468.95. To ensure that standard errors were estimated robustly, observations were "clustered" by a pseudo primary sampling unit (PSU) and adjustments were made for 57 clusters where households in the same PSU.
Table 3 presents the average marginal effects of the independent variables on purchase shares from different food venues. Average marginal effects that are statistically different from zero at the 5%, 1%, and 0.1% levels are indicated with one, two, or three asterisks, respectively; coefficients that are not statistically different from zero at the 5% level or below receive no asterisk. Of the model's 120 coefficients for average marginal effects, 24 are significant at the 10% level.

A few other points must be made about the interpretation of the coefficients in Table 3. For binary variables, the coefficients represent the average change in purchase shares from different food venues resulting from a shift in the variables' minimum to its maximum, across all households. For continuous variables, the coefficients represent the mean of the change in food venue purchase shares as a result of a marginal change in the explanatory variables for all observations. Furthermore, because food venue purchase shares must always sum to one—as they are defined by a finite amount of total weekly food expenditures—the sum of the average marginal effects for any one explanatory variable is zero; in other words, what an explanatory variable might take away from one share, it gives to other shares. The upcoming discussion will highlight coefficients deemed to have statistical relevance in explaining difference in food venue purchase shares across all households in the sample.

Discussion

It is useful to review these results through the lens of the conceptual model. First, Table 3 provides some statistically significant results relating to one-mile proximity to a superstore or supermarket—variables that represent the neighborhood food environment. Specifically, the model finds that households living within one mile of a superstore are associated with a 5.4% increase in food expenditures at a superstore and a 10% decrease in food expenditures at a supermarket, which are unsurprising. However, this condition is also correlated with a 5.0% increase in food spending on FAFH; this may make sense if FAFH establishments are often located near superstores or if superstores and FAFH locations attract similar customers. Finally, living within one mile of a supermarket is associated with a 12% decrease of food expenditures at superstores, a corresponding 10% increase of food expenditures at supermarkets, and no significant effect on the share of FAFH. While not fully supporting the assumption that consumers will only shop near their residence, these findings do suggest that proximity to a food venue location is, in fact, an important determinant of store choice for many consumers. If so, then the variety of foods offered at nearby superstores and supermarkets are feasibly correlated to food acquisition, consumption, and health.

Relatedly, car access is a variable with statistically significant results. Specifically, vehicle ownership or lease by a household member is correlated with a 4.7% decrease in food expenditures at other FAH locations and a 3.6% increase at FAFH locations. This may be because consumers are more likely to go some distance for a specific FAFH location, but only frequent other FAH locations that are nearby. Either way, this finding highlights that transportation access is an important consideration along with the neighborhood food environment.

Second, the results find that neither income nor household size is a statistically significant predictor for any food purchase share in model, all else equal. Thus, our results do not find additional evidence that a household's socioeconomic status, on its own, influences store choice. However, there may be particular location types for which income or household size is associated with a greater or lesser share of food expenditure if these effects canceled each other in either of the aggregated categories. Still, we maintain that income and household size remain important controls in the model.

Third, the results in Table 3 suggest that SNAP participation does influence store choice, or to be exact, the percentage of weekly food expenditures that are spent at a particular store. It is important to reiterate that this is true even after controlling for proximity to store type (i.e., neighborhood food environment) and household size and income. Specifically, the model estimates that households with at least one member receiving SNAP benefits will spend 5.7% more of food expenditures at a superstore relative to non-SNAP households. This is compensated by SNAP households spending an estimated 7.3% less of food expenditures on FAFH relative to non-SNAP households. Both coefficients are highly significant and suggest that, all else equal, SNAP participation is associated with a lesser share of weekly food expenditures being made on FAFH, and a greater share at superstores. One might consider these findings in the context of the literature linking FAFH with adverse nutritional outcomes.[40,41] Together, they support a hypothesis which suggests that SNAP may encourage healthier food consumption, although this contradicts some of the current literature.[26-29] This may be because store choice affects food acquisition differently for SNAP and non-SNAP recipients—that is, SNAP participation affects food venue choice away from FAFH venues, but encourages unhealthy food purchases at FAH stores. Regardless, the results suggest that more research is warranted to understand the complex relationship between SNAP participation, food store choice, food acquisition and health outcomes.

Conclusion

This study aimed to identify and measure the relevance of consumer determinants of food venue choice. After reviewing the literature, a conceptual model was designed that viewed food venue choice as a function of the neighborhood food environment, household characteristics, and SNAP participation. Using nationally representative cross-sectional data from the USDA's FoodAPS, we examined how a set of explanatory proxy variables affected the shares of household weekly food expenditures made at different types of food venues—superstores, supermarkets, other FAH food venues, and all FAFH food venues. This was possible by using the fractional multinomial logit model, which enabled the analysis to consider all food venue choices simultaneously and compare their relative importance for food acquisition via purchase shares.

Results were reported as average marginal effects in Table 3, where the estimated coefficients represent the average change in food purchase shares at the different food venues across the sample given one-unit changes in the explanatory variables. The analysis estimated that close proximity to a superstore or supermarket increased the share of food purchases made at that store type. Car access increases the share of food purchases made at FAFH venues and decreased the share of purchases made at FAH venues other than a superstore or supermarket. SNAP participation also played a role, increasing the share of purchases at superstores and decreasing the share spent at FAFH venues, on average. Notably, neither income nor household size significantly impact purchase shares between the food venue categories.

This study's limitations should also be considered when interpreting the findings and planning future research. First, as this study uses food purchases to measure the relative importance of one food venue over others, it effectively discounts the importance of markdown food and omits food venues (e.g., family, neighbors, colleagues, soup kitchens) from whom food may be free. As this may serve a larger percentage of caloric intake for lower-income households, this is an important consideration in connecting food venue choice to consumption and health outcomes. For example, future work using the FoodAPS dataset could consider using a fractional multinomial logit analytical framework to look at the shares of calories and nutrients coming from different sources. However, a limitation of the fractional multinomial logit model is that it is unable to incorporate changes to the outcomes that are due to differences in characteristics between the outcomes themselves. Thus, the availability and quality of certain food as well as food venue characteristics—two other factors that are important to primary food shoppers when choosing a food venue[17]—are not controlled for the in the model. Incorporating all of these food venue factors into a decision-making model for consumers is another challenge to excite future work.

These results provide some interesting considerations for the literature, especially given the reliability of the data and the analytical approach. Both the neighborhood food environment, including transportation access, play a role in determining food venue choice for enough consumers for it to matter. While several localized studies have also found this to be true, this evidence is based on a nationally representative sample. In addition, SNAP participation affects food venue choice, though more research is needed to study the relationship between SNAP, food venue choice, food purchasing decisions and health; it may be that while SNAP participation leads to fewer purchases at FAFH venues, it may also negatively affect food purchasing decisions at FAH venues, and it is unclear whether this trade-off results in better or worse health outcomes relative to SNAP-eligible-not-receiving households. What is clear is that the impact of SNAP benefits on food acquisition is complex, and quick endorsements or critiques of its impact on health food purchases should be cautiously considered in light of an ever expanding literature.

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The Influence of SNAP Participation and Food Environment on Nutritional Quality of Food at Home Purchases

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Abstract

A growing body of research describes how individuals make food shopping decisions in both time and space. The FoodAPS dataset provides a unique opportunity for understanding these patterns among a large sample across income, SNAP status, and settings. We addressed three questions in our research: (1) Where do participants shop for food at home (FAH) and how do individual characteristics interact with store characteristics and distance? (2) How does the nutritional content of foods purchased change as time from SNAP distribution increases? and (3) How does store choice influence the nutritional quality of FAH purchases? We used a conditional logit model to answer the first question, determining that overall, participants choose full-service supermarkets, larger stores, and stores closer to home but that store choice is influences by SNAP status, ethnicity, race, sex, car ownership and the level of urbanization of the county of residence. For the second question, we used general linear modeling to determine changes over time in dietary quality of FAH purchases, as measured by composite Health Eating Index (HEI) score. We found an increase in HEI-2010 score in the days immediately following SNAP distribution followed by a decrease until 20 days after distribution and then a moderate increase to the end of the SNAP-cycle. For the final question, we used a generalized estimating equation (GEE) model for repeated-measures to analyze the impact of store type on composite HEI score of FAH events. We found that purchases made at limited assortment stores had significantly higher HEI scores while dollar stores had significantly lower HEI scores than purchases at conventional supermarkets. Participating in SNAP had significant positive impact on composite HEI scores, relative to households income-eligible for SNAP but not participating. These results require closer consideration but have important implications for policies relating to what types of foods stores should be subsidized, through healthy food financing initiatives and SNAP and WIC authorization, and the way SNAP benefits are distributed over the course of the month.

Executive summary

A growing body of research describes how individuals make food shopping decisions in both time and space. We have collaborated on numerous local-scale studies which provide a strong theoretical and methodological foundation for broader food access questions. In these studies, we relied on relatively small convenience samples and a combination of in-person surveys, in-depth qualitative interviews, food store receipts, and food store audits. The FoodAPS dataset provided us with a unique opportunity for understanding these patterns among a large sample across income, SNAP status, and urban, suburban and rural settings.

We addressed three questions in our research:

1. Where do participants shop for food at home (FAH) and how do individual and household characteristics interact with store characteristics and distance?
2. How does the nutritional content of foods purchased change as time from SNAP distribution increases?
3. How does store choice influence the nutritional quality of FAH purchases?

Question 1: Store choice

We used a conditional logit model to answer this first question. To define the choice set—the relevant set of stores from which participants likely choose their primary food store—we created shopping clusters by grouping nearby block groups where participants lived.

Overall, we found that participants choose full-service supermarkets, larger stores, and stores closer to home but that store choice is influences by SNAP status, ethnicity, race, sex, car ownership and the level of urbanization of the county of residence. Specifically, participants receiving SNAP were even more likely to choose larger stores while participants in highly urban areas were less likely to choose larger stores than their suburban and rural counterparts. Hispanic participants were more likely than non-Hispanic participants to choose full-service supermarkets.

White participants were more likely to travel further than non-white participants, as were participants who owned a car and participants living in less urbanized areas.

Question 2: Nutritional quality of FAH and time from SNAP distribution

For the second question, we used general linear modeling to determine changes in dietary quality of FAH purchases, as measured by composite Health Eating Index (HEI) score of FAH purchases. Control variables included age of the primary respondent as a continuous variable and sex, race and ethnicity as categorical variables.

Total HEI-2010 scores by household had a wide distribution from 24.73 at the 5th percentile to 70.20 at the 95th. Mean HEI-2010 among SNAP households was 46.16 (SD=13.96). Date of SNAP distribution was well distributed across the month. We found an increase in HEI-2010 score in the days immediately following SNAP distribution followed by a decrease until 20 days after distribution and then a moderate increase to the end of the SNAP-cycle.

To account for skewed spending directly following SNAP distribution, the number of days since SNAP (DSS) was grouped into four time buckets based on raw distribution for regression analysis: 1) ≤1 day, 2) 2-5 days, 3) 6-19 days and 4) >19 days. Unadjusted regression of DSS against HEI-2010 score yields a 5.27-point decrease in household HEI-2010 between the second and fifth DSS as compared to ≤1 DSS ($p<0.01$). After controlling for demographic and household characteristics and amount of last SNAP benefit, the decrease in HEI-2010 in 2-5 DSS is 5.8 points ($p<0.01$). This mean drop in HEI-2010 continues in the 6-19 and the >19-DSS brackets although they have smaller decreases of 4.23 points ($p<0.05$) and 4.53 points ($p<0.01$) respectively.

Question 3: Nutritional quality of FAH and store type

For the final question, we used a generalized estimating equation (GEE) model for repeated-measures to analyze the impact of store type on composite HEI score of FAH purchases. The primary independent variable was store type based on sub-channel categories in the

TDLinx/STARS dataset.

Controlling for the host of shopper characteristics (age, race/ethnicity, education, car ownership), purchases at natural/gourmet and limited assortment stores had significantly higher composite HEI scores than conventional supermarkets while purchases at dollar stores and all other stores had significantly lower composite HEI scores than conventional supermarkets. Purchases by households enrolled in SNAP did not have significantly different composite HEI scores from households that were not SNAP eligible, but purchases by households that were eligible for SNAP based on household income but not receiving SNAP had significantly lower composite HEI scores than households enrolled in SNAP. Smaller shopping trips (involving expenditures of less than $30) had significantly lower composite HEI scores than larger shopping trips (involving expenditures of more than $30). Shopping trips further from home had lower HEI scores than food shopping trips closer to home.

Research implications

These results together provide additional evidence of significant spatial and temporal elements to food shopping that must be considered in any analysis of “food deserts” or access to healthful foods. They confirm what we have learned from our previous research in Philadelphia and Chester PA about the relevance of distance from home to food shopping and the many ways that relationship varies based on race, ethnicity, sex, car ownership, and the level of urbanization in an area. They also confirm what we have learned about the relationship between healthfulness of food purchases and the type of food store where they are purchased. Identifying a distinct temporal pattern in the healthfulness of foods purchased based on days since SNAP distribution provides an important additional consideration in understanding food shopping patterns among low-income households. We are still considering the implications of the research about store type and HEI but would suggest based on these findings that public financing and SNAP authorization of dollar stores or other smaller stores (such as convenience stores) should be reconsidered because they tend to involve lower nutritional quality than supermarkets and other larger-format foods stores.

Research limitations and next steps

We recognize that these results are somewhat preliminary and require some additional adjustments to finalize our models. We would have liked to use the many HEI component scores for the second and third research questions, but we had too many questions about how to represent those scores to proceed. As we learn more about how these scores work, we will incorporate these additional outcome variables.

Introduction

A growing body of research describes how individuals make food shopping decisions in both time and space, adding needed complexity to our understanding of "food deserts." We have collaborated on numerous local-scale studies which provide a strong theoretical and methodological foundation for broader food access questions. We have worked with several colleagues (S Kumanyika, K Glanz, A Karpyn, C Cannuscio, K DiSantis, J Hirsch, M Barnett) to develop a better understanding of food shopping behavior of low-income urban residents and how the community and consumer food environments (Glanz et al., 2005) impact diet quality and obesity risk. Relying on in-person surveys, in-depth qualitative interviews, food store receipts, and food store audits, our studies have led to the following conclusions:

- **Most people travel beyond the closest supermarket to do most of their food shopping** (Cannuscio et al., 2012; Hillier et al., 2011). Most people shop at multiple food stores (DiSantis et al., 2012; Chrisinger et al., in preparation). People travel further to shop at stores with greater availability of healthful foods (Cannuscio et al., 2012). These conclusions are consistent with other recent studies, including Black et al., 2013 and Zenk et al., 2011.

- **Distance from home is only one of many significant factors in food store choice.** Food store choice also varies by use of federal food assistance benefits (Hillier et al., 2011), vehicle ownership, race/ethnicity, and gender, and activity space of food shoppers and proximity to transit, prices, size, and availability of healthful foods at stores (Hillier et al., in press; Liese et al., 2013; Kerr et al., 2012; Jilcott et al., 2011). Food shoppers have different expectations for different types of food shopping trips, and this has consequences for mode of transportation (Hirsch & Hillier 2013).
- **The type of food store chosen (i.e., full-service supermarket, limited assortment, convenience store) influences the healthfulness of foods purchased** (Chrisinger et al., in review; Jilcott et al., 2011; Gustafson et al., 2013; Gustafson, et al., 2012).

The FoodAPS data set has allowed us to test the generalizability of our findings from Philadelphia and offer insights on the interactions between food environment, food choice, and food assistance.

In our initial proposal from May 2014, we identified three research questions:

1. Where do participants shop for food at home (FAH) and how do individual/household characteristics interact with store characteristics and distance?
2. How does store choice influence the nutritional quality of FAH purchases, controlling for individual and household characteristics?
3. How does the local food environment influence the nutritional quality of FAH purchases?

For all three questions, we proposed to investigate how SNAP participation interacts with the outcomes of interest. In September 2015, we requested an amendment to these original research questions, reflecting the interest of a new doctoral student, Eliza Whiteman, in the time of month of food purchases. Because of the considerable time required to work with the nutrition data, we decided not to pursue our original research question about the local food environment, thus substituting our original third research question with the following:

3. How does the nutritional content of foods purchased to be consumed at home change as time from SNAP distribution increases?

This final report is organized around these three research questions. We report on the research methods, data, results and discussion for each of these research questions separately, then address our findings from all three research questions together in the final conclusion section. We acknowledge that we have work to do in finalizing all of these models; we anticipate that feedback from the University of Kentucky and Economic Research Services team will be very helpful in that process.

Question 1: Methods

Consistent with our approach in Hillier et al, 2015, we used a conditional logit model to determine how individual shopper, trip distance, and food store characteristics interact and help explain food store choice. We approached the question of choice set—the pool of stores from which individual shoppers are choosing—differently, however. These two elements of our discrete choice model are described below.

Conditional logit model

Given a set of *individuals* (*households*) $i \in I$ and *stores*, $s \in S$, if the set of store alternatives relevant for individual, i, is denoted by $S_i \subseteq S$, then our *conditional logit model* takes the general form

$$(1) \qquad P_i(s) = \frac{\exp(V_{is})}{\sum_{s' \in S_i} \exp(V_{is'})} \quad , \; s \in S_i \, , i \in I$$

where $P_i(s)$ denotes the probability that store s is chosen by individual i from set S_i. These choice probabilities are assumed to depend on the *value*, V_{is}, of each store s to individual i. As in linear regression, these values are assumed to be representable as linear functions of a relevant set of store attributes, $(x_{sj} : j = 1,.., J)$, such as size and availability of healthful foods at store s. These values may differ among individuals, depending on attributes, $(z_{ik} : k = 1,.., K)$, such as the sex and race of the individual. Such value differences can be captured by interacting individual attributes with each store attribute. The primary measure of accessibility was the travel distance from individual i's residence to each store s, designated as *home distance*, $d_1(is)$. However, we were also interested in the distance to store s from the place where i spends the most time (such as job location), here designated as *place distance*, $d_2(is)$. As with store attributes, the value of these distance accessibilities may differ among individuals. For example, such distances may be less important for car owners. Such effects can again be captured by interacting these distances with individual attributes. Hence in the most general model considered here, values of stores for individuals are taken to be linear functions of the form:

$$(2) \qquad V_{is} = \sum\nolimits_{j=1}^{J}\left[\beta_j x_{sj} + \sum\nolimits_{k=1}^{K}\beta_{kj} z_{ik} x_{sj}\right] + \sum\nolimits_{h=1}^{2}\left[\theta_h d_h(is) + \sum\nolimits_{k=1}^{K}\theta_{kh} z_{ik} d_h(is)\right]$$

where the first term on the right hand side involves store attributes together with individual interaction effects and the second term involves distances (residential and place) together with their individual interaction effects.

Following standard terminology, coefficients β_j and θ_h are referred to as the "main effects" for store attribute j and distance attribute h, respectively. Similarly, for any given individual attribute, k, coefficients β_{kj} and θ_{kh} are referred to as "interaction effects" between k and, respectively, store attribute, j, and distance attribute, h. To interpret these coefficients, note for example that the effects of store attribute j can be isolated by considering two hypothetical stores, s and s', that differ only with respect to attribute j. To capture the effects of a unit change in attribute, j, suppose in addition that $x_{sj} - x_{s'j} = 1$. Then the relative likelihood of any individual i choosing store s versus s' is seen from (1) and (2) to be of the form:(3)

$$P_i(s)/P_i(s') = \exp\left[\beta_j(x_{sj} - x_{s'j}) + \sum_{k=1}^{K}\beta_{kj}z_{ik}(x_{sj} - x_{s'j})\right] = \exp\left(\beta_j + \sum_{k=1}^{K}\beta_{kj}z_{ik}\right)$$

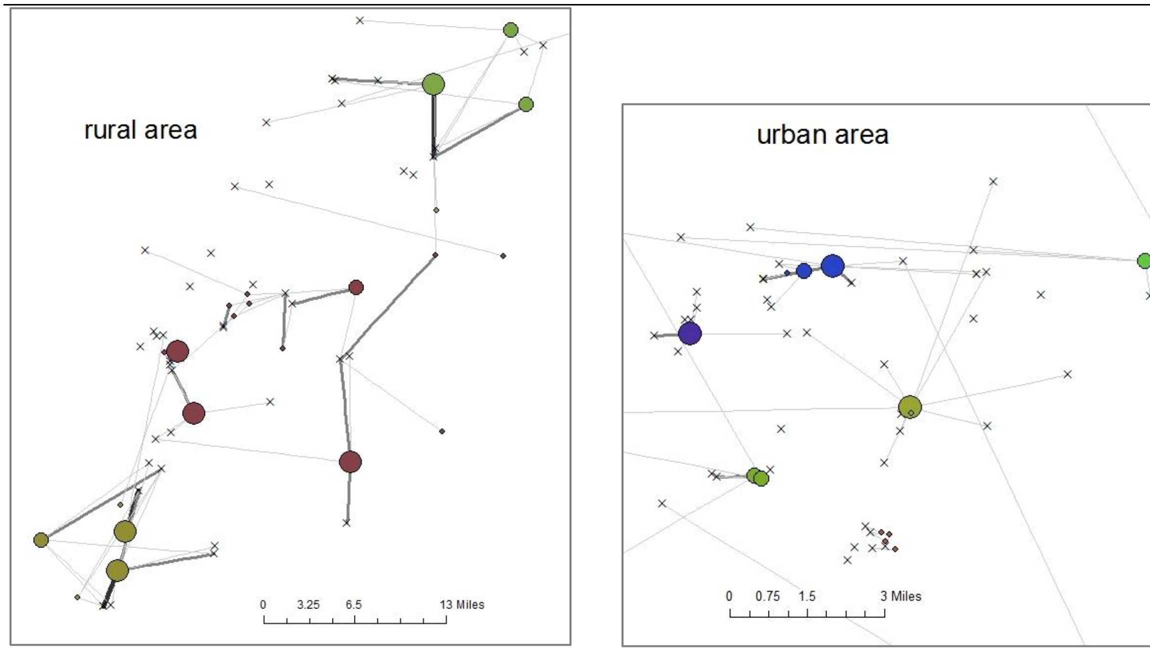
So in this context it is clear that "main effect", β_j, reflects that component of change in the relative likelihood of choosing s versus s' which is common to *all* individuals, i.[1] Similarly, β_{kj}, reflects the additional component of change in this relative likelihood that is specific to individuals with k^{th} attribute level, z_{ik}.[2] Parallel interpretations can be given to the distance parameters, θ_h and θ_{kh}.

Store choices and choice sets

We defined the relevant *store choice* for each individual i to be the primary food store used by the primary adult respondent in the FoodAPS household. We identified the relevant choice set, S_i, for each individual i to be the set of all store choices made by individuals in i's shopping cluster. We created these shopping clusters by grouping nearby block groups where participants lived using visual inspection of maps in ArcGIS showing lines between block group centroids and the primary food stores chosen by participants in each block group. Each block group could only be in one shopping cluster. In Figure 1.1 below, the small dots represent block group centroids of participants, the x's represent all food stores, and the large colored dots represent primary stores

[1] Technically one should add "for all individuals for whom both s and s' are relevant options". But since β_j is clearly independent of these particular option choices, we ignore this complication.
[2] By taking logs in (3), these can also be interpreted as linear changes in "log odds", similar to logistic regression. Alternatively, one can obtain interpretations in terms of "elasticities" and "cross-elasticities" of substitution, as for example in Section 3.6 of Train (2009).

chosen, graduated based on the number of people in the dataset who chose that as their primary store. The colors show distinct food shopping clusters.



This generated 221 shopping clusters that included a maximum of 105 different participants and 20 different stores.

Ideally, this choice set would include all of the store-choice options actually perceived by each individual to be relevant. But since this data is typically not available (and indeed may not even be fully known to individuals themselves), it is necessary to define such sets exogenously.[3]

Question 1: **Data**

The primary food store (from the household dataset) served as the dependent variable. Shopper characteristics served as independent variables. These included sex (**SEX**; female or not), race (**RACE**; white or not), ethnicity (HISP; Hispanic or not); SNAP participation (**SNAP**), car

[3] For additional discussion of such choice-set identification issues, see for example Fotheringham (1988) and Pelligrini (1997).

ownership (**CAR**), and distance to primary store from home (**DIST**) from the individual and household FoodAPS datasets. We also included the percent urban population of the county in which the participant lived (**URBAN**; from 2010 US Census) to better understand urban/rural/suburban differences, particularly in regard to distance traveled to primary food store.

Store characteristics also served as independent variables. These included store type (**SUPMKT**, full-service supermarket or not) and square footage (**SQFT;** continuous) from the TDLinx/STARS datasets.

Question 1: Results

Only primary shoppers for whom characteristics were known about their primary food store were included in the analyses. Data on store characteristics were incomplete for 693 of the primary stores chosen, leading to a sample of 4015 (reduced from 4826). We further eliminated participants choosing stores too far to be relevant choices for others in their shopping cluster. We did this manually, visually inspecting all participant-primary food store combinations in ArcMap that involved a distance of 10 miles or more. This led us to develop the rule that if a store trip was more than twice as long as the next longest trip in the shopping cluster, we would eliminate it. This led to the removal of an additional 18 participants and a final sample of 3997.

SQFT, **SUPMKT** and **DIST** were the three significant main effects in the model. Overall, participants were more likely to choose larger stores, full-service supermarkets rather than other types of food stores, and stores closer to home. Interaction effects show that participants receiving SNAP were even more likely to choose larger stores (**SQFT-SNAP**) while participants in highly urban areas were less likely to choose larger stores than their suburban and rural counterparts (**SQFT-URBAN**). Hispanic participants were more likely than non-Hispanic participants to choose full-service supermarkets (**SUPMKT-HISP**). White participants were more likely to travel further than non-white participants (**DIST-RACE**), as were participants who owned a car (**DIST-CAR**) and participants living in less urbanized areas (**DIST-URBAN**).

Question 1: Discussion

None of these results are surprising and all are consistent with our findings from Philadelphia. All things being equal, people choose larger supermarkets closer to home. But of course, all things are not equal and these results indicated differences across sex, race, ethnicity, car ownership, and rura/urban locations.

We conducted additional analyses to see if there was anything more to be said about SNAP participation. To do so, we first constructed a logistic regression of **SNAP** on the other shopper attributes. These results were qualitatively the same as the pairwise correlations, and show that **SNAP** is most strongly (negatively) related to **RACE**. So one experiment was to drop **RACE** and see if there is an effect on **SNAP**. Here only **SQFT-SNAP** increased in significance. Finally we removed **HISP** and **SEX** as well, just to see if there was any effect. Again the conclusion was the same, so that there seem to be no further interesting conclusions that can be drawn about shoppers with **SNAP**. As one last check, we removed **SNAP** altogether, and found that **DIST-RACE** and **DIST-CAR** were slightly more significant, but with no real qualitative changes.

Finally, we considered other attributes in the same way. By dropping **SEX**, one obtains more significant **SQFT-SNAP** and **DIST-CAR**, but no qualitative changes. Similarly, dropping **HISP** or **RACE** (already done) had no qualitative effects. These results are also consistent with the general lack of correlation among these attributes. So the above regression results were adopted as final.

Question 2: Research methods

Statistical analyses were conducted using STATA 14 software on NORC Thin Client hardware. General linear modeling was used to determine changes in dietary quality as the number of days since SNAP benefit distribution increased. Regressions were controlled for household size, household income, and amount of last SNAP benefit as continuous variables. Regressions were also controlled for the age of the primary respondent as a continuous variable and for sex, race and ethnicity as categorical variables.

Question 2: Data

The Healthy Eating Index-2010 (HEI-2010) total score was used as the primary outcome variable for measuring dietary quality. The HEI-2010 was developed by the National Cancer Institute and the USDA to measure how American diets compare nutritionally to the Dietary Guidelines for Americans. The HEI-2010 total score is comprised of 12 components – eight measured for adequacy – 1) total fruit, 2) whole fruit, 3) total vegetables, 4) greens and beans, 5) whole grains, 6) dairy, 7) total protein foods, 8) seafood and plant proteins, 9) fatty acids – and three for moderation – 10) refined grains, 11) sodium, and 12) empty calories. Because the index uses a density measure and follows a universal set of standards, the index can be applied to measure and compare nutritional quality of foods at various scales including individual consumption or purchasing, restaurants, and the broader food environment (Jahns et al. 2015).

SNAP participation was determined by self-report and administrative matching. The number of days since SNAP benefits were distributed (DSS) was defined as a continuous variable by determining time from last reported SNAP disbursement to start of data collection week. For those households nearing the end of the benefit cycle at the time of the initial survey, it was assumed they received their benefits on the same day the next month, therefore their benefits would be renewed during the study period.

Question 2: Results

FoodAPS contains a nationally representative sample of 4,826 households. Of the sample, 1,581 households were current SNAP participants while 1,233 were eligible for SNAP, but not participating. After removing observations where data were missing for DSS or where households had no FAH purchases for the data collection week, there were 1,263 remaining SNAP households. The majority of primary respondents were female (n=1,014), white (n=819) and had at least one child living in the home (n=785). Nearly sixty percent of the SNAP households in this analysis possessed a high school degree or less and 46.6% had an annual income of less than $15,000. (See Table 2.1).

Total HEI-2010 scores by household had a wide distribution from 24.73 at the 5th percentile to 70.20 at the 95th. Mean HEI-2010 among SNAP households was 46.16 (SD=13.96). Date of SNAP distribution was well distributed across the month. Visual assessment of a mean lowess curve revealed an increase in HEI-2010 score in the day immediately following SNAP distribution followed by a decrease until 20 days after distribution and then a moderate increase to the end of the SNAP-cycle. To account for skewed spending directly following SNAP distribution, DSS was grouped into four time buckets based on raw distribution for regression analysis – 1) ≤1 day, 2) 2-5 days, 3) 6-19 days and 4) >19 days. As shown in Table 2, unadjusted regression of DSS against HEI-2010 score yields a 5.27 point decrease in household HEI-2010 between the second and fifth DSS as compared to ≤1 DSS ($p<0.01$). After controlling for demographic and household characteristics and amount of last SNAP benefit, the decrease in HEI-2010 in 2-5 DSS is 5.8 points ($p<0.01$). This mean drop in HEI-2010 continues in the 6-19 and the >19-DSS brackets although they have smaller decreases of 4.23 points ($p<0.05$) and 4.53 points ($p<0.01$) respectively.

Question 2: Discussion

Episodic food insecurity and inconsistent consumption of macronutrients both have significant health implications. The data analyzed in this study from USDA's FoodAPS study provide further evidence of the dynamic nature of food acquisitions and dietary quality over the SNAP-cycle. When controlling for demographic and household characteristics, on average study participants had an HEI-2010 total score of 34.31 for the week immediately following the day of their benefit distribution. If data collection took place 2-5 days from SNAP distribution, household HEI-2010 decreased by 5.8 points ($p<0.01$), which represents nearly a half a standard deviation from overall mean HEI-2010. Such a large decrease in diet quality in the days following SNAP distribution suggests SNAP participants are more able to acquire healthful foods when benefits are flush and that dietary quality is compromised as benefits are diminished. It is important to note that on the whole SNAP participants in this study had a lower HEI-2010 total score than the national average of 49.8 for men and 52.7 for women (Guenther et al. 2014). Research on the comparative healthfulness of SNAP diets has been mixed and to better understand these differences it would be useful to analyze HEI-2010 of non-SNAP FoodAPS study participants in the future.

Study Limitations

Data for this study were collected for one week per household. This means that it is not possible to compare how an individual household's dietary patterns and food purchasing acquisitions change as DSS increases. Instead, this analysis compares the dietary quality for the week of data collection by household compared to DSS to determine if on average, households further from SNAP distribution have poorer HEI-2010 scores. While date of SNAP distribution was randomly distributed throughout the sample, this may still pose slight endogeneity problems as those households with less healthy food purchasing habits may exhibit this pattern throughout the month. Another limitation of the study is that FoodAPS provides food-purchasing data at the household level and not food consumption data. We cannot deduce from the data exactly what each individual consumed or whether the items purchased in that week were consumed during that same time period.

Implications for research and practice

This study demonstrates that increasing time from SNAP distribution is associated with a reduction in overall dietary quality. This fluctuation in dietary quality may be a result of once monthly food assistance benefit distribution, which has already been demonstrated in the literature to produce fluctuations in food spending and calorie consumption leading to episodic food insecurity. Increasing SNAP distribution to bimonthly may help to smooth these fluctuations in diet, however to properly assess this it would be useful to first compare the food shopping patterns of SNAP households to eligible non-SNAP households as well as to a higher income cohort. This analysis was not possible within the FoodAPS dataset as data collection took place at a variety of different times in the month and cannot be matched with time of income receipt for those households not participating in SNAP, however future studies could be designed to answer this question. Additionally, a pilot program where SNAP households are randomly assigned to receive benefits once or twice per month could be implemented to assess efficacy of increasing benefit distribution on diet quality.

Question 3: Research Methods

A generalized estimating equation (GEE) model for repeated-measures was performed using SAS software.

Question 3: Data

The unit of analysis was a shopping trip that involved purchase of food to be eaten at home (FAH event). The outcome variable was nutrition quality, as measured by the composite Healthy Eating Index (HEI) score of all food items purchased during FAH events.

The primary independent variable was store type based on sub-channel categories in the TDLinx/STARS dataset. See table 3.2 for a description of these categories.

Additional control variables included store characteristics including store size (in square feet) total annual sales, trip characteristics including weekday or weekend, week of month, amount spent, payment type (SNAP, WIC, cash or check, debit, credit or other), and distance traveled to store from home. Shopper/household characteristics were also included in the model: age, race/ethnicity, sex, education level of shopper, income level of household, car ownership, household size, current SNAP status (current receiving, eligible but not receiving, not eligible).

Question 3: Results

A total of 4,962 shoppers made a total of 11,472 shopping trips. Table 3.1 provides descriptive statistics on shoppers and their trips. Shopping trips were more likely to be made during the week than weekend and in later in the month. Participants spent a median of $19.79 per shopping trip, with 63.6% of trips involving expenditures of less than $30. Cash, check or debit was the most common form of payment, followed by SNAP (15.6%) and credit card (13.4%).

Question 3: Discussion

Our results provided some surprises. We were surprised that purchases made at limited assortment stores had higher HEI scores than conventional supermarkets, even in the multivariate model. This finding is worth closer analysis to see what specific foods people are buying and at which specific limited assortment stores they are making their purchases. Also surprising was that purchases made closer to home had higher composite HEI scores. Again, further analysis is warranted to make sense of that finding which is counter-intuitive to the idea that discerning shoppers would put greater effort into traveling to stores with more nutritious foods. Most of our findings were not surprising, either, particularly in regard to the relatively low nutritional quality of foods purchased at dollar stores and the positive relationship between educational status and composite HEI scores. That smaller food trips generally involve foods of lower nutritional value is not surprising but it is important, representing an important point of intervention. It would be worth adjusting the $30 threshold to see at what expenditure level nutritional quality starts to improve. A significant SNAP effect, indicating that households receiving SNAP are purchasing more healthful foods than households that are income-eligible for SNAP but not receiving SNAP, is not surprising but is very encouraging.

Conclusion

The results from these three different analyses together provide additional evidence of significant spatial and temporal elements to food shopping that must be considered in any analysis of “food deserts” or access to healthful foods. They confirm what we have learned from our previous research in Philadelphia and Chester PA about the relevance of distance from home to food shopping and the many ways that relationship varies based on race, ethnicity, sex, car ownership, and the level of urbanization in an area. They also confirm what we have learned about the relationship between healthfulness of food purchases and the type of food store where they are purchased. Identifying a distinct temporal pattern in the healthfulness of foods purchased based on days since SNAP distribution provides an important additional consideration in understanding food shopping patterns among low-income households. Policy implications for WIC, SNAP, HFFI funding

We recognize that these results are somewhat preliminary and require some additional adjustments to finalize our models. We would have liked to use the many HEI component scores for the second and third research questions, but we had too many questions about how to represent those scores to proceed. As we learn more about how these scores work, we will incorporate these additional outcome variables. We applied for and have been granted access to the FoodAPS dataset for an additional 12 months which will allow us to take these next steps.

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Table 1.1 Conditional Logit Results

VAR	PARAM	Z-VAL	PROB
SQFT	0.016974	6.644335	**0.000000**
SQFT-RACE	0.001983	1.038583	0.298998
SQFT-HISP	0.001182	0.633739	0.526251
SQFT-SNAP	-0.002815	-1.909759	**0.056164**
SQFT-CAR	-0.001719	-1.114230	0.265181
SQFT-SEX	-0.001604	-1.064844	0.286946
SQFT-URBAN	-0.007207	-4.955493	**0.000001**
SUPMKT	0.016943	2.536975	**0.011181**
SUPMKT-RACE	-0.003815	-0.755090	0.450195
SUPMKT-HISP	0.011398	2.442443	**0.014588**
SUPMKT-SNAP	-0.002724	-0.704852	0.480902
SUPMKT-CAR	0.001277	0.318852	0.749838
SUPMKT-SEX	-0.001735	-0.460274	0.645320
SUPMKT-URBAN	-0.004859	-1.289173	0.197338
DIST	-0.373611	-8.671101	**0.000000**
DIST-RACE	0.063106	1.877245	**0.060485**
DIST-HISP	0.010510	0.350533	0.725939
DIST-SNAP	-0.004271	-0.207091	0.835939
DIST-CAR	0.053792	1.962564	**0.049697**
DIST-SEX	0.036760	1.695529	**0.089975**
DIST-URBAN	-0.174488	-7.488753	**0.000000**

SUCCESS RATE = 38.0285%
MODEL SUCCESS RATE = 25.6263%
RANDOM SUCCESS RATE = 18.2648%

Table 2.1. Demographic Characteristics of Sample

	n	%
Total	1263	100.0
Age of Primary Respondent		
18-30	323	25.6
31-45	412	32.6
46-60	359	28.4
>60	169	13.4
Sex of Primary Respondent		
Male	249	19.7
Female	1,014	80.3
Child in Home	785	62.2
Race of Primary Respondent		
White	819	64.8
Black/African American	246	19.5
American Indian or Alaska Native	< 20	< 1.6
Asian	< 20	<1.6
Native Hawaiian or Other Pacific Islander	< 20	<1.6
Other Race	130	10.3
Multiple Races	35	2.8
Hispanic	311	24.6
Education level		
Less than high school	345	27.3
High school or GED	410	32.5
Some college	405	32.1
College graduate	102	8.1
Annual Household Income		
Less than $15k/yr	589	46.6
$15-24,999k/yr	302	23.9
$25-34,999k/yr	173	13.7
$35-49,999k/yr	101	8.0
$50-74,999k/yr	98	7.8

Being older was associated with an increase in HEI-2010 of 0.12 points for each year ($p<0.001$). Each additional year of education resulted in a 0.49 point increase in HEI-2010 ($p<0.001$) and being Hispanic was associated with a 4-point larger score ($p<0.001$). While there was a very strong positive association between primary respondents who identified as Asian, Native Hawaiian or Other Pacific Islander and HEI-2010 score, these outcomes were not statistically significant. With the exception of White and Black, the sample size within each race category was very small.

Table 2.2. Mean HEI-2010 Score by Time Since SNAP

	Freq.	Mean	SE	95% CI
Days Since SNAP				
≤ 1 day	80	49.92	1.46	47.02 - 52.83
2-5 days	197	44.65	0.98	42.72 - 46.58
6-19 days	600	46.27	0.59	45.12 - 47.42
> 19 days	386	45.98	0.69	44.63 - 47.33

Table 2.3. Days since SNAP (DSS) regressed on HEI-2010

	Unadjusted					Adjusted				
	β1	SE	CI		p	β1	SE	CI		p
Days Since SNAP Distribution										
<=1 day	49.922	1.557	46.867	52.977	0.000	34.309	4.254	25.963	42.655	0.000
2 - 5 days	**-5.273**	1.847	-8.895	-1.650	**0.004**	**-5.799**	1.835	-9.398	-2.199	**0.002**
6-19 days	**-3.651**	1.658	-6.904	-0.399	**0.028**	**-4.227**	1.649	-7.462	-0.991	**0.011**
>19 days	**-3.942**	1.711	-7.299	-0.585	**0.021**	**-4.528**	1.702	-7.867	-1.190	**0.008**
Age						0.115	0.031	0.055	0.176	**0.000**
Sex						-0.062	1.017	-2.057	1.932	0.951
Race										
Black/African American						-1.516	1.036	-3.548	0.516	0.144
Am. Indian or Alaska Nat.						-0.494	3.377	-7.119	6.132	0.884
Asian						7.347	4.032	-0.564	15.258	0.069
Nat. Hawaiian/Oth. Pac. Islander						15.514	7.970	-0.123	31.151	0.052
Other Race						-0.769	1.545	-3.800	2.263	0.619
Multiple Races						-0.981	2.382	-5.653	3.692	0.618
Hispanic						**3.965**	1.134	1.740	6.189	**0.000**
Children in the home						0.183	1.179	-2.130	2.497	0.876
Income						0.000	0.000	0.000	0.000	0.120
Education						**0.487**	0.149	0.194	0.781	**0.001**
SNAP benefit amount						0.002	0.003	-0.003	0.007	0.440

Table 3.1: Descriptive data on participants, shopping behaviors, and food expenditures

Individual Characteristics (n=4,962 with at least one trip)	*n (%)*
Age > 40	2,969 (59.8)
Sex (Female)	3,364 (67.8)
Race/ethnicity	
White (non-Hispanic)	3,006 (60.6)
Black/Af Am (non-Hispanic)	624 (12.6)
Hispanic (any)	1,013 (20.4)
Other (non-Hispanic)	319 (6.4)
SNAP/Income Status	
SNAP household	1,614 (32.5)
SNAP eligible, NOT receiving SNAP	1,183 (23.8)
Non-SNAP eligible	2,165 (43.6)
Education	
<HS	808 (16.3)
HS/GED	1,476 (29.7)
Some college or more	2,666 (53.7)
Missing	12 (0.2)
Own/lease car *	4,275 (86.2) [9 missing (0.2)]
Food Expenditures and Trip Characteristics (n=11,472)	
Weekend	3,308 (28.8)
Week of month	
First (days 1-7)	2,413 (21.0)
Second (days 8-14)	2,827 (24.6)
Third (days 15-21)	3,010 (26.2)
Fourth + Fifth (days 22-31)	3,222 (28.1)
Amount spent ($)	
Median [IQR]	19.79 [8.36-44.23]
% less than $30	7,294 (63.6)
Median [IQR] distance traveled from home (miles)	2.37 [1.17-5.40] [552 missing]
Payment type (can be multiple, the below is prioritization order)	1,791 (15.6)
SNAP (any)	226 (2.0)
WIC	4,730 (41.2)
Cash or check	3,000 (26.2)
Debit card	1,534 (13.4)
Credit card	41 (0.4)
Other (TANF or gift card)	145 (1.3)
Missing	

** This is actually at household level, but will treat as at the individual level.*

Table 3.2 provides descriptions of store categories and Table 3.3 shows the distribution of shopping trips by store category. Trips to conventional supermarkets made up the largest proportion of shopping trips (54.4%) followed by supercenters (19.3%). Composite HEI scores were highest at natural/gourmet stores, followed by conventional clubs, limited discount, conventional supermarkets and supercenters. Composite HEI scores were lowest at dollar stores and all other stores. Mean component HEI scores for fruits, greens and beans, and whole grains were 0 for all store categories, reflecting the reality that these healthful foods are not purchased in significant enough quantities to conduct meaningful analysis or that more work is needed for us to understand the HEI component scores. HEI component scores for vegetables could be determined; average scores were highest at natural/gourmet stores followed by limited discount stores.

Table 3.2. Store Categories and Descriptions

Store Category*	Description
conventional supermarkets	Large food stores with surface or structured parking, including both chain and independently-operated retailers; often include several in-store departments, such as a bakery, meat counter, or prepared foods section (full-service)
Discount/limited assortment supermarket	Large food stores, smaller than supermarkets and with fewer or no in-store departments, but larger than small retailers; may also emphasize price discounts (i.e. deep discount stores).
Supercenter	Household retailers, like Target, Kmart, Walmart, and CVS, who devote most store space to non-food items, but also offer a limited selection of grocery items. Even though some general retailers may offer large quantities of food (i.e. big box stores), they typically have a limited amount of perishable foods and no in-store departments.
Natural/gourmet	
Dollar store	
Conventional club	Membership-only warehouse retailers selling bulk quantity items.
Other	All other vendors including military commissaries, produce markets, co-ops, convenience stores
***Adapted from common categories used in food environment research (Morland, et al., 2002)**	

Table 3.3. **Distribution of 11,472 food shopping trips made by 4,962 by HEI score**

Store Type	Number (%) of trips by store type	Amount spent*	Overall HEI score*	HEI Fruits*	HEI vegs*	HEI greens and beans*	HEI whole grains*
conventional supermarket	6,238 (54.4)	34.43±0.54 20.00 [9.08-42.86]	47.20±0.17 47.16 [37.49-56.70]	0.42±0.02 0 [0-0]	2.20±0.03 1.64 [0-5]	0.99±0.02 0 [0-0]	1.54±0.04 0 [0-0]
Supercenter	2,217 (19.3)	46.07±1.07 28.46 [12.60-59.88]	47.03±0.28 46.93 [37.94-56.01]	0.40±0.03 0 [0-0]	1.91±0.04 1.18 [0-4.13]	0.83±0.04 0 [0-0]	2.05±0.07 0 [0-3.20]
Discount/ limited assortment	569 (5.0)	30.63±1.47 19.54 [9.26-39.33]	47.58±0.56 47.62 [37.44-56.96]	0.37±0.05 0 [0-0]	2.59±0.09 2.73 [0-5]	0.99±0.08 0 [0-0]	1.52±0.13 0 [0-1.14]
Conventional club	361 (3.1)	100.25±5.56 66.47 [32.54-132.44]	51.85±0.81 51.50 [40.29-63.37]	0.42±0.06 0 [0-0]	1.97±0.11 1.02 [0-4.77]	1.07±0.11 0 [0-0]	1.94±0.19 0 [0-2.36]
Natural/ gourmet	270 (2.4)	38.16±2.15 30.15 [15.34-49.30]	55.26±0.89 57.46 [46.00-65.79]	0.56±0.09 0 [0-0]	2.91±0.13 3.78 [0-5]	1.80±0.14 0 [0-5]	2.27±0.23 0 [0-3.90]
Dollar store	570 (5.0)	13.43±0.63 8.00 [4.00-16.41]	42.49±0.49 41.09 [34.71-50.07]	0.16±0.03 0 [0-0]	1.20±0.08 0 [0-2.21]	0.29±0.05 0 [0-0]	1.32±0.13 0 [0-0]
Other	1,247 (10.9)	18.50±0.85 8.71 [4.00-20.50]	43.08±0.39 42.99 [33.34-53.34]	0.37±0.03 0 [0-0]	1.46±0.06 0 [0-4.04]	0.52±0.04 0 [0-0]	0.89±0.08 0 [0-0]

* Presenting as:
Mean ± standard error
Median [IQR]

Differences in HEI composite scores persisted in the multivariate GEE models (See Table 3.4), purchases at natural/gourmet and limited assortment stores had significantly higher composite HEI scores than conventional supermarkets. Purchases at dollar stores and all other stores had significantly lower composite HEI scores than conventional supermarkets. Purchases by households enrolled in SNAP did not have significantly different composite HEI scores from households that were not SNAP eligible, but purchases by households that were eligible for SNAP based on household income but not receiving SNAP had significantly lower composite HEI scores than households enrolled in SNAP. Shopping trips by participants with at least some college education had significantly higher composite HEI scores than shopping trips by participants with less than a high school education or with a high school education but no college. Smaller shopping trips (involving expenditures of less than $30) had significantly lower composite HEI scores than larger shopping trips (involving expenditures of more than $30). Shopping trips further from home had lower HEI scores than food shopping trips closer to home. Finally, purchases made using WIC or credit card had significantly higher composite HEI scores than purchases made using cash or check. Purchases made using SNAP did not have composite HEI scores that were significantly different from those made with cash or check.

Table 3.4. Results of Adjusted Multivariate GEE Models assessing predictors of HEI scores, displayed as effect (95% CI).

NOTE: The below is based on the complete case (non-missing) total of n=10,789	Composite HEI	HEI Fruits*	HEI Vegs*	HEI Greens and Beans*	HEI whole grains*
Store Type (ref: Conventional Supermarket)					
Supercenter	-0.53 (-1.18, 0.12)				
Discount/limited assortment	1.41 (0.29, 2.53)				
Conventional club	1.58 (-0.04, 3.19)				
Natural/gourmet	6.46 (4.72, 8.19)				
Dollar store	-2.25 (-3.32, -1.19)				
Other	-3.37 (-4.35, -2.39)				
Age > 40	1.20 (0.65, 1.76)				
Sex (Female)	1.35 (0.73, 1.96)				
Race/ethnicity (ref: White [non-Hispanic])					
Black/Af Am (non-Hispanic)	0.11 (-0.73, 0.95)				
Hispanic (any)	2.02 (1.30, 2.75)				
Other (non-Hispanic)	2.21 (0.99, 3.44)				
SNAP/Income Status (ref: non-SNAP elig.)					
SNAP household	-2.17 (-2.98, 1.37)				
SNAP eligible (non-household)	-0.96 (-1.69, -0.24)				
Education (ref: Some college +)					
<HS	-0.81 (-1.59, -0.03)				
HS/GED	-1.07 (-1.70, -0.44)				
Own/lease car	-0.32 (-1.14, 0.50)				
Weekend	-0.10 (-0.64, 0.44)				
Week of month (ref: first [days 1-7])					
Second (days 8-14)	-0.19 (-0.92, 0.54)				
Third (days 15-21)	-0.26 (-1.03, 0.50)				
Fourth + fifth (days 22-31)	-0.33 (-1.06, 0.40)				
Amount spent <$30	-6.29 (-6.84, -5.75)				
Distance traveled from home (miles)	-0.03 (-0.06, -0.01)				
Payment type (ref: cash or check)					
SNAP (any)	0.27 (-0.62, 1.15)				
WIC	10.97 (9.02, 12.92)				
Debit card	0.26 (-0.39, 0.91)				
Credit card	1.68 (0.77, 2.60)				
Other (TANF or gift card)	-0.71 (-4.79, 3.38)				

Causes and Consequences of the Calorie Crunch

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Abstract

Monthly welfare programs such as the Supplementary Nutrition Assistance Program (SNAP) produce consistent cycles of expenditure and consumption amongst recipients. Food insecurity and negative behavioral outcomes track these cycles. This paper leverages new data from the USDA, the FoodAPS survey, and to answer a variety of questions related to these phenomena: Are consumption and expenditure cycles correlated? Who bears the burden of food shortages at the end of each benefit month? Does diet quality track food expenditure? I find robust expenditure and consumption cycles in the FoodAPS data, but contrary to popular belief, they are only weakly correlated. The youngest children are spared from cyclical food shortages, but school-aged children experience them when they are out of school. Universal participation of the sample in school meal programs while in school (and the complete lack of participation in summer meal programs) suggests that these programs may mitigate a great deal of children's food insecurity. Diet quality declines over the course of the month, compounding the impact of fewer meals on health. Food access issues cannot explain the identified cycles. We interpret these findings as evidence consistent with a consumption-driven calorie crunch in which the expenditure cycle is a response to the previous month's consumption deprivation.

Executive summary

Many researchers have documented the fact that SNAP recipients experience expenditure and consumption cycles. When benefits arrive there is a large spike in grocery expenditures and calories consumed. Over the remainder of the month, expenditure and consumption consistently decline. Reports of food insecurity follow these cycles. Crime and school misbehavior also track these cycles, encouraging research into their causes, consequences, and potential solutions.

This paper leverages a new data source, the USDA's FoodAPS Survey, to examine a variety of issues related to expenditure and consumption cycles. Most notably, these are the first data to offer simultaneous expenditure and consumption diaries. Often, researchers assume expenditure and consumption cycles to be a single phenomena, however this has gone untested until now. Additionally, the FoodAPS measures consumption at the meal level, making this the first paper to measure consumption cycles in terms of missed meals.

We find evidence of large and significant cycles in both expenditure and consumption in the FoodAPS data. Expenditure decays by roughly 4.6% per day over the course of the benefit month. Consumption falls by roughly 0.7 daily meals from the first day to the last day of the benefit month, and this measurement is robust to a new technique that uses the non-SNAP households in the FoodAPS as a control group. However, the correlation between expenditure and consumption cycles is much weaker than expected.

Children do not experience consumption cycles as severely as adults (or in many cases, at all). This is most consistently true for children under five years old, indicating that parents shelter the most vulnerable for shortfall. However, school-aged children do experience consumption cycles when school is out of session. This suggests that school meal programs may play a vital role in limiting cyclicality in food insecurity, given the near universal participation of

the children in SNAP households. Primary school students appear to be the most affected by school breaks.

Because the meal consumption measures do not capture the contents of meals, a decrease in meal frequency could theoretically be ameliorated by an increase in meal quality, however this does not appear to be the case. Diet quality decreases over the course of the benefit month, according to self-reports, measurements of protein-to-carbohydrate ratios, and a variety of other measures.

It is commonly suggested that poor local food availability could be the root cause of expenditure cycles, which in turn cause consumption cycles. Using the geographic data in the FoodAPS, we find that travel time to the grocery store is not predictive of a more severe expenditure cycle.

This paper is designed to advance our understanding of the calorie crunch using the new FoodAPS data. The results suggest that summer meal programs for children could fill an important gap in food sufficiency at the end of the benefit month and the access-based explanations of these phenomena are perhaps less plausible than consumption-based explanations like self-control and bargaining failures.

Introduction

In a cross section of households receiving food benefits from the Supplementary Nutrition Assistance Program (SNAP) in 2011 and 2012, roughly 61% were food insecure, 31% were very food insecure and 25% of households had food-insecure children (Mabli *et al.*2013). While there is substantial work devoted to estimating the impact of program participation on nutritional and health outcomes, much less is dedicated to understanding what determines food insecurity within the program.[1] The literature on within-month expenditure and consumption cycles (the "calorie crunch") addresses this to some degree, but does not directly estimate the changing frequency of missed meals, one of the core consumption markers that defines food insecurity. This paper utilizes a new data source, the USDA's FoodAPS survey, to expand our understanding of the calorie crunch in a variety of ways. Most notably we measure consumption trends using changes in missed meals over the course of the month and demonstrate that its incidence within the household likely depends on the operation of school meal programs.

Consumer expenditure and consumption-smoothing failures that stem from benefit timing are typically studied to evaluate theory rather than because of their direct impact on well-being. Shapiro (2005), Hastings and Washington (2010) and Smith *et al.* (2016) use SNAP benefit receipt to examine present-biased discounting, firm price responses and income fungibility, respectively. This may be due in part to a structural calibration exercise in Shapiro (2005) that suggests very small welfare losses from the calorie crunch. Recent work on the behavioral consequences of benefit timing puts a spotlight back on the direct impact of cyclicality in food consumption. Foley (2011) shows that crime in areas with highly time-concentrated disbursements of welfare (including SNAP) increases over the benefit month. Seligman *et al.*

[1] See Bhattacharya and Currie (2001) and Hoynes and Schanzenbach (2009) on food insecurity. See Devaney and Moffitt (1991) on nutritional intake. See Currie and Cole (1991), Currie and Moretti (2008), Almond *et al.* (2011) and Kreider *et al.* (2012) on child health. See Hoynes *et al.* 2016 on long-run outcomes.

(2014) find that hypoglycemia hospital admissions are more common at the end of the month in low-income communities, and Gennetian *et al.* (2015) show that school disciplinary actions for middle and high-school students in SNAP households in Chicago increase by 51% from the first to the last week of the benefit month. Given what appear to be significant consequences of food-budget exhaustion, and the high rates of food insecurity within SNAP, we need a better understanding of what happens within households as resources run out and why.[2]

The FoodAPS survey from the USDA allows us to investigate a variety of features of the calorie crunch for this first time. First, we estimate the calorie crunch in terms of missed meals. This extends the benefit-timing literature to directly inform food insecurity. Second, we use the targeted sample of eligible and near-eligible non-participants in order to construct the most robust estimates of the calorie crunch to date. Using these individuals to difference out calendar-day expenditure and consumption means that other cyclical income sources that are roughly correlated with SNAP receipts and specific to a low-income population are controlled for. Third, we use simultaneous household expenditure and meal consumption logs to determine whether the failure to smooth consumption and expenditure are related phenomena. Given past work using expenditure (Hastings and Washington 2010, Castner and Henke 2011, Smith *et al.* 2016, Kuhn 2016) and consumption (Wilde and Ranney 2000, Shapiro 2005, Todd 2015), verifying this relationship is important. Fourth, we decompose the consumption impacts of benefit timing within households by age and gender. Are children spared the worst or do adults and school meal programs shelter them? Are mothers or fathers the ones who feel the impacts of food shortfall? Finally, we assess a common casual suggestion about the calorie crunch: that it is a symptom of poor food access.

[2] Food insecurity per se matters for reported health quality in both adults and children and for specific health outcomes (Gundersen and Kreider 2009, Gundersen and Ziliak 2015).

We find strong declines in both expenditure on food and consumption of food in the FoodAPS data. The meal consumption estimates, unique to this paper, indicate a loss of roughly 3 meals per benefit-month in our most conservative specification with estimates up to 12 meals per benefit-month in others. This estimate is per individual, and is relative to the counterfactual of constant meal consumption at the level established on the first day of the benefit month. Both expenditure and consumption estimates are robust to using eligible and near-eligible non-participants as a control group. Expenditure and consumption cycles are correlated within households, but only weakly. This is evidence that consumption cycles are the primitive phenomena, and they may sometimes feed back into expenditure declines, not the other way around. Indeed, we find no relationship between local food access and consumption or expenditure trends. Men and women experience similar consumption cycles, with dual-parent households doing better overall than single parents. We find that young children experience almost no calorie crunch in terms of missed meals. Primary school-aged children only experience a calorie when school is not in session, indicating that school meal programs play a valuable role in smoothing consumption. This is not true for older children.

Many of the 18 questions the USDA uses to evaluate food insecurity relate to missed meals (USDA 2015). For example, question 4 reads, "In the last 12 months, did you or other adults cut the size of your meals or skip meals because there wasn't enough money for food?" Question 9 reads, "In the last 12 months did you or other adults ever not eat for a whole day because there wasn't enough money for food?" And question 16 reads, "In the last 12 months, did any of the children ever skip a meal because there wasn't enough money for food?" By showing that the calorie crunch is a robust phenomenon by this measurement, we wish to emphasize that the in all likelihood, the food insecure SNAP households are also sometimes food secure SNAP households and vice versa. In fact, we find in the FoodAPS that the likelihood of being categorized as having “very low food security” is increasing over the course of the benefit month despite the retrospective framing of the food security questionnaire. Targeting insecurity associated with benefit timing means re-thinking disbursement timing and technique in addition to increasing benefit amounts (which Todd (2015) demonstrates is effective in mitigating the calorie crunch). Additionally, our results indicate that interventions targeting the point of consumption may be more effective that interventions targeting the point of sale.

The remainder of the paper is organized as follows. Section 2 describes the data and methodology. Section 3 presents the results and Section 4 concludes.

Data and methods

The USDA’s National Household Food Acquisition and Purchase Survey (FoodAPS) surveyed 4826 U.S. households between April 2012 and January 2013. 1581 households were SNAP participants, 1312 were eligible or near-eligible non-participants with incomes less than 185% of the poverty threshold and 1933 had incomes greater than 185% of the poverty threshold. Our primary analysis is restricted to households receiving SNAP benefits, but we also use the eligible and near-eligible non-participants as a control group in some specifications. Households reported their spending on all food items (both for at-home and away-from-home consumption) and meal consumption for a one-week period following an initial interview. The initial interview collected in-depth background information both at the household and individual levels. Geographic information relating home locations to store location is also included in the data.

Understanding survey timing is critical for our sample construction. The in-depth initial interview occurred before the households completed either their expenditure or meal diaries. We call the initial interview date day 0. Days 1 to 7 following the initial interview are diary days. On day 0, households reported the calendar date on which they last received SNAP benefits. A total of 1609 households reported a past SNAP receipt. There were no expenditures logged for 95 of those households. 123 did not match to any meal diaries and 44 households had blank meal diaries for all members. We keep only households for which we have matched expenditures and consumption. 133 of the matched households either reported or were confirmed to no longer be in the program. 80% of the remaining household-days require no adjustment based on last reported SNAP receipt: they fall within 30 days following the report and the reported disbursement occurred on a feasible day.[3] For households with missing last receipt reports and infeasible last receipt reports, we turn to administrative data that the USDA matched to households in the sample.[4] We only use disbursements on a feasible date that occurred no later than the first day of the diaries. This nets an additional 101 households. Finally, because rates of program churn are high (Mills *et al.* 2014), we observe considerable movement out of SNAP in the data and we identify benefit timing effects precisely based on the day of benefit receipt, we do not impute a more recent date of SNAP receipt that would contradict a household's report of their last benefit receipt. We impute days since receipt when it does not contradict a report.[5] This leaves us with a final sample of 1167 SNAP households with 8169 diary days and 25,571 diary-member, ranging from zero to 30 days since benefit receipt.

Following Shapiro (2005) and Kuhn (2016), we wish to estimate expenditure and consumption as a function of days since benefit receipt. Each state has its own SNAP disbursement schedule, with most states spreading it out over the beginning of the month. Figure

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[3] No disbursements arrive on the 24th or later. Additionally, the 30-day requirement is adjusted down to a 29-day requirement when SNAP was last disbursed in a month with 30 days, a 28-day requirement for months with 29 days and a 27-day requirement for months with 28 days.

[4] This follows the USDA's approach or prioritizing reports over the administrative data due to match uncertainty.

[5] For example, imagine that a household reports a last benefit receipt of April 17th, 2012 during their initial interview on May 15th, 2012. May 16th, 2012, the first day of the diary, is 29 days since receipt. The second day of the diary is 30 days since receipt, which gets reset to 0 days since receipt since it does not contradict the report during the May 15 interview. In some consumption specifications, we will exclude these imputed benefit households. This is based on what appear to be very different consumption patterns from non-imputed benefit households, conditional on days since supposed receipt. See Section 3.2 for more detail.

1 shows the distributions of SNAP receipt calendar dates in our sample. There is a large spike on the first of the month followed by a steady flow over the next 10 days, with a gradual trail off from there. No state disburses SNAP after the 23rd of the month. Since disbursement rules based off last names, social security numbers and benefit ID numbers, there are no observable differences across households based on time of receipt (Kuhn 2016). However, given the bunching at the beginning of the month, it is generally true that SNAP receipt is correlated with other early-month occurrences like bills and income. For this reason, we use household and individual fixed-effects models in addition to OLS and similar approaches. Also, we take a novel approach in Section 3.1 by using the average expenditure of our sample of eligible and near-eligible non-participants to difference out the calendar-day expenditure of SNAP participants in the sample.

In general, our expenditure models will take the form

$$y_{h,t} = f(\alpha_h + \beta dss_{h,t} + X'_{h,t}\Gamma) + \epsilon_{h,t} \qquad (1)$$

where $y_{h,t}$ is household h's expenditure on food on diary day t, $\alpha_h$is the intercept term, which may be restricted to be the same across all households depending on specification, $dss_{h,t}$ is the number of days since SNAP receipt for household h on diary day t, and $X_{h,t}$ is a vector of days-since-receipt control variables, including week of calendar month, a weekend indicator variable and a indicator variable for whether the household was called by a survey representative to confirm their recording of daily expenditures.[6] $f(\cdot)$ is usually the identity function, yielding a linear model, but we will use some other specifications as well, most notably Poisson regression.

Our consumption models are slightly different because the data are individual-specific. For individual *i*,

[6] These are also indexed by *h* because the mapping from *t* to days since SNAP depends on the household.

$$c_{i,h,t} = f(\alpha_i + \beta dss_{h,t} + X'_{h,t}\Gamma) + \epsilon_{i,h,t}$$

where $c_{i,h,t}$ is a measure of consumption for individual *i*, in household *h* on diary day *t*. Depending on specification, α_i may be restricted to be the same for all individuals, all individuals in household *h* or first-differenced out. We choose to first-difference the data for our individual fixed-effect specifications because serial correlation in the error term is likely. Standard errors are always clustered at the household level.

Expenditure data are collected at the item level and transaction levels in the FoodAPS. To construct daily household expenditure, we aggregate all food expenditures on a given diary day. This includes groceries for at home consumption and meals purchased away from home (unless specified otherwise). While SNAP funds cannot be used for many of these purchases, our goal is to capture total food expenditure and consumption regardless of budget source. Consumption data are collected at the individual level on each diary day. Breakfast, lunch, dinner and three potential snacks (am, pm and evening) can be reported as either consumed or not. We aggregate daily meal consumption by summing the breakfast, lunch and dinner indicators to avoid worrying about within-day across-meal substitution for any given meal. In the Appendix, we do present results for each meal individually, snack consumption and examining entire days without any consumption.

Results

We present the results in five sections. First, we present the estimates of expenditure cycles amongst SNAP recipients in the FoodAPS data. Second, we estimate consumption cycles and compare them within-household to the expenditure cycles. Third, we explore the incidence of food shortfall by age and gender. Fourth, we investigate whether the nature of consumption, in terms of nutritional quality, changes over the month in addition to quantity. Finally, we explore the relationship between local food access and expenditure and consumption trends.

Expenditure cycles

We find substantive and statistically significant expenditure cycles in the FoodAPS. Our primary specifications model the expenditure decline linearly, using OLS and a first-differenced fixed-effect approach in columns (1) and (2) of Table 1. We also present fixed-effect Poisson regression estimates in column (3) because expenditure decay over the full benefit months appears exponential (see Figure 2, Panel A). Linear models should work well when the day benefits arrive is removed and will be comparable to our preferred approach to the consumption data. Estimates without that day are in columns (4), (5) and (6). In Appendix Table A1, we consider a variety of alternative specifications, including a Tobit model for expenditures censored below at $0, a mean-differenced fixed-effect model, a standard Poisson model, as well as linear probability, first-differenced linear probability, Probit and conditional-Logit models of whether non-trivial expenses are recorded in Appendix Table A2. All of the estimates identify significant negative effect days since benefit receipt.

From the first to the last day of the benefit month in a 31-day cycle, average total food expenditures fall roughly from $94 to $19 (the median decreases from $44 to $3). The linear estimate of the per-day decline is $0.56 per day. Poisson regression, which should fit this sample better, indicates a decline of roughly 4.1% per-day. Much of the decline comes from the spike in spending on the day of receipt: average spending on the second day of the benefit month is roughly $38.[7] Removing that day cuts the magnitude of the linear estimate considerably, but a steady and significant decline of $0.23 per day remains. The assumption of linearity is more appropriate for this sample (see Figure 2, Panel B). Food for home consumption only follows a

[7] This is why the estimate of the daily decline differs so considerably from the slope of the line connecting the first data point in the benefit month to the last day in the benefit month. Removing the first 2 days of the month reconciles this.

similar path at lower levels (results in Appendix Table A3).

These effects of the benefit cycle operate on both the intensive and extensive margins, but the extensive margin effects are almost entirely concentrated in the first few days of the benefit month (see Figure 2, Panel C). 75% of households report non-trivial expenditures on the day that benefits arrive. This falls to 66% on the day after benefits arrive and 56% by the end of the month. This trend is more dramatic when we restrict attention to purchases for food-at-home (FAH): 62% shop on the day benefits arrive, 46% shop on the day after they arrive, and only 35% shop on the last day of the cycle. Non-trivial expenditures are defined as spending at least a dollar on food.

For robustness, we take a unique approach that utilizes non-SNAP households in the FoodAPS. We difference the expenditures of SNAP households from those of non-SNAP households on the same calendar day. For example, if a SNAP household reports $20 of expenditures on May 15, 2012, and the average expenditure among non-SNAP households on May 15, 2012 is $30, we replace the SNAP household's observation with -$10. We limit the non-SNAP households in this sample to those with income less than 185% of the federal poverty level.[8] Our estimates barely change with this procedure. Average SNAP household spending is about $74 greater than non-SNAP household spending on the day of receipt and about $5 less on day 30 of a 31-day cycle. The linear estimate of the downward trend in $0.55 per day in this specification with the full sample and $0.22 with day 1 removed. Full results are presented in Appendix Table A4. See Figure 2, Panel D for the full path of the difference over the benefit cycle. Given that food benefit cycles are not perfectly randomly distributed with respect to other income and benefit receipts (see Figure 1, which demonstrates that disbursements are more

[8] This reduces our sample size slightly, losing 4 SNAP households and 55 household-days on which we have no non-SNAP observations.

common near the beginning of the month), this procedure should increase confidence that the observed cycles are truly driven by the SNAP cycle.

Consumption cycles

Consumption cycles as measured by meals are unique to this study; we have no benchmark for assessing the magnitude of the decline in likelihood of consuming a meal over the course of the month. It is important to remember that this is a coarse measure since we do not observe the contents of meals. Estimates with meal consumption measured at both the household and individual level are presented in Table 2. To model the outcome variable of the number of meals (breakfast, lunch or dinner) eaten by in individual in a day, we use an OLS specification and a first-differenced fixed-effect specification since a linear model should fit these data well (see Figure 3). We also utilize a Tobit model for censoring at 0 and 3 meals per-day. Since calories are relatively substitutable within a day, we prefer to study the sum of meal indicators rather than isolating any meal in particular. The coefficients represent the per-day decline in the number of meals eaten by an individual in columns (3)-(6), and in the case of the household-level estimates in columns (1)-(3), the decline in the average number of meals eaten by an individual within the household. Standard errors are clustered at the household level in all specifications.

There is a significant decline in number of meals eaten over the course of the month. The daily decline in number of meals eaten is an intuitive metric for interpreting the regression results, but they do not properly convey the big picture. The smallest estimate in Table 2, Panel A is a decline of 0.005 meals per day. This extrapolates to 0.15 fewer meals consumed on day 30 of a benefit month than day zero. Alternatively, this corresponds to about 2.33 fewer meals eaten over the course of the month than if consumption remained constant at its day 0 level. The largest estimate in Table 2, Panel A is a decline of 0.027 meals per day. This is about 0.81 fewer meals on day 30 than day 0 or roughly 12.56 fewer meals eaten over the course of the month. In Appendix Table A5 we break this decline up by meal, consider the likelihood of going an entire day without a meal, and snacks. The likelihoods of eating breakfast, lunch and dinner all fall significantly over the course of the month, with roughly similar magnitudes. The probability of going an entire day without a meal is significantly increasing over the month, and the number of snacks eaten per day declines significantly, with a magnitude similar to the decline in the number of meals eaten.

We also present estimates of the consumption trend with imputed data excluded. Specifically, observations that are assigned a days-since-receipt value based on a receipt of benefits over a month in the past are excluded from the estimates in Table 2, Panel B. For example, if a household taking the initial survey on May 15th reported last receiving food benefits on April 17th, we would have a direct observation of 29 days since benefit receipt on May 16th, the first diary day. We would then have 6 imputed observations of 0-5 days since benefit receipt from May 17th to May 22nd, assuming that benefits arrived on the same calendar day (as they should) each month. Despite verification of program participation in the sample, estimates of program churn (movement in and out of SNAP) are high: a 2011 study of SNAP participation in six states by Mills *et al.* showed that 17-28% of participating households had exited and re-entered SNAP in the last 4 months. Furthermore, Figure 3 demonstrates that reported consumption on days imputed at the beginning of the benefit month is very different than reported consumption on direct observations on the same days of the benefit month. The estimates using the non-imputed sample are larger in each specification than those using all data, but the magnitudes are not substantially different.

An advantage of having simultaneous expenditure and consumption reports from the same household is that we can ask whether two empirically-verified phenomena –expenditure cycles and consumption cycles— are related to one another as is commonly assumed. To do this, we estimate benefit-month trend coefficients for every household in the sample using both food expenditure and meal consumption and then estimate their correlation. Because the expenditure data is at the household level, we use meal consumption data aggregated to the household level as well. Given only seven observations per household, the estimates are noisy, and we present both trimmed and untrimmed estimates. Expenditure estimates are truncated at -$10 and $10/per day and consumption estimates are trimmed at -0.1 and 0.1 average meals per day. Results are in Table 3, with both trend variables standardized. As expected, there is an overall positive relationship between expenditure and consumption trends within households, however it is weak. Using either the whole sample or the trimmed sample, we find that a 1 standard deviation increase in the expenditure trend is correlated with about a 0.05 standard deviation increase in the consumption trend (p = 0.118 and p = 0.160, respectively). We also implement a specification that allows for a changing correlation between consumption and expenditure trends over the course of the month.[9] Oddly, the whole sample and trimmed sample yield opposing results. In the full sample, we find a positive and significant correlation that emerges at the end of the month: a one standard-deviation increase in the expenditure trend correlates with a one-tenth of a standard deviation increase in the consumption trend in week 4 of a benefit month (p = 0.006). In the trimmed sample, we find a positive a significant correlation at the beginning of the month --a one standard-deviation increase in the expenditure trend correlates with a 0.15 standard deviation increase in the consumption trend in week 1 of a benefit month (p = 0.021)—that decays to zero by week 4.

In summary, we strongly replicate the findings of prior literature on the failures to smooth expenditure and consumption over the SNAP benefit cycles. We find larger magnitudes

[9] We assign a household to a week of the month based on the first day of their seven-day diary.

of expenditure cycles than other work, although this varies depending on the specification. We are the first to identify consumption-smoothing failures as measured by missed meals and find strong and significant downward trends over the benefit month. This is consistent with Shapiro (2005) that identifies a decline in caloric intake. These two phenomena are correlated within households, but not as strongly as expected. Additionally, we leverage the targeted sampling of the FoodAPS to show that both types of trends are robust to being measured as calendar-day differences from the average non-SNAP household expenditure and consumption. Given that SNAP disbursements are not uniformly distributed with respect to other income sources, this is an important robustness check that has been missing from the literature.

Incidence of food shortfall within households

This section is devoted to decomposing the consumption findings from Section 3.2 within a household. Are children more vulnerable because they rely on others for meals or are the sheltered by well-meaning parents? Perhaps school meal programs protect kids directly. Are women in dual-adult households more vulnerable because they must bargain with a spouse? Kuhn (2015) finds that household composition determines, in part, the severity of the expenditure trend over the SNAP month. Households will more young children and dual-adults exhibit the strongest declines.[10] A proposed explanation for this finding is that the aggregation of preferences within the household and bargaining between decision makers can lead to dynamically inconsistent behavior (Jackson and Yariv 2014, Hertzberg 2012). Even if EBT has ameliorated some of the problems associated with food purchasing decisions (Kuhn 2015), the intra-household allocation of purchased food remains an important issue. The dynamics of this allocation over the benefit cycle have not been investigated.

[10] This is true prior to the implementation of EBT only. After the introduction of EBT, much of this heterogeneity is gone.

Age differences

We start by examining consumption cycles by age. Minors are split into three six-year age buckets. Indicators for each group are interacted with the days since benefit receipt variable. Table 4 shows the results of adding these interaction terms to regressions of the same form as columns (4) and (6) of Table 2. We also implement a household fixed-effects specification that allows within-household differences in trends to more directly contribute to our estimate of differential trends by age. First-differencing the data generates trend estimates from individual variation, and these trends are compared across age category with no regard to household; every adult is compared with equal weight to every child 0-5 years old, for example. The household fixed-effects allow within-household differences to inform the age parameters in the model such that a child's difference in trend from their parent matters more than a child's difference in trend from any random adult. Results are presented in Table 4 for both the full sample and non-imputed data only.

There are level differences in consumption favoring children, but more interestingly, we find that the decline in meal consumption is much less dramatic for the youngest children. While our estimate of the consumption trend for adults varies considerably across specifications, the interaction between the trend variable and an indicator for age < 6 is always positive and comparable to the negative coefficient on the trend itself. The sum of those coefficients is never significantly different than zero. There is some evidence that children 6-12 and 12-17 years-old experience less severe consumption declines, but this is sensitive to specification. In Appendix Tables A6, A7 and A8, we present results separately by meal, finding that breakfast consumption most closely mimics the pattern of results found for all meals pooled.

To generalize from our discrete age cutoffs, Figure 4 presents the average daily decline in the number of meals consumed as it varies by according to a 5th order polynomial in age. This is implemented using the OLS specification on the full sample. The graph is truncated at age 60, above which the standard errors increase considerably. We estimate a positive consumption trend for individuals 11 and under, significant at the 5% level for kids 8 and younger. The trend is negative for individuals older than 11, significant at the 5% level for those 15 and older. Figure 5 shows the evolution of the difference in average daily meal consumption from its level at the beginning of the benefit month. We group all kids under 12 and all individuals over 11 based on Figure 4. Furthermore, we smooth the data using a 5-period moving average before differencing it from the day 2 moving average value. Both groups experience upward trends in consumption over the first week of the month. Starting in the second week of the, consumption begins a prolonged decline for individuals 12 and older and remains steadily above its initial value for kids under 12. The fourth week of the month brings a steep decline for everyone, retuning young kids to about the level they started the month at and pushing older individuals down to 0.15 meals per day below that value.

We believe there are two primary mechanisms through which these age differences could operate: parental sheltering of kids and school meal provision. In the case of the first mechanism, we would expect to see adults in households without kids exhibiting less severe consumption declines. However, this comparison is confounded by selection into parenting. If parents tend to be more patient and effective budgeters than non-parents in the sample of SNAP participants, we would expect to see the opposite. Our estimate of the effect of days since benefit receipt on meal consumption for adults in households with no children is significantly larger in magnitude than for adults in households with kids (-0.004 meals per day for adults in households with kids and -0.012 meals per day for adults in households without kids, p = 0.060). This is consistent with parents being more patient than non-parents. When we re-estimate all the models in Table 4 with the sample limited to households with kids, we get slightly weaker estimates of the age-group interactions because of this change in the adult population. Overall, all we can say with respect to the sheltering hypothesis is that whatever sheltering may be occurring is not large enough to overwhelm selection effects.

To investigate the role of school meal provision, we stratify our sample based on whether school is in session at the time of the meal diary. School meal provision cannot fully explain the differential trends by age that we see because the most persistent differences are for kids who are mostly too young for school. Figure 4 shows a significantly positive consumption trends for kids 10 and under, and while the effect is not consistent across specification, column (1) of Table 4 does show a sizeable differential trend for kids from 6 to 11, and columns (1) and (4) show differential trends for kids from 12 to 17. We do not use measures of school breakfast and lunch program participation, cost and frequency because they exhibit almost no variance within our sample of SNAP participants.[11] However, 36.3% of the school-aged children in our sample are on break from school, and participation in summer programs with meals is very low.

We classify an entire household as either in school or on break to allow adults' consumption trends to differ as well. This eliminates households without any school-aged children, meaning that our estimation sample for the youngest children is very different. The sample is split according to school status; we estimate our model on each sample and then test the equality coefficients across samples. Additionally, we re-construct the age groups to represent school types: not school age (< 5), primary school (4 < age < 11), middle school (10 < age < 14) and high school (13 < age < 18).[12] For this comparison to inform the impact of school in session kids' meal trends, it must be that other factors associated with being out of school are

[11] 93.8% of children in our SNAP sample receive breakfast at school, 96.6% receive lunch at school, almost all for free.
[12] Because data on completed/upcoming grade is not recorded for students who are on break from school, we use this age classification rather than a direct observation of school type.

not driving differential consumption over the benefit month. Since the variation we use is almost entirely the comparison of summer to the rest of the year, this is a non-trivial concern. Changing weather patterns or seasonal work could affect the way people shop and eat. Results using the OLS specifications from columns (1) and (4) of Table 4 are presented in Table 5. Reassuringly, adult consumption trends are not more extreme when the kids are out of school. We find that primary school-age kids indeed experience a shift from doing better than adults when school is in to doing worse than adults when school is out. The OLS specifications in columns (1) and (2) show a statistically significant difference between the interaction terms associated with primary school across school status. The limited-sample estimates show a similar reversal, but the difference is not significant. We do not find evidence of differences by school status for middle school and high school students.

If school meal programs do explain the difference by school break status for primary school students, why aren't there effects for middle and high-school students? As kids get older, they may experience more social stigma associated with participating in meal programs. They may also prefer to use their free time before school and during the lunch break for other activities. The FoodAPS measures the number of days per week children get complete lunches and breakfasts at school in addition to whether their schools offer breakfast and lunch. While SNAP-participating children essentially all have access to these programs, there is some variation in the reported weekly usage. We regress lunch and breakfast program usage on indicators for middle and high school age, with primary school age as the omitted category. High-school students get 0.26 (S.E. = 0.124, $p = 0.040$) fewer lunches per week and 0.68 (S.E. = 0.179, $p < 0.001$) fewer breakfasts per week than primary school students. We do not find any differences for middle school students.

Gender differences

We follow our approach to age differences by interacting gender with the days since benefit receipt variable. Results are in Table 6. If women are disadvantaged in a household bargaining model that binds when resources are scarce, we should expect to see gender differences in consumption trends emerge when we limit the sample to households with multiple adults (in this case, defined specifically as a spouse or unmarried partner to the primary recipient). However, given the finding in the previous that are household-level differences associated with having kids that are likely due to selection, it is reasonable to believe that similar differences exist based on relationship status. Indeed, we find evidence that women in dual-adult households experience less severe consumption declines (comparing columns (1) and (4) of Table 6). Adding a household fixed effect or first-differencing (columns (2) vs. (5) and (3) vs. (6) of Table 6) mitigates this difference, indicating that dual-adult households do better overall. Differences across gender are limited to the first-differenced models in which we find evidence that men in dual-adult households experience more severe consumption declines.

If parental sheltering is responsible for some of the attenuated consumption decline for kids, there is scope for differential investment by child gender. However, specifications that feature interactions between gender and the child age groups used earlier reveal no consistent or significant evidence of differences in consumption trends by gender.

Consumption quality

Our measure of consumption captures the consequences of benefit cycles only when they amount to lost meals. Reductions in the amount and quality of food would mean that the consumption cycles are even more harmful than our estimates indicate. Given that the proportional decline in expenditure is much larger than consumption, we can say that the ratio of expenditure to number of meals consumes is also falling over the course of the month. However, this depends on the assumption that expenditures are converted into meals relatively quickly instead of slowly through the consumption of non-perishables. We obtain some direct evidence of changing diet using self-reported data from the initial survey on diet quality, the perceived costs of eating healthy and fruit/vegetable sufficiency. The likelihood of reporting very low adult food security increases by 4% over the course of the benefit month (p = 0.331). Self-reported own diet quality decreases by 0.12 standard deviations (p = 0.243) over the course of the benefit month. The likelihood of reporting sufficient fruit and vegetable consumption decreases by about 6% over the benefit month (p = 0.180).

Another way of assessing meal quality is to examine whether there are changes over the month in the types of food purchased for consumption at home. For example, more costly meats at the beginning of the month might be replaced by cheaper, less nutritious carbohydrates at the end of the month. Those carbohydrate foods are likely to be non-perishable and may be purchased at the beginning of the month as well. Therefore, we consider the time-path of the relationship between different food categories over the course of the month. Our first comparison is between protein and carbohydrates.[13] We feel that this comparison gets directly at the basis of a meal: chicken or pasta? This is measured by subtracting carbohydrate expenditures from protein expenditures on a given day and dividing by the total expenditures on food for home consumption on that day. Therefore, this is a measure of basket composition, conditional on grocery shopping. Shopping days with no reported expenditure on either protein or carbohydrate goods are excluded. We also consider substitution in accompanying foods: are fruits and vegetables at the beginning of the month replaced by snacks and sweets at the end of the month? Finally, we pool food categories into "good" (milk and dairy, protein, and fruits and

[13] Specifically comparing items classified as "proteins" to "grains" as characterized by the USDA.

vegetables) and "bad" (grains and snack and sweets) groups. We regress these measures on days since benefit receipt in specification akin to those in Table 4. Results are in Table 7.

Purchases of protein goods as a fraction of total expenditures fall relative to carbohydrate purchases as a fraction of total expenditures over the course of the month, however the magnitude is small. On day zero, households that make a purchase of either food type spend about 17% more on protein goods. This falls to about 10% by the end of the benefit month. Estimates for the comparison between combined milk and dairy, protein and fruit and vegetable expenses, and combined carbohydrate and sweet and snack expenses are very similar. We do not observe a substitution over time between fruits and vegetables and sweets and snacks.

These broad categories don't fully capture the dynamic of a household adjusting its purchasing patterns to reflect a shrinking budget. We can leverage the detail of the FoodAPS to use the energy content and weight of the items purchased instead. With resources running out, we expect to see an increase in the calories per dollar of food purchased in order to obtain sufficient energy and an increase in grams per dollar purchased in order to satiate appetites. We find suggestive evidence of this. kCal per dollar spent on food is estimated to increase by roughly 20% over the course of the benefit month, from 409 kCal/$ to 492 kCal/$ ($p = 0.130$). Additionally, edible grams of food per dollar increases about 37% from 304 g/$ to 417 g/$ over the benefit month ($p = 0.001$).[14] These changes are likely linked to a shift away from protein towards carbohydrates over the course of the month.[15] Within carbohydrates, purchases shift away from food with dietary fiber content over the course of the month, towards food with a

[14] Therefore, the caloric density by weight is actually going down over the course of the month because the growth rate of g/$ exceeds that of kCal/$.
[15] The ratio of protein grams less carbohydrate grams to total grams purchased declines by 6% over the course of the month ($p = 0.205$). There do not appear to be substitutions towards or away from fats over the course of the month.

higher sugar content.[16]

Food access

A common suggestion is that the calorie crunch among benefit recipients might be a direct reflection of transactions costs in shopping. If SNAP participants are not located near grocery stores, then planning a large shopping trip to coincide with benefit arrival seems natural. Later in the month, a dwindling supply of stored food combined with poor local options for fresh food results in reduced consumption. If different types of households live nearby or far away from grocery stores, this could be responsible for the systematic differential severity in consumption declines found in this paper and Kuhn (2016). The FoodAPS has precise information on household-specific travel times to their primary grocery stores that can be used in conjunction with reported travel times. We use this information to explore the role that food access could play in our results.

All households report their travel time to their primary grocery store. For most households, the location of this store and the respondent's home address are used to calculate driving and waling travel times. The match between reported travel time and calculated travel time according to the reported transportation mode is good, although it is not perfect. While we use households reported travel times, because their perception of the time costs of shopping are what matters for their shopping decision, we drop reported times that are in the extremes of the distribution of mismatch between reported and calculated times.[17] The two-way travel times we use vary from 2 to 180 minutes.

First, we verify that households with higher travel times shop less and spend more when they

[16] The ratio of dietary fiber grams less sugar grams to total carbohydrate grams purchased declines by 9% over the course of the month ($p = 0.053$).

[17] Specifically, we calculated the difference between the reported and calculated times and drop observations that are lower than the 5th percentile or higher than the 95th percentile of the difference distribution.

shop. We limit our expenditure sample here to food for at-home consumption and continue to define shopping as an indicator for whether at least $1 was spent on food for at-home consumption. In Table 8, column (1), we show that travel time does correlate negatively with shopping likelihood. A 10-minute increase in round trip travel time relates to a 1% reduction in the likelihood of grocery shopping. Column (2) demonstrates that expenditures are higher –roughly $1.74 for every 10 minutes of travel. Increasing the shopping threshold increases the size of the coefficients in both columns (1) and (2), with both being statistically significant. Thus, our basic predications for how travel time should interact with shopping pan out.

If travel time were a primary driver of the changes in shopping and expenditures over the course of the month, we would expect to see the gap in shopping between nearby and far away household expand over the course of the benefit month. At the end of the benefit month, distant households should be less likely to shop (at least relative to the baseline likelihood gap at the beginning of the month, which could be positive, negative or zero). In other words, when we add days since receipts and its interaction with travel time to the regressions from Table 8, column (1), we should negative coefficients on the interaction term. We do not find strong evidence in favor of this hypothesis. The coefficient on the interaction term in column (3) is a tightly estimated zero, indicating that there is a level gap in shopping likelihood associated with distance but that it isn't changing over the benefit cycle. Food access is not driving shopping patterns that lead to the calorie crunch. Figure 6 shows the shopping trends over the month based on round trip sample time. The data is roughly divided into equal thirds with groups of 10 minutes or less, 10-20 minutes and 20 minutes or more. The data are noisy, but the 20 minutes or more group is below the two closer groups consistently, but there are no clear time trends in the relationship across groups.

In Section 3.2, we established that while expenditure and consumption trends are correlated within households, they are not highly correlated. We thus estimate the direct relationship between travel time and consumption. Using both OLS and first-differenced individual fixed effects models, there is no time changing relationship between travel time and meal consumption. The OLS specification shows no level relationship either. Based on these findings, we think it is unlikely that food access is a primary cause of either the calorie crunch or its differential incidence across households.

Discussion and conclusion

The FoodAPS offers our first look at simultaneous expenditure and consumption profiles for SNAP households. We replicate previous research with our measures of expenditure, and provide the first results measured in terms of missed meals, which have direct implications for food security classification. Also, we show that quality of diet decreases over the benefit month; people eat fewer meals that consist of more carbohydrates and less protein. While households exhibit strong downward trends in both consumption and expenditure throughout the benefit month, these behaviors are only loosely correlated. This finding should prompt a more careful examination of how consumption decisions are made within the home, whereas the bulk of current policy interest focuses on intervention at the point of sale. For instance, long travel time to the primary grocery store, a commonly proposed explanation for poor purchasing and consumption habits, has no relationship to dynamic outcomes. On the other hand, when we examine within-household incidence of declines in consumption, we find that age is an important determinant of missed meals at the end of the month. The youngest children are sheltered from the calorie crunch regardless of school status, but primary-school age children are sheltered only when school is in session.

SNAP, the National School Lunch Program (NSLP) and the School Breakfast Program (SBP) have all been shown to positively impact children's health. We have already discussed the literature linking SNAP to health outcomes. Gleason and Suitor (2003) show that the NSLP improves nutritional intake, but also increases dietary fat consumption and indeed, Schanzenbach (2009) links the NSLP to increased childhood obesity. Gundersen *et al.* (2012) estimate an overall positive impact on health. Bhattacharya *et al.* (2006) show improvements in nutritional intake and overall diet quality for SBP participants and Dotter (2013) demonstrates that universally-free breakfast programs have lasting impacts on academic achievement. Given our results, we suspect that some of the positive impacts of these programs may operate through the mitigation of cyclical food insecurity associated with the calorie crunch. While participation in school meal programs is essentially universal in our SNAP sample, this does not mean redemption of those meals is. Breakfast is the most commonly skipped meal: 67% of low-income children don't eat breakfast every day, with 19% of all children skipping breakfast on any given day (Moag-Stahlberg 2011, O'Neil *et al.* 2015). Interventions that increase usage of the SBP and NSLP could mitigate cyclical food insecurity associated with SNAP in addition to raising the level of consumption. Additionally, participation in summer break programs with meal provision is essentially nonexistent. Current efforts to expand summer meal programs for children may also help smooth consumption.

A puzzling aspect of our results is that there appear to be very little impact of school meal programs for middle or high-school children. This could mean that our interpretation of the difference in calorie crunch by school status is incorrect. Or, it could indicate that older children underutilize these programs. We expect that stigma associated with these programs would increase with age. Mirtcheva and Powell (2009) show that as the eligibility rate of a school increases, NSLP usage increases. This is driven by behavior in high schools. Bhatia *et al.* (2011) remove paid lunch options at high and middle schools in San Francisco and find increased uptake of NSLP lunches that exceeded the number of students originally paying for lunch. Expanding usage of NSLP and SBP at these levels could reduce cyclical food insecurity and potentially alleviate the associated behavioral problems identified by Gennetian *et al.* (2015).

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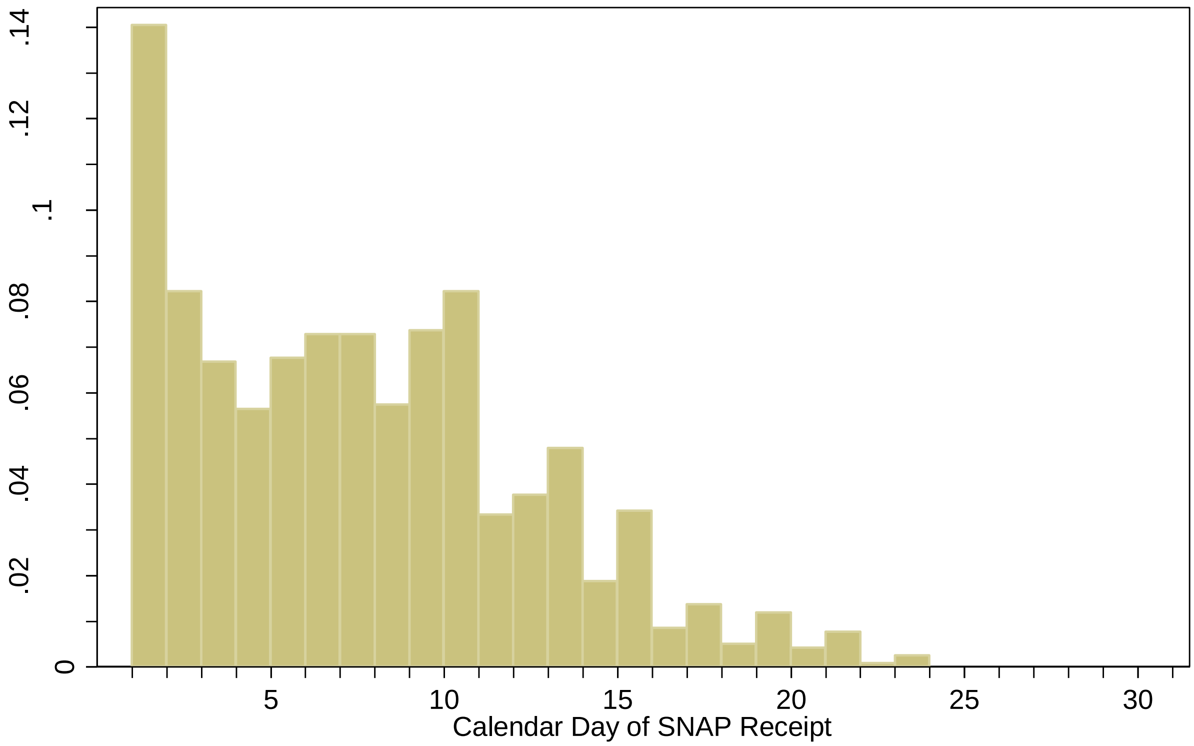

Figure 1: Distribution of Benefit Receipt in Sample

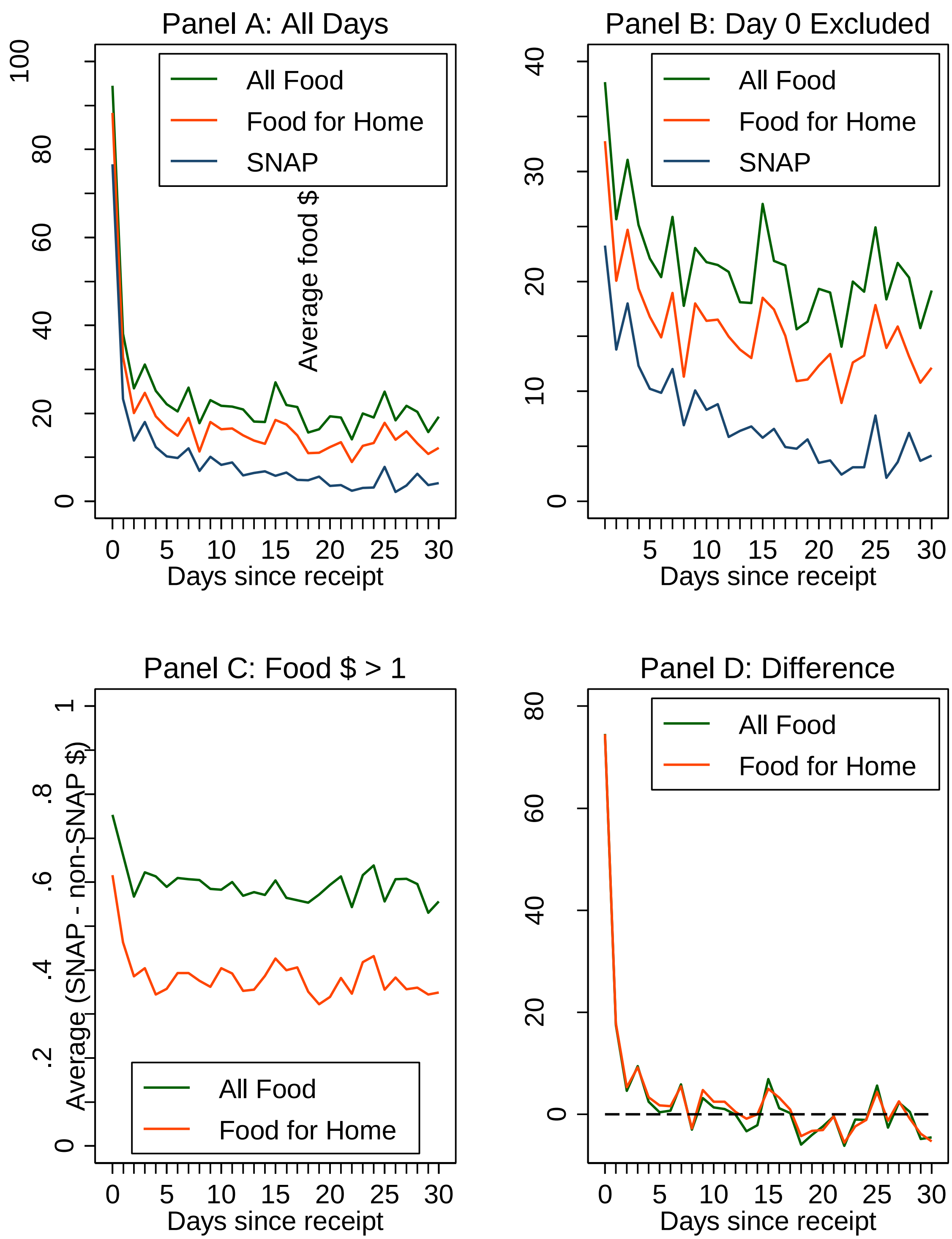

Figure 2: Expenditure Trends over the Benefit Month

Table 1: Estimates of Household Expenditure Trend						
Date range:	All			Days since receipt > 0		
Model:	OLS	FD	FE Poisson	OLS	FD	FE Poisson
	(1)	(2)	(3)	(4)	(5)	(6)
Days since receipt	-0.555*** (0.067)	-3.819*** (0.386)	-0.041*** (0.006)	-0.231*** (0.058)	-2.343*** (0.332)	-0.018*** (0.006)
Constant	31.570 (1.538)			23.952 (1.327)		
Clusters	1167	1167	961	1167	1167	920
N	8169	6784	6585	7914	6559	6241

***: $p < 0.01$. Standard errors clustered by household are in parentheses beneath the estimates. Week of month, a weekend indicator and an indicator for whether the diary day was a day on which the survey team called to check up on the respondent's expenditure logs are included as controls in all specifications. Columns (2) and (5) feature fewer observations than columns (1) and (4) due to first-differencing. Columns (3) and (6) feature fewer observations than columns (1) and (4) because households with no variation in the dependent variable are dropped. Moving from columns (1), (2) and (3) to (4), (5) and (6) results in the loss of observations due to the exclusion of the day of benefit receipt from the sample.

Table 2: Estimates of Meal Consumption Trend at Household and Individual Levels						
Unit of Analysis:	Household			Individual		
Model:	OLS	Tobit	FD	OLS	Tobit	FD
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All Data						
Days since receipt	-0.006*** (0.002)	-0.009*** (0.003)	-0.025*** (0.004)	-0.005*** (0.002)	-0.012*** (0.004)	-0.022*** (0.004)
Constant	2.249 (0.040)	2.441 (0.056)		2.310 (0.041)	3.079 (0.096)	
Clusters	1167	1167	1167	1167	1167	1167
N	8169	8169	6784	25,571	25,571	21,225
Panel B: Non-imputed Data Only						
Days since receipt	-0.010*** (0.003)	-0.015*** (0.004)	-0.027*** (0.004)	-0.009*** (0.003)	-0.022*** (0.006)	-0.023*** (0.004)
Constant	2.347 (0.056)	2.589 (0.083)		2.411 (0.055)	3.327 (0.132)	
Clusters	1088	1088	1044	1088	1088	1044
N	6819	6819	5731	21,119	21,119	17,738

***: $p < 0.01$. Standard errors clustered by household are in parentheses beneath the estimates. Week of month and a weekend indicator are included as controls in all specifications. The number of meals in a day can range from 0 to 3 for an individual: breakfast, lunch and dinner. Averaged within a household, the meals variable is defined continuously between 0 and 3. Columns (3) and (6) have fewer observations than the other models at the same analysis unit because of the first differencing.

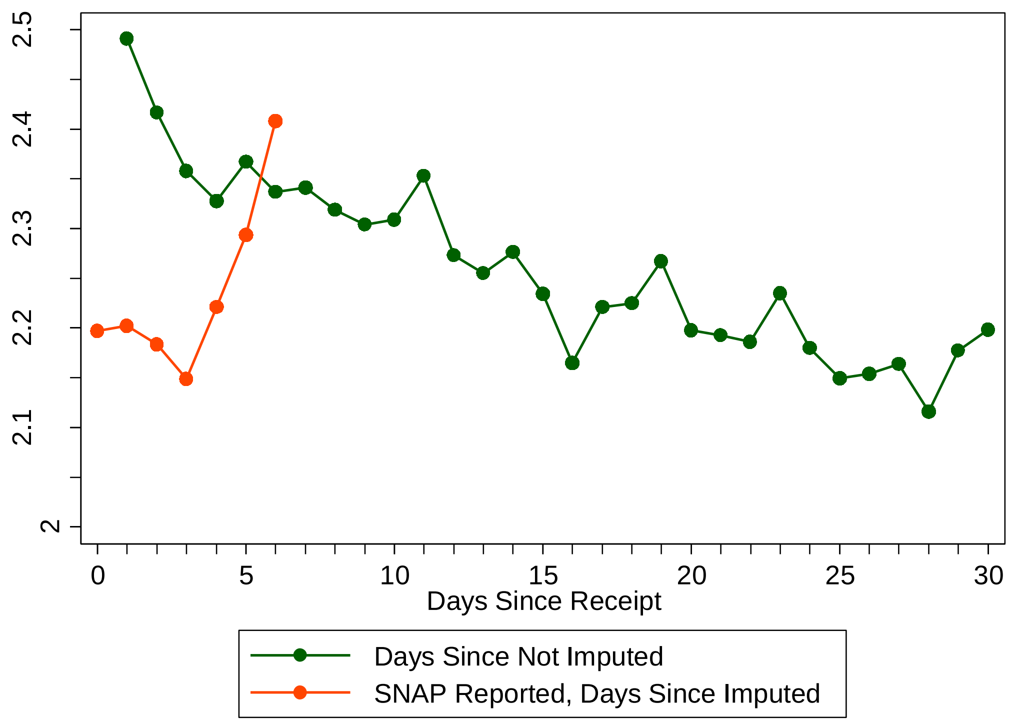

Figure 3: Consumption Trends over the Benefit Month

Table 3: Intra-Household Correlation between Expenditure and Consumption Trend Estimates

Dep. Var.:	Household Meal Consumption Trend			
Estimates:	All	Trimmed	All	Trimmed
	(1)	(2)	(3)	(4)
Household Expenditure Trend	0.046 (0.029)	0.054 (0.039)	-0.048 (0.048)	0.155** (0.067)
Week of Month			-0.034 (0.024)	0.025 (0.031)
Household Expenditure Trend X Week of Month			0.051** (0.021)	-0.060* (0.033)
N	1167	615	1167	615

**: $p < 0.05$, *: $p < 0.10$.

Table 4: Number of Daily Meals Consumption Trend by Age Group						
Sample:	All			Non-Imputed Data Only		
Model:	OLS	HH FE	FD	OLS	HH FE	FD
	(1)	(2)	(3)	(4)	(5)	(6)
Days since receipt	-0.007*** (0.002)	-0.001 (0.001)	-0.022*** (0.004)	-0.012*** (0.003)	-0.002 (0.002)	-0.024*** (0.005)
Age < 6	0.441*** (0.061)	0.377*** (0.048)		0.402*** (0.088)	0.357*** (0.065)	
Days since receipt X age < 6	0.007** (0.003)	0.005* (0.002)	0.012 (0.008)	0.010** (0.005)	0.006* (0.003)	0.018** (0.009)
5 < age < 12	0.336*** (0.069)	0.365*** (0.048)		0.379*** (0.090)	0.402*** (0.068)	
Days since receipt X 5 < age < 12	0.007* (0.004)	0.001 (0.003)	0.003 (0.008)	0.006 (0.005)	-0.001 (0.004)	0.004 (0.009)
11 < age < 18	0.064 (0.081)	0.202*** (0.051)		-0.070 (0.132)	0.168** (0.075)	
Days since receipt X 11 < age < 18	0.009** (0.004)	0.001 (0.003)	-0.013 (0.010)	0.016** (0.007)	0.003 (0.004)	-0.015 (0.012)
Constant	2.199 (0.041)			2.311 (0.056)		
Clusters	1167	1167	1167	1088	1088	1044
N	25,571	25,571	21,225	21,119	21,119	17,738

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$. Standard errors clustered by household are in parentheses beneath the estimates. Week of month and a weekend indicator are included as controls in all specifications. The number of meals in a day can range from 0 to 3 for an individual: breakfast, lunch and dinner. Columns (3) and (6) have fewer observations than the other models in the same sample because of the first differencing.

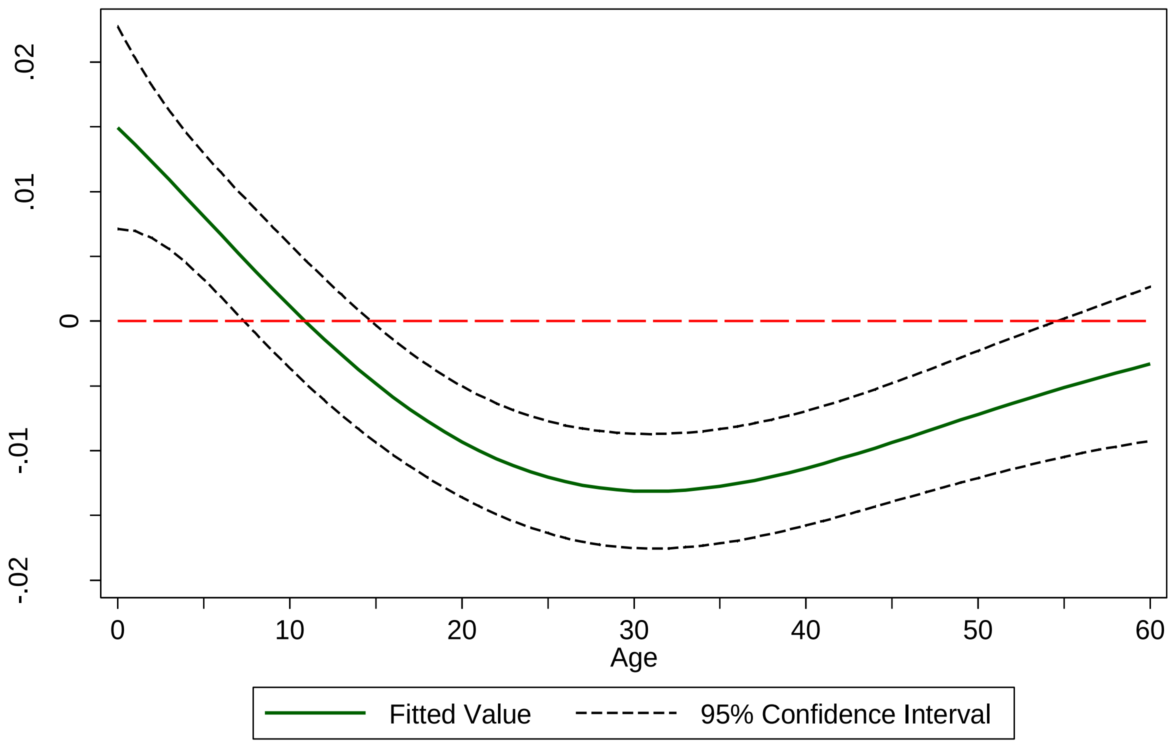

Figure 4: Consumption Trend by Age

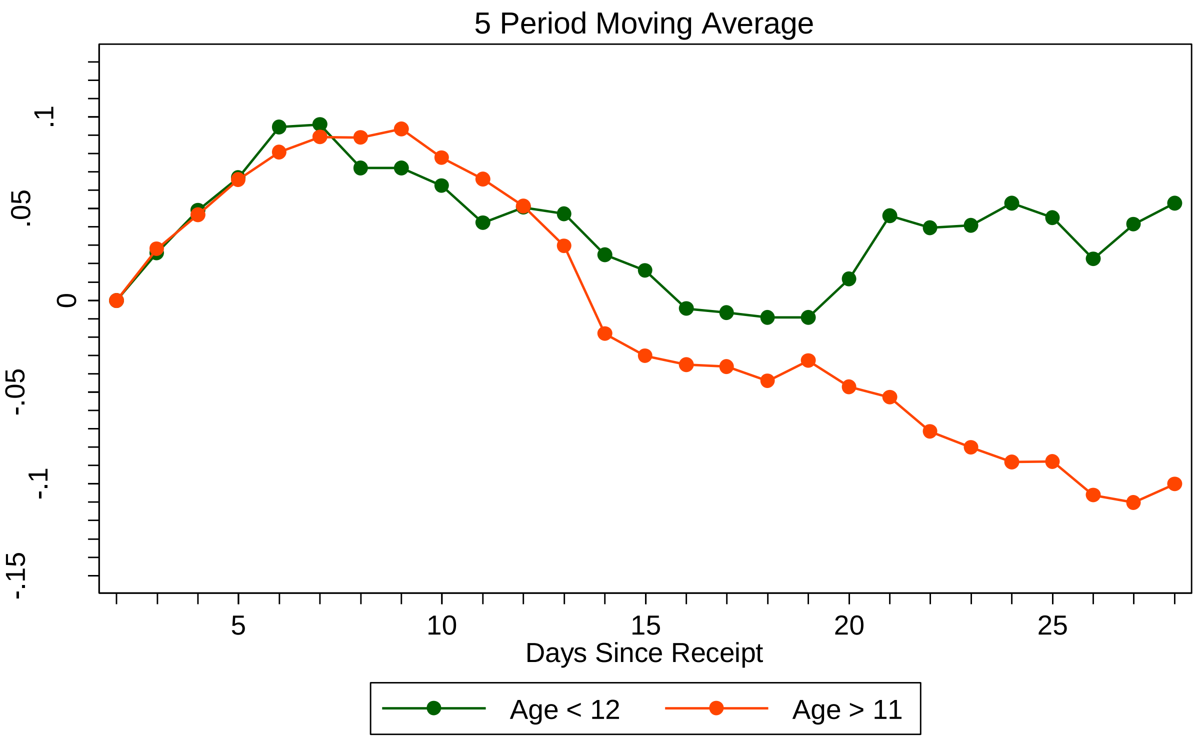

Figure 5: Smoothed Differences in Consumption from their Initial Value

Table 5: Difference in Consumption Trends by School Break Status				
Sample:	All		Non-Imputed Data Only	
School:	Open	Closed	Open	Closed
	(1)	(2)	(3)	(4)
Days since receipt	-0.004 (0.003)	-0.002 (0.004)	-0.007 (0.005)	-0.001 (0.006)
Difference:	-0.002 $\chi^2 = 0.22$ ($p = 0.637$)		-0.006 $\chi^2 = 0.56$ ($p = 0.455$)	
Days since receipt X not school-age	0.003 (0.005)	-0.001 (0.007)	0.003 (0.007)	-0.002 (0.009)
Difference:	0.004 $\chi^2 = 0.16$ ($p = 0.688$)		0.005 $\chi^2 = 0.22$ ($p = 0.637$)	
Days since receipt X primary school	0.007 (0.005)	-0.008 (0.007)	< 0.001 (0.006)	-0.013 (0.010)
Difference:	0.015* $\chi^2 = 3.04$ ($p = 0.081$)		0.013 $\chi^2 = 2.18$ ($p = 0.260$)	
Days since receipt X middle school	-0.002 (0.006)	-0.001 (0.010)	-0.001 (0.009)	0.011 (0.015)
Difference:	-0.001 $\chi^2 < 0.01$ ($p = 0.953$)		-0.012 $\chi^2 = 0.48$ ($p = 0.468$)	
Days since receipt X high school	0.009 (0.006)	0.009 (0.008)	0.014 (0.009)	0.017 (0.014)
Difference:	< 0.001 $\chi^2 < 0.01$ ($p = 0.996$)		-0.003 $\chi^2 = 0.03$ ($p = 0.862$)	
Constant	2.156 (0.071)	2.199 (0.089)	2.246 (0.098)	2.168 (0.125)
Clusters	529		487	
N	15,743		12,850	

*: $p < 0.10$. Level effects of school age are excluded for presentation. Standard errors clustered by household are in parentheses beneath the estimates unless otherwise indicated. Week of month and a weekend indicator are included as controls in all specifications. The number of meals in a day can range from 0 to 3 for an individual: breakfast, lunch and dinner.

Table 6: Number of Daily Meals Consumption Trend by Gender						
Sample:	All Data			Dual-Adult HHs		
Model:	OLS	HH FE	FD	OLS	HH FE	FD
	(1)	(2)	(3)	(4)	(5)	(6)
Days since receipt	-0.007*** (0.002)	< 0.001 (0.001)	-0.016*** (0.005)	-0.003 (0.003)	0.001 (0.002)	-0.013** (0.006)
Male?	-0.042 (0.045)	0.009 (0.032)		-0.011 (0.046)	0.004 (0.040)	
Days since receipt X Male?	0.001 (0.002)	< 0.001 (0.002)	-0.014** (0.006)	-0.001 (0.002)	< 0.001 (0.002)	-0.016** (0.007)
Constant	2.203 (0.045)					
Clusters	1162	1162	1162	494	494	494
N	15,386	15,386	12,765	8358	8358	6933

***: $p < 0.01$, **: $p < 0.05$. Standard errors clustered by household are in parentheses beneath the estimates. All data are from adults. Week of month and a weekend indicator are included as controls in all specifications. The number of meals in a day can range from 0 to 3 for an individual: breakfast, lunch and dinner. First-differenced models have fewer observations both because of the differencing and because we exclude across benefit-month differences.

Table 7: Expenditure Bundle Trends over the Benefit Month			
Food Comparison:	$Protein - $Carb / $Total	$Fruit & Vegetable - $Snack & Sweet / $Total	$Good - $Bad / $Total
	(1)	(2)	(3)
Days since receipt	-0.002*** (0.001)	> -0.001 (0.001)	-0.002** (0.001)
Constant	0.168 (0.016)	-0.035 (0.017)	0.159 (0.019)
Clusters	950	968	1110
Observations	1775	1941	2977

***: $p < 0.01$, **: $p < 0.05$. Standard errors clustered by household are in parentheses beneath the estimates. Week of month, a weekend indicator and an indicator for whether the diary day was a day on which the survey team called to check up on the respondent's expenditure logs are included as controls in all specifications. Days without any expenditure on either category being compared are excluded, therefore the number of observations depends on how frequently the items in question were purchased.

Table 8: Travel Time, Grocery Shopping and Grocery Expenditures				
Dependent variable:	1(Exp. ≥ 1)	Exp. | Exp. ≥ 1	1(Exp. ≥ 1)	Exp. | Exp. ≥ 1
	(1)	(2)	(3)	(4)
Round trip travel time (minutes)	-0.001*** (< 0.001)	0.174* (0.098)	-0.002*** (0.001)	0.381 (0.257)
Days since receipt			-0.003*** (0.001)	-1.039*** (0.274)
Days since receipt X Round trip travel time (minutes)			< 0.001 (< 0.001)	-0.014 (0.014)
Constant	0.437 (0.016)	45.299 (3.696)	0.478 (0.020)	55.621 (5.532)
Clusters	941	893	941	893
N	6587	2406	6587	2406

***: $p < 0.01$, *: $p < 0.10$. Standard errors clustered by household are in parentheses beneath the estimates. Week of month, a weekend indicator and an indicator for whether the diary day was a day on which the survey team called to check up on the respondent's expenditure logs are included as controls in all specifications. The food expenditures are limited to purchases made for food at home because the travel time is calculated based on the distance to the respondent's primary grocery store. Reported travel time is used, but set to missing if it is an outlier in the distribution of mismatch between reported and calculated travel times (truncated at the 5th and 95th percentiles).

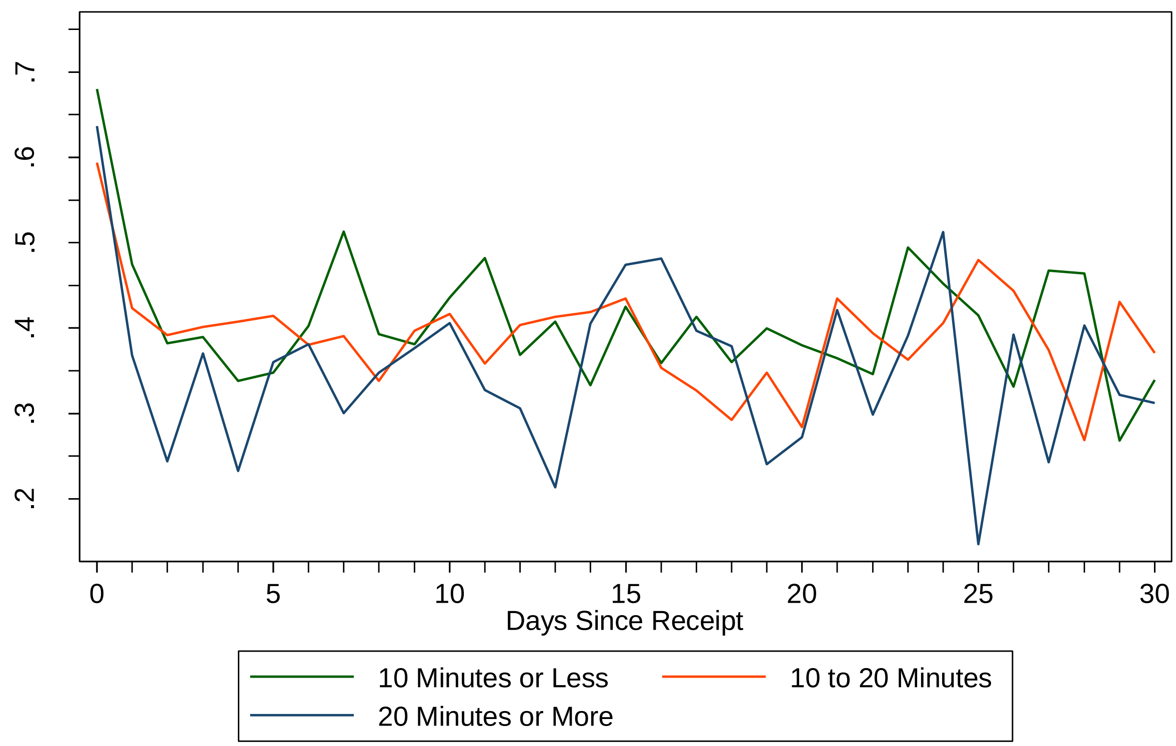

Figure 6: Round Trip Travel Time and Shopping Likelihood over the Benefit Month

Appendix

Table A1: Alternative Estimates of Household Expenditure Trend						
Date range:	All			Days since receipt > 0		
Model:	Tobit	MD	Poisson	Tobit	MD	Poisson
	(1)	(2)	(3)	(4)	(5)	(6)
Days since receipt	-0.763*** (0.111)	-0.958*** (0.144)	-0.027*** (0.003)	-0.318*** (0.101)	-0.327*** (0.118)	-0.012*** (0.003)
Constant	13.561 (2.196)	36.678 (2.153)	3.530 (0.063)	5.818 (2.209)	25.727 (1.856)	3.207 (0.066)
Clusters	1167	1167	1167	1167	1167	1167
N	8169	8169	8169	7914	7914	7914

***: $p < 0.01$. Standard errors clustered by household are in parentheses beneath the estimates unless otherwise indicated. Week of month, a weekend indicator and an indicator for whether the diary day was a day on which the survey team called to check up on the respondent's expenditure logs are included as controls in all specifications. Columns (4)-(6) feature fewer observations due to the excluded day of SNAP receipt.

Table A2: Extensive Margin Estimates of Household Shopping Trend				
Model:	LPM	FD LPM	Probit	Household Conditional Logit
	(1)	(2)	(3)	(4)
Days since receipt	-0.002** (0.001)	-0.008*** (0.002)	-0.002** (0.001)	-0.004*** (0.001)
Constant	0.615 (0.017)		0.614 (0.017)	
Clusters	1167	1167	1167	1050
N	8169	7002	8169	7350

***: $p < 0.01$, *: $p < 0.10$. Standard errors clustered by household are in parentheses beneath the estimates unless otherwise indicated. Week of month, a weekend indicator and an indicator for whether the diary day was a day on which the survey team called to check up on the respondent's expenditure logs are included as controls in all specifications. Marginal effects are presented in columns (3) and (4). Column (2) features fewer observations because of the first-differencing. Column (4) features fewer observations because households without variation in the dependent variable are dropped.

Table A3: Estimates of Household Food at Home Expenditure Trend						
Date range:	All			Days since receipt > 0		
Model:	OLS	FD	FE Poisson	OLS	FD	FE Poisson
	(1)	(2)	(3)	(4)	(5)	(6)
Days since receipt	-0.590*** (0.062)	-3.458*** (0.360)	-0.052*** (0.008)	-0.267*** (0.050)	-2.022*** (0.304)	-0.025*** (0.008)
Constant	26.290 (1.440)			18.688 (1.162)		
Clusters	1167	1167	835	1167	1167	787
N	8169	6784	5656	7914	6559	5277

***: $p < 0.01$. Standard errors clustered by household are in parentheses beneath the estimates unless otherwise indicated. Week of month, a weekend indicator and an indicator for whether the diary day was a day on which the survey team called to check up on the respondent's expenditure logs are included as controls in all specifications. Columns (2) and (5) feature fewer observations than columns (1) and (4) due to first-differencing. Columns (3) and (6) feature fewer observations than columns (1) and (4) because households with no variation in the dependent variable are dropped. Moving from columns (1), (2) and (3) to (4), (5) and (6) results in the loss of observations due to the exclusion of the day of benefit receipt from the sample.

Table A4: Estimates of Household Expenditure Trend Measured as a Difference from the Expenditures of non-SNAP Households						
Date range:	All			Days since receipt > 0		
Dep. var:	Expenditures ($)		1(Exp. ≥ 1)	Expenditures ($)		1(Exp. ≥ 1)
Model:	OLS	FD	FD LPM	OLS	FD	FD LPM
	(1)	(2)	(3)	(4)	(5)	(6)
Days since receipt	-0.555*** (0.069)	-3.864*** (0.394)	-0.038*** (0.004)	-0.223*** (0.060)	-2.365*** (0.340)	-0.034*** (0.004)
Constant	10.413 (1.582)			2.621 (1.380)		
Clusters	1167	1167	1167	1167	1167	1167
N	8154	6769	6769	7899	6544	6544

***: $p < 0.01$. Standard errors clustered by household are in parentheses beneath the estimates unless otherwise indicated. Week of month, a weekend indicator and an indicator for whether the diary day was a day on which the survey team called to check up on the respondent's expenditure logs are included as controls in all specifications. Columns (2), (3), (5) and (6) feature fewer observations than columns (1) and (4) due to first-differencing.

Table A5: Estimates of Meal Consumption Trend at Household and Individual Levels						
Unit of Analysis:	Household			Individual		
Model:	OLS	Tobit	FD	OLS	Probit	FD
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Breakfast Only						
Days since receipt	-0.003*** (0.001)	-0.007*** (0.003)	-0.010*** (0.002)	-0.002** (0.001)	-0.002** (0.001)	-0.009*** (0.002)
Constant	0.655 (0.019)	0.898 (0.054)		0.682 (0.018)	0.682 (0.018)	
Panel B: Lunch Only						
Days since receipt	-0.001* (0.001)	-0.005* (0.003)	-0.006*** (0.002)	-0.002** (0.001)	-0.002** (0.001)	-0.005*** (0.002)
Constant	0.732 (0.017)	1.208 (0.063)		0.766 (0.018)	0.765 (0.017)	
Panel C: Dinner Only						
Days since receipt	-0.002** (0.001)	-0.009** (0.004)	-0.009*** (0.002)	-0.001 (0.001)	-0.001 (0.001)	-0.007*** (0.002)
Constant	0.862 (0.014)	2.109 (0.112)		0.861 (0.014)	0.861 (0.014)	
Panel D: Breakfast, Lunch, Dinner all Missed						
Days since receipt	0.001* (< 0.001)	0.013* (0.008)	0.011*** (0.001)	0.001 (< 0.001)	0.001 (< 0.001)	0.009*** (0.001)
Constant	0.047 (0.010)	-2.884 (0.308)		0.046 (0.009)	0.047 (0.008)	
Panel E: Snacks (any)						
Days since receipt	-0.002*** (< 0.001)	-0.013*** (0.004)	-0.014*** (0.002)	-0.001** (< 0.001)	-0.001** (< 0.001)	-0.012*** (0.002)
Constant	0.938 (0.010)	2.661 (0.147)		0.934 (0.010)	0.932 (0.009)	
Clusters	1167	1167	1167	1167	1167	1167
N	8169	8169	6784	25,571	25,571	21,225

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$. Standard errors clustered by household are in parentheses beneath the estimates. Week of month and a weekend indicator are included as controls in all specifications. All variables are binary on the individual level. Averaged within a household, the variables are defined continuously between 0 and 1. Columns (3) and (6) have fewer observations than the other models at the same analysis unit because of the first differencing. Marginal effects are presented in column (5).

Table A6: Breakfast Consumption Trend by Age Group						
Sample:	All			Non-Imputed Data Only		
Model:	OLS	HH FE	FD	OLS	HH FE	FD
	(1)	(2)	(3)	(4)	(5)	(6)
Days since receipt	-0.004*** (0.001)	-0.001* (0.001)	-0.010*** (0.002)	-0.006*** (0.001)	-0.002** (0.001)	-0.011*** (0.002)
Age < 6	0.215*** (0.028)	0.223*** (0.027)		0.197*** (0.040)	0.211*** (0.037)	
Days since receipt X age < 6	0.005*** (0.001)	0.003* (0.001)	0.009** (0.004)	0.006*** (0.002)	0.003* (0.002)	0.011*** (0.004)
5 < age < 12	0.175*** (0.030)	0.211*** (0.027)		0.182*** (0.039)	0.237*** (0.036)	
Days since receipt X 5 < age < 12	0.005*** (0.002)	< 0.001 (0.001)	-0.001 (0.004)	0.005** (0.002)	-0.001 (0.002)	< 0.001 (0.004)
11 < age < 18	0.040 (0.036)	0.105*** (0.029)		-0.021 (0.058)	0.082* (0.044)	
Days since receipt X 11 < age < 18	0.004* (0.002)	< 0.001 (0.002)	-0.007 (0.005)	0.007** (0.003)	0.002 (0.003)	-0.006 (0.005)
Constant	0.625 (0.020)			0.681 (0.027)		
Clusters	1167	1167	1167	1088	1088	1044
N	25,571	25,571	21,225	21,119	21,119	17,738

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$. Standard errors clustered by household are in parentheses beneath the estimates. Week of month and a weekend indicator are included as controls in all specifications. Breakfast consumption is a binary variable. We use linear probability models for fixed-effect flexibility and because the mean of the dependent variable is not too close to zero or one. Columns (3) and (6) have fewer observations than the other specification on the same sample because of the first differencing.

Table A7: Lunch Consumption Trend by Age Group						
Sample:	All			Non-Imputed Data Only		
Model:	OLS	HH FE	FD	OLS	HH FE	FD
	(1)	(2)	(3)	(4)	(5)	(6)
Days since receipt	-0.002*** (0.001)	< 0.001 (0.001)	-0.003 (0.002)	-0.004*** (0.001)	> -0.001 (0.001)	-0.004 (0.003)
Age < 6	0.165*** (0.025)	0.114*** (0.020)		0.146*** (0.035)	0.090*** (0.026)	
Days since receipt X age < 6	0.001 (0.001)	0.001 (0.001)	-0.004 (0.004)	0.003 (0.002)	0.002* (0.001)	-0.001 (0.004)
5 < age < 12	0.134*** (0.030)	0.128*** (0.023)		0.154*** (0.036)	0.130*** (0.032)	
Days since receipt X 5 < age < 12	0.001 (0.002)	> -0.001 (0.001)	-0.002 (0.004)	< 0.001 (0.002)	> -0.001 (0.002)	-0.003 (0.004)
11 < age < 18	0.072** (0.033)	0.093*** (0.022)		0.040 (0.049)	0.090*** (0.033)	
Days since receipt X 11 < age < 18	0.001 (0.002)	-0.001 (0.001)	-0.010* (0.005)	0.003 (0.003)	> -0.001 (0.002)	-0.012** (0.006)
Constant	0.718 (0.018)			0.762 (0.025)		
Clusters	1167	1167	1167	1088	1088	1044
N	25,571	25,571	21,225	21,119	21,119	17,738

***: $p < 0.01$, **: $p < 0.05$. Standard errors clustered by household are in parentheses beneath the estimates. Week of month and a weekend indicator are included as controls in all specifications. Lunch consumption is a binary variable. We use linear probability models for fixed-effect flexibility and because the mean of the dependent variable is not too close to zero or one. Columns (3) and (6) have fewer observations than the other specification on the same sample because of the first differencing.

Table A8: Dinner Consumption Trend by Age Group						
Sample:	All			Non-Imputed Data Only		
Model:	OLS	HH FE	FD	OLS	HH FE	FD
	(1)	(2)	(3)	(4)	(5)	(6)
Days since receipt	-0.001* (0.001)	< 0.001 (< 0.001)	-0.009*** (0.002)	-0.002** (0.001)	> -0.001 (0.001)	-0.009*** (0.002)
Age < 6	0.061*** (0.022)	0.040** (0.018)		0.059** (0.030)	0.056** (0.022)	
Days since receipt X age < 6	0.001 (0.001)	0.001 (0.001)	0.007* (0.004)	0.001 (0.002)	< 0.001 (0.001)	0.008* (0.004)
5 < age < 12	0.027 (0.024)	0.027** (0.013)		0.042 (0.035)	0.036* (0.019)	
Days since receipt X 5 < age < 12	0.001 (0.001)	0.001 (0.001)	0.005 (0.003)	0.001 (0.002)	< 0.001 (0.001)	0.007* (0.004)
11 < age < 18	-0.048 (0.030)	0.004 (0.019)		-0.089* (0.046)	-0.004 (0.024)	
Days since receipt X 11 < age < 18	0.004** (0.002)	0.001 (0.001)	0.004 (0.005)	0.006** (0.002)	0.001 (0.001)	0.003 (0.006)
Constant	0.855 (0.014)			0.869 (0.021)		
Clusters	1167	1167	1167	1088	1088	1044
N	25,571	25,571	21,225	21,119	21,119	17,738

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$. Standard errors clustered by household are in parentheses beneath the estimates. Week of month and a weekend indicator are included as controls in all specifications. Dinner consumption is a binary variable. We use linear probability models for fixed-effect flexibility and because the mean of the dependent variable is not too close to zero or one. Columns (3) and (6) have fewer observations than the other specification on the same sample because of the first differencing.

The Effects of Benefit Timing and Income Fungibility on Food Purchasing Decisions among SNAP Households

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Abstract

The Supplemental Nutrition Assistance Program (SNAP) is the largest nutritional safety net in the United States. Prior research has found that participants have higher consumption shortly after receiving their benefits, followed by lower consumption towards the end of the benefit month. This "SNAP benefit cycle" has been found to have negative effects on beneficiaries. We examine two behavioral responses of SNAP participants that may work in tandem to drive much of the cycle: short-run impatience – a higher preference to consume today; and fungibility of income – the degree of substitutability between a SNAP dollar and a cash dollar. Using data from the National Food Acquisition and Purchase Survey (FoodAPS), we find evidence of both behavioral responses. The degree of short-run impatience and fungibility of income is found to differ significantly across poverty levels and use of grocery lists to plan food purchases. Food purchase planning education could be used to counter the observed benefit cycle. Deeper analysis of the purchase data suggests that the benefit cycle is primarily associated with a decrease in the purchase of healthful and perishable foods—which could lead to lower dietary quality. We also find evidence that suggests households compensate for the effects of the SNAP benefit cycle by acquiring free food, primarily from schools. This highlights the importance of programs like the National School Lunch Program for SNAP households.

Executive summary

Prior research has found that SNAP participants have higher food consumption shortly after receiving their benefits, followed by lower consumption towards the end of the benefit month. This "SNAP benefit cycle" can lead to consumption patterns that have negative effects on beneficiaries. For example, SNAP beneficiaries consume fewer calories towards the end of the benefit cycle, suggesting potential increased risk of food insecurity. There is evidence of increased hospital admissions due to hypoglycemia among low-income individuals at the end of the benefit month as well.

We consider two behavioral mechanisms that might lead to such benefit cycles. The first mechanism suggests that households exhibit short-run impatience and therefore have a higher preference for today's consumption. As such, they spend more of their SNAP resources early in the month, leaving themselves at higher risk to negative income shocks later in the month. In addition, we explore whether a second behavioral phenomenon, income fungibility, could be exacerbating the degree of the cycle. This behavioral mechanism suggests that SNAP households exhibit a higher propensity to spend on food when using benefit income rather than cash income. As a result, a one-dollar increase in SNAP benefits generates more spending on food than an equal increase in cash income. Put differently, SNAP income is budgeted differently than an equal amount of cash income.

To empirically examine SNAP-spending patterns, we use data from the National Food Acquisition and Purchase Survey (FoodAPS). The survey is a newly developed nationally representative measure of daily food acquisitions by SNAP households. Importantly, FoodAPS respondents report daily food spending by venue (i.e., at home and away from home), as well as the type of income used to make the purchase (i.e., SNAP and non-SNAP income).

We find significant evidence of time-inconsistent spending. Specifically, households spend roughly 96 cents of every food dollar (regardless of its income source) on food at home the day benefits are issued. This propensity to spend on food at home falls by 10 cents in the three days that follow. By the end of the month, households are spending just over three-quarters of their food budget on food at home. Given that food at home is of higher nutritional value than food away from home, this spending pattern may have important implications for household dietary quality throughout the month.

In addition, SNAP households have a consistently higher propensity to spend on food at home out of SNAP benefits than out of non-SNAP expenditures, regardless of the time of month. Specifically, we find that an increase in SNAP benefits will generate 5.2% more in food-at-home spending than an equal increase in non-SNAP income. This finding implies that SNAP income is less fungible than an equal amount of cash income despite the fact that economic theory suggests the two should be equally fungible.

We next examine how households might overcome their impatience and/or budgeting difficulties. To do so, we examine differences in monthly spending patterns for households that frequently utilize grocery lists compared to those that do not. We view grocery lists as a type of self-commitment mechanism. We also explore how severe resource constraints impact purchasing decisions. We find strong evidence that households who plan more frequently, as well as those who are less resource constrained, have smoother spending on food at home throughout the month. Moreover, these households tend to budget SNAP income more similarly to cash income, just as economic theory would suggest. These results suggest that small measures to facilitate household food planning could be an effective way to mitigate the SNAP benefit cycle.

Simple commitment strategies could be taught through the SNAP Education program that could help mitigate the SNAP benefit cycle. For example, teaching households how to plan and budget their benefits may help overcome some of their behavioral shortfalls. Another policy prescription could be to make bi-monthly or weekly disbursements the default option for SNAP disbursements. Previous findings have suggested that increasing the frequency of payments could encourage smoother consumption over the month. Some households, however, may prefer to make one large grocery trip per month due to costs. Those who prefer or need a single monthly payment can simply enroll in that option.

We further break down the SNAP purchase data into specific food categories. Over the benefit cycle, we find that household purchases of more healthful foods (defined by the Healthy Eating Index) and perishable foods decline over the month. Alternatively, purchases of less healthful and non-perishable foods, such as snacks and sugar-sweetened beverages, are constant over the month. This suggests that the SNAP benefit cycle may result in purchases of foods with lower nutritional quality. At the same time, storability appears to be an important consideration of the SNAP benefit cycle as well.

Finally, we examine a component of food acquisition by low-income households that has not been extensively investigated to date: the acquisition of free food. Over the course of the benefit month, SNAP household food purchases decline, but the acquisition of free food remains relatively constant. As a result, free food tends to compensate for a reduction in food purchases via cash and SNAP spending. As SNAP households are highly dependent on schools for their largest share of free food, this highlights the importance of school lunch programs for SNAP households.

Introduction

The Supplemental Nutrition Assistance Program (SNAP) is the nation's largest food assistance program providing over 45 million low-income Americans a monthly benefit. Administrative records reveal that more than 80% of SNAP benefits are redeemed within the first two weeks of issuance (Castner and Henke 2011), a consumption pattern known as the "SNAP benefit cycle." This cycle has been linked to potentially negative consequences for participants: SNAP beneficiaries consume fewer calories towards the end of the benefit cycle, suggesting potential increased risk of food insecurity (Shapiro 2005; Todd 2014; and Wilde and Ranney 2000). Seligman et al. (2014) finds that there is a 27% increase in hospital admissions due to hypoglycemia among low-income individuals at the end of the benefit month, with no observed increase in higher-income populations.

The behavioral mechanism most frequently attributed to payment benefit cycles is time-inconsistent preferences (e.g., Shapiro 2005; Mastrobuoni and Weinberg 2009). A time-inconsistent household exhibits short-run impatience and therefore has a higher preference for today's consumption. An impatient household has a higher tendency to spend when resources are flush. This is *inconsistent* with the household's preference to spend at the end of the month. Households may therefore put themselves at a higher risk to negative income shocks and food insecurity later in the month.

Economic theory predicts that SNAP households who receive benefit income less than their food budget should not treat SNAP differently than non-SNAP income (Southworth, 1945). Yet, previous literature has found that SNAP households exhibit a higher marginal propensity to spend (MPS) on food when using benefit income rather than cash income (Fraker, Martini and Ohls 1995; Levedhal 1995; Breunig and Dasgupta 2002, 2005). This means a one-dollar increase in SNAP benefits generates more spending on food than an equal increase in cash income. We explore whether this second behavioral phenomenon, referred to in the literature as income fungibility, could be exacerbating the degree of the cycle.[i]

Laibson (1998) shows that an impatient SNAP household will spend relatively more upon receiving benefits, and a higher MPS out of SNAP can increase this effect. If this occurs, then part of the SNAP benefit cycle is being driven by income fungibility and cannot be completely attributed to time-inconsistent preferences. Understanding time-inconsistent preferences *and* income fungibility can help guide the development of policy prescriptions to reduce the SNAP benefit cycle.

We estimate food Engel curves using data from the National Food Acquisition and Purchase Survey (FoodAPS). The survey is a newly developed nationally representative measure of daily food acquisitions by SNAP households. FoodAPS respondents report daily food spending by venue (i.e., at home and away from home), as well as the type of income used to make the purchase (i.e., SNAP and non-SNAP income). Further, respondents report the acquisition of free food from a variety of sources (e.g. school, family and friends). The data also includes nutritional content of the food items allowing us to assess the nutritional content of purchases as well as the overall healthfulness of purchases throughout the month.

Methods

To examine how time inconsistency and income fungibility affect SNAP-spending patterns, we start with a simple Engel curve specification:

(1) $w_k = \alpha_k + \beta_k ln(X) + Z'\phi_k,$

where w is the share of total daily food expenditures (X) on k = {*food at home (FAH), food away from home (FAFH)*}, Z includes the natural logarithm of *household size*, indicators for race/ethnicity and a variable indicating the presence of a child under 6. Time subscripts are excluded throughout to simplify notation.

Following previous empirical findings (Moffitt 1989; Levedahl 1995; Breunig and Dasgupta 2002, 2005), we express total daily expenditures as a linear function of cash and SNAP expenditures, $X = I + \gamma S$. The difference between the marginal propensity to spend cash income (MPS_I) and the MPS for SNAP (MPS_S) is indicated by γ. If γ=1, the two sources of income are perfectly fungible and spending with cash or SNAP has no influence on the effective discount factor.

An important consideration with a hyperbolic preference framework is that discount factors are inconsistent across time. To examine potential time-inconsistent preferences, we modify equation (1) to allow budget shares to shift via the intercept and slope (cf. Blundell and Lewbel, 1991) as households progress through the benefit month:

(2) $$w_k = \alpha_k + \beta_k ln(X) + Z'\phi_k + D_t{}'\delta_k + [\ln(X) \cdot D_t]'\eta_k$$

where D_t is a flexible specification of the number of days since receiving SNAP benefits. We specify D_t to be a set of six indicators corresponding to days 0, 1-3, 4-6, 7-14, 15-21, and 22-30.[ii] The effect of D_t acts as a demand shifter estimated by the vector δ_k. This allows us to capture any intra-monthly consumption that is determined strictly by temporal variation. The vector η_k allows the MPS out of both cash and SNAP to change over the benefit month through its interaction with the log of total expenditures.

Marginal Propensities to Spend

We estimate the average MPS out of SNAP for an entire benefit month as:

(3) $$MPS_S = \frac{\partial X_k}{\partial S} = w_k + (I + S)\frac{\gamma_k(\beta_k + D_t'\eta_k)}{I + \gamma_k S},$$

where we use the daily average values for expenditure share (w_k), cash (I), SNAP (S) and days since receiving SNAP (D_t). The remaining parameters are estimated from equation (2). We calculate the average MPS out of cash over the benefit month as:

(4) $$MPS_I = \frac{\partial X_k}{\partial I} = w_k + (I + S)\frac{(\beta_k + D_t' \eta_k)}{I + \gamma_k S}.$$

To estimate the MPS at different points in the benefit month, we evaluate all terms in (3) and (4) during the time period of interest. To test for fungibility, we take the difference between (3) and (4),

(5) $$MPS_{(S-I)} = (I + S)\frac{(\beta_k + D_t' \eta_k)(\gamma_k - 1)}{I + \gamma_k S}.$$

If $\gamma_k = 1$, there is no difference in the propensities to use SNAP and cash on food-at-home purchases (i.e., they are perfectly fungible). To examine the interaction between fungibility and impatience, we estimate equation (5) at different points in the benefit month in the same manner as described above.

Expenditure Patterns by Food Type

To explore how the SNAP benefit cycle persists across different types of food, we modify equation (2) to specify a log-log model as:

(6) $$E_j = \alpha_j + \beta_j ln(I + S) + \gamma_j P + Z'\phi_j + D_t{}'\delta_j + [\ln(I + S) \cdot D_t]'\eta_j + P \cdot D_t{}'P\phi_j$$

where the dependent variable, E_j, is now the log of the expenditure share for food product *j*. Due to a limited number of observations, we no longer estimate the fungibility of income, so that $X = I + S$. Further, we add *P*, which is the share of SNAP expenditures out of the entire budget: *S/(I + S)*. This simplified model allows us to focus on the trend in spending over the month with specific food products.

Free Food Acquisition

By definition, free food does not have a price so we cannot estimate changes in free food acquisition using an expenditure share dependent variable. We therefore modify equation (6) to examine the share of free food in terms of grams for specific food categories. For example, we evaluate grams of dairy a household acquired for free relative to a household's total acquisition of dairy. We also examine the share of nutrition from free food relative to all other food. Both of these variables allow us to track how free food acquisition changes over the month following the receipt of SNAP benefits.

Data

The National Food Acquisition and Purchase Survey (FoodAPS) is a nationally representative survey that collected daily food acquisitions of households over a seven-day period between April 2012 and January 2013. Respondents recorded food acquisitions in two diaries: food at home (FAH) and food away from home (FAFH). Each diary entry corresponds to an "event," such as a grocery-shopping trip or a sit-down meal at a restaurant. For the FAH diary, households were asked to scan UPC codes, either on the food package or provided in the diary for loose/bulk items, and to write down the total expenditure for that event. Similarly for the FAFH diary, households provided the total expenditure for the event and were asked to write down each item purchased. In both diaries households were also asked to provide the receipt if one was given. Importantly, households also record the type of income used to make the transaction. All analyses use the sum of the total expenditures for each event for FAH and FAFH by diary day.

FoodAPS emphasizes households participating in the Supplemental Nutrition Assistance Program (SNAP) and was stratified accordingly. Of the 4,826 households surveyed, 1,581 households had at least one member currently on SNAP. The initial interview took place prior to the start of the seven-day diary, in most cases the day before the first diary day. During this interview, households were asked the date they last received their SNAP benefits. Using this date and the diary dates, we calculated the number of days since receiving benefits. Thus, day zero indicates the day of benefit arrival and day 30 the last possible day of the cycle.

There were 261 households that were nearing the end of their benefit cycle during the initial interview. For example, suppose the initial interview took place on day 28th of the benefit cycle. In this case the first and final dairy days would have been calculated as the 29th and 35th days of the benefit cycle. For these households, we assumed benefits were again received on the same calendar day as the previous month so that the cycle starts over during the survey. After this adjustment and excluding households that reported receiving their benefits more than 30 days prior to the initial interview, our final sample consisted of 1,427 SNAP households.[iii]

We make use of the standard demographic characteristics in the empirical section (household size, race/ethnicity, and the presence of children under the age of 6). As well, we consider reported frequency of grocery list usage. The survey asked how often households use a grocery list – never, seldom, sometimes, most of the time or always. We categorize “infrequent grocery list users” as those that reported never or seldom. All other households are categorized as “frequent grocery list users.”

The data also provide nutritional information for each of the items in the food diaries. This extensive process developed by the USDA, Economic Research Service allows us to develop various measures of the nutritional content of household food acquisitions. Together with food descriptions, we create four broad categories of food: healthful or unhealthful and perishable or non-perishable (Table 1). The term healthful is based on the Healthy Eating Index

(HEI) definition which suggests certain foods should be eaten more (*adequacy*). Alternatively, unhealthful foods are based on the HEI suggestion for foods that should be eaten in moderation (*moderate*). We identify perishable and non-perishable foods using a classification from the University of Nebraska (http://food.unl.edu/food-storage). While these are broadly defined categories, they allow us to examine how the SNAP benefit cycle impacts the types of foods being eaten.

Summary measures

Our final sample of 1,427 SNAP households contributed 3,400 purchase days. In the empirical methods below, we discuss zero purchase days. In short, we treat each purchase day as conditionally independent. Also note we will be examining *purchases* rather than *acquisitions.*

Figure 1 presents graphical evidence of spending patterns. On the day of benefit receipt, the average SNAP household spends $141.95 on food. Over half of this expenditure is from non-SNAP income ($72.97) and the remainder largely comes from SNAP income ($62.62) with relatively few FAFH purchases ($6.36). Throughout the rest of the benefit month the average household consistently spends more out-of-pocket on FAH than with benefit income. Interestingly, during the last two weeks of the benefit month, FAFH significantly outpaces non-SNAP FAH purchases.

Table 2 presents average per-day spending for the entire month in column 1. SNAP households spend an average of $45.70 per day on food (conditional on a positive purchase), with over 86% ($39.59) spent on items for at-home consumption. Columns 2 and 3 split purchase days by those made in the first week of the benefit month and by the rest of the month. We can see that *total food expenditures* drop by over $25 per day. This drop is entirely from *FAH expenditures*, and *FAFH expenditures* remain level at about $6 per day. Although total food spending significantly declines over the benefit month, the share of expenditures devoted to food-at-home in week 1 (88%) are not significantly different than the last three weeks (85%).

Table 3 presents demographic characteristics and average weekly expenditures for our sample. To get a sense of how “beginning-of-the-month” households compare to those randomly surveyed during the rest of the month we split the sample accordingly. Column 2 includes households that have at least one diary day corresponding to benefit days 0, 1, 2 or 3 (labeled “Week 1”). In this manner we are capturing household diaries that “straddle” the day benefits are disbursed (e.g., when the diary starts on day 28), or when diaries begin shortly after benefit disbursement. All other household dairies falling outside this range are in column 3 (labeled “Weeks 2-4”). The p-values in column 4 test the significance between households randomly surveyed towards the beginning of the benefit cycle versus those that are surveyed during the rest of the month. We expect demographics to be insignificant. Yet, we see that the proportion of *Hispanics* dropped significantly from 27 to 20%. Likewise we see that the proportion of *frequent grocery list users* also falls. As expected, all expenditures drop significantly over the month expect for FAFH.

Table 4 describes expenditures for different categories of foods (e.g. healthful, unhealthful, perishable and non-perishable) for the first 3 days after receiving SNAP and the last 2 – 4 weeks. There was no difference in expenditures over the 2- to 4-week period, so the data is grouped together as such. As can be seen, both total food expenditures and SNAP expenditures go decrease after the first 3 days since receiving SNAP benefits. Further, expenditures go down significantly from the first 3 days to the rest of the month for all of the broad food categories. This does not indicate, however, that the MPS for these food categories changes over the month.

There are many instances of free food acquisitions in the FAFH diaries (e.g., friend's/relative's home, food pantries, school meal programs, home gardens, and fishing/hunting), but relatively few free food events in the FAH diaries. The majority of free food for SNAP households comes from school with family and friends being the next largest source (Figure 2). The former is likely from the National School Lunch Program. Alternatively, non-SNAP households (Figure 3) obtain the majority of their free food from family and friends and the share received from school is about half as much as SNAP households.

For estimation purposes, we aggregate free food it into 5 large categories: dairy, fruits, vegetables, grains and protein. We also examine free food based on its contribution to: calories, carbohydrates, fat and added sugar. While these are not extensive descriptions of household diets, they help provide an idea about how SNAP households utilize free food throughout the month.

Results

All parameters from equation (2) are estimated using maximum likelihood and can be found in tables 5 and 6[iv]. The marginal propensities are presented graphically in figures 4-8 with corresponding estimates in tables 7-8. The top panel of each figure plots the marginal propensities to spend (MPS) on food at home out of SNAP and non-SNAP expenditures throughout the benefit month using equations (6) and (7), respectively.[v] A decline in the estimates over the month is consistent with hyperbolic discounting. The bottom panel of each figure estimates the difference in the propensities to spend using equation (8). Here, a positive difference is evidence against the fungibility of SNAP and non-SNAP income. For example, on the day benefits are received (day 0), SNAP households spend roughly $0.09 more on food at home when using a SNAP dollar rather than a non-SNAP dollar. Finally, the compounding effect of time-inconsistent preferences and income fungibility can be seen in the bottom panel when the difference in MPS varies over the month.

All standard errors are calculated using the delta method and clustered at the household level. In the results that follow, there are cases where we find a statistically significant difference in the two MPS values in the bottom panel, but their individual confidence intervals overlap in the top panel. While this might seem contradictory, it is explained by the fact that the formulas for the standard errors include some parameters that cancel out when testing for a significant difference. In other words, the covariance between the two MPS values is positive, making the standard error of their difference smaller.

Full SNAP Sample

Figure 4 shows the purchasing path for the full sample of SNAP households. The purchasing path drops significantly from the day of benefit receipt ($t = 0$) to days 1-3 of the cycle. This is true for both SNAP and non-SNAP food expenditures and is consistent with the hypothesis of hyperbolic preferences. Specifically, the propensity to spend SNAP on food at home (MPS_S) falls from 0.94 on the day benefits are received and levels off at about 0.88 over the remaining days of the first two weeks (i.e., days 1-14). Over the last two weeks of the benefit month, the average SNAP household's propensity to spend SNAP on food at home continues to fall from 0.84 to 0.80. The propensity to spend non-SNAP income (MPS_I) has a similar time path falling from 0.84 to 0.77 by month's end.

We examine the bottom panel for evidence of any compounding effects by testing if the difference in MPS is constant over the month. Although there appears to be a slight dip at the beginning of the month, we cannot reject the null that they are equivalent.

Our results pertaining to income fungibility and hyperbolic preferences as separate phenomena are consistent with previous findings (Fraker Fraker, Martini and Ohls 1995; Levedhal 1995; Breunig and Dasgupta 2002, 2005; Shapiro 2005; Mastrobuoni and Weinberg 2009). One important finding is that fungibility is not just a short-term behavioral response that dissipates as the month progresses. Moreover, the *difference* in MPS between cash and SNAP does not change significantly over the entire month, suggesting an insignificant compounding effect. Next, we investigate heterogeneity of our results in certain subpopulations.

SNAP households that use a "commitment mechanism"

Hyperbolic SNAP households can create an endogenous liquidity constraint on their benefits by adhering to some rule-of-thumb. All that is required is the self-imposed constraint be committed to one period ahead. For example, to overcome splurging at the grocery store households may pre-commit benefits to certain food items. Simply committing to a grocery list could function as a self-imposed liquidity constraint.

We categorize "infrequent grocery list users" as those that reported never or seldom using a grocery list. All other households are categorized as "frequent grocery list users."[vi] We re-estimate our model for each type of household: frequent grocery list users in figure 5 and infrequent grocery list users in figure 6. Point estimates and standard errors can be found in table 8.

For frequent grocery list users we again find that the propensity to spend on food at home out of cash and SNAP fall after the first day of the benefit month (Figure 5 and Table 8). In the bottom panel we can see the lack of fungibility between SNAP and non-SNAP income is relatively flat throughout the month – households tend to spend about $0.04-0.05 more out of a

SNAP dollar versus a cash dollar on food at home. Estimates are only marginally significant in the last two weeks of the benefit month.

Looking at infrequent grocery list users (Figure 6 and Table 8), we see inconsistent purchasing patterns over the first four days of the benefit month where these households have a much higher propensity to spend SNAP on food at home than their own cash. Infrequent grocery list users spend $0.24 more on food at home using a SNAP dollar compared to a non-SNAP dollar. This stark difference persists over the next three days where we see a 0.17 difference on days 1-3. By the latter half of the first week of the benefit cycle, infrequent grocery list users are statistically indistinguishable from frequent grocery list users, although the point estimates remain slightly higher.

Two important differences between infrequent and frequent grocery list users emerge. First, the difference between the MPS by income source on the day of benefit issuance is about five times higher for infrequent list users (0.24 versus 0.05). We believe that frequent grocery list users have demonstrated the sort of pre-planning and commitment that likely translates into better budgeting skills. As a result, food planning can help mitigate the compounding effects of fungibility and impatience, especially on the day benefits are received. Second, the propensity to spend a SNAP dollar on food at home on the day of benefit issuance is much higher for frequent list users: 0.96 versus 0.85. This again may be an indication that food planning could help households pre-commit a larger percentage of food dollars to food at home. Moreover, those with better budgeting skills may place a priority on using their resources for purchasing food from SNAP eligible venues.

Poverty differences

Households that have higher levels of impoverishment face more severe resource constraints than other SNAP households. Given that food is a necessity, *a priori*, one may expect tighter liquidity constraints to force households to be more in tune with their food budgets. On the other hand, the severity of poverty is likely to be correlated with (unobservable) budgeting and planning skills.

To test these hypotheses, we divided households into those with income less than 100% of the poverty guidelines and those over the poverty guideline.[vii] Point estimates and standard errors for the MPS out of each income source are reported in table 9, and results are presented graphically in figures 7 and 8. As shown in the top panels of figures 7 and 8, both types of households exhibit evidence of hyperbolic discounting. The bottom panels of the figures reveal that households with income above 100% of the poverty guidelines have a consistent difference in the MPS out of SNAP and non-SNAP ranging insignificantly from 0.026 to 0.04. Households below the poverty line exhibit a much higher propensity to spend SNAP on the day of issuance. Specifically, these households spend $0.19 more on food at home out of SNAP than out of pocket. This difference in MPS falls to about 0.13 over days 1-6 before leveling around 0.05. Thus, in this subpopulation (those below the poverty guideline), an interaction effect appears to exist. This evidence suggests that unobservable characteristics (such as budgeting skills in general) are driving the differences rather than resource constraints pushing households to be more in tune with their food budget.

SNAP Cycle by Food Category

We further examine the SNAP cycle across our broad food categories (e.g. healthful, unhealthful, perishable and non-perishable) which reveals interesting purchasing patterns. In the first day after receipt, the MPS of SNAP and non-SNAP for healthful foods is significantly larger than the rest of the month (Figure 9). After that, however, the MPS for SNAP and non-SNAP are not significantly different over time. In contrast, the MPS for SNAP for unhealthful foods (Figure 10) is significantly lower in days 1-3, but not significantly different the rest of the month. The MPS for non-SNAP is not significantly different across the month.

Looking at perishable foods (Figure 11) we see a similar pattern as healthful foods, where the MPS of SNAP and non-SNAP are significantly larger in the first day after benefit receipt, and then constant over time. The non-perishable foods follow a similar pattern as well (Figure 12), with the MPS of SNAP being larger in day 0 than days 1-3 and days 4-6. However, the MPS for cash is not significantly different over time.

Taken all together, these results suggest that the SNAP benefit cycle is primarily driven by changes in healthful foods, i.e. foods the HEI suggests should be eaten more often. The same can also be said for perishable foods, which by definition, do not last as long. Importantly, perishable foods tend to also be fresher, more healthful foods. Unfortunately, this analysis could not be run for foods that were also healthful *and* perishable, due to limited observations in the data.

Free Food Acquisition

Looking at the acquisition of free food offers important insights into how SNAP households may utilize free food over the benefit month. In particular, across all the food categories (Table 10) we find that there is a significant increase in free food acquisition on all days relative to day 0, which is the reference day. Importantly, after days 1 – 3, the acquisition of free food increases significantly as well across all food categories, but for the rest of the month (i.e. days 4 – 30) there is not a significant increase in the acquisition of free food. In practical terms, this means a greater share of each food category comes from sources of free food during the first week after receiving SNAP benefits. This contrasts with the SNAP benefit cycle, which shows a decline in MPS or of SNAP and cash after the first few days of receiving benefits. This suggests that free food may be used strategically to offset spending from SNAP and cash over the month. This is particularly important given that the primary source of free food for SNAP households is the school, presumably school lunches.

Looking at calories and other nutritional content (Table 11), we notice a similar pattern that is slightly less drastic. Specifically, during the first 3 days, the amount of calories and nutrition from free food is not significantly different relative to day 0. After day 4, however, free food provides a significantly larger proportion of calories and nutrition. Again, this contrasts with the SNAP benefit cycle pattern of purchases. That is, as the propensity to spend on food declines the first days after receiving SNAP, the share of food from free sources increases.

It is important to note that over the month, the amount of free food acquired does not change significantly. Rather, the amount of food *purchased* decreases, making the share of free food relatively larger. Again, this emphasizes the importance of *other* sources of food for SNAP households.

Conclusions and discussion

This research investigated the purchasing patterns of SNAP households over the benefit month. We find that SNAP households exhibit time-inconsistent preferences and do not view a SNAP dollar as fully fungible with a non-SNAP dollar. We also find that these two behavioral mechanisms tend to exacerbate the SNAP benefit cycle, especially during the first week of issuance.

The tendency to make large food purchases at the beginning of the month may be a sign that households are stocking up; thus, food consumption could be smoother than food purchasing behavior over the month. We cannot directly test this hypothesis because detailed consumption data were not collected. Previous research, however, has consistently demonstrated that the consumption paths of SNAP households largely follow their purchasing paths (Wilde and Ranney 2000 Shapiro 2005; Todd 2014); thus, our finding that the propensity to spend on food at home out of SNAP benefits is higher than out of non-SNAP income may be a reason for concern.

We uncover a previously unknown finding that the propensity to spend on food at home out of SNAP is consistently higher than out of non-SNAP income throughout the benefit month. We find some evidence that the lack of income fungibility is higher at the beginning of the month, indicating that households view SNAP as less fungible when benefits are flush. For low-income populations in general, the tendency to have a higher rate of spending out of one budgeted category may increase the risk to income shocks, particularly at the end of the month.

The compounding effects of fungibility and impatience are strongest for households that do not frequently engage in grocery trip planning (i.e., infrequent users of grocery lists) and those who are severely resource constrained (i.e., under the federal poverty guidelines). Likewise, we find similar comparisons between SNAP households living above and below the poverty guidelines. Again, this higher-than-average MPS out of SNAP is concentrated during the first week and levels off throughout the remainder of the month. Households above the poverty line, on the other hand, consistently spend more out of SNAP throughout the benefit month.

Our finding that grocery list users tend to treat SNAP and non-SNAP income in a similar manner throughout the benefit month suggests that simple commitment strategies could be taught through the SNAP Education program. Guiding households on how to plan and budget their benefits may help overcome some of their behavioral shortfalls. Previous authors have also suggested increasing the frequency of payments as a potential remedy (Wilde and Ranney 2000; Shapiro 2005; Hastings and Washington 2010). Doing so could enforce smoother consumption over the month. Some households, however, may prefer to make one large grocery trip per month. It might well be the case that these households are constrained in their ability to shop more frequently and forcing a bi-monthly or weekly disbursement may increase the cost of grocery shopping.

An alternative policy prescription could be to make bi-monthly or weekly disbursements an option when signing up for SNAP. Those who prefer or need a single monthly payment can simply enroll in that option. Such an approach would allow households to select into the payment option that best suited their needs. We suspect additional transaction costs to be minimal due to the electronic nature of the benefit transfer.[viii] Our results show the benefit-cycle effect is largest in the first few days, however, suggesting that the often-recommended policy of bi-monthly benefit distribution may not be the cure-all. A possible negative consequence is a reduction in participation if the perceived amount of benefits is lower due to the bi-monthly arrangement.

Our research also sheds light on the types of purchases that might be driving the SNAP benefit cycle. In particular, we find that healthful and perishable foods tend to follow the benefit cycle pattern, whereas unhealthful and non-perishable foods are purchased more consistently throughout the month. This emphasizes the potential nutritional implications of the SNAP benefit cycle. Incentives to encourage more healthful purchases throughout the month could prove to be beneficial. For example, the Healthy Incentives Pilot (HIP) offers cash back for buying fruits and vegetables (Klerman et al 2015; Wilde et al 2015). Such a program could possibly encourage more consistent purchases of healthful foods.

Finally, we also provide preliminary results highlighting the role that free food plays for SNAP recipients. While the SNAP cycle progresses throughout the month and food purchases decline, the acquisition of free food increases. This also translates into more calories and nutrition from free food. Since free food for SNAP households primarily comes from the school lunch program, it is important to consider the year round availability of this resource. To be sure, some locations already provide alternative ways to disperse free food outside the school year.

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Tables

Table 1. Household food purchases aggregated into four groups.

	healthful	*unhealthful*
Perishable	dairy, protein, fruit and vegetables	french fries, hash browns
Non-perishable	whole grains, beans nuts, canned fish	snacks, sugar-sweetened beverages, refined grains

Table 2. Average Daily Spending for SNAP Households Conditional on a Positive Purchase

Variable	Full Sample	Week 1	Weeks 2-4	p-value[a]
Total food expenditures	45.70	62.69	37.17	<0.001
	(1.85)	(3.88)	(1.63)	
Food-at-home	39.59	56.13	31.28	<0.001
expenditures	(1.66)	(3.62)	(1.45)	
Food-away-from-home	6.11	6.56	5.89	0.554
expenditures	(0.51)	(0.95)	(0.60)	
SNAP expenditures	19.95	37.58	11.10	<0.001
	(1.33)	(3.31)	(0.87)	
Food-at-home share	0.86	0.88	0.85	0.153
	(0.01)	(0.01)	(0.01)	
No. of daily observations	3400	1031	2369	

Note: All calculations use survey weights. Standard errors in parentheses are clustered at the household level. Week 1 is defined as purchasing days in the first seven days of the diary week. Weeks 2-4 are the rest of the month.
[a]p-values represent a two-sample t-test of week 1 versus weeks 2-4.

Table 3. Household Characteristics and Total Weekly Expenditure Patterns

Characteristic	Full Sample	Week 1[a]	Weeks 2-4[a]	p-value
Household size	3.04	3.34	2.88	0.023
	(0.09)	(0.17)	(0.10)	
Non-Hispanic White	0.47	0.47	0.47	0.949
	(0.02)	(0.04)	(0.03)	
Hispanic	0.23	0.27	0.20	<0.001
	(0.02)	(0.04)	(0.02)	
Non-Hispanic Black	0.27	0.25	0.29	0.390
	(0.02)	(0.03)	(0.03)	
Child under 6 present	0.29	0.33	0.27	0.179
	(0.02)	(0.04)	(0.01)	
Frequent grocery list user	0.68	0.73	0.65	0.096
	(0.02)	(0.03)	(0.03)	
Below 100% poverty	0.58	0.54	0.60	0.251
	(0.02)	(0.04)	(0.03)	
Total food expenditures	130.04	175.32	105.03	<0.001
	(6.51)	(11.30)	(7.46)	
Food-at-home expenditures	93.35	140.50	67.31	<0.001
	(4.56)	(9.75)	(3.62)	
Food-away-from-home expenditures	36.68	34.81	37.72	0.691
	(4.30)	(3.53)	(6.39)	
SNAP expenditures	47.05	83.19	27.09	<0.001
	(3.25)	(7.53)	(2.17)	
Food-at-home share	0.66	0.72	0.62	0.001
	(0.02)	(0.02)	(0.02)	
No. of households	1427	446	981	

Notes: All calculations use survey weights.
[a] Week 1 households are defined as those that have at least one diary day corresponding to benefits days 0, 1, 2 or 3. All other households are defined as Weeks 2-4.

Table 4. Household Food-at-Home Expenditures

	Full Sample	0-3 days	Weeks2-4	p-value[a]
Total food expenditure	105.39	151.54	79.90	<0.001
	(4.74)	(9.73)	(4.03)	
SNAP expenditure	44.76	80.18	25.20	<0.001
	(3.18)	(7.36)	(2.09)	
Healthful food	36.35	58.01	24.39	<0.001
	(2.17)	(4.83)	(1.51)	
Unhealthful food	19.75	28.78	14.76	<0.001
	(1.00)	(2.10)	(0.85)	
Perishable food	34.46	55.07	23.08	<0.001
	(2.06)	(4.64)	(1.42)	
Non-perishable food	35.65	54.31	25.34	<0.001
	(1.87)	(3.95)	(1.48)	

Notes: a. Test of statistical difference in expenditures from days 0-3 and weeks 2-4.

Table 5. Parameter Estimates from Equation (2) for Full SNAP Sample and by Grocery List Usage

Variables	Full Sample	Frequent List Users	Infrequent List Users
ln(X)	-0.0175***	-0.0087	-0.0490***
	(0.0047)	(0.0052)	(0.0101)
SNAP purchases	0.0032*	0.0021	0.0086***
	(0.0012)	(0.0098)	(0.0017)
ln(X) × Days 1-3	-0.0118*	-0.0124	-0.0206
	(0.0071)	(0.0129)	(0.0154)
ln(X) × Days 4-6	-0.0116	-0.0202	0.0179
	(0.0077)	(0.0165)	(0.0206)
ln(X) × Days 7-14	-0.0108*	-0.0138	0.0027
	(0.0062)	(0.0107)	(0.0123)
ln(X) × Days 15-22	-0.0120*	-0.0200*	0.0139
	(0.0062)	(0.0116)	(0.0116)
ln(X) × Days 23-30	-0.0172**	-0.0215**	-0.0013
	(0.0076)	(0.0104)	(0.0167)
ln(household size)	-0.0362***	-0.0495***	-0.0034
	(0.0112)	(0.0139)	(0.0200)
Days 1-3	-0.0366**	-0.0242	-0.0560
	(0.0168)	(0.0289)	(0.0553)
Days 4-6	-0.0466***	-0.0527	-0.0497
	(0.0178)	(0.0417)	(0.0543)
Days 7-14	-0.0479***	-0.0554*	-0.0394
	(0.0151)	(0.0296)	(0.0507)
Days 15-22	-0.0613***	-0.0740**	-0.0569
	(0.0158)	(0.0308)	(0.0512)
Days 23-30	-0.0576***	-0.0807**	-0.0129
	(0.0196)	(0.0337)	(0.0452)
Non-Hispanic White	0.0360	0.0401	0.0015
	(0.0250)	(0.0276)	(0.0270)
Non-Hispanic Black	-0.0130	-0.0084	-0.0363
	(0.0273)	(0.0307)	(0.0277)
Hispanic	-0.0050	-0.0137	-0.0035
	(0.0291)	(0.0329)	(0.0284)
Presence of child < 6	0.0146	0.0583***	-0.0707**
	(0.0183)	(0.0202)	(0.0311)
Constant	0.9793***	0.9859***	1.0050***
	(0.0282)	(0.0339)	(0.0515)
sigma	0.2174***	0.2087***	0.2256***
	(0.0063)	(0.0075)	(0.0100)
Observations	3400	2205	1195

Notes: Dependent variable is the daily share of total food expenditures on food at home. Standard errors in parentheses are clustered at the household level.
* *p<0.1*, ** *p<0.05*, *** *p<0.01*

Table 6. Parameter Estimates from Equation (2) for Households Above and Below the Poverty Line

Variables	<100% Poverty	>100% Poverty
ln(X)	-0.0241**	-0.0114*
	(0.0095)	(0.0065)
SNAP	0.0062	0.0017
	(0.0137)	(0.0028)
ln(X) × Days 1-3	-0.0118	-0.0130
	(0.0172)	(0.0104)
ln(X) × Days 4-6	-0.0233	-0.0072
	(0.0207)	(0.0091)
ln(X) × Days 7-14	-0.0068	-0.0150**
	(0.0144)	(0.0068)
ln(X) × Days 15-22	-0.0030	-0.0216**
	(0.0113)	(0.0088)
ln(X) × Days 23-30	-0.0211	-0.0117
	(0.0153)	(0.0102)
ln(household size)	-0.0239*	-0.0486**
	(0.0136)	(0.0212)
Days 1-3	-0.0284	-0.0471**
	(0.0234)	(0.0230)
Days 4-6	-0.0604**	-0.0367*
	(0.0306)	(0.0199)
Days 7-14	-0.0327*	-0.0645***
	(0.0195)	(0.0217)
Days 15-22	-0.0510**	-0.0693***
	(0.0226)	(0.0238)
Days 23-30	-0.0394*	-0.0763**
	(0.0220)	(0.0366)
Non-Hispanic White	0.0116	0.0770**
	(0.0272)	(0.0350)
Non-Hispanic Black	-0.0403	0.0385
	(0.0293)	(0.0416)
Hispanic	-0.0111	0.0125
	(0.0319)	(0.0422)
Presence of child < 6	-0.0184	0.0419*
	(0.0237)	(0.0236)
Constant	0.9977***	0.9527***
	(0.0488)	(0.0449)
sigma	0.2092***	0.2238***
	(0.0085)	(0.0091)
Observations	1989	1411

Notes: Dependent variable is the daily share of total food expenditures on food at home. Standard errors in parentheses are clustered at the household level.
* *p<0.1*, ** *p<0.05*, *** *p<0.01*

Table 7. Marginal Propensity to Spend on Food at Home, All SNAP Households

Time period	SNAP	Non-SNAP	Difference
Full month	0.8608***	0.8092***	0.0516***
	(0.0082)	(0.0119)	(0.0061)
Day 0	0.9354***	0.8424***	0.0930***
	(0.0205)	(0.0448)	(0.0336)
Days 1-3	0.8751***	0.8118***	0.0633***
	(0.0197)	(0.0316)	(0.0164)
Days 4-6	0.8751***	0.8245***	0.0506***
	(0.0246)	(0.0347)	(0.0154)
Days 7-14	0.8760***	0.8267***	0.0493***
	(0.0126)	(0.0182)	(0.0082)
Days 15-22	0.8468***	0.8075***	0.0394***
	(0.0135)	(0.0178)	(0.0061)
Days 23-30	0.8083***	0.7653***	0.0430***
	(0.0205)	(0.0246)	(0.0076)

Notes: Standard errors in parentheses are clustered at the household level. Marginal propensity to spend (MPS) is calculated as the propensity to spend on food at home out of SNAP and non-SNAP food expenditures for the given time period.

* *p<0.1*, ** *p<0.05*, *** *p<0.01*

Table 8. Marginal Propensity to Spend on Food at Home, by Grocery List Usage

Time period	SNAP	Non-SNAP	Difference
Frequent list users			
Full month	0.8693***	0.8253***	0.0440
	(0.0098)	(0.0295)	(0.0272)
Day 0	0.9593***	0.9119***	0.0474
	(0.0189)	(0.0547)	(0.0463)
Days 1-3	0.9086***	0.8648***	0.0439
	(0.0194)	(0.0503)	(0.0386)
Days 4-6	0.8905***	0.8318***	0.0587
	(0.0274)	(0.0603)	(0.0459)
Days 7-14	0.8866***	0.8483***	0.0382
	(0.0134)	(0.0313)	(0.0267)
Days 15-22	0.8426***	0.8062***	0.0363*
	(0.0159)	(0.0290)	(0.0210)
Days 23-30	0.8030***	0.7653***	0.0377**
	(0.0279)	(0.0343)	(0.0180)
Infrequent list users			
Full month	0.8418***	0.7624***	0.0793***
	(0.0149)	(0.0217)	(0.0110)
Day 0	0.8502***	0.6072***	0.2430***
	(0.0404)	(0.0705)	(0.0629)
Days 1-3	0.7942***	0.6194***	0.1749***
	(0.0384)	(0.0664)	(0.0534)
Days 4-6	0.8395***	0.7960***	0.0436
	(0.0488)	(0.0706)	(0.0292)
Days 7-14	0.8561***	0.7709***	0.0853***
	(0.0273)	(0.0354)	(0.0173)
Days 15-22	0.8549***	0.8019***	0.0530***
	(0.0252)	(0.0328)	(0.0104)
Days 23-30	0.8222***	0.7610***	0.0612***
	(0.0241)	(0.0360)	(0.0167)

Notes: Standard errors in parentheses are clustered at the household level. Marginal propensity to spend (MPS) is calculated as the propensity to spend on food at home out of SNAP and non-SNAP food expenditures for the given time period.

* *p<0.1*, ** *p<0.05*, *** *p<0.01*

Table 9. Marginal Propensity to Spend on Food at Home, by Poverty Level

Time period	SNAP	Non-SNAP	Difference
Above 100% poverty			
Full month	0.8426***	0.8054***	0.0372***
	(0.0118)	(0.0153)	(0.0098)
Day 0	0.9367***	0.8983***	0.0385
	(0.0215)	(0.0400)	(0.0247)
Days 1-3	0.8471***	0.8071***	0.0400**
	(0.0323)	(0.0442)	(0.0191)
Days 4-6	0.8791***	0.8535***	0.0256*
	(0.0342)	(0.0451)	(0.0147)
Days 7-14	0.8467***	0.8071***	0.0396***
	(0.0166)	(0.0191)	(0.0108)
Days 15-22	0.8191***	0.7794***	0.0397***
	(0.0209)	(0.0262)	(0.0121)
Days 23-30	0.8105***	0.7833***	0.0272***
	(0.0381)	(0.0404)	(0.0104)
Below 100% poverty			
Full month	0.8752***	0.8002***	0.0750***
	(0.0114)	(0.0343)	(0.0281)
Day 0	0.9339***	0.7455***	0.1883**
	(0.0310)	(0.1013)	(0.0877)
Days 1-3	0.9014***	0.7789***	0.1225**
	(0.0239)	(0.0740)	(0.0598)
Days 4-6	0.8714***	0.7426***	0.1288**
	(0.0351)	(0.0790)	(0.0595)
Days 7-14	0.8982***	0.8358***	0.0624**
	(0.0179)	(0.0419)	(0.0302)
Days 15-22	0.8713***	0.8301***	0.0412**
	(0.0178)	(0.0301)	(0.0164)
Days 23-30	0.8064***	0.7481***	0.0583***
	(0.0223)	(0.0352)	(0.0197)

Notes: Standard errors in parentheses are clustered at the household level. Marginal propensity to spend (MPS) is calculated as the propensity to spend on food at home out of SNAP and non-SNAP food expenditures for the given time period.

* *p<0.1*, ** *p<0.05*, *** *p<0.01*

Table 10. Share of free food purchased, in grams, over the month by food category

Variables	Dairy	Vegetables	Grains	Fruit	Protein
Days 1-3	0.110*	0.152**	0.093	0.196***	0.129**
	(0.060)	(0.066)	(0.061)	(0.074)	(0.062)
Days 4-6	0.153***	0.159***	0.131**	0.210***	0.140**
	(0.056)	(0.060)	(0.056)	(0.067)	(0.059)
Days 7-14	0.147***	0.185***	0.135**	0.238***	0.162***
	(0.054)	(0.057)	(0.054)	(0.066)	(0.057)
Days 15-22	0.176***	0.202***	0.174***	0.271***	0.203***
	(0.055)	(0.058)	(0.055)	(0.066)	(0.057)
Days 23-30	0.177***	0.202***	0.182***	0.263***	0.173***
	(0.054)	(0.057)	(0.055)	(0.065)	(0.057)
Log(HH size)	-0.047***	-0.080***	-0.085***	0.004	-0.082***
	(0.017)	(0.018)	(0.017)	(0.025)	(0.017)
Non-Hispanic White	0.001	0.064	0.001	-0.013	0.032
	(0.044)	(0.058)	(0.046)	(0.052)	(0.050)
Non-Hispanic Black	0.060	0.107*	0.040	0.061	0.091*
	(0.046)	(0.059)	(0.048)	(0.053)	(0.051)
Hispanic	0.027	0.055	0.028	-0.027	0.071
	(0.047)	(0.060)	(0.048)	(0.055)	(0.051)
Presence of child < 6	-0.016	-0.007	-0.007	0.009	-0.008
	(0.019)	(0.020)	(0.019)	(0.023)	(0.020)
HH average income	-0.001	-0.001	-0.000	-0.001	-0.001
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Constant	0.589***	0.524***	0.610***	0.484***	0.583***
	(0.073)	(0.083)	(0.074)	(0.091)	(0.079)
Observations	2573	2636	2743	2024	2561

Notes: Standard errors in parentheses and clustered at the household level.
* *p<0.1*, ** *p<0.05*, *** *p<0.01*
For all models, days 1-3 are statistically lower than Days 4-6 and beyond.

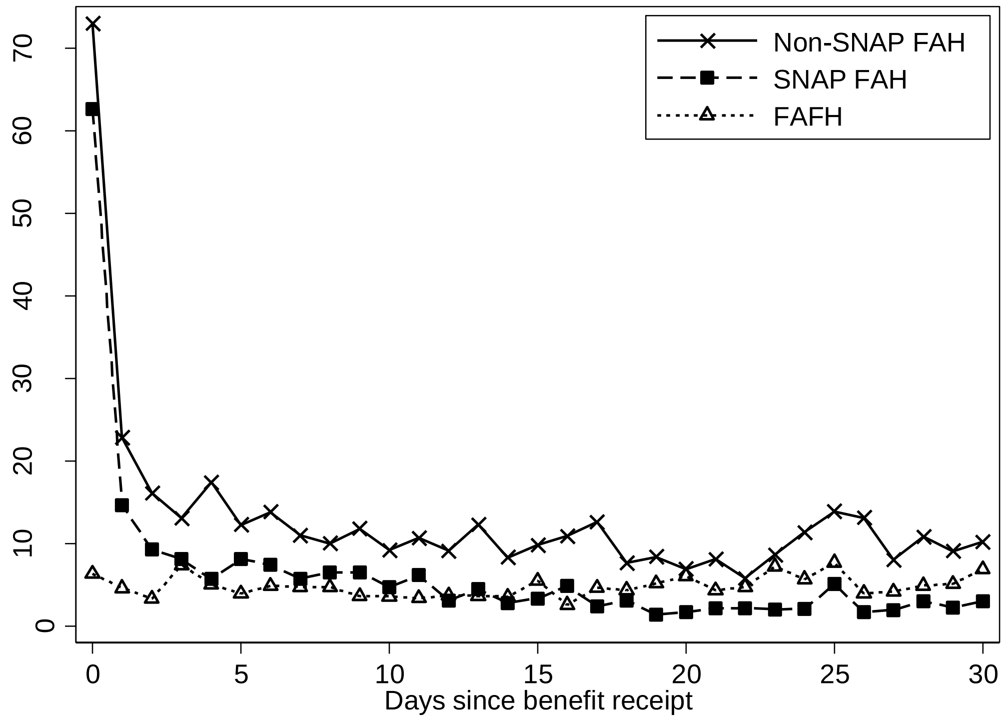
Table 11. Share of free food purchased, in grams, over the month by calories and nutrients

	calories	carbs	fat	added sugar
Days 1-3	0.069	0.075	0.078	0.077
	(0.058)	(0.058)	(0.059)	(0.063)
Days 4-6	0.115**	0.120**	0.114**	0.140**
	(0.054)	(0.054)	(0.054)	(0.058)
Days 7-14	0.115**	0.123**	0.119**	0.154***
	(0.051)	(0.052)	(0.052)	(0.056)
Days 15-22	0.135***	0.153***	0.135**	0.177***
	(0.052)	(0.052)	(0.053)	(0.056)
Days 23-30	0.160***	0.172***	0.148***	0.189***
	(0.052)	(0.052)	(0.053)	(0.055)
Log(HH size)	-0.102***	-0.099***	-0.103***	-0.110***
	(0.017)	(0.018)	(0.017)	(0.019)
Non-Hispanic White	0.002	-0.008	0.013	0.030
	(0.046)	(0.048)	(0.046)	(0.051)
Non-Hispanic Black	0.050	0.036	0.059	0.049
	(0.048)	(0.049)	(0.048)	(0.053)
Hispanic	0.016	0.007	0.022	0.049
	(0.049)	(0.051)	(0.049)	(0.054)
Presence of child < 6	-0.007	-0.005	-0.014	-0.009
	(0.019)	(0.020)	(0.019)	(0.021)
HH average income	-0.000	-0.000	-0.000	-0.000
	(0.002)	(0.002)	(0.003)	(0.002)
Constant	0.592***	0.585***	0.610***	0.550***
	(0.072)	(0.073)	(0.072)	(0.079)
Observations	2884	2870	2882	2773

Notes: Standard errors in parentheses and clustered at the household level.
* *p<0.1*, ** *p<0.05*, *** *p<0.01*
For all models, days 1-3 are statistically lower than Days 4-6 and beyond.

Figures

Figure 1. Average daily expenditures over the benefit month



Notes: The disbursement of SNAP benefits occurs on day 0.

Figure 2. Sources of Free Food for SNAP households

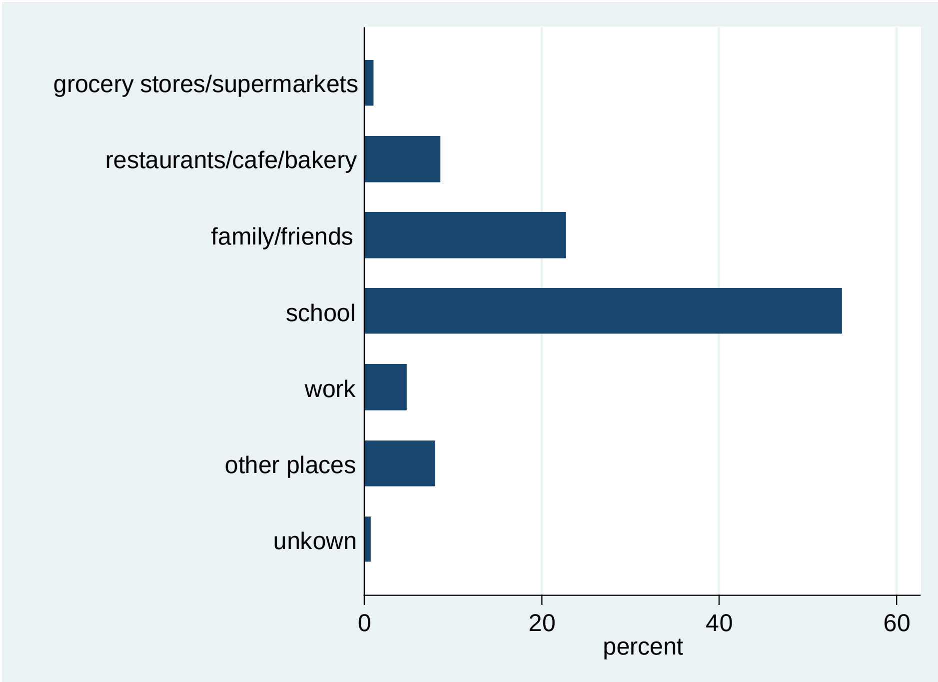


Figure 3. Sources of Free Food for non-SNAP households

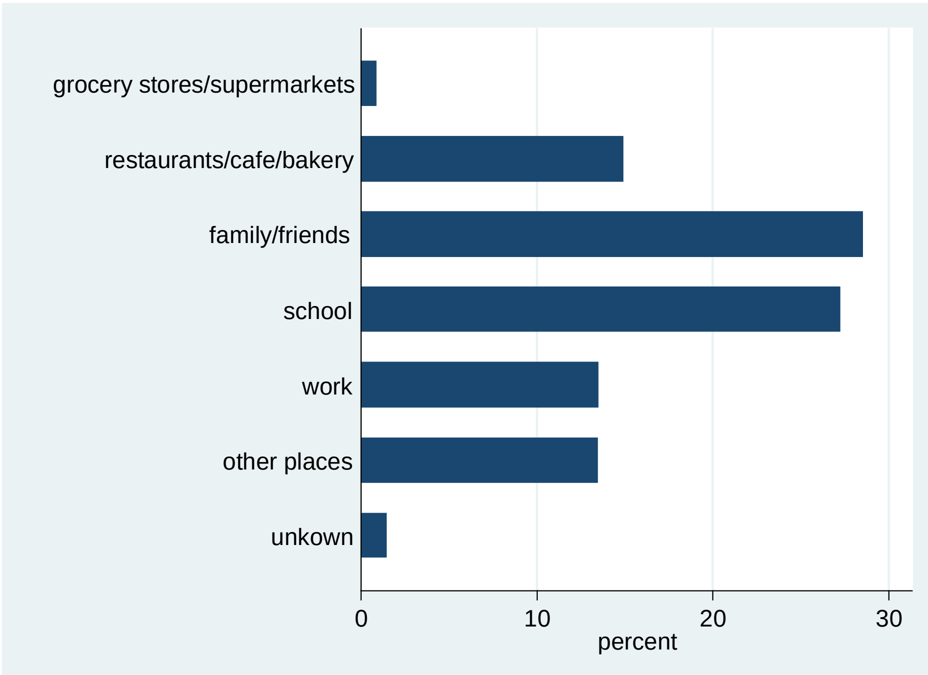
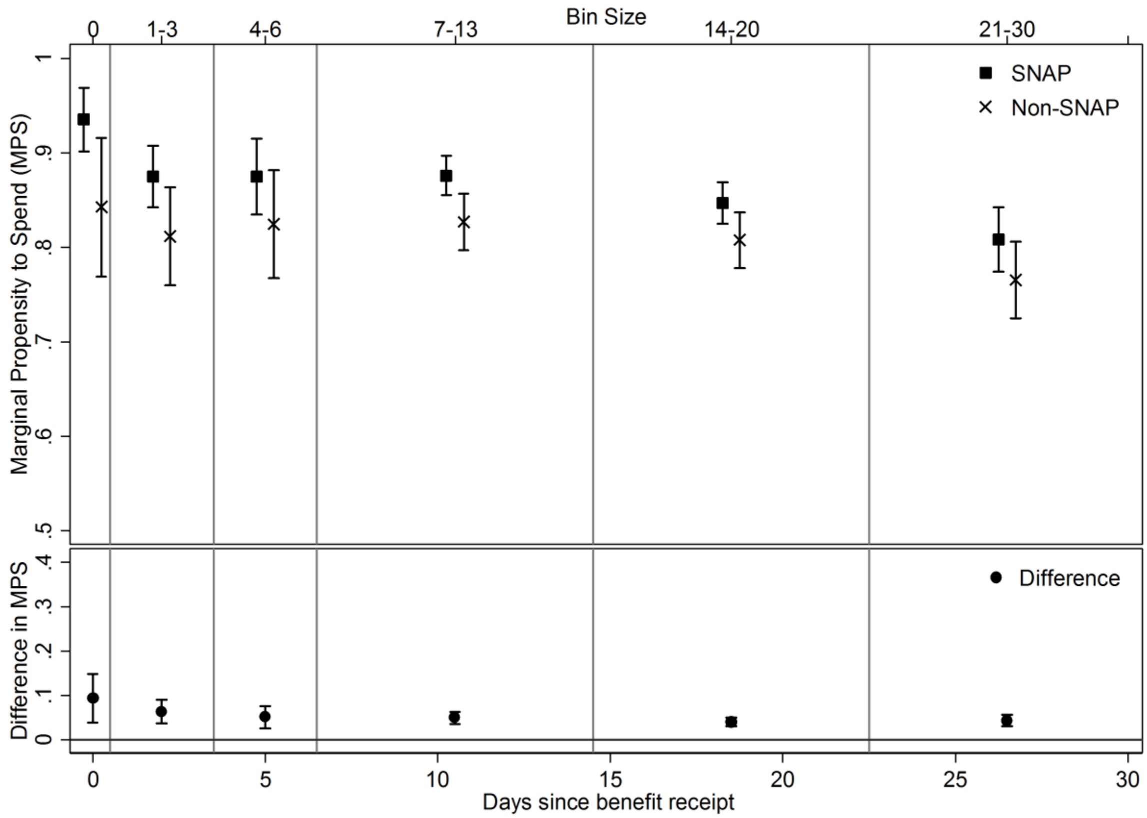
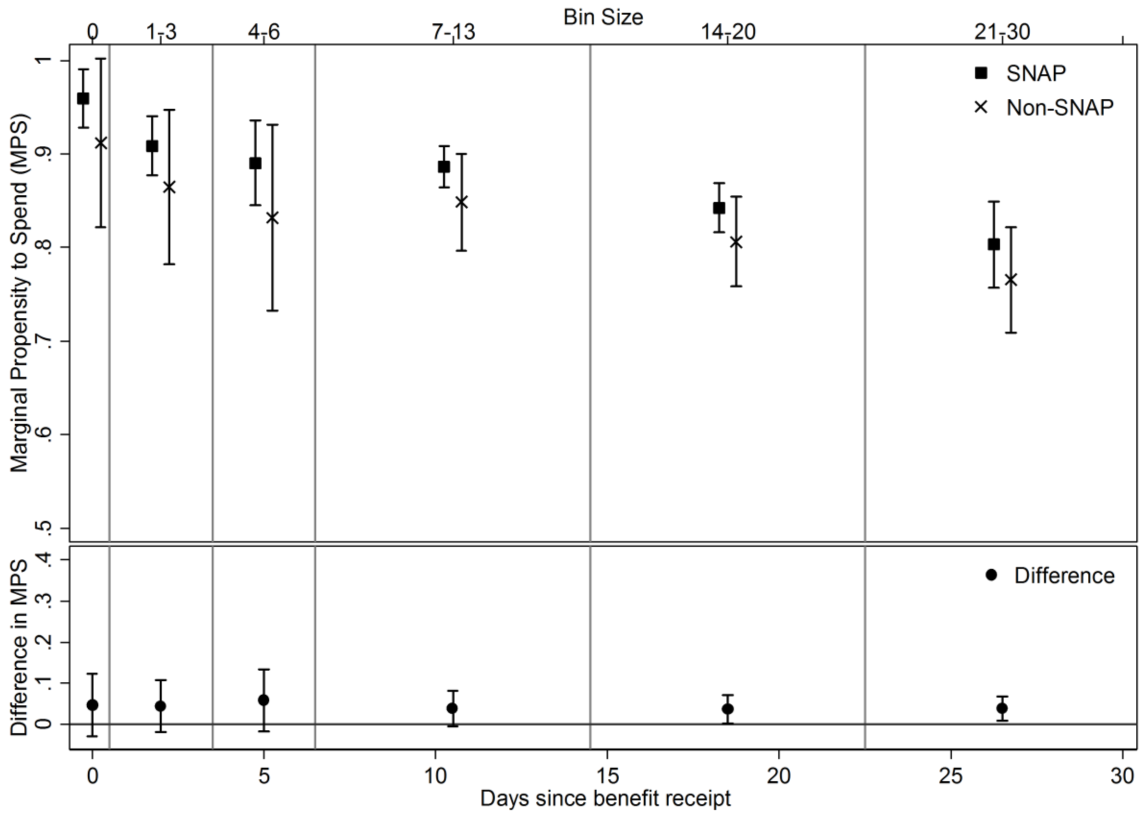


Figure 4. Marginal propensity to spend on food at home, all SNAP households



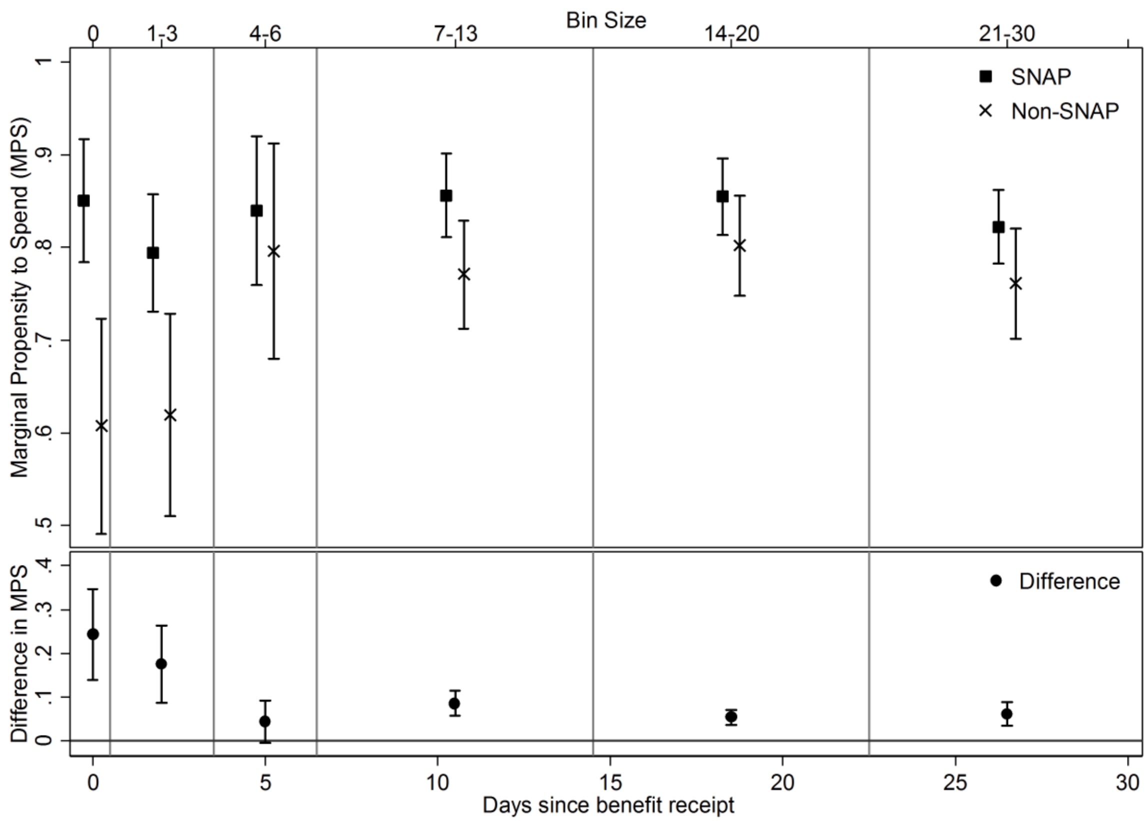
Notes: All point estimates are accompanied by 95- % confidence intervals and correspond to a range of days since benefit receipt shown on the top *x*-axis as “bin size.” Standard errors are clustered at the household level. See table 5 for estimates.

Figure 5. Marginal propensity to spend on food at home, frequent grocery list users



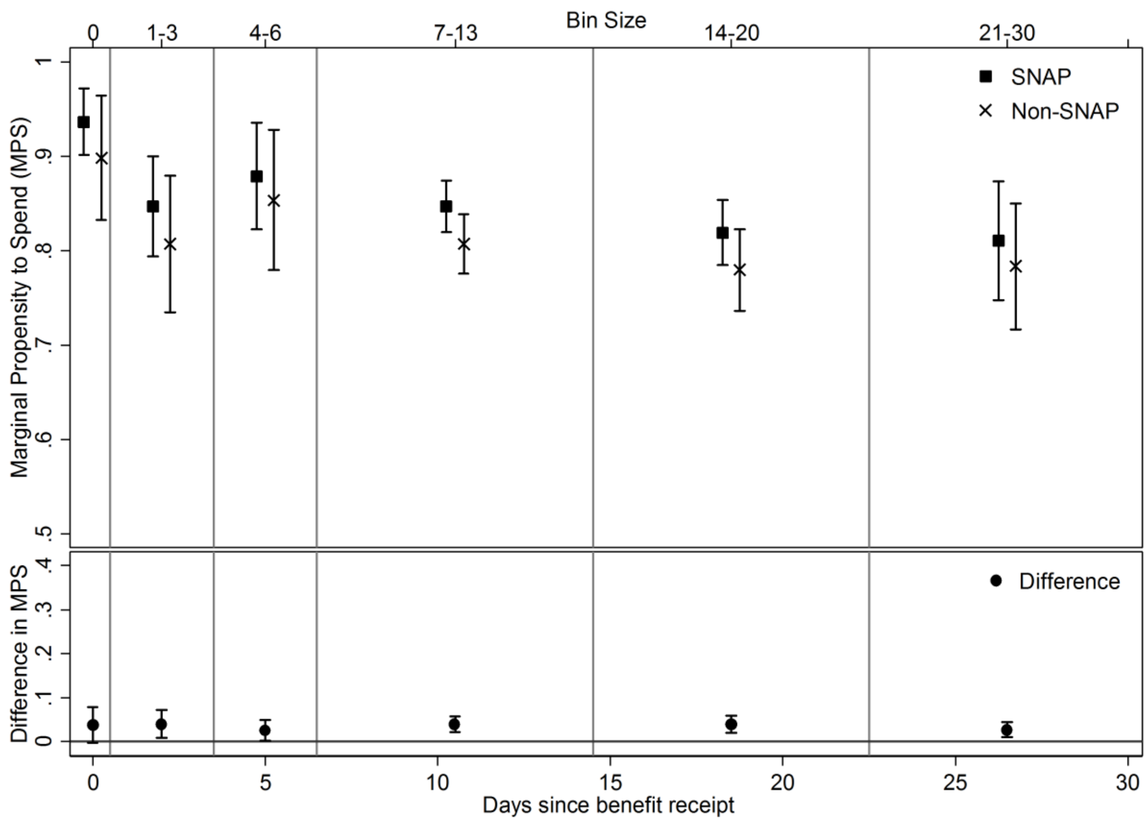
Notes: All point estimates are accompanied by 95- % confidence intervals and correspond to a range of days since benefit receipt shown on the top *x*-axis as "bin size." Standard errors are clustered at the household level. See table 6 for estimates.

Figure 6. Marginal propensity to spend on food at home, infrequent grocery list users



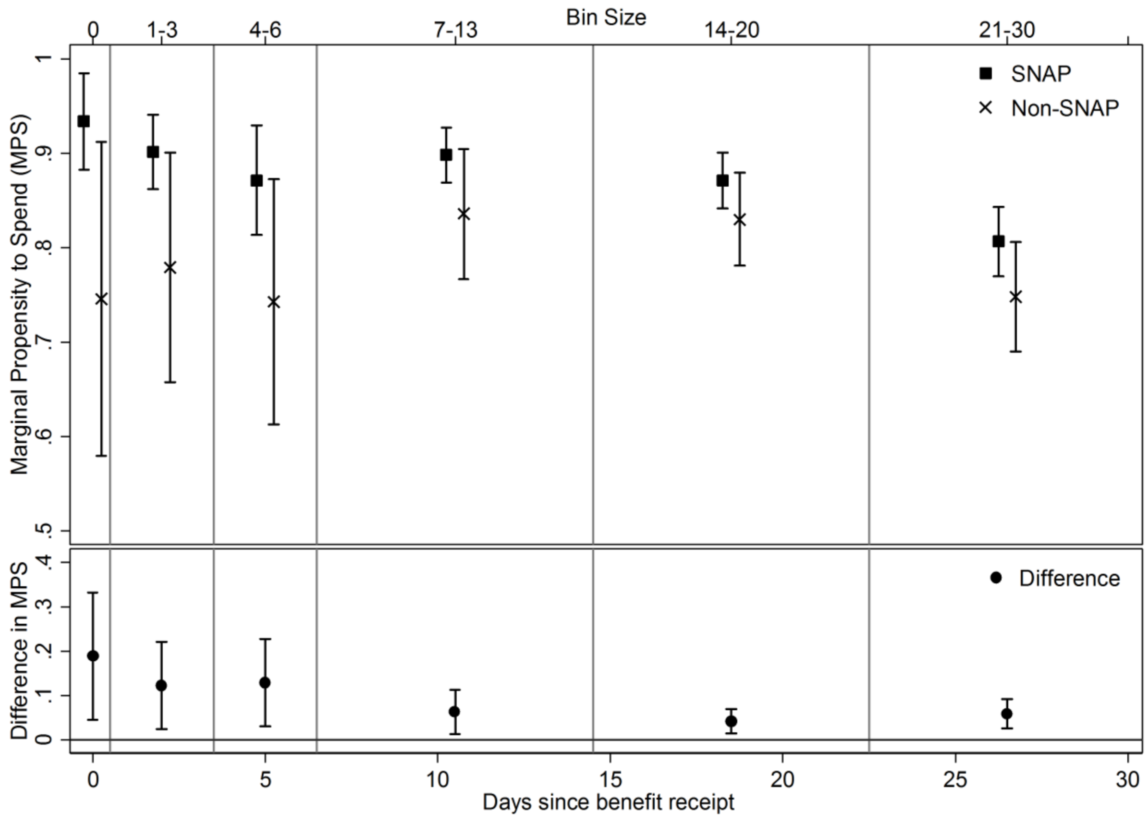
Notes: All point estimates are accompanied by 95- % confidence intervals and correspond to a range of days since benefit receipt shown on the top *x*-axis as “bin size.” Standard errors are clustered at the household level. See table 6 for estimates.

Figure 7. Marginal propensity to spend on food at home, >100% of poverty guidelines



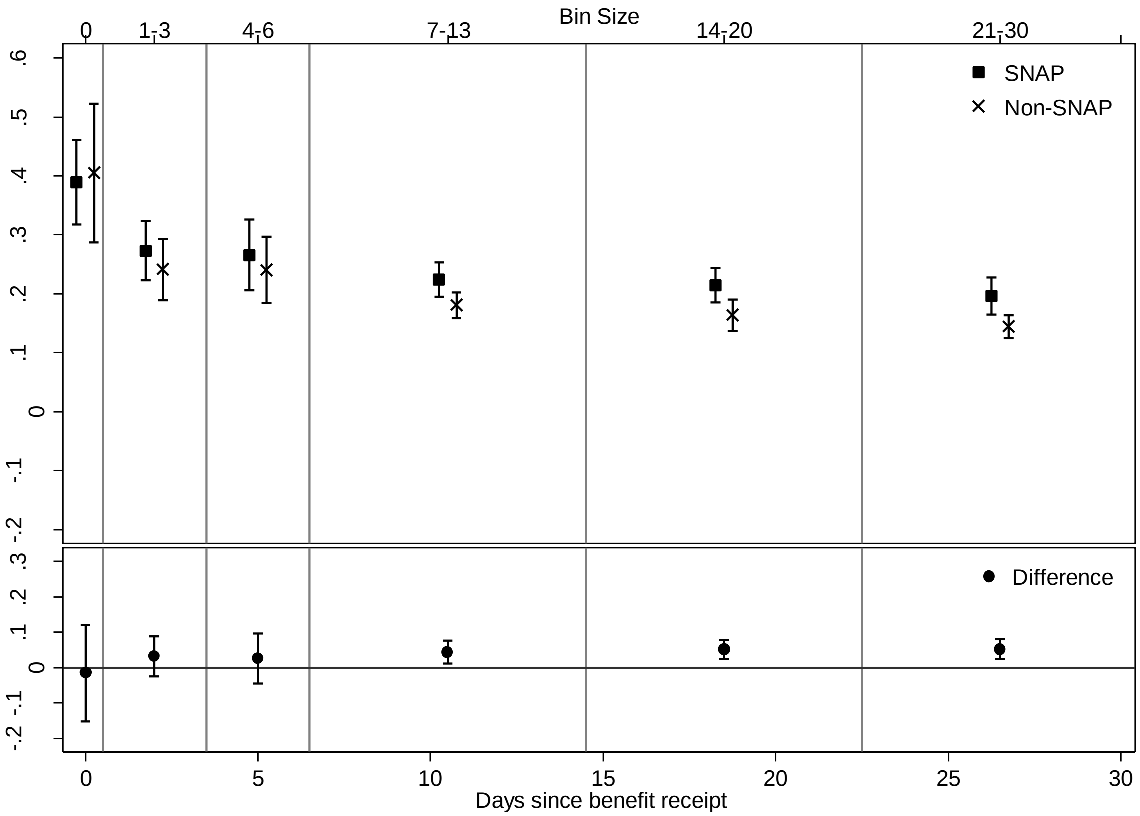
Notes: All point estimates are accompanied by 95- % confidence intervals and correspond to a range of days since benefit receipt shown on the top *x*-axis as "bin size." Standard errors are clustered at the household level. See table 7 for estimates.

Figure 8. Marginal propensity to spend on food at home, <100% of poverty guidelines



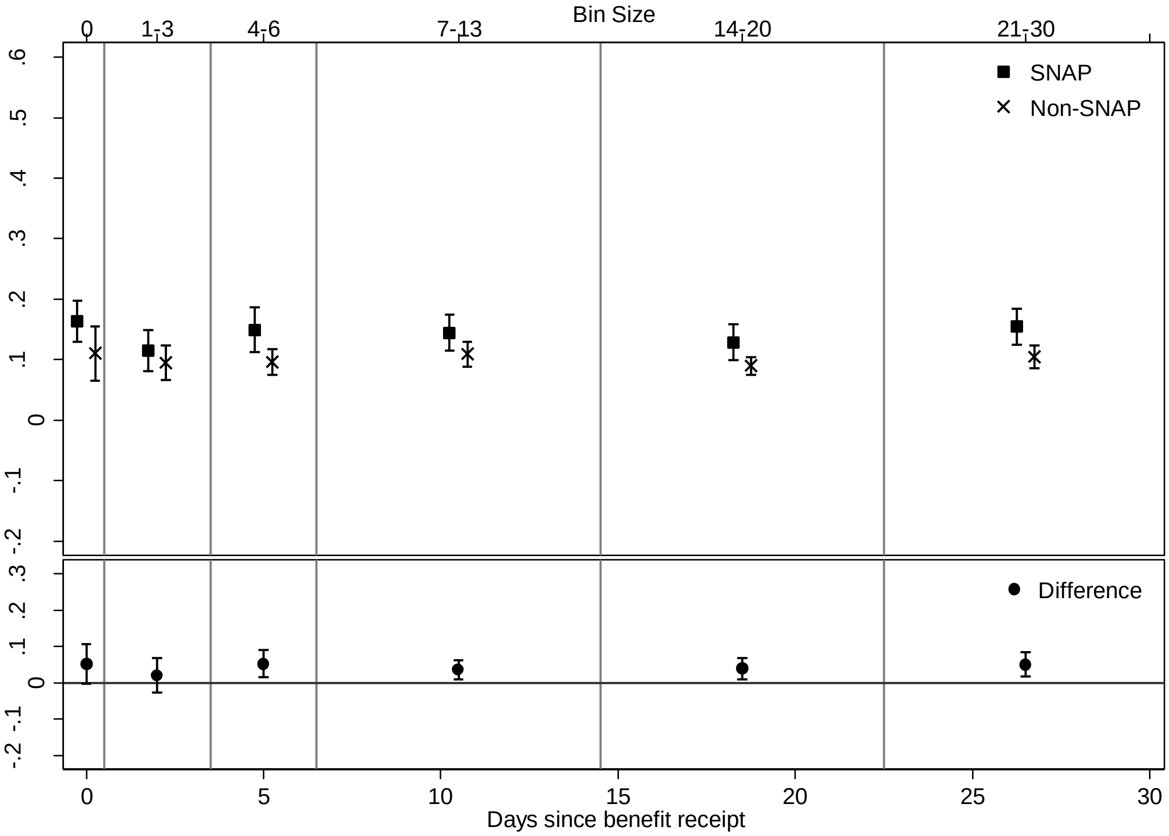
Notes: All point estimates are accompanied by 95- % confidence intervals and correspond to a range of days since benefit receipt shown on the top *x*-axis as "bin size." Standard errors are clustered at the household level. See table 7 for estimates.

Figure 9. Marginal propensity to spend on healthful food



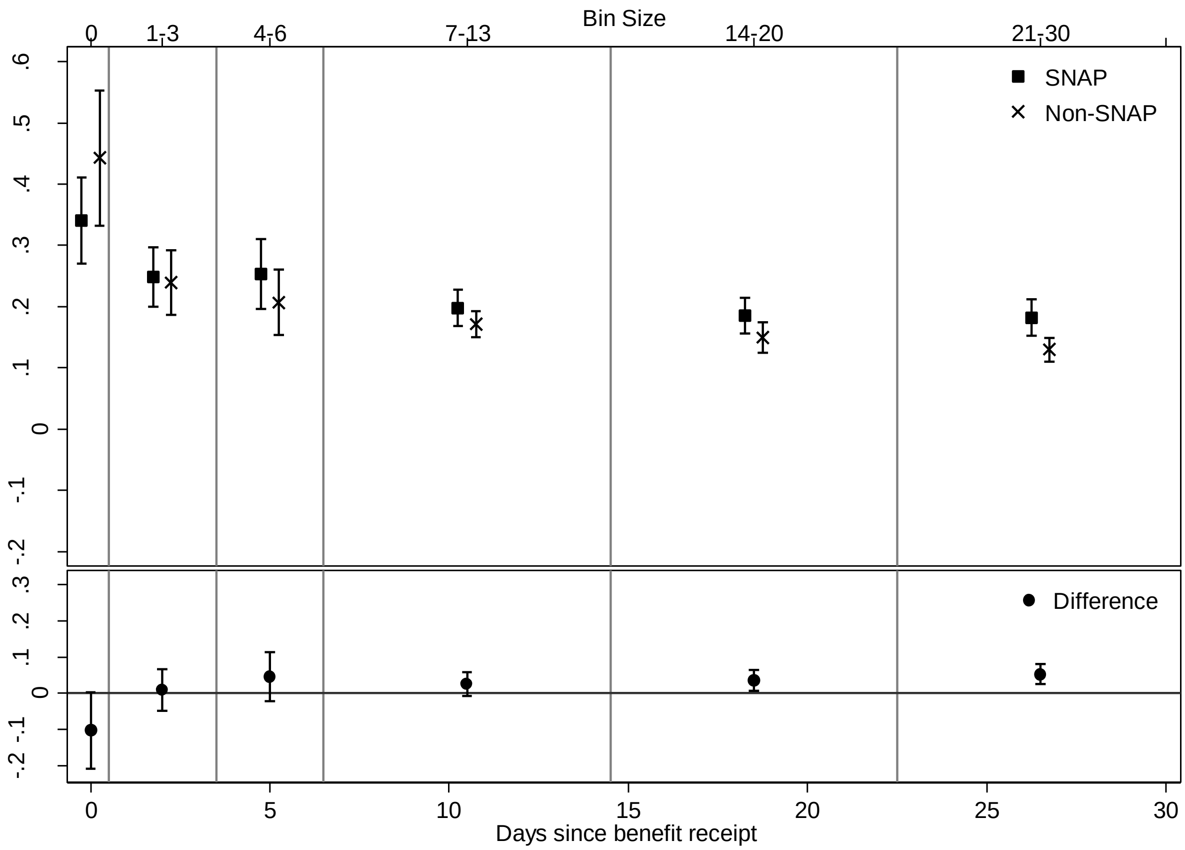
Notes: All point estimates are accompanied by 95- % confidence intervals and correspond to a range of days since benefit receipt shown on the top *x*-axis as "bin size." Standard errors are clustered at the household level.

Figure 10. Marginal propensity to spend on unhealthy food



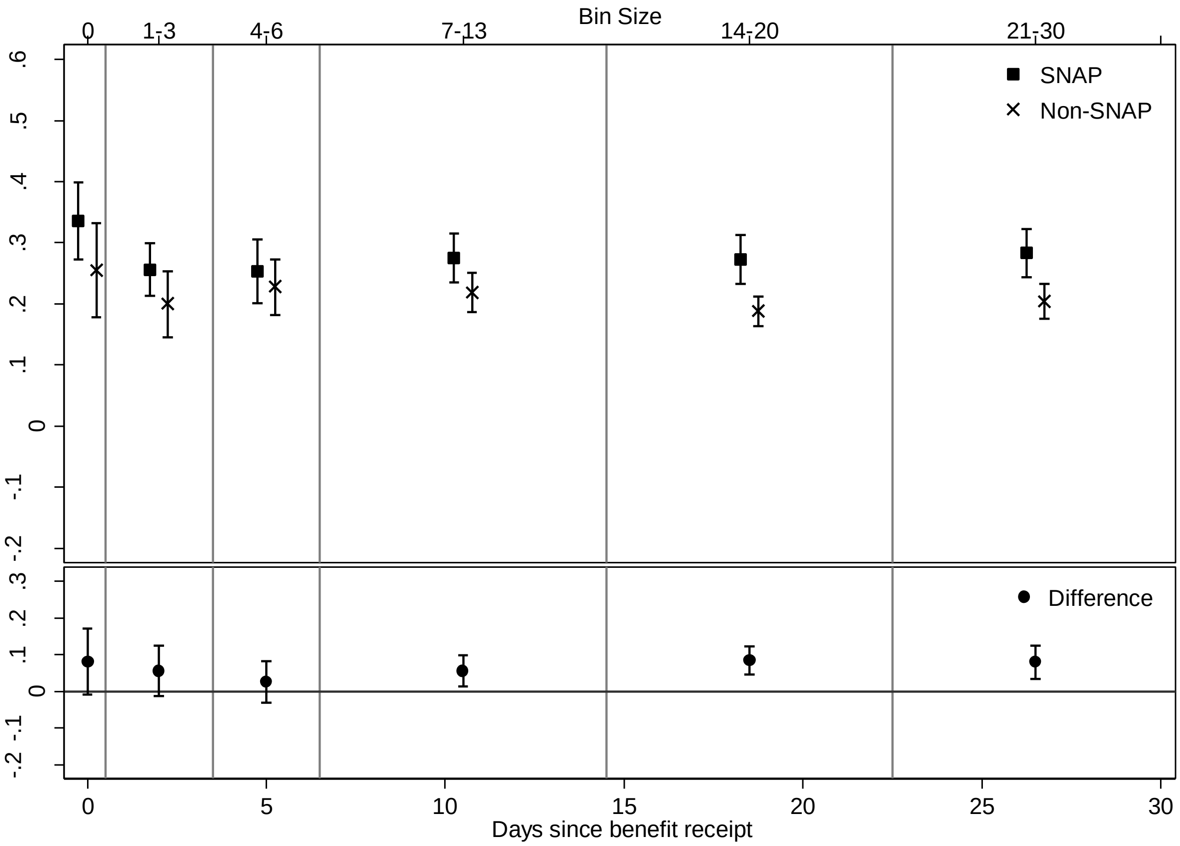
Notes: All point estimates are accompanied by 95- % confidence intervals and correspond to a range of days since benefit receipt shown on the top *x*-axis as "bin size." Standard errors are clustered at the household level.

Figure 11. Marginal propensity to spend on perishable food



Notes: All point estimates are accompanied by 95- % confidence intervals and correspond to a range of days since benefit receipt shown on the top *x*-axis as "bin size." Standard errors are clustered at the household level.

Figure 12. Marginal propensity to spend on nonperishable food



Notes: All point estimates are accompanied by 95- % confidence intervals and correspond to a range of days since benefit receipt shown on the top *x*-axis as “bin size.” Standard errors are clustered at the household level.

[i] Income fungibility, or the idea that "money in one mental account is not a perfect substitute for money in another account" (Thaler 1999), has also been investigated as a 'cash-out effect' (e.g.,Moffitt 1989) and a 'labeling effect' (e.g,, Kooreman 2000).

[ii] Specifying D_t as a continuous variable fails to capture the stark nonlinearities of the SNAP cycle. We also considered other bin widths for D_t and came to similar conclusions. Likewise, D_t could take on a high-order polynomial or be fully nonparametric through the use of a kernel.

[iii] Administrative data was linked to the sample in an attempt to confirm current SNAP enrollment. Over 82% of our sample was confirmed (N=1,172). A small portion (N=26) did not grant permission for data matching, and the remaining 229 households could not be linked due to administrative data limitations. Results are robust to excluding the latter two groups although estimates are not as precisely estimated.

[iv] During the survey week, there are multiple occasions where the household does not make a food purchase. Consequently, the dependent variable of equation (4) is often zero. We view these zeros not as censoring, rather as actual choices to not shop. In other words, a censored tobit approach would not be appropriate. We attempted to account for the decision to make a purchase on a given day using a Heckman two-step approach (Heckman 1979). Our exclusion restrictions included indicators for the diary day (1-7) and month of the year. The parameter estimate on the inverse Mills ratio is insignificant in all specifications. Moreover, likelihood ratio tests cannot reject the null that the models are equivalent. Consequently, our estimated are based on non-zero purchase days.

[v] Previous studies investigating the marginal propensity to spend on food out of SNAP typically use the monthly SNAP benefit allotment rather than actual SNAP spending; these studies find varying estimates falling between zero and one due to study design, survey period and methodological approach (Cuffey, Beatty and Harnick, 2014).

[vi] We also considered placing households that report using grocery lists sometimes in the infrequent user category. Result did not change substantially.

[vii] SNAP eligibility is set at 130 percent of the poverty guidelines.

[viii] Shapiro (2005) provides a back-of-the-envelope calculation of increased transaction costs due to more frequent disbursements using data from Maryland in 1993. These calculations are however and they precede the move to electronic benefit transfer (EBT) in 2003.

Food Store Choice of Poor Households:
A Discrete Choice Analysis of the National Household Food Acquisition and Purchase Survey

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Abstract

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. 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 (1) 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 (2) willingness to pay is heterogeneous across income group, Supplemental Nutrition Assistance Program (SNAP) 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.

Introduction

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, "by 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." Financing for the HFFI comes after numerous studies indicating a link between disparities in access to healthy foods and poor health outcomes.[1] However, despite the growing body of research on food 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—over the four years of the study—in dietary habits.

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, 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 consumption at-home and away-from-home. These data allow us to address holes in the existing literature which are vital to understanding store choice and to implementing policies to improve food access.

This article builds upon a long literature examining food store choices. An early study by Arnold, Oum, and Tigert (1983) finds that the determinants of store choice among FAH shoppers includes 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 et al. 2013), the degree of competition between food stores (Hausman and Leibtag 2007) and prices offered by various outlet types (Broda et al. 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: 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 el- igible but not 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.[2] 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, and schools (Stewart et al. 2004)—this is an important data limitation. With the FoodAPS datasets we are able to address these previous data limitations 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 ge- ographic 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 (Ver Ploeg et al. 2015). 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 frame- work 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 out- lets 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).[3] 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—i.e., the main food shopper or meal planner—provided information about the household 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 write information in provided food books. Three phone calls with the PR occurred over the week to collect additional information. Together, these records describe 15,999 food-at-home (FAH) acquisition events and 38,869 food-away-from-home (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 each household could have visited within their Primary Sampling Unit or within adjacent PSUs.[4] 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 1 mile radius. With these data, we are able to construct comprehensive pictures of the local food environments in which the surveyed households live.[5] Previous studies, 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 FPL, and above 185% of FPL.[6] 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".[7] 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. Faded text indicate the estimate is not statically different at the 5% significance level from the reference group (SNAP households). 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, 8) Fast Food, and 9) Other Category.[8] *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 the most per week at Superstore outlets ($56.78), followed by Supermarket ($39.58), Restaurant ($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.[9] 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.[10] 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 Market.

It is important to note here that expenditures for SNAP households include the SNAP benefits they spend, and that SNAP 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.[11] 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.[12] In looking at the 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.[13] A census block group is identified as a food desert if: (1) it qualifies as a "low-income com- munity" based on having a poverty rate of 20 percent 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 borrow a vehicle. For the overall sample, the average population density is 5013 persons per square mile, 33% of households live in rural areas, 5% live 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 deserts (9%) and to report not having car access (15%) than non-eligible non-SNAP households.

Finally, table 3 presents household (HH) and primary respondent (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.[14] 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.

We allow households to choose between nine outlet categories for purchasing food-at- home (FAH) and food-away-from-home (FAFH). 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.[15]

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:

$$(1) \qquad U_{ijt} = \alpha_t + \alpha_j + \beta_i X_{ijt} + \varepsilon_{ijt} + \mathcal{E}_{ijt}.$$

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 X_{ijt} contains the attributes of outlet type j at time t (i.e., distance from home), the vector β_i represents the marginal utility placed on each of the X attributes. The error term ε_{ijt} captures determinants of household marginal utility that are unobserved to the econometrician but seen by the household when making choices, while $\mathcal{E}_{ijt}$ captures all remaining (unobserved to all) determinants of utility.

Distributional assumptions about β_i and $\mathcal{E}_{ijt}$ drive the econometric model choice. If we assume that $\mathcal{E}_{ijt}$ are independently and identically distributed extreme value (type I), then we have a logit choice model. If we specify that $\beta_i = \beta + \sigma_z Z_i$, 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 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, $U_{iOCt} = \mathcal{E}_{iOCt}$. 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 form:

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

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 OLS:

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

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

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

where s_{ijt} is household i's share of expenditures made at outlet type j during the seven days of the survey. 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 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 vector $\beta_i^{distance}$ $_i$ represents the marginal utility household *i* places on distance. We hypothesize that $\beta^{distance}_i$ 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 route 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 house- hold's week-to-week store choices—namely, the distance from home to the closest outlet of the given type. This instrument 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 our instrument is exogenous to the omitted reasons households choose one outlet over another outlet 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 (Ver Ploeg et al. 2015). 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,[16] outlet category dummies, and a constant term referring to the omitted outlet category (Supermarket). It also includes week-in-year fixed effects to control for seasonality[17] and a rich set of controls for household characteristics.[18] 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 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 (for example, 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, (9th) Farmers Market. Omitting household characteristic control variables (column 3) and time fixed effects (column 4) does not alter the revealed preference rank- ing.[19] 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 on- line. 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 for the 783 non-SNAP households with income between 101 −185% of FPL (i.e., mid-income non-SNAP), and finally, column 5 for the 1,825 non-SNAP households with income larger 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 out- side 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 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 the columns 1–4 we divide the households by the food desert status of the census blockgroup in which they live and by self-reported vehicle access. In the FoodAPS sample, one percent 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 which 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.

Next, in the 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 being 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.[20] 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:

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

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).[21] 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 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.[22]

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 significant 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 Super- markets than the other household groups. Given that SNAP households can 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 the 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 outlets 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 Super- stores, 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.[23]

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 household may need to be compensated to shop at Farmers Markets.[24] 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) living 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 dataset's rich assortment of household and local food environment characteristics in the model. While it is reassuring that we find our instrument corrects the positive bias for 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.

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 outlet 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.

Notes

[1]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 et al. 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 areas can mitigate the likelihood of adults experiencing food insecurity (Bonnano and Li 2015).

[2]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.

[3]This article uses the FoodAPS data as of September 25, 2015. For more information about FoodAPS, please see the USDA, ERS Website (accessed October 12, 2015).

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

[5]For all outlet categories except Farmers Market, distances are measured from each household's home. For Farmers Market, 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.

[6]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.

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

[8]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.

[9]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%.

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

[11]"Supplemental Nutrition Assistance Program: Using SNAP Benefits." USDA Food and Nutrition Service. Website (accessed October 12, 2015).

[12]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.

[13]"Creating Access to Healthy, Affordable Food: Food Deserts." *United States Department of Agriculture, Agricultural Marketing Service.* Website (accessed October 9, 2015).

[14]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.

[15]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.

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

[17]Week-in-year fixed effects also allows 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.

[18]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.

[19]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.

[20]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, now preferred to Supermarkets.

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

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

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

[24]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 Website (accessed October 12, 2015).

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Table 1: **Summary Statistics: Weekly Food Store Choices**

Variable	Overall (1)	SNAP (2)	non-SNAP income ≤ 100% FPL (3)	non-SNAP income 101 - 185% FPL (4)	non-SNAP 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)
Ave. Distance Traveled (mi.)					
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 in parentheses. Bold text in columns 3-5 indicate the estimate is statistically different from the reference group—SNAP households (column 2)—with a p-value ≤ 0.05.

Table 2: **Summary Statistics: Retail Food Environment**

Variable	Overall	SNAP	non-SNAP income ≤ 100% FPL	non-SNAP income 101 - 185% FPL	non-SNAP income > 185% FPL
	(1)	(2)	(3)	(4)	(5)
Num. of stores in 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 (mi.)					
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 (person/sq mile)	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 indicate the estimate is statistically different from the reference group—SNAP households (column 2)—with a p-value ≤ 0.05.

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 in parentheses. Bold text in columns 3-5 indicate the estimate is statistically different from the reference group—SNAP households (column 2)—with a p-value ≤ 0.05.

Table 4: **Mean Utility Estimates for the Outlet Choice Model**

	OLS (1)	**IV** (2)	**IV** (3)	**IV** (4)
D. **Log Expend. Share**				
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 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.
+ p < 0.10 * p <0.05 ** p <0.01 *** p<0.001.

[a]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.

Table 5: **Mean Utility Estimates, by SNAP Participation & Income Group**

			non-SNAP		
			income ≤ 100% FPL	**income 101 - 185% FPL**	**income > 185% FPL**
	Overall	**SNAP**			
	(1)	(2)	(3)	(4)	(5)
D. **Log Expend. Share**					
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 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 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 and 185% FPL, and above 185% FPL. + $p < 0.10$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$.

[a]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.

Table 6: **Mean Utility Estimates, by Car Access & Food Desert Status, Urban & 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)
D. **Log Expend. Share**								
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 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 samples of FoodAPS households. Columns (1) to (4) divide households by whether they state 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) divide households by whether they state prices or closeness-to-home (and not prices) as their reason for shopping at their primary food store. + $p < 0.10$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$.

[a]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.

Table 7: **Willingness to Pay in Distance Traveled, by SNAP Participation & Income Group**

			non-SNAP		
	Overall	**SNAP**	**income ≤ 100% FPL**	**income 101 - 185% FPL**	**income > 185% FPL**
	(1)	(2)	(3)	(4)	(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***
	*	(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 in parentheses. + $p < 0.10$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$. 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 cost (AAA 2013).

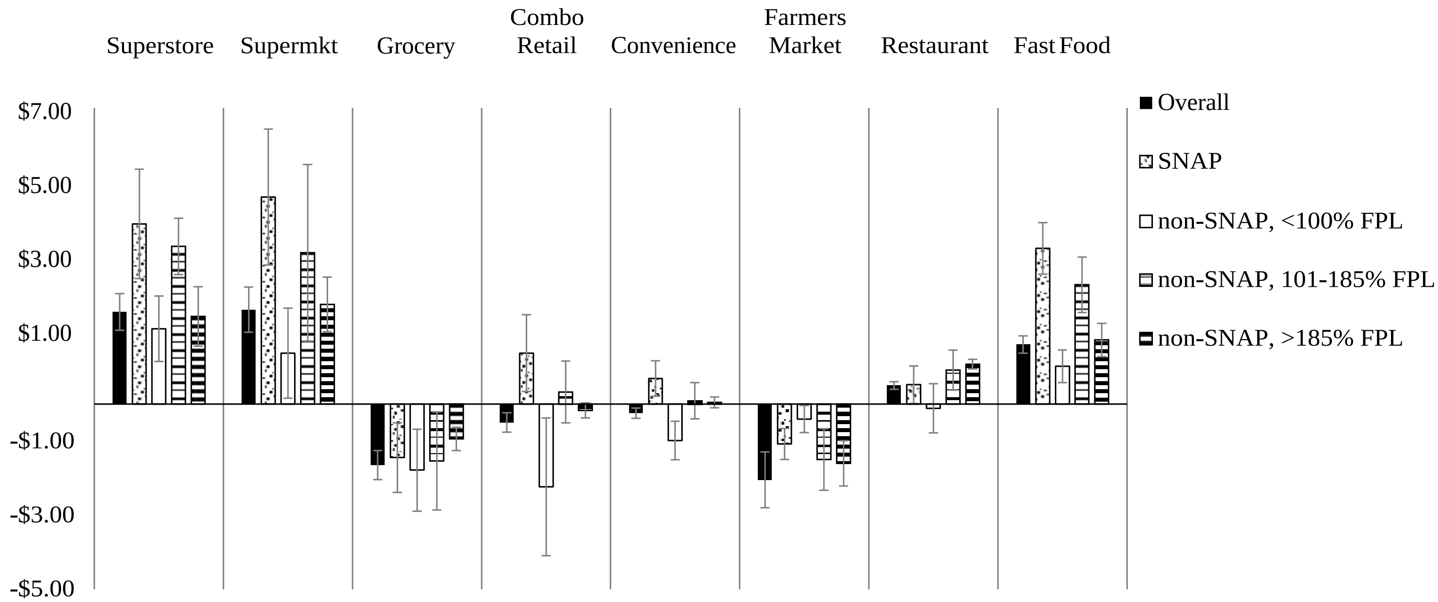

Figure 1: Weekly willingness to pay for an outlet type to be located one mile closer to home

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.