

The economics of food, nutrition, and poverty

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Abstract

Low-income households around the United States experience difficulties with food insecurity wherein they struggle to secure enough food for all of their household members. This issue becomes even more complex when considering the nutritional makeup of the food that they are able to secure. This issue is of importance to public policy, especially given rising rates of diet-related diseases among low-income individuals. This thesis explores public policy efforts aimed at improving the consumption of healthy and nutritious foods for low-income individuals. In this dissertation I first investigate the impact of increasing the payout of Supplemental Nutrition Assistance Program payouts on low-income participants' consumption of different food groups. Secondly, I compare the simulated impact on fruits and vegetables purchases of increasing the food budget of low-income households to providing them a discount on fruits and vegetables. Finally, I evaluate the preferences of food pantry clients towards healthy modifications to their food.

Table of Contents

Acknowledgements	i
Abstract	ii
List of Figures	vii
Chapter 1. Introduction	1
Chapter 2. Do larger food budgets lead to healthier food choices for low-income households?	3
2.1 Introduction.....	3
2.2 Background on SNAP and ARRA.....	5
2.3 Conceptual framework.....	10
2.4 Data.....	14
2.5 Identification and empirical strategy	16
2.5.1 <i>Model specification</i>	18
2.5.2 <i>Treatment and comparison groups</i>	20
2.6 Results.....	29
2.6.1 <i>DID results</i>	29
2.6.2 <i>Falsified treatment period</i>	30
2.7 Discussion and policy implications	31
2.8 Conclusion	34

Chapter 3. Evaluating the impact of policy mechanisms on low-income households	36
.....	
3.1 Introduction.....	36
3.2 Background.....	38
3.2.1 <i>Nutrition, poverty, and public policy</i>	38
3.2.2 <i>Income and consumption</i>	41
3.3 Data.....	42
3.3.1 <i>Descriptive statistics</i>	43
3.3.2 <i>Price construction</i>	45
3.3.3 <i>Income</i>	48
3.3.4 <i>Expenditure</i>	51
3.4 Methods.....	52
3.4.1 <i>The Quadratic Almost Ideal Demand System</i>	52
3.4.2 <i>Policy simulations</i>	54
3.4.3 <i>Compensating variation</i>	57
3.5 Results.....	58
3.5.1 <i>Engel curves</i>	59
3.5.2 <i>Income elasticity</i>	61
3.5.3 <i>Impact of policy mechanisms on fruits and vegetables expenditure shares</i>	63
3.5.4 <i>Impact of discount on economic welfare</i>	65
3.6 Discussion and policy implications.....	66
3.7 Conclusion.....	68

Chapter 4. Measuring food pantry client preferences for healthy food options	70
4.1 Introduction.....	70
4.2 Literature review.....	72
4.2.1 <i>Food, health, income, and perceptions</i>	72
4.2.2 <i>Food pantries in the United States</i>	76
4.2.3 <i>Preferences and contingent valuation</i>	78
4.3 Data.....	80
4.3.1 <i>Collection design</i>	80
4.3.2 <i>Sample descriptive statistics</i>	82
4.4 Conceptual framework.....	84
4.5 Empirical methods	85
4.5.1 <i>Choice conjoint</i>	85
4.5.2 <i>Random Coefficient Logit</i>	90
4.5.3 <i>Expectations from RCL</i>	91
4.6 Results and Discussion	93
4.6.1 <i>Comparison to Dietary Recalls</i>	96
4.7 Conclusion	100
Chapter 5. Concluding remarks	103
Bibliography	106
Appendices.....	130

List of Tables

Table 2-1. Food groups considered in analysis.....	16
Table 2-2. Definition of treatment and comparison for each comparison, based on the poverty threshold	23
Table 2-3. Descriptive statistics of treated and comparison	24
Table 2-4. Pre-ARRA average expenditure shares	26
Table 2-5. Balancing test for PSM.....	28
Table 2-6. DID results.....	29
Table 2-7. Falsified DID results.....	31
Table 3-1. Descriptive Statistics of Nielsen Homescan Data 2016.	44
Table 3-2. Prices (\$ per unit) for each food group by region and quarter.	47
Table 3-3. Quarterly Mean Expenditure and Expenditure Shares	51
Table 4-1. Descriptive statistics	83
Table 4-2. Attributes and levels used in Choice Experiment.....	86
Table 4-3. RCL estimates	94
Table 4-4. WTP estimates from choice conjoint	95
Table 4-5. Dietary recall descriptive statistics	98
Table 4-6 Nutrient consumption by WTP values	99

List of Figures

Figure 2-1. SNAP participation (1990-2015)	9
Figure 2-2. Average benefit amounts (1990-2015).....	10
Figure 2-3. Utility optimization with SNAP	12
Figure 2-4. Illustration of the difference-in-differences approach.....	17
Figure 3-1. Kernel density comparison graph of Income as a % of the Poverty Threshold for Nielsen and IPUMS-CPS.	50
Figure 3-2. Comparison of Food Expenditure Shares to FPL	52
Figure 3-3. Quadratic prediction plots of expenditure shares by food group against log of total food-at-home expenditures.	60
Figure 3-4. Income elasticity of food groups- QUAI model	62
Figure 3-5. Impacts of discount versus income transfer	63
Figure 3-6. CV from discount.....	65
Figure 4-1 Example of choice conjoint question	88

Chapter 1. Introduction

Budgetary constraints are commonly identified barriers preventing low-income households to purchase healthy foods. Were these barriers eliminated, would these individuals purchase healthier food choices or would their preferences keep them in a similar consumption pattern? This dissertation attempts to answer this question using policy evaluation, policy simulations, and a choice-based conjoint analysis.

In 2009, the Supplemental Nutrition Assistance Program (SNAP) payout was increased in response to the Great Recession. In chapter 2, I use this policy change to examine how the budget shares allocated to various food groups changed as low-income participants received more money going explicitly to their food-at-home purchases. Through multiple specifications of difference-in-difference, I find that those who received the budget increase increased their spending on snacks, confectionery goods, and sweetened beverages, with no other statistically significant result. This finding suggests that a similar policy to the 2009 increase would not be an effective policy to increase the purchase of healthy foods among low-income households.

Food assistance remains a highly controversial topic in the U.S., especially given that major programs such as SNAP cost \$71 billion in 2016. Though these programs help promote food security, a concern remains as to whether program participants attain healthy diets. To evaluate the impact of food assistance programs on diets of program participants, we need to understand how low-income households respond to changes in relative prices among food groups and total food expenditures. Chapter 3 estimates a Quadratic Almost Ideal Demand System model for food among low-income households

using Nielsen Homescan data. Then, simulated changes in food purchase patterns from food assistance in terms of cash transfer are compared to those from an equal-cost program providing a discount on the purchase price of fruits and vegetables. The results show that Engel curves for fruits and vegetables, and meats are non-linear while they are more or less linear for other food groups. Accounting for this, a discount program promotes increases in the budget share spent on fruits and vegetables for all low-income households, as does the income transfer program. However, this income transfer program is more effective than the discount just below the poverty line, while the discount is more effective just above the poverty line.

Chapter 4 uses a choice-based conjoint analysis to elicit food pantry clients' preferences towards healthy modifications to their food. A Random Parameter Logit is estimated and used to predict the premium that food pantry clients would be willing to pay to modify their food to make them healthier. Results show that food pantry clients are not willing to pay anything for whole grains, but are willing to pay a premium for reduced fats in their meal. However, their consumption patterns do not match their preferences stated in the conjoint analysis.

The goal of this dissertation is to inform policy and other public efforts on potential ways to improve the diets of low-income individuals while safeguarding their choice.

Chapter 2. Do larger food budgets lead to healthier food choices for low-income households?

2.1 Introduction

Food security, where all individuals have access to food without worries, is a vital policy goal at all levels of government. Programs intended to address food security have focused on providing financial means to afford food, but such focus on simply meeting the caloric requirement may not be sufficient in ensuring adequate consumption of nutritious foods. In the 2000, 17% of deaths in the U.S. were caused by poor diet and physical activity (Mokdad, Marks, Stroup, & Gerberding, 2004). Additionally, what we eat is strongly linked to many chronic diseases and obesity in the United States (Baskin, Ard, Franklin, & Allison, 2005).

Unfortunately, like most of us growing up, America needs to be reminded to eat its fruits and vegetables. The Dietary Guidelines Advisory Committee, a joint effort between the United States Department of Agriculture (USDA) and the United States Department of Health and Human Services, issued a report in 2015 outlining the under-consumption of fruits, vegetables, and wholegrains by Americans.

The issue is accentuated by income status and food prices (Lin, 2005; Drewnowski, & Eichelsdoerfer, 2010). Low-income households choose less nutritious diets and spend less on fruits and vegetables than higher income counterparts (Jones, Akbay, Roe, & Chern, 2003; Stewart, Blisard, and Jolliffe, 2003; Blisard, Stewart, and Jolliffe, 2004).

Compared to the USDA's Thrifty Food Plan (TFP), low-income household spent about half and three-quarters of the TFP amounts for fruits and vegetables and for meats and dairy products, respectively, while spending nearly 100% of the TFP amounts for cereals and baked goods (Stewart & Blisard, 2006). They were also less likely to purchase foods with higher fiber and consume relatively high amounts of energy dense sugars and refined grains (Turrell & Kavanagh, 2006; Drewnowski & Specter, 2004). More generally, though the overall healthfulness of diets in most U.S. households are improving (Beatty, Lin, & Smith, 2014), the healthfulness gap between rich and poor households is increasing (Wang, Leung, Li, Ding, Chiuve, Hu, & Willett, 2014).

Budgetary constraints are a key barrier to healthy diets by the poor (Dachner, Ricciuto, Kirkpatrick, & Tarasuk, 2010), who would expect to buy healthier options were they to have a larger food budget (Inglis, Ball, & Crawford, 2009). For example, if they were to receive a larger food budget would they buy more fruits and vegetables? Stewart, Blisard, and Jolliffe (2003) found that small increases in income for low-income households did not increase their spending on fruits and vegetables. The question remains what impact an increase in funds specifically aimed at purchasing food has on purchases of fruits and vegetables.

This chapter addresses empirically how expanding the food budget of low-income households may affect their food purchases by exploiting a natural experiment brought on by the American Recovery and Reinvestment Act (ARRA). To help with growing economic concerns due to the Great Recession of 2007-2009, the AARA, among other provisions, realized an average of 17% increase in SNAP benefit payouts to eligible

participants (Nord & Prell, 2011). SNAP provides monetary assistance to low-income eligible participants that can only be used to purchase food to be consumed in the home (food-at-home: FAH). Thus, I examine the changes in budget shares across different food groups of eligible low-income households in response to increases in their FAH budgets in the form of larger SNAP payouts. This study differs from the wide array of literature that looks at general income changes and their impact on food choices in that I specifically look at the impact of an increase in the household budget that can solely be allocated to FAH. The rationale is that the funds specifically allocated to FAH might be mentally accounted à la Thaler (1985) in a different way than general income. Using a difference-in-differences approach, the main effect detected is an increase in spending towards snacks, confectionery good, and sweetened beverages. The effects remains statistically significant after adjusting for multiple comparisons using the Dunn-Šidák correction (Šidák, 1967).

The chapter proceeds in the following order. Section 2.2 provides a background on SNAP, the ARRA, and food choices related to income, followed by conceptual framework of examining the impact of increase in food budget (section 2.3). Following section 2.4 with an overview of the Consumer Expenditure Survey data used in the analysis, section 2.5 explains the empirical approach used and the identification strategy. Section 2.6 presents results, which are discussed in section 2.7; section 2.8 concludes.

2.2 Background on SNAP and ARRA

Supplemental Nutritional Assistance Program (SNAP) is a social safety net program in the United States that aims to improve food security for low-income participants with a

2016 budget of nearly \$71 billion (United States Department of Agriculture, 2017).

SNAP benefits provided to low-income eligible participants can solely be used on the purchase of food to be consumed at home. Benefits cannot be spent on items such as alcoholic beverages, foods to be consumed at the grocery store (salad bar food, deli items), or non-food items sold at grocery stores. Able-Bodied Adults Without Dependents (ABAWD) can participate in SNAP if employed when receiving benefits.

ABAWDs are allowed very small spells of unemployment if they want to maintain SNAP benefits.

Participation in SNAP usually increases the individual's budget share spent on food items (Carlos, Boonsaeng, Chen, & Okrent, 2014), more specifically FAH (Burney, 2015), suggesting that the program promotes food purchasing for people who would otherwise be under-consuming food. Another interesting point to note is that SNAP is found to reduce spending on food-away-from-home (Burney, 2018). The program has been effective at improving food security in times of economic downturn (Beatty & Tuttle , 2014; Kumcu & Kaufman, 2011).

SNAP eligibility is largely dependent on household income relative to the Federal Poverty Line (FPL). The FPL is determined by considering household size and number of children in the household, among other things. To determine eligibility, the income amount reported by a household wishing to receive SNAP benefits first goes through a series of deductions. The amount obtained is compared to the FPL to estimate whether a household is eligible. About 72% of households eligible for SNAP participated in the program in 2009, with the likelihood of participation rising as household income went

down (Congressional Budget Office, 2012). According to the Congressional Budget Office (2012), 85% of households that were SNAP participants in 2010 were below the FPL.

The linking of SNAP eligibility to income, and indirectly the FPL, is intuitive as low-income households are more likely to struggle in purchasing adequate amounts of food. This approach targets households at risk of being food insecure and provides them with benefits which smooth their food consumption. Beside income, other determinants such as countable resources, disability status, or immigrant status affect SNAP eligibility.

SNAP recipients have similar diets to non-recipients who are of comparable income level and demographics (Gregory, Michele, Andrews, & Coleman-Jensen, 2012). Being of low-income and low-income groups suggests SNAP participants tend to consume less nutritious foods than higher income groups (Jones et al., 2003).

In the years 2007-2009, the United States experienced what is now commonly referred to as the Great Recession, associated with a rise in unemployment rates, decreased stock prices, and decreased housing values (Federal Reserve Bank of St. Louis, 2017). During that period, households were shifting their food budgets from food-away-from-home to more FAH purchases (Beatty & Senauer, 2012). The same study also evidence of frugality in food shopping, such as looking for sale prices on foods or using coupons, among other strategies.

Rising unemployment rates, increases in job losses, and slow growth of new businesses prompted the US congress to pass the American Recovery and Reinvestment Act of 2009. This act allocated funds to numerous projects, such infrastructural development at the state level, but also a temporary increase in SNAP payouts in order to reduce the

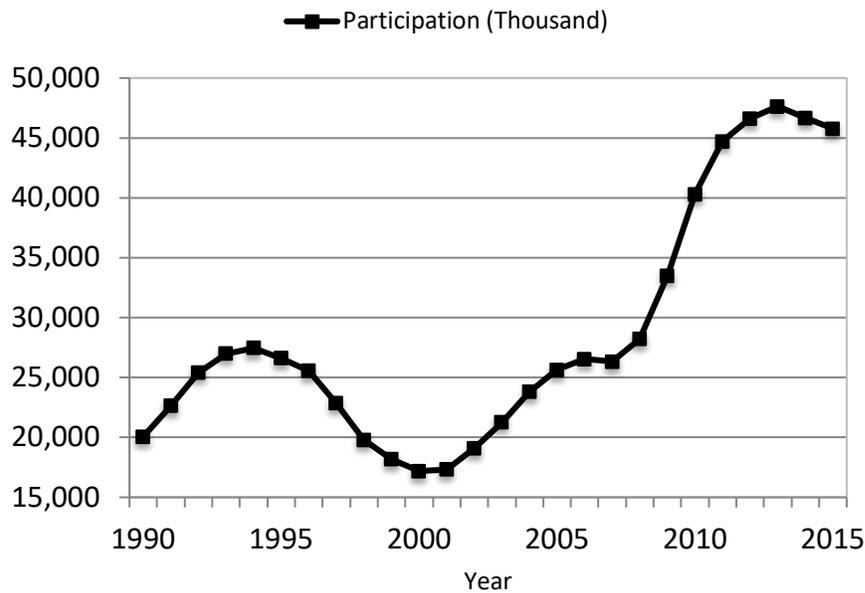
pressure being put on the already narrow food budgets of low-income households. The constant amounts of increase were set for households of various size so that those receiving the maximum benefit would receive an increase of 13.6%. For households that were not receiving the maximum benefits, their rates of increase were greater, translating to an overall average increase of 17% in SNAP payouts per participant (Nord & Prell, 2011). Such a policy change provides an appropriate setup to analyze the consumption decisions of low-income households receiving an exogenous increase in their food budget. Additionally, the ABAWD employment requirements were temporarily removed to account for the increased likelihood of unemployment during that period.

The ARRA was passed in February 2009, with the SNAP benefit increase and ABAWD work requirement elimination taking effect in April 2009. The increase is considered to have been successful in providing a food security safety net during the recession aftermath. Kim (2016) found that the ARRA caused an increase in both food and non-food expenditure (housing, transportation, education) for participating households. Nord and Prell (2011) establish that food security of participants improved as benefits were increased. Beatty and Tuttle (2014) found that participants spent more money on FAH due to the ARRA expansion. The expansion ended in November 2013, where benefit amounts were reduced and eligibility was restored to similar guidelines from the pre-ARRA period.

Average SNAP participation and benefit amount per SNAP participant between 1990 and 2015 are depicted in Figure 2-1 and Figure 2-2. There is a reduction in participation between 1993 and the early 2000s, followed by a gradual increase each year. The average

benefit rises steadily over this pre-recession period.¹ As the recession hits, participation surges and continues to increase through 2012. This is expected as harsh economic times, as well as high unemployment, would cause reductions in household incomes which might lead to SNAP eligibility. This is further explained by the ARRA relaxing of the ABAWD restriction. In 2009, the average benefit amount increases drastically, as per the ARRA. Benefits increase on average once more in 2010, before staying more or less steady until 2013. Both participation and benefits declines after 2013, when the ARRA policy ended.

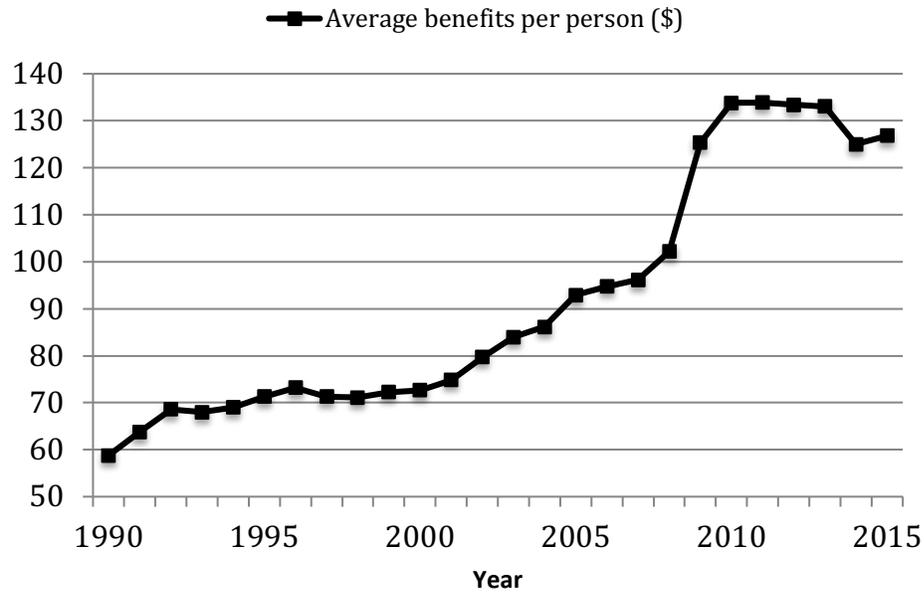
Figure 2-1. SNAP participation (1990-2015)



Source: Author’s calculation using United States Department of Agriculture data (2016)

¹ Benefit amounts shown are not adjusted to a base year. This is to highlight the jump in nominal benefit amounts associated with the ARRA.

Figure 2-2. Average benefit amounts (1990-2015)



Source: Author’s calculations using United States Department of Agriculture data (2016)

2.3 Conceptual framework

To understand the impact of an increase in food budget on food purchases, I assume that food budgets are separable from the overarching household budget. Then, one can model the household optimization problem for food purchases where utility defined over purchases of n food products is maximized subject to a food budget constraint. For a SNAP participating households, the food budget is augmented by SNAP benefits:

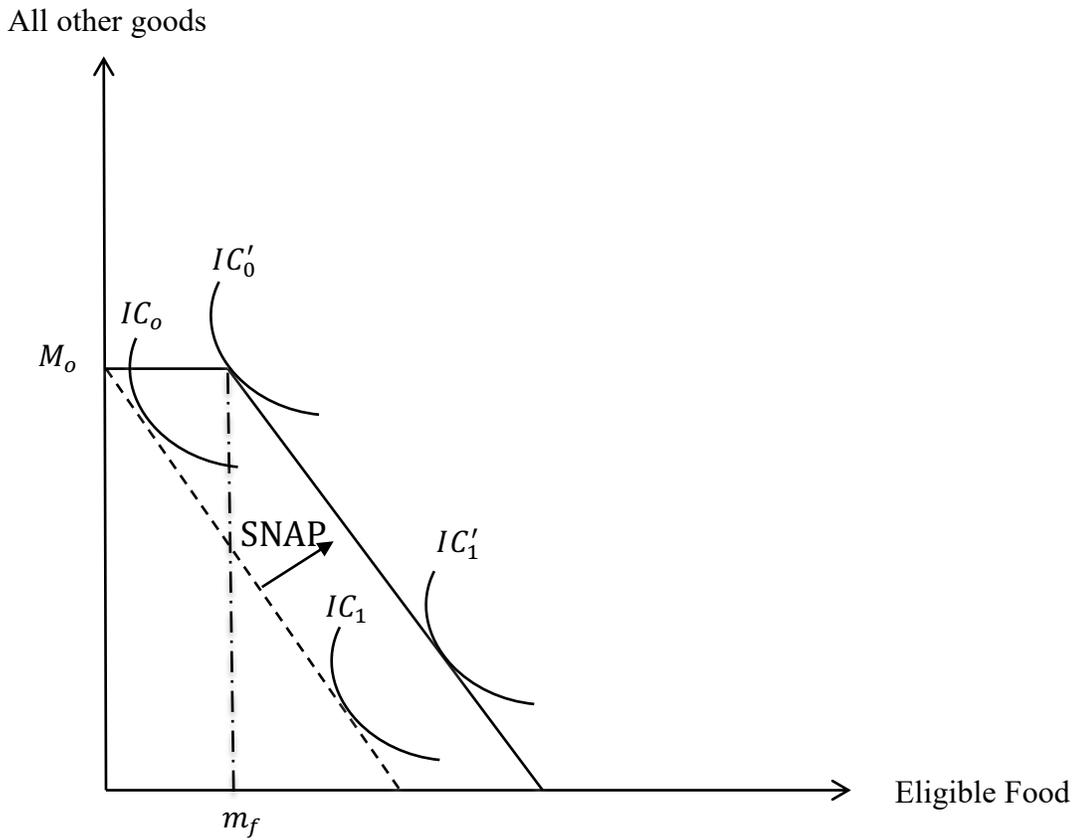
$$(1) \max_{X_1, \dots, X_n} U(X_1, \dots, X_n)$$

$$st. \sum_{i=1}^n P_i X_i \leq W^1, W^1 = W^0 + S$$

where X_i represents the i -th food product with price P_i , W^0 is the household budget on food, and the term S represents the funds received from SNAP. For non-participating household, $S = 0$ and $W^1 = W^0$. Therefore, this naïve approach assumes that SNAP expands participants' budget sets.

Figure 2-3 illustrates the utility maximization with SNAP participation. The original budget faced by the household starts at M_0 and is displayed by the dashed line, while the budget set for SNAP participants is shown by the solid line also starting at M_0 . In fact, M_0 represents the maximum of “all other goods” affordable to the household with or without SNAP. Note that the SNAP budget line is kinked because of the restrictions on certain food items to be purchased with SNAP benefits. If a household maximizes its utility via indifference curve IC_0 under the non-SNAP budget, then it consumes food amounts lower than m_f , which is deemed to be insufficient food. Therefore, with SNAP the household should at least consume m_f of food, due to the kinked budget line. Only if the household was consuming more than m_f of food (shown at IC_1), would SNAP participation affect the household in the way described in equation 1. The household modeled by IC_1 is described as “infra-marginal.” Hoynes and Schanzenbach (2009) find that most SNAP households are infra-marginal.

Figure 2-3. Utility optimization with SNAP



Beside utility maximization, there could be behavioral factors that explain the allocation of SNAP benefits. Thaler’s classic 1985 piece formalizes mental accounting, a concept that many economic agents use. An example he provides is of a couple who gain \$300 as reparation for the loss of a shipped fish. They then spend \$225 on dinner, something they have never done before and would not have done otherwise. Since the \$300 was linked to their “food” and “gain” accounts, they do not think twice about spending it, rejecting the fungibility of money. Relating this concept to SNAP, Smith, Berning, Yang, Colson, and Dorfman (2016) find that a SNAP dollar is not exactly fungible with a non-SNAP dollar, suggesting evidence of mental accounting. In the context of this current study, the “gain”

obtained from the ARRA SNAP benefit increase could be mentally accounted as an increase in FAH-specific expenses instead of a general income increase. If so, the impacts would differ from previous findings which looked at impacts of income increases on household food choices.

Moreover, traditional utility maximization focuses on the impacts of price and income on quantities. All food has multiple, varying attributes besides price, which include nutritional content and hedonic dimensions such as taste. The challenge arises particularly because preferable nutritional content and hedonic dimensions do not align—empty calories can have desirable taste, for example—and much of nutritional content may not be fully known to the decision maker. Thus, while we expect food in general to be a normal good, particularly for low-income, food insecure households, changes in purchases due to an increase in food budget constraint most likely are not consistent across food products.

The current analysis follows a reduced form approach that circumvents the estimation of utility maximization or Thaler's mental accounting models, but maintains the assumption that the utility derived from FAH consumption is separable from the general utility function that consumers generate for all goods. Instead, it is an attempt to extract the causal impact of the ARRA FAH budget increase on purchase decisions for an insight into the behavior of low-income households when faced with additional funds to be spent solely on FAH.

2.4 Data

The Consumer Expenditure Survey (CEX) is administered by the Bureau of Labor Statistics (BLS) to collect information on spending habits from nationally representative households, called Consumer Units (CU). Because the reliability or interpretation of results are hardly affected, the terms “households” and “CU” are used interchangeably in this chapter. Used for a variety of purposes, notably in calculations of the Consumer Price Index, the CEX data are reported as quarterly observations and made available publicly in a yearly installment.

The CEX combines responses from two surveys: an interview and a diary. The interview survey contains demographic information about CUs as well as their total expenditure. The current study uses information from the diary, which is completed by each CU and contains detailed food purchase information for a two-week period, as well as household characteristics and demographics. The diary data set is suitable for this analysis as it provides a clear measure of expenditure spent on a variety of foods by CUs. It is quarterly, cross-sectional with different CUs each time. Since the ARRA expansion occurs in April of 2009, CEX diary data for all four quarters of the years 2006 to 2012 are considered. A limitation worthy of note is that the interviewer records for each CU at the beginning of the interview survey, whether they had received SNAP benefits in the past month. Wilde and Ranney (2000) find that SNAP households’ food spending peaks in the first three days after receiving SNAP benefits. Because I do not have data on specifically when in the prior month households in this study receive their benefits, it is

not possible to know whether or not the spending recorded during the two weeks of CEX diary occurred during the food spending peak described by Wilde and Ranney (2000).

For the analysis, I use FAH spending information from the CEX based on food groups of interest, discussed below. It is important to note that the ARRA expansion represent only an average of approximately \$20 increase in monthly SNAP benefits per person (Nord & Prell, 2011), which is also depicted in Figure 2-2. Additionally note that the CEX diary records only two weeks of spending. Therefore, the effects detected can be expected to be quite small, representing only a two-week period. The study period is set from 2006 through 2012 excluding the period between the ARRA announcement and the policy taking effect (January to March 2009) to account for potential anticipation effects which might affect behavior.

Food groups were specified as (i) fruits and vegetables (including processed), (ii) meats, seafood, and dairy, (iii) processed meats, (iv) snacks, confectionery goods, and sweetened beverages, (iv) starches and (v) all other goods. These groups were specified as such loosely based on the USDA's food categories used in their food plan reports and findings from the public health literature (Caspi, Grannon, Wang, Nanney, & King, 2018), with additional categories (processed meats, snacks) of interest. Table 2-1 outlines the breakdown of foods included in each of these groups.

Table 2-1. Food groups considered in analysis

Fruits and Vegetables	Meats, Seafood, and Dairy	Processed Meats	Snacks, Confectionery Goods, and Sweetened Beverages	Starches	Other foods
Fresh fruits	Poultry	Sausages	Crackers	Rice	Condiments
Fresh vegetables	Beef	Canned meat	Salted peanuts	Flour	Salt
	Pork	Bologna	Chips	Cereals	Sugar
Processed fruits	Other meats	Lunch meat	Donuts	Pasta	Sauces
Processed vegetables	Dairy	Smoked, cured, or	Muffins		Tea
	Eggs	salted meats	Sugar sweetened beverages		Coffee
	Seafood				Other non-sweetened beverages

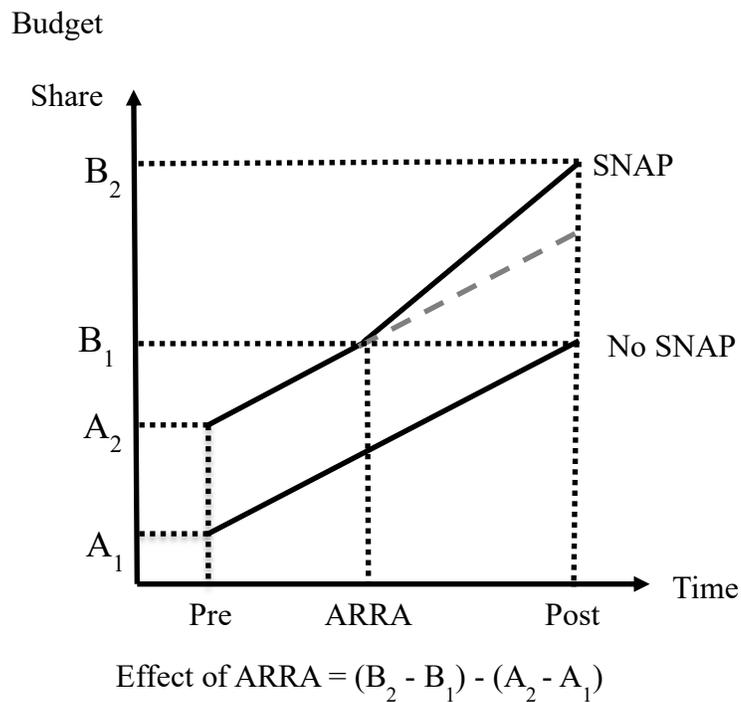
2.5 Identification and empirical strategy

To identify the effect of the SNAP increase on participants' food choices, I apply a difference-in-differences (DID) strategy. To obtain the causal impact of a policy change on an outcome of interest, one could simply find the difference in outcome before and after the policy change. However, this naïve approach would only work if the only change that occurs is the policy change. In order to account for potential trends unrelated to the policy, one can difference out a comparison in the pre-and post-intervention

outcome via a comparison group. This group then acts as a counterfactual to the treated group, with the only difference between them being the treatment (policy).

The DID application is further illustrated in Figure 2-4. Here, I difference out the pre-ARRA expenditure between those who receive SNAP and those who do not ($A_2 - A_1$). This procedure is repeated for post-ARRA expenditure shares ($B_2 - B_1$) for those who receive SNAP and those who do not. When we find the difference between those two differences, the answer obtained is the causal impact of the ARRA on budget shares. In this scenario, those who do not receive SNAP but are still of low-income (the comparison group) serve as a counterfactual to what trends we could expect from SNAP recipients if there was no policy change.

Figure 2-4. Illustration of the difference-in-differences approach



2.5.1 Model specification

Analogous to the example in Figure 2-4, DID effect can be computed as (Angrist and Pischke, 2008):

$$(2) \text{ Effect of ARRA} = [E(Y_1|X, D = 1) - E(Y_1|X, D = 0)] \\ - [E(Y_0|X, D = 1) - E(Y_0|X, D = 0)]$$

where Y represents spending with subscripts of 0 and 1 indicating pre- and post-ARRA, respectively, X represents observables, and D represents treatment when equal to 1 (receiving SNAP benefits) and 0 otherwise.

This effect can thus be estimated via OLS using the specification:

$$(3) \quad Y_{it} = \beta_0 + \beta_1 POST_t + \beta_2 SNAP_{it} + \gamma SNAP_{it} * POST_t + \alpha X_{it} + \epsilon_{it}$$

Similar to equation 2, Y_{it} represents the spending for household i in time t . $POST_t$ is a dummy variable indicating that t is in the post-ARRA period (April 2009 onward), while $SNAP_{it}$, also a binary variable, assumes the value of 1 for household i receiving SNAP benefits (treated) in the month preceding the time they were interviewed in t . The treatment effect is given by obtaining the average marginal effect of the coefficient γ on the interaction term. X_{it} include household characteristics to control for the equation, namely urban/rural residency, race of head, gender of head, a dummy indicating whether the head or spouse is currently unemployed, highest education attained in the household, the region where the household resides, the state where the household resides, the number of earners in the household, household size, quarter that the household was surveyed, and

an interaction between region, year and quarter to account for regional seasonality. In order to account for stochastic dependency among equations, I use the Dunn–Šidák (Šidák, 1967) correction to determine statistical significance of estimated coefficients.²

For DID to be reliable, it must meet the parallel trends assumption where the treatment and comparison groups must be subject to similar pressures, so that the only different factor between them is the treatment. In Figure 2-4, the assumption implies the two lines in the diagram must have the same slope prior to the ARRA.

To test this assumption, I falsify the post-ARRA period to take place halfway in the pre-intervention period to test for the equivalence between the treatment and comparison groups. Insignificant effects would imply that there are no detectable treatment effects between the two groups in the pre-ARRA period, an indication that any effects detected with the true post-ARRA is due to the ARRA. In Figure 2-4, the first difference is obtained by differencing the starting points A_1 and A_2 . Then the second difference is then obtained by differencing any two points prior to the ARRA between the two groups. The difference between those two differences should be zero if parallel trends holds.

²The adjusted significance level $\alpha_1 = 1 - (1 - \alpha_0)^{\frac{1}{m}}$, where α_0 is the original significance level (5%), and m is the number of comparisons. Based on this formula, the corrected significance level for the current study is around 1%.

2.5.2 Treatment and comparison groups

A crucial detail in a successful estimation of DID is properly constructed treatment and comparison groups. Since the ARRA only affects households who receive SNAP, those who are treated are thus SNAP participants. The task of deciding which households to include in the comparison group is tricky. Those households must be similar and comparable to the SNAP participants, particularly in terms of income levels, given the overarching goal of this chapter of understanding the behavior of low-income households in general.

The Census Bureau Poverty Thresholds³ (United States Census Bureau, 2016) vary by household size, the number of children, and presence of individuals over the age of 65 to provide a better picture of whether a household is low income than nominal income levels. Dividing a household's income by its corresponding poverty threshold yields a distance metric of how far from the poverty line the household income level is. The CUs considered in this analysis are those CUs which income level is at the most 200% of the poverty threshold. For illustrative purposes, according to a report based on the Current Population Survey Annual Social and Economic Supplements data, the median income for a married couple in the U.S. in 2016 was \$87,057, while the poverty threshold for a household of two with no children was \$16,072 (Semega, Fontenot, & Kollar, 2017).

³ The poverty thresholds are also often referred to as the "Federal Poverty Line."

Therefore, a household of two with no children making 200% of poverty in income in 2016 would be earning \$32,144, which is still well below the median income.

As much as 40% of SNAP participants report non-participation in the Current Population Survey (Meyer & Mittag, 2015). It is thus possible that some respondents who are SNAP participants report non-participation in the CEX, leading to them being placed incorrectly in the comparison group. Such an occurrence would cause treatment effect estimates to be inaccurately pulled towards zero. It is less likely that those who report participation being in fact non-participants except for data input errors or mistakes on the part of respondents.

Furthermore, consider households who are eligible for SNAP but choose not to participate in the program. Ideally, these households would be included in the comparison group. The problem is that it is likely that these households have systematically different behavior from eligible households who choose to participate, which would be obscure from the data. Therefore, there is a potential problem of unobserved heterogeneity.

In an effort to minimize these issues, I follow a similar approach to Nord and Prell (2011). Since the base income eligibility for SNAP is 130% of poverty, households between 130% and 150% of poverty could potentially be eligible, because certain deductions are applied to household income in determining eligibility. These households are thus problematic in that they could report non-participation in SNAP but receive SNAP in reality. They are thus excluded from the analysis. Households between 150% and 200% are less likely to be eligible, even after deductions, but likely share similar spending patterns across food groups with SNAP recipients. Because they are likely

ineligible, they are unlikely to receive SNAP and misreport their participation.

Unobserved heterogeneity is also minimal for this group, because their ineligibility precludes them from facing the decision to participate or not. Therefore, I assign those households between 150% and 200% of poverty to the comparison group.

As stated earlier, the probability of such issues arising in the treatment group are minimal. Therefore, there is no need to vary the treatment group around the poverty line measure. However, for sensitivity, I create two treatment groups depicted in Table 2-2.

One encompasses households at or below 130% of poverty, who have the highest likelihood of participation. The other contains all households in the sample which report participation. Results are expected to be similar in both cases, and any glaring differences would indicate that I cannot draw any reliable conclusions from the analysis.⁴

⁴ To further investigate whether the definition of treatment and comparison groups around the poverty line influenced results, various models with different definitions were estimated. Some of those definitions included all non-participating households up to 200% of poverty as the comparison group. Changing said definition only mattered marginally. These results are available upon request.

Table 2-2. Definition of treatment and comparison for each comparison, based on the poverty threshold

	Definition 1	Definition 2
Treatment (SNAP participants)	$\leq 130\%$ of poverty	$\leq 200\%$ of poverty
Comparison (Non-participants)	$> 150\%$ and $\leq 200\%$ of poverty	$> 150\%$ and $\leq 200\%$ of poverty

Table 2-3 shows descriptive characteristics⁵ of the treated and comparison groups for both definitions. The main differences between groups arise from education. Both treatment groups have a larger proportion of households where the highest attained education is less than high school: 26-30% in treatment compared to 12.5% in comparison group. The treatment group also has a larger proportion of households with highest education being an associate’s or bachelor’s degree or a graduate degree than both treatment groups. Another notable difference is the bigger proportion of white reference persons in the comparison group, and the larger proportion of African-American reference persons in the treatment group.

⁵ Note that all of the reported characteristics are included as controls in each estimated model.

We must bear in mind that although having similar demographic distributions across those groups would be desirable, these differences do not compromise the reliability of the DID design. In fact, it is expected that those groups would bear different demographic characteristics due to their construction being centered around income and the poverty line.

Table 2-3. Descriptive statistics of treated and comparison

	Comparison	Treated (Definition 1)	Treated (Definition 2)
Residency			
Urban	89.2	89.1	89.2
Rural	10.8	10.9	10.8
Highest Education Attained (by reference person and spouse if present)			
Never attended school	0.1	0.2	0.3
Less than HS	12.5	30.1	26.3
High school	31.0	36.2	35.0
Some college	22.0	18.1	23.2
Associate's/Bachelor's degree	27.4	13.4	13.6
Graduate degree	7.0	1.9	1.7
Race of reference person			
White	81.4	63.9	64.9
African American or Black	13.9	30.6	29.7
Native/ Pacific Islander/ Native Hawaiian	0.8	1.8	1.8
Asian	3.0	1.5	1.6
More than one race	0.9	2.2	2.1

	Comparison	Treated (Definition 1)	Treated (Definition 2)
Head or spouse unemployed			
Both employed	46.4	37.8	43.1
At least one unemployed	53.7	62.2	56.9
Region			
Northeast	16.6	15.7	16.5
Midwest	20.9	19.0	19.8
South	39.1	48.7	43.0
West	23.4	16.7	20.7
Mean No. of Earners	1.3	0.8	1.0
Mean Fam. Size	3.2	3.7	3.8
N	2802	1142	2095

Source: Author's calculations using CEX 2006-2012

Note: All numbers shown are column percentages, except for means and N.

A relevant test of difference in demographics is testing of whether these demographics are statistically different in each treatment group moving from the pre-ARRA period to the post-ARRA period, which might be an indication of how the policy change might have influenced the group composition. No statistically significant difference was recorded between the composition of the treatment group under definition 1 pre- and post-ARRA. Statistically significant differences were recorded for the treatment group under definition 2 for the number of earners and the highest education attained. The differences observed both in the data, and in comparing the pre-ARRA versus post-ARRA would be cause for concern were there a suspicion of endogeneity. However, the ARRA is plausibly exogenous to households in that they had no impact on benefit levels

and such. Therefore, those differences become less problematic (Beatty and Tuttle, 2015).

Table 2-4 shows the average expenditure shares for the period prior to the ARRA.

Statistically significant differences from the comparison group are indicated by asterisks.

While having no statistically significant differences are desirable, the results do not reject the parallel trends assumption. In fact, it is believable that the treated and the untreated would have different budget share spending as there is a difference in income relative to the poverty line between them. The largest difference is seen from fruits and vegetables on which comparison group spent an average of around 17% of their budget while the treated spent nearly 14% of their budget.

Table 2-4. Pre-ARRA average expenditure shares

	Comparison	Treated (Definition 1)	Treated (Definition 2)
Fruits and vegetables	17.1%	14.1% **	14.0% **
Meats, seafood, and dairy	24.0%	25.2% *	25.0%
Processed meats	5.5%	5.2%	5.4%
Snacks, confectionery goods, sweet beverages	20.8%	22.2%	22.4%
Starches	7.8%	8.7% **	8.8% **
Other foods	24.8%	24.5%	24.4%

Source: Author's calculations using CEX 2006-2012.

Note: * and ** signify $p < 0.05$ and $p < 0.01$, respectively.

Additionally, for sensitivity, I also use Propensity Score Matching (PSM), introduced by Rosenbaum and Rubin in 1983, with Kernel matching⁶ to construct treatment and comparison groups. This method centers on using observable characteristics to create a probability of being treated for each observation. A probit model is estimated with a binary variable indicating treatment as the dependent variable, and observable characteristics one wishes to match on are used as independent variables. The predicted probabilities then serve as an indication of the likelihood of being selected into treatment and can be used as weights to match treated and untreated observations in the DID specification. The variables I use for matching are the number of earners in the household, household size, highest education attained in the household, whether the household is in a rural area, the race and gender of the reference person, the state where the household resides as well as the geographic region, the quarter in which the household was surveyed, the household income as a percent of the poverty line, and finally the total expenditure on food. Note that I use all households up to 200% of poverty as potential matches for those treated.

The validity of the matching is verified by a balancing test. This test is basically a t-test between the treatment and comparison groups created by PSM. Having no significant differences between the two groups is ideal as it implies that the groups are balanced in terms of the observable characteristics used for matching.

⁶ I only show results for the Epanechnikov Kernel. Results using Gaussian, Biweight, Uniform and Tricube Kernels, as well as quintile matching, were not qualitatively different and are available upon request.

Table 2-5 shows the results of the balancing test. No statistically significant differences were detected between the treated and control groups, indicating a successful matching procedure based on the observable factors used.

Table 2-5. Balancing test for PSM

Weighted Variables	Mean Control	Mean Treated	Difference	t	Pr(T > t)
Number of earners	1.275	1.203	-0.072	0.9	0.3663
Family size	4.295	4.322	0.027	0.17	0.8622
Highest education attained	2.298	2.238	-0.06	0.65	0.5153
Rural residency	0.024	0.036	0.012	0.74	0.4584
Race of reference person	1.359	1.335	-0.024	0.33	0.7394
Reference person is female	0.554	0.548	-0.006	0.13	0.8972
State of residence	29.743	29.943	0.2	0.15	0.8805
Region of residence	2.58	2.564	-0.017	0.18	0.8541
Quarter	6.863	6.937	0.074	0.25	0.8053
% of poverty line	105.92	103.005	-2.915	0.72	0.4698
Total food expenditure	118.179	115.944	-2.235	0.26	0.7927

Source: Author's calculations using CEX 2006-2012.

Note: * and ** signify $p < 0.05$ and $p < 0.01$, respectively.

2.6 Results

2.6.1 DID results

The estimates represent the impact of the ARRA on the budget shares of low-income households. Only the treatment effects are presented in the text with full regression tables shown in the Appendix. The impacts identified in both definitions are quite similar, which help establish robustness of our estimates.

Table 2-6 shows the results for all DID specifications. The main trend observed is the recurring significant increase in spending on snack, confectionery goods, and sweetened beverages for all comparisons. This effect is the only one that remains statistically significant even after the Dunn-Šidák correction. It is therefore cogent to conclude that the increase in budget has caused an increase spending of \$8-\$12 over two weeks for treated households. There are a few other statistically significant results at the 5% level but those results do not remain statistically significant based on the Dunn-Šidák correction.

Table 2-6. DID results

	Definition 1	Definition 2	Matching
Fruits and Vegetables	6.617 (4.400)	4.686 (3.349)	2.692 (3.332)
Meats, Seafood, and Dairy	6.311 (5.643)	4.997 (4.325)	4.384 (4.718)
Processed Meats	2.210 (1.920)	2.316 (1.378)	1.914 (1.159)

	Definition 1	Definition 2	Matching
Snacks, Confectionery Goods, and Sweetened Beverages	12.15 *† (4.446)	10.10 *† (3.300)	7.83 *† (3.008)
Starches	1.668 (1.761)	1.637 (1.448)	0.641 (1.722)
Other Foods	13.498* (5.801)	6.737 (5.195)	5.521 (5.394)
N	1598	1890	3478

Source: Author's calculations using CEX 2006-2012.

Notes: : * and † signify $p < 0.05$ and $p < 0.0102$ (Dunn-Šidák correction), respectively. Robust standard errors used. Sample sizes vary slightly with each dependent variable. See appendices for more precise sample sizes.

2.6.2 Falsified treatment period

To test whether consumption trends are similar prior to the ARRA, I falsify the treatment to take place between the third quarter of 2007 and 2008. Therefore, the pre-ARRA period becomes 2006-Q1 to 2007-Q2, while the post-ARRA period becomes 2007-Q2 to 2008-Q4. If the treatment and control groups had experienced similar trends, all average marginal effects of this DID specification should be close to zero and insignificant.

Table 2-7 shows the falsified results. Fortunately, I do not find any significant effects in the pre-treatment period which makes a strong case for trends between the treatment and comparison groups to be considered parallel.

Table 2-7. Falsified DID results

	Definition 1	Definition 2	Matching
Fruits and Vegetables	-5.062 (6.223)	-3.913 (4.979)	0.0611 (5.174)
Meats, Seafood, and Dairy	-11.570 (7.862)	-6.415 (6.412)	-0.948 (7.636)
Processed Meats	-5.403 (3.201)	-2.601 (2.267)	-2.535 (1.768)
Snacks, Confectionery Goods, and Sweetened Beverages	-11.449 (6.014)	-4.059 (4.801)	3.438 (4.236)
Starches	-4.860* (2.445)	-4.070 (2.246)	-2.105 (2.720)
Other Foods	-15.014 (8.442)	-14.474 (9.435)	-16.13 (9.699)
N	700	775	1,104

Source: Author's calculations using CEX 2006-2012.

Notes: : * and † signify $p < 0.05$ and $p < 0.0102$ (Dunn-Šidák correction), respectively. Robust standard errors used.

2.7 Discussion and policy implications

The main takeaway from the analysis is that, with an increase in food budget, low-income households increase their budget share for snacks, confectionery goods, and sugar sweetened beverages. This tendency to allocate additional dollars differently across food groups for a given expansion in FAH budget, instead of proportional increases towards all food groups, supports mental accounting among low-income households by differentiating dollars spent on different food groups. There is likely a hedonic element

that encourages spending on snacks, sweetened beverages, and confectionery goods, over the other food groups.

It is also worthy of note that, though not all impacts are statistically significant, most of them are positive implying a potential increase in spending due to the ARRA. This corroborates Beatty and Tuttle (2014), who found that SNAP benefit increases had a positive impact on food spending. What I find is that relative to the increased spending on other food groups, households spent more on snacks, confectionery goods, and sugar sweetened beverages, amounting to \$7.83-\$12.15 during a two-week period. Though these changes in budget shares might be small, its economic significance should not be ignored. Doubling this amount to be representative for a month-long period yields an increase of \$15-\$24. This amount implies that most of the additional benefits from the ARRA have likely been allocated to this food group. The choice to spend the extra money on snacks is somewhat unsurprising. Given how small the monthly increases in benefits were, it is a fairly reasonable expectation to spend that money on snack foods which usually have good shelf life and yield high calories for relatively lower cost than other foods.

A point of policy deliberation is the design of the food assistance program itself. Income and prices are two economic levers to affect food choices. Policy programs such as SNAP are designed to encourage consumption of food through augmenting income and have been shown to effectively push low-income households to buy more food (Beatty and Tuttle, 2014). Designed with little nutritional considerations, however, the extra food purchased might not be as healthy. Wilde, McNamara, and Ranney (1999) find notable

differences in the nutritional intake of SNAP participants compared to participants in the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC). WIC had a negative impact on the intake of added sugars, while SNAP had a positive impact. They attribute the clear nutritional component included in WIC, as opposed to SNAP, to this distinction.

Food prices, on the other hand, have a direct link to the healthfulness of diets (Beydoun, 2011). Thus, alternative policy mechanisms such as a discount on fruits and vegetables might more effectively promote an increase in their consumption than an increase in food budgets. A pilot of an incentive program that provided 30% discount on the purchase of targeted fruits and vegetables to SNAP participants yielded increases in the purchase of said fruits and vegetables (Bartlett & Abt Associates, 2014). Additionally, Prell and Smallwood (2017) suggest that the most effective economic mechanism at increasing the consumption of fruits and vegetables would be a cash value voucher (CVV) specified for fruits and vegetables. With a CVV, households are granted a predetermined amount of fruits and vegetables. Therefore, they are more likely to purchase the total value worth of those goods. Available evidence on the effectiveness of CVV among low income individuals is promising (Young, 2013; Herman, 2008).

Some argue for behavioral nudges in the retail setting as an alternative policy tool to encourage healthy food purchases by SNAP participants. Indeed, fruits and vegetables placed in check-out aisle endcaps increased their purchase by SNAP participants (Payne and Niculescu, 2018). While acknowledging the likely limited effectiveness of policy-designed nudges in a retail environment that is already rife with behavioral tools from

retailers and manufacturers, Just and Gabrielyan (2018) suggest approaches to make such nudges more viable and effective. For example, one can ensure that interventions are viewed not only positively by the shoppers but also as designed to change behaviors to improve their health. Quite importantly, these interventions must also either leave the profits of retailers and manufacturers unaffected or increase them. Lusk (2014) however warns of a potential pitfall of behavioral approaches in guiding consumers toward what they should want. Moreover, purchasing goods does not necessarily mean that they will be consumed. Policies that might encourage fruits and vegetable purchases do not ensure that those who buy them will eat them.

Thus, policy makers should be cognizant that programs, such as SNAP, aimed at expanding the food budget of low-income households are more successful at addressing food insecurity than at promoting healthy eating. Alternate policy programs and mechanisms should be investigated further to determine whether they would be better suited to impact the healthfulness of food purchases.

2.8 Conclusion

This chapter examined how low-income households allocate their food expenditure when it increased in the form of SNAP benefits that are restricted to be spent on food at home. The main finding is that the increase in food budget caused recipients to increase their spending on snacks, confectionery goods, and sugar sweetened beverages.

This finding illustrates that the budget expansion provided with the ARRA did not encourage purchases of healthy food options. If the goal of public policy is to increase the consumption of healthy foods such as fruits and vegetables, a program similar to SNAP

which provides food budget funds might not be a suitable avenue. In the current setup of the program, food security is the primary concern and research has shown that it is successful at improving food security for participants. Therefore, a different approach should be used to encourage the consumption of fruits and vegetables. Other policy mechanisms such as discounts or cash value vouchers might prove to be better economic incentives to encourage the purchase of healthy foods.

Chapter 3. Evaluating the impact of policy mechanisms on low-income households

3.1 Introduction

Food security is usually measured in absolute consumption of food and the ease with which households acquire food, with little regard to the composition of one's diet. As such, food assistance has long focused on the provision of enough calories to sustain daily activities rather than on which nutrients were included in the calories. Due to the impact of food prices, diets vary largely by income status (Lin, 2005; Drewnowski, & Eichelsdoerfer, 2010). Economic costs are viewed as barriers for proper diet by low-income households (Dachner, Ricciuto, Kirkpatrick, & Tarasuk, 2010), who would expect to buy healthier options were they to have a larger food budget (Inglis, Ball, & Crawford, 2009).

A food group that is under-consumed in the American diet is fruits and vegetables. The Dietary Guidelines Advisory Committee, a joint effort between the United States Department of Agriculture (USDA) and the United States Department of Health and Human Services, issued a report in 2015 clearly outlining this under-consumption of fruits, vegetables, and wholegrains by Americans. In the same report, they found that sugars and fats were overconsumed, contributing to the rise of chronic diet-related diseases. When analyzing energy density of foods and income levels, Drewnowski and Specter (2004) found that the overconsumption of energy dense foods (sugars, refined grains) were relatively high at low incomes, which they attributed to prices of those goods making them affordable food options for those living at low-income levels.

Conversely, fruits and vegetables were under-consumed. It is of no help that the worse foods for one's diets are also more palatable for many.

Food assistance programs, such as the Supplemental Nutrition Assistance Program (SNAP), provide funds for low income Americans to afford food. Yet the income increase might not prove enough to overcome the relative cost of healthy diets. The question that I pose then is: could low-income households be better off from other food assistance mechanisms that enhance the affordability of healthy food purchases?

The main objective of this chapter is to estimate a food demand system for low-income households and simulate the impacts of two mechanisms of food assistance on low-income households for comparison: an income transfer program (similar to SNAP⁷) and a price discount favoring certain food groups. Using Nielsen Homescan data for the year 2016, I aggregate foods into five groups (fruits and vegetables, meats and dairy, fats, sugar and confectionery goods, all others) in the food demand system. Fruits and vegetables are chosen as the token healthy food group, since their healthfulness is unanimous but they are under-consumed by U.S. households, as mentioned above. To account for potential non-linearity in the Engel curves of each of those food groups, a Quadratic Almost Ideal Demand System is used to estimate consumer demand. Using the estimated parameters, I simulate the impact of the policy mechanisms on each household

⁷ SNAP benefits are only similar to an income transfer for households that are consuming more than a certain amount of food without benefits (infra-marginal households). More on this in Section 3.4.1 .

and compute the associated changes in fruits and vegetables budget shares. In order to further evaluate the impact of the price discount, I calculate the associated compensating variation for each household as a measure of economic welfare. The hypothesis is that the most desirable or cost-effective policy mechanism could differ across households depending on their proximity to the poverty threshold. The contribution of this chapter lies in the illustration of the impact of food assistance in cash transfer across low-income households accounting for non-linear Engel curves and how targeted food assistance aimed at encouraging healthy purchases affect low-income households relative to income transfer.

The chapter proceeds as follows: Section 3.2 provides background information on food assistance; Section 3.3 covers the data; Section 0 defines the conceptual framework behind the methodology used and outlines the estimation strategy; illustrates general data composition, and the procedure involved in constructing group prices; Section 3.5 covers results; Section 3.6 discusses policy implications; and Section 0 provides concluding remarks.

3.2 Background

3.2.1 Nutrition, poverty, and public policy.

Semega, Fontenot, and Kollar (2017) report to the United States Census Bureau that the poverty rate in the U.S. for the year 2016 was 12.7%. Poverty is linked to multiple social problems, of which a key issue is that of food security. The United States Department of Agriculture (2017b) described very low food security as “reports of multiple indications of disrupted eating patterns and reduced food intake.” Notably, this definition centers on

food intake with no mention of the type of food being ingested. A household could thus be food secure but be nutritionally poor. Studies have found that low-income households had less nutritious diets than higher income households (Jones, Akbay, Roe, & Chern, 2003) and were less likely to purchase foods that had high fiber, and low fat, sugar, and salt (Turrell & Kavanagh, 2006). Even though the overall healthfulness of diets of most households in the U.S. are improving (Beatty, Lin, & Smith, 2014), the quality gap between rich and poor households is increasing (Wang et al., 2014). Nutrition is thus of importance to low-income households as poor nutrition is linked to numerous chronic diseases. It is estimated that, in the year 2000, about 17% of all deaths in the U.S. were caused by poor diet and physical activity (Mokdad, Marks, Stroup, & Gerberding, 2004).

Market forces appear to obstruct low income households from obtaining a nutritious diet. Not only is their income limited, but the cost of a nutritious diet is higher in food deserts (Fan, Baylis, Gundersen, & Ver Ploeg, 2015), which are census tracts with more than 20% poverty rate and where a significant portion of residents live far from a food retail location (United States Department of Agriculture, 2017a). Food assistance programs such as SNAP provide funds to qualifying low-income households to purchase food. A common belief is that further restricting SNAP eligible foods to prevent unhealthy food purchases might help improve SNAP participants' diets. Such an approach would likely reduce the effectiveness of the program at countering food insecurity (Gregory, Ver Ploeg, Andrews, & Coleman-Jensen, 2012). Therefore, public policy should consider alternative mechanisms and programs if the goal is to promote healthful diets. The ideal scenario is to use a policy mechanism that has a positive impact at least equal to that of a program such as SNAP. An alternative to assistance aimed at increasing food budgets is

that of subsidizing the price of certain healthy foods, effectively acting as a discount.

Dong and Lin in their 2009 report to the United States Department of Agriculture found that a 10% subsidy on the prices of fruits and vegetables could potentially increase their intake by low-income households by 2.1-5.2 percent.

Public policy has long used mechanisms to influence consumption. Most recently, taxes on Sugar Sweetened Beverages were evaluated as a possible deterrent to their consumption. Franck, Grandi, and Eisenberg (2013) do argue that though the revenue generated from such taxation might be helpful, the mechanism will likely not prove quite effective at reducing obesity. Prell and Smallwood (2017) theoretically evaluate three hypothetical mechanisms to influence the purchase of fruits and vegetables: a bonus where each Dollar spent on fruits and vegetables is doubled, a rebate where a proportion of spending on fruits and vegetables is repaid to participants, and finally a cash value voucher where participants receive a voucher which provides them with an assured Dollar amount of fruits and vegetables.. They find that though, all three mechanisms influence consumption of fruits and vegetables positively, the cash value voucher is expected to be the most effective at increasing the purchase of fruits and vegetables.

The purpose of this chapter is to evaluate the impact of these programs on low-income households, compare their relative effectiveness as increasing fruits and vegetable purchases, and determine whether any one of them helps households more than the other.

3.2.2 Income and consumption.

Since the days of Engel (1895), and later of Working (1943) and Leser (1963), the relationship between expenditure and income have been central to the analysis of consumer behavior. According to Engel's law, as income increases the budget share spent on food decreases. The complex relationships between changes in income and expenditure share have been of great interest to economists. This body of work has looked at various aspects of consumer spending with early measurement efforts by Davidson, Hendry, Srba, and Yeo (1978) and has ranged from alcohol consumption (Atkinson, Gomulka, & Stern, 1990), to more recent efforts on healthcare expenditure in OECD countries (Baltagi & Moscone, 2010).

Engel curves display the relationship between household expenditure on a particular good at varying levels of income. Burzig and Herrmann (2012) used the Engel curve to analyze spending patterns on food-at-home and food-away-from-home in Germany. They found that the theoretical expectations hold true and budgets behave as expected with changes in income. That is, as income increases, so does spending on food-at-home. However, the share spent on food-at-home goes down with additional income. Using a comparable approach, Magana-Lemus and co-authors (2013) found that an increase in tortilla prices affected low income Mexican households almost twice as much as higher income households.

Estimating consumer demand helps to better understand the relationship between consumer expenditure on specific goods and income. Deaton and Muellbauer's (1980) Almost Ideal Demand System is a popular approach to demand estimation but their

specification assumes linear Engel relationships. Complex Engel relationships were operationalized by Banks, Blundell, and Lewbell (1997) using a Quadratic Almost Ideal Demand System. They found that Engel relationships were in fact non-linear for some commodity groups, notably clothing and alcohol. In intuitive terms, the income elasticity of clothing revealed it was a luxury for some income levels but a necessity for others. This prompted a need for the use of higher order terms in demand estimations to allow for flexible Engel curves. The innovation of a flexible demand specification led to numerous areas of study, notably on revealed preferences (Blundell, Browning, & Crawford, 2003), welfare evaluation (Banks, Blundell, & Lewbel, 1996), household allocations and bargaining (Browning & Chiappori, 1998; Browning, Chiappori & Lewbel, 2006), as well as investigations into shape-invariant Engel curves (Blundell, Chen, & Kristensen, 2007).

3.3 Data

The dataset used in this study is the Nielsen Homescan Database for the year 2016 as it incorporates rich expenditure information, as well as detailed household characteristics. The data are collected via a shopper panel who record all their purchases and prices. Nielsen selects a subset of those who sign up for the program based on the needs of the data with a goal is to obtain a representative panel of U.S. consumers. Participants are then given a scanner with which they scan the barcode of the products they are purchasing.

The strength of the dataset lies in its completeness. Not only does it include helpful household level characteristics, it also includes a complete purchase history of

participants. Nielsen data are not without flaws, however. There are concerns about accuracy, sample selection, as well as misreporting (Einav, Leibtag, & Nevo, 2008; 2010) in the data. The main issue arises from participants misreporting their purchases, as well as underrepresentation of some income groups. Though these issues are present, there are no clear ways to correct for them.

3.3.1 Descriptive statistics

The Federal Poverty Line (FPL) (United States Census Bureau, 2016) proves to be a useful way to identify households that could be eligible for, and use, the food assistance programs simulated in this chapter. The FPL varies based on household size and income. For instance, a household of two with no children in 2016 had a FPL of \$16,072. Dividing that household's income by the FPL then provides a distance metric of how far above or below the poverty line that household is. Households at or below 200% of poverty are used in this analysis. To illustrate that this cutoff is adequate, consider a household of two with no children in the year 2016. The median U.S. income for a household consisting of two adults was \$87,057, while the poverty threshold for a household of two with no children was \$16,072 (Semega, Fontenot, & Kollar, 2017). For instance, a household of two adults at 200% of poverty would make \$32,144, which is still well below the U.S. median income for that household type. These households would be living above poverty but would not be considered wealthy.

Table 3-1 shows a breakdown of demographics for the entire 2016 Nielsen sample (used for demand estimation, see Section 3.4.1) and the selected sample of households at or below 200% of FPL (used for policy simulation, see Section 3.4.2). The full and

restricted samples share similar demographics. About three quarters of household heads are white. The mode of households are headed by individuals at or above 55 years of age. For comparison, the model in the American Community Survey (ACS) 2016 was 45-54 years of age. An interesting figure is that about 45% of households do not have a male head present. The mean household size is slightly above 2, which coincides with two thirds of the sample having no children. This is similar to the which ACS 2016 reports a mean household size of 2.53 and 68% of households having no children present.

Table 3-1. Descriptive Statistics of Nielsen Homescan Data 2016.

Descriptive Statistics	Whole Sample	≤ 200 FPL
Non-White (%)	24.5	25.6
White (%)	75.5	74.4
Female Head (%)		
Not present in hh	21.7	20.7
Under 25 Years	1.0	1.8
25-29 Years	4.4	5.4
30-34 Years	10.1	9.8
35-39 Years	7.0	6.8
40-44 Years	7.0	6.3
45-49 Years	8.0	6.7
50-54 Years	9.6	8.6
55-64 Years	16.2	16.2
65+ Years	15.0	17.7
Male Head (%)		
Not present in hh	30.1	44.8
Under 25 Years	0.5	0.7

Descriptive Statistics	Whole Sample	≤ 200 FPL
25-29 Years	2.7	2.9
30-34 Years	7.4	6.4
35-39 Years	6.5	5.4
40-44 Years	6.5	4.9
45-49 Years	7.5	4.8
50-54 Years	9.1	6.4
55-64 Years	15.0	11.8
65+ Years	14.6	12.0
No children in hh	68.3	65.8
Child present in hh	31.7	34.2
Mean hh size	2.6	2.6
N	63,139	15,139

Note: All figures shown are percentages, unless specified as a mean. Nielsen Homescan data sampling weights used.

Source: Author's calculations using Nielsen Homescan Data 2016.

3.3.2 Price construction

Prices are an important component of this analysis. The well acknowledged problem with demand estimation is that of dimensionality. Ideally demand should to be estimated for all possible goods. This is however infeasible. Therefore, to estimate demand, I assume weak separability and treat food-at-home as being part of the first stage of a two-stage budget. The second stage then include food groups that I define as fruits and vegetables, meats and dairy, fats, soda and confectionery goods, and all other goods. This solves the

dimensionality problem and allows for estimation. These food groups are based on findings from Caspi, Grannon, Wang, Nanney, and King (2018), who found that these groups incorporated food products of similar healthfulness. “Fruits and vegetables” is the main group of interest for the analysis as it has the highest healthfulness out of all the other groups.

Each of these food groups consists of many individual products. For prices for each group, I calculate the geometric mean of prices for each product in the group and assign it as the group price. Using the geometric mean of prices entails the risk of having too little price variation, thus coarsening the measure of price levels too much. To counter the reduction in variation, the price for each food group x in a region r and quarter t is calculated as the geometric mean for all individual commodity prices in that group for that region and quarter:

$$(4) \quad P_{xtr} = e \left(\frac{\sum_{j=1}^n \bar{w}_{jtr}}{\sum_{k=1}^n \bar{w}_{ktr}} * \log P_{jtr} \right)$$

where P_{xtr} is the price for product group x faced by region r , at quarter t , and \bar{w}_{jtr} is the average budget share of product j (part of group x) at quarter t in region r . A breakdown of prices by region and quarter are shown in Table 3-2.

Table 3-2. Prices (\$ per unit) for each food group by region and quarter.

	Q1	Q2	Q3	Q4
Fruits and vegetables				
New England	2.35	2.37	2.44	2.33
Middle Atlantic	2.46	2.48	2.49	2.47
East North Central	2.16	2.17	2.18	2.15
West North Central	2.31	2.32	2.31	2.27
South Atlantic	2.28	2.32	2.29	2.26
East South Central	2.15	2.15	2.16	2.06
West South Central	2.12	2.13	2.12	2.09
Mountain	2.21	2.22	2.19	2.18
Pacific	2.35	2.36	2.34	2.29
Total (National mean)	2.26	2.28	2.27	2.24
Meats and dairy				
New England	4.99	5.13	5.15	5.09
Middle Atlantic	4.98	5.07	5.03	5.10
East North Central	4.56	4.68	4.57	4.62
West North Central	4.49	4.51	4.45	4.58
South Atlantic	5.22	5.22	5.18	5.25
East South Central	4.71	4.83	4.71	4.76
West South Central	4.94	5.00	4.94	4.98
Mountain	5.08	5.09	5.12	5.20
Pacific	5.64	5.71	5.67	5.77
Total (National mean)	5.01	5.08	5.02	5.09
Fats				
New England	3.33	3.32	3.39	3.32
Middle Atlantic	3.36	3.37	3.39	3.38
East North Central	3.13	3.05	3.11	3.09

	Q1	Q2	Q3	Q4
West North Central	3.25	3.19	3.24	3.17
South Atlantic	3.44	3.35	3.38	3.38
East South Central	3.24	3.16	3.17	3.19
West South Central	3.42	3.39	3.40	3.43
Mountain	3.52	3.48	3.52	3.54
Pacific	3.74	3.74	3.75	3.82
Total (National mean)	3.40	3.35	3.38	3.39

Soda and confectionery goods

New England	2.80	2.76	2.73	2.86
Middle Atlantic	2.83	2.79	2.82	2.90
East North Central	2.68	2.65	2.65	2.72
West North Central	2.77	2.75	2.76	2.80
South Atlantic	2.79	2.76	2.75	2.83
East South Central	2.60	2.59	2.57	2.62
West South Central	2.78	2.76	2.74	2.78
Mountain	2.95	2.94	2.91	2.96
Pacific	3.16	3.13	3.13	3.22
Total (National mean)	2.83	2.80	2.79	2.86

Note: Nielsen Homescan data sampling weights used.

Source: Author's calculations using Nielsen Homescan Data 2016.

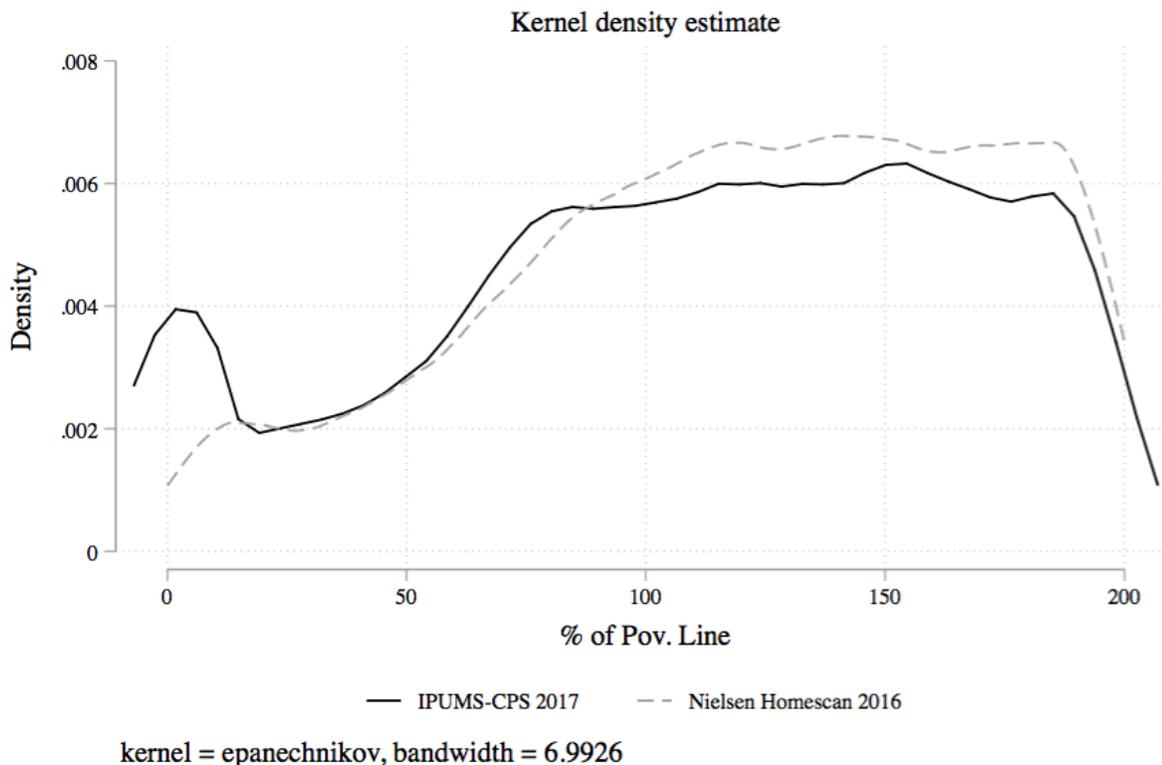
3.3.3 Income

A possible pitfall of Nielsen Homescan Data is the reported household income. The income figure used is not only presented as a range of possible income, it is also lagged by two years. For the 2016 data, the income amounts reported are household incomes for the year 2014. In order to obtain a usable measure of income, albeit not current, I assign each household's income to be a random number in the range of income provided.

The reported income is important in the calculation of the distance from FPL, mentioned earlier. A possible assumption in the case of this study is that lagged household income figures for the sample are representative of households in the year 2016. In order to assert whether this assumption is reasonable, I compare the kernel density of households in the sample to the Current Population Survey (CPS) 2017. The goal is to assert whether the income from 2014 as a proportion of FPL properly represents this measure for the U.S. in 2016.

Figure 3-1 shows the kernel density graph of income calculated as a percentage of the poverty threshold, comparing the Nielsen Homescan 2016 data (income from 2014) and the IPUMS-Current Population Survey data 2017 (income from 2016) for households at or below 200% of FPL.

Figure 3-1. Kernel density comparison graph of Income as a % of the Poverty Threshold for Nielsen and IPUMS-CPS.



Notes: Nielsen homescan sampling data weights used; IPUMS-CPS sampling weights used. Source: Author's calculations using Nielsen Homescan Data 2016, United States Census Bureau Poverty Thresholds 2014/2016, and IPUMS-CPS 2017.

Reassuringly, the kernel densities for both datasets appear to track closely together. The CPS has a higher density of households at the left tail of the distribution but the densities are almost identical between 25% and 50% of poverty. Then the CPS has a slight higher density between 50% to 100% of poverty, beyond where Nielsen has a higher density for the rest of the sample. The similar poverty distributions between the Nielsen data and the

CPS support the assumption that the lagged income variable reported in Nielsen for the year 2016 is fairly representative of incomes in 2016.

3.3.4 Expenditure

Table 3-3 shows the average total food expenditure and the average expenditure shares from the sample. The average food expenditure per quarter was about \$768 per households. The majority of this expenditure was spend on soda, snacks, and confectionery good. Fruits and vegetables and fats had expenditure shares of 12% and 13%, respectively while meats, seafood, and dairy were at 15%. These figures follow the findings from Garasky et al. (2016).

Table 3-3. Quarterly Mean Expenditure and Expenditure Shares

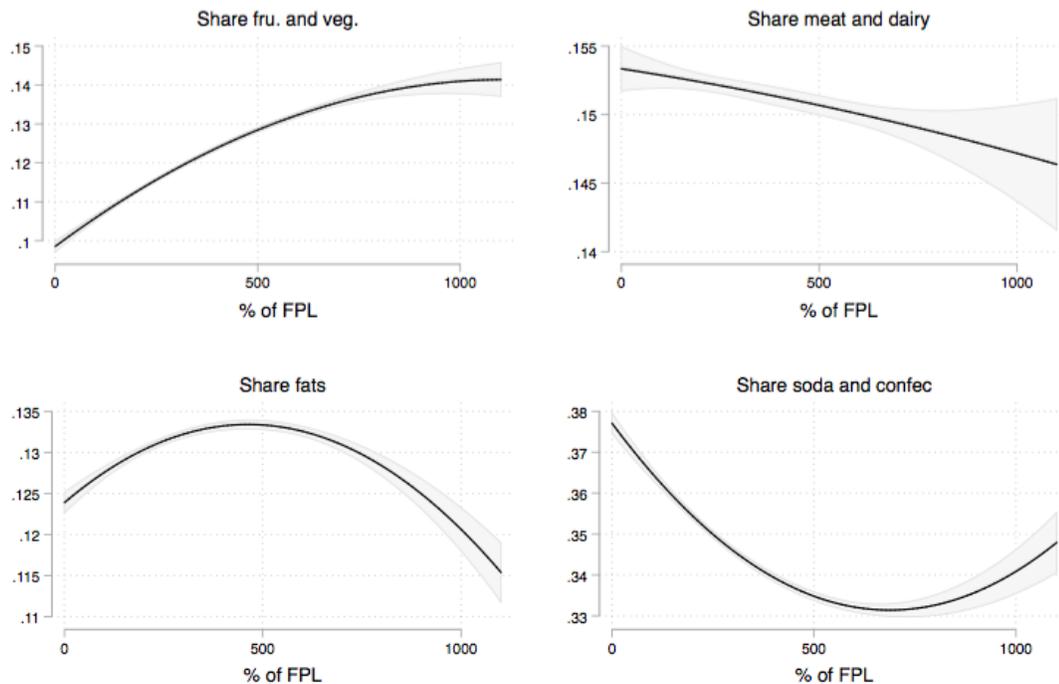
	Whole Sample	≤ 200% FPL
Total Food Expenditure	\$ 767.95	\$ 706.90
Expenditure Share on Fruits and Vegetables	12%	11%
Expenditure Share on Meat, Seafoods, and Dairy	15%	15%
Expenditure Share on Fats	13%	13%
Expenditure Share on Soda, Snacks, and Confectionery Goods	35%	36%
Expenditure Share on Other Foods	26%	26%

Notes: Nielsen homescan sampling data weights used
 Source: Author’s calculations using Nielsen Homescan 2016.

Figure 3-2 shows a comparison of food expenditure on each food group to the FPL. The most striking trend is on fruits and vegetables. As we move to the right (lower levels of poverty), the share spent on fruits and vegetables goes up. In contrast, the shares for meats and dairy go down with lower levels of poverty but with increasing variability. Shares for fats increase with income but at about 500% of poverty, start to decline.

Conversely, shares for soda, snacks, and confectionery goods initially decline with income but then increase at around 700% of poverty.

Figure 3-2. Comparison of Food Expenditure Shares to FPL



Notes: Nielsen homescan sampling data weights used; Lines are quadratic prediction plots.
Source: Author's calculations using Nielsen Homescan 2016.

3.4 Methods

3.4.1 The Quadratic Almost Ideal Demand System

The selection of a functional form is fundamental to estimating demand, especially given that it must respect the theoretical properties of consumer demand. Deaton and Muellbauer's (1980) Almost Ideal Demand System (AI) has thus become one of the most widely used models for estimating consumer demand.

The Engel relationship for different goods need to be more flexible than what is captured in the AI model. Banks, Blundell, and Lewbel (1997) recognized this issue and illustrated how empirical Engel curves are not linear at all expenditure levels. In order to accommodate such relationships, the Quadratic Almost Ideal Demand System (QUAI) includes an extra quadratic term in the AI model which allows for more flexibility. The model defines an indirect utility function as:

$$(5) \quad \log V(\mathbf{p}, Y) = \left\{ \left[\frac{\log Y - \log a(\mathbf{p})}{b(\mathbf{p})} \right]^{-1} + \lambda(\mathbf{p}) \right\}^{-1}, \text{ where } \lambda(\mathbf{p}) = \sum_{i=1}^n \lambda_i \ln p_i$$

where Y is household income, and \mathbf{p} is a vector of prices. There are n goods indexed by i . The two indices $a(\mathbf{p})$ and $b(\mathbf{p})$ are defined as:

$$(6) \quad a(\mathbf{p}) = \alpha_0 + \sum_{i=1}^n \alpha_i \log p_i + \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \gamma_{ij} \log p_i \log p_j$$

$$(7) \quad b(\mathbf{p}) = \beta_0 \prod_{i=1}^n p_i^{\beta_i}$$

After some algebra and applying duality, the QUA model reduces down to a share equation of the form:

$$(8) \quad w_i = \alpha_i + \sum_{j=1}^n \gamma_{ij} p_j + \beta_i \log \frac{Y}{a(\mathbf{p})} + \frac{\lambda_i}{b(\mathbf{p})} \left[\log \frac{Y}{a(\mathbf{p})} \right]^2$$

where w_i is the budget share of good i and p_j is the price of good j . The last term in equation (8) provides flexibility to this functional form.

To estimate a QUA model Blundell and Robin (1999) propose a method to estimate similar conditionally linear systems using iterated linear least squares. The system is

iteratively estimated via Seemingly Unrelated Regressions (SUR) and the parameters that make up $a(\mathbf{p})$ and $b(\mathbf{p})$ are replaced by those obtained in each iteration until they converge. The Stone Price Index is the starting value of the iteration for $a(\mathbf{p})$ while the starting value for $b(\mathbf{p})$ is 1. The theoretical requirements of symmetry and homogeneity are imposed in the model via constrained SUR estimation. The allure of this approach as opposed to simply estimating QUAJ non-linearly is the computation of the $a(\mathbf{p})$ and $b(\mathbf{p})$ terms in each iteration, which is quite useful for post-estimation simulations.

It is also worthy of note that if the coefficient on quadratic term in equation (8) (λ_i) is zero, the model simplifies down to the Almost Ideal Demand System (Deaton and Muellbauer, 1980)⁸.

3.4.2 Policy simulations

The estimated QUAJ model parameters are used simulate the impact of food assistance mechanisms on the budget share spent on fruits and vegetables, an under-consumed healthy food. The two policy mechanisms considered are an income transfer program and a discount on the price of fruits and vegetables. The impacts of these programs are measured by the associated changes in budget shares from each of the proposed mechanisms. The income transfer program serves as a representation of the status-quo.

⁸ Replacing the QUAJ model with the AI model in this chapter produced similar results. However, due to the quadratic nature of Engel curves (see section **Error! Reference source not found.**), and the non-zero λ_i parameters (see appendix), the QUAJ is confirmed as the better model to use in this case.

Currently SNAP is the largest food assistance program in the U.S. SNAP provides funds to participants which they can use to purchase food. The amount of funds they receive is dependent on their income level and food expenditures they are expected to incur under the USDA's Thrifty Food Plan. For proper comparison, this chapter's empirical strategy closely simulates a similar program. This income transfer program is an attempt to mimic the benefits households would obtain were they to receive SNAP benefits.

An important point to note is that SNAP is not a pure income transfer program, because SNAP benefits can only be used on a group of predetermined foods. Most SNAP households are, however, infra-marginal (Hoynes and Schanzenbach, 2009), which means that SNAP benefits have the same impact on them as receiving additional income. For simplicity, this chapter assumes that all seemingly eligible households in Nielsen would be infra-marginal, thus receiving assistance as an income transfer.

In simulating program impacts that are comparable, I assume a hypothetical budget of \$710 million to fund each program. This amount corresponds to 1% of the 2016 SNAP budget (\$71 billion) and serves well for illustration purposes. Changing this amount should not affect the reliability of this study's findings, since scaling the nominal benefits measured up or down will not change their relative comparison⁹. This remains true as

⁹ When this amount was scaled up or down, comparative results were unchanged, while nominal results changed as expected. Results for amounts equivalent to 5% of the SNAP budget (\$3.55 billion), as well as 1% and 5% of the Women, Infants, and Children program budget (\$59.5 million, \$297.5 million, respectively) are available in the Appendix B.

long as the budget does not turn prices for fruits and vegetables negative due to a discount rate of 100% or larger. Furthermore, using the totality, or a big proportion, of the SNAP budget to hypothetically fund these programs is unrealistic as a discount program is unlikely to cost as much as SNAP.

The next step in the analysis is thus to use the available budget to fund each of the possible policy programs and measuring how households gain from them in terms of food expenditure. For the income transfer program, the benefits should be similar to that obtained from SNAP. SNAP benefits are calculated by subtracting 30% of the household's income from the USDA's Thrifty Food Plan amount they are expected to spend on food expenditure based on the household size¹⁰. Replicating this payout rule would provide accurate benefit amounts but total benefits would exceed the budget discussed above. Therefore, benefits need to be proportionally adjusted so that they total the budget.

As for the discount, our hypothetical budget would allow for a discount of approximately 12%. This amount is calculated by first aggregating the expenditure on fruits and vegetables in the Nielsen sample at 200% of FPL or lower and expanding this amount using Nielsen's projection weights to be representative of U.S. consumers. The discount

¹⁰ As a result of this calculation, households who are further above the FPL will receive less than households below the FPL.

rate is then obtained by computing what proportion of this total amount could be covered by the hypothetical program budget.

Another detail worthy of consideration is the eligibility criterion for using these programs. The dataset does not include an indicator for participation in SNAP and mimicking the eligibility criterion for SNAP would prove impossible given the information available. Therefore, for simplicity, I assume that all households at 130% of poverty or below are eligible for both of those programs. This 130% figure is the basis of consideration for SNAP eligibility in most cases. It is worthy of note that the QUAJ is estimated for the entirety of the Nielsen sample while the simulation is only computed for households at 130% or poverty or lower.

3.4.3 Compensating variation

To verify that the result above is not entirely due to the SNAP payout rule, I attempt to measure the economic welfare of the discount on households along the poverty spectrum. Using QUAJ model parameters, compensating variation (CV), a prominent measure of economic welfare, for the price change associated with the discount program can be calculated post estimation. CV measures how income would have to change to reflect the impact of the discount on a households' utility. It can be intuitively interpreted as the income gain equivalent to the discount. Therefore it is a measure of welfare gain associated with a reduction in prices.

The CV is calculated as:

$$(9) \quad CV(\mathbf{p}^0, \mathbf{p}^1, Y) = C(\mathbf{p}^0, u^0) - C(\mathbf{p}^1, u^0)$$

where \mathbf{p}^1 is a vector of prices including the discount price, and \mathbf{p}^0 is the vector of original prices. The term $C(\mathbf{p}^0, u^0)$ is the household expenditure function under original prices. The expenditures under the discount, $C(\mathbf{p}^1, u^0)$, is computed from the cost function, derived from the indirect utility function in equation 5:

$$(10) \quad \log C(\mathbf{p}, u) = \log a(\mathbf{p}) + \frac{b(\mathbf{p}) \log u}{1 - \lambda(\mathbf{p}) \log u}$$

Plugging the indirect utility function back into $C(\mathbf{p}^1, u^0)$ gives:

$$(11) \quad \log C(\mathbf{p}^1, u^0) = \log a(\mathbf{p}^1) + \frac{b(\mathbf{p}^1) \left\{ \left[\frac{\log W - \log a(\mathbf{p}^0)}{b(\mathbf{p}^0)} \right]^{-1} + \lambda(\mathbf{p}^0) \right\}^{-1}}{1 - \lambda(\mathbf{p}^1) \left\{ \left[\frac{\log W - \log a(\mathbf{p}^0)}{b(\mathbf{p}^0)} \right]^{-1} + \lambda(\mathbf{p}^0) \right\}^{-1}}$$

Taking the exponent of the right-hand side of equation 11 gives the value of $C(\mathbf{p}^1, u^0)$.

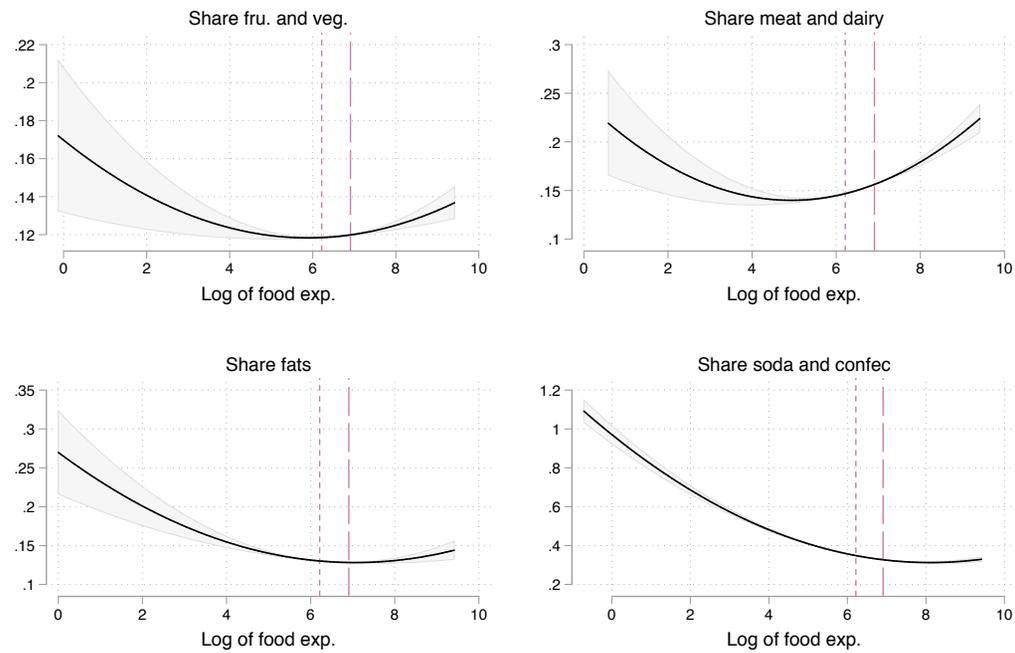
3.5 Results

A first set of results show the Engel curves for different food groups. I then use the estimated model parameters from the QUA1 specification to derive income elasticities of the respective food groups. The full set of estimated parameters and demand elasticities evaluated at the same means are included in Appendix B. To facilitate the interpretation of results, a graphical representation is used. Another set of results display the changes in budget shares for fruits and vegetables under the different simulated policy mechanisms at different levels of the FPL. Finally, I show the welfare that households gain from the discount in the form of the compensating variation.

3.5.1 Engel curves

To obtain a basic glimpse of the Engel curves for various food groups and food expenditure, I plot the log of food expenditure against the budget share spent on each food group using a quadratic prediction plot (Figure 3-3). As the log food expenditure increases, the share spent on fruits and vegetables decreases first, with a turning point happening around \$500 of quarterly food-at-home expenditure. For meats and dairy, the turning point happens at lower levels of food expenditure and is more drastic. More general downward trends are observed for fats, and soda and confectionery goods. More importantly, it is apparent that not all of these Engel relationships for food groups are linear, and applying demand systems such as AI could be misleading in imposing linearity. This extends Banks et al.'s (1997) findings that food as one commodity had a linear Engel curve, but from Figure 3-3, it is apparent that not all food groups have linear Engel relationships.

Figure 3-3. Quadratic prediction plots of expenditure shares by food group against log of total food-at-home expenditures.



Note: Shaded area represents 95% confidence intervals; Nielsen Homescan data sampling weights used. Short dashed lines represent quarterly food-at-home expenditure equivalent to \$500, while the long dashed lines represent \$1000.
 Source: Author's calculation using Nielsen Homescan data 2016.

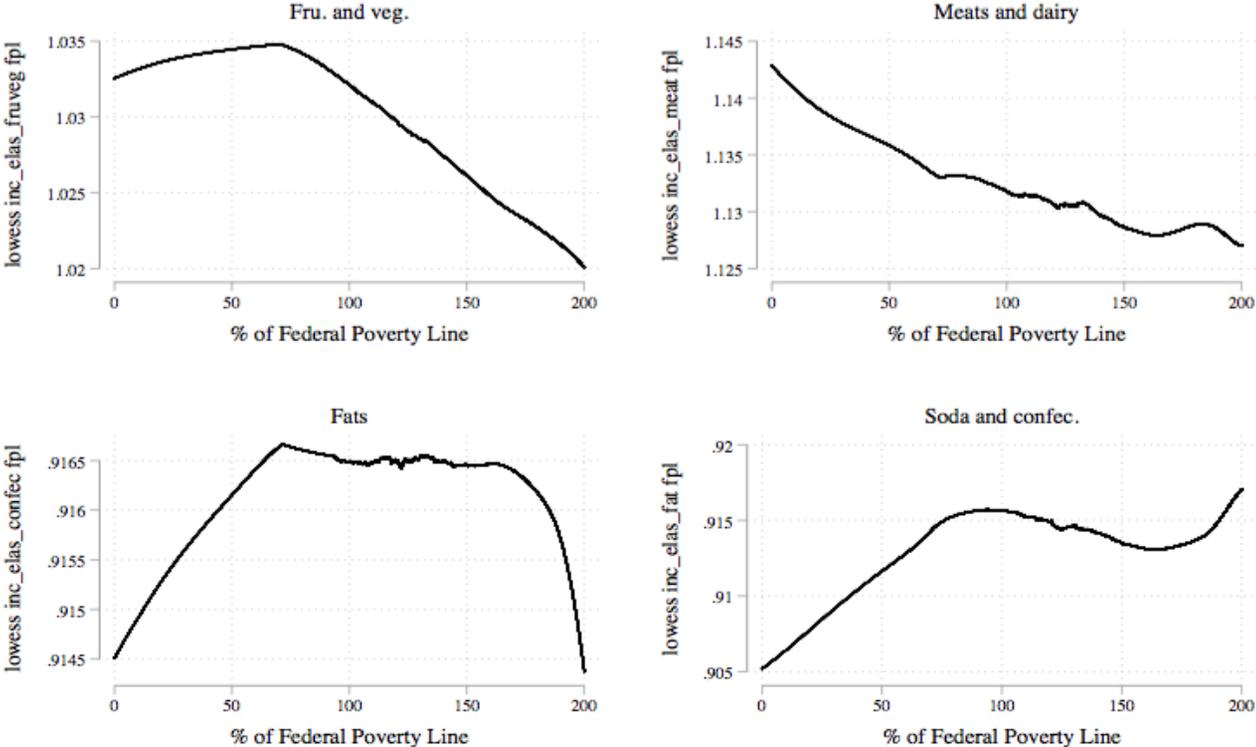
3.5.2 *Income elasticity*

I compute income elasticities using model parameters. Figure 3-4 shows Locally Weighted Scatterplot Smoothing (LOWESS) plots of each food group's elasticity against the percentage of poverty line for each household. A LOWESS is a non-parametric approach to fitting a line through data that can be noisy. It is also useful when a parametric line of best fit is not the most appropriate approach due to the data structure.

From Figure 3-4, fruits and vegetables are a luxury at all income levels but at approximately 70% of the poverty line, the income elasticity trends downward. This is indicative that at some higher levels of income, we could observe this food group becoming a necessity (income elasticity less than 1). A similar general trend is observed for meats and dairy: they are a luxury at all levels of poverty but becoming less income elastic further above the poverty line a household finds itself. Looking back to Figure 3-3, these two goods exhibited non-linearity in their Engel curves. An interesting point to consider is that Banks et al.'s (1997) analysis included more aggregated commodity groups (e.g., food, clothing, and transportation) while the analysis presented here shows groups within the food category.

In contrast, soda, snacks, and confectionery remain a necessity but increasingly more responsive to income at lower poverty levels. The changes in income elasticity for fats below the 200% FPL are minimal.

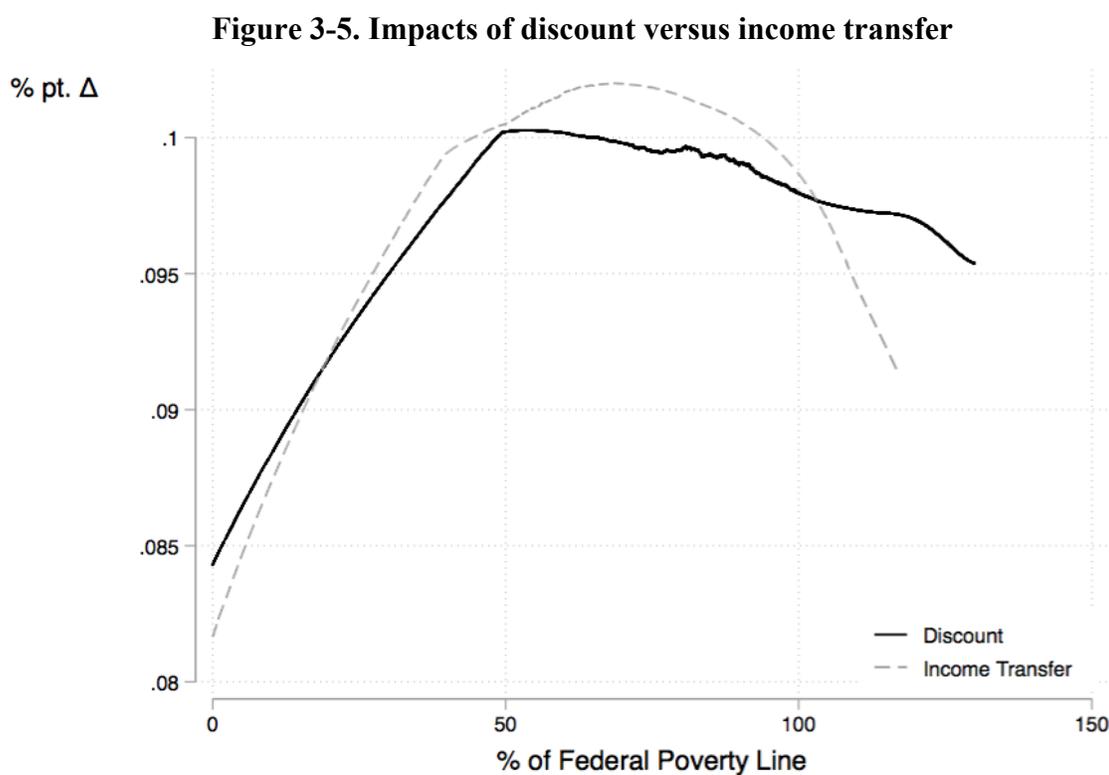
Figure 3-4. Income elasticity of food groups- QUA I model



Note: Lines shown are Locally Weighted Scatterplot Smoothing.
 Source: Author's calculations using Nielsen Homescan 2016.

3.5.3 Impact of policy mechanisms on fruits and vegetables expenditure shares

Figure 3-5 shows the change in fruits and vegetables budget shares associated with the two policy mechanisms in relation to the poverty distance metric. The impacts only affect households that are at 130% of poverty or lower as they are the only ones eligible for these programs.



Note: Lines shown are Locally Weighted Scatterplot Smoothing.
Source: Author's calculations using Nielsen Homescan 2016.

The percentage point changes obtained from the simulation may appear to be rather small, but it is important to remember that the discount and benefit amounts being obtained by each of those households are both rather small. The average amount discounted for each household is about \$9 per quarter (about \$3 per month), while the

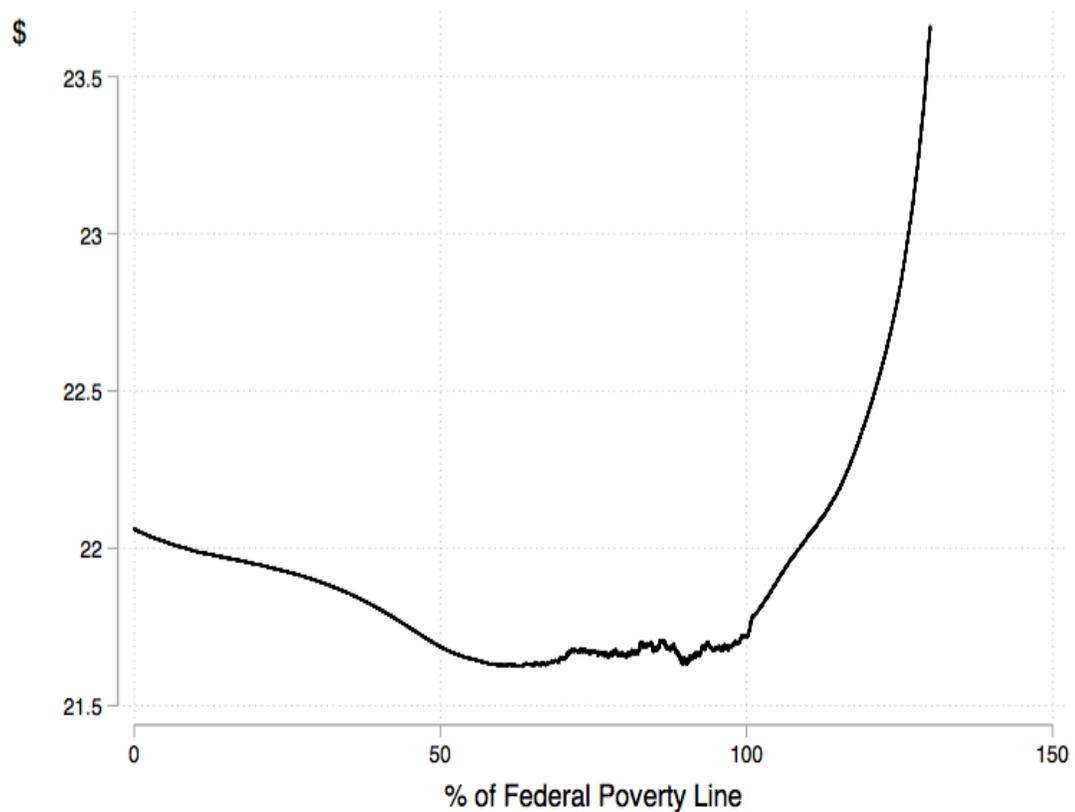
corresponding average income transfer received per quarter is approximately \$16 per quarter (about \$5 per month). Additionally, note that the average budget share spent on fruits and vegetables for these households is 10% per quarter. The more relevant point here is not those magnitude of the impacts but rather the comparative impacts of those two policies on fruits and vegetables budget shares, as the magnitudes could be proportionally ramped up if the policymaker wished to fund a program with a larger budget than the hypothetical one used here.

The trend lines in Figure 3-5 demonstrate that both programs yield similarly notable percentage point increases in fruits and vegetable budgets for the very poor (from 0 to about 20% of poverty), with the discount providing a marginally higher percentage point increases. However, the income transfer produces higher percentage point increases in budget shares beyond that point, with the widest gap identified between 50% and 100% of poverty. At a point above the poverty line (approximately 105% of poverty), the percentage point increases for the discount surpasses that of the income transfer. This implies that for households just below the poverty line, receiving additional food assistance money is more effective at increasing purchases of fruits and vegetable than receiving a discount. However, the discount stands to do better than the income transfer at promoting fruits and vegetables purchases beyond the poverty line. This is likely due to those above the poverty line receiving less assistance from the income transfer program due to the SNAP payout rules, which intuitively provides larger payouts to those below the poverty line.

3.5.4 Impact of discount on economic welfare

Figure 3-6 shows the CV, measured in Dollar amounts, associated with the discount in relation to the % of poverty distance metric.

Figure 3-6. CV from discount



Note: Lines shown are Locally Weighted Scatterplot Smoothing.
Source: Author's calculations using Nielsen Homescan 2016.

It is clear that the discount produces positive economic welfare for all eligible households, as expected. However, above the poverty line (100% of poverty), the economic welfare drastically increases from approximately \$21.70 to about \$23.5. In contrast, it was more or less steady between \$22.05 and \$21.60 below that point. This

indicates that those households beyond the poverty line gain more economic welfare from the discount than those below the poverty line. Such a finding goes hand in hand with the findings discussed in section 3.5.3 : those above the poverty line would experience larger budget share increases from the discount than from income transfer, and they stand to receive more economic welfare from the program than those below the poverty line.

3.6 Discussion and policy implications

An important aspect of food assistance has always been to promote food security and provide much needed leeway to low-income households. In this sense, it is not surprising that income transfer is currently the most common and most effective food assistance mechanism in the U.S. Looking at the results presented in the previous section, it is clear that this food assistance mechanism is quite helpful for households that are at high levels of poverty. On average, the benefit per SNAP participant in 2016 was about \$125 a month. Intuitively, it is highly unrealistic that a discount of similar value could be provided on fruits and vegetables.

When shrinking those benefits to amounts comparable to a realistic discount rate, it is apparent that both policy mechanisms do promote the purchase of fruits and vegetables. However, the income transfer yields larger percentage point increases in the budget shares spent on fruits and vegetables below the poverty line. This indicates that providing these households with money to buy food is a bigger promoter of fruits and vegetables purchases than a discount. Above the poverty line however, since the amount of money received from the income transfer is lower, the discount is able to provide a larger percentage point increase in the purchase of fruits and vegetables. Households above the

poverty line and around 100% of poverty gain more from the discount program. This is likely because they make too much income to receive much from the income transfer compared to their counterparts below the poverty line.

Furthermore, looking at the measure of economic welfare (CV), it is clear that the discount produces economic welfare gains for all households in the sample. However, households above the poverty line gain more from the discount than those below the poverty line. It is likely that those households are able to purchase enough fruits and vegetables to fully reap the economic gains from the discount whereas those below the poverty line might not be buying quite enough fruits and vegetables in the first place to gain similar levels of welfare.

What does this all mean for public policy? To answer this question, one must consider what public policy decides to pursue as a goal. For those who are at or below the poverty line, income transfer appears to be best at promoting fruit and vegetable purchases. Removing this type of assistance in favor of the other program would hurt these households. Unless the income transfer assistance is provided in addition to the other mechanism, this course of action would be quite detrimental. The results presented in this study show that providing income to households below the poverty line does better at promoting the purchase of fruits and vegetables.

Conversely, for households who are not at such dire levels of poverty, the discount program might prove to be more beneficial. They would purchase more fruits and vegetables from this program than from the income transfer, since it might not be providing them much benefits. Thus, if income transfer is to be slashed in favor of the

discount program evaluated here, it would only be viable for those who are at various points above the poverty line as they alone stand to purchase more fruits and vegetables from this program. Furthermore, they gain more welfare than their counterparts below the poverty line.

Therefore, a policy recommendation would be to ensure income transfer assistance for households living at high levels of poverty. If the policy goal is limited to promoting the purchase of healthy foods, only households beyond the poverty line stand to increase their budgets on fruits and vegetables from the discount. They should thus be the primary target of a discount program. Below the poverty line, the policy goal should be to provide them with more money to purchase food as this would produce larger increases in expenditures spent on fruits and vegetables. Though a healthy eating promotion programs such as the discount should in no way replace needs-based income transfer, they could instead be used in conjunction with it to promote healthy food purchases for those who are not living in dire poverty.

3.7 Conclusion

This chapter has been an attempt to compare the impact of two policy mechanisms aimed on the purchase of fruits and vegetables. The two policy mechanisms in questions were an income transfer program and a discount on the price of fruits and vegetables. A fictitious budget amount equivalent to 1% of the 2016 SNAP budget was used to determine the feasible magnitude of these programs. This resulted in a viable discount of about 12% on fruits and vegetables.

Comparing the impact of both of these policies reveals that income transfer results in increases in budget shares spent on fruits and vegetables below the poverty line. Above the poverty line, the discount produced larger increases in budget shares spent on fruits and vegetables, as well as more economic welfare. Therefore, if encouraging healthy food purchases is a policy goal, households close to or above the poverty line should be the target of the discount program. For those below the poverty line, increasing the amount of money they have to spend on food is the best policy to promote fruits and vegetable purchases.

Chapter 4. Measuring food pantry client preferences for healthy food options

4.1 Introduction

Food pantries provide much needed food assistance to low-income consumers with long-term food insufficiency rather than emergency needs (Daponte et al., 1998), even if the stated goal of food pantries is to provide emergency food assistance. While food pantries address caloric needs, pantry clients tend to suffer from poor diet quality. Duffy et al. (2009) provide evidence of this in their study centered on female pantry users in Eastern Alabama. In general, low-income households tend to have more nutritionally poor diets than their counterparts (Jones et al., 2003). This phenomenon has long been attributed to healthy food costing more than unhealthy food (Blisard, Smallwood, and Lutz, 1999; Darmon, Briend, and Drewnowski, 2004; Drewnowski, 2010) and thus less affordable for those with low income. One important aspect of food demand that should not be ignored, however, is consumer preference. Preferences are the machinery that links demand to consumer behavior.

In his classic 1948 piece, Paul Samuelson pioneered the concept of revealed preferences, wherein one can classify consumer preferences by observing their choices over different available bundles. In other words, studying consumption behavior of an economic agent would provide a reasonable idea of what their preferences are. However, one needs to wonder what are missed in this observed behavior. Amartya Sen (1973, 1993) has, among other reproaches, expressed that revealed preferences framework does not allow for a link to behavioral aspects of choice such as norms, values, or objectives. A possibility worthy

of consideration is that food shelf clients are expected to eat like their counterparts but might have different food consumption norms that lead to their under-consumption of healthy food. The stated preferences method on the other hand asks economic agents, through hypothetical scenarios, what their preferences are.

This paper aims to understand preferences of food pantry clients towards healthy food options relative to their current consumption patterns. The end goal is to estimate how much value, if any, food pantry clients would place on healthy modifications, suggested by the United States Department of Health and Human Services (2017), to common food items offered at food pantries. Understanding these preferences could help us translate hypothetical food choices to true consumption decisions, and has the potential to enlighten our understanding of how low-income individuals value healthy diet. To establish the consumption habit of participants, dietary recall data wherein food pantry clients are asked to recall all the food they have consumed in the prior 24 hours were collected and compiled in a descriptive analysis. To obtain a robust measure of preferences, a choice-based conjoint analysis was administered to participants with the data analyzed using the random utility theory (estimated with a mixed logit model). In said conjoint, participants were asked to choose between two hypothetical carts of food each with specific nutritional profiles that could be modified to be healthy based of the Dietary Guidelines for Americans 2015-2020 (e.g., soup containing regular amounts of sodium or 25% less sodium). Using the estimated model parameters based on the experiment data, willingness-to-pay measures are calculated.

This chapter proceeds as follows: Section 4.2 discusses relevant literature on this topic and the investigation at hand; Section 4.3 goes over the data; Section 4.4 reviews the conceptual framework; Section 4.5 explores the methods used; Section 4.6 details the study results; and Section 4.7 provides concluding remarks.

4.2 Literature review

4.2.1 Food, health, income, and perceptions

Eating habits are clearly linked to many chronic diseases and obesity in the United States (Baskin et al., 2005). It is estimated that about one third of Americans are obese (Ogden et al. 2006; Ogden et al. 2012). According to the United States Center for Disease Control and Prevention (2017), chronic diseases are the leading cause of death in the United States. Their root cause is poor nutrition. In 2012 the Center for Disease Control estimated that half of the adults living in the U.S. had at least one chronic disease, with about a quarter of adults having more than one. Mokdad et al. (2004) estimated that about 17% of all deaths in the U.S. in the year 2000 were caused by poor diet and physical activity.

Nutrition related chronic diseases have especially been noted in the past few decades. Despite public health efforts to mitigate illnesses linked to people's diets, the prevalence of hypertension, for example, has sustained. Almost 30% of U.S adults suffered from hypertension between 2010-2011 (Nwankwo et al., 2013). Non-hispanic Black adults were the group with the highest rate of prevalence. Coresh et al. (2007) find that the incidence of kidney failure has increased by over 10% since 1988. Much of this can be attributed to dietary issues which pave the way for health complications such as

hypertension and diabetes, which in turn are connected to higher risks of cardiovascular diseases (Mozaffarian et al., 2016).

Carbohydrate consumption plays a key role in obesity and illnesses associated with it (Heller and Heller, 1994; Foster et al., 2003; Stern et al., 2004). Richards et al. (2007) measured households' habits and addictions in terms of nutrients and found addiction to carbohydrates. Moreover, a low-carbohydrate diet was found to be a stronger catalyst to weight loss than a low-fat diet (Samaha et al., 2003). However, this point is highly debated throughout the literature. Geiselman and Novin, all the way back to 1982, argued that not all carbohydrates were equally important in the prevention of obesity. Wylie-Rosett, Segal-Isaacson and Segal-Isaacson (2004) argue that the type of carbohydrates matter. Carbohydrates from fructose, non-starchy vegetables, and high fiber legumes might help curb appetite and thus curb the likelihood for obesity. Similarly, DeWit et al. (2012) found that saturated fats are a primary culprit in increasing obesity.

Rosin (2008) argues that obesity is not only a public health, but also an economic and social problem. An expansive strand of the literature looks at the causes of childhood and adult obesity as well as issues of energy intake and energy expenditure. Lakdawalla and Philipson (2009) discuss the role of technological change in inducing weight gain and leading to higher rates of obesity. Particularly, the authors posit that agricultural innovations which drive food prices down and other technologies which make home life more sedentary have all contributed to this phenomenon. Finkelstein et al. (2009) estimated that over 30% of per capita health care expenditures between 1998 and 2006

were linked to obesity. This represents an increase of about \$40 billion in medical costs connected to obesity.

Economists have long been interested in determining the best policy prescription for promoting healthy foods, debating subsidies on fruits and vegetables (Powell et al., 2013) or taxes on sugar (Dharmasena and Capps, 2012; Escobar et al., 2013) or fat (Cash et al., 2005). Okrent and Alston (2012) instead propose a tax on all calories, which is hypothesized to yield the lowest deadweight loss per pound of fat reduction in an average adult weight. These policy instruments are expected to improve the healthfulness of food and beverage consumption through food prices.

Economics and environmental factors play a large role in poor food intake (Chou et al., 2004; Drewnowski and Darmon, 2005). Evidence from Turrell et al. (2002; 2006) show that individuals with low income are less likely than their higher income counterparts to purchase foods rich in fiber and low in fats. In fact, low-income households tend to have less nutritious diets than higher income households in general (Jones et al., 2003), making choices that do not follow accepted dietary guidelines (Giskes et al., 2007). Wang et al. (2014) found that even though the healthfulness in diets of most households in the U.S. are improving, the gap in diet between the rich and the poor has been increasing. A behavioral study by Mazzocchi et al. (2014) found that among older Italians, those of low income had a lower demand for dietary quality. Seligman et al. (2010) also found that food insecurity was associated with chronic diseases such as hypertension and diabetes, as well as cardiovascular risk factors. It is therefore of primary importance for public policy to help address the diet of food insecure, and low-income households.

Others have diverted from prices and focused on actual food preferences and the environment within which food decisions are made. Hawkes et al. (2015) explain that healthy food preferences can be learned by modifying the environment at different stages such as the point-of-purchase. The authors make a case for tailored policy interventions and programs that address the particulars of people's demographic characteristics, socio-economic factors, behavioral tendencies, and preferences.

Paisley and Sparks (1998) in a study of dietary fat intake find that the perceived need to reduce fat intake, cognitive and affective components of attitude and past behavior were important predictors of fat intake reduction. Therefore, it is likely that healthy modifications to food are integral in the decision of which food to consume. Opting for a healthy modification to food implies that individuals consider nutritional aspects of food in their decision-making, which may or may not align with their preferences for other aspects of food. It is impossible to assert whether all consumers regard equally important relative to other attributes of food in their food choices.

Studies suggest consumers value health claims both in food-at-home and food-away-from-home environments. Bimbo and co-authors (2014) found that health claims on yogurt products influence consumer perception of products. They found a large variation in the marginal price of food surrounding around the health claims they represent, based around the type of benefits associated with that claim and its strength. Similarly, Allen and Goddard (2012) find that health beliefs and one's understanding of nutrition can predict the purchase and consumption of milk and yogurt products. However, consumers do not seem to distinguish between nutrition and health claims of the food they consume

(Williams, 2005). In fact, health claims can discourage them for seeking further nutrition information about their food as they assume the food is already healthy enough. In a study of restaurant menus, Kozup, Creyer, and Burton (2003) found that consumer perceptions were favorable to products that indicate or claim healthy attributes. They perceived lower risk of diseases from consuming said food, and were more likely to purchase it. Additionally, consumers seem to be willing to pay a premium for nutritional information. Gracia and Nayga (2009) found that consumers were willing to pay twice as much for cereal with nutritional information that for another with limited information. Therefore, it is apparent that consumers do value health claims and healthy attributes of their food. Having information on the healthfulness of a food item is valuable to them, and increases their likelihood of consuming it.

4.2.2 Food pantries in the United States

It is a community goal to ensure adequate food for all individuals. As a response to addressing food insecurity, food banks and food pantries spread around the United States around the 1980's. Food banks often are larger organizations, with centralized warehouses, responsible for collecting emergency foods and distributing them to other, often smaller, agencies such as food pantries or meal programs (Bhattarai et al., 2005). Food pantries work by serving their clients directly. They receive food products from food banks and donations, and often purchase food to meet their client needs (Simmet, 2017). According to the United States Department of Agriculture, households visiting food pantries obtain an average of 38.2 pounds of food per visit (Coleman-Jensen et al., 2016).

Food banks and pantries materialized as an emergency response for those who needed temporary assistance for their dietary needs. However, a recent survey of food pantry clients showed that more and more households rely on this form of food assistance, not for acute, emergency needs, but as a part of their long term household food plans. For instance, in the *Hunger in America 2014* study by Weinfield et al., over 50% of food pantry clients surveyed visited a food pantry for 6 months or more in the prior year (Feeding America, 2014). According to the Food Security Supplement of the Current Population Survey of December 2016, of all households below 185 percent of the poverty level, 4.8% used a food pantry (Coleman-Jensen et al., 2016). This estimate is expected to be a lower bound due to underrepresentation of individuals in this income group.

Socio-demographic profiles for food pantry are often distinct. Pantry users often report having too little money to spend on food and often time have to consume less nutritious foods to stretch their budget (Daponte et al., 1998). Algert, Reibel, and Renvall (2006) found that though many of the food pantry clients in their study appear eligible to receive food assistance, such as SNAP, but a substantial number of them do not receive the benefit, thus needing the assistance from food pantries. The *Hunger in America 2010* study found age to be particularly important with 56% of recurring users being over the age of 65 and only 22% in the 18-29 age group. Bhattarai et al. (2005) found that single parent households, low income women, more food-insecure families, as well as nonmetropolitan individuals are more likely to report going to food pantries. Duffy et al. (2005) found that individuals living in the South of the U.S. are the least likely to seek food assistance from pantries while those in the North-East are the most likely.

A study of food pantry clients in Hartford, CT (Robaina & Martin, 2013) found that over half of their sample was food insecure. While they did not find an association between insecurity and obesity, women in their sample were four times more likely to be obese than men. In contrast, Campbell et al. (2011) found that clients of the Food Bank of Central New York showed preferences for meat, fruits, and vegetables, over snacks, candy, and soda.

4.2.3 Preferences and contingent valuation

Samuelson pioneered work on revealed preferences in 1948. From this work, axioms were developed which ensured consistency of choice. It is exactly on this consistency of choice that RP is usually criticized. An example provided by Sen (1993) is about a dinner guest deciding whether to take the last apple on the table or not. The guest might choose not to take the last apple out of politeness but were there two apples, the guest might take one. This behavior would not quite connect to the consistency requirements explained in revealed preferences .

Ciriacy-Wantrup (1947) argued it is important to assign a market valuation to non-market goods or other intangibles, such as preferences. The term for such an exercise is contingent valuation. Usually the valuation is elicited by surveys where respondents are asked how much they are willing to pay for a specific occurrence (e.g., a non-market commodity, a course of action, a public park). The preferences obtained from such elicitation are known as stated preferences (SP). Intuitively, respondents state their preferences via elicitation.

SP elicitation methods include open-ended value elicitation, dichotomous or multiple discrete choice questions, and choice experiments (sometimes called choice-based conjoint) . Bishop and Heberlein (1979) were among the first to use the open-ended contingent valuation in studying outdoor recreation. Choice experiments have most commonly been used in marketing and transportation studies (Louviere, 1988).

Participants in a choice experiment are asked to pick one from multiple alternatives that vary in attribute. The method is consistent with random utility theory (Adamowicz et al., 1998).

The willingness-to-pay (WTP) measure can be estimated from elicited SP data, and is widely used in a wide array of disciplines as values of things that do not have a market price. Numerous studies have used this valuation measure to examine preferences of economic agents towards various non-market items and intangibles, ranging from adding a quality-adjusted life-year to their lives (Hirth et al., 2000), the importance of customer satisfaction (Homburg et al., 2005), and buying “Fair Trade” coffee (De Pelsmacker et al., 2005).

Contingent valuation proves useful in food research. Popular research topics relate to understanding how consumers value credence attributes of foods, which cannot be easily verified. Credence attributes include country of origin and production processes, such as organic (Krystallis and Chryssohoidis, 2005; Batte et al., 2007) or genetically modified products (Boccaletti and Moro, 2000; Huffman et al., 2003), as well as health claims. A study by Vandermersch and Mathijs (2004) studied consumers’ WTP for domestic milk in Belgium. They found that socio-demographic and behavioral factors affected how

much of a premium consumer were willing to pay for domestic milk. Furthermore, Ribeiro et al. (2005) use contingent valuation to obtain a WTP measure of consumer avoidance of transgenic products. They found a monthly benefit gained by consumers from the avoidance of those products. Heng, Peterson, and Li (2013) use a choice conjoint to calculate the WTP of consumers towards farm animal welfare, more specifically towards laying hens. They found that most consumers were willing to pay a premium for “cage-free” eggs and eggs produced using other non-conventional, which might improve hens’ welfare. Brooks and Lusk (2010) pool data from a stated preference experiment with scanner data to obtain consumer preferences for milk from cloned cows versus organic milk. They found that consumers were willing to pay a larger premium, about three times the premium for organic milk, to avoid milk from cloned cows.

4.3 Data

The data used for this paper were collected at eight food pantries in Minnesota as part of the SuperShelf project. Two pantries were located in Minneapolis, while the remaining were in Litchfield, Hutchinson, Anoka, Northfield, Duluth, and Saint Paul. SuperShelf is a project led by a team of researchers at the University of Minnesota trying to improve the healthfulness of options available and picked at food pantries (Caspi et al., 2019).

4.3.1 Collection design

First contact with food pantry clients was unannounced to the clients. SuperShelf approached clients proposing that they participate in the study in exchange for financial remuneration. Those who chose to participate were asked to complete a survey about demographic information, health information, as well as a conjoint choice task. The

purpose of the survey was primarily to obtain health related data on food pantry clients. Furthermore, the survey was used establish whether clients were satisfied with the offerings (food, service, environment) of their food pantry, but also to get an estimate of their health and well-being as part of the broader SuperShelf initiative.

During this encounter, participants were also asked to show the contents of their bags to the research team in order to record which food items they had chosen to bring home from the pantry for the day. Additionally, the same participants were contacted¹¹ via phone two additional times, based on their availability within three weeks of the first contact, to participate in a 24-hour dietary recall of what they ate. Not all clients involved in the on-site survey were able to participate in the dietary recall section¹².

The dietary recall was conducted by the Nutrition Coordinating Center (NCC) at the University of Minnesota using the Nutritional Data Systems for Research (NDSR) software. NDSR is a proprietary software used specifically for collecting dietary recall data and converting it to nutrients. When a participant is contacted for a dietary recall, NCC staff asks them to recall what food they have eaten in the past 24 hours. The interview occurs in five distinct passes which gives respondents plenty of opportunity to properly recall what they ate. Each study participant received a portion sizing guide, which they would use to estimate the amount of food they have consumed. The NCC

¹¹ Recalls were unannounced.

¹² About 91% of survey respondents participated in at least one recall.

staff inputs the food and portion size information into NDSR, which then converts the records into 169 nutrients. NDSR can accommodate more than 18000 foods, as well as respondent specific foods.

4.3.2 Sample descriptive statistics

Table 4-1 shows descriptive statistics of study participants compared to the 2017-2018 American Community Survey (ACS) where applicable. The majority of study participants were between 45 and 64 years old with about a third of the sample between the age of 25 and 44. A 2004 study in Iowa (Garasky et al., 2004) found that the mean age of food pantry users was between 39 to 49 years old. The average for rural clients was about 49 years old; suburban clients, 40 years old; and finally urban clients, 39 years old. Another study found that 44% of pantry users were 60 years or older (Feeding America, 2011).

In terms of gender, the majority of the study participants were female. Coleman-Jensen et al. (2016) also found a higher number of households with female heads or women living alone were pantry users compared to their counterparts. Close to half of the sample received Supplemental Nutrition Assistance Program (SNAP) benefits, while about 12% received Women, Infants, and Children (WIC) benefits. The Food Security Supplement to the Current Population Survey showed that about 29.7% of food pantry users obtained SNAP benefits and 21.7% received WIC benefits in the past 30 days. Thus, rates of participation in these programs are lower compared to the U.S. sample for WIC but higher for SNAP.

The average number of children in the households was about 1.5, which is slightly lower than the U.S average of 1.9. For the age group 18-24, the data had a lower representation than the ACS, while the representation was similar for the group aged 25-44. SuperShelf participants were more represented in the age group 45-64 than the ACS, while those 65 or above were underrepresented. SuperShelf had a comparable proportion of females compared to the ACS, while the ACS showed a higher proportion of males.

Table 4-1. Descriptive statistics

Descriptive Statistics	SuperShelf	ACS 2017-2018
Age (%)		
18-24 years old	3.31	12.2
25-44 years old	33.11	34.1
45-64 years old	51.66	33.5
65 years old and over	11.92	20.1
Gender (%)		
Female	59.60	51.3
Male	39.07	48.7
Transgender	0.66	-
Prefer not to answer	0.66	-
No. of children in HH (Mean)	1.50	1.9
<hr/>		
N	151	

Source: Author's calculations using SuperShelf data

4.4 Conceptual framework

This study uses the random utility theory to model consumer preferences for healthy food attributes. Assuming that choices are made based on attributes, consumer n with income Y_n will choose among J mutually exclusive alternatives that are uniquely defined by a vector of attributes Z_j and prices P_j . The utility maximization problem is then expressed as:

$$(12) \quad U_n[\mathbf{Z}, \mathbf{p}, Y_n] = \max [U_{1n}(Z_1, Y_n - P_1), \dots, U_{Jn}(Z_J, Y_n - P_J)],$$

where $\mathbf{Z}=(Z_1, \dots, Z_J)$

Equation (12) can be rewritten in terms of observable and unobservable components, where alternative i is chosen if and only if:

$$(13) \quad V_{in}(Z_i, Y_n - P_i) + \epsilon_{in} > V_{jn}(Z_j, Y_n - P_j) + \epsilon_{jn}$$

where $V_{in}(\cdot)$ is the observable part of the utility function and ϵ_{in} is the random part of the utility.

Assuming utility is linear in parameters, the function takes the form:

$$(14) \quad U_{in} = \beta' Z_i + \lambda(Y_n - P_i) + \epsilon_{in}$$

where β and λ are coefficient vectors.

The marginal rate of substitution (MRS) between attribute Z_{ik} and money (in this case, income) gives us the marginal WTP (MWTP) for attribute k . Intuitively, the WTP is therefore the monetary value (income) associated with a marginal occurrence of the

attribute. Since this study uses binary attributes (0 for an unmodified food item, 1 for a healthy modification), the MRS thus becomes the marginal monetary value associated with the healthy food modification. To obtain this MRS, totally differentiate equation (14) such that:

$$(15) \quad dY_n \cdot \frac{dU_{in}}{dY_n} + dZ_{ik} \cdot \frac{dU_{in}}{dZ_{ik}} = 0$$

Therefore, the MWTP is given by:

$$(16) \quad MRS_{nik} = \frac{dY_n}{dZ_{ik}} = - \frac{\frac{dU_{in}}{dZ_{ik}}}{\frac{dU_{in}}{dY_n}} = - \frac{\beta}{\lambda} = MWTP_{nik}$$

4.5 Empirical methods

4.5.1 Choice conjoint

In order to obtain respondents' preferences for each healthy modification, a choice conjoint was designed where food pantry clients were exposed to a hypothetical choice task where they were asked to decide which bundle of food they would like to buy out of two potential bundles. Each bundle had the same products but the products varied by prices and attributes. Given that the target audience for this conjoint are low-income individuals who are at a high risk of food insecurity, the conjoint was designed carefully with the respondents social circumstances at the forefront. Each alternative provided in the choice task was designed to look like a meal that food pantry clients would be likely to eat and were able to afford. Each alternative consisted of a shopping cart with food items designed for a meal at home, consisting of a cheese sandwich, soup, and beverage.

The items were a loaf of sliced bread, cheese slices, a can of condensed soup, and a half gallon of drink. Their nutritional profiles were varied in the choice experiment, and Table 4-2 shows the attributes and levels.

Table 4-2. Attributes and levels used in Choice Experiment

Attributes	Level
Sodium content	25% less sodium, regular sodium
Grains	100% whole grain, refined grains
Saturated Fats	25% less (saturated) fat, regular (saturated) fat
Added Sugars	100% fruit juice (no added sugars), fruit drink (added sugars)
Price	\$4.19, \$4.49, \$4.89

The choices vary based on sodium content, grain type, saturated fat content, and added sugars. The can of soup represents the sodium attribute that can be regular sodium or 25% less sodium. Similarly, the sliced cheese represents the possible modification for saturated fats, while the bread represents whole or refined grains. The drink represents added sugars versus no added sugars.

Obtaining the WTP measures, as described in Section 4.4 , therefore provides us with how respondents value each of the healthy modifications. These attributes were selected based on United States Department of Health and Human Services’ (2017) Dietary Guidelines for American 2015-2020 which, among other recommendations, stipulate that Americans should “consume an eating pattern low in added sugars, saturated fats, and sodium,” as well as consuming more grains, of which at least half should be whole grains.

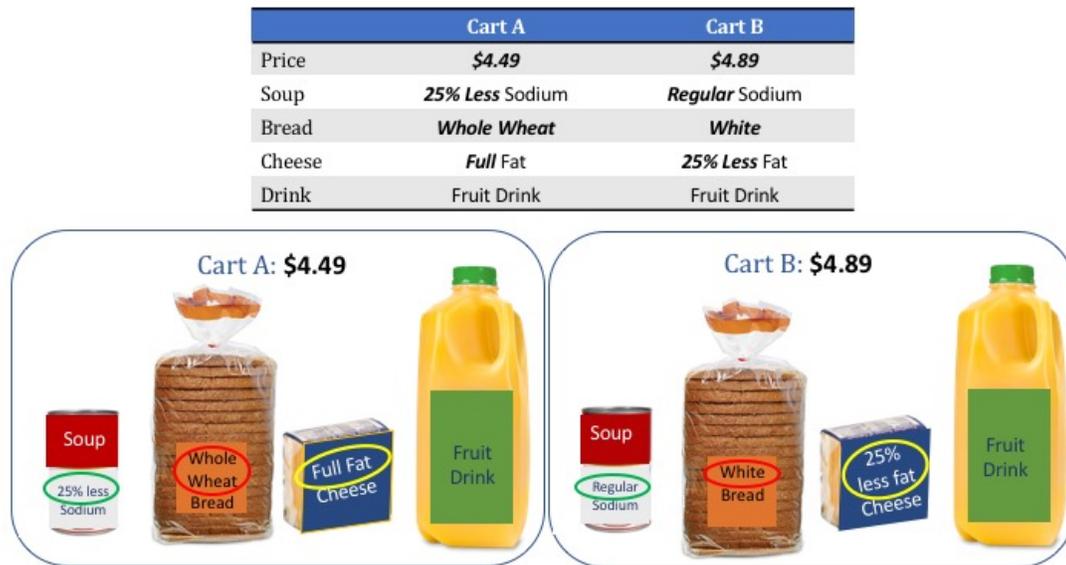
Prices were selected after consultation with food pantry staff and members of the SuperShelf team to establish a realistic budget for food pantry clients to afford. It was imperative that price not serve as the only determinant for choice, especially given the financial difficulties participants likely experience. Therefore, the three price points were selected based on what the research team, food pantry staff, and SuperShelf team members estimated as an affordable expenditure on a meal for food pantry clients.

Figure 4-1 shows an example of one of the potential questions a participant would see in the choice conjoint¹³. To ensure proper understanding of the task by participants, both a table showing the attributes and a visual representation are used. Participants then had the choice to pick either “cart” or neither. Each participant was asked to make six choices in total, with changing attributes for each cart. It is worthy of note that the attributes on each cart were not necessarily the complete opposite of each other. For example, in the image below both juice bottles are a fruit drink. In this particular question, the attribute “100% fruit juice” is therefore not available.

The nutritional profile of each cart follows a fractional factorial design (Louviere, Hensher, and Swait, 2000). Twelve profiles were generated into six choice scenarios. The questions were pretested during a pilot study to check for potential anchoring effects or systematic skipping of questions. None were apparent in either the pretest or the actual study.

¹³ Scenario text introducing the conjoint task can be seen in the Appendix C.

Figure 4-1 Example of choice conjoint question



A limitation of this approach is the hypothetical nature of the task. Loomis (2011) investigated how close such contingent valuation tasks were to true valuations and found that SP tends to be overly optimistic and overvalue true preferences. This is usually referred to as hypothetical bias, where respondents respond to hypothetical scenarios differently than they would in real life scenarios.

Furthermore, a potential source of bias comes from projection bias (Loewenstein, O'Donoghue, Rabin, 2003) wherein an economic agent wrongfully assumes that his or her current preferences reflect future preferences. This is especially true when habit formation is involved, which Naik and Moore (1996) find to be the case in food consumption. Study participants could thus be displaying their current preferences with

SP but exhibit a different set of preferences when they later choose to consume food, represented in the RP.

A third source of bias comes from the mental shortcut known as the availability heuristic (Tversky & Kahneman, 1973) wherein agents evaluate choices based on easily available information. In the hypothetical scenario that SP is collected, nutritional information is presented at the forefront to individuals. When individuals make food selections at retail (revealed preferences), this information is less prominent and must be sought. Thus the interest that study participants might have regarding nutrients is likely exaggerated in the hypothetical scenario.

Survey participants commented on the difficulty of the choice task. Although the task is arguably similar in complexity to actual decisions made while shopping, attribute-non-attendance, where individuals discard information partially in making decisions, is a concern. Hensher (2006) finds evidence that participants in such task tend to exclude attribute due to the complexity of a task, and others have similarly documented (Scarpa et al., 2009, 2012; Alemu et al., 2013). The choice design with multiple products each representing a specific attribute could help alleviate issues of attribute non-attendance. In the current choice task setup, it is unlikely that a respondent would concentrate on a single attribute such as reduced saturated fats in cheese, but then completely disregard attributes associated with the bread they would eat along with the cheese. Thus, even if the task was identified as complex, the likelihood of experience attribute non-attendance is reduced due to the expected combination of the products representing specific attribute levels.

4.5.2 Random Coefficient Logit

The collected responses were analyzed using a random coefficient (mixed) logit model (RCL) (McFadden and Train, 2000). Discrete choice models such as RCL estimate consumer demand in the characteristic space, rather than in the traditional commodity space. This not only allows for reasonable data needs, it is also suited to measuring preferences related to food, which are likely determined by characteristics rather than the amounts of food. RCL is basically an empirical application of the model described in section 4.4 . The main advantage of the RCL is that it has enough flexibility to approximate random utility models while allowing for heterogeneous preferences.

The model starts with the following form:

$$(17) \quad U_{njt} = \gamma_{njt} + \lambda_n p_{njt} + \epsilon_{njt}$$

where U_{ijt} is the utility for individual n , from product j , at time t , γ_{njt} is the mean utility level and p_{njt} is a vector of prices, while ϵ_{njt} is the idiosyncratic error term which is distributed **iid extreme value type 1**.

The term γ_{njt} can be expanded to:

$$(18) \quad \gamma_{njt} = \sum_k \beta_{nk} z_{jk}, k = 1, 2, 3, \dots$$

where z_{jk} is the vector of the k th product characteristics the consumer is interested in.

Therefore, this framework implies that the mean utility of individual n is dependent on product characteristics. In this specification, β can either be continuous or discrete. When the model has continuously distributed coefficient, it becomes the RCL (Hole, 2007).

Hole's Stata program for RCL (the command known as `-mixlogit-`), which is based on simulation method, is used for estimation assuming β is normally distributed. Using the parameters in this model, the WTP measure can be calculated for each attribute as stated in equation (16).

4.5.3 Expectations from RCL

The Dietary Guideline for Americans clearly stipulates that whole grains are under-consumed in the USA. Lang and Jebb (2003) find that the typical consumers of whole grains tend to be of higher socio-economic status, older, and exercise regularly, a combination of traits unlikely to all be present in our participant pool. Therefore, we can expect that our participants will not likely value whole grains. Multiple studies have shown the positive effect of the consumption of whole grains in reducing the risks of various diseases (Liu et al., 1999; Cho et al, 2013; Slavin, 2003). Whole grains intake has been linked to creating a protective mechanism against cancer, cardiovascular disease, diabetes and obesity, as well as providing improvements to the gut environment and the immune system (Slavin, 2003).

Discussion around sodium intake has been prominent since the 1990s and highly debated (Cohen et al., 2008; Ruusunen and Puolanne, 2005; Alderman et al., 1998). Particularly, some studies have shown that higher sodium intake is linked to increased risks of hypertension, cardiovascular diseases, and general mortality (Yang et al., 2011). Another 2011 study showed that, on average, the total daily sodium intake per individual in developed countries is up to 25 times greater than the minimum requirement (Albarracín

et al., 2011). It is quite reasonable to expect that participants in this study might be more likely to place higher values for lower sodium products.

Similarly, the topic of fat intake has also been in the limelight. For both men and women, increased fat intake, especially saturated fat, has conventionally been linked with heightened risks for coronary heart disease (Hu et al., 1997; Ascherio et al., 1996). The United States Department of Agriculture's dietary guidelines encouraged low consumption of fats compared to carbohydrates since the 1970s (Ludwig, 2016). This guideline has since been revised to remove the upper limit of fat intake. However, fat intake remains an issue of concern for many.

Added sugar has garnered more recent attention. Both fruit juice and fruit drinks are known to have high sugar contents. While 100% fruit juice will have no added sugar, fruit drinks are produced from adding sugar. Given the awareness around sugar intake, which is linked to higher risks of heart disease, stroke and type 2 diabetes (Rodríguez et al., 2016) is quite recent, participants may not be familiar with dietary recommendations and make decisions simply based on their experience with how the products tasted in the past.

4.6 Results and Discussion

Table 4-3 shows results from the RCL estimation. The positive coefficients on reduced sodium, reduced fat, and drinking fruit juice rather than a fruit drink are all indicators that participants see benefits in healthy modifications to their food following the Dietary Guidelines for Americans. Although, not all of these results are statistically significant, the directions and magnitudes are quite meaningful. The only two statistically significant coefficients are on saturated fats and price. The negative coefficient on price follows from economic theory as it indicates that participants experience disutility from higher prices.

The Standard Deviation (SD) measures the degree to which the preferences established in the model vary among individual respondents. A statistically significant SD implies that there are some who value a certain attribute, while others do not. For instance, statistically insignificant mean coefficient on whole grains and a statistically significant SD imply that about half of the respondents gain positive utility from whole grains while the other half prefer refined grains. This is because a normal distribution is assumed for the whole grain coefficient. The only attribute where the SD is insignificant is fat, which suggests that there is a general consensus among respondents about the value of reduced fat.

Table 4-3. RCL estimates

	Mean	SD
100% Whole Grain	-0.131 (0.097)	0.570*** (0.138)
25% Less Sodium	0.093 (0.103)	0.598*** (0.148)
No Added Sugar Drink	0.260* (0.117)	0.761*** (0.163)
25% Less Saturated Fat	0.359*** (0.104)	0.496 (0.271)
Price	-0.866*** (0.252)	
Wald Chi-Square	122.04 ***	
N (individuals)	151	
N (choices)	828	

Notes : * indicates $p < 0.01$, ** $p < 0.005$, *** $p < 0.001$. The Wald Ch-square test's null hypothesis is that all coefficients are jointly equal to zero.

Source: Author's calculations using SuperShelf data

Table 4-4 shows the averages of individual WTP estimates from the choice conjoint. The average WTP for whole grain among participants is negative 15 cents for a bundle of food priced around \$4-5 for a meal. More than a third (35%) of respondents are estimated to value whole grains over refined grains, which is the smallest proportion of the sample. Other healthy modifications are valued on average. The average WTP on fats is the highest, indicating that participants are willing to pay 42 cents for 25% less fats per meal. This further implies that participants are willing to pay two cents for a one percentage

point reduction in fat from their meals. What is striking is that 94% of respondents are estimated to hold positive values for fat reduction, suggesting that among the healthy eating guidelines considered in this study, avoidance of fat has been most widely recognized among food pantry clients in our sample. As for sweet beverage, participants on average are willing to pay 30 cents more for 100% fruit juice than fruit drink with added sugar. The proportion of respondents with positive WTP is the second highest and exceed those preferring lower sodium. It could be that low sodium products might be more associated with poor flavor than the difference in sweetness between 100% fruit juice and fruit drink.

Table 4-4. WTP estimates from choice conjoint

	WTP (\$)	% with WTP < 0	% with WTP > 0
100% Whole Grain	-0.15	65%	35%
25% Less Sodium	0.11	40%	59%
No Added Sugar Drink	0.30	29%	68%
25% Less Saturated Fat	0.41	6%	94%

Source: Author's calculations using SuperShelf data

4.6.1 Comparison to Dietary Recalls

In order to verify whether there is some evidence of bias (as explained in Section 4.5.1 I use the dietary recall data as a baseline of how study participants usually eat.

Table 4-5 shows the mean daily consumption of nutrient of interest for dietary recall participants¹⁴. On an average day, participants consumed about 1960 k-Calories¹⁵. For illustrative purposes, Table 4-5 also shows the recommended nutrition for healthy adults from the Dietary Guidelines for Americans. Note that recommended calories and nutrients per meal vary by person height and weight.

The average percentage of calories from carbohydrates (42.2 grams) was within the range stated in the Dietary Recalls for Americans (45-65%). Similar trends are seen for the percent of calories from protein. Though the Dietary Guidelines do not provide clear indications of how much of these macronutrients to consume, it does state that Americans should consume 5-6 ounces of protein foods and 27-29 grams of oils in a day. Percent calories from saturated fats suggest that although the estimation results showed wide acknowledgement of the benefit of reduced fat content, study participants are consuming above the daily advised amount for percent of calories from that. The discrepancy suggest the gap between understanding of the dietary guidelines and actual food intake of food

¹⁴ Not all conjoint respondents participated in the recall, which explains a smaller sample size in the recall.

¹⁵ Computed using NDSR software proprietary methodology.

pantry clients. Food pantry clients may indeed face limited access to affordable healthy food options in their food environment.

In terms of other nutritional profiles, the food pantry clients in our sample also diverged from the recommended guidelines. The guidelines state that less than 10% of daily calories should come from added sugars¹⁶. All in all, the guidelines stipulate that added sugars should be limited in one's diet. Though statistically significant, having a drink that contained no added sugars was seen to have a positive utility associated and a positive WTP. However, participants consume 67 grams of added sugars per day on average. A similar trend is seen with sodium which once again is consumed more than the recommended amount in the Dietary Guidelines for Americans but was seen to have a positive association to utility and a positive WTP.

The guidelines also stipulate that about 6-7 ounces of grains should be consumed in a day, with 50% or more being whole grains. Assuming three meals in a day, this is equivalent to 8-10 ounce equivalents of grains per day. Respondents consumed only about 7 ounces of grains on average in a day, with only 22% of those grains being whole grains while the guidelines recommend over 50%.

¹⁶ Assuming a 2000 calorie diet, 10% would be equivalent to 200 calories, or 12 teaspoons. According to the USDA's food equivalents database 2013-2014, this is about 50.4 grams. Thus the number used in

Table 4-5. Dietary recall descriptive statistics

	Mean	Dietary Guidelines for Americans 2015-2020
Energy (kCals)	1960.5	1800-2200
Calories from Carbohydrates (%)	49.2	45-65
Calories from Protein (%)	17.1	10-35
Calories from Saturated Fats (%)	11.4	≤ 10
Added sugars (g)	67.8	50.4
Sodium (mg)	3076.6	2300
Grains Consumed (oz)	7.0	8-10
% Refined Grains	78%	< 50%
% Whole Grains	22%	≥ 50%
N	136	

Source: Author's calculations using SuperShelf data, compared to Dietary Guidelines for Americans 2015-2020.

To further investigate, Table 4-6 breaks down the average consumption of nutrients based on whether the individual's estimated WTPs were positive or negative. For instance, among 35% of respondents who were estimated to value whole grains, the average consumption of whole grains was 22%, compared to 65% of respondents who valued refined grains consuming 23%. These means are likely statistically the same. For sodium and added sugar, respondents who were estimated to value healthier intake (i.e., low sodium and no added sugar) report consuming more of them than their counterparts.

Only for saturated fats, the agreement with the dietary guidelines and intake patterns align. The majority of respondents who were estimated to value reduced fat options

consumed slightly lower levels of saturated fats, albeit higher than the recommended levels.

Table 4-6 Nutrient consumption by WTP values

	Mean Actual Consumption ($WTP_n > 0$)	Mean Actual Consumption ($WTP_n < 0$)	Dietary Guidelines
Whole Grains (%)	22%	23%	$\geq 50\%$
N	87	157	
Sodium (mg)	3201.38	2,998	2300
N	138	106	
Added sugar (g)	71.43	60	50.4
N	178	66	
Saturated Fats (%)	11.27	12.8	≤ 10
N	231	13.0	

Source: Author's calculations using SuperShelf data, compared to Dietary Guidelines for Americans 2015-2020.

4.7 Conclusion

The goal of this study was to estimate the preferences of low-income households, and more specifically food pantry clients. It is apparent from the results that the majority of study participants value healthy modifications to their food. This is informed by the proportions of participants that are estimated to positively value these healthy modifications. Reduced fat options were valued by most of the participants and averaged the highest WTP. The only healthy modification that were not valued by the majority of respondents was whole grains. Participants attributed disutility and had negative WTP for this attribute.

However, when analyzing the actual food consumed by study participants in a dietary recall, it became apparent that these hypothetical preferences do not translate into actual consumption. Participants consumed more added sugars, sodium, and saturated fats than what is recommended by the Dietary Guidelines for Americans. They also consumed less whole grains than needed but that fact is in harmony with the RCL and WTP results. Furthermore, when comparing consumption patterns for those with positive WTP to those with negative WTP, consumption patterns appear fairly similar. In fact, those with negative WTP tend consume more whole grains, less sodium, and less added sugars than those with positive WTP for those attributes. The only attribute where those with positive WTP are making the healthier choice is saturated fat, as they consume less of it than those with negative WTP. However, they still consume more of it than what is advised by the Dietary Guidelines. It is therefore likely that, though study participants have identified healthy modifications to their foods as being something they might want to

incorporate in their diets, though they are not fully putting this plan of action into practice.

What should we do with these findings? The first thing to consider is that food pantry participants, though of low-income, are display a hypothetical willingness to spend more to have healthier food. This implies that these foods with healthy modifications should be made more affordable for these households. Additionally, food pantries and food distribution efforts for low-income households should attempt to offer more of these items since their clients have a clear preference for them. For public policy, a food assistance effort which would make foods with the attributes favored by this study's participants affordable would likely provide a benefit.

However, we cannot be sure if food pantry users, and low-income individuals in general will correctly follow the Dietary Guidelines for Americans. A possible reason for this mismatch is that, though participants in this study understood the need for most of the healthy modifications, they might not really know the correct amount they should be consuming. For instance, knowing what 10% of less of one's daily calories coming from oil is equivalent to in terms of food being consumed might be too hard of mental gymnastics for the average person. Additionally, we cannot exclude the potential of hypothetical bias and being too optimistic when answering survey questions. Participants could have wanted to show their best self by picking what they deemed the healthier options were in the choice task.

In summary, this study has shown that the food pantry clients who participated in this study seem to have a desire to follow the Dietary Guidelines established by the United

States Department of Health and Human Services but are clearly not doing so. An investigation into the barriers that might be preventing them from following the guidelines should be conducted to evaluate the underlying reason why those participants are not eating according to the guidelines, though they seem willing to pay a premium for healthy modifications to their food.

Chapter 5. Concluding remarks

This dissertation has attempted to evaluate, predict, and measure the impact of policy on the food choices on low-income individuals, as well as trying to better understand their preferences. While there is no clear demarcation as to what the best course of action is to improve the healthfulness of low-income individuals' diets, it is apparent that poverty plays a central role in limiting their choices and possibilities.

Chapter 2 investigated the impact of the ARRA expansion on SNAP recipients' choice of food purchases. A difference-in-difference approach is used under multiple specifications, one involving propensity score matching. The only statistically significant impact across the board is an increase spending on soda, snacks, and confectionery goods. It is important to remember that the ARRA expansion was equivalent to a rather small increase in food budgets which might explain why recipients decided to spend the money on snacks and soda.

In order to investigate whether increasing food budgets is in fact effective at increasing the purchase of healthy foods, chapter 3 uses scanner data to estimate a QUAID demand system. Using the model parameters, simulations were used to predict what the purchase of fruits and vegetables would have been under an equal budget policy program that would either increase low-income households' food budgets, or giving them a discount on fruits and vegetables. The results show that giving those households more money to purchase food was more effective than giving them a discount on fruits and vegetables at increasing the purchase of said fruits and vegetables.

While findings from chapters 2 and 3 appear to be at odds, they emphasize the complexity of food and nutritional choices made under low-income environment. Together, they suggest a public policy effort aimed at promoting healthy foods cannot be a “one size fits all” policy. A nimble approach, centered around the heterogeneous preferences and behaviors within low-income households should be adopted, where benefits and policy mechanisms can be tailored to specific groups. This approach can be analogous to the “personalized medicine” approach, wherein a doctor prescribes personalized treatment to his or her patient, rather than prescribing treatment for all patients with similar symptoms. Here, chapter 2 finds that increasing food budgets did not help increase the purchase of fruits and vegetables, while chapter 3 shows that using a personalized approach for various levels of poverty has the potential to be successful.

Finally, chapter 4 investigated the mindset of food pantry clients towards healthy food modifications such as reduced sodium or reduced fat foods, as suggested by the Dietary Guidelines for Americans. A choice conjoint was designed to elicit preferences of food pantry clients who agreed to participate in the study. The data was then used to estimate a random parameter logit model. Most participants valued reduced fat options in their food. However, when comparing these results with their food recall data, their actual intake diverged from the recommended guidelines. While this could partially be due to the hypothetical nature of the choice task, the findings highlight the difficulty food pantry clients face in consuming food in ways that follow the Dietary Guidelines.

The main contribution of this dissertation is that the work detailed here focuses on nutrition as being a necessity for low-income individuals. Food security is often

measured in terms of total food consumption and meeting daily requirements, with less emphasis put on nutritional qualities of said food. Therefore, promoting food security in terms of calories is not enough. It is my hope that nutritional quality one day plays a more central role in policy and other public efforts to promote food security among low-income individuals. It is central for public policy efforts to recognize how complex nutrition is for the average person and how having low-income exacerbates this difficulty. To successfully address this issue, it is necessary to consider all aspects of consumer choice from theoretical demand theory to behavioral economics. It is my hope that one day, no household goes hungry, all have proper nutrition, and good health.

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Appendices

Appendix A. Appendices for Chapter 2

Table A 1. Two-period difference-in-difference – Fruits and vegetables

	Definition 1	Definition 2
Difference-in-Difference		
Post-ARRA period	-4.260 (13.249)	-3.366 (12.701)
Treatment	-8.334* (3.363)	-7.155*† (2.634)
Post-ARRA period*Treatment	6.617 (4.400)	4.686 (3.349)
Covariates		
Number of earners	-0.933 (1.254)	-0.453 (0.855)
Family Size	4.348† (0.781)	4.464† (0.730)
<i>Highest education attained in CU (College/Associate Degree omit.)</i>		
Never attended school	72.127*† (26.244)	77.577*† (21.073)
Less than HS	1.480 (2.752)	1.046 (2.590)
High school	-2.028 (2.124)	-3.180 (2.082)
Some college	-4.133 (2.154)	-4.622* (2.155)

	Definition 1	Definition 2
Graduate degree	12.151*† (3.989)	10.657*† (3.965)
<i>Residency (Urban omit.)</i>		
Rural	-13.776 (7.416)	-16.170*† (6.198)
<i>Race of reference person (White omit.)</i>		
African American or Black	-5.286* (2.620)	-4.471 (2.460)
Native/ Pac. Isl./ Nat. Hawa.	5.053 (11.816)	4.522 (10.778)
Asian	2.688 (4.182)	2.129 (3.601)
Multi-Race	3.151 (10.401)	-1.323 (8.910)
<i>Gender of reference person (Male omit.)</i>		
Female	0.118 (1.508)	-0.021 (1.423)
Quarter*Year Included	Yes	Yes
N	1598	1890

Notes: * $p < 0.05$, † $p < -0.0102$ (Dunn-Šidák correction). Robust standard errors used.

Table A 2. Two-period difference-in-difference – Meats, Seafood, Dairy

	Definition 1	Definition 2
Difference-in-Difference		
Post-ARRA period	-25.900 (16.052)	-25.621 (15.486)
Treatment	-5.960 (4.319)	-3.746 (3.428)
Post-ARRA period*Treatment	6.311 (5.643)	4.997 (4.325)
Covariates		
Number of earners	0.139 (1.533)	0.747 (1.074)
Family Size	7.613*† (0.940)	7.149*† (0.869)
<i>Highest education attained in CU (College/Associate Degree omit.)</i>		
Never attended school	154.929 (79.976)	131.689 (68.277)
Less than HS	2.696 (3.429)	2.175 (3.274)
High school	2.118 (2.825)	0.805 (2.710)
Some college	-2.363 (2.799)	-2.002 (2.834)
Graduate degree	5.085 (4.423)	4.399 (4.273)
<i>Residency (Urban omit.)</i>		
Rural	3.053 (8.048)	2.859 (6.931)

	Definition 1	Definition 2
<i>Race of reference person (White omit.)</i>		
African American or Black	1.831 (3.519)	3.803 (3.743)
Native/ Pac. Isl./ Nat. Hawa.	28.047 (24.893)	26.507 (23.309)
Asian	11.239 (5.899)	11.040* (5.435)
Multi-Race	2.415 (6.676)	0.077 (5.543)
<i>Gender of reference person (Male omit.)</i>		
Female	-0.392 (1.996)	1.127 (1.846)
Quarter*Year Included	Yes	Yes
N	1598	1890

Notes: * p<0.05, † p<~0.01 (Dunn-Šidák correction). Robust standard errors used.

Table A 3. Two-period difference-in-difference – Processed Meats

	Definition 1	Definition 2
Difference-in-Difference		
Post-ARRA period	8.711 (8.578)	7.013 (7.913)
Treatment	-3.912* (1.547)	-2.889*† (1.119)
Post-ARRA period*Treatment	2.210 (1.920)	2.316 (1.378)
Covariates		
Number of earners	-1.104*† (0.392)	-0.755*† (0.283)
Family Size	1.636*† (0.303)	1.706*† (0.268)
<i>Highest education attained in CU (College/Associate Degree omit.)</i>		
Never attended school	3.993 (4.641)	2.082 (3.883)
Less than HS	-0.191 (1.056)	-0.442 (0.995)
High school	0.441 (0.917)	-0.136 (0.864)
Some college	0.458 (1.125)	0.217 (1.017)
Graduate degree	-0.160 (1.486)	-0.122 (1.464)
<i>Residency (Urban omit.)</i>		
Rural	-7.352 (4.307)	-7.626* (3.785)

	Definition 1	Definition 2
<i>Race of reference person (White omit.)</i>		
African American or Black	-0.183 (1.122)	-0.515 (1.020)
Native/ Pac. Isl./ Nat. Hawa.	2.431 (3.148)	1.171 (2.876)
Asian	-0.322 (1.983)	-0.687 (1.721)
Multi-Race	0.348 (3.953)	-0.736 (3.176)
<i>Gender of reference person (Male omit.)</i>		
Female	-0.115 (0.657)	-0.006 (0.601)
Quarter*Year Included	Yes	Yes
N	1598	1890

Notes: * $p < 0.05$, † $p < 0.01$ (Dunn-Sidák correction). Robust standard errors used.

Table A 4. Two-period difference-in-difference – Soda, Snacks, and Confectionery goods

	Definition 1	Definition 2
Difference-in-Difference		
Post-ARRA period	0.483 (14.727)	3.964 (14.391)
Treatment	-14.631*† (3.303)	-10.505*† (2.557)
Post-ARRA period*Treatment	12.153*† (4.446)	10.101*† (3.300)
Covariates		
Number of earners	-2.050* (1.017)	-1.448* (0.712)
Family Size	5.700*† (0.692)	5.833*† (0.660)
<i>Highest education attained in CU (College/Associate Degree omit.)</i>		
Never attended school	1.249 (12.431)	1.214 (9.488)
Less than HS	-1.976 (2.601)	-4.245 (2.451)
High school	-1.473 (2.083)	-2.534 (2.051)
Some college	-1.696 (2.349)	-2.137 (2.204)
Graduate degree	0.678 (3.652)	-0.811 (3.640)

	Definition 1	Definition 2
<i>Residency (Urban omit.)</i>		
Rural	8.289 (8.186)	12.297 (7.460)
<i>Race of reference person (White omit.)</i>		
African American or Black	-8.079*† (2.414)	-9.733*† (2.276)
Native/ Pac. Isl./ Nat. Hawa.	6.081 (7.861)	7.126 (7.078)
Asian	-1.972 (3.495)	-4.822 (3.090)
Multi-Race	-4.547 (6.488)	-3.542 (7.810)
<i>Gender of reference person (Male omit.)</i>		
Female	-1.301 (1.499)	-0.998 (1.400)
Quarter*Year Included	Yes	Yes
N	1598	1890

Notes: * p<0.05, † p<~0.01 (Dunn-Šidák correction). Robust standard errors used. CEX weights used.

Table A 5. Two-period difference-in-difference – Starches

	Definition 1	Definition 2
Difference-in-Difference		
Post-ARRA period	2.933 (5.975)	2.481 (5.426)
Treatment	-4.627*† (1.480)	-2.806* (1.211)
Post-ARRA period*Treatment	1.668 (1.761)	1.637 (1.448)
Covariates		
Number of earners	-1.085* (0.515)	-0.866* (0.338)
Family Size	2.767*† (0.466)	2.677*† (0.423)
<i>Highest education attained in CU (College/Associate Degree omit.)</i>		
Never attended school	34.488 (26.449)	35.551 (20.958)
Less than HS	-2.068 (1.111)	-2.266* (1.076)
High school	-1.297 (0.964)	-1.739 (0.926)
Some college	-1.780 (0.951)	-1.610 (0.945)
Graduate degree	0.923 (1.600)	0.459 (1.587)
<i>Residency (Urban omit.)</i>		
Rural	2.391 (2.231)	2.179 (2.158)

	Definition 1	Definition 2
<i>Race of reference person (White omit.)</i>		
African American or Black	-0.182 (1.170)	-0.045 (1.106)
Native/ Pac. Isl./ Nat. Hawa.	26.671 (19.336)	25.270 (17.536)
Asian	4.165 (2.140)	3.234 (2.069)
Multi-Race	0.871 (2.453)	0.076 (1.881)
<i>Gender of reference person (Male omit.)</i>		
Female	-0.530 (0.719)	-0.408 (0.669)
Quarter*Year Included	Yes	Yes
N	1598	1890

Notes: * p<0.05, † p<~0.01 (Dunn-Šidák correction). Robust standard errors used.

Table A 6. Difference-in-difference – All Other Foods

	Definition 1	Definition 2
Difference-in-Difference		
Post-ARRA period	10.311 (25.020)	15.719 (23.801)
Treatment	-11.543*† (4.338)	-4.253 (4.362)
Post-ARRA period*Treatment	13.498* (5.801)	6.737 (5.195)
Covariates		
Number of earners	-0.879 (1.481)	-2.108* (1.075)
Family Size	6.357*† (0.941)	6.782*† (0.896)
<i>Highest education attained in CU (College/Associate Degree omit.)</i>		
Never attended school	11.443 (13.651)	41.081 (31.118)
Less than HS	-5.816 (3.532)	-6.842* (3.297)
High school	-3.681 (2.800)	-4.165 (2.704)
Some college	-1.108 (3.226)	0.226 (3.172)
Graduate degree	7.314 (5.208)	8.118 (5.245)
<i>Residency (Urban omit.)</i>		
Rural	4.671 (8.060)	3.036 (7.822)

	Definition 1	Definition 2
<i>Race of reference person (White omit.)</i>		
African American or Black	-8.533*† (3.317)	-9.849*† (3.250)
Native/ Pac. Isl./ Nat. Hawa.	33.851* (13.672)	35.157*† (11.531)
Asian	-3.596 (5.855)	-6.711 (4.974)
Multi-Race	-9.682 (7.753)	-3.591 (10.942)
<i>Gender of reference person (Male omit.)</i>		
Female	0.490 (2.040)	0.739 (1.940)
Quarter*Year Included	Yes	Yes
N	1598	1890

Notes: * p<0.05, † p<~0.01 (Dunn-Šidák correction). Robust standard errors use

Appendix B. Appendices for Chapter 3

Table B 1. Regression results - QUAI

	Fruits and Vegetables	Meats, Seafood, and Dairy	Fats	Sugar, snacks, and confectionery
$\log p_{fruits\ and\ veg}$	0.015* (0.003)	0.016* (0.002)	-0.009* (0.002)	0.015* (0.004)
$\log p_{meats}$	0.016* (0.002)	0.072* (0.005)	0.022* (0.004)	-0.104* (0.005)
$\log p_{fats}$	-0.009* (0.002)	0.022* (0.004)	-0.117* (0.007)	0.080* (0.006)
$\log p_{sugar\ and\ conf.}$	0.015* (0.004)	-0.104* (0.005)	0.080* (0.006)	-0.125* (0.009)
$\log \frac{Y}{a(\mathbf{p})}$	0.043* (0.003)	0.067* (0.004)	0.029* (0.003)	-0.011* (0.005)
$\log \frac{1}{b(\mathbf{p})} \left[\frac{\log Y}{a(\mathbf{p})} \right]^2$	-0.003* (0.000)	-0.004* (0.000)	-0.003* (0.000)	-0.001* (0.000)

	Fruits and Vegetables	Meats, Seafood, and Dairy	Fats	Sugar, snacks, and confectionery
<i>Controls</i>				
Non-White	-0.006* (0.000)	-0.022* (0.000)	0.021* (0.000)	0.019* (0.001)
Female head age	0.002* (0.000)	-0.000* (0.000)	0.000* (0.000)	0.001* (0.000)
Male head age	0.000* (0.000)	0.001* (0.000)	-0.000 (0.000)	0.000 (0.000)
Log(household size)	-0.009* (0.000)	0.008* (0.000)	0.010* (0.000)	0.005* (0.001)
Child in the household	0.000 (0.001)	-0.007* (0.001)	0.001 (0.000)	0.015* (0.001)
Constant	-0.012 (0.012)	-0.150* (0.013)	0.023* (0.011)	0.408* (0.018)
N	57945	57945	57945	57945

Notes: * indicates $p < 0.05$.

Source: Author's calculation using Nielsen Homescan data 2016

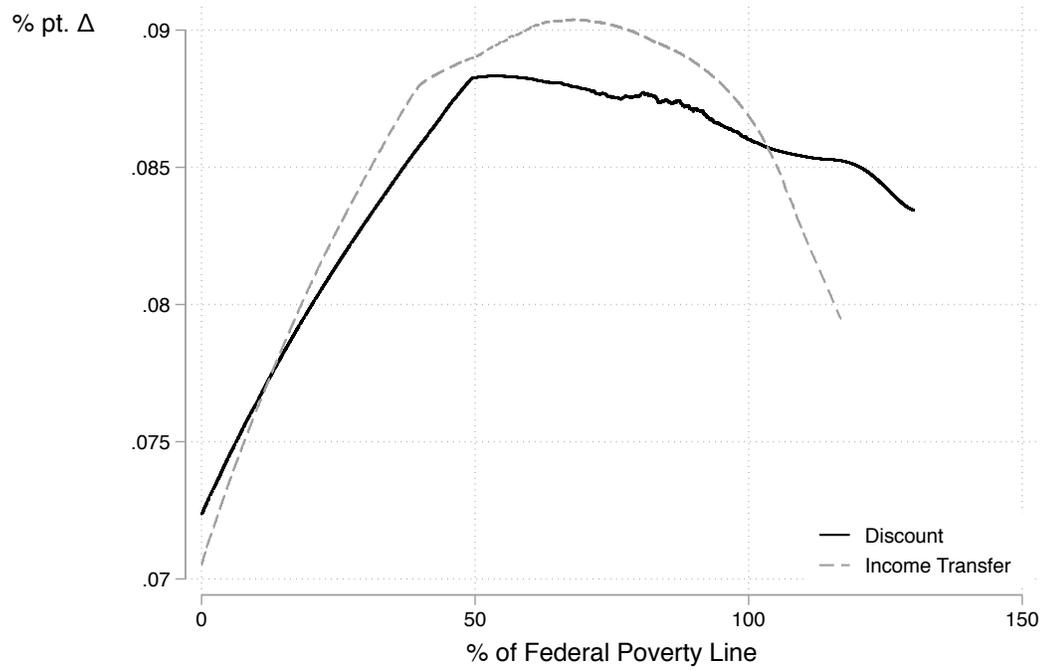
Table B 2. Own-Price Elasticities

	Uncompensated own-price elasticity	Compensated own- price elasticity		Own-price elasticities in the literature ^a
Fruits and Vegetables	0.845	0.718	Fruit	0.16–3.02
			Vegetables	0.21–1.11
Meats, seafood, and dairy	0.172	0.008	Beef	0.29–1.42
			Pork	0.17–1.23
			Poultry	0.16–2.72
			Fish	0.05–1.41
			Dairy	0.19–1.16
			Milk	0.02–1.68
			Cheese	0.01–1.95
			Eggs	0.06–1.28
Fats	1.842	1.712	Fats/Oils	0.14–1.00
Sugar, snacks, and Confectionery goods	1.339	1.025	Sweets/Sugar	0.05–1.00
			Soft drinks	0.13–3.18
			Juice	0.33–1.77
All other foods	1.245	0.98		

^a Andreyeva, Long, & Brownell (2010).

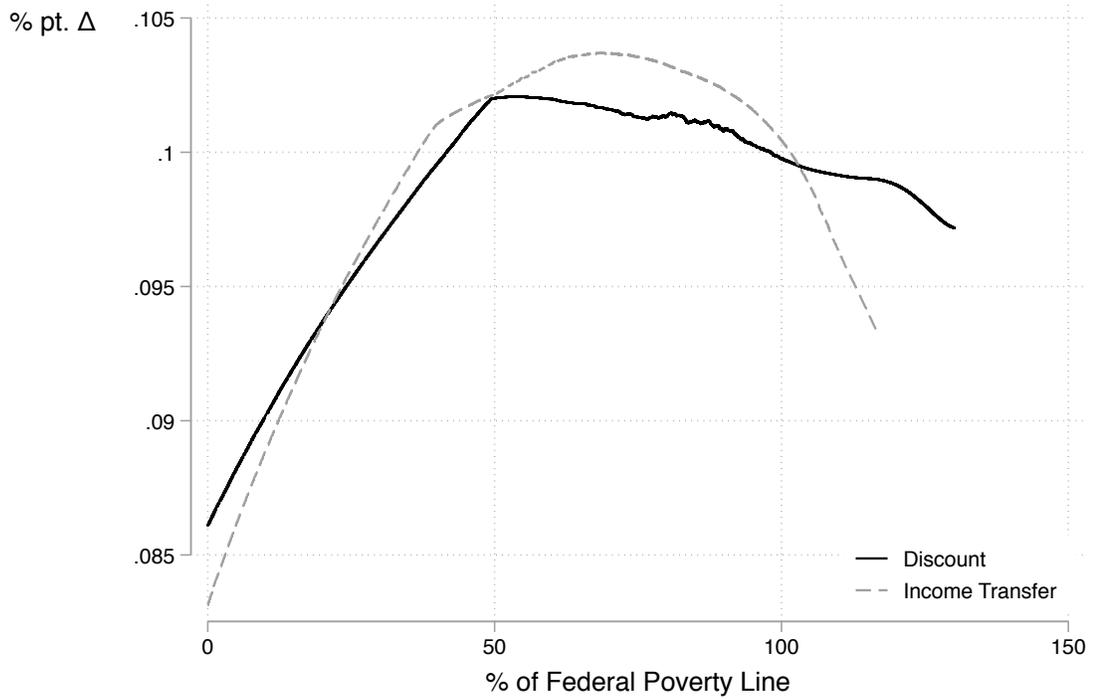
Notes: This tables shows the computed absolute values for own-price elasticities from the QUA model detailed in Section 3.4.1 For comparison, elasticity ranges from Andreyeva, Long, & Brownell (2010) are shown. Andreyeva, Long, & Brownell (2010) compiled the results for 160 studies computing the own-price elasticities of various foods.

Figure B 1. Comparison between income transfer and discount simulations for 5% of SNAP budget.



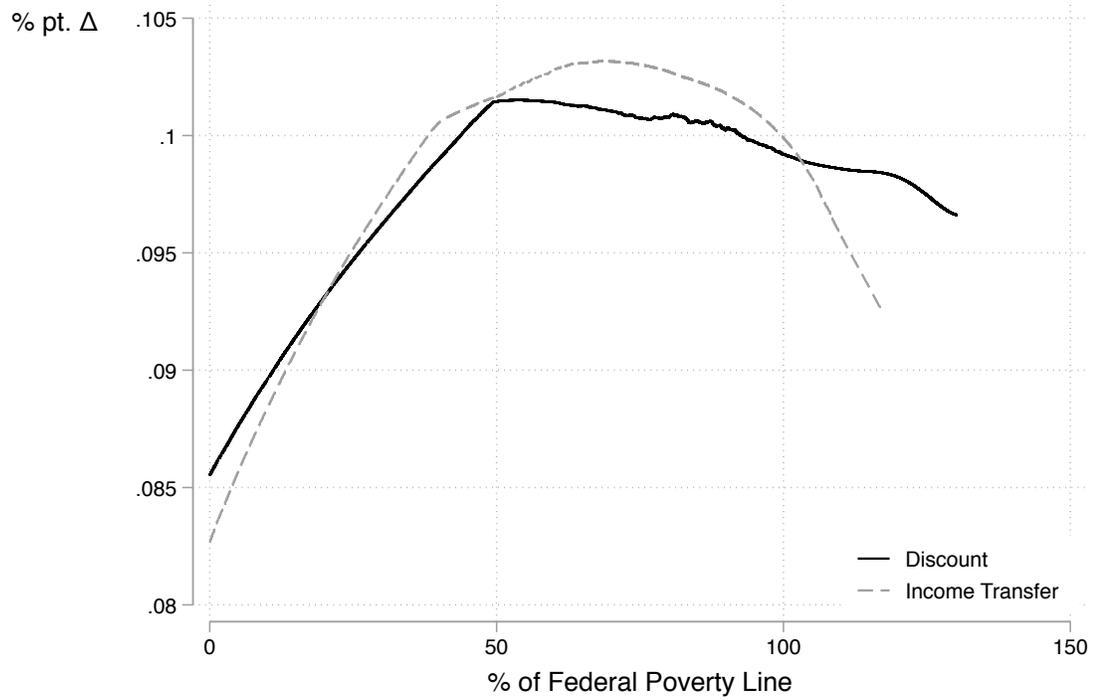
Note: Lines shown are Locally Weighted Scatterplot Smoothing.
Source: Author's calculations using Nielsen Homescan 2016.

Figure B 2. Comparison between income transfer and discount simulations for 1% of Women, Infants, and Children budget.



Note: Lines shown are Locally Weighted Scatterplot Smoothing.
Source: Author's calculations using Nielsen Homescan 2016.

Figure B 3. Comparison between income transfer and discount simulations for 5% of Women, Infants, and Children budget.



Note: Lines shown are Locally Weighted Scatterplot Smoothing.
Source: Author's calculations using Nielsen Homescan 2016.

Table B 3.T-test of difference between discount and income transfer

	Mean	SE	SD
% Change - Income Transfer	.0986622	.0006158	.0668712
% Change - Discount	.0985181	.0006159	.066885

H_0 : mean(diff) = 0

H_a : mean(diff) \neq 0 ; Pr(|T| > |t|) = 0.0000

Source: Author's calculation using Nielsen Homescan data 2016

Appendix C. Appendices for Chapter 4

Figure C 1. Sample narrative question – Choice conjoint.

Imagine you are at your usual grocery store. You are about to purchase several items: a loaf of bread, a can of vegetable soup, a package of sliced cheese, and a fruit-flavored beverage. You can choose one cart with these items: Cart A, Cart B, or neither. The nutrition of the items is different in the two carts. The price of each cart is also different. Compare the two carts and tell us which one you would pick.

	Cart A	Cart B
Price	\$4.89	\$4.49
Soup	Regular Sodium	25% Less Sodium
Bread	White	Whole Wheat
Cheese	25% Less Fat	Full Fat
Drink	Fruit Drink	Fruit Drink



48) Which cart would you pick?

- Cart A
- Cart B
- Neither