EFFECTS OF A PRODUCE PRESCRIPTION PROGRAM ON NUTRITIONAL OUTCOMES AND FOOD PURCHASES IN NORTH CAROLINA

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## ABSTRACT

Amy Elizabeth Lo: Effects of a Produce Prescription Program on Nutritional Outcomes and Food Purchases in North Carolina
(Under the direction of Shu Wen Ng)

The goal of this project is to assess if participation in a $40/month produce prescription program for the federal Supplemental Nutrition Assistance Program (SNAP) participants with diet sensitive health conditions (SuperSNAP) is associated with changes in food purchase composition and nutritional outcomes compared to matched SNAP beneficiaries. We also assessed if the onset of the COVID-19 pandemic contributed to any other shifts.

This study used retail transaction data (October 2019-April 2022) linked with nutrition label data to assess changes in purchase composition across key food categories and nutrient profile changes. We applied a linear mixed effects model with overlap weights to perform a difference-in-difference analysis of purchases by SuperSNAP program enrollees (treatment) compared to SNAP participants who were not in SuperSNAP (control).

The analytical sample included 1,447 SuperSNAP shoppers and 41,003 control shoppers. SuperSNAP participation was associated with a 6.7% (95% CI (5.9, 7.6), $p < 0.000$) increase in share of calories from fruits, vegetables, nuts, and legumes without additives. Compared to control shoppers, share of total calories purchased by SuperSNAP shoppers decreased by 1.7% (95% CI (-2.2, -1.1), $p < 0.000$) from sugar sweetened beverages and 2.1% (95% CI (-2.8, -1.5), $p < 0.000$) from ultra-processed non-essential foods. We did not find differences in these shifts in purchase compositions since the onset of COVID-19 pandemic. This study shows the promise of targeted produce prescription programs for SNAP participants in encouraging shifts in purchase composition.

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| | |
|---|---|
| CDC | Centers for Disease Control |
| DGA | Dietary Guidelines for Americans |
| DID | Difference-In-Differences |
| FQHC | Federally Qualified Health Center |
| FV | Fruits and Vegetable |
| FVLN | Fruits, Vegetables, Nuts, and Legumes with and without Additives |
| FVLNNA | Fruits, Vegetables, Nuts, and Legumes without Additives |
| GusNIP | Gus Schumacher Nutrition Incentives Pilot |
| NC | North Carolina |
| PLU | Product Look Up Code |
| PM | Processed Meats and Seafood |
| PS | Propensity Score |
| SNAP | Supplemental Nutrition Assistance Program |
| SSB | Sugar Sweetened Beverages |
| UPNF | Ultra Processed Non-essential Foods |
| US | United States |
| USDA | United States Department of Agriculture |

# INTRODUCTION

Higher fruit and vegetable intake is associated with a reduced risk of cardiovascular disease, cancer, and all-cause mortality.[1] However, much of the United States (US) population is not meeting recommended amounts of fruit and vegetable (FV) intake according to the Dietary Guidelines for Americans (DGA).[2] According to 2015 Behavioral Risk Factor Surveillance System data gathered by the Centers for Disease Control (CDC), 12.2% of Americans met fruit intake recommendations and 9.3% met vegetable intake recommendations.[2] In North Carolina specifically, 10.4% met fruit intake recommendations and 8.1% met vegetable intake recommendations.[2] Many factors are associated with a low FV intake, one of which is food insecurity.[3] In 2021, 14.8% of North Carolina (NC) households were food insecure.[4] The largest federal program that seeks to reduce food insecurity is the Supplemental Nutrition Assistance Program (SNAP), which provides benefits to supplement food purchases to approximately 41 million Americans with low incomes.[5] Approximately 12.4% of NC's population received benefits from SNAP in 2019,[6] which covers 73% of food insecure people in NC.[7] Although the SNAP program has made strides to alleviate food insecurity, the average FV intake among Americans on SNAP remains below that of the general population.[8] These results have prompted the recent shift in focus within SNAP as well as in other US Department of Agriculture (USDA) programs beyond food insecurity to include nutrition security, defined as "consistent access to the safe, healthy, affordable foods essential to optimal health and well-being".[9,10]

The COVID-19 pandemic has had immense implications for health, employment, the food supply chain, and prices of food.[11] In particular, food insecurity prevalence rose for certain subpopulations during the pandemic and may not have abated for certain subpopulations. A statewide online survey in Michigan conducted in June 2020 indicated those who were food insecure were more likely to decrease consumption of FV since the start of the pandemic due to concerns about poor quality, poor availability, high price, reduced store trips, and concerns of contamination.[3] Additionally, a national online survey fielded during March 2020 in adults who earned less than 250% of the federal poverty line found that those who were food insecure were unable to comply with the national guidance to have two weeks' worth of food on hand.[11] In addition to the reported initial spike of needs and activity for local food banks, the current literature indicates that effects of the COVID-19 pandemic, followed by other events (e.g., Ukraine war, bird flu) have resulted in higher food prices that may be long lasting.[12] Therefore in lieu of broader socio-political reform to more effectively address poverty, there is need for long term support for food insecure populations in the form of welfare policy reform and expansion.[12]

Many solutions have been proposed to increase FV intake. Cost and accessibility have been identified as major obstacles to improving healthy food access.[13] Produce prescription and healthy food incentive programs have become an important area of research to assess their ability to improve healthy food access. Literature has shown their growing success in increasing produce consumption, improving diet quality, reducing food insecurity, and modestly improving conditions of diet related disease in underserved populations.[14] By providing a voucher or extra funds that can be used only for purchasing FV, cost of these foods can become less of a concern when grocery shopping, and can help increase purchases of allowable produce, while also preserving the autonomy of SNAP participants.[15] However, studies to date examining purchase changes in the context of FV incentives programs have been mostly performed in the farmers market setting.[15] While the farmers market often offers advantages such as fresh FV available at a low price and support for local growers, it also has limitations on hours, accessibility, and the perishability of the produce.[16] Moreover, past studies suggest that farmers markets are not frequented by certain subpopulations such as African Americans and Hispanics and thus FV incentive programs through other retail settings that can allow greater geographical access and diversity of FV options (including frozen, canned and dried beyond fresh FV) compared to farmers markets should also be considered.[16]

Moreover, while past studies have found that produce prescription programs have resulted in an increase in the purchase of FV, it is unclear how these programs shift purchase composition and the nutritional profile of purchases across participants' grocery basket. This is important to understand this because even though the benefits are targeted towards FV, participants have the ability to shift their "out-of-pocket" resources as they choose, and it is unknown how these changes effect diet quality and subsequent health outcomes. Another aspect of existing studies that calls for more research is the lack of strong comparison groups for evaluating produce prescription programs' impact on a range of outcomes.[15] For example, retention rates and dissimilarity between treatment and control groups were indicated as being a major barriers to making quality comparisons and obtaining meaningful results.[15] Additionally, incentive programs were largely implemented in urban settings, thus leaving the effects of such a program in rural settings unknown.[15] However, recent work has shown that dichotomized urban-rural status of a county does not appear to effect SNAP participants' purchasing patterns at least in NC although other dimensions about the food environment might.[17] Tokens, vouchers, and discounts have been tried as delivery methods of the incentives, and those incentives that offer greater buying power instead of discounted FV were found to be more effective for program retention and greater use, and may be more appealing to retailers.[15] Indeed, increases in spending may have effects beyond health-related outcomes such as multiplier effects in the local economy and increased earnings for local food retailers.[18] These economic advantages stem partly from the fact that food insecurity costs the US $160 billion annually and reinforces the important economic advantages of addressing food and nutrition insecurity.[19] Furthermore, interventions targeting vulnerable populations such as SNAP participants may have a larger effect on reducing healthcare costs in some cases because SNAP participants tend to have worse health outcomes and self-assessed health status than non-participants.[15] To investigate such improvements in health, a behavioral response observed in those who participate in such FV incentive programs must be established more thoroughly, and gaps in the existing literature should be addressed.

This thesis seeks to address these gaps by assessing SuperSNAP, a produce prescription program run by Reinvestment Partners and funded by the Gus Schumacher Nutrition Incentive Program (GusNIP) under the USDA, designed to improve diet quality for SNAP participants.[20] SuperSNAP was set in North Carolina among adult SNAP beneficiaries with diet-sensitive health conditions (e.g., diabetes, hypertension) were recruited from nine Federally Qualified Health Centers (FQHCs) across NC.[20] It provides an extra $40 per month to SNAP beneficiaries and can be spent at any of the nearly 500 NC locations of a specific large chain retail grocery store.[20] Program enrollees can use the SuperSNAP benefit to buy fresh, frozen, canned or dried fruits and vegetables with no added sugar, added fat, or added salt (products eligible under the Women, Infants, and Children Cash Value Benefits and thus easy to implement given that the eligible items are already identified for another federal program).[20] Access to the program expired if participants did not spend any SuperSNAP benefits for two consecutive months. Unused benefits at the end of each month rolled over for two months.[20] At its peak, the program had around 800 active participants with participants rolling in and out from October 2019 until the end of the program in April 2022.[20] We used this retailer's transaction data from loyalty card purchases from October 2019-April 2022 to: estimate the SuperSNAP program's impact on purchasing composition and a range of nutritional outcomes and explore the effects before, and during the COVID-19 pandemic.

## METHODS

### Sample

The transaction data used in this study spans 31 months (October 2019 – April 2022) and comes from a large chain retailer which includes 496 locations across 86 counties of NC's 100 counties. The transaction data includes every item sold in each shopping episode at the barcode level including barcode/item number, item description, item size, price, unit of measure, quantity sold, tender types used in the transaction, as well as date of sale, the store where each item was sold and the loyalty-card ID used in the transaction. The enrollment data on SuperSNAP participants includes month of enrollment, first month of use, two-item food insecurity level, household size, whether their household has someone under the age of 19 or above the age of 65, and share of grocery shopping at the participating retailer.

From the transaction data, we used tender type to define a loyalty card shopper as a SNAP participant if they had ever used SNAP benefits to pay for their shopping episode. We chose this definition based on analysis of the proportion of months shoppers used their SNAP benefits. Our analysis is at the loyalty-card ID-month level.

Three different steps were taken to clean the data (See Figure 1 for how they affected sample size). Loyalty-card IDs in the top 1% of expenditure and calories were dropped from our dataset as we suspect they are store loyalty cards used at the cash register for patrons who did not have a loyalty card, but wanted to get discounts. To address remaining outliers and to ensure that extreme values do not bias results, the top 0.1% of all the variables we matched on (see Appendix 1 for full list of variables) were top-coded at the 99.9$^{th}$ percentile. This means the top 0.1% values of each variable were replaced the 99.9$^{th}$ percentile value. This data cleaning step was executed based on reasonable plausibility of values as determined by the research team. Given the outcome measures of interest described later (share of calories and nutrients per 1000 kilocalories), observations with zero calorie purchased across a month were dropped as well to retain only data that pertained to the study's objectives.

**Linkage to Nutrition Data and Outcome Categorization**

Existing nutrition label data at the barcode-level came from several sources, including the USDA's National Nutrient Database for Standard Reference and Mintel Global New Product Database. [21,22] Data from these sources were merged with the transaction data and used to categorize items sold as foods or non-foods. Unpackaged items that did not have barcodes and instead had product look up (PLU) codes such as fresh FV were linked to the USDA's Food and Nutrient Database for Dietary Studies for nutrient values and for appropriate categorization. We were thus able to derive nutrient values (e.g., calories, sodium, fiber), and categorize foods into nutritionally relevant food groups (see next section).

**Outcome Measures**

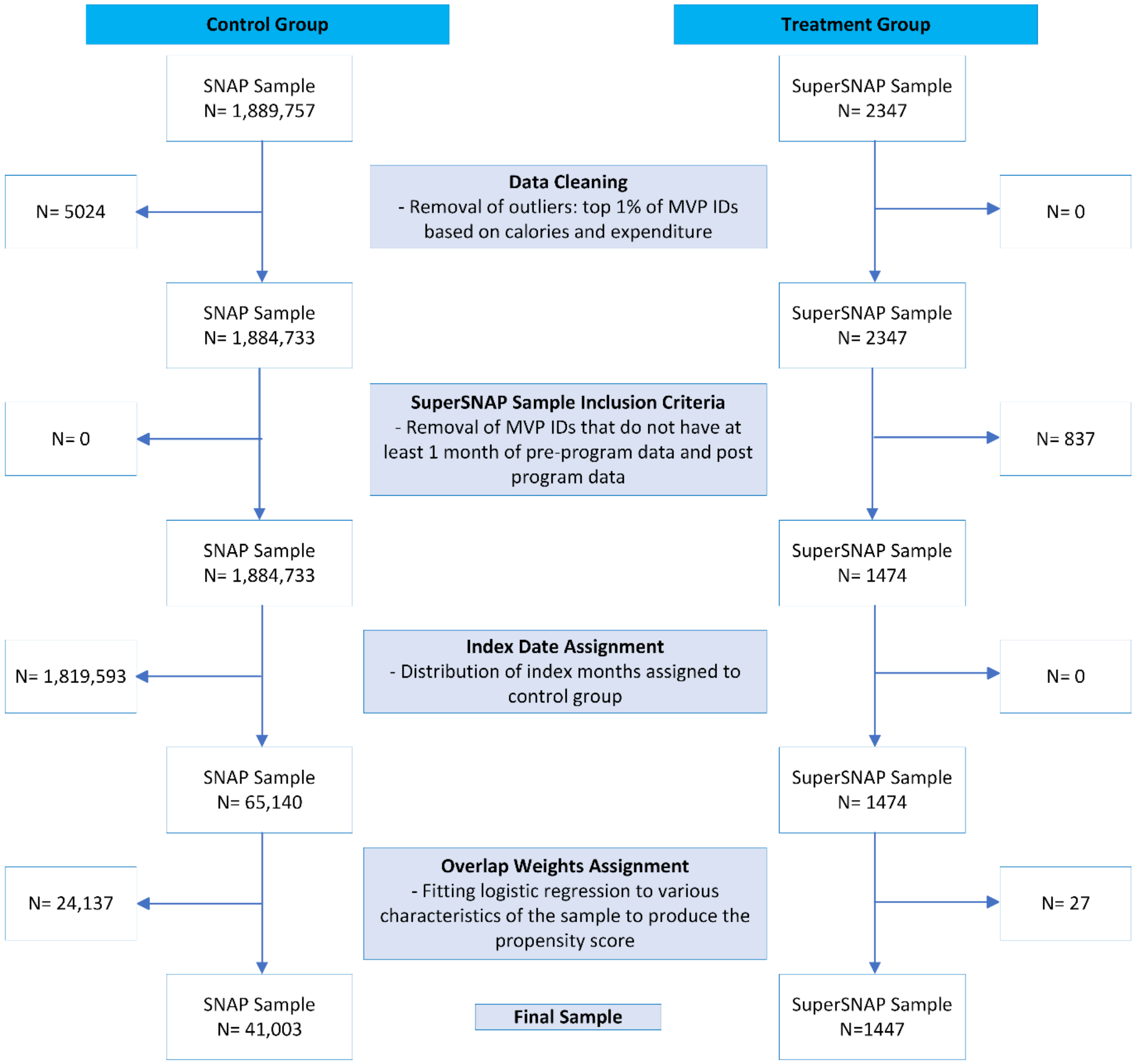
The primary outcomes for this study are: the share of total calories coming from five food groups: fruits, vegetables, nuts, and legumes with and without additives (FVNL and FVNLNA, respectively), sugar-sweetened beverages (SSB), ultra processed non-essential food (UPNF), and processed meats and seafood (PM). UPNF includes desserts and sweet snacks, salty snacks, and candy chocolate and gum. Other papers have used the same groupings in their analyses to examine purchasing patterns.[17,20,23]

The secondary outcomes included milligrams of sodium per 1000 calories, total milligrams of sodium, grams of protein per 1000 calories, grams of saturated fat per 1000 calories, grams of total fat per 1000 calories, grams of added sugar per 1000 calories, total grams of fiber, total grams of carbohydrate, grams of carbohydrate per grams of fiber, and grams of carbohydrate per 1000 calories to more closely examine health-related nutrients. We focused on nutritional measures outcomes of interest in this study because of the downstream analysis to include health outcomes from electronic health records, so we can better assess potential "dose-response" relationships between nutritional changes and health outcome changes. Moreover, we used relative measure for all the outcomes for a number of reasons. First, because we are only able to observe purchases from a single store chain and not overall purchases or dietary intake. Second, we did not have any demographic information about shoppers including household size which makes interpretation of absolute measures challenging. Finally, the onset of COVID-19 likely meant significant changes in the amount of food purchases from stores. Consequently, using share of calories by food groups and nutrient relative to calories mitigated these limitations.

**Statistical Analyses**

The goal of this study was to estimate the SuperSNAP program's impact by comparing food purchase composition and nutritional and outcomes between SuperSNAP program participants (treatment group) and a comparable group of shoppers who did not enroll in the program but still received SNAP benefits (control group). Those included in our treatment group had to have a minimum of 1 month of pre-SuperSNAP program data and an index date. Index date is defined as the month enrollment into SuperSNAP. In keeping with the goal to match our treatment and control group, we assigned a pseudo-index date to the control group with the same distribution as the treatment group (See Figure 1 flow chart to see how it affected sample size). We conducted sensitivity analysis to explore the alternative definition of index date in which it is established as the first month during which the participant used SuperSNAP benefits. We did this to determine if there were any notable differences between a group that was assigned a treatment (intent-to-treat) and a group that actually received treatment (treatment on treated).

**Figure 1. Control and Treatment Sample Flow Chart**




Because we did not have demographic data for all shoppers and program participation was not randomized, we used overlap weighting to simulate randomization. Overlap weighting is a propensity score (PS) method where each unit receives a weight equal to the probability of being in the other group, i.e., the control group for treated units and the treated group for control units.[24] We implemented this method by logistic regression of SuperSNAP participation on a comprehensive list of variables describing purchases and the index date (see Appendix 1 for full list of variables), estimated on pre-index date, shopper-month-level data, and using the predicted probabilities corresponding to each shopper's last pre-index date observation to derive the overlap weights.[20,23] Overlap weighting also allowed us to not lose any observations with more extreme predicted probabilities by down-weighting them rather than dropping them altogether and is especially useful in situations when either the treatment and/or control sample size might be of concern.[24]

We employed these overlap weights in a difference-in-differences (DID) framework using linear mixed models with SuperSNAP participation (1 or 0), time in relation to index date (0, before index date; 1, on or after index date), and their interaction (the DID estimate of the program's impact).

To estimate the effect of the COVID-19 pandemic on the program's impact, we estimated another series of models with an indicator variable equal to 0 before March 2020 and 1 thereafter, and its interactions with SuperSNAP participation, time, and their interaction. The triple interaction is the COVID-19 pandemic's effect on the program's impact. We chose March 2020 as the start of the COVID-19 pandemic because that is when the North Carolina state of emergency was declared.

Because the store at which an individual shopped may have provided information about geographic characteristics and socioeconomic status and because those who shopped at the same stores may have been more similar than those who shopped at different stores, we used a random intercept term for most shopped at store ID (the store that received a majority of expenditures for a given shopper ID in a given month). To account for repeated measurements within shopper ID numbers, we also included a random intercept term for shopper ID. Additionally, we included a term that accounts for seasonality, assigning numbers 1 through 12 for each month of the year.

## RESULTS

### Sample Characteristics

Our primary analysis included 1447 SuperSNAP participants based on their enrollment month and required at least 1 month of pre-enrollment transaction data. The control group included 41,003 SNAP participants who never enrolled in SuperSNAP or any other similar programs implemented during this time (e.g., Healthy Helping).[23]

Table 1 shows the self-reported characteristics of the treatment group at the time of enrollment, as defined by enrollment (main analysis, N=1447) and as defined by usage (sensitivity analysis, N=1633). While it may seem counterintuitive that the analytical sample size is larger among those who use the program in the sensitivity analysis, this is because program users were more likely to have more than one-month of pre-program use for the timeframe of the data we had access to. In our main analysis, the mean (SD) household size was 2.1 (1.7), 328 participants reported having at least 1 member aged 19 years or younger, 221 participants reported having at least 1 member aged 65 or older, and 34 participants reported having both at least 1 member aged 19 years or younger and at least 1 member aged 65 or older. More than half (882 participants) were determined to be food insecure, and 125 participants were enrolled in WIC benefits at the time of enrollment to SuperSNAP. The majority of SuperSNAP participants reported their frequency of monthly food shopping at the retailer as “usually” and “always”. The characteristics in the sensitivity analysis treatment sample where we use month of first use date instead of enrollment date as the index date were similar to those in our main analysis.

**Table 1. Sample Characteristics of SuperSNAP enrollees at point of program enrollment used in main and sensitivity analyses**

| Self-reported characteristic at time of enrollment | Enrolled in SuperSNAP with at least 1 month of pre-enrollment data (N= 1447)<br>Main analysis treatment sample | Participants that used SuperSNAP Benefit with at least 1 month of pre-use data (N= 1633)<br>Sensitivity analysis treatment sample |
|---|---|---|
| Mean Household Size (SD) | 2.1 (1.7) | 2.1 (1.7) |
| Missing | 266 | 287 |
| Households with at least 1 members < aged 19 years (%) | 328 (22.7) | 381 (23.3) |
| Households with at least 1 members > aged 65 years (%) | 221(15.3) | 239 (14.6) |
| Households with both at least 1 member < aged 18 years and 1 members > aged 65 years (%) | 34 (2.3) | 37 (2.3) |
| Missing or Neither (%) | 864 (59.7) | 977 (59.8) |
| Food Insecure (%) | 882 (60.9) | 1,004 (61.4) |
| Missing (%) | 446 (30.8) | 502 (30.7) |
| Enrolled in WIC (%) | 125 (8.6) | 145 (8.9) |
| Missing (%) | 397 (27.4) | 442 (27.1) |
| Frequency of monthly food shopping at SuperSNAP grocery store (%) | | |
| Never | 11 (0.8) | 15 (0.9) |
| Seldom | 86 (5.9) | 106 (6.5) |
| About Half the Time | 243 (16.8) | 278 (17.0) |
| Usually | 386 (26.7) | 438 (26.8) |
| Always | 389 (26.9) | 424 (25.9) |
| Missing | 332 (22.9) | 372 (22.8) |

Note: The sample generated from using the month of first use of program benefits is larger because more SuperSNAP users/participants had at least 1 month of pre-use data than had pre-enrollment data.

SuperSNAP enrollees' average time from enrollment to last month of use was 16.8 months with a standard deviation of 6.7 months and a range of 0 to 28 months. Half of the total sample's enrollment months was between months 2 and 11 (November 2019 to August 2020).

**Overlap Weighted Pre-Program Outcome Measures**

To contextualize the estimated changes in the primary outcomes, Appendix 2 shows the overlap weighted pre-program outcome means in the SuperSNAP treatment group and control group. Outcomes are reported in mean amount of calories from the five primary outcomes per day, assuming there are 30 days in a month. The breakdown by outcome in SuperSNAP treatment and control groups are comparable, as expected after overlap weighting. Outcomes only cover prioritized food categories strongly linked to health outcomes and do not cover the total calories purchased but represent about 60 percent of total calories purchased. Further disaggregation of the total data will be able to capture a larger portion of total calories purchased.

**Changes in Purchase Composition and Nutritional Profile Associated with SuperSNAP**

Table 2 shows the difference-in-differences results between the SuperSNAP treatment group and the control group. Share of total calories purchased by shoppers in SuperSNAP increased by 6.7 percentage points (95% CI (5.8, 7.7), p-value <0.000) from the FVNL food category and 6.7 percentage points (95% CI (5.9, 7.6), p-value <0.000) from the FVNLNA food category. Compared to shoppers only in SNAP, share of total calories purchased by shoppers in SuperSNAP decreased by 1.7 percentage points (95% CI (-2.2, -1.1), p-value <0.000) from the SSB food category and 2.1 percentage points (95% CI (-2.8, -1.5), p-value <0.000) from the UPNF food category. The decrease in share of calories purchased from processed meat and seafood was not statistically significant. Figure 2 contextualizes the changes found in Table 2 and depicts the model adjusted means for four of the five primary outcomes.

For secondary outcomes, a statistically significant change was found in every outcome except for milligrams of sodium per 1000 calories. The SuperSNAP treatment group's grams of carbohydrates per 1000 calories purchased increased by 5.92 (95% CI (4.5, 7.3), p-value <0.000). Their grams of carbohydrates per grams of fiber purchased decreased by 11.37 (95% CI (-14.3, -8.4), p-value <0.000). Both absolute measures, total grams of fiber and total grams of carbohydrate increased by 178.72 (95% CI (164.8, 192.7), p-value <0.000) and 2521.99 (95% CI (2243.1, 2800.9), p-value <0.000) respectively.

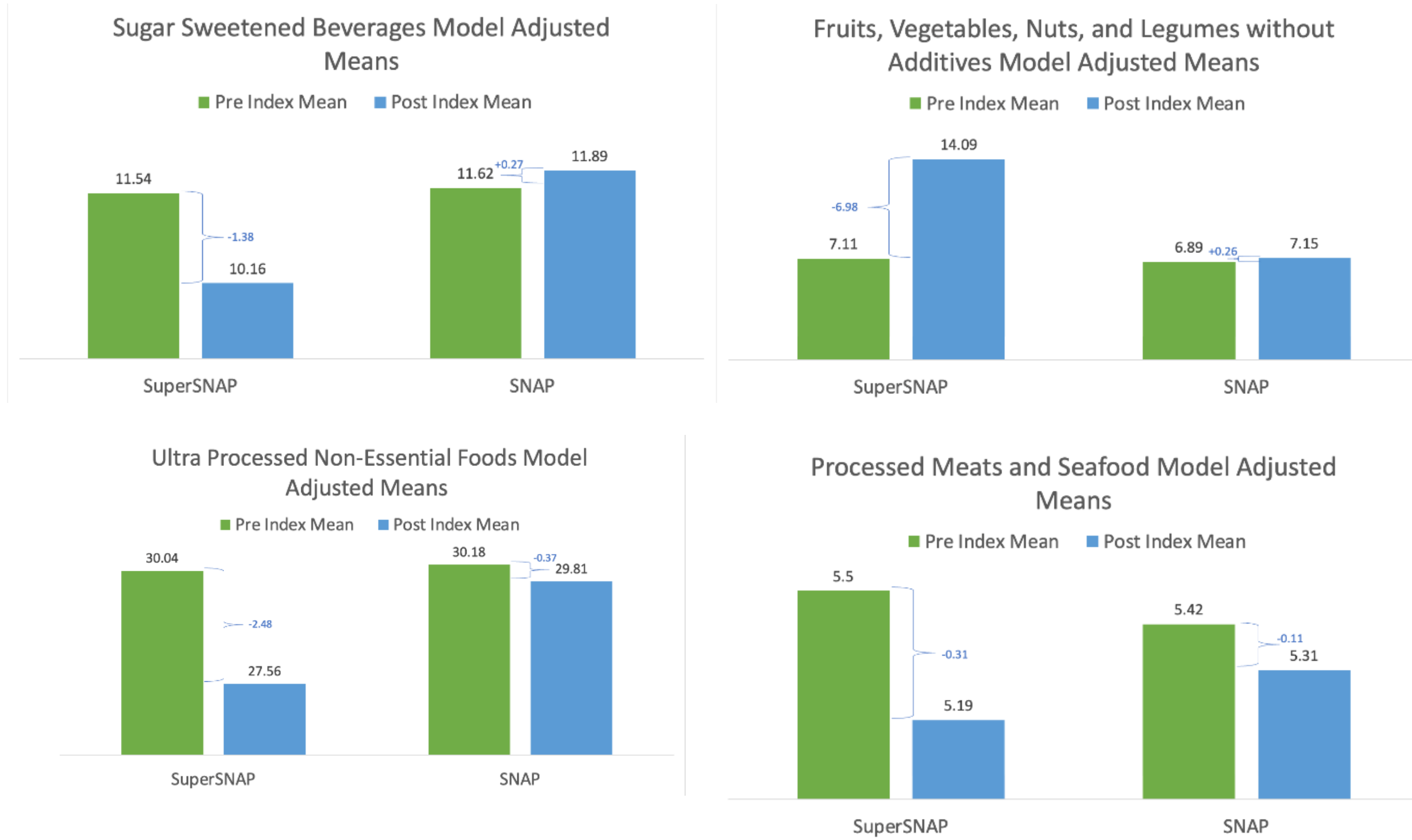
The treatment group's added sugar per 1000 calories purchased increased by 2.40 (95% CI (1.2, 3.7), p-value <0.000), grams of total fat per 1000 calories purchased decreased by 1.87 (95% CI (-2.4, -

1.4), p-value <0.000), and grams of saturated fat per 1000 calories purchased decreased by 0.92 (95% CI (-1.1, -0.7), p-value <0.000). Grams of protein per 1000 calories purchased decreased by 0.61 (95% CI (-1.0, -0.2), p-value = 0.001). While the total milligrams of sodium purchased increased by 27891.03 (95% CI (20418.2, 35363.8), p-value <0.000), the ratio of milligrams of sodium per 1000 calories decreased by a statistically insignificant value of 39.63 (95% CI (-153.7, 74.5), p-value = 0.496).

**Table 2. Model Adjusted Changes associated with SuperSNAP**

| | Percentage Point Changes Associated with SuperSNAP | |
|---|---|---|
| **Primary Outcomes: Share of Calories from** | Estimate (95%CI) | p-value |
| Fruits, Vegetables, Nuts, and legumes with and without additives | 6.7 (5.8, 7.7) | 0.000 |
| Fruits, Vegetables, Nuts, and legumes without additives | 6.7 (5.9, 7.6) | 0.000 |
| Processed Meats and Seafood | -0.2 (-0.5, 0.0) | 0.099 |
| Sugar Sweetened Beverages | -1.7 (-2.2, -1.1) | 0.000 |
| Ultra Processed Non-essential Foods | -2.1 (-2.8, -1.5) | 0.000 |
| **Secondary Outcomes: Nutrients** | Estimate (95%CI) | p-value |
| Milligrams of Sodium per 1000 Calories | -39.6 (-153.7, 74.5) | 0.496 |
| Total Milligrams of Sodium per month | 27891.0 (20418.2, 35363.8) | 0.000 |
| Grams of Protein per 1000 Calories | -0.6 (-1.0, -0.2) | 0.001 |
| Grams of Saturated Fat per 1000 Calories | -0.9 (-1.1, -0.7) | 0.000 |
| Grams of Total Fat per 1000 Calories | -1.9 (-2.4, -1.4) | 0.000 |
| Grams of Added Sugar per 1000 Calories | 2.4 (1.2, 3.7) | 0.000 |
| Total Grams of Fiber per month | 178.7 (164.8, 192.7) | 0.000 |
| Total Grams of Carbohydrate per month | 2522.0 (2243.1, 2800.9) | 0.000 |
| Grams of Carbs per Grams of Fiber | -11.4 (-14.3, -8.4) | 0.000 |
| Grams of Carb per 1000 Calories | 5.9 (4.5, 7.3) | 0.000 |

**Figure 2. Bar graphs showing the mean share of total calories from food groups before and after the index date in the SuperSNAP and SNAP groups**



**Is the onset of COVID-19 moderate changes in food purchase composition and nutritional profile under SuperSNAP?**

Table 3 shows the exploratory COVID-19 pandemic analysis results. There were no statistically significant differences in SuperSNAP's estimated impact on the primary outcomes before and during COVID-19. However, we do see that the percentage point decrease in share of calories coming from SSBs is greater during the COVID-19 pandemic. We also found that the percentage point decrease in share of calories coming from UPNF is lessened during the pandemic.

Among the secondary outcome measures, during COVID-19 SuperSNAP's estimated impact decreased by 5.18 (95% CI (-10.2, -0.1), p-value =0.045) for grams of carbohydrates per 1000 calories purchased, and increased by 1424.15 (95% CI (658.2, 2190.1), p-value <0.000) for total grams of carbohydrates and by 63.66 (95% CI (27.7, 99.6), p-value = 0.001) for total grams of fiber. The SuperSNAP estimated impact on grams of total fat per 1000 calories purchased increased 2.33 (95% CI (0.3, 4.4), p-value = 0.028) after the onset of COVID-19.

**Table 3. Difference-in-Difference analysis pre COVID-19 Pandemic, During COVID-19 Pandemic, and the Difference-in-Difference-in-Difference analysis showing the impact of the COVID-19 pandemic on the SuperSNAP effects on purchasing**

| | Estimated Percentage Point Changes Associated with SuperSNAP Pre COVID-19 Pandemic | | Estimated Percentage Point Changes Associated with SuperSNAP During COVID-19 Pandemic | | Difference between Estimated Changes Associated with SuperSNAP Pre-Pandemic and During Pandemic | |
|---|---|---|---|---|---|---|
| **Primary Outcomes: Share of Calories from** | Estimate (95%CI) | p-value | Estimate (95%CI) | p-value | Estimate (95%CI) | p-value |
| Fruits, Vegetables, Nuts, and legumes with and without additives | 7.9 (5.3, 10.6) | 0.000 | 6.8 (5.8, 7.8) | 0.000 | -1.2 (-3.8, 1.5) | 0.394 |
| Fruits, Vegetables, Nuts, and legumes without additives | 8.2 (5.6, 10.8) | 0.000 | 6.7 (5.8, 7.6) | 0.000 | -1.5 (-4.0, 1.2) | 0.276 |
| Processed Meats and Seafood | -0.1 (-1.1, 1.0) | 0.918 | -0.2 (-0.5, 0.2) | 0.313 | -0.1 (-1.2, 1.0) | 0.849 |
| Sugar Sweetened Beverages | -0.0 (-1.9, 1.8) | 0.971 | -1.6 (-2.3, -1.0) | 0.000 | -1.6 (-3.5, 0.3) | 0.102 |
| Ultra Processed Non-essential Foods | -4.3 (-6.5, -2.1) | 0.000 | -2.3 (-3.0, -1.5) | 0.000 | 2.1 (-0.3, 4.4) | 0.085 |
| **Secondary Outcomes: Nutrients** | Estimate (95%CI) | p-value | Estimate (95%CI) | p-value | Estimate (95%CI) | p-value |
| Milligrams of Sodium per 1000 Calories | -236.5 (-881.3,408.4) | 0.472 | -28.4 (-162.0, 105.2) | 0.676 | 208.0 (-449.5, 865.6) | 0.535 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Total Milligrams of Sodium per month | 5013.02 (-38786.8, 48812.9) | 0.822 | 28275.81 (20218.7, 36332.9) | 0.000 | 23262.8 (-19329.3, 65854.9) | 0.284 |
| Grams of Protein per 1000 Calories | 0.2 (-1.2, 1.6) | 0.791 | -0.5 (-0.9, -0.1) | 0.017 | -0.7 (-2.1, 0.7) | 0.337 |
| Grams of Saturated Fat per 1000 Calories | -1.5 (-2.3, -0.7) | 0.000 | -.9 (-1.1, -0.6) | 0.000 | 0.6 (-0.1, 1.4) | 0.101 |
| Grams of Total Fat per 1000 Calories | -4.0 (-6.0,-2.0) | 0.000 | -1.7 (-2.2, -1.1) | 0.000 | 2.3 (0.3, 4.4) | 0.028 |
| Grams of Added Sugar per 1000 Calories | 6.3 (0.7, 11.9) | 0.026 | 2.0 (0.6, 3.4) | 0.005 | -4.3 (-9.8, 1.2) | 0.129 |
| Total Grams of Fiber per month | 116.1 (78.7, 153.6) | 0.000 | 179.8 | 0.000 | 63.7 (27.7, 99.6) | 0.001 |
| Total Grams of Carbohydrate per month | 1175.4 (373.2, 1977.7) | 0.004 | 2599.6 (2321.1, 2878.0) | 0.000 | 1424.2 (658.2, 2190.1) | 0.000 |
| Grams of Carbs per Grams of Fiber | -11.1 (-18.3, -3.9) | 0.002 | -12.1 (-15.5, -8.6) | 0.000 | -1.0 (-8.1, 6.2) | 0.792 |
| Grams of Carb per 1000 Calories | 10.5 (5.5, 15.6) | 0.000 | 5.3 (3.9, 6.8) | 0.000 | -5.2 (-10.2, -0.1) | 0.045 |

**Sensitivity Analysis**

As indicated earlier, we conducted a sensitivity analysis wherein we used the first month of SuperSNAP use (rather than month of enrollment) as index date. We found that changes associated with SuperSNAP were similar to results found in the original analysis (See Appendix 3).

## DISCUSSION

In this quasi-experimental study, we found that SuperSNAP participation was associated with meaningful shifts in purchasing and nutritional compositions. We saw an increase in share of total calories from fruits, vegetables, nuts, and legumes with and without additives (FVNL), fruit, vegetables, nuts, and legumes without additives (FVNLNA), as well as a decrease in share of total calories from sugar sweetened beverages (SSB) and ultra processed non-essential foods (UPNF). Decreases in the ratio of carbs to fiber, grams of total and saturated fat per 1000 calories, and grams of protein per 1000 calories were observed in association with program use. We also saw no statistically significant change in sodium per 1000 calories and a slight increase in added sugars per 1000 calories. Given that we saw a decreased share of calories coming from SSBs and UPNF, this change may have come from added sugars in the FVLN category or other categories not included as primary outcomes. In our exploratory analyses, we found that the COVID-19 pandemic was not associated with any statistically significant differences in the effect of SuperSNAP.

As seen in Figure 2, the mean share of calories coming from FVLNNA almost doubled after enrollment into the SuperSNAP program. According to 1999-2008 NHANES data, SNAP participants consumed an average of 0.9 cups of vegetables (recommended intake is >2.5 cups) and an average of 0.7 cups of fruit (recommended intake is >2 cups).[25] Assuming the SuperSNAP participants consumed their purchases, doubling intake would increase their average intake to nearly match the recommended intake for fruit and more than 70% of the recommended intake for vegetables, outpacing low-income nonparticipants. However, the mean household size of the SuperSNAP treatment group was 2.1 (see Table 1) and likely shared groceries with their household. Future produce prescription programs aiming to improve FV intake should consider accounting for household size especially if the enrollee is the main household member responsible for grocery purchasing.

There are several implications of this study. Many of the pre-existing studies on produce incentives have been held in the farmers market setting using tokens and vouchers.[14,15] While those studies have some advantages, scalability is limited because of the accessibility constraints (e.g., hours, location) and lack of cultural foods that may make certain people unlikely to use the program.[16] In addition, fresh produce's shelf life is limited.[16] This program was able to offer fresh, canned, and frozen fruit and vegetables for purchase with program benefits, which have been shown to be equally nutritious.[26]

The SuperSNAP program exemplified a produce prescription program in a widely accessible large chain grocery store setting. These factors indicate the potential for high volume scalability also in terms of potential financial sustainability from federal (e.g., Medicaid, Medicare) and/or private sources (e.g., private insurance or philanthropic organizations). The present results, particularly for the shares of calories from FVNL and from foods linked to chronic disease, exhibit the potential for this program to address health outcomes, which will be explored in future research.

In addition to SuperSNAP's potential for scalability and its impact on determinants of health outcomes, it showed resilience after the onset of COVID-19 pandemic. Though we did not find any statistically significant outcomes, these results may indicate that despite the COVID-19 pandemic's wide-reaching effects on the food supply chain, job security, and social norms, little was changed in terms of SuperSNAP's implications for food purchasing.[11,12] However, the analysis only had a maximum of 4 months of pre-COVID-19 pandemic data which may limit our ability to truly detect changes in trends due to COVID-19. Changes in share of calories from all but PM pre- and during COVID-19 were found to be statistically significant. Notably, the pandemic was associated with a smaller percentage point decrease in share of calories from UPNF and a greater percentage point decrease in share of calories from SSB. More investigation into why these changes occurred is needed to fully understand these results. Changes in share of calories coming from fruits, vegetables, nuts, and legumes appeared to be dampened by the pandemic, possibly due to supply chain disturbance and reluctance to purchase fruits and vegetables online.

An earlier study conducted on the same SuperSNAP program similarly found increased share of spending on fruits, vegetables, nuts, and legumes and a decreased share of spending on less healthy food categories and SSB associated with the program.[20] Because our results were similar, we believe there is prolonged behavior change linked with program use, but further work must be done to investigate whether these associations are sustained after program cessation. As mentioned before, the average program retention was 16.8 months. Compared to other incentive program studies, the program use length was substantial, possibly indicating program satisfaction and practicality.[14,15] Further investigation on user perspectives were explored in a separate survey study to be published in a separate paper. Future research aims to combine this study's results with clinical measures using electronic health records data.

**Strengths and Limitations**

There are strengths associated with this study. First, it utilizes a robust objective dataset spanning up to 31 months, covering a major chain grocery store in North Carolina. Second, our study uses a strong statistical method that addresses confounding through propensity score based weighting and difference-in-differences analysis that does not eliminate extreme propensity scores. Rather, it weights them accordingly because overlap weights are bounded by 0 and 1. Consequently, these methods provide strong internal validity to the results. Overlap weighting also leads to estimators of average effects on the overlap population (i.e. treated and control units whose observed characteristics overlap the most). This is relevant because the effects that are estimated could be interpreted as the effects of extending SuperSNAP. In an income-based program like SNAP, this would mean extending eligibility to those previously just above the income limit by increasing the income limit by a small amount.

There are several limitations to keep in mind with our study. The data used in this study was based only on transactions and cannot show change in diet quality of the participant or their household. However, change in purchasing behavior in the setting of a highly frequented grocery store may translate to improved diet quality. While many of the participants indicated that they did a large portion of their monthly food shopping at the large chain grocery store, we cannot account for purchases made without the use of their loyalty cards or at different stores like convenience stores or mass merchandizers. In addition, SuperSNAP participants (treatment group) were likely systematically different from our SNAP participants (control group) because of non-random enrollment based on diet sensitive chronic disease status, which may have impacted how conscientious participants were of their purchasing. We attempted to address this with our rigorous statistical methods, but confounding cannot be ruled out. Similarly, some SuperSNAP participants were not captured in our analysis because of the limits of data collection and definition of index date. Those who may have pre-index date data and enrolled in October 2019 were not included. However, this does not seem to affect our results as evidenced by the sensitivity analysis. Moreover, the data did not include socio-demographic measures and so we were only able to create propensity scores based on prior food purchasing behaviors and were unable to account for socio-demographic characteristics. Therefore, generalization of our results to a greater population should be cautious and further study addressing these limitations should be explored.

**Conclusions**

In this quasi-experimental study on SuperSNAP, a produce prescription program, we found that program enrollment was associated with a meaningfully large increase in share of total calories purchased from FVNL and FVNLNA and a decrease in share of total calories purchased from SSB and PM categories. Future studies should investigate purchasing behaviors after program cessation, the link between purchasing changes and clinical outcomes as assessed by electronic health record data, and other large scale measures that can preserve healthful changes in purchasing habits.

## APPENDIX 1: WEIGHTED AND UNWEIGHTED MEANS OF VARIABLES MATCHED ON FOR PROPENSITY SCORE GENERATION

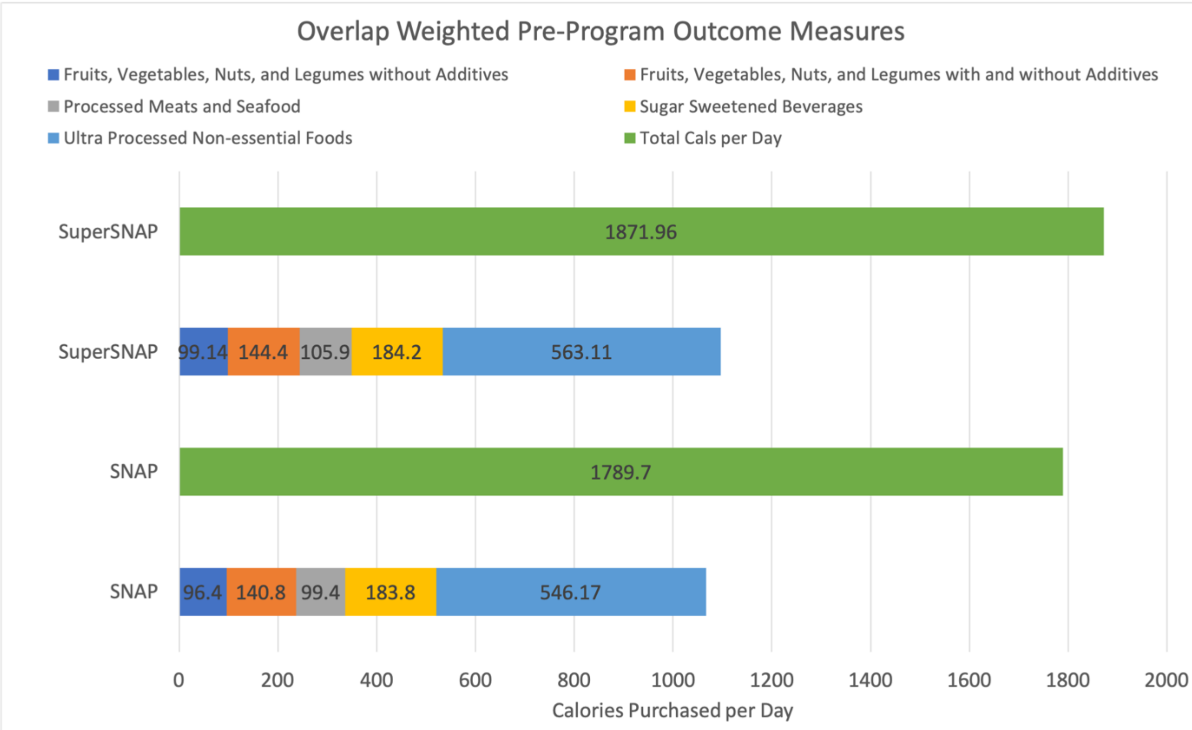
| | Weighted | | Unweighted | |
|---|---|---|---|---|
| | **SNAP** | **SuperSNAP** | **SNAP** | **SuperSNAP** |
| The number of shopping episodes that an MVP ID used SNAP in a month | 1.8 | 2.2 | 1.1 | 2.3 |
| (SD) | (2.7) | (2.7) | (2.1) | (2.7) |
| Percentage of transactions used with non-SS coupon/offer code during month | 0.1 | 0.1 | 0.1 | 0.1 |
| (SD) | (0.1) | (0.1) | (0.1) | (0.1) |
| Food/Beverage total cals (kcal) purchased | 53,692.1 | 56,158.8 | 54,566.0 | 56,494.7 |
| (SD) | (52,613.8) | (52,859.5) | (52,194.9) | (53,085.2) |
| Energy (kcals) on CCG during month | 863.1 | 923.2 | 903.0 | 914.3 |
| (SD) | (2,079.5) | (2,125.1) | (2,134.9) | (2,105.5) |
| Energy (kcals) on UPNF during month | 16,385.1 | 16,893.2 | 16,712.1 | 16,955.0 |
| (SD) | (17,935.3) | (17,781.9) | (17,988.1) | (17,705.4) |
| Energy (kcals) on DSS during month | 6,750.1 | 6,906.8 | 6,832.9 | 6,931.4 |
| (SD) | (8,864.3) | (8,557.3) | (8,838.1) | (8,567.3) |
| Energy (kcals) on FVLN during month | 4,224.7 | 4,330.6 | 4,520.0 | 4,335.0 |
| (SD) | (5,144.8) | (5,109.3) | (5,431.1) | (5,121.7) |
| Energy (kcals) on FVLNNA during month | 2,893.1 | 2,974.2 | 3,102.3 | 2,984.9 |
| (SD) | (3,858.8) | (3,865.3) | (4,062.7) | (3,895.5) |
| Energy (kcals) on PMS during month | 2,982.1 | 3,178.6 | 2,997.2 | 3,228.2 |
| (SD) | (4,438.4) | (4,565.0) | (4,391.0) | (4,617.9) |
| Energy (kcals) on SaltyS during month | 3,715.2 | 3,726.1 | 3,944.5 | 3,700.4 |
| (SD) | (5,093.6) | (5,172.4) | (5,312.5) | (5,102.6) |
| Energy (kcals) on SSB during month | 5,514.3 | 5,525.1 | 5,379.4 | 5,556.1 |
| (SD) | (7,946.9) | (7,710.2) | (7,795.5) | (7,715.2) |
| Energy (kcals) on ST during month | 2,038.1 | 2,115.8 | 1,991.2 | 2,142.2 |
| (SD) | (5,043.4) | (5,134.6) | (4,913.9) | (5,160.8) |
| g of carbs / 1000 kcals of total food and beverages for that month | 139.5 | 136.8 | 139.1 | 136.8 |
| (SD) | (42.7) | (41.8) | (41.7) | (41.8) |
| g of carbs / g of fiber of total food and beverages for that month | 36.1 | 35.8 | 34.5 | 35.8 |
| (SD) | (97.6) | (96.7) | (91.1) | (96.3) |
| mg of sodium / 1000 kcals of total food and beverages for that month | 1,952.8 | 1,901.7 | 1,992.1 | 1,900.6 |
| (SD) | (4,663.0) | (3,799.5) | (4,945.2) | (3,812.2) |
| Percentage of UPNF with no nutritional information ($) | 0.1 | 0.1 | 0.1 | 0.1 |
| (SD) | (0.2) | (0.2) | (0.2) | (0.2) |

| | | | | |
|---|---|---|---|---|
| Percentage of UPNF with no nutritional information (oz) | 0.1 | 0.1 | 0.1 | 0.1 |
| (SD) | (0.2) | (0.2) | (0.2) | (0.2) |
| Percentage of SaltyS with no nutritional information ($) | 0.0 | 0.0 | 0.0 | 0.0 |
| (SD) | (0.1) | (0.1) | (0.1) | (0.1) |
| Percentage of SaltyS with no nutritional information (oz) | 0.0 | 0.0 | 0.0 | 0.0 |
| (SD) | (0.1) | (0.1) | (0.1) | (0.1) |
| Percentage of ST with no nutritional information ($) | 0.0 | 0.0 | 0.0 | 0.0 |
| (SD) | (0.1) | (0.2) | (0.2) | (0.2) |
| Percentage of ST with no nutritional information (oz) | 0.0 | 0.0 | 0.0 | 0.0 |
| (SD) | (0.1) | (0.2) | (0.2) | (0.2) |
| Percentage of PMS with no nutritional information ($) | 0.2 | 0.2 | 0.2 | 0.2 |
| (SD) | (0.3) | (0.3) | (0.3) | (0.3) |
| Percentage of PMS with no nutritional information (oz) | 0.2 | 0.2 | 0.2 | 0.2 |
| (SD) | (0.3) | (0.3) | (0.3) | (0.3) |
| Percentage of FVLNNA with no nutritional information (oz) | 0.1 | 0.1 | 0.1 | 0.1 |
| (SD) | (0.1) | (0.1) | (0.1) | (0.1) |
| Percentage of FVLN with no nutritional information ($) | 0.1 | 0.1 | 0.1 | 0.1 |
| (SD) | (0.1) | (0.1) | (0.1) | (0.1) |
| Percentage of FVLN with no nutritional information (oz) | 0.0 | 0.0 | 0.1 | 0.0 |
| (SD) | (0.1) | (0.1) | (0.1) | (0.1) |
| Percentage of SSB with no nutritional information ($) | 0.1 | 0.1 | 0.1 | 0.1 |
| (SD) | (0.2) | (0.2) | (0.2) | (0.2) |
| Percentage of SSB with no nutritional information (oz) | 0.1 | 0.1 | 0.1 | 0.1 |
| (SD) | (0.2) | (0.2) | (0.2) | (0.2) |
| Percentage of CCG with no nutritional information ($) | 0.0 | 0.0 | 0.0 | 0.0 |
| (SD) | (0.2) | (0.2) | (0.2) | (0.2) |
| Percentage of CCG with no nutritional information (oz) | 0.0 | 0.0 | 0.0 | 0.0 |
| (SD) | (0.2) | (0.2) | (0.2) | (0.2) |
| Food/Beverage/NonFood total dollars ($) spent | 196.2 | 199.4 | 216.5 | 198.1 |
| (SD) | (188.0) | (184.7) | (202.8) | (183.7) |
| Food/beverage total dollars ($) spent | 175.1 | 179.9 | 187.4 | 179.3 |

| | | | | |
|---|---|---|---|---|
| (SD) | (168.9) | (168.0) | (175.7) | (167.1) |
| Expenditure ($) on CCG during month | 2.7 | 3.0 | 2.8 | 2.9 |
| (SD) | (6.0) | (6.3) | (6.0) | (6.2) |
| Expenditure ($) on DSS during month | 14.4 | 14.8 | 15.1 | 14.8 |
| (SD) | (18.6) | (18.2) | (19.0) | (18.2) |
| Expenditure ($) on FVLN during month | 21.5 | 22.4 | 23.8 | 22.2 |
| (SD) | (25.8) | (26.3) | (27.7) | (26.0) |
| Expenditure ($) on FVLNNA during month | 17.0 | 17.7 | 18.8 | 17.6 |
| (SD) | (21.8) | (22.5) | (23.4) | (22.2) |
| Expenditure ($) on PMS during month | 14.1 | 15.0 | 14.8 | 15.1 |
| (SD) | (18.6) | (19.3) | (19.4) | (19.4) |
| Expenditure ($) on SSB during month | 22.5 | 22.5 | 23.6 | 22.5 |
| (SD) | (30.5) | (29.8) | (31.7) | (29.8) |
| Expenditure ($) on ST during month | 1.5 | 1.6 | 1.6 | 1.6 |
| (SD) | (3.2) | (3.3) | (3.5) | (3.3) |
| Expenditure ($) on SaltyS during month | 10.0 | 10.1 | 10.9 | 10.0 |
| (SD) | (14.3) | (15.2) | (15.0) | (14.9) |
| Volume (oz) on CCG during month | 9.4 | 10.2 | 9.9 | 10.0 |
| (SD) | (22.4) | (23.8) | (22.8) | (23.3) |
| Volume (oz) on DSS during month | 91.9 | 94.3 | 91.5 | 94.6 |
| (SD) | (122.4) | (117.5) | (119.2) | (117.6) |
| Volume (oz) on FVLN during month | 192.3 | 200.6 | 204.6 | 201.1 |
| (SD) | (226.5) | (228.2) | (235.4) | (229.9) |
| Volume (oz) on FVLNNA during month | 160.2 | 167.2 | 171.5 | 167.8 |
| (SD) | (199.4) | (202.8) | (208.0) | (204.4) |
| Volume (oz) on PMS during month | 56.0 | 61.9 | 57.0 | 62.8 |
| (SD) | (81.5) | (86.6) | (82.8) | (88.1) |
| Volume (oz) on SaltyS during month | 28.5 | 28.8 | 30.2 | 28.6 |
| (SD) | (39.0) | (40.0) | (40.4) | (39.4) |
| Volume (oz) on SSB during month | 567.5 | 572.6 | 573.6 | 575.9 |
| (SD) | (765.7) | (748.5) | (769.6) | (753.3) |
| Volume (oz) on ST during month | 22.6 | 24.3 | 22.5 | 24.6 |
| (SD) | (54.5) | (57.4) | (54.0) | (57.6) |
| Percent of all transactions using the tender type of cash | 0.3 | 0.3 | 0.3 | 0.3 |
| (SD) | (0.3) | (0.3) | (0.3) | (0.3) |
| Percent of all transactions using the tender type of paper check | 0.0 | 0.0 | 0.0 | 0.0 |
| (SD) | (0.0) | (0.0) | (0.0) | (0.0) |
| Percent of all transactions using the tender type of payroll check | 0.0 | 0.0 | 0.0 | 0.0 |
| (SD) | (0.0) | (0.0) | (0.0) | (0.0) |

| | | | | |
|---|---|---|---|---|
| Percent of all transactions using the tender type of store coupons | 0.0 | 0.0 | 0.0 | 0.0 |
| (SD) | (0.0) | (0.0) | (0.0) | (0.0) |
| Percent of all transactions using the tender type of vendor coupons | 0.0 | 0.0 | 0.0 | 0.0 |
| (SD) | (0.0) | (0.0) | (0.0) | (0.0) |
| Percent of all transactions using the tender type of EBT card - F | 0.3 | 0.4 | 0.2 | 0.4 |
| (SD) | (0.4) | (0.4) | (0.3) | (0.4) |
| Percent of all transactions using the tender type of EBT card - C | 0.0 | 0.0 | 0.0 | 0.0 |
| (SD) | (0.0) | (0.0) | (0.0) | (0.0) |
| Percent of all transactions using the tender type of gift card | 0.0 | 0.0 | 0.0 | 0.0 |
| (SD) | (0.0) | (0.0) | (0.0) | (0.0) |
| Percent of all transactions using the tender type of EBT WIC | 0.0 | 0.0 | 0.0 | 0.0 |
| (SD) | (0.1) | (0.1) | (0.1) | (0.1) |
| Percent of all transactions using the tender type of credit card | 0.1 | 0.1 | 0.1 | 0.1 |
| (SD) | (0.2) | (0.2) | (0.3) | (0.2) |
| Percent of all transactions using the tender type of debit card | 0.3 | 0.2 | 0.4 | 0.2 |
| (SD) | (0.3) | (0.3) | (0.4) | (0.3) |
| Number of Shopping trips in a month that used more than one tender type | 1.3 | 1.5 | 1.2 | 1.5 |
| (SD) | (1.9) | (2.0) | (1.8) | (2.1) |

## APPENDIX 2: OVERLAP WEIGHTED PRE-PROGRAM OUTCOME MEASURES



## APPENDIX 3: SENSITIVITY ANALYSIS USING MONTH OF FIRST USE AS INDEX DATE

| | Percentage Point Changes Associated with SuperSNAP | |
|---|---|---|
| **Primary Outcomes: Share of Calories from** | Estimate (95%CI) | p-value |
| Fruits, Vegetables, Nuts, and legumes with and without additives | 6.8<br>(5.9, 7.5) | 0.000 |
| Fruits, Vegetables, Nuts, and legumes without additives | 6.7<br>(5.9, 7.4) | 0.000 |
| Processed Meats and Seafood | -0.2<br>(-0.4, 0.1) | 0.175 |
| Sugar Sweetened Beverages | -1.9<br>(-2.3, -1.5) | 0.000 |
| Ultra Processed Non-essential Foods | -2.2<br>(-2.9, -1.5) | 0.000 |
| **Secondary Outcomes: Nutrients** | | |
| Milligrams of Sodium per 1000 Calories | -44.2<br>(-116.9, 67.0) | 0.436 |
| Total Milligrams of Sodium per month | 35711.0<br>(28729.5, 42692.5) | 0.000 |
| Grams of Protein per 1000 Calories | -0.6<br>(-1.0, -0.2) | 0.001 |
| Grams of Saturated Fat per 1000 Calories | -0.8<br>(-0.9, -0.6) | 0.000 |
| Grams of Total Fat per 1000 Calories | -1.5<br>(-2.0, -1.1) | 0.000 |
| Grams of Added Sugar per 1000 Calories | 2.0<br>(0.9, 3.1) | 0.000 |
| Total Grams of Fiber per month | 196.8<br>(184.1, 209.5) | 0.000 |
| Total Grams of Carbohydrate per month | 2947.9<br>(2678.5, 3217.2) | 0.000 |
| Grams of Carbs per Grams of Fiber | -12.0<br>(-14.4, -9.5) | 0.000 |
| Grams of Carb per 1000 Calories | 5.2<br>(4.0, 6.5) | 0.000 |

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