U.S. Food Assistance Participation and Demand for Food

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Abstract: Many U.S. policymakers have implemented or introduced price policies (e.g., taxes, subsidies) with the aim to encourage healthy eating behaviors. Many of these policies have been directed to lower income and households on food assistance as diet quality and consequently health outcomes tend to be worse for them. To evaluate ex ante food price policy proposals, a current set of price and income elasticities of demand for food for households delineated by food assistance participation and income can help policymakers predict the effects of proposed fiscal incentives to eat more healthfully and compare costs and benefits of proposed policies. This research provides timely estimates of demand for food purchased at retail establishments using the 2021-23 Circana Consumer Network Panel.

Diet quality falls along a socioeconomic gradient, leading to disparities in diet-related health outcomes. Policymakers have looked to domestic food and nutrition assistance programs to mitigate barriers to accessing healthy foods with a particular focus on making healthier foods more affordable (e.g., Health Incentives Program and Double Up Food Bucks Program). Having a current set of elasticities of demand for food for the food assistance population can help policymakers predict the effects of proposed fiscal incentives to eat more healthfully and compare costs and benefits of proposed policies. However, such current information is currently missing in the literature.

Several studies find significant differences in price responsiveness across household incomes. Park et al. (1996) used the 1987-88 Nationwide Food Consumption Survey and found that own-price elasticities for foods were similar across incomes above and below 130% of the poverty threshold but income elasticities were consistently higher for the lower income households. Using the 1992 Consumer Expenditure Survey paired with monthly Consumer Price Indexes, Raper et al. (2002) found similar results across incomes. In contrast, Huang and Lin (2000) found considerable variation in own-price and expenditure elasticities of demand across similar income groups although differences were not systematic for any particular food. More recent studies based on scanner data found differences in own-price and expenditure elasticities of demand across lower and higher income households (Zhen et al., 2014; Zhen et al., 2023).

Within the lower income category, the Supplemental Nutrition Assistance Program (SNAP) is of particular interest to policymakers. Roughly 80 percent of income-eligible households (those at or below 130% of the Federal poverty threshold) participate in SNAP but this rate rises upward to 90 percent during economic shocks like the COVID-19 pandemic (U.S.

Department of Agriculture Food Nutrition Service 2024). Households that choose to participate in SNAP appear to be more disadvantaged, on average, compared with eligible nonparticipant households, having lower household income and experiencing higher food insecurity (Tiehan et al., 2017). In addition, food spending, dietary intake and diet quality also appears to differ considerably between income-eligible nonparticipants and participants (Gregory et al., 2014; Tiehan et al., 2017). This suggests that preferences, and hence, price and income sensitivity of SNAP households may be different from their non-participating income-eligible counterparts.

Only a handful of studies estimate price and income responsiveness of SNAP households but are based on cross-sectional data before 2013. Yen et al. (2003), Lin et al. (2010) and Lin et al. (2014) used the 1996-97 National Food Stamp Program Survey to estimate elasticities of demand for food stamp participants using a censored Translog demand system. Yen et al. (2003) found their estimates to be consistent (i.e., in magnitude of own-price and expenditure elasticities) with estimates from the literature based on data for the entire population and argue that that food-consuming behavior by food stamp recipients is not entirely different from the more affluent segment of the population. In comparing their estimates with those previously published for low-income households (Park et al. 1996; Raper et al. 2002; Huang and Lin 2000), Lin et al. (2014) found limited consistency in own-price elasticities across foods with these other studies. Ultimately, Lin et al. (2014) used their estimated elasticities to simulate price and income changes to the food stamp program (e.g., subsidies on under-consumed foods like fruits, vegetables and dairy as well of increased in overall benefit amounts) on food consumption and diet quality. Similarly, Ver Ploeg and Zhen (2022) used the 2012 National Household Food Acquisition and Purchase Survey to estimate an Exact Affine Stone Index demand system for SNAP participants. Although they do not explicitly report the elasticities of demand in their analysis, Ver Ploeg and Zhen (2022) showed that the simulated effects of expanded SNAP benefits under the 2021 revised Thrifty Food Plan based on these demand estimates increased food spending around 8 percent for participants and modestly improves diet quality. However, Ver Ploeg and Zhen (2022) acknowledged that a limitation of their analysis was that their demand system estimates are based on older, less timely data.

This research extends the previous literature by examining demand for foods by households on SNAP and those that are not after the COVID-19 pandemic using longitudinal data. Because the pandemic followed by the historic food price inflation may have had long-lasting impacts on consumer preferences for food their price responsiveness, we examine demand during the period of 2021–23, the most current data available. We exploit the longitudinal nature of the 2021–23 Circana Consumer Network Panel, which previous structural demand system estimates for SNAP participants have not done before. This allows us to examine the effects of within-household price variation on food demand, controlling for unobserved time-invariant preferences for food. The first section describes the data steps and variable construction necessary for estimating demand for households participating in SNAP using the Consumer Network as a longitudinal panel. The second section compares preliminary summary statistics of food demand by households participating in SNAP and those that do not. The last section describes the limitations of the current analysis and methods to address some of these limitations that will be pursued in future iterations of this research.

Data and Methods

We use the 2021–23 Circana household scanner data to estimate demand for 27 foods purchased at retailer establishments. The Circana Consumer Network (household scanner data) includes information on expenditures, quantities and prices paid by roughly 120,000 households on food purchases (Muth et al. 2016). About half of these households provide sufficient data to be deemed reliable and about 60 percent of the reliable reporters are in more than one year between 2021 and 2023. The household scanner data also includes sociodemographic information on annual income, race, ethnicity, household size, education and employment of household heads, geographic residence, and SNAP participation.

Identifying SNAP households is of particular importance to this research. SNAP households are identified if they responded yes to the annual survey question in June or July each year or the household indicated that it used SNAP benefits for at least one shopping trip during the year. We used both variables to identify SNAP households to be more inclusive of all potentially participating households because households tend to underreport SNAP participation in surveys (Gregory, 2025).

Food groups are constructed to align with final purchase categories in the Economic Research Service Food Dollar data product. Because Circana changes their product classification as new product trends arise or new data are acquired, which is the case for our period of study period, it was necessary to classify data consistently across years. The Food Dollar final purchase categories are based on items produced by food manufacturing industries as categorized by the 2012 North American Industry Classification System and include: cereals; bakery products; beef; pork; other meats; poultry; fish and seafood; fresh milk; processed dairy products; fresh eggs; processed eggs; fats and oils; fresh fruits; fresh vegetables; canned frozen and dried minimally processed fruits and vegetables; sugar and sweets; snack foods; frozen prepared foods; processed fruit and vegetable canning and drying; seasonings, sauces and dressings; tree nuts and peanuts; fresh cut produce and grab-and-go foods; miscellaneous foods; juices; coffee, tea and beverage making materials and soft drinks and bottled water. Appendix table A1 provides more details on how these food categories are defined. We use the product classification hierarchy in Circana's 2021–23 product dictionaries to assign UPCs to each of these 27 food categories.

Currently the Consumer Network data are set up to be used for cross-sectional analysis. The Consumer Network provides post-stratification weights that project the cross-sectional sample for a year to be representative of select demographic targets (e.g., income, age, race/ethnicity) based on U.S. Census American Community Survey (Muth et al. 2016). However, many respondents participate in the sample year-after-year and the data can be used as a longitudinal panel which allows the researcher to control for time-invariant fixed effects. This is especially important for modeling demand as consumer preferences are largely unobservable and observable characteristics

In order to exploit the panel nature of the Consumer Network data and produce nationally representative estimates, we construct longitudinal post-stratification weights for households in the 2021-23 panel. We used the same demographic targets and applied two adjustments to them: (1) a nonresponse adjustment to distribute the weights for households that were not in the panel for all years in 2019-2023 to those that were; and (2) a calibration adjustment so that the longitudinal weights sum to similar population targets as those used.

Using the methods developed by Muth et al. (2024), we define a "nonrespondent" as households in the reference year (in our case, 2023) but not in all years between 2021 and 2023. Roughly 91% of the static panel 2021–2023 longitudinal nonrespondents are households that joined sometime after 2021 but remained respondents in each year after the initial year. The remainder of the longitudinal nonrespondents had some other response pattern over 2021–2023. Applying a nonresponse adjustment separately from the calibration model allows for a different model to be used that incorporates additional variables correlated with nonresponse. Under the assumption of missing at random, if variables in the nonresponse model are correlated with both nonresponse and outcomes, adjusting for nonresponse will reduce bias because of nonresponse. Such variables were identified in the Consumer Network data for all respondents and nonrespondents by examining the relationships of the select demographic variables with panel response and with 2023 household expenditures.[1]

Table 1 shows considerable variation in response rates across demographic variables. For example, response rates varied from 52 percent for household heads less than 35 years of age to 91 percent for those over the age of 65. This is similarly shown for household size, Hispanic/non-Hispanic, sex, marital status, education, presence of children, rent/own home, and dog ownership. As such, these variables were identified as being important predictors of nonresponse.[2] Additional robustness checks were conducted by modeling the relationships between nonresponse and household expenditures and these covariates using a Classification and Regression Tree (CART).[3] The variable importance based on the logistic model estimated with

[1] In this analysis, correlation between the variables used in the nonresponse model and the outcome, 2023 household food expenditures, are examined. It's not practical to examine every outcome variable, but it's still important to limit the predictors to those at least plausibly correlated with outcomes, which might be all of the demographic characteristics. In addition, omitting some variables from the propensity model that are correlated with response (e.g., income) isn't necessarily a problem because there are other predictors that are correlated with income included in the model. Further, it is undesirable to overfit the model. Lastly, other outcomes of interest like budget shares and quantities are usually correlated with food expenditures so substituting these other outcomes for food expenditures would likely have limited impact on the findings.

[2] Some variables were coarsened prior to modeling when sample sizes were small or because of practical similarity. For example, home owners make up a sizeable majority of the panel and were much more likely to be respondents then either renters or 'other', so renter and other home ownership were combined. Other variables that were coarsened included marital status (married, widowed, divorced/separated, single versus married, not married), employed (work less than 35 hours per week, work more than 35 hours per week, not employed versus employed, not employed).

[3] CART models find predictors and cut points in the predictors that are used to split the sample into more homogenous subsamples. The splitting process is repeated on subsamples so that a series of splits defines a binary tree. Each cut point has a prediction for the outcome variable at the end. The split points are determined by a numerical method called recursive binary splitting such that minimizes the Gini impurity, a measure of how mixed up the data are in a subset, within a subset. CART methods have properties that make them attractive for prediction such as robustness against outliers, multicollinearity and skewed distributions, and flexible enough to fit interactions and nonlinear relationships.

CART indicated that the demographic variables identified in the response rate analysis were good predictors of nonresponse as well as household expenditures.

Before the nonresponse adjustment is made, weight trimming was used in which about 3% of the projection factor total was distributed from the largest projection factors across the full sample before nonresponse adjustment. Weight trimming helps in mitigating variance inflation. This affected about 160 respondents. There are different methods for deciding cutoffs for trimming but here it was determined by the extreme outliers in the upper tail of distribution.

The method used for the nonresponse adjustment is a propensity score adjustment. In this method, the nonresponse-adjusted weight, $w_{i,NR}$, is calculated as:

$$w_{i,NR} = \begin{cases} 0,\ if\ case\ i\ is\ a\ nonrespondent \\ w_i \times 1/\hat{p}_i,\ if\ case\ i\ is\ a\ respondent \end{cases}$$

where w_i is the "base weight" for the reference year and $\hat{p}_i$ is the predicted response propensity (i.e., probability of response) from a logistic model of respondent status on household characteristics (size, rent/own, dog ownership, and presence of children) and characteristics of the household reference person (Hispanic/non-Hispanic, sex, education) from the response rate analysis.

The CART model was used to fit the logistic model because it automatically detects important interactions between the covariates. The data were randomly split into a training (90%) and test (10%) data sets, and the logit model was estimated on the training data set.[4] Ten-fold cross-validation was used on the training data set to evaluate whether the nonresponse logit

[4] The complexity parameter in the CART was determined by trial and error. This parameter controls the trade-off between the model complexity and fit (accuracy) to the training data. The default value for the complexity parameter in rpart in R is 0.01: larger values result in a smaller (simpler) tree, potentially leading to underfitting but are generally better for bias, which is the main concern here.

model estimated with CART overfit the data.[5] Overfitting occurs when a model learns the training data set too well, leading to poor performance on the test data. Based on ten-fold cross-validation, accuracy is roughly 78% for the validation and test datasets. Because the prediction accuracies are similar between the validation and test datasets this indicates that the nonresponse logit model is not overfit. Although accuracy indicates that the model fit could be improved by including additional variables, doing so will not mitigate the bias if the variables are not correlated with the outcome and will increase the unequal weighting effects (UWE).

The second step was to calibrate the nonresponse-adjusted weights to similar control totals as those used for the cross-sectional weights. That is, after calibration, the weights should sum to the control totals for the subgroups included in the calibration model. The calibration procedure is a generalized raking procedure, with bounds on the adjustment factors to limit variance inflation. Control totals used in the calibration are for Census division and demographic targets. Before the calibration adjustment is made, the trimmed nonresponse-adjusted weights are trimmed again. About 0.6% of the weight total was distributed from the largest nonresponse-adjusted weights across the respondent sample before calibration.

As noted previously, we used control totals reconstructed from 2023 projection factors. Some additional coarsening of variables was conducted at the calibration stage because of model convergence issues. Convergence issues usually occur because of small sample sizes for a particular control total. For this application, age of reference person across Census divisions had the smallest sample sizes, especially for younger reference persons. As such, these categories

[5] K-fold cross-validation is a method of resampling the data in order to evaluate a machine learning model like CART. Data are split randomly into K subsets. K-1 subsets are used to train the model while the Kth subset is used as the validation set. Errors are calculated between the predicted outcomes based on the training data and the actual outcomes based on the validation data. This is repeated K times until the model is not trained and is tested on all K subsets. The average of prediction errors for the K folds indicates the overall accuracy of the model.

were combined for calibration (i.e., less than 35 years old and between 35 and 44 years of age combined into one category of less than 45 years of age). Appendix Table A.2 shows the control total values used for calibration.

To estimate standard errors for the longitudinal panel using Taylor series variance estimation, we developed pseudo sampling strata and primary sampling units (PSUs) within the Circana data to approximate its nonprobability sample design. This is done because the actual sampling strata and PSUs are not provided, and the data do not contain replicate weights for standard error estimation. Metropolitan statistical areas (MSAs) were used to define strata in a manner consistent with the approach developed for variance estimation with Nielsen Homescan (Muth et al., 2016). For Circana households in a ZIP Code within the 20 largest MSAs among the 2021–2023 respondent households, the MSA functions as the stratum. Other households were assigned to strata based on Census division and county size (as defined in Consumer Network data).

The random group method detailed by Wölter (1985) was used to form PSUs, such that households were randomly assigned to PSUs, with each PSU containing at least ten households, and each stratum having at least two PSUs. To do this, information from the Census Bureau’s population estimates (Census Bureau 2024) is combined with the Circana’s demographic information. In particular, households in the static panel are assigned to the 20 largest MSAs while the others are assigned to Census divisions based on the Census data, which becomes the strata. Using the random group method, households within each strata are randomly assigned to PSUs within strata.

Results

The weighted and unweighted average quarterly expenditures by SNAP households and their non-SNAP counterparts are presented in Tables 2a-2c. The differences between the weighted and unweighted estimates are generally small and not statistically significant. The differences are also consistent over time across food categories and SNAP/non-SNAP households. However, there are some notable exceptions.

To better understand this variation across food categories and SNAP participation, we calculate the average absolute differences between the weighted expenditures and the unweighted expenditures (Figure 1). The average quarterly expenditures are more than a dollar different between the weighted and unweighted estimates for SNAP and non-SNAP households for bakery products, cereals, beef, pork, fish and seafood, coffee, tea and beverage making materials, ready-to-eat foods, sugar and sweets, tree nuts and peanuts and miscellaneous foods and ingredients. In these food categories, the differences are generally larger for the SNAP sample compared to the non-SNAP sample except for sugar and sweets, bakery products and beef. Differences are also apparent between the weighted and unweighted estimates for additional foods only for the SNAP sample: fresh vegetables, fruit and vegetable juices, fluid milk, processed milk products, soft drinks and bottler water and frozen foods.

Assuming the weighted estimates are more accurate than the unweighted estimates, we also examine differences in weighted food expenditures between the SNAP and non-SNAP households (Figure 2). SNAP household average quarterly expenditures were generally higher than non-SNAP expenditures except for nuts, fresh fruits and fresh vegetables. The weighted expenditures for soft drinks and bottled water, frozen foods and bakery products are $10 to $20 more per quarter for SNAP households compared to non-SNAP households. Some caution should be used in interpreting these results as these estimates do not control for household size and other characteristics that affect the level of expenditures on food purchased by a household.

As a share of the food budget, the differences between the weighted expenditures for SNAP and non-SNAP households are generally small and statistically insignificant. Figure 3 shows these differences and 95-percent confidence intervals. The largest differences that are statistically significant are for soft drinks and bottled water, fresh fruits, fresh vegetables, frozen foods and processed dairy products. The differences in distribution of the share of the food budget on the different foods could reflect differences in preferences for the food categories or differences in prices paid.

Limitations and future research

This research presents the initial steps in estimating demand for foods by SNAP participants and their non-participating counterparts using the Circana Consumer Network Panel as a longitudinal dataset. First, we categorized foods to align with ERS Food Dollar final purchase categories. This will allow us to have a consistent set of UPCs within each food category even when Circana changes their food classification hierarchy. Second, we developed longitudinal weights for respondents that are in the static panel in all years from 2021 through 2023. This will allow us to produce demand system estimates that are representative of the U.S. noninstitutionalized household population. Lastly, we identify households participating in SNAP in at least one year between 2021 and 2023 and those that did not using survey-based participation questions and method of payment for scanned foods questions.

We will use the Nonstationary Translog model (Lewbel and Ng 2005) or Generalized Differential Demand System (Eales, Durham and Wessells 1997) to estimate demand for our 27 foods because it is well-suited to deal with the econometric properties of the panel data. Specifically, these models readily incorporate differencing in the specification, allowing us to control for time-invariant fixed effects that arise from unobserved household-level heterogeneity in preferences. Hence, demand-induced shifts in prices arising from quality or time search preferences will be differenced from the data before estimation. One of these differential demand systems will be applied to the two subsamples—those that participated in SNAP during the study period and those that did not. We will also estimate the demand system with and without weights to gauge the impact of the weights on the estimates.

There are several notable limitations to the current data analysis described in the study which we are planning to address in the next iteration of the research. Although products with a UPC contain both quantities and expenditures, Consumer Network data contain only expenditures and not quantities for random weight items. Due to variation in how items are priced and sold by retailers (i.e., sometimes by the pound, sometimes by the count), it is difficult to collect accurate information from households for these products. In order to ensure data quality and reduce the household burden associated with reporting these products, panelists are instructed to report only the total expenditure, and not the quantity, for random weight purchases. Without quantities, researchers are also unable to calculate prices or unit values for random weight foods, which is necessary for estimating demand.

To overcome this barrier, our next steps will be to impute prices for random weight foods reported in the Consumer Network using the Circana's OmniMarket Core Outlets retail scanner data. In particular, we will use a hedonic model of prices of random weight items reported in the Circana OmniMarket Core Outlets data (retail scanner data) on food product, metropolitan statistical area, quarter-year and channel indicators, and use the estimated coefficients from this model to impute the missing random weight prices in the Consumer Network. This model will be estimated using a generalized linear model.

Another limitation of the current data set is the coarseness of the subsamples—those on SNAP during any period in 2021–23 and those that are not. Future iterations of this research will investigate incorporating SNAP as yearly indicator to capture within-person variation in SNAP participation on food demand. We will also try delineating the samples by SNAP participating and nonparticipating households by income quartiles to better compare those households who are eligible for participating in SNAP but chose not to participate.

Ultimately, this research and its proposed extensions builds on the previous literature by estimating demand for foods by SNAP and nonparticipating households using the timeliest data available. Because the COVID-19 pandemic followed by the historic food price inflation may have impacted consumer responsiveness to prices and income, a timelier set of demand elasticities for food assistance participants will improve the accuracy of predicted changes in food demand and diet quality due to anticipated policy changes under the new administration.

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Table 1. Response Rate Analysis

Variable	Respondent Sample Counts 2023	2021–2023	Longitudinal Response Rates (%)
Overall	60,263	46,877	77.8
Age of Householder			
<35	6,535	3,418	52.3
35–44	10,532	7,152	67.9
45–65	31,246	25,467	81.5
65+	11,950	10,840	90.7
Hispanic			
Yes	6,796	4,780	70.3
No	53,467	42,097	78.7
Race			
Black	7,312	5,470	74.8
Not Black	52,951	41,407	78.2
Annual Household Income			
<$35K	14,040	10,177	72.5
$35–$49.9K	8,930	6,888	77.1
$50K–$99.9K	22,712	18,005	79.3
$100K+	14,581	11,807	81
Children in Household			
Yes	15,122	10,401	68.8
No	45,141	36,476	80.8
Household Size			
1 person	15,999	12,844	80.3
2 persons	25,687	20,705	80.6
3 persons	14,239	10,364	72.8
4+ persons	4,338	2,964	68.3
County Size			
A	24,020	18,885	78.6
B	18,999	14,781	77.8
C	9,316	7,125	76.5
D	7,928	6,086	76.8
Sex			
Male	12,074	9,871	81.8
Female	48,189	37,006	76.8

Table 1. Response Rate Analysis (continued)

Variable	Respondent Sample Counts		Longitudinal Response Rates (%)
	2023	2021–2023	
Occupation			
Prof	12,262	9,442	77
Mgmt	6,971	5,333	76.5
Cler	3,512	2,687	76.5
Sales	3,241	2,359	72.8
Skill	1,510	1,134	75.1
Mach	1,687	1,216	72.1
Labor	417	306	73.4
Svc	3,856	2,664	69.1
None	26,523	21,563	81.3
Marital Status			
Married	36,948	29,062	78.7
Widowed	4,917	4,145	84.3
Divorced/separated	9,191	7,040	76.6
Single	9,207	6,630	72
Own/Rent			
Owner	45,727	37,242	81.4
Renter	13,055	8,639	66.2
Other	1,481	996	67.3
Cat owner			
No	40,658	31,783	78.2
Yes	19,605	15,094	77
Dog owner			
No	34,617	27,570	79.6
Yes	25,646	19,307	75.3
Region			
Northeast	10,509	8,144	77.5
Midwest	14,358	11,458	79.8
South	23,838	18,069	75.8
West	11,558	9,200	79.6

Source: Authors' calculations using 2021-23 Circana Consumer Network Panel.

Table 2a. Weighted and Unweighted Average Quarterly Expenditures, by Food Category and SNAP participation, 2021

	Unweighted				Weighted			
Food category	SNAP participants		Non-participants		SNAP participants		Non-participants	
Canned, frozen and dried fruits and vegetables	27.47	0.19	26.37	0.07	27.72	0.23	26.66	0.23
Processed fruit and vegetable canning and drying	28.98	0.20	26.21	0.07	29.17	0.16	25.75	0.16
Fresh fruits	39.56	0.31	43.79	0.13	40.26	0.35	44.25	0.35
Fresh vegetables	32.54	0.24	38.96	0.11	31.41	0.30	38.64	0.30
Bakery products	83.23	0.44	73.19	0.15	83.39	0.41	71.94	0.41
Beef	32.26	0.32	27.91	0.11	30.73	0.25	25.88	0.25
Cereals	35.34	0.23	32.34	0.09	37.71	0.24	33.89	0.24
Coffee, tea and beverage materials	29.65	0.30	28.18	0.10	27.61	0.22	26.11	0.22
Fresh eggs	7.51	0.07	7.80	0.03	7.54	0.08	7.91	0.08
Processed eggs	0.38	0.02	0.61	0.01	0.39	0.03	0.65	0.03
Fats and oils	25.30	0.16	25.62	0.06	24.67	0.15	25.05	0.15
Fish and seafood	26.45	0.30	23.50	0.10	24.38	0.23	22.20	0.23
Fruit and vegetable juices	22.93	0.21	17.06	0.07	25.92	0.16	17.19	0.16
Fresh fluid milk	17.66	0.16	16.14	0.06	19.75	0.17	16.68	0.17
Processed dairy products	87.96	0.49	84.63	0.17	87.77	0.49	85.32	0.49
Miscellaneous foods and ingredients	23.27	0.37	16.32	0.08	31.28	0.34	19.53	0.34
Not included in analysis	36.49	0.83	49.95	0.36	31.41	0.74	46.00	0.74
Tree nuts and peanuts	13.24	0.17	17.30	0.08	12.01	0.19	16.38	0.19
Other meats	41.62	0.29	34.76	0.10	40.40	0.26	33.90	0.26
Pork	37.95	0.28	31.75	0.09	35.70	0.22	30.18	0.22
Poultry	35.84	0.28	28.24	0.09	36.57	0.26	29.73	0.26
Ready-to-eat foods	59.54	0.60	54.73	0.24	58.95	0.59	52.35	0.59
Frozen foods	50.04	0.41	36.81	0.13	54.53	0.32	37.25	0.32
Seasonings, sauces and dressings	20.96	0.14	18.20	0.07	21.34	0.13	18.55	0.13
Snack foods	46.22	0.32	37.90	0.10	48.20	0.27	38.10	0.27
Soft drinks and bottled water	71.08	0.57	50.40	0.18	70.44	1.12	49.87	1.12

Source: Authors' calculations using 2021-23 Circana Consumer Network Panel.

Table 2b. Weighted and Unweighted Average Quarterly Expenditures, by Food Category and SNAP participation, 2022

	Unweighted				Weighted			
Food category	SNAP participants		Non-participants		SNAP participants		Non-participants	
Canned, frozen and dried fruits and vegetables	26.96	0.20	26.62	0.08	26.60	0.49	25.96	0.20
Processed fruit and vegetable canning and drying	37.02	0.25	33.00	0.09	37.38	0.68	33.43	0.25
Fresh fruits	40.05	0.32	45.19	0.14	41.06	0.92	45.60	0.37
Fresh vegetables	36.51	0.26	44.22	0.12	34.65	0.72	43.27	0.32
Bakery products	91.11	0.50	80.42	0.17	90.33	1.38	78.68	0.49
Beef	45.86	0.39	38.21	0.13	43.55	0.98	35.95	0.32
Cereals	41.77	0.29	40.33	0.12	43.52	0.79	42.20	0.33
Coffee, tea and beverage materials	30.83	0.34	29.60	0.11	28.05	0.67	27.06	0.22
Fresh eggs	11.22	0.10	11.10	0.04	11.01	0.27	11.02	0.10
Processed eggs	0.48	0.03	0.63	0.01	0.53	0.12	0.65	0.03
Fats and oils	29.72	0.20	29.41	0.08	28.46	0.51	28.27	0.18
Fish and seafood	24.56	0.28	23.28	0.10	22.97	0.68	21.88	0.22
Fruit and vegetable juices	19.67	0.20	15.06	0.07	21.56	0.65	15.35	0.17
Fresh fluid milk	23.04	0.19	21.04	0.07	25.02	0.74	21.64	0.20
Processed dairy products	90.99	0.51	88.90	0.19	89.70	1.39	88.53	0.55
Miscellaneous foods and ingredients	16.48	0.26	13.01	0.07	22.32	1.33	15.34	0.29
Not included in analysis	32.22	0.67	47.17	0.34	26.67	1.34	43.28	0.75
Tree nuts and peanuts	9.16	0.14	12.74	0.07	7.64	0.23	11.24	0.14
Other meats	34.89	0.27	29.27	0.10	34.11	0.69	29.38	0.25
Pork	40.61	0.31	34.85	0.10	38.41	0.82	32.88	0.26
Poultry	31.53	0.28	25.79	0.09	30.98	0.72	26.47	0.25
Ready-to-eat foods	59.63	0.64	55.63	0.27	56.30	1.56	52.95	0.68
Frozen foods	50.80	0.44	38.02	0.14	53.56	1.22	38.06	0.34
Seasonings, sauces and dressings	21.21	0.15	18.98	0.06	21.15	0.39	19.19	0.13
Snack foods	49.11	0.34	41.82	0.11	49.86	0.92	42.23	0.31
Soft drinks and bottled water	79.44	0.64	56.96	0.19	79.41	1.93	55.72	0.72

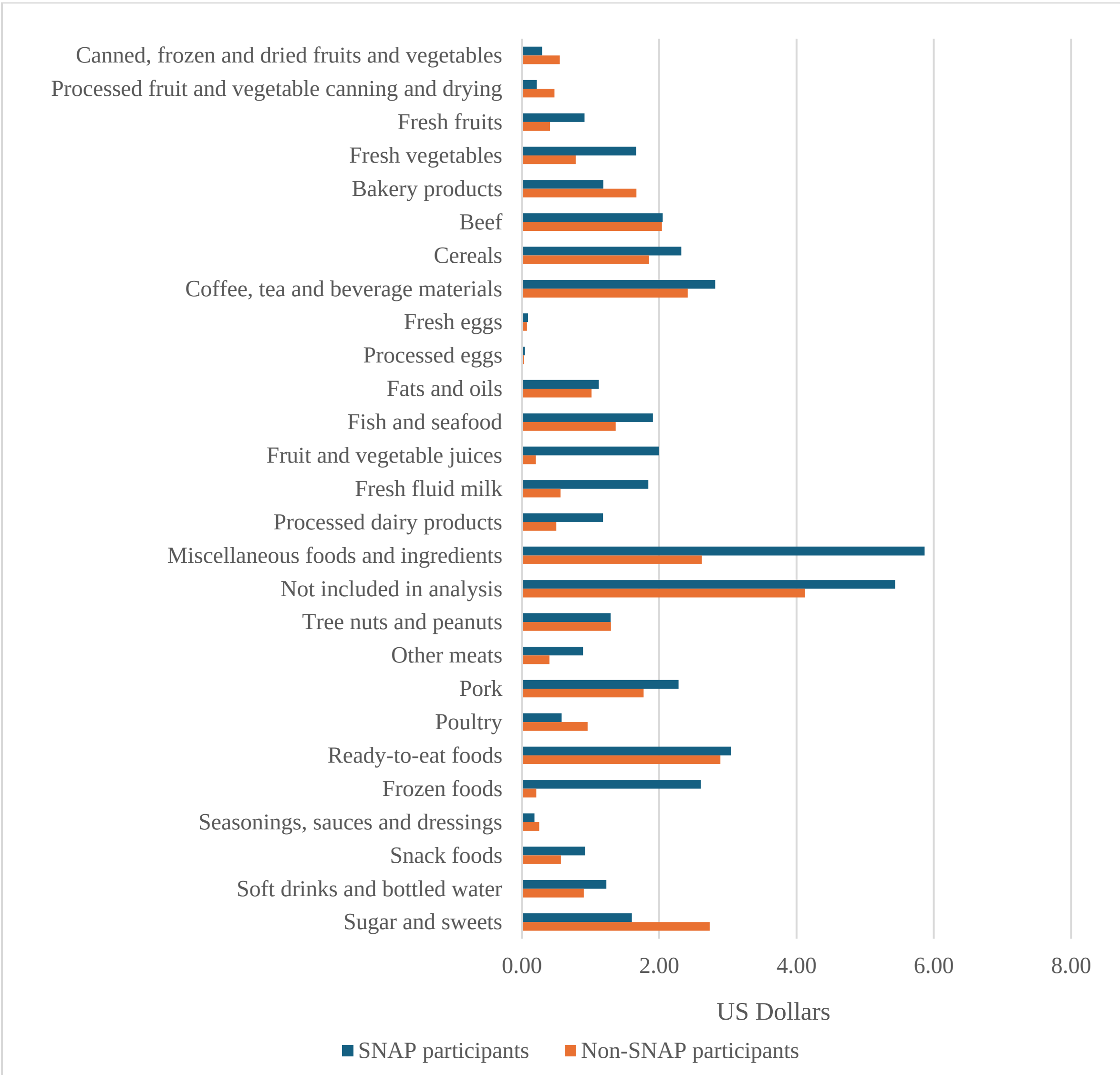
Source: Authors' calculations using 2021-23 Circana Consumer Network Panel. Note: foods not included in analysis include alcohol and nonfood.

Table 2c. Weighted and Unweighted Average Quarterly Expenditures, by Food Category and SNAP participation, 2023

	Unweighted				Weighted			
Food category	SNAP participants		Non-participants		SNAP participants		Non-participants	
Canned, frozen and dried fruits and vegetables	28.05	0.23	28.06	0.08	27.78	0.59	27.35	0.21
Processed fruit and vegetable canning and drying	35.79	0.25	33.60	0.09	35.89	0.69	34.12	0.26
Fresh fruits	38.98	0.34	45.70	0.14	40.01	1.02	46.06	0.38
Fresh vegetables	35.70	0.28	43.96	0.12	33.69	0.80	42.88	0.32
Bakery products	92.39	0.53	84.70	0.18	89.77	1.55	82.68	0.51
Beef	43.05	0.38	37.16	0.14	40.74	0.98	35.33	0.33
Cereals	42.01	0.34	41.63	0.12	44.85	0.97	43.77	0.35
Coffee, tea and beverage materials	29.58	0.28	29.98	0.11	25.94	0.59	27.33	0.23
Fresh eggs	10.21	0.10	10.00	0.04	10.17	0.27	9.97	0.10
Processed eggs	0.40	0.02	0.62	0.01	0.47	0.08	0.65	0.03
Fats and oils	30.72	0.22	30.37	0.08	29.26	0.56	29.02	0.19
Fish and seafood	22.71	0.26	23.19	0.10	20.65	0.62	21.80	0.23
Fruit and vegetable juices	19.11	0.21	15.03	0.07	20.23	0.60	15.21	0.16
Fresh fluid milk	21.25	0.19	19.80	0.06	22.70	0.67	20.35	0.19
Processed dairy products	90.14	0.53	90.50	0.19	88.08	1.49	90.05	0.57
Miscellaneous foods and ingredients	16.03	0.28	12.90	0.08	19.77	1.06	15.23	0.34
Not included in analysis	32.30	0.76	45.43	0.39	26.60	1.37	40.90	0.81
Tree nuts and peanuts	7.57	0.11	12.10	0.06	6.44	0.23	10.64	0.13
Other meats	34.58	0.28	29.86	0.10	33.91	0.76	30.10	0.27
Pork	36.80	0.29	32.70	0.10	34.41	0.71	30.92	0.25
Poultry	28.41	0.26	24.61	0.09	27.95	0.73	25.31	0.25
Ready-to-eat foods	59.17	0.67	58.85	0.29	53.96	1.45	55.23	0.71
Frozen foods	49.47	0.44	39.80	0.15	50.04	1.13	39.65	0.36
Seasonings, sauces and dressings	20.42	0.15	19.43	0.06	20.31	0.40	19.63	0.14
Snack foods	47.96	0.39	43.64	0.12	48.00	0.93	44.73	0.38
Soft drinks and bottled water	78.71	0.64	61.27	0.29	75.69	1.64	60.34	1.21

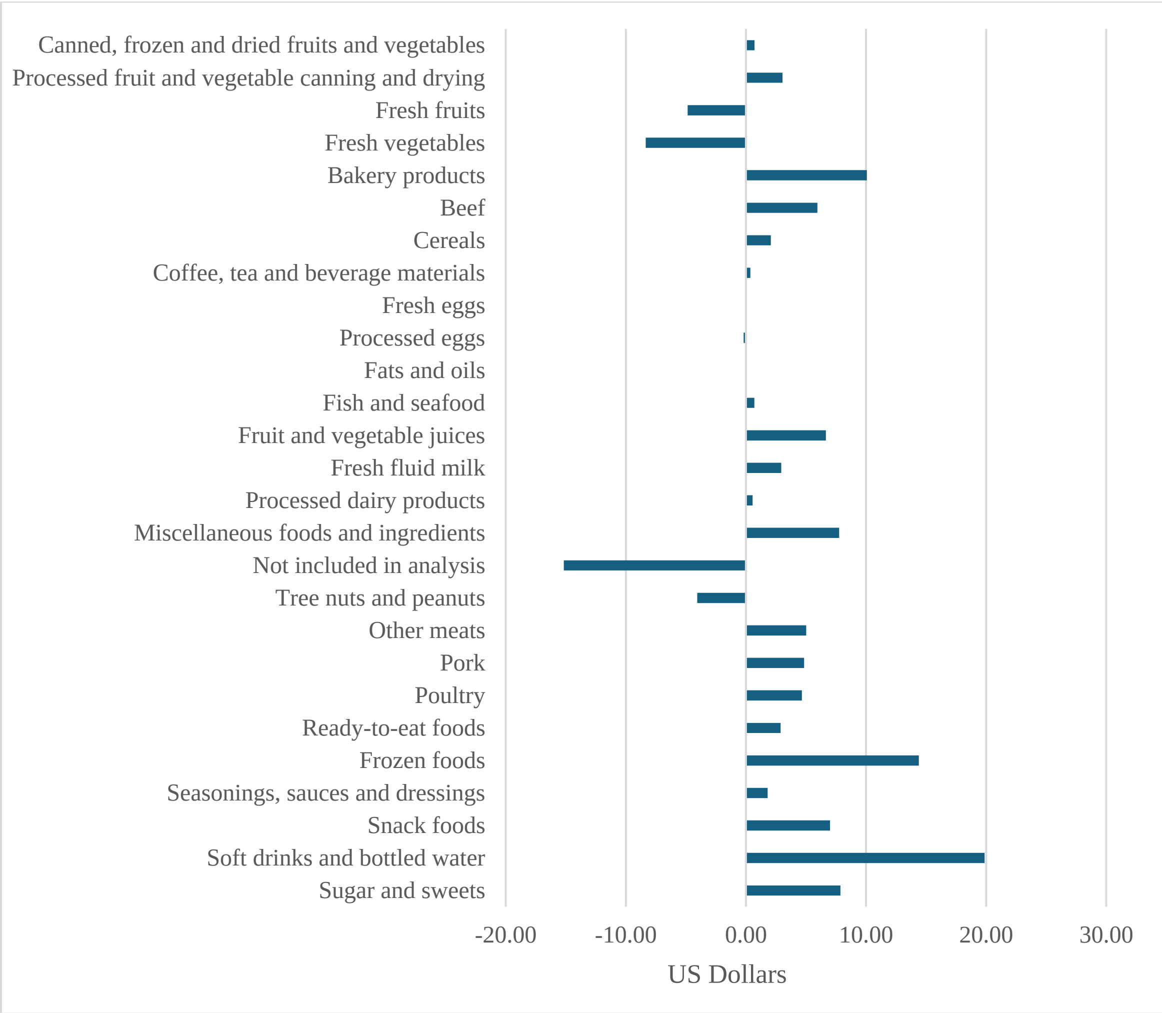
Source: Authors' calculations using 2021-23 Circana Consumer Network Panel. Note: foods not included in analysis include alcohol and nonfood.

Figure 1. Average Absolute Difference in Weighted and Unweighted Expenditures Across All Year, by Food Category and SNAP Participation



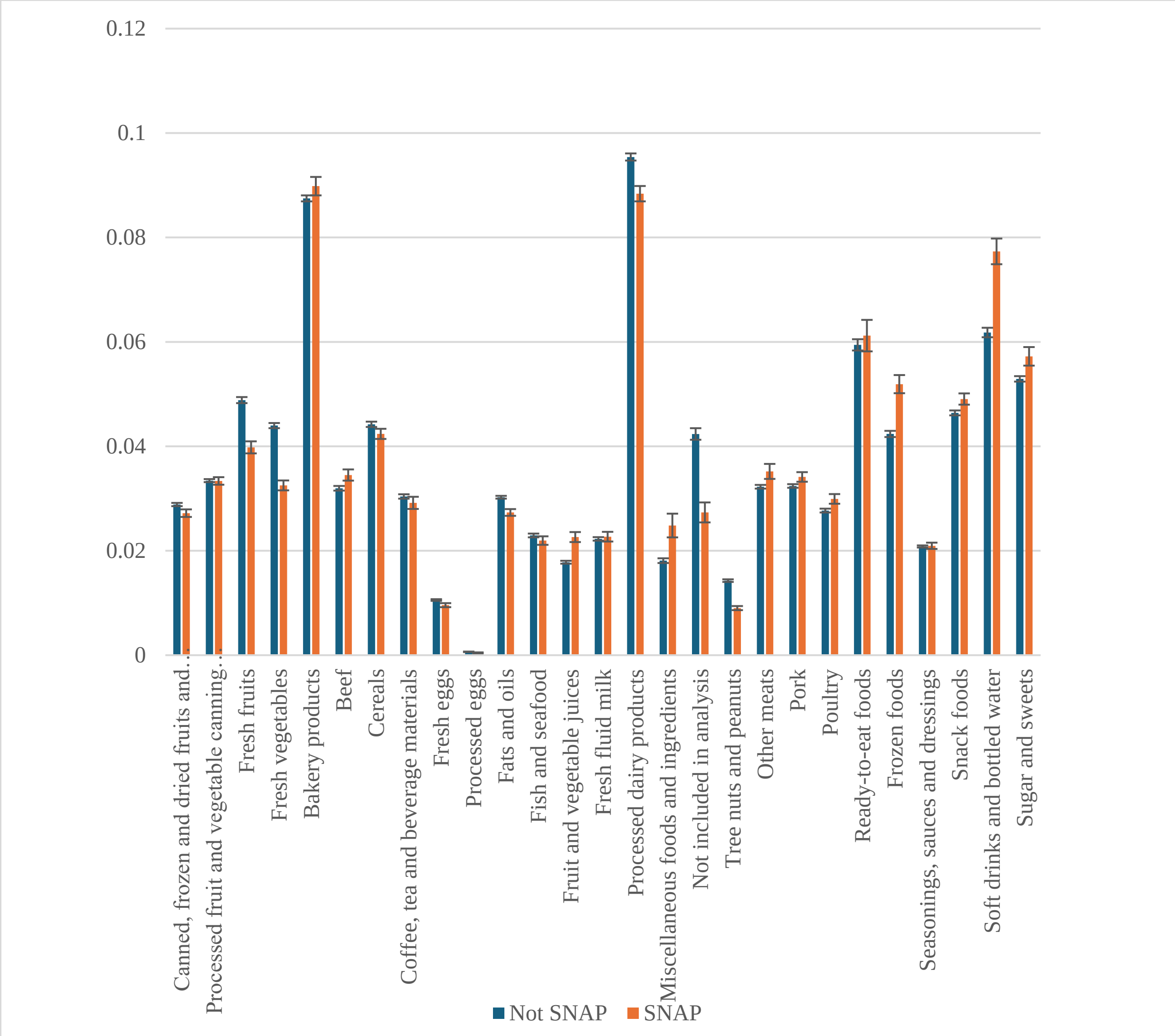
Source: Authors' calculations using 2021-23 Circana Consumer Network Panel. Note: foods not included in analysis include alcohol and nonfood.

Figure 2. Average Difference in Weighted Expenditures Between Households Participating and Not Participating in SNAP Across All Years, by Food Category



Source: Authors' calculations using 2021-23 Circana Consumer Network Panel.

Figure 3. Average Share of the Food Budget, by Food Category and SNAP Participation



Notes: Brackets around each bar represent 95-percent confidence intervals.

Source: Authors' calculations using 2021-23 Circana Consumer Network Panel.

Appendix Table A.1. Food Category Description

Food dollar code	Food dollar description	Associated NAICS industries	Product description
XF201	Food at home: Cereals	Corn farming (11115*); flour milling and malt manufacturing (31121*); breakfast cereal manufacturing (31123*); fruits and vegetable canning, pickling and drying (31142*); cookie, cracker, pasta manufacturing (31182*), soybean and other oilseed processing (311224*), all other food manufacturing (311990*)	Popcorn; milled flour or meal from grains only; breakfast cereal foods (not infant); macaroni and noodle products packaged with other ingredients (not canned or frozen); flour mixes, dough, dry pasta; soy flour and grits; packaged macaroni and noodle products with other purchased ingredients
XF202	Food at home: Bakery products	Bread and bakery product manufacturing (31181), cookie, cracker, pasta manufacturing (31182*); tortilla manufacturing (31183)	Fresh and frozen bread and other bakery products; cookies and crackers (not stuffed); tortillas
XF203	Food at home: Beef	Animal except poultry slaughtering (311611*); meat processed from carcasses (311612*)	Fresh and frozen (not canned or made into sausage) beef and veal products
XF204	Food at home: Pork	Animal except poultry slaughtering (311611*); meat processed from carcasses (311612*)	Fresh and frozen (not canned or made into sausage) pork products
XF205	Food at home: Other meats	Fishing, hunting and trapping (1142*); animal except poultry slaughtering (311611*); meat processed from carcasses (311612*)	Large game including deer, bison; lamb and mutton products; processed meats like canned meats (excluding baby food and dog/cat food), sausages, lunch meats and other cooked meats
XF206	Food at home: Poultry	Poultry processing (311615)	Fresh, frozen and canned poultry and small game (e.g., rabbits) products; meat products made from combination of poultry and other meats

XF207	Food at home: Fish and seafood	Fishing, hunting and trapping (1142*); seafood product preparation (3117)	Fresh, frozen, and canned fish and seafood, including seaweed, surimi
XF208	Food at home: Fresh milk	Fluid milk manufacturing (311511*)	Fluid milk products and dairy-based beverages including plain and flavored milks of all fat content, cream, eggnog, and milk-based beverages
XF209	Food at home: Processed dairy products	Fluid milk manufacturing (311511*); cheese manufacturing (311513); dry, condensed and evaporated dairy product manufacturing (311514*), ice cream and frozen dessert manufacturing (311520)	Manufactured processed fresh milk products like cottage cheese, yogurt, sour cream, dips, milk substitutes; all types of cheeses; nondairy creamer, dry milk alternatives; ice cream, frozen yogurts, frozen ices, sherbets, frozen tofu and frozen (non-bakery) desserts
XF210	Food at home: Fresh eggs	Poultry and egg production (1123*)	All fresh, unprocessed eggs
XF211	Food at home: Processed eggs	All other miscellaneous food manufacturing (egg substitutes and processed) (311999*)	Eggs substitutes and processed eggs manufacturing
XF212	Food at home: Fats and oils (including mayonnaise)	Wet corn milling (311221*), fats and oils refining and blending (311225); snack food manufacturing (31191*), seasonings and dressing manufacturing (31194*), soybean and other oil processing (soybean oil) (311224*), butter manufacturing (311512*), animal slaughtering, rendering and processing (lard) (31161A*)	Corn oil; vegetable and cooking oils, shortening, margarines; peanut butter and other nut butters; salad dressings including mayonnaise and sandwich spreads; soybean oil; lard and other animal fats
XF213	Food at home: Fresh Fruits	Fruit and tree nut farming (1113*)	All fresh whole fruits
XF214	Food at home: Fresh vegetables	Vegetables and melon farming (1112); food crops grown under cover (11141); all other miscellaneous crop farming (111998*)	All fresh whole vegetables and herbs

XF215	Food at home: Canned, frozen, and dried fruits and vegetables	Flour milling and malt manufacturing (31121*); frozen food manufacturing (31141*); fruit and vegetable canning, pickling and drying (31142*); dry pea and bean farming (11113*)	Vegetable/bean flours and meals; whole fruits and vegetables; canned and dried minimally processed fruits and vegetables; dried beans and peas
XF216	Food at home: Sugar and sweets	Wet corn milling (311221*), sugar and confectionary product manufacturing (3113), fruit and vegetable canning, pickling and drying (31142*), all other food manufacturing (311999*)	Corn sweeteners; jams, jellies and preserves; including sugars, syrups, honey, confections; ready-to-mix desserts, sweetening syrups including maple, honey and molasses, frosting, pie filling, pudding and gelatin
XF217	Food at home: Snack foods	Other snack foods manufacturing (311919)	Chips, corn snacks, popped popcorn, pretzels, tortilla chips
XF218	Food at home: Frozen prepared foods	Frozen specialty food manufacturing) (311412)	Frozen dinner, entrees, sides dishes; frozen pizza; frozen whipped topping; frozen waffles, pancakes and French toast
XF219	Food at home: Processed fruit and vegetable canning and drying (e.g., soups, catsup, pickles)	Specialty canning (311422*)	Canned soups, broths and stews, baked beans, canned baby foods, gravies, salsa, spaghetti sauces, chili sauce, canned pie fillings, soup mixes, bouillon, catsup/ketchup and other tomato sauces and pastes, pickles and pickled products
XF220	Food at home: Seasonings, sauces (except tomato), and dressings (excluding mayo)	Mayonnaise, dressing, and other prepared sauce manufacturing (311941*); spice and extract manufacturing seasoning and dressing manufacturing (311942)	Non-tomato- and non-gravy-based sauces like vinegar, dips, prepared horseradish, mustard, simmer sauces, soy sauce, tartar sauce, vinegar, Worcestershire sauce, dry spices, dry sauce mixes, pectin
XF222	Food at home: Tree nuts and peanuts (unprocessed)	Fruit and tree nut farming (nuts) (111335)	All nuts (excluding butters)
XF223	Food at home: Fresh cut	Perishable prepared food manufacturing (311991)	RTE produce and deli items including party trays

	produce plus grab and go foods		
XF224	Food at home: Miscellaneous foods and ingredients	Specialty canning (311422*); dry, condensed, and evaporated dairy product manufacturing (311514*); all other miscellaneous manufacturing (311999*)	Baby foods; all types of infant formula; baking powder, yeast, meat substitutes, drink powder mixes (except chocolate, coffee, milk based, tea), gelatin and puddings
XF225	Food at home: Fruit and vegetable juices	Frozen fruit, juice, and vegetable manufacturing (311411*); fruit and vegetable canning, pickling and drying (canned, fresh, concentrate fruit and vegetable juices) (311421*)	All forms and types juices and juice concentrates
XF227	Beverage at home: Coffee, tea, and beverage materials (except soft drinks)	Coffee and tea manufacturing (31192); flavoring syrup and concentrate manufacturing (31193); spice and extract manufacturing (311942*), soft drink manufacturing (312111*); ice manufacturing (312113)	Roasted coffee, instant coffee, tea bags, loose tea, tea mixes; liquid beverage bases; ready-to-drink coffees and teas; ice
XF228	Beverage at home: Soft drinks and bottled water	Soft drink manufacturing (312111*); bottled water manufacturing (312112)	Carbonated and noncarbonated soft drinks including fruit flavored drinks

Notes: A star denotes that only part of a NAICS industry's production is included in the product.

Source: Authors' interpretation based on the U.S. Department of Agriculture Economic Research Service Food Dollar.

Table A.2. Control Totals for Calibration

variable	Division 1	Division 2	Division 3	Division 4	Division 5	Division 6	Division 7	Division 8	Division 9	Total
Total	6,016,365	16,419,662	18,942,502	8,906,652	26,717,589	7,901,557	15,489,459	9,631,934	18,085,642	128,111,362
Household size										
1	1,778,537	4,548,228	5,244,630	2,544,224	7,305,590	2,065,214	3,693,013	2,246,372	4,660,405	34,086,213
2	1,951,453	5,226,558	6,377,360	3,093,236	9,095,351	2,545,955	5,093,971	3,198,297	5,684,461	42,266,642
3	1,756,073	4,913,926	5,516,575	2,351,966	7,721,333	2,428,915	4,816,505	2,661,764	5,446,343	37,613,400
4+	530,302	1,730,950	1,803,937	917,226	2,595,315	861,473	1,885,970	1,525,501	2,294,433	14,145,107
Age of reference person										
<35	1,384,284	4,107,401	4,941,292	2,455,570	6,950,918	2,066,918	4,494,690	2,799,212	4,873,216	34,073,501
35-44	1,026,911	2,868,714	3,238,455	1,588,962	4,655,005	1,541,319	2,853,274	1,746,894	3,368,502	22,888,036
45-64	2,424,083	6,463,752	7,527,521	3,208,344	10,050,192	3,093,428	5,646,488	3,392,418	6,843,290	48,649,516
65+	1,181,087	2,979,795	3,235,234	1,653,776	5,061,474	1,199,892	2,495,007	1,693,410	3,000,634	22,500,309
Ethnicity of reference person										
Hispanic	412,095	2,259,000	1,263,898	346,293	3,104,154	348,450	3,627,307	1,719,074	4,447,318	17,527,589
Non-Hispanic	5,604,270	14,160,662	17,678,604	8,560,359	23,613,435	7,553,107	11,862,152	7,912,860	13,638,324	110,583,773
Race of reference person										
White	482,693	2,087,594	2,233,919	589,035	5,843,320	1,422,948	2,210,921	359,526	1,063,938	16,293,894
Not White	5,533,672	14,332,068	16,708,583	8,317,617	20,874,269	6,478,609	13,278,538	9,272,408	17,021,704	111,817,468
Household income										
<$35,000	1,364,967	3,764,821	4,802,877	2,269,017	6,925,483	2,373,018	4,051,670	1,990,056	3,944,847	31,486,756

variable	Division 1	Division 2	Division 3	Division 4	Division 5	Division 6	Division 7	Division 8	Division 9	Total
$35,000-$49,999	551,010	1,687,676	2,380,081	1,160,348	3,300,624	1,103,917	1,914,615	1,186,730	1,748,731	15,033,732
$50,000-$99,999	1,640,615	4,611,632	5,945,099	2,812,693	7,873,926	2,392,420	4,878,816	3,270,717	4,895,682	38,321,600
$100,000+	2,459,773	6,355,533	5,814,445	2,664,594	8,617,556	2,032,202	4,644,358	3,184,431	7,496,382	43,269,274
Presence of children										
Yes	1,980,119	5,737,137	6,497,535	3,064,409	9,112,699	2,930,434	6,037,208	3,775,771	6,487,987	45,623,299
No	4,036,246	10,682,525	12,444,967	5,842,243	17,604,890	4,971,123	9,452,251	5,856,163	11,597,655	82,488,063
County size										
A	1,841,599	10,575,676	7,239,899	2,310,668	9,766,444	181,359	5,483,452	3,031,368	11,179,486	51,609,951
B	2,935,640	3,243,383	5,148,138	2,136,941	9,255,120	3,668,283	5,606,677	3,328,439	3,863,880	39,186,501
C	800,398	1,697,103	3,414,156	1,919,522	5,115,006	1,943,196	2,197,152	1,727,953	2,059,309	20,873,796
D	438,728	903,500	3,140,309	2,539,521	2,581,019	2,108,719	2,202,178	1,544,174	982,967	16,441,114