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Do SNAP Recipients Get the Best Prices?

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Abstract

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

Executive summary

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

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

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

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

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

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

Introduction

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

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

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

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

Literature review

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

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

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

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

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

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

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

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

and Lane 1981). Race has also been associated with variation in food prices paid by households. Black and Hispanic households are significantly less likely to use coupons than other racial groups (Cronovich, Daneshvary, and Schwer 1997).

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

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

Education level may also have an effect on purchasing decisions. In theory, individuals with more education may be more likely to understand and implement cost saving strategies, such as using coupons, to pay lower prices for food (Narashman 1984). In contrast to this theory,

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

Cronovich, Daneshvary, and Schwer (1997) did not find a statistically significant relationship between coupon usage and college education. However, the authors did find a statistically significant relationship between, households with at least one full time college student and coupon usage. This is likely explained by the differences in incomes between college graduates and college students.

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

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

Data

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

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

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

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

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

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

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

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

Information regarding food retailers are also broken into four categories: supermarket, non-

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

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

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

Methods

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

The Expensiveness Index

This index compares the cost of a household's food basket at average prices paid by all households in the sample to the cost actually paid by the household. The price index construction

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

follows the method used by Aguiar and Hurst (2007). First, we calculated total expenditures for household *j* in period *m* are (X_m^j)

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

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

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

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

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

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

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

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

Regression Analysis

The model we use is:

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

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

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

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

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

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

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

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

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

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

Results

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

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

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

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

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

Discussion and conclusion

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

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

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

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

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

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

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

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Table 1: Food Items Surveyed*

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

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

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

Table 2 Summary Statistics

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

Table 3 Variable Categories and Explanations

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

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

Table 4 OLS Results

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

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

Table 5 IV Using the Lewbel Method

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

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