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RESEARCH ARTICLE

Do SNAP Recipients Get the Best Prices?

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Abstract
We developed an expensiveness index and used the Food Acquisition and Purchase Survey data set to examine empirically whether Supplemental Nutrition Assistance Program (SNAP) participants pay higher prices compared with nonqualifying and qualifying, but nonparticipating, households. Purchasers' ability to minimize food expenditures has significant effects on the program's effectiveness and on participants' food security. Using ordinary least squares and two techniques that control for the endogeneity of SNAP participation, we found no significant effect of SNAP participation on food prices. Moreover, we found that SNAP participants pay, on average, lower prices than do nonparticipants. We conclude by providing suggestions for policy improvements and implications for future research.

Keywords: SNAP; FoodAPS; food purchasing decisions; consumer behavior

JEL Classifications: G18; Q18; I38; P36

1. Introduction

The Supplemental Nutrition Assistance Program (SNAP) is the federal government's most extensive policy (concerning funding and participation) designed to help lower-income households pay for food items. In 2015, SNAP cost approximately $74 billion in federal spending and included 46 million participants (U.S. Department of Agriculture, Food and Nutrition Service [USDA-FNS], 2015b). This article empirically analyses whether SNAP participants pay different food prices compared with nonparticipants and, more importantly, whether SNAP participation influences the prices households pay for food items.

Although most studies analyzing consumer behavior assume households are price takers, prices paid are not completely exogenous. Prices also stem from households' optimizing behavior (Stigler, 1961). This is important from a policy analysis perspective. A large literature assesses SNAP's impact by evaluating its overall effect on participants' food expenditures exclusively, ignoring the separate potential impact of the program on the price and quantity components of expenditures. Further, a better understanding of price differences between SNAP recipients and other populations can help to assess the adequacy of SNAP allotments (Institute of Medicine and National Research Council, 2013).

Our analysis uses the National Household Food Acquisition and Purchase Survey (FoodAPS) data set. FoodAPS is the first nationally representative survey of U.S. households' detailed food purchases, including data on food quantities and prices. FoodAPS also includes detailed information about household composition, sociodemographic characteristics, households' local food market structure, and whether the household participates in SNAP.

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There are various reasons why SNAP participants might pay higher or lower prices than non-SNAP recipients. These reasons can be categorized in demand- and supply-based explanations. Demand-related explanations for potential differences in food prices paid by SNAP participants and nonparticipants include the same theories used to explain differences between the marginal propensities to spend on food out of SNAP benefits (MPS) and cash income (MPC). For example, Senauer and Young (1986) argue that program participation might induce a sense of "responsibility" among recipients motivating them to expand their food spending, generating a higher marginal impact of SNAP benefits relative to cash on food spending.

The same sense of responsibility can motivate program participants to search for lower prices. These authors also suggest that receiving a monthly SNAP allotment might allow households to make larger purchases allowing them to take advantage of bulk price discounts (although they also suggest a monthly distribution might motivate households to make comparatively more expensive purchases). More recently, Beatty and Tuttle (2015) suggest differences in marginal propensities to spend out of SNAP benefits and cash income might be explained by Thaler's (1999) insight, which postulates that households categorize income based on its source. Thus, income from different sources might be allocated to different expenditure categories and motivate different price shopping behaviors.

Another demand-related explanation of potential differences in prices paid by SNAP participants and nonparticipants is households' participation in SNAP's educational program (SNAP-Ed). SNAP-Ed includes four components: dietary quality and nutrition; physical activity; food access, food security, and shopping behavior; and food resources management. Information obtained from the latter two components might assist SNAP-eligible households in paying lower food prices (USDA-FNS, 2015a).

With respect to supply-related explanations of differences in prices paid by SNAP participants and nonparticipants, previous policy literature suggests that some retailers might be able to anticipate SNAP-generated demand shifts during benefit distribution periods and take advantage by raising their prices. Hence, SNAP participants might pay higher prices compared with non-SNAP recipients shopping elsewhere or with consumers who shop at the same store but purchase food throughout the SNAP cycle (Hastings and Washington, 2010). However, it is important to emphasize that supply-related explanations are related to consumer behavior because retailers respond to demand shifts.

This study contributes to the literature examining the relationship between SNAP and food prices, the literature examining the effect of SNAP participation on food purchasing behavior, and the larger literature analyzing determinants of food prices. A large literature examines the impact of SNAP participation on food spending. However, to the best of our knowledge, none of these studies have examined the direct effect of SNAP participation on prices households pay for food.

In contrast to the previous literature that examines the relationship between SNAP participation and food prices by focusing on retailers' prices, the SNAP benefit distribution period, and food expenditure patterns on the part of SNAP-eligible households (Goldin, Homonoff, and Meckel, 2016; Hastings and Washington, 2010), we provide a direct comparison of prices paid by SNAP participants and nonparticipants and use instrumental variable (IV) procedures to estimate a causal effect of SNAP participation on prices paid. The FoodAPS data set also includes a larger geographic sample, a wider variety of food products, and a larger set of explanatory variables, allowing us to contribute to the literature examining determinants of food prices.

We find SNAP participating households pay, on average, comparatively lower prices than non-SNAP households. However, after controlling for household, food consumer competency-related, and food market structure variables using a linear model and ordinary least squares (OLS) estimation procedures, we do not find evidence of an association between SNAP participation and food prices. We also test and estimate the causal effect of SNAP participation on prices paid using IV estimation procedures. Our results suggest SNAP participation does not affect the prices paid for food items. These results are consistent across a variety of model specifications and procedures.

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2. Literature review

In this section, we review the literature examining the impact of SNAP on food expenditures, the literature analyzing the relationship between SNAP participation and food prices, and the literature examining other factors that affect the prices consumers pay for food.

2.1. SNAP's effects on food expenditures

Cuffey, Beatty, and Harnack (2016) identify 51 studies conducted between 1974 and 2014 examining the effect of SNAP benefits (using MPS) on food-at-home spending or the difference in effects between SNAP benefits and other income (MPS – MPC). Average MPS and MPC values from previous studies were 0.327 and 0.105, respectively. The reported average difference between MPS and MPC was 0.245. A limitation of most of the studies identified in the authors' review is that they do not correct for systematic biases that might be present because of unobservable factors. Most of the literature that the authors' review also did not consider potential separate effects of SNAP participation on quantity purchased and prices paid for food items.

A more recent study by Hastings and Shapiro (2017) uses retail panel and administrative data to motivate three methods for causal inference on the effect of SNAP participation on food expenditures. Estimated MPS ranges from 0.5 to 0.6. These authors also explore the effect of SNAP participation on shopping effort (which is related to prices paid) by analyzing store brand share changes and coupon redemption behavior after households start receiving SNAP benefits. Both store brand share and coupon redemption drop after households enter the program.

2.2. Food prices and SNAP

Hastings and Washington (2010) use 26 months of scanner data (2006–2008) from three Nevada stores to explore these retailer price changes in response to consumer demand shifts generated by regular SNAP benefits distribution. First, they construct a price index for a SNAP recipient's typical food basket. They subsequently estimate a linear regression model with the price index as the dependent variable and as explanatory variables dummies for the week of the month. They find that the price of the basket was comparatively more expensive during the weeks after SNAP benefit distribution. They also find that SNAP participants did comparatively more food shopping when they received their benefits. Both findings suggest that SNAP recipients might pay higher aggregate food prices than do nonrecipients, although they do not directly compare prices paid by participants and nonparticipants. Using a similar empirical approach and weekly scanner price data (2006–2012) from the 48 contiguous states and Washington, D.C., Goldin, Homonoff, and Meckel (2016) find similar monthly cycles in the food expenditures of SNAP-eligible households. However, the authors find no evidence that retailers' food prices are associated with the SNAP issuance timing.

With respect to the relation between SNAP-Ed efforts and prices participants pay, Kaiser et al. (2015) find SNAP-Ed participation is associated with the use of behaviors related to cost minimization including using coupons and comparing prices of goods. However, SNAP-Ed currently constitutes approximately 1% of SNAP's total budget and number of participants, making its impact relatively minimal.[1] These factors suggest that SNAP-Ed is unlikely to have a major influence on SNAP participants' food costs.

Although a separate food assistance program, previous literature examining the impact of the Women, Infants, and Children (WIC) program's impact on prices charged by manufacturers and retailers for WIC-eligible products provides similarly mixed results. Examining California retailers, Saitone, Sexton, and Volpe (2015) find that WIC food prices vary widely by retailer size but that only smaller vendors excessively mark up these products. Using data on manufacturers of

[1]Although SNAP-Ed is a small component of the larger SNAP program, its funding has quadrupled from approximately $100 million to more than $400 million since 2000 (USDA-FNS, 2017b).

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infant formula WIC rebate bids (1986–2007) from several states, Davis (2012) finds WIC has no impact on wholesale price.

2.3. Other determinants of food prices

Previous literature finds a consistent positive relationship between higher household income and prices paid for food items. One explanation for this relationship is that better-quality food is more affordable at higher income levels (Aguiar and Hurst, 2007; Kyureghian, Nayga, and Bhattacharya, 2013). Consistent with this hypothesis, some health literature finds that lower-income households purchase comparatively more food items with greater energy density and higher fat content, but these are typically less expensive (Drewnowski and Specter, 2004; Morland, Wing, and Roux, 2002). Even when food items are of the same quality, higher-income households may be willing to pay higher prices because they face comparatively higher trade-offs to search for lower prices (Becker, 1965). Cronovich, Daneshvary, and Schwer (1997) find that households earning more than $75,000 annually were less likely to use coupons compared with those that thought their income was "inadequate" (p. 1639).[2]

A household's level of education, similar to household income, may also affect purchasing decisions. In theory, individuals with more education are more likely to understand and implement cost-saving strategies, such as using coupons, to pay lower prices for food (Narashman, 1984). However, Cronovich, Daneshvary, and Schwer (1997) find no statistically significant relationship between coupon use and college education. Conversely, the authors found a statistically significant relation between coupon use and households with at least one full-time college student.

Household composition and age of household members also affect food decisions and food prices. Households with comparatively more children are less likely to form specific buying habits (Békési, Loy, and Weiss, 2013) or use coupons (Cronovich, Daneshvary, and Schwer, 1997). Households with comparatively older shoppers are more likely to develop buying patterns based on past purchases (Békési, Loy, and Weiss, 2013), purchase food products believed to have higher nutritional quality (Blanciforti, Green, and Lane, 1981), and be more willing to search for lower food prices (Aguiar and Hurst, 2007).

Racial composition also may help explain disparities in prices paid for food. African American and Hispanic households are significantly less likely to use coupons than are other racial groups (Cronovich, Daneshvary, and Schwer, 1997). Geographic proximity to food providers (in many cases related to neighborhoods' racial composition) also affects a household's local food environment. Cummings and Mcintyre (2006), as well as Zenk et al. (2005), find that predominantly African American neighborhoods are more likely to be located farther from food retailers than are neighborhoods with other racial compositions. When combined with limited transportation options, this affects where a household can shop, which influences food prices (Chung and Myers, 1999; Morland, Wing, and Roux, 2002). According to Kunreuther (1973), households in similar situations are "more likely to patronize the neighborhood store than to travel some distance to [a] chain store" (pp. 373–74). Hoch et al. (1995) find that "isolated stores display less price sensitivity than stores close to their competitors" (p. 28). Rose et al. (2009) find that citizens of New Orleans who did not own a means of transportation paid approximately $11 per month more in travel costs than did those with their own vehicles.[3]

Although many of these factors are beyond the household's control, behaviors that reduce or improve their ability to pay comparatively lower food prices are not. For example, with budgeting and financial education, food purchasers may be able to use cost-saving strategies better, such as using coupons (Cronovich, Daneshvary, and Schwer, 1997; Narashman, 1984). Similarly, lower-income households may fail to recognize that certain food items exhibit "size effects," in which

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

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

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lower unit prices are available if larger quantities are purchased (Beatty, 2010; Kunreuther, 1973; Mendoza, 2011; Rao, 2000). Educational programs could improve consumer knowledge and result in increased use of these and other money-saving buying strategies.

Our analyses extend the literature by examining the effect of SNAP participation on prices paid. The FoodAPS data set provides a more direct means to examine prices SNAP participants paid and includes more explanatory variables than were available in the previous literature.

3. Data

The FoodAPS data set contains information from a nationally representative survey of U.S. households' food purchases collected from April 2012 to January 2013. FoodAPS includes six data subsets: individual, household, events, items, places, and geodata. These subsets contain data on individual and household characteristics, food items purchased, the location where they were purchased, local food market information, and geographic distance from the household to food retailers. FoodAPS includes 55,307 observations of 4,826 families who chose from 208 different food group items. Table 1 provides a complete list of food items.

FoodAPS data were collected using a multistage sampling design. In the first stage, a stratified sample of 50 primary sampling units (PSUs) was selected, in which PSUs were counties or groups of counties. Each unit reflects overall sample targets and estimated populations for each PSU. In the second stage, eight secondary sampling units (SSUs) or block groups within each of the 50 PSUs were selected. Stage three selected addresses within each SSU (Krenzke and Kali, 2016).

The survey collected information on all food purchases made by members of each household over 7 days. Data about acquisitions of food at home were collected using three methods: (1) using survey booklets in which households recorded information about each purchase event/placed visited, (2) using handheld scanners, and (3) using saved receipts for items (postsurvey). During each survey day, respondents had to record in the survey booklet all places from which food for consumption at home was acquired, record the amounts spent, and attach the corresponding receipts. Households had to subsequently scan every item purchased to obtain quantitative information. If items could not be scanned, households had to manually enter information about the items in the survey booklet (product description and amount).

Data about each purchase event documented in the survey booklet were first collected over the phone and later cross-checked using receipt information. Prices were assigned using the receipt information (USDA, Economic Research Service [USDA-ERS], 2016). FoodAPS identified the primary food shopper as the primary respondent for each household.[4]

The data collection process included interviews before and after food purchases were recorded. A screening interview was conducted first to determine a household's eligibility to participate in FoodAPS and to collect information on households' income and income sources.[5] The initial interview built the household roster and collected demographic information about each household member, including age, sex, race, marital status, and education level.[6] Information about participation in government programs, including SNAP, and about shopping behaviors or habits was also collected during the initial interview. The second and final interview collected information on household income, nonfood expenditures, dietary knowledge, and whether there were any complicating factors that affected food purchase decisions.[7]

[4]Adults and youths also were given food books to record food purchases. Adults were defined as those 19 years old or older, and youths as those 11 years old and younger. The primary food purchaser was assigned to record all food purchases for children under 11 years old. Food purchases were recorded in food books that were collected after the sampling period.

[5]Verification requirements included that the household was within the scope of the data set and data were obtained from the household's primary residence (rather than a vacation home).

[6]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.

[7]For example, if there were any guests present during the week or if household members had any dietary restrictions.

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Table 1. Food items surveyed[a]

Aloe vera and juices	Dinners	Mayonnaise
Appetizers/snack rolls	Dinners/entrees	Meat (FRZ)
Aseptic juices	Dip/dip mixes	Meat (RFG)
Asian food	Dips	Meat
Baby food	Dough/biscuit dough	Mexican food
Baby formula/electrolytes	Dried fruit	Mexican sauce
Baked beans/canned bread	Dried meat snacks	Microwave package/dinner entry
Baked goods	Drink mixes	Milk
Bakery snacks	Dry beans/vegetables	Milk flavoring/cocoa mixes
Baking mixes	Dry dinner mix (add meat)	Mustard and ketchup
Baking needs	Dry fruit snacks	Mutzod food
Baking nuts	Dry packaged dinner mixes	Natural cheese
Baking syrup/molasses	Energy drinks	Noncarbonated water (including flavored)
Barbeque sauce	English muffins	Non fruit drinks
Beer/ale/alcoholic cider	Entrees	Nonchocolate candy
Bottled juices	Evaporated/condensed milk	Novelties
Bottled water	Fish/seafood FRZ	Other breakfast food
Bread/dough	Fish/seafood	Other condiments
Bread crumbs/batter	Flour/meal	Other foods
Breakfast foods	Frankfurters	Other salty snacks (not nuts)
Breakfast meats	Fresh bread and rolls	Other sauces
Breath fresheners	Fresh eggs	Other snacks
Butter	Frosting	Pancake mixes
Cake (not snack)/coffee cake	Frozen meat (not poultry)	Pasta
Canned juices	Fruit and vegetable preservative	Pasta (FRZ)
Canned/bottled fruit	Fruit	Pasta (RFG)
Canned/prepared tea	Gelatin/pudding product/mixes	Pastry/doughnuts
Carbonated beverages	Glazed fruit	Peanut butter
Cheesecakes	Grated cheese	Pickles/relish (RFG)
Chocolate candy	Gravy/sauce mix	Pickles/relish/olives
Cocktail mixes	Gum	Pies and cakes
Coffee	Ham	Pies (FRZ)
Coffee cappuccino drinks	Hot cereal	Pizza (FRZ)
Coffee creamer	Ice cream cones/mixes	Pizza (RFG)
Cold cereal	Ice cream/sherbet	Pizza products
Cookies	Instant potatoes	Plain vegetables
Corn on the cob	Jellies/ jam/honey	Popcorn/popcorn oil
Cottage cheese	Juice/drink concentrate	Potatoes/onions (FRZ)
Crackers	Juices	Poultry/ poultry substitutes
Cream cheese/cream cheese spread	Juices/drinks	Poultry (FRZ/RFG)
Creams/creamers	Lunch meat	Powdered milk
Dessert toppings	Luncheon meats	Premixed cocktails/coolers
Desserts	Lunches	Prepared deli/ gourmet food (RFG)
Desserts/toppings	Margarine/spreads/butters	Prepared vegetables (frozen)
Dinner sausage	Marshmallows	Processed cheese

Table 1. (*Continued*)

Processed poultry (FRZ/RFG)	Spreads (RFG)	UWF mushrooms
Rice	Steak/ Worcestershire sauce	UWF onions
Rice/popcorn	Stuffing mixes	UWF oranges
Salad dressing (RFG)	Sugar	UWF other fruit
Salad dressing	Sugar substitutes	UWF other vegetables
Salad toppings	Syrup	UWF peas
Salad/coleslaw (RFG)	Tea bags/ loose	UWF peppers
Salty snacks	Tea instant mix	UWF potatoes
Seafood (FRZ)	Tea/coffee ready to drink	UWF radish
Seafood (RFG)	Tea/coffee (RFG)	UWF spinach
Seafood	Tarts/toaster pastries	UWF sprouts
Shortening and oil	Tomato products	UWF tomatoes
Side dishes (RFG)	Tortillas/ eggrolls/wonton wrap (RFG)	UWF yams
Snack bars/ granola bars	Uncooked meats (RFG)	UWF tofu/ soybean
Snack nuts/seeds /corn nuts	UWF beans	UWF vegetables
Soup	UWF broccoli	Vinegar
Soup/sides/other (FRZ)	UWF cabbage	Vitamins
Sour cream	UWF carrots	Weight control/ nutritional liquid
Spaghetti/Italian sauce	UWF cauliflower	Weight control/ protein supplement
Specialty nut butter	UWF celery	Whipped toppings (RFG)
Spices/seasonings (not salt or pepper)	UWF cucumber	Wine
Spices/seasonings	UWF grapefruit	Yogurt
Spirits/liquors	UWF lettuce	
Sports drinks	UWF mixed vegetables	

[a]Where RFG refers to refrigerated items; FRZ, to frozen items; and UWF, to uniform weight fresh items.

Households also were asked whether they participated in SNAP, when they last received SNAP benefits, and the amount they received. To verify that households' answered truthfully, all households that provided consent were matched with administrative records from the caseload and Anti-Fraud Locator Retailer Transactions (ALERT) data.[8] This verification process reduces the recurring problem of underreporting in the SNAP literature (Almada, McCarthy, and Tchernis, 2015).

The FoodAPS Retail Environment Study Data provide food access and food market information. The food access data include county-level information on the total number of food retailers. Information about food retailers is assigned to four categories: supermarkets, nonsupermarkets, farmers' markets, and farmers' markets that accept SNAP. Supermarkets are categorized as food retailers with annual sales greater than $2 million.

The nonsupermarket category includes grocery stores with annual sales less than $2 million and includes convenience stores, pharmacies, gas stations, dollar stores, and specialty stores such as bakeries. Data on the distance to the nearest SNAP-authorized retailers were compiled in the geography component of the FoodAPS database, which uses the PSU to collect information on the availability of food vendors, types of food vendors available, and their geographic distance from the surveyed household's place of residence.

[8]Only 122 households did not provide consent.

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4. Theoretical model

We assume the following utility maximization household model:

$$Max_{q,z,t_q} U\left(q, z; K_U\right) s.t. \left(P + \mu t_q\right) q + z = I + \mu T, \text{ and } P = P\left(t_q, K_p\right), \tag{1}$$

where q stands for food consumed and z stands for all other commodities in the utility function $U(.)$. K_U represents household characteristics affecting consumer preferences. The variable μ is the endogenously determined opportunity cost of time. P is the price of food. I represents income. T represents total time available, and t_q is total time spent on food price search. In addition to a "full income budget" constraint (Becker, 1965), our utility maximization model includes the price function $P(t_q, K_p)$, which depends on the time spent on price search (t_q) and households' characteristics affecting this technology (K_p) (Aguiar and Hurst, 2007). The price function is meant to represent households' shopping ability to obtain lower prices. We also assume the utility maximization process is conditional on other choices households make at a higher decision level (e.g., labor supply).

Reduced functions for optimal values of q, z, and t_q are thus given by $q = q(I, T; K_U, K_p)$, $z = q(I, T; K_U, K_p)$, and $t_q = t_q(I, T; K_U, K_p)$ Substituting $t_q(I, T; K_U, K_p)$ in $P(t_q, K_p)$, we obtain the reduced form model $P = P(I, T; K_U, K_p)$. This function form gives us our price function and serves as the basis of our empirical analysis. To evaluate the effect of SNAP participation on prices, we include it as an argument in the price function such that[9]

$$P = P\left(I, T, SNAP; K_U, K_p\right). \tag{2}$$

4.1. The expensiveness index

Following Aguiar and Hurst's (2007) method, we construct a food price index that we refer to as an expensiveness index to address the variety of food products each household purchased. This expensiveness index reflects the cost of a household's food basket at the average prices all households in the sample paid relative to the actual cost of the basket at the prices which the household paid (Aguiar and Hurst, 2007; Beatty, 2010).[10] We calculated total expenditures for household j in period m ($\boldsymbol{X_m^j}$) as follows:

$$\boldsymbol{X_m^j} = \sum\nolimits_{i \in I, t \in m} p_{i,t}^j q_{i,t}^j = \sum\nolimits_{i \in I, t \in m} X_{i,t}^j, \tag{3}$$

where $p_{i,t}^j$ denotes the price paid per ounce, $q_{i,t}^j$ denotes the number of ounces purchased, and $X_{i,t}^j$ denotes expenditures for good i and shopping trip t. We calculated the average price paid for product i across all households in period m ($\bar{p}_{\mathrm{i},m}$) as

$$\bar{p}_{\mathrm{i},m} = \sum\nolimits_{j \in J, t \in m} \left(\frac{X_{i,t}^j W_j}{\bar{q}_{i,m}} \right), \tag{4}$$

where $\bar{q}_{i,m} = \sum\nolimits_{j \in J, t \in m} q_{i,t}^j$ is the total quantity of food item i all households purchased during period m, and W_j is the survey households' weights.[11] The cost of household j's food basket at average prices is

[9]Also note that previous studies evaluating the effect of SNAP participation have focused on a food expenditure function $E = P(I, T, SNAP; K_U, K_p)q(I, T, SNAP; K_U, K_p)$; thus, they have not been able to analyze the effect of SNAP participation on prices.

[10]We used the household as our unit of measurement for the food basket rather than family size because the primary food purchaser reported the items purchased for all household members (not solely for family members).

[11]The FoodAPS data set oversamples households that received SNAP benefits (in comparison with the national percentage); thus, the use of the weights allowed the calculation of values representative of the national population.

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$$\tilde{X}_j = \sum\nolimits_{i \in I} \bar{p}_{i,m}\, q^j_{i,t}. \tag{5}$$

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

$$P^j = \frac{X_j}{\tilde{X}_j}. \tag{6}$$

We normalized the price index around 1 by dividing the index for each household by the mean expensiveness index overall. An expensiveness index greater than 1 indicated that a household spent more than average on its food basket, and a value less than 1indicated that the household spent less than average. In our final analysis, equations (1) and (2) considered the entire period of observation for all households (10 months) as a single period ($m = 1$).

4.2. Regression model

We used the following linear model:

$$P^j = \alpha + \beta_{SNAP} SNAP + \beta'_{X^H} \boldsymbol{Z}_j^{\boldsymbol{H}} + \beta'_{X^C} \boldsymbol{Z}_j^{\boldsymbol{C}} + \beta'_{X^M} \boldsymbol{Z}_j^{\boldsymbol{M}} + e_j. \tag{7}$$

As previously noted, P^j represents our expensiveness index and was regressed against our $\boldsymbol{Z^H}$, $\boldsymbol{Z^C}$, and $\boldsymbol{Z^M}$ vectors that consisted of our household, food consumer competency-related, and food market environment variables, respectively. Term e_j is random error, and the β'_s are coefficients. *SNAP*, our primary variable of interest is a binary variable that indicates the household participated in the SNAP program. Households were identified as SNAP recipients if they indicated they received benefits and their participation was confirmed by administrative match (to avoid misreporting participation that could bias our results).[12] Non-SNAP households included both low-income SNAP-eligible households and noneligible households. High-income noneligible households were also included in the comparison group to better capture price differences stemming from supply related explanations including strategic retailer behavior targeting stores with low-income consumers (including SNAP participants and nonparticipants).

Our household control vector included the logarithm of the annual household income, its squared value, and the logarithm of the household size.[13] We used the same age distinctions as those of Beatty (2010) to determine the effects of household composition on prices paid for food items, in which we included the percentage of household members over 60 years old, between 5 and 17 years old, and less than 5 years old. Table 2 provides a complete list of all variables used and how they were measured. Table 3 provides variable summary statistics.

4.3. OLS regression estimation methods

We first used the OLS approach with different groups of control variables in our analysis. OLS allowed us to explore the association between the expensiveness index and all explanatory variables. In model 1, we included only our SNAP variable. Model 2 included the SNAP variable and our household control vector. Model 3 included the SNAP variable along with our household and food consumer competency-related control vectors. Model 4 included the SNAP variable and all of our control vectors. Adding explanatory variables to the model allowed us to explore how the relationship between our expensiveness index and the SNAP variable changed as different control categories were introduced.

[12]Only 145 households that reported participation in the program were not confirmed in the sample used in our analysis. We also estimated a model including the nonconfirmed cases. A dummy variable was used to differentiate these households. The results were robust to the exclusion of these households.

[13]We calculated this by multiplying the reported monthly income by 12 and taking the logarithm, because annual income was not reported during the interview process. SNAP benefits were not included in our income variable.

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Table 2. Variable categories and explanations

Category	Variable	Definition
	ExpensivenessIndex	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 characteristics vector ($\mathbf{X}^{\mathbf{H}}$)	LogAnnualIncome	Represents the logarithm of household's income per year
	LogHouseholdSize	Represents the logarithm of household size
	PercentElderlyMembers	Represents percentage of household size composed of members more than 60 years old
	PercentChildren	Represents percentage of household size composed of members between the ages of 5 and 17
	PercentSmallChildren	Represents percentage of household size composed of members less than 5 years old
	SinglePerson	Binary variable indicating household is composed of one individual
	Age	Represents the age of the primary food purchaser
	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
	AssociateDegree	Binary variable representing primary food purchaser holds an associate's degree
	Bachelor'sDegree	Binary variable representing primary food purchaser holds a bachelor's degree
	Master'sorAbove	Binary variable representing primary food purchaser holds a master's degree or a higher degree
	OwnsCar	Binary variable representing the household owns a vehicle
	OwnsHouse	Binary variable representing the household owns its place of residency
	RuralLocation	Binary variable representing household lives in a rural census tract according to the U.S. Census Bureau
	Black	Binary variable representing the primary food purchaser is black
	Asian	Binary variable representing the primary food purchaser is Asian
	Hispanic	Binary variable that holds a value of 1 if the primary food purchaser is Hispanic
	FinancialCapacity	Binary variable indicating the household has at least $2,000 in liquid savings

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Table 2. (*Continued*)

Category	Variable	Definition
Food consumer competency-related vector ($\mathbf{X}^c$)	UsesGroceryList	Binary variable representing primary food purchaser "almost always" or "most of the time" shops with a grocery store list
	HealthInterest	Binary variable representing household tried to follow the recommendations of the MyPyramid plan
Market variables vector ($\mathbf{X}^M$)	DistNearSNAPRet	Represents distance in miles to nearest retailer accepting SNAP benefits
	DensityofSupermarket	Represents the number of supermarkets per 1,000 people at the county level
	DensityofNonSupermarkets	Represents the number of nonsupermarkets per 1,000 people at the county level
	West	Binary variable representing household is in the West region of the United States
	South	Binary variable representing household is in the South region of the United States
	Midwest	Binary variable representing household is in the Midwest region of the United States
	StateUnemployment	State unemployment rate
	StateIncomePerCapita	State income per capita
	CountyPopulation	Population in the county (thousands)
Instrumental variables	StreamlinedApplication	Binary variable representing if a state allows for households to utilize a streamlined application process for recipients of the Supplemental Security Income
	OnlineApplication	Binary variable representing if a state allows households to submit a SNAP application online (statewide)
	Recertification $>$ Year	Percentage of SNAP units (with earnings) in the state with recertification periods longer than a year

Note: SNAP, Supplemental Nutrition Assistance Program.

4.4. Instrumental variable methods

The SNAP variable might still be correlated with some unobservable food price determinants even after including a large set of control variables. For example, previous SNAP recipients may be impatient, which is an unobserved trait (Hastings and Washington, 2010). Similarly, the ability to search and process information to compare prices effectively might also be correlated with the ability to find assistance programs and correctly apply for them (e.g., filling out relevant paperwork).

We used an IV approach to account for the endogeneity of selection into the SNAP program (Ratcliff, McKernan, and Zhang, 2011). We used three state policy variables as outside instruments to identify the causal SNAP participation variable: a dummy variable representing whether the state allows households to use a streamlined application process for recipients of Supplemental Security Income, a binary variable representing whether the state allows households to apply for SNAP benefits online, and the proportion of SNAP units with earnings that have recertification periods longer than a year.[14] All of these instruments reduce the cost to participate in SNAP.

[14]A reviewer suggested the recertification variable is the result of a policy outcome rather than a direct measure of the policy itself. However, endogeneity is assumed to stem from unobserved household level variables. It seems unlikely for state-level recertification variables be correlated with unobserved household factors.

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Table 3. Summary statistics

Variable	Observations	Mean	Standard Deviation	P5[a]	P95[a]
ExpensivenessIndex	3,601	0.99	0.39	0.58	1.56
SNAP	3,601	0.28	0.45	0	1
LogAnnualIncome	3,601	9.33	3.13	0	11.70
AnnualIncome	3,601	39,736.01	49,331.25	0	120,000.00
LogHouseholdSize	3,601	0.94	0.59	0	1.79
HouseholdSize	3,601	3.01	1.72	1	6.00
PercentElderlyMembers	3,600	0.21	0.37	0	1
PercentChildren	3,600	0.14	0.21	0	0.57
PercentSmallChildren	3,600	0.08	0.15	0	0.50
SinglePerson	3,600	0.19	0.39	0	1
Age	3,597	46.05	16.07	23.00	74.00
Male	3,601	0.25	0.43	0	1
GED	3,601	0.29	0.45	0	1
SomeCollege	3,601	0.27	0.45	0	1
AssociateDegree	3,601	0.12	0.32	0	1
Bachelor'sDegree	3,601	0.15	0.36	0	1
Master'sorAbove	3,601	0.07	0.26	0	1
FinancialCapacity	3,601	0.36	0.48	0	1
OwnsCar	3,601	0.83	0.37	0	1
OwnsHouse	3,601	0.50	0.50	0	1
RuralLocation	3,601	0.29	0.45	0	1
Black	3,601	0.11	0.32	0	1
Asian	3,601	0.18	0.39	0	1
Hispanic	3,601	0.04	0.20	0	1
GroceryList	2,951	0.40	0.49	0	1
HealthInterest	3,601	0.17	0.37	0	1
West	3,601	0.23	0.42	0	1
South	3,601	0.36	0.48	0	1
Midwest	3,601	0.25	0.43	0	1
DistanceNearSNAPRet	3,601	0.90	1.39	0.06	3.90
DensityofNonSupermarkets	3,601	0.26	0.12	0.10	0.47
DensityofSupermarket	3,601	0.12	0.04	0.06	0.19
CountyPopulation	3,567	12.57	22.98	0.23	98.19

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Table 3. (*Continued*)

Variable	Observations	Mean	Standard Deviation	P5[a]	P95[a]
StateIncomePerCapita	3,601	42,054.14	6369.35	35,979	45,413.00
StateUnemployment	3,601	7.63	1.78	6.70	9.00
StreamlinedApplication	3,601	0.62	0.49	0	1
OnlineApplication	3,601	0.03	0.17	0	1
Recertification > Year	3,601	2.17	3.02	0	10.24

[a]These are the 5th and 95th percentiles, except for StateIncomePerCapita and StateUnemployment, which correspond to the 20th and 80th percentiles. We do not report minimum and maximums because of data disclosure concerns. The 20th and 80th percentiles for StateIncomePerCapita and StateUnemployment are percentiles of the empirical distribution containing only state-level data, not household-level data.
Note: SNAP, Supplemental Nutrition Assistance Program.

We obtained these variables for 2012 and 2013 from the USDA's SNAP Policy Database (https://www.ers.usda.gov/data-products/snap-policy-data-sets/). Following the method used by Ng and Bai (2009), we only included instruments with a t-statistic greater than 2.50 using a first stage regression approach. We also only included instruments that had the expected sign in the first stage regression to ensure their theoretical validity.[15]

It is important to note that these variables are determined at the state level and are not controlled by sample members. However, it is possible that changes in state-level SNAP policies are correlated with state-level macroeconomic conditions that could affect aggregate food demand and prices. We controlled for this by including state-level unemployment and income per capita controls in the IV models.[16] We also tested the instruments' validity using a Hansen test for over-identification (Wooldridge, 2010).

We also used the IV method developed by Lewbel (2012) both as a robustness check and to obtain potential efficiency gains (Almada, McCarthy, and Tchernis, 2015; Baum, 2011; Lewbel, 2007, 2012). Lewbel's (2012) procedure works as follows. For simplicity, the main model for price P in equation (7) can be rewritten as

$$P = \boldsymbol{Z}'\boldsymbol{\gamma_1} + \beta_{SNAP}SNAP + e, \tag{8}$$

where index j has been omitted, Z is the vector of all explanatory variables excluding the *SNAP* variable, $\boldsymbol{\gamma}_1$ is the corresponding vector of parameters, and e represents the error term. A reduced form model for participation in the SNAP program can be written as

$$SNAP = \boldsymbol{Z_S\gamma_2} + \varepsilon, \tag{9}$$

where $\boldsymbol{Zs}$ is the vector of variables affecting participation including both $\boldsymbol{Z}$ and a vector of outside instruments $\boldsymbol{H}$ (i.e., $Z_s = [\boldsymbol{Z}\,\boldsymbol{H}]$). $\boldsymbol{\gamma}_2$ is the vector of coefficients in the participation equation, and ε is the error term. Identification and estimation of equations (8) and (9) are based on the following moment conditions and heteroscedasticity of the errors (Lewbel, 2012):

$$\boldsymbol{E}(\boldsymbol{Z}e) = 0, \boldsymbol{E}(\boldsymbol{Z_S}\varepsilon) = 0, \;\; Cov(\boldsymbol{Z_L}, e\varepsilon) = 0, \tag{10}$$

where $\boldsymbol{Z_L}$ can be equal to $\boldsymbol{Z_S}$ or a subset of it. The first two sets of moment conditions correspond to the standard moment conditions used when instruments and explanatory variables are

[15]We identified nine policy variables from the USDA's SNAP policy database as potential instruments that did not have missing observations. To test for IV sensitivity, we tested regressions separately, including all nine variables identified as potential instruments and found minimal differences in the results. We also tested our regressions separately, including the three policy variables individually.

[16]*StateUnemployment* represents the level of state unemployment during the year each household's purchases were recorded. Data on state unemployment figures were obtained from the U.S. Bureau of Labor Statistics. *StateIncomePerCapita* represents the state income per capita during the year each household's purchases were recorded. Data on state income per capita were obtained from the Bureau of Economic Analysis of the U.S. Department of Commerce.

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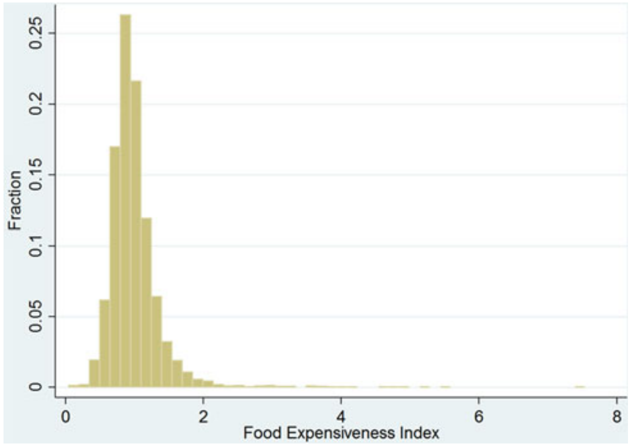

Figure 1. Expensiveness index distribution.

exogenous. The third set of moment conditions requires $\boldsymbol{Z_L}$ to be uncorrelated with the product of errors. Although the last moment conditions are not very intuitive, the validity can be assessed using a Hansen's overidentification test. More importantly, the third moment conditions make it possible to identify and estimate parameters in equations (8) and (9) without outside instruments or to use this additional information to improve efficiency. In our application, $\boldsymbol{Z_S} = \boldsymbol{Z_L}$; thus, the additional moment conditions were used to gain efficiency and to test the sensitivity of our results to additional model assumptions. Implementation of the procedure was carried out using STATA (Baum, 2011).

5. Empirical results

Figure 1 displays a histogram of the expensiveness index. Although the data included some unexpectedly large and low index values, 98% of the data lies between 0.43 and 2.21 times the average cost of a households' food basket. As shown in Table 3, the mean household size in our sample was 3 people (mean logarithm = 0.94). Our SNAP variable had a mean value of 0.28, indicating that approximately 28% of our households sampled were confirmed participants. *FinancialCapacity* had a mean of 0.36, indicating that approximately 36% of our households sampled had at least $2,000 in liquid assets. *Supermarket* and *Nonsupermarket* county densities ranged from 0 per 1,000 people to more than 0.19 and 0.47 per 1,000, respectively.

All the SNAP variable coefficients in Tables 4 and 5 represent estimates of the difference in the average value of the expensiveness index between SNAP participants and nonparticipants, without controlling (model 1) or controlling (models 2–4) for other factors affecting the index. The baseline specification using OLS (Table 4) indicated that SNAP participants' mean expensiveness index was approximately 0.10 points lower (i.e., 10%) than that of SNAP nonparticipants, which is a large significant and economic difference.[17] To put things in perspective, a 10% difference in price corresponds to approximately $9 per week for SNAP recipients, as their average weekly expenditures on food at home are approximately $93.35 (Smith et al., 2016).

When we controlled for household variables, the difference in the index value between SNAP participants and nonparticipants estimated was still negative and statistically and economically significant. However, the magnitude (in absolute value) decreased to approximately 4%. When

[17]This includes noneligible and eligible, but nonparticipating households.

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Table 4. Determinants of the expensiveness index: ordinary least squares results

	Model 1		Model 2		Model 3		Model 4	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
SNAP	−0.096***	0.013	−0.039**	0.016	−0.027	0.016	−0.026	0.016
Log Annual Income			−0.016	0.010	−0.024**	0.011	−0.019*	0.011
LogAnnualIncome^2			0.002*	0.001	0.002**	0.001	0.002*	0.001
LogHouseholdSize			−0.092***	0.028	−0.070**	0.029	−0.070**	0.029
PercentElderlyMembers			0.028	0.024	0.026	0.026	0.026	0.026
PercentChildren			−0.017	0.048	−0.059	0.046	−0.053	0.047
PercentSmallChildren			0.015	0.049	−0.001	0.054	0.006	0.055
SinglePerson			−0.031	0.030	−0.032	0.029	−0.031	0.029
Age			−0.003***	0.001	−0.002***	0.001	−0.003***	0.001
Male			−0.027**	0.014	−0.028*	0.015	−0.026*	0.015
GED			0.008	0.016	−0.001	0.017	−0.003	0.017
SomeCollege			0.037**	0.016	0.029*	0.018	0.029	0.018
AssociateDegree			0.088***	0.028	0.070**	0.027	0.063**	0.027
Bachelor'sDegree			0.098***	0.021	0.101***	0.023	0.092***	0.023
Master'sorAbove			0.173***	0.031	0.196***	0.036	0.183***	0.036
FinancialCapacity			0.067***	0.015	0.062***	0.016	0.065***	0.016
OwnsHouse			−0.002	0.013	−0.004	0.015	0.007	0.015
OwnsCar			−0.054**	0.024	−0.039*	0.022	−0.030	0.022
Black			−0.032	0.022	−0.028	0.023	−0.028	0.023
Hispanic			−0.032*	0.017	−0.035*	0.018	−0.043**	0.019
Asian			−0.097**	0.039	−0.093**	0.043	−0.096**	0.044
GroceryList					−0.006	0.014	−0.002	0.014
HealthInterest					0.009	0.018	0.014	0.018
RuralLocation							−0.031*	0.018
West							−0.065***	0.025
South							−0.051**	0.021
Midwest							−0.085***	0.023
DistNearSNAPRet							−0.012***	0.004
Density of Non Supermarkets							−0.155***	0.057
Density of Supermarket							0.175	0.167
County Population							0.000	0.000
Constant	1.019***	0.008	1.211***	0.051	1.171***	0.044	1.258***	0.050

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Table 4. (*Continued*)

	Model 1		Model 2		Model 3		Model 4	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
N	3,601		3,597		2,949		2,920	
F-statistic (*P* value)	54.35 (0.000)		9.41 (0.000)		8.88 (0.000)		8.21 (0.000)	
R^2	0.013		0.066		0.070		0.080	

Notes: Model 1 regresses our expensiveness index on our Supplemental Nutrition Assistance Program (SNAP) variable. Model 2 includes SNAP and household variables. Model 3 includes SNAP, household, and food consumer competency-related variables. Model 4 includes our SNAP, household, food consumer competency-related, and market variables. *$P \leq 0.1$, **$P \leq 0.05$, and ***$P \leq 0.01$. Regressions are reported with robust standard errors. SE, standard error.

we controlled for food competency-related and market environment variables, the estimated difference in the expensiveness index value decreased to less than 3% and became insignificant.

The R^2 of models 1–4 increased substantially from model 1 to model 2 (from 0.013 to 0.066) and from model 3 to model 4 (from 0.070 to 0.080) but very little from model 2 to 3 (from 0.066 to 0.070).[18] This provides evidence that sociodemographic factors and market environment characteristics are more important in explaining the expensiveness index than food competency-related factors.

Using OLS, we also found a consistent, negative statistically significant relationship between household size and our expensiveness index. Our estimates indicate each additional household member is associated with a decrease in the expensiveness index of approximately 0.07 to 0.09 points, similar to the 0.10 value reported in the United Kingdom by Beatty (2010). In contrast to Beatty (2010), we do not find evidence that household composition affects the expensiveness index.

The primary food purchaser's age also had a consistent, negative statistically significant relation to the expensiveness index where a 1-year increase in the primary food purchaser's age was associated with a decrease in the expensiveness index of approximately 0.002 to 0.003 points. Household income was also found to have a positive relationship with the expensiveness index.[19] At the mean income (approximately $40,000), a 1% increase in income was associated with an approximately 0.02% increase in the index. This elasticity value is smaller to the 0.08 value reported by Beatty (2010).

Higher levels of education had a positive and statistically significant relationship with higher food prices. Our findings indicated that primary food purchasers who earned at least a college degree were associated with a 0.07- to 0.19-point increase (i.e., 7%–19%) in the expensiveness index (relative to primary food purchasers with less than a GED). Primary food purchasers who earned a bachelor's degree were associated with an approximately 0.10-point increase (i.e., 10%) in the expensiveness index. Primary food purchasers who earned a master's degree or higher were associated with an approximately 0.17- to 0.20-point (i.e., 17%–20%) increase in the expensiveness index. These effects are estimated after controlling for income and may reflect differences in food quality across education groups. As noted previously, some studies argue that comparatively more educated households may be able to implement cost-saving strategies to pay lower prices. However, these studies hold food quality levels constant (Narashman, 1984).

We also found predominantly Hispanic and Asian households also pay lower prices than other ethnic and racial groups. *FinancialCapacity* had a consistent and positive statistically significant relationship with the expensiveness index where a household with $2,000 or more in liquid assets

[18]The R^2 in models 1 to 4 are not completely comparable, as they were estimated using different numbers of observations, but the pattern remained when the models were estimated using observations available for model 4.

[19]The minimum value of the quadratic function was very close to $0. To avoid problems with $0 income values, we used Log(income + 1) in the models, where Log(.) refers to the natural logarithm.

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Table 5. Determinants of the expensiveness index

	IV-2SLS Method						Lewbel IV Procedure					
	Model 2		Model 3		Model 4		Model 2		Model 3		Model 4	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
SNAP	−0.036	0.124	0.016	0.121	−0.049	0.115	−0.007	0.025	0.009	0.026	−0.002	0.025
LogAnnualIncome	−0.015	0.018	−0.026	0.017	−0.017	0.017	−0.024**	0.010	−0.030***	0.011	−0.028***	0.010
LogAnnualIncome2	0.002	0.002	0.003	0.002	0.002	0.002	0.002***	0.001	0.003***	0.001	0.003***	0.001
LogHouseholdSize	−0.096***	0.035	−0.079**	0.034	−0.065*	0.034	−0.080***	0.022	−0.082***	0.024	−0.084***	0.024
PercentElderlyMembers	0.030	0.024	0.030	0.026	0.025	0.026	0.023	0.022	0.025	0.024	0.025	0.024
PercentChildren	−0.009	0.047	−0.051	0.046	−0.049	0.047	−0.044	0.038	−0.055	0.042	−0.040	0.042
PercentSmallChildren	0.017	0.059	−0.005	0.064	0.012	0.061	0.024	0.046	0.033	0.049	0.044	0.049
SinglePerson	−0.032	0.030	−0.033	0.029	−0.028	0.028	−0.025	0.024	−0.032	0.026	−0.034	0.025
Age	−0.003***	0.001	−0.003***	0.001	−0.003***	0.001	−0.003***	0.001	−0.002***	0.001	−0.002***	0.001
Male	−0.027*	0.014	−0.026*	0.015	−0.026*	0.015	−0.017	0.013	−0.024*	0.014	−0.022	0.014
GED	0.007	0.016	−0.001	0.017	−0.003	0.018	0.007	0.014	0.003	0.015	0.001	0.015
SomeCollege	0.037**	0.017	0.032*	0.018	0.028	0.018	0.042***	0.015	0.036**	0.016	0.028*	0.016
AssociateDegree	0.083***	0.029	0.068**	0.027	0.058**	0.029	0.064***	0.022	0.063***	0.024	0.054**	0.024
Bachelor'sDegree	0.096***	0.025	0.104***	0.027	0.088***	0.026	0.090***	0.020	0.109***	0.022	0.098***	0.022
Master'sorAbove	0.171***	0.032	0.195***	0.037	0.179***	0.036	0.168***	0.029	0.198***	0.034	0.176***	0.034
FinancialCapacity	0.062***	0.020	0.062***	0.022	0.058***	0.021	0.057***	0.015	0.063***	0.016	0.064***	0.016
OwnsHouse	0.000	0.015	0.001	0.018	0.005	0.017	0.008	0.012	0.009	0.014	0.017	0.014
OwnsCar	−0.047*	0.026	−0.025	0.027	−0.029	0.027	−0.018	0.018	−0.016	0.018	−0.010	0.018
Black	−0.032	0.022	−0.029	0.023	−0.032	0.024	−0.027	0.020	−0.032	0.022	−0.043**	0.022
Hispanic	−0.042**	0.018	−0.044**	0.019	−0.045**	0.020	−0.035**	0.016	−0.043**	0.017	−0.046***	0.018
Asian	−0.114***	0.040	−0.107**	0.045	−0.110**	0.046	−0.097***	0.038	−0.103**	0.043	−0.100**	0.041

Table 5. (*Continued*)

	IV-2SLS Method						Lewbel IV Procedure					
	Model 2		Model 3		Model 4		Model 2		Model 3		Model 4	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
GroceryList			−0.006	0.014	0.000	0.014			−0.008	0.012	−0.003	0.012
HealthInterest			0.006	0.019	0.013	0.020			0.003	0.016	0.005	0.016
RuralLocation					−0.026	0.018					−0.031*	0.016
West					−0.030	0.026					−0.029	0.024
South					0.020	0.027					0.029	0.024
Midwest					−0.018	0.031					−0.009	0.024
DistNearSNAPRet					−0.012***	0.005					−0.010**	0.004
DensityofNonSupermarkets					−0.171***	0.061					−0.168***	0.053
DensityofSupermarket					0.143	0.169					0.248	0.155
CountyPopulation					−0.001*	0.000					−0.001**	0.000
Statepcap	0.046***	0.012	0.055***	0.013	0.061***	0.017	0.053***	0.011	0.058***	0.012	0.070***	0.015
StateUnemployment	0.010**	0.005	0.009*	0.005	0.014**	0.006	0.006	0.004	0.006	0.005	0.013**	0.005
Constant	0.939***	0.097	0.850***	0.101	0.857***	0.141	0.854***	0.073	0.833***	0.082	0.770***	0.103
N	3,597		2,949		2,920		3,597		2,949		2,920	
Wald chi-square/*F*-statistic (*P* value)	240.69 (0.000)		232.18 (0.000)		266.37 (0.000)		11.03 (0.000)		10.64 (0.000)		9.49 (0.000)	
R^2	0.071		0.075		0.085		0.067		0.074		0.083	
First stage *F*-statistic	22.326		21.294		14.556		50.575		41.460		33.267	
Hansen *J*-statistic (*P* value)	3.472 (0.176)		1.865 (0.394)		1.085 (0.581)		23.053 (0.517)		25.092 (0.514)		33.439 (0.495)	

Notes: Model 1 regresses our expensiveness index on our Supplemental Nutrition Assistance Program (SNAP) variable. Model 2 includes SNAP and household variables. Model 3 includes SNAP, household, and food consumer competency-related variables. Model 4 includes our SNAP, household, food consumer competency-related, and market variables. *$P \leq 0.1$, **$P \leq 0.05$, and ***$P \leq 0.01$. Regressions are reported with robust standard errors. IV-2SLS, instrumental variable two-stage least squares; SE, standard error.

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Table 6. First sage regression results (IV-2SLS): coefficients of outside relevant instruments

Variable	Model 2 Coefficient	Model 3 Coefficient	Model 4 Coefficient
StreamlinedApplication	0.107*** (0.014)	0.112*** (0.016)	0.092*** (0.022)
OnlineApplication	0.0724* (0.0011)	0.092** (0.043)	0.189** (0.048)
Recertification > Year	0.002 (0.002)	0.004 (0.003)	0.021*** (0.005)
N	3,597	2,949	2,920
R^2	0.268	0.279	0.289
F-statistic (*P* value)	<0.001	<0.001	<0.001

Notes: The first stage regression also included as explanatory variables all the other variables included in IV models 2, 3, and 4 (Table 5). $^{*}P \leq 0.1$, $^{**}P \leq 0.05$, and $^{***}P \leq 0.01$. Regressions are reported with robust standard errors.

was associated with a 0.06- to 0.07-point (i.e., 6%–7%) higher expensiveness index than were households with less than $2,000 in liquid assets.

We found no statistically significant relationship between the expensiveness index and our food competency-related variables. However, we found negative statistically significant relationships between the expensiveness index and if the household lives in a rural location, if there are higher densities of nonsupermarket stores per 1,000 people, and for longer distances to the nearest SNAP-authorized retailer. This last result indicates proximity to authorized SNAP retailers is not necessarily associated with paying lower food prices. We also found that households' in the South, West, and Midwest regions of the United States paid lower food prices relative to the East region. Detailed results of our findings using the OLS approach are reported in Table 4.

In the next set of regressions, we used a classical IV approach to account for endogeneity of our SNAP variable. We first evaluated the weakness of the instruments using the first stage *F*-statistic. In all cases, the estimated first stage *F*-statistic values were larger than 14, suggesting that the instruments are not weak. The effects of the instruments in the first stage regression on the probability of SNAP participation were also found statistically significant and economically important (see Table 6). For example, model 4 indicates that if a state allows households to use a streamlined application process for recipients of the Supplemental Security Income, and to submit a SNAP application online, the probability of households participating in SNAP increases by 9.2% and 18.9%, respectively. Similarly, a 1% increase in the share of SNAP units at the state level with earning and recertification periods longer than a year increases the probability of participation by 2.0% (Table 6).

Finally, our overidentification restriction tests failed to reject the null hypothesis that the instruments are uncorrelated with the error term in each regression, providing evidence our instruments are valid. Moreover, because the overidentification test is the same as comparing IV estimates of the SNAP effect using the different instruments, it also provides some evidence of homogeneity of effects (Wooldridge, 2010).[20]

[20]Each IV estimates a unique effect specific to the population of compliers for that instrument (i.e., a local average treatment effects [LATE]) when there is treatment effects heterogeneity, and the coefficient estimated using all IV corresponds to a weighted average of the LATEs. In this case, the population of compliers includes households that are induced to (or not to) participate because of our IV policy variables. As one of our reviewers noted, the instruments only affect a small proportion of the population (see Table 2).

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Using our IV approach, we found no significant effects of SNAP participation on the expensiveness index across all model specifications. It should be mentioned that the test of whether a causal treatment effect is null only requires the validity of the instrument (Swanson, Labrecque, and Hernán, 2018; VanderWeele et al., 2014). Thus, the validity of the test for the null effect of SNAP participation on prices is robust to additional assumptions such as homogeneity of treatment effects. Other statistically significant relationships remained largely the same when we compared the results of the OLS and IV approaches.[21] Detailed findings using the IV approach are reported in Table 5.

Our last set of regressions (also reported in Table 5) used Lewbel's (2012) IV approach. We implemented the procedure with a generalized method of moments estimator. Overidentification restrictions tests (Hansen *J*-statistic) failed to reject the null hypothesis that the moment conditions implied by the approach were valid, which provides evidence to the validity of the approach (including the key assumption that the product of the errors is uncorrelated with the exogenous explanatory variables). The value of the *F*-statistics using this approach was greater than 10 for each regression.

We again found no statistically significant effect of SNAP participation on our expensiveness index, although the additional moment conditions appear to provide important gains in efficiency by reducing the standard errors of the SNAP coefficient compared with our previous IV approach. The similarity of our results indicates robustness of our estimated effects of SNAP participation on the expensiveness index. We also find little difference in the statistically significant relationships and quantitative effects of other variables on our expensiveness index compared with our previous approaches.

5.1. Sensitivity analysis

We also conducted a series of sensitivity analyses to evaluate the robustness of our results to various model assumptions with a special emphasis on the robustness of the SNAP coefficient (Table 7). The first groups of robustness checks consider alternative subsample groups. Although our regression models controlled for income level, the sample includes both high- and low-income participants. Thus, observed differences in the expensiveness index might be because of differences in the income level. To test the sensitivity of our analysis to difference effects stemming from varying income levels, we also estimated our models using a subsample of households that receive SNAP benefits and SNAP-eligible nonparticipants (Table 7, S2). A household is SNAP eligible if its annual income is less than 130% of the poverty threshold. These thresholds are determined by the U.S. Department of Health and Human Services (HHS) annual poverty guidelines. We followed the 2012 and 2013 guidelines for the 48 contiguous states and Washington, D.C., to determine SNAP eligibility[22] and found no statistically significant effect of SNAP participation on our expensiveness index for SNAP-eligible, but nonparticipating households.

The other results were very similar to our previous findings. For example, the OLS regressions indicated that SNAP participants' mean expensiveness index was approximately 0.08 points lower (i.e., 8%) than that of SNAP-eligible nonparticipants (relative to the previous 10% difference).

[21] Additional endogeneity concerns with the models relate to the food competency-related and food market environment variables. *HealthInterest* and *UsesGroceryList* could be related to short-run impatience. The identifying assumption associated with the causal effects of our county-level food retailer variables is that unobservable county characteristics are unassociated with our variables (Courtemanche and Carden, 2011). When we estimated the effect of SNAP participation with and without these sets of potentially endogenous variables, our empirical findings did not change. Further, ours results on the effect of SNAP and the coefficients related to food consumer competency and households' characteristics remained unchanged when we also estimated a model with county-level fixed effects rather than the market environment characteristics. Similar problems of endogeneity also can be present in the variable *DistNearSNAPRet*, which was measured at the block group level.

[22] The Department of Health and Human Services has different requirements to meet poverty guidelines for Alaska and Hawaii. However, FoodAPS did not include any households located in either state.

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Table 7. Summary of Sensitivity Analysis: SNAP Coefficient

	OLS Method				IV-2SLS Method			Lewbel IV Procedure		
Alternative Estimation Condition	Model 1	Model 2	Model 3	Model 4	Model 2	Model 3	Model 4	Model 2	Model 3	Model 4
S1. Baseline specification	−0.096*** (0.013)	−0.039** (0.016)	−0.027 (0.016)	−0.026 (0.016)	−0.036 (0.124)	0.016 (0.121)	−0.049 (0.115)	−0.007 (0.025)	0.009 (0.026)	−0.002 (0.025)
S2. Sample restricted to SNAP-eligible households only	−0.079*** (0.022)	−0.054** (0.024)	−0.036 (0.023)	−0.035 (0.023)	−0.071 (0.149)	0.064 (0.149)	−0.087 (0.116)	−0.099* (0.058)	−0.081 (0.064)	−0.104 (0.057)
S3. Sample removing outlying observations	−0.068*** (0.010)	−0.016 (0.012)	−0.001 (0.013)	−0.001 (0.014)	−0.081 (0.076)	−0.051 (0.149)	−0.087 (0.079)	0.010 (0.018)	0.030 (0.019)	0.015 (0.019)
S4. Use of maximum number of observations available for model 4 (2,920) in all models	−0.091*** (0.014)	−0.027 (0.016)	−0.026 (0.016)	−0.026 (0.016)	0.024 (0.124)	0.023 (0.121)	−0.049 (0.115)	0.0120 (0.026)	0.007 (0.026)	−0.002 (0.025)
S5. Use of seasonal dummies	−0.096*** (0.013)	−0.035** (0.016)	−0.021 (0.016)	−0.020 (0.016)	−0.024 (0.131)	0.036 (0.129)	−0.030 (0.117)	−0.002 (0.025)	0.017 (0.026)	0.001 (0.025)
S6. Adding dummy for first week of month	−0.096*** (0.013)	−0.039** (0.016)	−0.027 (0.016)	−0.026 (0.017)	−0.038 (0.124)	0.013 (0.121)	−0.052 (0.116)	−0.008 (0.024)	0.012 (0.026)	0.002 (0.024)
S7. Use of state dummies instead of regional dummies				−0.020 (0.017)			0.443 (4.53)			−0.027 (0.023)
S8. Estimation using sample weights	−0.135*** (0.019)	−0.055** (0.028)	−0.034 (0.032)	−0.021 (0.031)	−0.086 (0.496)	0.137 (0.418)	0.115 (0.339)	−0.046 (0.060)	−0.005 (0.070)	−0.010 (0.058)
S9. Use of log(expensiveness index) as dependent variable	−0.090*** (0.011)	−0.025** (0.013)	−0.017 (0.014)	−0.018 (0.015)	0.056 (0.103)	0.130 (0.106)	0.001 (0.106)	0.002 (0.022)	0.012 (0.025)	−0.002 (0.023)
S10. Clustered standard errors	−0.096*** (0.014)	−0.039*** (0.014)	−0.027* (0.015)	−0.026 (0.016)	−0.036 (0.178)	0.016 (0.155)	−0.049 (0.140)	NA	NA	NA

Notes: Model 1 regresses our expensiveness index on our Supplemental Nutrition Assistance Program (SNAP) variable. Model 2 includes SNAP and household variables. Model 3 includes SNAP, household, and food consumer competency-related variables. Model 4 includes our SNAP, household, food consumer competency-related, and market variables. *$P \leq 0.1$, **$P \leq 0.05$, and ***$P \leq 0.01$. Regressions are reported with robust standard errors. IV-2SLS, instrumental variable two-stage least squares.

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The SNAP coefficient that estimates this difference remained statistically significant but decreased to 5% when we added household control variables. When we controlled for food competency variables and market environments, the difference was approximately 3.5% and became statistically insignificant (Table 7, S2).

We also tested the robustness of our findings by removing outlying observations (Table 7, S3). We defined outliers as values exceeding 150% of the difference between the interquartile below and above the first and third quartile values, respectively. We removed outlier values above and below these thresholds in the expensiveness index, the logarithm of annual household income, the density of supermarkets in a county, the logarithm of household size, the distance to the nearest SNAP-authorized retailer, the density of nonsupermarkets in a county, and the county population variables. Removing these observations increased our R^2 values from 0.08 to 0.12 for our OLS and IV regressions for our models with all control vectors. However, there was little change in the statistically significant relationships.

To test whether changes in statistical significance or coefficient values of the SNAP variable are caused by a decrease in the number of observations from models 1 to 4, we estimated each model using all the available observations (2,920) to estimate model 4 (Table 7, S2). The results were again largely similar to those in the baseline specification.[23]

We also considered additional and alternative sets of controls for our model. To see whether seasonal food price fluctuations affected the expensiveness index, we included summer, autumn, and winter binary variables (with spring as our base variable; Table 7, S5). Although these variables were statistically significant, our other results remained largely the same. To account for the previous literature showing that SNAP households spend much of their food dollars at the beginning of the month, we included a dummy variable indicating whether the survey took place in the first week of the month (Table 7, S6) literature. This variable was not statistically significant and did not affect our regression results. We then included state dummy variables instead of regional dummies and implemented the three econometric procedures for model 4 (Table 7, S7). The results using OLS were very similar to those in the baseline specification. However, the SNAP coefficient, and corresponding standard error, changed considerably when using the IV-2SLS (instrumental variable two-stage least squares) method and Lewbel IV procedure. However, all other results remained largely similar, and the SNAP variable was still not statistically significant. However, because our instruments are state-level policy variables, adding state dummies when using the standard IV procedure generated a weak instrument problem.

We also used sample weights to estimate our empirical model, as well as the log of the expensiveness index rather than the expensiveness index (Table 7, S8 and S9). Both procedures added little explanatory power.[24] Finally, we used clustered standard errors (S10, Table 7). Following Abadie et al. (2017), we used the survey sample clusters (50 in total) for standard error calculations. The clusters corresponded to the PSUs described in Section 3. Our results were robust to the use of these types of standard errors.

6. Discussion and conclusion

We used the FoodAPS data set to empirically examine whether SNAP participants pay different food prices compared with nonparticipating households and whether SNAP participation influences the prices households pay for food items. Because FoodAPS includes more household

[23]Moreover, SNAP maintained a negative and statistically significant relation with our expensiveness index only in model 1.

[24]An earlier version of the manuscript included a variable that indicated whether an individual has ever skipped meals because of budgeting problems. As pointed out by a reviewer, this variable measures not only budgeting abilities or numeracy but also vulnerability to food insecurity, so it was excluded from the model. Exclusion of this variable did not have an appreciable effect on other regression results.

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characteristics, measures of shopping behavior, and food market variables, our analysis also contributes to the literature by examining a broader set of factors associated with food prices.

Although SNAP participants' mean expensiveness index was found to be 9% lower than that of nonparticipants, we found SNAP participation had no statistically significant relationship with food prices when we controlled for household, food consumer competency-related, and food market structure variables using OLS. We obtained similar results when we used an IV approach and Lewbel's (2012) method.

A larger body of literature evaluating the effectiveness of the SNAP program focuses on its effect on participants' food expenditures. Our results suggest that the price component of food expenditures is not affected by SNAP participation. In other words, participants' price shopping behavior does not seem to be affected by their participation. However, our results also suggest more efforts to promote cost-cutting shopping behavior could be fruitful to improve program effectiveness. Educational efforts, such as SNAP-Ed, may provide some assistance helping program patrons take advantage of bargaining opportunities. Unfortunately, FoodAPS does not provide information on which households participated in SNAP-Ed. Efforts to collect data regarding which SNAP-participating households also participate in SNAP-Ed would be most helpful in determining SNAP-Ed's effects on several outcomes in addition to food prices.

Our findings also have some implications regarding food market environments and food prices. The concentration of nonsupermarket retailers was associated with comparatively lower prices paid for food items. Although smaller stores (nonsupermarkets) typically charge comparatively higher prices than do larger stores (supermarkets), higher concentrations of nonsupermarkets may result in price competition for consumer patronage.

Finally, it is important to note several limitations in our analyses. First, we used a wide variety of food items, but the approach used does not account completely for product quality, as we had no specific food product brand information. Second, although the expensiveness index is constructed to control for differences in quantities (quantities in the index numerator and denominator are the same), it is still possible that some of the observed differences in the index may be because of differences in quantities. Third, the household expensiveness index is interpreted as an overall measure of food prices, but it includes two components: a food basket and food item prices. Future work using the index could explore the effect of SNAP on the individual components of the index. Fourth, we did not include food items purchased for consumption outside the home, such as meals from fast-food vendors or other restaurants, which are not part of the SNAP program. These four limitations provide important opportunities for future research.

Another limitation is the use of cross-sectional data. Although we use IVs to try to infer the causal effect of SNAP participation on prices, future use of panel data might allow researchers to handle the effects of important unobservables better. Panel data could also help ameliorate some limitations of IV procedures such as the loss of efficiency and small sample biases.

Although our analysis provides important policy implications and contributes to multiple lines of research, much work remains to be done. Additional analysis assessing the impact of other food consumer competency and local food market factors on food prices paid, as well as differences in prices paid using SNAP benefits and other sources of income, could also provide fruitful information to guide SNAP efficiency improvement efforts. More research is also needed to explore the effect of SNAP participation on nonfood expenditures.

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