Do Obese and Nonobese Consumers Respond Differently to Price Changes? Implications of Preference Heterogeneity for Using Food Taxes and Subsidies to Reduce Obesity

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Abstract

Preference heterogeneity in food demand has important health and equity implications for targeted taxes and subsidies intended to enhance diet quality and reduce obesity. We study the role of obesity in the purchases of food at home and food away from home using data from the nationally representative National Household Food Acquisition and Purchase Survey. We develop a method for incorporating the complex survey design and retail scanner data into the estimation of a 21-good Exact Affine Stone Index demand system with endogenous prices and truncated purchases. We find significant preference heterogeneity associated with the obesity status of household members. Counterfactual simulations find that 1) a sweetened beverage tax is effective in increasing the healthfulness of grocery purchases by lower-income obese consumers; 2) the nutritional benefits of a fruit and vegetable subsidy are concentrated on nonobese consumers with little improvement in obese consumers' Healthy Eating Index and an increase in their total calories purchased; and 3) a fiscally neutral healthy food subsidy fully funded by an unhealthy food tax benefits nonobese consumers both financially and nutritionally more than it does obese consumers. These findings show that lowering healthy food prices without raising the cost of unhealthy foods is unlikely to reduce obesity. Policymakers in favor of a systems approach of simultaneously taxing unhealthy foods and subsidizing healthy foods should be mindful of the distributional effects of this policy on obese consumers and the lower-income population.

Keywords: soda tax, fruit and vegetable subsidy, FoodAPS, EASI demand, preference heterogeneity, nutrition inequality

JEL classification: D12, H23, I14, I18

We study the distributional effects of food and beverage taxes and subsidies aimed at reducing prevalence of obesity and improving population diet quality. Unlike harmful goods such as tobacco and illicit drugs, which the majority of the population does not use, food is a necessity and most people, regardless of weight status, consume both foods considered to be healthy by nutrition science and foods deemed less healthy or unhealthy. As such, it is important to examine whether obesity-oriented pricing strategies are most impactful on the diets of the obese consumers and how the financial benefits and costs of the policies are distributed among obese and nonobese, and lower- and higher-income consumers.

Obesity is a major public health threat in the United States. In 2017–2018, 43.0% of US adults are obese, an increase of 15.5 percentage points relative to 1999–2000 (Ogden et al. 2020). For 2006, the most recent year estimates are available, annual obesity-related medical costs were $147 billion (in 2008 dollars), of which slightly less than half is paid for by Medicare and Medicaid (Finkelstein et al. 2009, Exhibit 4). Much of the policy attention is focused on promoting healthy eating because of the etiological association of suboptimal diets with obesity and diet-related noncommunicable diseases (Danaei et al. 2009). Prominent among the existing obesity policies are pricing strategies that lower the cost of healthy foods relative to unhealthy foods through targeted taxes and subsidies. For example, in 2020, seven US cities[1] tax sweetened beverages at one penny per ounce or higher with the explicit goal of reducing added sugar take from beverages. While there is a consensus that all or significant portions of these excise taxes are passed through to retail prices (e.g., Falbe et al. 2015; Cawley and Frisvold 2017; Roberto et al. 2019; Powell and Leider 2020), results on intake and purchases are mixed with some reporting significant reductions (Falbe et al. 2016; Cawley et al. 2019) and others finding insignificant changes (Cawley et al. 2020a).

Although these evaluation studies hold the promise of identifying the causal effect of prices by leveraging the city taxes as quasi experiments, threats to identification and measurement issues still exist. Taylor et al. (2019) found that media coverage and the outcome of an election with a referendum on the Berkeley sugar-sweetened beverage (SSB) tax caused significant reductions in SSB purchases well before the tax was implemented. Allcott, Lockwood and Taubinsky (2019a, p. 216) caution that the effect of the tax on demand could be confounded

[1] They are: Berkeley, San Francisco, Oakland, and Albany, California; Philadelphia, Pennsylvania; Seattle, Washington; and Boulder, Colorado.

by effects of interest groups' advertising campaigns and public debates, which frequently follow the proposal of a SSB tax. On the measurement side, resource constraints often force evaluators to collect data only on beverage intakes and all studies except one (Silver et al. 2017) use the less expensive, but also less accurate, beverage frequency questionnaires rather than the more accurate 24-hour dietary recalls (Subar et al. 2003). The lack of information on intakes of other foods prevents an evaluation of changes in overall diet and an examination of the potential unintended consequence of substitution toward other unhealthy foods. Cross-border tax avoidance is also an issue that limits the generalizability of the city results to potential state or national taxes (Rojas and Wang 2021). Therefore, the quasi experimental design based on city SSB taxes cannot provide ex ante insights into innovative policies such as broad-based taxes and subsidies that have not been implemented and their national implications.

An alternative to quasi experiments is to use econometric estimates of price elasticity of demand to simulate the effect of price changes on food purchases and nutrition. Practitioners of the econometric-simulation approach have made significant progress in model specification and policy relevance of the simulations. Early studies (e.g., Lin et al. 2011; Zhen et al. 2011; Dharmasena and Capps 2012) focused only on beverage purchases, assumed price exogeneity, and ignored the complication of nonpurchases. The more recent literature has accounted for the substitution between sugar-sweetened beverages and other foods (Harding and Lovenheim 2017), price endogeneity (Allcott, Lockwood and Taubinsky 2019b), censored purchases in addition to substitution and endogeneity (Zhen et al. 2014), and the varying sugar content of SSBs (Zhen, Brissette and Ruff 2014).

In this study, we estimate a complete food demand system with flexible functional form, in which an indicator for the presence of at least one obese household member interacts with food prices and total expenditures. We find significant preference heterogeneity associated with the obesity status of household members. For example, households with obese members appear to value variety by treating healthier and less healthy options of otherwise similar foods as complements, while households without obese members are more willing to substitute between healthy and less healthy options. The finding of complementarity demonstrates that demand models restricting goods to be substitutes may not be adequate when studying demand for goods across categories. The counterfactual simulations show that a sweetened beverage tax is effective in increasing the healthfulness of grocery purchases by lower-income obese consumers; the nutritional benefits of a fruit and vegetable subsidy are concentrated on nonobese consumers, with little change in obese consumers' diet quality and an increase in caloric intake; and a fiscally-neutral healthy food subsidy fully funded by an unhealthy food tax benefits nonobese consumers both financially and nutritionally more than it does obese consumers. These findings of heterogeneous impacts highlight the complexity of using pricing policies to improve population diet and health and the importance of considering equity in designing such policies.

In addition to contributing to the policy debate, we innovate in three areas. First, our food demand system includes foods purchased for at-home as well as away-from-home consumption. While demand for food at home (FAH) and food away from home (FAFH) has been modeled as a system using aggregate data (e.g., Okrent and Alston 2012), we present the first complete food demand system estimated with household-level data. The benefit of using micro data to estimate demand is obvious. It allows for an examination of whether preference heterogeneity is associated with observed consumer characteristics that are of policy interest. Because taxes and subsidies carry deadweight loss (Harberger 1964), understanding whether these policies are effective in promoting healthy eating for obese consumers is important for cost-effective and equitable policymaking. We provide the first evidence regarding the effect of obesity-related preference heterogeneity on total food demand and overall healthfulness. We also identify economically important cross-price relationships between FAH and FAFH. This means that findings from previous micro studies using household scanner data on FAH purchases cannot be extrapolated to total diets.

Second, we develop a process that combines a household purchase survey with retail scanner data to create food group-level price indices and their instrumental variables. Previous studies using the econometric-simulation approach rely overwhelmingly on household and retail scanner data on packaged foods due to the depth and granularity of the reported purchases. However, this also results in substantial underreporting of purchases in categories made up of random-weight items such as loose fruit and vegetables and meats and cheese packaged in the store (Zhen et al. 2009). The USDA Food Purchase and Acquisition Survey (FoodAPS) collects 7-day purchase data on all FAH and FAFH items. With FoodAPS providing data on purchase quantities and expenditures, we supplement these data with retail scanner data to construct price indices that include costs of unpurchased items, and to create instrumental price variables to correct for the unit value bias and the omitted variable bias. We also introduce a method developed in the international price comparison literature to create instruments for products not covered in retail scanner data (e.g., all restaurant foods). Collectively, these incremental data preparation steps are essential to obtaining demand estimates consistent with economic theory, such as downward-sloping demands.

Third, we advance Zhen et al.'s (2014) instrumental variables truncated demand system estimator to account for the complex survey design of FoodAPS. Zhen et al.'s approach is an extension of the Amemiya generalized least squares (AGLS) estimator for a single truncated equation with endogenous regressors (Amemiya 1979; Newey 1987) to a system of truncated equations. The popular cluster-robust sandwich variance estimator (Williams 2000)[2] does not have full rank when the number of parameters in each demand equation is greater than the number of clusters. This rank deficiency in the covariance matrix of the reduced-form parameters prevents the structural parameters of the demand system from being recovered using, for example, a minimum distance estimator. We avoid this by bootstrapping the covariance matrix of the system AGLS estimator. Few applications of truncated demand systems account for cluster sampling or complex design of the survey in general. This stands in contrast to the standard practice of reporting cluster-robust standard errors in other fields of econometrics (Cameron and Miller 2015). Unlike reduced-form regressions where only the standard errors are affected by clustering, accounting for the complex survey design affects both the point estimates and the standard errors of the structural parameters in a multi-step estimation of a utility-theoretic demand system. The reason is that, to recover the structural parameters, the minimum distance estimator uses the inverse of the variance-covariance of the first-step reduced-form parameters as weighting matrix. To facilitate the accounting for complex survey design in demand system estimation, we provide a user-friendly code in SAS that can be changed to fit a number of specifications of the demand equations.

The remainder of this article is structured as follows. The next section reviews the somewhat niche literature correlating food preferences with the weight status of the consumer. Before the empirical approach, we present some FoodAPS descriptive statistics to motivate the probe into preference heterogeneity. Presentation of the empirical results follows the discussion

[2] In complex survey, this method is also known as the Taylor series expansion.

of price indexing and instrumenting strategies. In the penultimate section, we compare our findings with estimates from previous experimental studies. The last section concludes.

Preference Heterogeneity Associated with Weight Status

When studying the implications of preference heterogeneity related to consumer weight status, it is important to take a holistic approach where demand for all foods is accounted for such that predictions on overall diet and health can be made. Several authors examined the role of weight status in preferences for food. In a laboratory setting, Epstein et al. (2007) experimented with subjecting a sample of US mothers to different price conditions. They found that the number of energy-dense items purchased by obese mothers was less price elastic than that of normal-weight mothers, and the substitutability between more and less energy-dense foods was lower among obese mothers compared to normal-weight mothers. However, another laboratory experiment that examined purchased amounts of calories and other macronutrients did not find mothers' weight status to moderate the price effects (Epstein et al. 2010). The divergent conclusions from two closely related studies underscore the importance of examining nutrition outcomes when studying pricing strategies.

Observational studies using purchase data have also been used to examine links between price effects and food choices. For example, Gandal and Shabelansky (2010) found that, among a sample of Israeli women, those women who stated price to be very important in food shopping were more likely to be obese, suggesting a positive association between price responsiveness and obesity. Okrent and Sweitzer (2016) take a revealed preference approach by estimating an Almost Ideal Demand system of 19 FAH food categories for households of the 2010-2014 IRI Consumer Network panel. Weight status indicators are interacted with the price and total expenditure variables to capture the role of weight status as a modifier of the price and expenditure effects. The authors find that demand by households with obese members is less price elastic than overweight and normal-weight households. Using the IRI InfoScan retail scanner data, Wang, Rojas and Colantuoni (2017) estimate a dynamic model of inventory holding by households for regular Coke and Pepsi in 2-liter bottles and 12-packs of 12-ounce cans. They find that, in counties with higher obesity rates, a larger proportion of the population is likely to stockpile Coke and Pepsi products when they are on sale. This intertemporal optimization behavior on the part of consumers results in soda consumption being less elastic to prices in areas with higher obesity rates and potentially diminishing the effect of a soda tax.

Data Sources and Stylized Facts

FoodAPS provides the household purchase data for our empirical analyses. FoodAPS was designed to fill a data gap in food assistance and nutrition policy research. For our purposes, the most unique advantage of FoodAPS is the complete coverage of foods purchased from all sources and of both packaged and random-weight foods. Alternative data sources such as household scanner data are known to underreport FAH purchases, not record random-weight purchases with sufficient product detail to understand diet behavior, and not provide any FAFH information. The mean FAH spending in the Consumer Network scanner panel is 26% lower than that of FoodAPS (Clay et al. 2016, table 4b). Underreporting creates two issues. First, it underestimates the magnitude of purchase changes following a price change. Second, setting aside the bias in the level of purchases, underreporting may create bias in the price elasticities of food demand. Zhen et al. (2019) compared price elasticities of FAH demand estimated from the Consumer Network data and those from the Consumer Expenditure Survey. Although the authors did not find underreporting in Consumer Network to systematically under- or over-estimate price elasticities, there are sizable differences in the price elasticities for comparable food groups between the two datasets.

A feature of FoodAPS is that a household reported purchases and acquisitions over a 7-day period and not all households purchase all categories of food in a given period. While a short reporting period reduces respondent burden and the degree of expenditure underreporting, it also leaves a significant fraction of food categories (e.g., grains, beverages) unpurchased by a household owing to infrequency of purchase and price-induced corner solutions. We explicitly account for nonpurchases in our demand model. Related to the truncated demand, prices of unpurchased foods are not available in FoodAPS. To fill in these missing prices, which are required in the truncated demand model, we link scanner data prices from thousands of retail stores in IRI InfoScan to FoodAPS purchase transactions by food type, purchase date, chain name, and store location. We discuss this process later in the section on price indices and instruments and in the technical appendix.

Between April 2012 and January 2013, FoodAPS surveyed 4826 households, 87 of which did not report any food acquisition events in the 7-day period. Our empirical investigation is based on data reported by the 4739 households that acquired a positive amount of food. Because FoodAPS oversampled lower-income households, 52% of our sample households were at or below 185% of federal poverty line—the income threshold for participating in the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC). We use the sampling weight throughout the empirical analysis.

Table 1 provides descriptive statistics for the FoodAPS sample. We classify households into four types based on household income and the obesity status of household members, where households with income at or below 185% of the poverty line are considered lower income, and whether one or more members of the household are obese. An adult is considered obese if his/her body mass index (BMI) is 30 or above (Ogden et al. 2020). A child aged 17 or younger is considered obese if his/her BMI is at or above the 95th age- and sex-specific percentile. Within either income group, households with obese members have more children and more adult members working at a job or business, are more likely to be Hispanic or black and less likely to be college educated. The difference in prevalence of tobacco use, a leading indicator of risky health behavior, between households with and without obese members is small compared to the much larger difference between lower- and higher-income households. This can be attributed to two countervailing forces. First, the diet quality of smokers is known to be lower compared to nonsmokers (Guenther et al. 2014). Second, smoking is a major appetite suppressant (Mineur et al. 2011), although the evidence is less clear on whether tobacco control efforts have contributed to the rising rates of obesity (Gruber and Frakes 2006; Nonnemaker et al. 2009; Courtemanche, Tchernis and Ukert 2018). Not surprisingly, the BMI of the primary respondent is a strong indicator for whether a household has one or more obese members. In FoodAPS, the primary respondent is also the main food shopper and meal planner. So we expect the classification of households based on the presence of one or more obese members to be an adequate way to register preference heterogeneity associated with obesity.

To adjust for the age- and sex-specific energy requirements, we also measure household size using the adult-male equivalent (AME). To calculate AME, we take the daily energy need, as established in the 2010 *Dietary Guidelines for Americans* (DGA) (USDA/US HHS 2010), of 2600 kcal for a moderately active male aged 26 to 45 years as the reference. The AME for each household member is the ratio of the person's age group- and gender-specific energy needs for moderately active living relative to 2600 kcal. The household AME is the sum of individual AMEs.

FoodAPS oversampled the under-resourced population. Using the survey weights, we estimate that lower-income households with obese members, lower-income households without obese members, higher-income households with obese members and higher-income households without obese members represent 18%, 10%, 35%, and 36% of the US population, respectively. A greater proportion of lower-income Americans live in households with obese members than in households without obese members, consistent with the empirically documented inverse income, or more broadly, socioeconomic status gradient in obesity (Baum and Ruhm 2009).

Food Categorization and Nutrient Profiling

We categorize FAH purchases into nine broad food categories that largely follow the Tier-1 classification scheme of ERS food groups (USDA ERS 2016). All FAFH purchases are assigned to a single FAFH category. Unlike the ERS scheme where 100% fruit and vegetable juice is classified as part of the fruit group, we count these juices as products of the beverage category. We exclude vitamins and meal supplements, baby food, and infant formula from the analysis because their contribution to total household dietary energy is trivial. Within each food category, we subdivide the products into a healthier food group and a less healthy food group based on the product's Guiding Stars rating (Fischer et al. 2011). In total, we have twenty food groups differentiated by food category and healthfulness. We estimate the demand curves at the food group level.

Guiding Stars is a nutrient profiling algorithm that rates a food product's healthfulness based on its nutrient densities per 100 kcal of the food. Nutrients (e.g., vitamins and minerals, fiber, and whole grains) encouraged by scientific advisories, such as the DGA, receive positive scores, and nutrients recommended in limited quantities (e.g., trans-fatty acids, saturated fatty acids, cholesterol, sodium, and sugars) receive negative scores. Foods with negative total scores are assigned a 0-star rating, which means that the food item does not meet the nutritional criteria to receive a star rating. Foods with positive total scores are classified into 1 star, 2 stars, and 3 stars to indicate good, better, and best nutrition value, respectively. In each category, the healthier and less healthy food groups consist of items rated at 1-3 stars and 0-star, respectively.

There are some notable observations from the nutrient profiling exercise. Because Guiding Stars are scored on a per 100-kcal basis, the star levels for zero-calorie diet drinks (34.2 percent) and all bottled water products cannot be calculated. Since nearly all diet drinks with some calories (65.8 percent) receive 0 star,[3] we assign all zero-calorie diet drinks to the unhealthy (0-star) beverage group and all bottled water to the healthy (1-3 star) beverage group. Most products in the 0-star vegetable group are canned and have high sodium levels. 77.7 percent of canned fruit products do not receive a star because they contain high levels of sugar and low levels of vitamins. Because calcium is not an input to Guiding Stars, a lot of skim/low-fat milk products do not receive a star either because they are sweetened or still have too much fat by the Guiding Star standard. 12.6 percent of 100% juice products have 0 star, while the rest have between 1 and 3 stars.

Unlike individual FAH items, FAFH contains full meals, combo meals (e.g., McDonald's Big Mac combo) and buffets. In the survey data, the combo meals and buffets can be separated into distinct food items (e.g., "Big Mac" can be separated to burger, drink, and fries) with nutrient content reported for each food item. The Guiding Stars rating is calculated based on nutrients at the item level. Therefore, for combos and buffets, we first assign the star rating to each item and then calculate a weighted star rating for the entire meal, with the gram share of each food item as weights. We treated meals with a weighted star rating of one or more as a starred food and others as 0-star foods. For eating occasions that consisted of a single food item, we use the same method used to assign Guiding Stars ratings to FAH.

Table 2 summarizes the unit value, budget share, and purchase quantity for each food group by income. A unit value for a food group is equal to the ratio of the expenditure on the food group to the purchase weight in hundred grams. There are several noteworthy observations. First, with few exceptions, the average unit values of foods purchased by higher-income households are greater than those of lower-income households. This is broadly consistent with previous research that found lower-income households use a variety of cost-minimization strategies to reduce the unit value of purchased foods (Broda, Leibtag and Weinstein 2009; Beatty 2010). Second, conditional on total food expenditures, mean expenditure shares are comparable between lower- and higher-income households for all FAH groups except the two meat and protein groups, on which the average lower-income household spent 2−3 percentage points more than the average higher-income household. In terms of FAFH shares in total food expenditures, higher-income households spent six and three percentage points more on 0-star and

[3] Only 0.8 percent of diet drinks receive a 1-star rating and no diet drinks receive 2 or 3 stars.

starred foods, respectively, than their lower-income counterparts. Third, higher-income households reported higher purchase quantities per AME than lower-income households in 17 of the 20 food groups. Because higher-income households spent substantially more on food than lower-income households ($138 vs. $88 per week) on average, the lower unit values of foods purchased by lower-income households may not be enough to compensate for their lower food expenditures.

Table 3 provides another way of summarizing preferences for healthfulness. It compares the quantity share of healthier products within each of our ten food categories by income and whether or not a household has at least one obese household member. The average share of healthier foods purchased by lower-income (higher-income) households without obese members is three (one) percentage points higher than households of the same income class with obese members. As such, demand for healthier options is inversely related to obesity, although the slope of the healthfulness-obesity gradient is moderate when measuring demand by quantity shares.

The third way to summarize preference heterogeneity is to compare differences in nutrient density. Table 4 conducts this comparison for nutrients and food components that are either encouraged by the DGA to increase (fiber, folic acid, iron, magnesium, calcium, potassium, whole grains, fruit, and vegetables) or limit (solid fats, added sugars, sodium, and refined grains). Two density measures are calculated for each nutrient and food component: amount per 100 grams of food, and amount per dollar of food expenditures. For lower-income households, those without obese members purchased higher or equal amounts of all but two nutrients (folic acid and iron) per 100 gram of food that the DGA encourages compared to those with obese members. The pattern is reversed when comparing lower-income households with and without obese members in the densities of dietary energy, solid fats, added sugars, sodium, and refined grains that the DGA recommends to limit. The patterns are somewhat less clear in the higher-income sample. Although, compared to households with obese members on a per-100 gram of food basis, higher-income households without obese members purchased more of all nutrients the DGA encourages to increase, they also purchased more solid fats, added sugars and energy.

The middle panel of table 4 presents nutrient densities per dollar of food expenditures. Compared to the per 100-gram measure, per dollar densities are a better indicator of consumer optimization given the budget constraint. The law of diminishing marginal product predicts that as income increases, a lower proportion of food expenditures is allocated for pure subsistence (Silberberg 1985). This implies an inverse relation between nutrient density per food dollar and income, which is confirmed for all nutrients and food components in table 4. Comparing nutrient density by obesity status within each income class, households with obese members tend to pack more nutrients, especially those the DGA recommends to limit, into the food dollar.

The lower panel of table 4 provides total purchases of select nutrients and food components. As one would expect from all normal goods, higher-income households purchase greater amounts of nutrients and food components regardless whether they are recommended by the DGA to increase or to limit. Within an income class, households without obese members purchase more food components the DGA encourages but also some to limit than households with obese members. Given the large number of nutrients and food components that contribute to a healthy diet, it is useful to examine a summary measure of the healthfulness of all foods purchased. The last row of table 4 reports one such measure—the Healthy Eating Index (HEI)-2010. While the Guiding Stars profiles the nutrients of individual foods, the HEI-2010 measures conformance of a diet or total food purchase with the 2010 DGA, per 1000 calories (Guenther et al. 2013). The HEI-2010 has 9 adequacy and 3 moderation components.[4] The lowest possible score in a component is zero and the maximum varies from 5 to 20 depending on the component. The HEI score is the sum of the 12 component scores and ranges between 0 (worst) and 100 (best). As a summary measure of diet quality, the HEI score differs between lower- and higher-income households and between households with and without obese members in ways consonant with the food group- and nutrient-specific comparisons in table 3 and 4. Conditional on whether or not there is at least one obese household member, the HEI of higher-income households is 4-5 points higher than that of lower-income households. Within an income class, the HEI of households without obese members is 2-3 points higher than those with obese members.

Taken altogether, these descriptive statistics on food purchasing patterns are consistent with households optimizing given the budget constraint and differences in preferences associated with the obesity status of household members. To understand the structural differences in

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[4] The adequacy components are total fruit, whole fruit, total vegetables, greens and beans, whole grains, dairy, total protein foods, seafood and plant proteins, and fatty acids. The moderation components are refined grains, sodium, and empty calories.

preferences across household types and predict how food choices would respond to price changes, we develop a structural model of food demand in the following sections.

The Demand Model

We use a flexible functional form demand system to characterize household food preferences. The main benefit of using a flexible functional form for demand modeling is that it imposes few a priori restrictions on the own- and cross-price elasticities. By contrast, the Lancaster-type (Lancaster 1966) characteristics demand models, which include the discrete-choice demand model (McFadden 1974; Berry, Levinsohn and Pakes 1995), restrict goods to be substitutes.[5] As will be discussed in the empirical results, some of the distributional effects are caused by complementarity between food groups. Demand models restricting goods to be substitutes will not be able to identify these effects.

We estimate a two-way Exact Affine Stone Index demand system (Lewbel and Pendakur 2009)

$$w_{hi}^{*} = \sum_{j=1}^{J}\left(a_{ij}\ln p_{hj} + a_{ijz}z_{hK}\ln p_{hj} + a_{ijy}y_h\ln p_{hj}\right) + \sum_{r=1}^{L} b_{ir}y_h^{r} + b_{iz}z_{hK}y_h + \sum_{k=1}^{K} g_{ik}z_{hk} + u_{hi} \quad i = 1, \dots, J-1 \tag{1}$$

where w_{hi}^{*} is the latent budget share of subgroup i for household h, p_{hj} is the price index of subgroup j, z_{hk} is the kth (out of a total of K) demand shifter for household h, z_{h1} is the constant, y_h is log deflated total expenditure equal to $\ln x_h - \sum_{j=1}^{J} w_{hj}\ln p_{hj}$ with x_h being household h's per capita nondurable expenditures, u_{hi} is the error term, J (=21) is the number of FAH and FAFH groups plus the *numéraire*, L is the highest order of polynomial for y_h, and a, b, and g are coefficients. The last demand shifter z_{hK} is the indicator for households with obese members, equal to 1 if household h has any obese members and 0 otherwise. The EASI demand in Eq. (1) is two-way because of the interactions between y_h and p_{hj}. This allows the Hicksian price effects to vary with total expenditures and is unique to the EASI functional form. In the family of almost ideal demand systems (Deaton and Muellbauer 1980), only Marshallian price effects differ for lower- and higher-income households through the income effects.

[5] An advantage of characteristics demand models over the flexible demand systems is the availability of estimates for the willingness to pay (WTP) for characteristics. However, the lack of WTP estimates does not impact, in any way, a flexible demand system's ability to model the relationship between prices and quantities demanded.

The interaction terms $z_{hK} \ln p_{hj}$ and $z_{hK} y_h$ allow the price and expenditure elasticities to differ by the presence of obese household members. In addition to the obesity indicator z_{hK}, other demand shifters include Census division dummies, calendar month dummies, the share of household members that are children, Hispanic, black, college-educated, and working adult, household size, primary respondent's age group, an indicator for whether the primary respondent uses the Nutrition Facts label always or most of the time, and the frequency of using a grocery list. The last two FoodAPS variables, which are rarely available from general-purpose expenditure surveys, help account for heterogeneity in nutrition attitudes and shopping patterns. To construct y_h, we define x_h as the sum of weekly per capita expenses on shelter, rental/homeowner's insurance, property taxes, public transport, health insurance and copays, doctor/hospital bills, prescription drug, child care, child support, and FAH and FAFH.

We follow the bulk of the truncated demand system literature (e.g., Perali and Chavas 2000; Dong, Gould and Kaiser 2004; Meyerhoefer, Ranney, and Sahn 2005) by using the Tobit model to characterize the zeros in food group-level purchases, where the latent budget share w_{hi}^* is related to the observed budget share w_{hi} by $w_{hi} \equiv \max(w_{hi}^*, 0)$. We use the extended AGLS estimator for censored equation systems (Zhen et al. 2014) to control for endogeneity in y_h and p_{hi}. The variable y_h is endogenous because the budget shares w_{hi} which are decision variables, are in the Stone index. We instrument y_h by $\bar{y}_h \equiv \ln x_h - \sum_{j=1}^{J} \bar{w}_j \ln \bar{p}_{hj}$, where $\bar{w}_j$ is the sample mean budget share and $\bar{p}_{hj}$ is the instrument for p_{hi} discussed in the next section.

Briefly, estimation of the EASI demand with accounting for clustered and stratified sampling proceeds in four steps. First, we regress the endogenous regressors (i.e., y_h^r, $\ln p_{hj}$, $y_h \ln p_{hj}$, $z_{hK} \ln p_{hj}$) on the exogenous regressors and the instruments using least squares. This produces a least squares residual for each endogenous regressor. Second, using single-equation Tobit, we regress the latent budget share w_{hi}^* on the exogenous regressors, the instruments, and all least squares residuals estimated from the previous step. This approach to addressing endogeneity in limited dependent variable models is known as the control function approach (Newey 1987) or the two-stage residual inclusion estimation in health economics (Terza, Basu and Rathouz 2008).

The standard errors of the coefficients from the Tobit regressions are incorrect because the least squares residuals are estimated (Murphy and Topel 1985). The standard approach to accounting for the estimated regressor problem is to build a sandwich covariance matrix for the coefficients of the first-step least squares regressions and the Tobit regression in the second step. The sandwich covariance can be modified to be cluster robust. However, as Cameron and Miller (2015) showed for the case of single-equation regressions, the cluster-robust sandwich covariance is not full rank when there are fewer clusters than coefficients. We show in the technical appendix that a system of equations only exacerbates the rank deficiency problem. To overcome this issue, we bootstrap the covariance matrix. In the third step, we generate 4000 bootstrap FoodAPS samples based on the PSU and stratum information. We repeat the first two steps 4000 times using the bootstrap samples. This creates 4000 vectors of coefficient estimates, which we use to build the covariance matrix for the least squares and reduced-form Tobit regression coefficients. In the fourth and final step, we use the minimum distance estimator to recover the structural coefficients of the EASI demand in equation (1) and their variance-covariance. This variance-covariance is cluster- and stratification-robust and accounts for the use of estimated covariates in the control function and the correlation between budget share equations. The technical appendix provides an in-depth discussion of the econometric approach.

Price Indexes and Instruments

There are two potential causes of price endogeneity when using micro data. First, there is the well-known unit value bias (Cox and Wohlgenant 1987; Deaton 1988). A unit value, calculated as the ratio of food-group expenditure to food-group quantity, embeds both market price variation and the consumer's quality choice. To obtain the price elasticities of quantities purchased, it is necessary to purge the quality element from the price variables in a demand model. Second, there is evidence that consumers conduct price search as an effective cost-minimization strategy (Gauri, Sudhir and Talukdar 2008). The intensity of price search is correlated with preferences, thus prices paid are endogenous.

We take a two-pronged approach to addressing price endogeneity. We create a price index for each food group i to account for within-group product heterogeneity. We then instrument the price index of household h using the average price index of other households and in other counties. We pay special attention to create price indexes and their instruments that are representative of the actual food prices faced by FoodAPS households and leverage all available information from FoodAPS and the IRI retail scanner data. In the sections below, we describe how we construct price indices for our food groups and the numeraire good.

FAH Groups

The initial prices used as inputs to the price index for each FAH group are calculated at the food code level, where 96.7% of the food codes are from either the USDA Food and Nutrient Database for Dietary Studies or the USDA National Nutrient Database for Standard Reference (USDA ERS 2016). For packaged foods, a food code encompasses a number of universal product codes (UPCs). UPC is the finest level of product differentiation available to consumers. For example, FoodAPS households reported purchasing 145 unique UPCs, differentiated by brand, size and flavor, under the food code 11432000 (yogurt, fruit variety, lowfat milk). The reason for not differentiating products at the UPC level is that a significant proportion of FAH purchases have missing UPCs because the items are random-weight or the UPCs are not reported.[6] Any remaining unit value bias resulting from within-food code substitutions is addressed by the instrumental variables. To provide pricing information on items available at the retail stores but not purchased by FoodAPS households, we link FoodAPS FAH items with products in the IRI InfoScan retail scanner data by food code. The linked food codes represent 76% of total FAH expenditures in FoodAPS. For each FAH group i, we create two sub-price indices p_{hi}^{L} and p_{hi}^{NL} for foods linked and not linked with InfoScan, respectively. p_{hi}^{L} is constructed as a Fisher Ideal index as

$$p_{hi}^{L} = \sqrt{\frac{\sum p_{kh} q_{k0}}{\sum p_{k0} q_{k0}} \frac{\sum p_{kh} q_{kh}}{\sum p_{k0} q_{kh}}} \qquad (2)$$

where p_{kh} is price of food code k of food group i, q_{kh} is quantity of k purchased by household h, and p_{k0} and q_{k0} are base price and quantity set to the FoodAPS sample averages, respectively. When $q_{kh} > 0$, p_{kh} is price paid by household h. When $q_{kh} = 0$, that is, h did not purchase k, we set p_{kh} to the InfoScan price of food code k at the store where h shopped in the survey week; and if the store is not in InfoScan, we set p_{kh} to the average price of food code k in InfoScan stores in the same county. Overall, 50% of total FAH expenditures in FoodAPS occurred in InfoScan stores. The Fisher Ideal controls for between-food code price variation by comparing prices of the same food code across households.

[6] For fruit and vegetables, the bulk of which are expected to be random-weight, 21% of the expenditures are reported with a UPC. For grains, milk products, prepared meals, fats and oils, beverages, and snacks, 73% of the expenditures are reported with a UPC.

Our approach to constructing p_{hi}^{NL}, the sub-price index for food codes not linked to InfoScan, is the household equivalent of the weighted country product dummy method (CPDW) originally developed for international price comparisons (Summers 1973; Rao 1990). We project food code-level prices onto a set of fixed effects using the following food group-specific weighted regression

$$\ln p_{kh} = \alpha_h + \beta_t + \gamma_{psu} + \delta_k + \epsilon_{kh} \tag{3}$$

where α_h, β_t, γ_{psu}, and δ_k are the household, week, primary sampling unit (PSU), and food code fixed effects, respectively; ϵ_{kh} is the residual; and the weight is the budget share of food code k among unlinked (with InfoScan) food codes of food group i purchased by household h. p_{hi}^{NL} is equal to $\exp\left(\hat{\alpha}_h + \hat{\beta}_t + \hat{\gamma}_{psu}\right)$ with a base value of one at the FoodAPS sample mean prices.[7] By excluding the food code fixed effects δ_k from the creation of p_{hi}^{NL}, the CPDW method removes the effect of product heterogeneity at the food code level from the price index.

With both sub-price indexes calculated, we construct the price variable p_{hi} in equation (1) as a Fisher Ideal index

$$p_{hi} = \sqrt{\frac{p_{hi}^{L} q_{0i}^{L} + p_{hi}^{NL} q_{0i}^{NL}}{1 \times q_{0i}^{L} + 1 \times q_{0i}^{NL}} \frac{p_{hi}^{L} q_{hi}^{L} + p_{hi}^{NL} q_{hi}^{NL}}{1 \times q_{hi}^{L} + 1 \times q_{hi}^{NL}}} \tag{4}$$

where q_{0i}^{L} and q_{0i}^{NL} are the sample mean purchase quantities of linked and unlinked food codes in food group i, respectively; q_{hi}^{L} and q_{hi}^{NL} are household h's purchase quantities of linked and unlinked food codes in food group i, respectively; and the ones in the denominators are base values of p_{hi}^{L} and p_{hi}^{NL}. The resulting p_{hi} summarizes price variations of all food codes that belong to food group i. This is important because a partial representation of the constituent food codes would cause measurement error bias in the price coefficients in equation (1).

Because of the use of food code-level prices as elements of the food group-level price index, p_{hi} does not control for a specific form of unit value bias arising from product differentiation within a food code. For example, a household with an above-average demand for food code 92410510 (soft drink, fruit flavored, caffeine free) may purchase larger volumes of private labels than someone who prefers quality over quantity and chooses name brands. An

[7] To set the base at the sample mean, we create a reference household 0 whose purchase prices and quantities are the averages for all FoodAPS households. By restricting the household, time, and PSU fixed effects for the reference household to zero, p_{hi}^{NL} has a normalized value of one at the sample mean.

omitted variable bias results when unobserved taste for quality is correlated with food code-level prices. Another potential source of price endogeneity comes from the correlation between unobserved preference heterogeneity and the intensity of price search. If households who have a higher demand for a food are more motivated to find lower prices, then we have a case of reverse causality: the between-household demand variation drive differences in prices. This would bias estimates of the causal effect of prices on demand. We create instrumental variables to address these endogeneity concerns.

To instrument p_{hi}^{L}, we calculate a retail Fisher Ideal price index using InfoScan at the chain-county-week level. The instrument $\bar{p}_{hi}^{L}$ is the weighted average of the retail index from the same retail chain in counties within a 500-mile radius (excluding the home county) of the store where h shopped, where the weight is the inverse distance to the donor counties. If a store does not belong to any chain in InfoScan, we use the retail price index from all chains to create its instrument. The instrument for p_{hi}^{NL} is calculated as $\bar{p}_{hi}^{NL} = \exp\left(\hat{\beta}_t + \hat{\gamma}_{psu}\right)$, which is equivalent to the time- and PSU-specific mean excluding the household h-specific component $\hat{\alpha}_h$ that may be endogenous with h's food demand. The final instrument for p_{hi} is created as a Fisher Ideal price index using $\bar{p}_{hi}^{L}$ and $\bar{p}_{hi}^{NL}$ as its elements. Our approach to instrumenting has its roots in Hausman (1997) who used average prices in neighboring cities to instrument city-level prices. Identification of the price coefficients in equation (1) is based on the assumption that demand shocks are uncorrelated between areas after controlling for observed determinants of demand, which include time-invariant regional demand shocks and time-varying national demand shocks captured by the Census division and monthly fixed effects in the z_{hk} variables (in equation 1), respectively. Allcott et al. (2019b) and DellaVigna and Gentzkow (2019) advocated the use of same-chain prices in other counties to further increase instrument strength and convincingly argued that much of the between-chain price variations is due to differences in supply costs, which can be used to identify demand curves. The Hausman-type instrumentation strategy is widely used in studies of differentiated product demand where a high degree of specificity is required of the price instruments to identify the large number of own- and cross-price coefficients.

FAFH Groups

Unlike the eighteen FAH groups where retail scanner data provide important supplemental information on prices, the price indices and their instruments for the two FAFH groups rely entirely on information collected by FoodAPS. For each FAFH group, we fit equation (3) to FAFH acquisitions at the item (e.g., potato chips) or bundle (e.g., burger, drink, and fries) level depending on the level at which paid price is reported. The advantage of the CPDW method is that product heterogeneity in items/bundles containing multiple food codes is accounted for by the food code fixed effects. In contrast, a matched-basket index such as the Fisher Ideal index treats a unique combination of food codes as a unique product. The sheer number of unique FAFH products makes using a matched-basket index unwieldy. The two FAFH price indices are $p_{hi} = \exp(\hat{\alpha}_h + \hat{\beta}_t + \hat{\gamma}_{psu})$ and the instruments are $\bar{p}_{hi} = \exp(\hat{\beta}_t + \hat{\gamma}_{psu})$, $i = 19$ (0-star FAFH) and 20 (1-3 star FAFH).

Numeraire

The price index for the numeraire good is calculated as follows. The Bureau of Economic Analysis creates the annual regional price parities (RPPs) to measure cost of living differences across metropolitan statistical areas in a given year. We multiply the 2012 RPPs with Bureau of Labor Statistics' monthly consumer price index (CPI) for all items to create the panel monthly RPPs. The panel RPP is linked with FoodAPS household based on county of residence and date of survey. For households in counties outside of a metropolitan statistical area (MSA), we impute their RPP using the average RPP of other counties within a 500-mile radius weighted by the inverse distances between the home county and these counties.[8] The price index for the numeraire good J for household h is calculated as

(5) $$p_{hJ} = \exp\left\{\frac{\ln(RPP_h) - \sum_{j=1}^{J-1} \bar{w}_j \ln p_{hj}}{\bar{w}_J}\right\}$$

where $\bar{w}_J$ is the sample mean budget share of the numeraire. The instrument $\bar{p}_{hJ}$ is created by $\overline{RPP}_h$ and $\bar{p}_{hj}$ for RPP_h and p_{hj} in equation (5), where $\overline{RPP}_h$ is the average RPP in other MSAs weighted by their inverse distance to household h's home MSA.

Empirical Results

The log real total expenditure polynomials y_h^r ($r = 1, \dots, L$) shape the Engel curves. We determine the optimal value of L through a sequence of tests on the joint significance of the b_{iL} coefficients starting with $L = 2$. If the test statistic is significant, we increase L by one to re-

[8] We obtain county distances from the National Bureau of Economic Research website: http://data.nber.org/data/county-distance-database.html

estimate the EASI demand. At $L = 3$, the minimum distance test (Wooldridge 2002, p. 444), which is χ^2-distributed with 20 degrees of freedom, produces a test statistic of 38.6 (p-value = 0.007). At $L = 4$, the test statistic is 27.8 and not statistically significant (p-value=0.114) at conventional levels. To avoid overfitting with too many polynomial terms, we choose $L = 3$ as the preferred specification for the Engel curves.[9] A test of the joint significance of the a_{ijz} coefficients on the price-obesity interaction terms strongly rejects the null of no interaction effects (p-value<1E−5).

Figure 1 plots the mean Marshallian price elasticites over the full sample. All own-price elasticities are negative and precisely estimated.[10] For every food group, consistent with a priori expectations, demand is more elastic with respect to its own price than other food prices. With the exception of grains and fruit, the healthier and less healthy foods of the same category are complements at the mean of the overall sample. When segmented by household type, the mean within-category cross-price elasticites (mean standard errors) between the healthier and less healthy options are −0.24 (0.07), −0.03 (0.07), −0.20 (0.07), and −0.01 (0.06) for lower-income households with obese members, lower-income households without obese members, higher-income households with obese members, and higher-income households without obese members, respectively. The finding of significant complementarity for households with obese members suggests that variety in terms of having both healthy and less healthy foods is important for these consumers. The lack of significant complementarity for households without obese members means that these households are more willing to substitute as taxes and subsidies change the relative prices of healthy and less healthy foods. These findings, which are new to the best of our knowledge, have policy implications as will be clear in our later pricing simulations.

In table 5, we present the overall, as well as household type-specific, mean Marshallian own-price elasticities. There is considerable preference heterogeneity that is associated with household members' obesity status. For example, within an income class, the own-price

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[9] As an additional guard against overfitting, we conducted these minimum distance tests without imposing the homogeneity and symmetry restrictions on parameters of the latent budget share equations (1). These parametric restrictions help increase the precision of the remaining parameters, which results in the joint tests easily rejecting the null at high orders of income polynomials.

[10] Table A1 of the technical appendix reports the elasticities that underlie figure 1 and their standard errors.

elasticity for 0-star grains (1-3 star beverages) among households without obese members is (less than) one half of the magnitude among households with obese members. However, demand by households without obese members is not always less elastic than those with obese members. For 1-3 star vegetables and fruit, demand of households without obese members is almost twice as elastic as that of households with obese members.

Table 6 presents expenditure elasticities for the overall sample and by household type. Consistent with Engel's law, expenditure elasticities for most food groups decline as household income increases. It also appears that overall food demand of households without obese members is less elastic with respect to total expenditure changes than that of households with obese members. This pattern is more salient among lower-income households compared to higher-income households.

Pricing Simulations

With a multitude of own- and cross-price effects, a more informative approach than comparing price and expenditure elasticities is to simulate various pricing strategies. To this end, we study three pricing scenarios: a one penny per ounce excise tax on 0-star beverages, a 30 percent subsidy on 1- to 3-star fruit and vegetables, and a fiscally neutral 10 percent subsidy on 1- to 3-star foods paid for by an 8.84 percent[11] tax on 0-star foods. Because our classification of 0-star beverages includes artificially sweetened beverages, the nature of our beverage tax is similar to Philadelphia's sweetened beverage tax except that the city's rate is at 1.5 pennies per ounce. The fruit and vegetable subsidy is of the same magnitude as the subsidy evaluated in the USDA Healthy Incentive Pilot experiment (Bartlett et al. 2014) with some differences in the eligible varieties of vegetables. The fiscally neutral subsidy-tax is new and benefits from the use of a nationally representative survey with adequate coverage on random-weight food purchases, which allows the projection of household-level estimates to the national level. For the sweetened beverage excise tax, we assume a 70 percent pass-through of the tax to retail prices. This is the average of ten studies of beverage excise tax pass-through rates in six US cities.[12] To simulate

[11] Based on the estimated EASI demand parameters, the 8.84 percent is the magnitude required to fully fund the 10 percent subsidy on starred foods and beverages.

[12] The ten studies are Roberto et al. (2019), Cawley et al. (2020b), and Seiler, Tuchman and Yao (2021) for Philadelphia, Silver et al. (2017) and Cawley and Frisvold (2017) for Berkeley, Cawley et al. (2021) for Boulder, Cawley et al. (2020a) and Léger and Powell (2021) for

the effect of pricing strategies on nutrient and food component purchases, we follow Huang (1996) by combining food group elasticities with nutrient and food component densities to derive the elasticities of nutrient and food component demand with respect to food group prices and total expenditures. These derived elasticities are then used to simulate purchase changes in nutrients and food components.

Table 7 reports the simulation results for the 1-penny-per-ounce tax on 0-star beverages. With a 70 percent pass-through, the sweetened beverage tax raises overall retail price by 21 percent. Because of differences in unit values, the percent increase is higher for lower-income households at 24% versus the 22% and 19% for higher-income households with and without obese members, respectively. On average, the tax is predicted to reduce weekly calories purchased (baseline mean = 19,972 kcal) by 361 kcal/AME and increase HEI (baseline mean = 53.07) by 0.25 points. Unlike the predictions of unintended increases in total fat and sodium purchases in Zhen et al.'s (2014) analysis of demand for a subset of FAH groups, our complete food demand system predicts a negligible change in solid fats and a weekly reduction of 194 mg/AME in sodium purchases (baseline mean = 26,606 mg) for an average consumer. Interestingly, because the percent reduction in calories is larger than the percent reduction in the quantity of solid fats and sodium, the density of sodium per 1000 kcal and energy share of solid fats, both moderation components of the HEI, increase with a sweetened beverage tax. The higher price of 0-star beverages, which are estimated to be a complement to fruit and vegetables, reduces fruit and vegetable demand and their densities per 1000 kcal of purchases. These indirect effects offset a portion of the positive direct effect on HEI of the sweetened beverage tax, primarily owing to the reduced energy share of added sugars.

The simulated changes are not uniform across household types. Households with obese members are expected to experience greater improvements in HEI than households of the same income class but without obese members. The increase in HEI is also predicted to be higher among lower-income households than among their higher-income counterparts. In fact, the HEI for higher-income households without obese members are not expected to change. Several factors help explain the lack of improvement in HEI for this household type. First, higher-income households without obese members are the only group that experiences a decline in total score of

Oakland, Falbe et al. (2020) for Oakland and San Francisco, and Powell and Leider (2020) for Seattle.

the nine HEI adequacy components. Second, this group's net improvement in the three moderation component scores is the lowest among the four household types.

Households without obese members increase calories from untaxed foods to compensate for reduced calories from 0-star beverages. In contrast, households with obese members reduce calories from untaxed foods, which reflects their complementary relationships with 0-star beverages. The magnitude of compensation is 43% $\left(\frac{405.78-233.12}{405.78}\right)$ and 26% $\left(\frac{286.21-210.45}{286.21}\right)$ of the caloric reduction from 0-star beverages for lower- and higher-income households without obese members, respectively. Among households with obese members, the additional reductions in calories from other foods equal 8% $\left(\frac{439.19-405.91}{405.91}\right)$and 35% $\left(\frac{568.46-419.57}{419.57}\right)$ of the caloric reduction from 0-star beverages for lower- and higher-income households, respectively.

Higher-income households with obese members have the highest overall weekly caloric reduction at 568 kcal/AME but the second lowest improvement in HEI. This is not surprising given that the HEI is density-based and the nutrition epidemiology literature has extensively documented a negative but imperfect correlation between energy intake and density-based diet quality indexes (Epstein et al. 2008; Ebbeling et al. 2012).

In terms of tax burden, there is little difference in the amount of taxes paid between lower- and higher-income households when controlling for the obesity status of household members. Across household types, households with obese members pay more sweetened beverage taxes per AME than households without obese members. In aggregate, our model predicts a weekly national tax revenue of $85 million.

Table 8 presents simulation results from a 30% subsidy on starred fruits and vegetables. The model predicts an average weekly increase of 774 calories per AME, one half of which comes from increased purchases of the subsidized fruits and vegetables and the rest from higher demand for other food and beverage due to their complementarity with starred fruit and vegetables. The magnitude of complementarity is highly variable across household types. The increases in calories from unsubsidized food and beverage are 5.9 $\left(\frac{1290.53-126.51-60.96}{126.51+60.96}\right)$ and 4.4 $\left(\frac{1221.9-118.89-109.42}{118.89+109.42}\right)$ times the amount from starred fruit and vegetables for lower- and higher-income households with obese members, respectively. The striking differences in caloric increases between the subsidized and unsubsidized purchases can be partially attributed to unsubsidized food and beverage being much more energy dense than starred fruit and vegetables.

The differences are less conspicuous when measuring purchase changes in grams[13]: the increases in unsubsidized food and beverage gram weight are 1.7 and 1.2 times the increases in starred fruit and vegetables for lower- and higher-income households with obese members, respectively. In contrast, the caloric increase in unsubsidized food and beverage purchases by lower-income households without obese members is 5 percent of the increase in starred fruit and vegetable purchases; and higher-income households without obese members compensate 41% of the increased calories from starred fruit and vegetable by reducing calories from other food and beverage. Because of the sizable increases in calories and other food components (e.g., refined grains) and nutrients (e.g., added sugars, sodium and solid fats), which the DGA recommends to limit, from unsubsidized food and beverage among households with obese members, the improvement of their HEI scores is negligible. The population average HEI increase of 1.5 points is entirely driven by the increases of 2.7 points or more among households without obese members.

In terms of subsidy receipts per AME, higher-income households and households without obese members receive more than lower-income households and households with obese members, respectively. The national outlay in fruit and vegetable subsidy is projected to be $655 million per week or $34 billion per year, 80% of which goes to higher-income households. This is obviously a huge expenditure considering that the total cost of the Supplemental Nutrition Assistance Program (SNAP) was $78 billion in FY2012,

Table 9 presents results of the fiscally neutral policy of subsidizing starred food and beverage at 10 percent and taxing 0-star food and beverage at 8.84 percent. This policy is simulated to reduce weekly purchases by 351 calories per AME with larger declines among lower-income households. Average improvement in HEI is predicted to be 2.3 points with greater (smaller) gains for households without (with) obese members. Within an income class, households without obese members experience a 1.5-point higher HEI improvement than households with obese members. Households with obese members are net tax payers at $0.57/AME and $0.86/AME per week for lower- and higher-income households, respectively. Owing to their higher demand for starred food and beverage, households without obese members receive a net subsidy valued at $0.65/AME and $0.42/AME per week for lower- and higher-

[13] To conserve space, we do not report gram changes in table 8.

income households, respectively. Compared to the sweetened beverage tax, household with obese members pay between 50 and 100 percent more in taxes under the fiscal neutral policy but also experience one to six times greater improvement in HEI.

Comparisons with Previous Literature

It is useful to compare our simulation results with those from past field, lab and quasi experiments on similar pricing policies. Because our sweetened beverage tax is most similar to Philadelphia's in the scope of products covered but one half penny less than Philadelphia's 1.5-penny per ounce tax, it is most convenient to compare our own-price elasticity estimate of −1.90 for 0-star beverages with those implied in the evaluations of the Philadelphia tax. At the higher end, Roberto et al.'s (2019) retail scanner data-based estimates of the sales reduction and tax pass-through imply an own-price elasticity of −2.77 for retail sales. At the lower end, the sales and price effects estimated in Seiler, Tuchman and Yao (2021), who also used retail scanner data, suggest a sales elasticity of −0.65. In the middle is Cawley et al.'s (2019) estimates of −1.01 for regular soda and −1.73 for diet soda based on purchase data collected through exit interviews at stores. Overall, our elasticity estimate for 0-star beverages for an average household falls within the ranges of elasticities implied by evaluations of the Philadelphia sweetened beverage tax. We do not find significant substitution to untaxed food and beverage calories at the population level. This is consistent with quasi experimental evidence from Philadelphia (Gibson et al. 2021) and Seattle (Oddo et al. 2021) based on retail scanner data. At the subpopulation level, our simulation does indicate meaningful caloric compensations among households without obese members, although the magnitude is not large enough to dominate the direct effect of a sweetened beverage tax. When examining micro-level responses using household scanner data, Lozano-Rojas and Carlin (2021) estimated that 15−27% of the reduction in beverage sugar in Philadelphia was offset by substitution to other sugary foods.

Our 30-percent fruit and vegetable subsidy simulation produces a 1.51-point improvement in HEI but a sizable 774 kcal/AME per week increase in total calories purchased among lower-income households. The results for total calories appear to be inconsistent with some previous studies but more in line with others, while the predicted increases in HEI fall within the ranges of previous literature. The Healthy Incentive Pilot (HIP) was a randomized controlled trial during 2011-2012 that provided a 30% fruit and vegetable subsidy to SNAP households. HIP targeted a group of fresh, canned, frozen and dried fruit and vegetables without added sugars, fats, and sodium, which was very similar in coverage to the starred fruit and vegetable groups in our demand system. HIP is associated with a 4.7-point increase in HEI (Olsho et al. 2016) and a statistically insignificant 49-kcal reduction in daily total energy intake (Bartlett et al. 2014, p 162). Harnack et al. (2016) conducted a 4-arm RCT to predict the effects of a 30-percent fruit and vegetable subsidy and a prohibition of using SNAP benefits toward sugary beverages and baked goods and candy on SNAP participants' diet quality. The authors found daily total calories and HEI of the subsidy arm (n = 68) to be 108.8 kcal lower and 1.8 points higher than the control arm (n = 66), respectively. But neither is statistically significant.

Bartlett et al and Harnack et al. measured energy intakes using 24-hour dietary recalls, while our demand system predicts purchase changes. Yu and Jaenicke (2020) estimated that 31.9% of food purchases in FoodAPS were wasted (i.e., not consumed). This means that our demand system-predicted increase in daily energy intake would be 75 kcal/AME $\left(\frac{774\times(1-0.319)}{7}\right)$—two thirds the predicted increase in energy purchased. Bartlett et al. (2014, p 162) cautioned that their sample size (n = 2009) was not large enough to determine whether the increased intake of subsidized fruit and vegetables replaced other food intakes. It is possible that communications from the HIP project office to the treatment group about the targeted fruits and vegetables contributed to the above-average HEI improvement. For example, participants in the treatment group were significantly more likely to report having received messages about eating a healthy diet that includes fruit and vegetables than those in the control group; and among those eating ⩾3 servings of fruit and vegetables per day at baseline, treated households subsequently had more positive attitudes toward fruit and vegetables than those in the control (Bartlett et al. 2014, p.132). If the treatment itself improved HIP participants' underlying preferences for fruit and vegetables, the HEI increase would be a combination of the effects of the subsidy and preference changes, the latter of which is not modeled in our simulations.

Our fruit and vegetable subsidy results are closer to the findings of Epstein et al. (2010), in which 42 mothers performed a series of purchasing tasks in a lab environment set up to simulate the experience of shopping in a real grocery store. Epstein and coauthors found that subsidizing healthy foods led to increases in total calories purchased and no change in the macronutrient profile of foods purchased.[14] The magnitude of the energy increase is large: a 10 percent reduction in healthy food prices results in a 9.8 percent increase in total energy purchased (Epstein et al. 2010, p 409).

We are not aware of any experimental studies on fiscally neutral pricing policies. The reason is that such an experiment requires ex ante quantification of how respondents would respond to taxes and subsidies, which is only possible with the econometric-simulation approach. Nevertheless, our fiscally neutral pricing results are qualitatively similar to previous experimental research combining both incentives and disincentives. For example, Harnack et al. (2016) found that prohibition of sugar drinks and snacks from SNAP food benefits plus a fruit and vegetable subsidy generated a larger improvement in HEI (4.3 points) than any one strategy alone.

Conclusion

This study aims to deepen our understanding of the implications of preference heterogeneity for nutrition-oriented pricing strategies. Using the nationally representative FoodAPS data, we estimate a 21-good complete food demand system that accounts for nearly all purchased calories and differentiates by food category and the nutrient profile of food products. We find substantial preference heterogeneity that is associated with the obesity status of household members. In particular, simulations based on the demand parameters provide three main findings. First, households with obese members would experience larger increases in the healthfulness of the food purchases following a sweetened beverage tax, than households of the same income class but without obese members. In addition, lower-income households experience greater improvement in healthfulness than their higher-income counterparts. Second, the positive effect of a fruit and vegetable price discount on healthfulness of purchases is almost entirely concentrated on households without obese members. Third, a fiscally neutral policy that taxes unhealthy food and uses the tax revenue to subsidize healthier options improves the healthfulness of purchases by households with and without obese members. The improvement in healthfulness is greater for households without obese members, who also receive a net subsidy. Households with obese members experience a smaller improvement in healthfulness of their purchases and are net tax payers.

[14] There were 32 healthy food and beverage items, 10 of which were fruits and vegetables, and an equal number of less healthy food and beverage items in Epstein et al.'s experiment.

The results on sweetened beverage taxes are encouraging for proponents of these taxes. The arguments against taxing sweetened beverages have been that these taxes would not improve nutrition of lower-income, nor obese consumers as much as that of higher-income and nonobese consumers, and there could be sizable unintended substitutions to less healthy, but untaxed foods and beverages that render the overall nutritional benefit of a beverage tax dubious. Our simulation exercise does not lend support to either argument.

Like many taxes on consumption goods (e.g., gasoline), the regressive nature of a sweetened beverage tax remains a concern.[15] To reduce regressivity, one proposal for recycling the tax revenue back to consumers is by subsidizing healthier foods (Valizadeh, Popkin and Ng 2021). Our fruit and vegetable subsidy and the fiscally neutral tax-subsidy simulations suggest that not everyone will benefit equally from such a strategy due to preference heterogeneity. Of greatest concern to nutrition policymaking is how a tax-subsidy would impact lower-income obese consumers. Our simulations predict that these consumers would receive the lowest fruit and vegetable subsidy amount and be net tax payers under the fiscally neutral tax-subsidy regime. Future research should explore other means of recycling nutrition-oriented food and beverage taxes that reduce the regressivity of such taxes. There are useful lessons to learn from the environmental economics literature. For example, West and Williams (2004) estimated that using revenues from a gasoline tax to fund labor tax cuts makes taxing gasoline use substantially less regressive.

These findings also have modeling implications for the literature on using food demand models to understand health and nutrition outcomes. Although flexible demand systems are theoretically preferred because of the flexibility in parameter estimates, practitioners are often forced to estimate a restricted functional form to reduce dimensionality.[16] This is even more true

[15] Regressivity refers to the extent to which the tax paid as a percent of income is inversely correlated with income. As lower-income and obese consumers pay very similar amounts of taxes as their higher-income and nonobese counterparts, a sweetened beverage tax is regressive.
[16] Dubois, Griffith and Nevo (2014) developed a direct utility function with constant elasticity of substitution over item-level food quantities, Cobb-Douglas sub-utility over food groups, and additive sub-utility over food characteristics. The authors used the model to understand the preference differences between France, the United Kingdom, and United States that could explain cross-country differences in diet quality and obesity prevalence. Allcott et al. (2019c) used this model to structurally identify the effect of food deserts on nutrition disparity. Although this novel utility function relaxes the between-food group weak separability assumption common

when prices need to be instrumented: great specificity is required of the instruments in order to individually identify the large number of free parameters in a flexible demand system. The strategy of creating strong and specific instruments using same-chain prices in other locations, as recently advocated by DellaVigna and Gentzkow (2019) and Allcott et al. (2020), makes it more practical to instrument prices in a large flexible demand system. Our multi-step approach to estimating a large demand with endogenous prices, truncated purchases and complex survey design should also facilitate applications of flexible demand systems in the future. As we have documented that some of the distributional effects of food taxes and subsidies result from the estimated complementarity between food groups, demand models restricting goods to be substitutes will not be able to shed light on this important implication of food pricing policies.

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in many characteristics demand models, foods are still restricted to be substitutes owing to the restricted sub-utility functional forms and characteristics entering the utility function additively.

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Table 1. Characteristics of the FoodAPS Households

	lower-income with obese members	lower-income without obese members	higher-income with obese members	higher-income without obese members
Share of HH members that are				
≤18 yrs	0.26	0.10	0.16	0.12
Hispanic	0.24	0.18	0.12	0.09
black	0.23	0.17	0.11	0.08
Share of adult HH members				
working at a job/business	0.37	0.29	0.67	0.64
with one or more years of college	0.36	0.47	0.64	0.77
that use tobacco	0.32	0.31	0.19	0.16
Primary respondent's BMI	33.33	24.57	31.79	24.19
Primary respondent's age	47.21	53.92	49.36	49.90
HH size (persons)	3.10	1.79	2.71	2.20
HH size (adult-male equivalents)	2.37	1.40	2.16	1.76
Sample size	1436	1035	1109	1159
Population (MM of people)	53.6	30.4	104.2	105.6

Notes: All except population are sample means weighted by the survey weights. HH=household. Population is projected based on the household size and sampling weights.

Table 2. Unit Values, Budget Shares, Purchase Quantities and Calories

	unit value ($/100g)		budget share		weekly quantity (100g/AME)	
Food group	lower-income	higher-income	lower-income	higher-income	lower-income	higher-income
1. grains, 0 star	0.50	0.53	0.01	0.01	1.18	1.20
2. grains, 1-3 star	0.31	0.41	0.04	0.04	6.80	7.02
3. vegetables, 0 star	0.34	0.41	0.01	0.01	0.82	1.06
4. vegetables, 1-3 star	0.23	0.29	0.05	0.05	9.26	11.08
5. fruit, 0 star	0.31	0.39	0.00	0.01	0.58	0.91
6. fruit, 1-3 star	0.33	0.39	0.04	0.04	5.66	7.70
7. milk products, 0 star	0.21	0.30	0.05	0.05	11.87	11.30
8. milk products, 1-3 star	0.11	0.12	0.01	0.01	3.13	6.51
9. meat and protein, 0 star	0.62	0.74	0.10	0.07	7.28	6.43
10. meat and protein, 1-3 star	0.72	0.79	0.08	0.06	4.92	5.49
11. prepared meals, 0 star	0.51	0.60	0.05	0.04	4.37	4.79

Table 2. Unit Values, Budget Shares, Purchase Quantities and Calories (Continued)

Food group	unit value ($/100g) lower-income	unit value ($/100g) higher-income	budget share lower-income	budget share higher-income	weekly quantity (100g/AME) lower-income	weekly quantity (100g/AME) higher-income
12. prepared meals, 1-3 star	0.43	0.54	0.03	0.02	2.90	3.04
13. fats and oils, 0 star	0.36	0.44	0.02	0.02	3.21	3.92
14. fats and oils, 1-3 star	0.42	0.45	0.01	0.01	1.19	1.13
15. beverages, 0 star	0.11	0.15	0.06	0.06	25.82	25.95
16. beverages, 1-3 star	0.10	0.15	0.04	0.04	18.13	18.62
17. snacks, 0 star	0.47	0.46	0.09	0.08	9.00	11.62
18. snacks, 1-3 star	0.88	0.95	0.02	0.02	1.04	1.34
19. FAFH, 0 star	0.78	1.06	0.23	0.29	13.42	19.72
20. FAFH, 1-3 star	0.87	1.10	0.06	0.09	3.39	5.87
N	2471	2268				

Notes: Sample means weighted by survey weights. The budget shares are shares of food groups in total food spending. Prepared meals include prepared meals, sides, and salads. Fats and oils include table fats, oils, salad dressings; and gravies, sauces, condiments and spices. Beverages include, among other nonalcoholic beverages, 100% fruit and vegetable juice. Snacks include sweets and salty snacks. FAFH=food away from home. Weekly quantities are in per adult-male equivalent.

Table 3. Importance of Starred Foods in Purchases

	Quantity share of starred foods in a food category			
Food category	lower-income with obese members	lower-income without obese members	higher-income with obese members	higher-income without obese members
grains	0.84	0.88	0.85	0.85
vegetables	0.92	0.92	0.92	0.91
fruit	0.91	0.91	0.90	0.89
milk product	0.20	0.22	0.32	0.40
meat and protein	0.38	0.44	0.46	0.47
prepared meals	0.40	0.39	0.39	0.38
fats and oils	0.28	0.25	0.24	0.21
beverages	0.37	0.49	0.38	0.46
snacks	0.12	0.08	0.12	0.09
FAFH	0.16	0.28	0.21	0.25
N	1436	1035	1109	1159

Notes: Sample mean shares weighted by survey weights.

Table 4. Nutrient Densities, Total Nutrient Purchases, and Overall Nutritional Quality

Nutrient/food component	lower-income with obese members	lower-income without obese members	higher-income with obese members	higher-income without obese members
	per 100 g of food			
dietary fiber (g)	0.92	0.98	0.95	1.14
folic acid (mcg)	14.23	12.67	12.38	13.29
iron (mg)	0.98	0.94	0.93	1.00
magnesium (mg)	15.59	16.62	16.29	18.87
calcium (mg)	53.57	53.76	53.77	57.11
potassium (mg)	150.80	161.47	156.76	173.81
whole grains (oz. eq.)	0.05	0.05	0.05	0.06
total fruit[a] (cup eq.)	0.05	0.05	0.05	0.06
total vegetables[b] (cup eq.)	0.08	0.10	0.09	0.11
solid fats (g)	2.65	2.42	2.52	2.79
added sugars (tsp eq.)	1.43	1.27	1.24	1.35
sodium (mg)	186.64	171.26	180.66	175.15
refined grains (oz. eq.)	0.38	0.35	0.34	0.34
energy (kcal)	137.25	130.13	130.50	137.44
	per dollar of food spending			
dietary fiber (g)	2.70	2.77	2.15	2.36
folic acid (mcg)	41.79	35.67	28.13	27.55
iron (mg)	2.88	2.64	2.11	2.08
magnesium (mg)	45.76	46.78	37.02	39.11
calcium (mg)	157.29	151.30	122.17	118.35
potassium (mg)	442.75	454.48	356.20	360.20
whole grains (oz. eq.)	0.13	0.14	0.12	0.13
total fruit[a] (cup eq.)	0.14	0.14	0.11	0.12
total vegetables[b] (cup eq.)	0.25	0.29	0.21	0.23
solid fats (g)	7.77	6.80	5.73	5.78
added sugars (tsp eq.)	4.20	3.56	2.83	2.80
sodium (mg)	547.99	482.04	410.49	362.97
refined grains (oz. eq.)	1.12	0.98	0.78	0.70
energy (kcal)	402.99	366.28	296.52	284.82
	weekly purchases per adult-male equivalent			
whole grains (oz. eq.)	6.0	6.7	8.0	9.7
total fruit[a] (cup eq.)	6.0	7.0	7.9	8.7

Table 4. Nutrient Densities, Total Nutrient Purchases, and Overall Nutritional Quality (Continued)

Nutrient/food component	lower-income with obese members	lower-income without obese members	higher-income with obese members	higher-income without obese members
	weekly purchases per adult-male equivalent			
total vegetables[b] (cup eq.)	11.0	14.3	14.6	16.7
solid fats (g)	344.8	339.4	396.0	425.4
added sugars (tsp eq.)	186.1	177.8	195.4	206.2
sodium (mg)	24305.7	24052.2	28381.6	26693.1
refined grains (oz. eq.)	49.5	48.9	53.9	51.3
energy (kcal)	17874.3	18276.0	20501.4	20946.4
HEI-2010[c]	48.75	50.68	52.75	55.69

Notes: Sample means weighted by survey weights. [a]includes whole fruit and fruit juice. [b]excludes legumes. [c]based on households that purchased a positive amount of dietary energy.

Table 5. Marshallian Own-price Elasticities

Food group	Overall	lower-income with obese members	lower-income without obese members	higher-income with obese members	higher-income without obese members
1. grains, 0 star	-0.748	-1.020	-0.498	-1.023	-0.518
	(0.088)	(0.090)	(0.092)	(0.090)	(0.084)
2. grains, 1-3 star	-1.240	-1.281	-1.282	-1.208	-1.235
	(0.066)	(0.071)	(0.060)	(0.071)	(0.062)
3. vegetables, 0 star	-1.916	-2.060	-2.038	-1.841	-1.880
	(0.102)	(0.108)	(0.111)	(0.100)	(0.098)
4. vegetables, 1-3 star	-1.423	-1.159	-2.050	-0.849	-1.757
	(0.131)	(0.121)	(0.152)	(0.125)	(0.132)
5. fruit, 0 star	-2.128	-1.612	-2.508	-1.620	-2.586
	(0.164)	(0.194)	(0.190)	(0.142)	(0.160)
6. fruit, 1-3 star	-1.347	-0.884	-1.704	-0.947	-1.710
	(0.106)	(0.103)	(0.111)	(0.101)	(0.109)
7. milk products, 0 star	-1.225	-1.887	-1.815	-0.969	-0.982
	(0.146)	(0.159)	(0.166)	(0.143)	(0.138)
8. milk products, 1-3 star	-1.669	-2.198	-1.445	-1.956	-1.327
	(0.089)	(0.121)	(0.089)	(0.093)	(0.073)

Table 5. Marshallian Own-price Elasticities

Food group	Overall	lower-income with obese members	lower-income without obese members	higher-income with obese members	higher-income without obese members
9. meat and protein, 0 star	-0.978	-1.178	-0.935	-1.084	-0.836
	(0.107)	(0.100)	(0.104)	(0.109)	(0.108)
10. meat and protein, 1-3 star	-1.980	-1.954	-1.708	-2.225	-1.888
	(0.061)	(0.057)	(0.055)	(0.068)	(0.058)
11. prepared meals, 0 star	-1.142	-1.405	-1.660	-0.794	-1.144
	(0.118)	(0.124)	(0.137)	(0.116)	(0.110)
12. prepared meals, 1-3 star	-1.848	-1.309	-1.455	-2.034	-2.032
	(0.107)	(0.108)	(0.110)	(0.109)	(0.104)
13. fats and oils, 0 star	-1.700	-2.365	-1.435	-2.063	-1.262
	(0.138)	(0.178)	(0.121)	(0.162)	(0.110)
14. fats and oils, 1-3 star	-1.738	-1.701	-1.858	-1.627	-1.797
	(0.086)	(0.089)	(0.089)	(0.089)	(0.082)
15. beverages, 0 star	-1.902	-1.672	-1.912	-1.857	-2.018
	(0.066)	(0.064)	(0.068)	(0.066)	(0.065)
16. beverages, 1-3 star	-1.733	-2.539	-1.034	-2.518	-1.060
	(0.088)	(0.106)	(0.079)	(0.096)	(0.079)
17. snacks, 0 star	-0.544	-0.983	-0.609	-0.614	-0.305
	(0.151)	(0.167)	(0.142)	(0.161)	(0.140)
18. snacks, 1-3 star	-2.312	-2.420	-2.214	-2.463	-2.188
	(0.137)	(0.149)	(0.147)	(0.147)	(0.122)
19. FAFH, 0 star	-0.777	-0.605	-0.582	-0.875	-0.828
	(0.076)	(0.080)	(0.088)	(0.071)	(0.074)
20. FAFH, 1-3 star	-0.880	-0.882	-0.853	-0.898	-0.874
	(0.078)	(0.082)	(0.077)	(0.083)	(0.074)
21. numeraire	-1.725	-1.846	-1.707	-1.772	-1.650
	(0.051)	(0.062)	(0.055)	(0.049)	(0.046)
N	4739	1436	1035	1109	1159

Notes: Sample mean estimates. Standard errors in parentheses.

Table 6. Total Expenditure Elasticities

Food group	Overall	lower-income with obese members	lower-income without obese members	higher-income with obese members	higher-income without obese members
1. grains, 0 star	1.229	1.810	1.775	1.050	0.970
	(0.148)	(0.178)	(0.196)	(0.141)	(0.152)
2. grains, 1-3 star	0.929	0.991	0.941	0.910	0.918
	(0.075)	(0.082)	(0.078)	(0.085)	(0.079)
3. vegetables, 0 star	1.506	1.743	1.563	1.543	1.371
	(0.171)	(0.183)	(0.191)	(0.155)	(0.173)
4. vegetables, 1-3 star	1.113	1.371	0.990	1.230	0.970
	(0.114)	(0.130)	(0.135)	(0.107)	(0.107)
5. fruit, 0 star	1.252	2.869	1.569	1.388	0.447
	(0.275)	(0.432)	(0.430)	(0.241)	(0.281)
6. fruit, 1-3 star	1.278	1.620	1.291	1.376	1.072
	(0.106)	(0.148)	(0.142)	(0.111)	(0.111)
7. milk products, 0 star	0.720	0.621	0.918	0.488	0.872
	(0.098)	(0.112)	(0.122)	(0.113)	(0.102)
8. milk products, 1-3 star	1.338	1.436	1.630	1.134	1.364
	(0.164)	(0.209)	(0.200)	(0.155)	(0.157)
9. meat and protein, 0 star	0.918	1.047	0.963	0.871	0.892
	(0.079)	(0.084)	(0.096)	(0.080)	(0.084)
10. meat and protein, 1-3 star	1.039	1.165	1.119	0.971	1.021
	(0.069)	(0.075)	(0.080)	(0.068)	(0.066)
11. prepared meals, 0 star	1.208	1.202	1.397	1.059	1.263
	(0.136)	(0.127)	(0.147)	(0.109)	(0.105)
12. prepared meals, 1-3 star	1.139	1.308	1.143	1.131	1.082
	(0.125)	(0.139)	(0.143)	(0.116)	(0.114)
13. fats and oils, 0 star	1.091	1.372	1.350	0.905	1.047
	(0.163)	(0.188)	(0.176)	(0.147)	(0.129)
14. fats and oils, 1-3 star	1.471	1.435	1.506	1.396	1.533
	(0.161)	(0.178)	(0.188)	(0.147)	(0.144)
15. beverages, 0 star	1.067	1.019	1.177	0.899	1.180
	(0.088)	(0.085)	(0.105)	(0.073)	(0.075)
16. beverages, 1-3 star	1.172	1.274	1.177	1.175	1.132
	(0.084)	(0.098)	(0.089)	(0.082)	(0.084)
17. snacks, 0 star	0.993	1.213	0.951	1.068	0.868
	(0.098)	(0.092)	(0.090)	(0.084)	(0.090)
18. snacks, 1-3 star	0.978	1.186	0.928	1.020	0.887
	(0.157)	(0.148)	(0.163)	(0.131)	(0.134)

Table 6. Total Expenditure Elasticities (Continued)

Food group	Overall	lower-income with obese members	lower-income without obese members	higher-income with obese members	higher-income without obese members
19. FAFH, 0 star	0.905	0.762	0.899	0.906	0.957
	(0.050)	(0.049)	(0.058)	(0.048)	(0.052)
20. FAFH, 1-3 star	1.198	1.257	1.036	1.335	1.124
	(0.070)	(0.082)	(0.087)	(0.066)	(0.070)
21. numeraire	0.975	0.947	1.005	0.961	0.985
	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)
N	4739	1436	1035	1109	1159

Notes: Sample mean estimates. Standard errors in parentheses.

Table 7. The Simulated Effects of a One Penny per Ounce Tax on Sweetened Beverages

Predicted changes in	overall	lower-income with obese members	lower-income without obese members	higher-income with obese members	higher-income without obese members
total fruit purchased (cup eq.)	-0.46	-0.48	-0.39	-0.56	-0.40
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)
total veg purchased (cup eq.)	-0.42	-0.06	-0.24	-0.46	-0.59
	(0.09)	(0.08)	(0.11)	(0.09)	(0.09)
whole grains purchased (oz. eq.)	0.23	0.13	0.25	0.19	0.30
	(0.06)	(0.05)	(0.06)	(0.07)	(0.06)
refined grains purchased (oz. eq.)	0.34	0.46	0.53	0.28	0.27
	(0.24)	(0.28)	(0.27)	(0.25)	(0.21)
sodium purchased (mg)	-193.52	-66.53	299.41	-556.43	-122.45
	(112.72)	(141.55)	(120.40)	(120.29)	(93.53)
added sugars purchased (tsp eq.)	-17.90	-24.20	-23.37	-19.42	-12.48
	(1.03)	(1.23)	(1.11)	(1.12)	(0.86)
solid fats purchased (g)	0.10	-4.83	6.33	-5.87	4.47
	(1.90)	(1.99)	(1.95)	(2.10)	(1.70)
total calories purchased	-360.56	-439.19	-233.12	-568.46	-210.45
	(68.72)	(74.55)	(72.18)	(75.57)	(59.90)
calories purchased from					
1. grains, 0 star	-13.63	15.66	4.80	-22.69	-23.42
	(6.01)	(7.89)	(6.93)	(5.24)	(5.62)

Table 7. The Simulated Effects of a One Penny per Ounce Tax on Sweetened Beverages (Continued)

Predicted changes in	overall	lower-income with obese members	lower-income without obese members	higher-income with obese members	higher-income without obese members
calories purchased from					
2. grains, 1-3 star	57.71	54.10	72.74	49.98	59.90
	(17.02)	(18.02)	(18.85)	(18.31)	(14.98)
3. vegetables, 0 star	-4.11	-3.44	-2.67	-5.45	-3.77
	(0.74)	(0.57)	(0.84)	(0.69)	(0.80)
4. vegetables, 1-3 star	-21.29	-3.22	-11.82	-25.21	-28.01
	(5.58)	(5.56)	(7.98)	(5.25)	(4.99)
5. fruit, 0 star	-2.51	0.78	-10.17	5.00	-7.02
	(1.82)	(1.48)	(2.27)	(1.68)	(1.90)
6. fruit, 1-3 star	-26.72	-17.59	-17.85	-33.29	-27.88
	(4.28)	(4.20)	(4.73)	(4.32)	(4.13)
7. milk products, 0 star	35.86	-45.50	134.59	-61.52	108.41
	(14.18)	(15.92)	(16.38)	(13.70)	(13.16)
8. milk products, 1-3 star	-9.60	-10.02	12.66	-30.31	-0.71
	(4.07)	(2.99)	(4.15)	(3.91)	(4.56)
9. meat and proteins, 0 star	-5.49	4.54	35.02	-34.11	-0.47
	(12.01)	(14.71)	(13.78)	(14.00)	(8.81)
10. meat and proteins, 1-3 star	-11.54	0.94	5.70	-23.06	-12.89
	(7.34)	(7.19)	(8.38)	(8.32)	(6.24)
11. prepared meals, 0 star	-32.62	0.28	26.49	-76.50	-30.18
	(9.30)	(11.52)	(10.76)	(10.33)	(7.16)
12. prepared meals, 1-3 star	-15.52	20.19	-6.05	-18.13	-29.65
	(6.57)	(8.42)	(7.85)	(6.70)	(5.35)
13. fats and oils, 0 star	-10.08	4.34	20.79	-31.81	-8.76
	(11.57)	(12.82)	(14.26)	(13.04)	(8.99)
14. fats and oils, 1-3 star	44.46	121.43	46.85	54.99	7.42
	(9.69)	(16.99)	(12.12)	(10.45)	(5.60)
15. beverages, 0 star	-362.69	-405.91	-405.78	-419.57	-286.21
	(11.86)	(14.56)	(13.52)	(14.03)	(8.56)
16. beverages, 1-3 star	-20.54	-58.69	-18.73	-48.60	15.10
	(7.96)	(6.89)	(10.62)	(8.99)	(6.59)
17. snacks, 0 star	-62.50	-164.72	-140.32	-21.65	-30.90
	(28.64)	(30.83)	(27.92)	(28.31)	(28.38)
18. snacks, 1-3 star	59.66	29.96	87.66	28.16	85.74
	(7.70)	(6.75)	(8.36)	(7.68)	(7.84)

Table 7. The Simulated Effects of a One Penny per Ounce Tax on Sweetened Beverages (Continued)

Predicted changes in	overall	lower-income with obese members	lower-income without obese members	higher-income with obese members	higher-income without obese members
calories purchased from					
19. FAFH, 0 star	57.97	15.13	-31.68	142.27	37.48
	(17.71)	(17.14)	(15.03)	(22.66)	(14.89)
20. FAFH, 1-3 star	-17.39	2.55	-35.36	3.04	-34.62
	(6.64)	(5.36)	(6.20)	(8.20)	(6.01)
density of					
total fruit (cup eq./1000 kcal)	-0.02	-0.02	-0.02	-0.02	-0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
total veg (cup eq./1000 kcal)	-0.01	0.01	0.00	0.00	-0.02
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
sodium density (g/1000 kcal)	0.02	0.03	0.03	0.01	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
share of energy from added sugars (percentage points)	-1.13	-1.73	-1.73	-1.07	-0.76
	(0.06)	(0.08)	(0.07)	(0.06)	(0.05)
share of energy from solid fats (percentage points)	0.29	0.20	0.46	0.22	0.33
	(0.05)	(0.06)	(0.05)	(0.05)	(0.04)
HEI	0.25	0.82	0.56	0.19	-0.01
	(0.11)	(0.13)	(0.12)	(0.11)	(0.09)
weekly tax paid ($)	0.35	0.38	0.29	0.42	0.30
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
projected weekly tax revenue (million $)	85.23	15.87	7.24	36.13	25.98

Notes: Sample means weighted by survey weights. All quantity statistics are reported on a per-AME-week basis, except for the projected tax revenue from the population. Standard errors in parentheses.

Table 8. The Simulated Effects of a 30 Percent Subsidy on Starred Fruit and Vegetables

Predicted changes in	overall	lower-income with obese members	lower-income without obese members	higher-income with obese members	higher-income without obese members
total fruit purchased	1.62	0.79	1.86	0.98	2.34
	(0.22)	(0.16)	(0.20)	(0.21)	(0.25)
total veg purchased	3.66	1.94	4.89	2.22	5.00
	(0.42)	(0.26)	(0.46)	(0.39)	(0.49)
whole grains purchased	-0.84	0.21	-0.68	-0.43	-1.60
	(0.20)	(0.12)	(0.17)	(0.19)	(0.24)
refined grains purchased	0.81	4.71	-0.48	3.46	-2.27
	(0.71)	(0.61)	(0.74)	(0.65)	(0.79)
sodium purchased	1203.12	1503.84	264.75	2216.44	613.47
	(336.02)	(338.69)	(329.26)	(332.19)	(340.51)
added sugars purchased	13.61	23.56	13.12	19.33	5.60
	(3.02)	(2.57)	(2.63)	(3.10)	(3.25)
solid fats purchased	5.12	16.76	-6.34	19.03	-6.19
	(6.86)	(5.79)	(6.24)	(7.23)	(7.17)
total calories purchased	774.05	1290.53	529.62	1221.90	314.90
	(183.53)	(155.06)	(179.01)	(179.39)	(198.71)
calories purchased from					
1. grains, 0 star	40.41	31.37	-26.15	91.67	26.08
	(19.14)	(20.99)	(16.77)	(19.71)	(18.85)
2. grains, 1-3 star	-231.82	53.71	-239.53	-125.75	-417.16
	(56.99)	(47.86)	(58.48)	(54.29)	(61.93)
3. vegetables, 0 star	2.99	7.97	1.21	7.94	-2.15
	(2.14)	(1.39)	(2.23)	(1.90)	(2.58)
4. vegetables, 1-3 star	223.34	126.51	332.63	118.89	303.42
	(28.85)	(19.63)	(34.26)	(26.00)	(32.55)
5. fruit, 0 star	-12.99	3.40	1.61	-16.73	-21.07
	(4.62)	(3.26)	(4.64)	(4.28)	(5.39)
6. fruit, 1-3 star	159.67	60.96	171.27	109.42	231.47
	(19.04)	(14.04)	(18.39)	(18.64)	(21.39)
7. milk products, 0 star	-189.47	-12.71	-240.48	-72.78	-328.79
	(58.18)	(49.78)	(54.96)	(55.73)	(64.31)
8. milk products, 1-3 star	17.73	-18.27	50.48	-46.41	70.61
	(10.07)	(5.71)	(8.11)	(9.47)	(12.83)
9. meat and proteins, 0 star	-71.09	-80.26	-326.84	127.83	-136.93
	(41.44)	(43.74)	(47.67)	(45.25)	(35.34)

Table 8. The Simulated Effects of a 30 Percent Subsidy on Starred Fruit and Vegetables (Continued)

Predicted changes in	overall	lower-income with obese members	lower-income without obese members	higher-income with obese members	higher-income without obese members
calories purchased from					
10. meat and proteins, 1-3 star	55.52	19.50	60.06	42.74	77.16
	(13.93)	(11.14)	(13.31)	(15.55)	(13.86)
11. prepared meals, 0 star	251.88	177.86	183.48	300.12	264.04
	(31.83)	(29.17)	(29.96)	(34.77)	(31.09)
12. prepared meals, 1-3 star	8.37	28.14	-6.06	25.50	-7.40
	(20.19)	(20.53)	(20.76)	(21.95)	(18.46)
13. fats and oils, 0 star	-22.63	-249.06	91.65	-193.10	155.38
	(53.82)	(48.53)	(56.25)	(58.92)	(50.77)
14. fats and oils, 1-3 star	11.28	59.60	-73.42	77.83	-29.57
	(23.43)	(30.99)	(29.35)	(23.09)	(18.88)
15. beverages, 0 star	124.88	59.13	59.74	191.89	117.86
	(17.83)	(17.10)	(16.52)	(23.42)	(14.08)
16. beverages, 1-3 star	-67.37	11.17	24.11	-102.14	-100.15
	(20.53)	(13.57)	(26.19)	(19.87)	(21.56)
17. snacks, 0 star	363.66	724.15	479.61	343.50	208.84
	(119.89)	(95.95)	(96.52)	(120.11)	(136.61)
18. snacks, 1-3 star	-175.55	-32.55	-149.20	-142.44	-263.00
	(27.37)	(21.22)	(21.81)	(30.04)	(29.41)
19. FAFH, 0 star	135.14	287.28	-57.16	421.11	-81.17
	(48.18)	(39.24)	(32.71)	(64.16)	(44.04)
20. FAFH, 1-3 star	150.09	32.62	192.61	62.82	247.43
	(21.69)	(12.16)	(19.01)	(23.79)	(24.39)
density of					
total fruit (cup eq./1000 kcal)	0.14	0.02	0.67	0.02	0.10
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
total veg (cup eq./1000 kcal)	0.31	0.06	1.42	0.06	0.22
	(0.02)	(0.01)	(0.05)	(0.02)	(0.03)
sodium density (g/1000 kcal)	-0.09	-0.02	-0.72	0.02	0.01
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
share of energy from added sugars (percentage points)	0.82	0.85	3.32	0.50	0.19
	(0.17)	(0.15)	(0.22)	(0.16)	(0.17)
share of energy from solid fats (percentage points)	-1.67	-0.40	-9.85	-0.18	-0.43
	(0.20)	(0.16)	(0.32)	(0.19)	(0.19)

Table 8. The Simulated Effects of a 30 Percent Subsidy on Starred Fruit and Vegetables (Continued)

Predicted changes in	overall	lower-income with obese members	lower-income without obese members	higher-income with obese members	higher-income without obese members
HEI	1.51	0.04	2.89	0.10	2.68
	(0.38)	(0.33)	(0.40)	(0.38)	(0.40)
Subsidy receipt ($)	2.98	1.60	2.67	2.63	3.88
	(0.09)	(0.05)	(0.08)	(0.08)	(0.12)
projected weekly subsidy outlay (million $)	654.53	64.49	63.11	214.17	312.76

Notes: Sample means weighted by survey weights. All quantity statistics are reported on a per-AME-week basis, except for the projected subsidy for the population. Standard errors in parentheses.

Table 9. The Simulated Effects of a Fiscally Neutral 10% Subsidy on Starred Foods Funded by a 8.8% Tax on 0-Star Foods

Predicted changes in	overall	lower-income with obese members	lower-income without obese members	higher-income with obese members	higher-income without obese members
total fruit purchased	-0.59	-0.62	0.01	-1.24	-0.27
	(0.18)	(0.14)	(0.15)	(0.20)	(0.18)
total veg purchased	1.88	0.97	3.09	0.72	2.72
	(0.32)	(0.22)	(0.36)	(0.28)	(0.37)
whole grains purchased	0.07	0.06	0.61	-0.55	0.37
	(0.20)	(0.14)	(0.16)	(0.22)	(0.21)
refined grains purchased	-0.18	-0.19	2.45	-2.14	0.47
	(0.68)	(0.66)	(0.65)	(0.71)	(0.67)
sodium purchased	-1756.64	-2398.22	-2362.99	-1218.56	-1742.62
	(300.17)	(343.46)	(313.23)	(297.06)	(282.44)
added sugars purchased	-11.90	-11.65	-9.84	-15.72	-9.64
	(2.41)	(2.27)	(2.23)	(2.51)	(2.44)
solid fats purchased	-36.94	-36.15	-51.59	-25.83	-40.95
	(6.13)	(5.58)	(6.08)	(6.29)	(6.22)
total calories purchased	-351.46	-458.43	-432.60	-304.60	-321.80
	(150.09)	(142.70)	(150.49)	(151.06)	(151.83)
calories purchased from					
1. grains, 0 star	-31.61	-3.32	-11.28	-37.58	-44.21
	(17.36)	(20.36)	(15.53)	(16.67)	(17.48)

Table 9. The Simulated Effects of a Fiscally Neutral 10% Subsidy on Starred Foods Funded by a 8.8% Tax on 0-Star Foods (Continued)

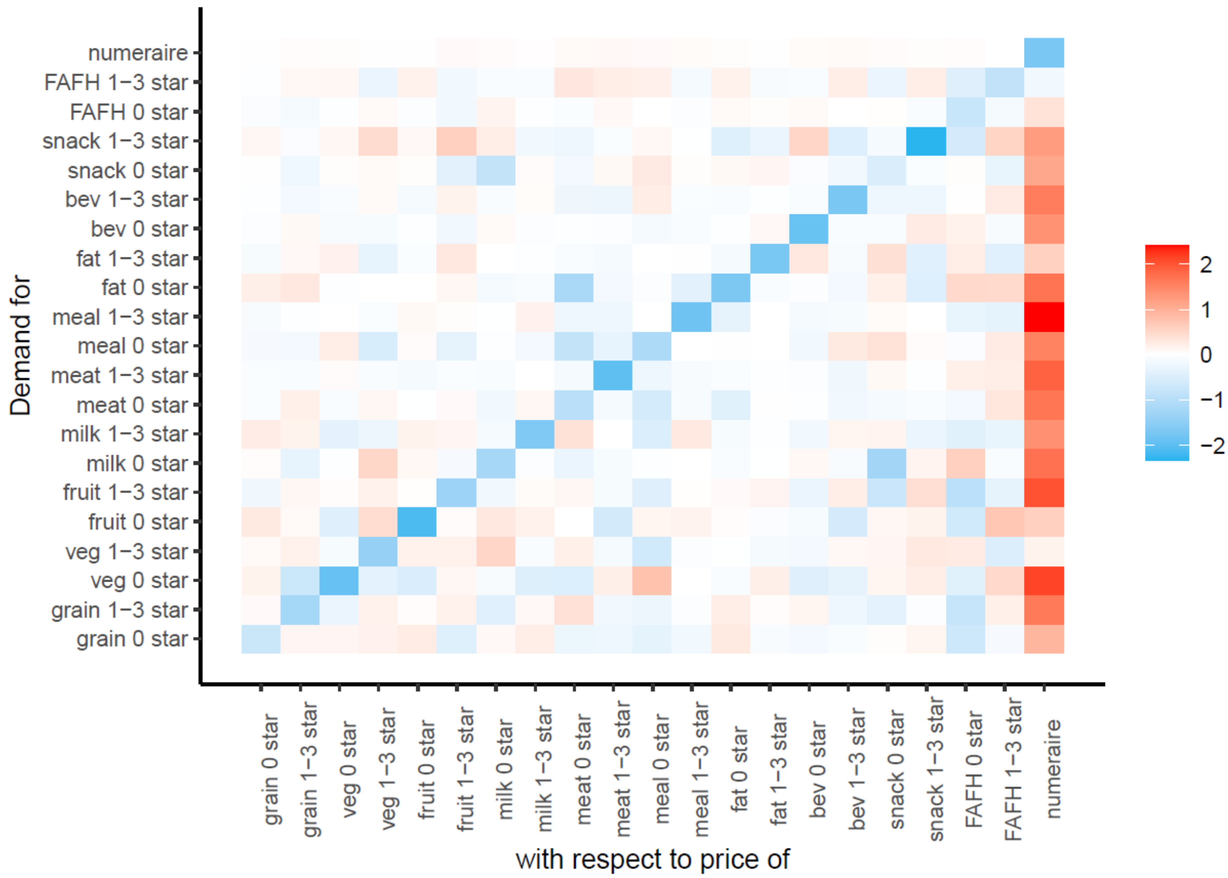
Predicted changes in	overall	lower-income with obese members	lower-income without obese members	higher-income with obese members	higher-income without obese members
calories purchased from					
2. grains, 1-3 star	-23.12	-15.37	228.61	-244.00	62.30
	(60.33)	(57.03)	(55.62)	(66.30)	(58.39)
3. vegetables, 0 star	-9.40	1.26	-12.03	-1.85	-18.38
	(1.79)	(1.18)	(1.86)	(1.50)	(2.21)
4. vegetables, 1-3 star	118.40	73.02	235.93	21.69	170.79
	(21.36)	(16.28)	(26.65)	(17.90)	(24.09)
5. fruit, 0 star	-23.63	0.37	-9.85	-23.37	-37.38
	(4.54)	(3.19)	(4.67)	(3.98)	(5.43)
6. fruit, 1-3 star	-65.45	-99.79	1.86	-143.16	-14.52
	(14.70)	(11.93)	(12.82)	(16.62)	(14.83)
7. milk products, 0 star	-278.07	-128.71	-489.24	-30.96	-455.53
	(60.55)	(52.28)	(63.21)	(55.74)	(66.45)
8. milk products, 1-3 star	30.12	6.59	14.96	27.35	46.18
	(9.64)	(6.48)	(6.99)	(9.60)	(11.74)
9. meat and proteins, 0 star	-409.40	-490.61	-423.29	-454.28	-339.19
	(37.03)	(42.98)	(42.40)	(39.68)	(30.86)
10. meat and proteins, 1-3 star	219.74	155.96	171.46	263.70	224.54
	(12.68)	(10.21)	(12.23)	(14.48)	(12.30)
11. prepared meals, 0 star	-49.89	-151.76	-129.15	-8.49	-18.35
	(27.45)	(31.89)	(27.62)	(30.37)	(23.44)
12. prepared meals, 1-3 star	85.78	35.16	68.24	91.43	105.70
	(18.21)	(18.90)	(20.14)	(17.68)	(17.70)
13. fats and oils, 0 star	-143.96	-251.67	-256.32	-104.41	-97.12
	(44.75)	(44.73)	(50.89)	(44.95)	(42.42)
14. fats and oils, 1-3 star	200.82	249.81	135.18	275.55	146.41
	(20.98)	(29.74)	(23.42)	(23.68)	(14.78)
15. beverages, 0 star	-180.52	-201.05	-226.67	-176.52	-160.00
	(16.26)	(17.54)	(18.01)	(19.39)	(12.67)
16. beverages, 1-3 star	108.32	185.90	29.15	241.38	1.58
	(18.24)	(14.19)	(19.72)	(19.65)	(18.05)
17. snacks, 0 star	-53.60	-77.45	157.92	-282.92	64.20
	(92.26)	(82.70)	(76.16)	(94.63)	(99.50)
18. snacks, 1-3 star	93.75	106.95	42.42	145.33	65.75
	(22.90)	(20.75)	(18.68)	(26.57)	(22.23)

Table 9. The Simulated Effects of a Fiscally Neutral 10% Subsidy on Starred Foods Funded by a 8.8% Tax on 0-Star Foods (Continued)

Predicted changes in	overall	lower-income with obese members	lower-income without obese members	higher-income with obese members	higher-income without obese members
calories purchased from					
19. FAFH, 0 star	-36.83	136.63	-83.84	106.26	-197.55
	(44.00)	(41.36)	(29.60)	(58.47)	(38.43)
20. FAFH, 1-3 star	97.09	9.64	123.33	30.26	172.97
	(18.12)	(11.49)	(15.71)	(19.80)	(20.01)
density of					
total fruit (cup eq./1000 kcal)	-0.02	-0.02	0.01	-0.05	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
total veg (cup eq./1000 kcal)	0.10	0.07	0.18	0.05	0.14
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
sodium density (g/1000 kcal)	-0.06	-0.09	-0.09	-0.03	-0.06
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
share of energy from added sugars (percentage points)	-0.61	-0.54	-0.50	-0.85	-0.49
	(0.14)	(0.16)	(0.15)	(0.14)	(0.13)
share of energy from solid fats (percentage points)	-1.22	-1.25	-1.92	-0.76	-1.32
	(0.19)	(0.19)	(0.21)	(0.19)	(0.18)
HEI	2.30	1.87	3.40	1.36	2.83
	(0.38)	(0.36)	(0.37)	(0.39)	(0.37)
taxes paid[a] ($)	0.10	0.57	-0.65	0.86	-0.42
	(0.09)	(0.06)	(0.08)	(0.10)	(0.10)
projected weekly tax revenue[b] (million $)	0.00	13.84	-23.28	52.99	-43.55

Notes: Sample means weighted by survey weights. All quantity statistics are reported on a per-AME-week basis, except for the projected subsidy for the population. Standard errors in parentheses. [a]negative values indicate subsidy received. [b]negative values indicate public expenditures.

Figure 1. Average Marshallian Price Elasticities, Overall Sample



Technical Appendix

Do Obese and Nonobese Consumers Respond Differently to Price Changes? Implications of Preference Heterogeneity for Using Food Taxes and Subsidies to Reduce Obesity

December 2021

The Construction of the Price Indexes and Their Instruments

For FoodAPS trips to InfoScan retailers, we aggregated total FAH expenditures at the household-trip-date-retailer-county level. For purchases at non-InfoScan retailers, we aggregated FAH expenditures to the household-trip-date-county level. We also calculated total FAH expenditures by household and the county in which it shopped. These total FAH expenditures are used as weights on the trip-level price indexes and their instruments (described below) to create household-level price indexes and instruments, which are used to estimate the EASI demand.

For each FAH food group j (j = 1, …, 18), the set of food codes ever purchased by FoodAPS household is defined as the universe of food group j. We mapped InfoScan food items to these food codes and extracted InfoScan sales data at the food-code-week-retailer-county level. Not all food codes can be mapped to items in InfoScan.

We identified FoodAPS trips in which the household purchased food group j and calculated expenditures on j at the household-retailer-county-trip-date level. For FoodAPS retailers not geocoded to a county, we used the visiting household's county of residence as replacement. For trips to InfoScan retailers, we linked them with InfoScan food code-level prices by trip date, retailer and county. For trips to non-InfoScan retailers, we linked them with InfoScan food code-level prices by trip date and county. We then constructed the Fisher Ideal price index for food group j for each trip in which group j was purchased. Elementary prices are FoodAPS prices for food codes purchased by the household and InfoScan prices for food codes not purchased on the trip. The household-level Fisher Ideal index, for purchasing households, is the weighted average of trip-level Fisher Ideal indexes, using trip-level expenditures on food group j as weights. The base prices and quantities for the Fisher Ideal index are sample averages over all FoodAPS households.

For households that shopped for FAH but did not purchase food group j in the 7-day survey period, we started with two Fisher Ideal price indexes: a county-level index p_{cj} based on InfoScan aggregated to county level, and a retailer-county level index p_{crj} based on InfoScan aggregated to retailer-county level, both at IRI week frequencies. We linked p_{cj} and p_{crj} to trips to non-InfoScan retailers and InfoScan retailers, respectively. We then weighted the trip-level indexes by FAH expenditure to create weighted average indexes p_{chj} and p_{rhj} for household h. Next, we weighted p_{chj} and p_{rhj} based on FAH expenditures at non-InfoScan retailers and InfoScan retailers to create a price index p_{hj} for households who shopped for FAH but did not purchase food group j during the survey.

Finally, for households who did not shop for FAH, we linked the InfoScan county-level index p_{cj} to the household's county of residence. For households who straddled two IRI weeks, we used the number of overlapping days between an IRI week and the 7-day survey period as weight to create a weighted average county-level index for the household. The weighted average is used as the price index of food group j for a household who did not purchase FAH in the survey.

To create an instrumental variable z_{hj} for p_{hj}, we repeat the above process but replace the trip-level price indexes with their instruments. For trips to InfoScan retailers, we use the average price index of the same retailer in the same IRI week but in other counties as the instruments. For trips to non-InfoScan retailers, we use weighted average county prices in all other counties within 500 miles as the instrument. The inverse distance is used as the weight.

Complex Survey Design-based Extended System AGLS Estimator

Zhen et al. (2014) extend Amemiya's generalized least squares (AGLS) estimator for a single-equation limited dependent variable with endogenous explanatory variables to a system of limited dependent variables. In this appendix, we build on the extended AGLS estimator to incorporate the complex sampling design of the survey used to estimate the demand system. Unlike reduced-form demand models, accounting for the survey sampling design in a utility-theoretic censored demand system not only affects the standard errors but also the structural parameter estimates themselves.

AGLS Estimation for Censored Demand System

The budget share equation (1) can be expressed in matrix notation as

(A1) $$w_{hi}^{*} = Y_h\beta_i + X_{1h}\alpha_i + u_{hi} = Z_h\delta_i + u_{hi}$$

where Y_h is the $1 \times (J + L)$ vector of endogenous regressors including log prices, real income, and its polynomials; X_{1h} is the $1 \times K$ vector of demand shifters; the vectors β_i and α_i contain structural parameters of the EASI model; and $Z_h = [Y_h, X_{1h}]$, and $\delta_i' = [\beta_i', \alpha_i']$. The subscript h indexes the H households in the sample.

The extended AGLS estimator entails applications of quasi-maximum likelihood (White 1982) and classical minimum distance (CMD) estimation (Wooldridge 2002, p. 442) in four steps. In the first step, estimate the following system of regressions by least squares:

(A2) $$Y_h = X_{1h}\Pi_1 + X_{2h}\Pi_2 + V_h$$

where X_{2h} is a $1 \times N$ vector of instruments excluded from equation (A1), we assume $N \geq (J + L)$ for identification; Π_1 and Π_2 are $K \times (J + L)$ and $N \times (J + L)$ coefficient matrices, respectively; V_h is a $1 \times (J + L)$ vector of residuals.

In the second step, substitute equation (A2) into equation (A1) and write the linear projection of u_{hi} on V_h in error form, $u_{hi} = V_h\rho_i + \varepsilon_{hi}$, to obtain the following reduced-form budget share equation:

(A3) $$w_{hi}^* = X_{1h}(\Pi_1\beta_i + \alpha_i) + X_{2h}\Pi_2\beta_i + V_h\beta_i + V_h\rho_i + \varepsilon_{hi} = X_h\omega_i + V_h\lambda_i + \varepsilon_{hi}$$

where $\varepsilon_{hi} \sim N(0, \sigma_{hi}^2)$, $X_h = [X_{1h}, X_{2h}]$, $\lambda_i (\equiv \beta_i + \rho_i)$ and ω_i are $(J + L) \times 1$ and $(K + N) \times 1$ vectors of parameters, respectively. By design, the error term ε_{hi} is independent of Y_h, X_h, and V_h (Newey 1987, p. 235). The vector ω_i is related to δ_i by $\omega_i \equiv D(\Pi)\delta_i$, where $\Pi' = [\Pi_1', \Pi_2']$, $D(\Pi) \equiv [\Pi, S_1]$, and S_1 is a $(K + N) \times K$ selection matrix such that $X_{1h} = X_h S_1$. The residual variance σ_{hi}^2 is specified to be a function of select demand shifters: $\sigma_{hi}^2 = \sigma_{i0}^2\left(1 + Z_{h,\sigma}\zeta_i\right)$, where $Z_{h,\sigma}$ is a $1 \times K_\sigma$ vector of demand shifters with $K_\sigma < K$. The scalar σ_{i0} and vector ζ_i are parameters. In some applications, numerical issues can occur when the same demand shifters appear in both Z_h and $Z_{h,\sigma}$ due to multicollinearity. Setting $Z_{h,\sigma}$ to a null vector and thereby restricting the residual variance to be homoscedastic will solve the problem.

As part of the second step, substitute least squares estimates $\hat{V}_h$ of V_h into equation (A3) and estimate equation (A3) individually for $i = 1, \ldots, J - 1$ using the Tobit estimator. Let $\theta_i' = [\omega_i', \lambda_i', \sigma_{i0}, \zeta_i{}']$ for $i = 1, \ldots, J - 1$, $\theta' = \left[\theta_1', \ldots, \theta_{J-1}'\right]$, and $\Phi' = [\mathrm{vec}(\Pi)', \theta']$. The correct variance for the estimator $\widehat{\Phi}$ of Φ must account for the fact that least squares *estimates* of V_h are used in the estimation of equation (A3) and that single-equation Tobit estimation misses the correlation across budget share equations. We can estimate the variance of $\widehat{\Phi}$ using a sandwich estimator or through bootstrapping.

The Sandwich Variance Estimator

The asymptotic variance of $\sqrt{T}\left(\widehat{\Phi} - \Phi\right)$ is

(A4) $\sqrt{T}(\widehat{\Phi}-\Phi)\overset{a}{\sim}N(0,G^{-1}\Psi(G^{-1})')$ with $\Psi=\begin{bmatrix}\Psi_{11} & \Psi_{12}\\ \Psi_{21} & \Psi_{22}\end{bmatrix}$ and $G=\begin{bmatrix}G_{11} & G_{12}\\ G_{21} & G_{22}\end{bmatrix}$

where Ψ_{11} and Ψ_{22} are the outer product of the score of equations (A2) and (A3), respectively; G_{11} and G_{22} are the Hessian of equations (A2) and (A3), respectively; and G_{21} and G_{12} account for the correlation between Π and θ. Independence of ε_{hit} from Y_h, X_h, and V_h implies $\Psi_{12}=\Psi_{21}=0$. Least squares estimation of equation (A2) means that $\Psi_{11}=\sum_{22}\otimes E[X_h'X_h]$ and $G_{11}=-I_{J+L}\otimes E[X_h'X_h]$, where $\sum_{22}$ is the variance-covariance of V_h and I_m denotes an m-dimensional identity matrix.

Let l_{hi} be the marginal log-likelihood of equation (A3), then

(A5) $$\Psi_{22}=E\left[\left(\partial l_{h1}/\partial\theta_1',\ldots,\partial l_{hJ-1}/\partial\theta_{J-1}'\right)'\left(\partial l_{h1}/\partial\theta_1',\ldots,\partial l_{hJ-1}/\partial\theta_{J-1}'\right)\right]$$

The fact that ω_i and λ_i appear only in the ith budget share equation implies

(A6) $$G_{22}=diag\{E(\partial^2 l_{h1}/\partial\theta_1\partial\theta_1'),\ldots,E\left(\partial^2 l_{hJ-1}/\partial\theta_{J-1}\partial\theta_{J-1}'\right)\}.$$

The G_{21} and G_{12} terms take the following form

(A7) $$G_{21}=G_{12}'=\begin{bmatrix}E(\partial^2 l_{h1}/\partial\theta_1\partial vec(\Pi)')\\ \vdots\\ E\left(\partial^2 l_{hJ-1}/\partial\theta_{J-1}\partial vec(\Pi)'\right)\end{bmatrix}=\begin{bmatrix}-\lambda_1'\otimes(E(\partial^2 l_{h1}/\partial\theta_1\partial\theta_1')S_2)\\ \vdots\\ -\lambda_{J-1}'\otimes\left(E\left(\partial^2 l_{hJ-1}/\partial\theta_{J-1}\partial\theta_{J-1}'\right)S_2\right)\end{bmatrix},$$

where $S_2'=\left[I_{K+N},0_{K+N,J+L+1+K_\sigma}\right]$, and $0_{m,n}$ denotes an $m\times n$ null matrix. Equation (A7) is an extension of Newey's (1987) equation A.15 from one to $J-1$ limited dependent variables. In fact, the variance estimator in (A4) is the system of equations version of the sandwich variance estimator for two-step maximum likelihood models (Hardin 2002). It is asymptotically equivalent to the Murphy-Topel (Murphy and Topel 1985) variance estimator when the assumed model distributions are correct. Compared with bootstrapping for standard errors, (A4) offers significant saving in computational time in large datasets because the demand model needs only be estimated once. The variance of $\widehat{\Phi}$ equals $\hat{G}^{-1}\widehat{\Psi}(\hat{G}^{-1})'/H$, where $\hat{G}$ and $\widehat{\Psi}$ are the sample estimates of G and Ψ, respectively.

When data are clustered, we need to account for the effect of clustering on the variance estimate. To calculate the cluster-robust sandwich variance, the sample estimates of Ψ_{11} and Ψ_{22} are constructed as

$$\widehat{\Psi}_{11} = \sum_{s=1}^{M}\left[\left(\sum_{h\in C_s}\left(\hat{V}_h \otimes X_h\right)'\right)\left(\sum_{h\in C_s}\left(\hat{V}_h \otimes X_h\right)\right)\right]/H, \text{ and}$$

$$\widehat{\Psi}_{22} = \sum_{s=1}^{M}\left[\left(\sum_{h\in C_s}\left(\partial l_{h1}/\partial\hat{\theta}_1', \dots, \partial l_{hJ-1}/\partial\hat{\theta}_{J-1}'\right)'\right)\left(\sum_{h\in C_s}\left(\partial l_{h1}/\partial\hat{\theta}_1', \dots, \partial l_{hJ-1}/\partial\hat{\theta}_{J-1}'\right)\right)\right]/H$$

where the subscript C_s denotes the sth cluster, M is the total number of clusters, and the expression for $\widehat{\Psi}_{11}$ follows from the structure of the sandwich cluster-robust variance for least squares (Cameron and Miller 2015, equation 11). The rank of $\widehat{\Psi}$, and by extension $\widehat{\Phi}$, is $\leq \min\{(K+N)\times(J+L)+(K+N+J+L+1+K_\sigma)\times(J-1), 2M-2\}$. To see this, note that the cluster-robust $\widehat{\Psi}$ can be rewritten as $\widehat{\Psi} = B'B/H$, where $B = diag\{B_{11}, B_{22}\}$,

$$B_{11} = \begin{bmatrix} \sum_{h\in C_1}\left(\hat{V}_h \otimes X_h\right) \\ \vdots \\ \sum_{h\in C_M}\left(\hat{V}_h \otimes X_h\right) \end{bmatrix}, \text{ and}$$

$$B_{22} = \begin{bmatrix} \sum_{h\in C_1}\left(\partial l_{h1}/\partial\hat{\theta}_1', \dots, \partial l_{hJ-1}/\partial\hat{\theta}_{J-1}'\right) \\ \vdots \\ \sum_{h\in C_M}\left(\partial l_{h1}/\partial\hat{\theta}_1', \dots, \partial l_{hJ-1}/\partial\hat{\theta}_{J-1}'\right) \end{bmatrix}.$$

There are two linear dependencies in B due to the optimization of least squares and maximum likelihood estimators: 1) $\sum_{s=1}^{M}\sum_{h\in C_s}\left(\hat{V}_h \otimes X_h\right) = \mathbf{0}$; and 2) $\sum_{s=1}^{M}\sum_{h\in C_s}\partial l_{hj}/\partial\hat{\theta}_j' = \mathbf{0}\ \forall j$. Hence, the rank of B is $\leq \min\{2M-2, (K+N)\times(J+L)+(K+N+J+L+1+K_\sigma)\times(J-1)\}$. Obviously, when the demand system is large relative to the number of clusters, $\widehat{\Phi}$ may not be full rank and not invertible. Because recovery of the structural parameters δ_i requires inversion of $\widehat{\Phi}$, the sandwich approach to building cluster-robust variance estimates does not work in large demand systems with too few clusters.

The Bootstrapped Variance

An alternative to the sandwich variance estimator is bootstrapping the variance of $\widehat{\Phi}$. In addition to the effect of clustering, we also account for the effect of the stratified sample on variance estimates. Our approach largely follows the bootstrap method reviewed in Rao, Wu and Yue (1992) and implemented in statistical packages such as Stata (StataCorp 2013, p. 189). Let N_B be the number of bootstrap replicates. In our FoodAPS application, we set $N_B = 4000$. Each replicate sample is produced by randomly sampling $n_t - 1$ primary sampling units (PSUs), i.e., clusters, with replacement from stratum t, where n_t is the number of PSUs in the tth stratum. All households within the selected PSU are included in the replicate sample. The adjusted sampling weight for household h from PSU s in stratum t is calculated to be $g_h m_s n_t/(n_t - 1)$, where g_h is the original sampling weight, m_s is the number of times PSU s is resampled. We normalize the adjusted sampling weight so that the sum of the normalized weights over all households in each replicate sample is equal to the sample size. The 4000 replicate samples are used to obtain 4000 replicate estimates of θ. The bootstrap variance estimate of Φ is

$$var(\widehat{\Phi}) = \frac{\sum_{r=1}^{N_B}(\hat{\theta}_{(r)} - \hat{\theta})(\hat{\theta}_{(r)} - \hat{\theta})'}{N_B}$$

where $\hat{\theta}_{(r)}$ and $\hat{\theta}$ are the estimates of θ based on the rth replicate sample and the full-sample, respectively.

Recovering the Structural Parameters

In the third step, the structural parameters δ_i from equation (A1) are recovered from estimates of the reduced-form parameters θ and Π using CMD estimation. Let $\varphi_i' = [\delta_i', \lambda_i', \sigma_{i0}, \zeta_i']$ for $i =$

$1, \ldots, J-1$, $\varphi' = [\varphi_1', \ldots, \varphi_{J-1}']$. The vector θ is related to φ by $\theta = h_1(\Pi)\varphi$, where $h_1(\Pi) = I_{J-1} \otimes \left(D(\Pi) \oplus I_{J+L+1+K_\sigma}\right)$. Extending equation (A.17) of Newey (1987) to $J-1$ limited dependent variables yields

(A8) $$\sqrt{T}\left(\hat{\theta} - h_1\left(\hat{\Pi}\right)\varphi\right) \overset{a}{\sim} N(0, \Omega_1)$$

where $\Omega_1 = \left[A, I_{m_1}\right](G^{-1}\Psi(G^{-1})')\left[A, I_{m_1}\right]'$, $m_1 = (J-1)(K+N+J+L+1+K_\sigma)$, and $A = \left[(-\beta_1' \otimes S_2)', \ldots, \left(-\beta_{J-1}' \otimes S_2\right)'\right]'$. The matrix A requires consistent estimates of β_i, which could be obtained by estimating equation (A1) with Y_{ht} replaced by its least squares prediction and with least squares residuals from equation (A2) used as additional regressors. The CMD estimator of φ is $\hat{\varphi} = (\hat{h}_1'\hat{\Omega}_1^{-1}\hat{h}_1)^{-1}\hat{h}_1'\hat{\Omega}_1^{-1}\hat{\theta}$, with asymptotic variance consistently estimated by $(\hat{h}_1'\hat{\Omega}_1^{-1}\hat{h}_1)^{-1}/H$.

In the fourth and final step, CMD estimation is applied again to impose the theoretical restrictions of symmetry $a_{ij} = a_{ji}$ and homogeneity $\sum_{j=1}^{J} a_{ij} = 0$ on the latent demand. Let $\varphi = h_2\gamma$, where γ is the column vector of theory-restricted parameters and h_2 is the selection matrix that maps the restricted parameters γ to the unrestricted parameters φ. The CMD estimator of γ is $\hat{\gamma} = \left(h_2'\hat{\Omega}_2^{-1}h_2\right)^{-1}h_2'\hat{\Omega}_2^{-1}\varphi$ with asymptotic variance $\left(h_2'\hat{\Omega}_2^{-1}h_2\right)^{-1}/H$, where $\hat{\Omega}_2 = \left(\hat{h}_1'\hat{\Omega}_1^{-1}\hat{h}_1\right)^{-1}$. The parameters of the budget share equation for the numéraire good are recovered using the adding-up restrictions on the latent demand: $\sum_{i=1}^{J} a_{ij} = \sum_{i=1}^{J} b_{ir} = 0$, $\sum_{i=1}^{J} g_{ik} = 1$ for $k = 1$, $\sum_{i=1}^{J} g_{ik} = 0$ for $k > 1$.

SAS Code

We provide x sets of SAS code for estimating a censored EASI demand system. Model 1 assumes price and total expenditure to be exogenous and calculates the sandwich variance estimates for $\hat{\Phi}$. Use `tobit_cl.sas` macro for cluster-robust variance. Model 4 instruments the endogenous prices and the deflated total expenditure and continues to take the sandwich variance estimation approach. Use `ivtobit_cl.sas` macro for cluster-robust variance. Model 8 maintains the assumption of price and total expenditure exogeneity in Model 1 but bootstraps the design-based variance estimates that account for clustering, stratification and sampling weights. Model 9 also bootstraps the design-based variance estimates but allows prices and the deflated total expenditure to be endogenous. Model 10 assumes price and total expenditure exogeneity and bootstraps the variance of $\widehat{\Phi}$ *without* accounting for clustering and stratification. It generates each replicate sample by randomly sampling H households with replacement. Model 11 produces the same type of variance estimates as Model 10 but instruments endogenous prices and the deflated total expenditure.

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Table A1. Average Marshallian price and expenditure elasticities over all households

Demand for food group	With respect to price of group					
	1	2	3	4	5	6
1. grains, 0 star	**-0.748**	0.122	0.111	0.160	0.237	-0.472
	(0.088)	(0.073)	(0.055)	(0.105)	(0.069)	(0.089)
2. grains, 1-3 star	0.059	**-1.240**	-0.303	0.182	0.034	0.168
	(0.040)	(0.066)	(0.035)	(0.067)	(0.035)	(0.056)
3. vegetables, 0 star	0.154	-0.734	**-1.916**	-0.389	-0.536	0.098
	(0.073)	(0.085)	(0.102)	(0.114)	(0.088)	(0.102)
4. vegetables, 1-3 star	0.071	0.166	-0.134	**-1.423**	0.174	0.174
	(0.048)	(0.057)	(0.040)	(0.131)	(0.051)	(0.077)
5. fruit, 0 star	0.271	0.071	-0.462	0.427	**-2.128**	0.045
	(0.082)	(0.078)	(0.079)	(0.130)	(0.164)	(0.124)
6. fruit, 1-3 star	-0.218	0.102	0.036	0.181	0.018	**-1.347**
	(0.043)	(0.051)	(0.037)	(0.081)	(0.051)	(0.106)
7. milk products, 0 star	0.039	-0.342	-0.028	0.500	0.091	-0.137
	(0.044)	(0.068)	(0.033)	(0.092)	(0.042)	(0.067)
8. milk products, 1-3 star	0.235	0.156	-0.382	-0.263	0.155	0.114
	(0.070)	(0.064)	(0.061)	(0.098)	(0.083)	(0.090)
9. meat and protein, 0 star	-0.066	0.189	-0.100	0.099	-0.012	0.059
	(0.036)	(0.038)	(0.028)	(0.065)	(0.034)	(0.049)
10. meat and protein, 1-3 star	-0.067	-0.097	0.046	-0.091	-0.154	-0.072
	(0.016)	(0.017)	(0.016)	(0.028)	(0.024)	(0.025)
11. prepared meals, 0 star	-0.138	-0.178	0.218	-0.559	0.048	-0.362
	(0.044)	(0.053)	(0.035)	(0.078)	(0.047)	(0.068)
12. prepared meals, 1-3 star	-0.122	-0.043	0.000	-0.071	0.079	0.025
	(0.047)	(0.059)	(0.039)	(0.090)	(0.056)	(0.073)
13. fats and oils, 0 star	0.205	0.293	-0.042	0.001	-0.001	0.097
	(0.063)	(0.071)	(0.048)	(0.121)	(0.068)	(0.095)
14. fats and oils, 1-3 star	-0.132	0.085	0.160	-0.333	-0.068	0.292
	(0.063)	(0.071)	(0.048)	(0.098)	(0.071)	(0.075)
15. beverages, 0 star	-0.057	0.079	-0.113	-0.135	-0.033	-0.200
	(0.022)	(0.023)	(0.021)	(0.032)	(0.030)	(0.032)
16. beverages, 1-3 star	-0.023	-0.168	-0.094	0.065	-0.157	0.153
	(0.032)	(0.030)	(0.025)	(0.050)	(0.041)	(0.044)
17. snacks, 0 star	0.012	-0.228	0.024	0.074	0.030	-0.412
	(0.036)	(0.054)	(0.032)	(0.072)	(0.039)	(0.067)

Table A1. Average Marshallian price and expenditure elasticities over all households (Continued)

	With respect to price of group					
Demand for food group	7	8	9	10	11	12
1. grains, 0 star	0.087	0.214	-0.280	-0.244	-0.371	-0.209
	(0.102)	(0.066)	(0.135)	(0.059)	(0.120)	(0.078)
2. grains, 1-3 star	-0.444	0.086	0.374	-0.187	-0.264	-0.046
	(0.085)	(0.032)	(0.076)	(0.034)	(0.077)	(0.052)
3. vegetables, 0 star	-0.115	-0.473	-0.499	0.201	0.770	0.004
	(0.101)	(0.075)	(0.134)	(0.076)	(0.124)	(0.086)
4. vegetables, 1-3 star	0.513	-0.103	0.195	-0.152	-0.677	-0.051
	(0.098)	(0.043)	(0.113)	(0.046)	(0.098)	(0.068)
5. fruit, 0 star	0.286	0.173	-0.003	-0.635	0.126	0.149
	(0.115)	(0.093)	(0.153)	(0.105)	(0.151)	(0.110)
6. fruit, 1-3 star	-0.187	0.054	0.098	-0.134	-0.466	0.015
	(0.073)	(0.040)	(0.088)	(0.043)	(0.087)	(0.058)
7. milk products, 0 star	**-1.225**	-0.058	-0.303	-0.125	-0.029	0.004
	(0.146)	(0.036)	(0.107)	(0.034)	(0.102)	(0.063)
8. milk products, 1-3 star	-0.160	**-1.669**	0.370	-0.007	-0.517	0.280
	(0.089)	(0.089)	(0.119)	(0.065)	(0.112)	(0.084)
9. meat and protein, 0 star	-0.193	0.103	**-0.978**	-0.147	-0.619	-0.113
	(0.066)	(0.029)	(0.107)	(0.033)	(0.072)	(0.044)
10. meat and protein, 1-3 star	-0.082	-0.002	-0.159	**-1.980**	-0.257	-0.109
	(0.021)	(0.017)	(0.034)	(0.061)	(0.032)	(0.024)
11. prepared meals, 0 star	-0.023	-0.169	-0.854	-0.351	**-1.142**	-0.004
	(0.087)	(0.039)	(0.101)	(0.044)	(0.118)	(0.061)
12. prepared meals, 1-3 star	-0.012	0.159	-0.247	-0.241	-0.007	**-1.848**
	(0.088)	(0.047)	(0.099)	(0.054)	(0.099)	(0.107)
13. fats and oils, 0 star	-0.140	-0.089	-1.172	-0.171	-0.046	-0.413
	(0.122)	(0.049)	(0.152)	(0.047)	(0.112)	(0.079)
14. fats and oils, 1-3 star	-0.002	-0.027	-0.099	-0.143	-0.006	-0.018
	(0.089)	(0.056)	(0.112)	(0.070)	(0.112)	(0.084)
15. beverages, 0 star	0.069	-0.065	-0.024	-0.060	-0.163	-0.087
	(0.029)	(0.024)	(0.044)	(0.037)	(0.041)	(0.030)
16. beverages, 1-3 star	-0.104	0.043	-0.237	-0.267	0.230	-0.070
	(0.042)	(0.032)	(0.060)	(0.037)	(0.056)	(0.039)
17. snacks, 0 star	-0.849	0.046	-0.175	0.080	0.272	0.026
	(0.095)	(0.032)	(0.091)	(0.031)	(0.080)	(0.053)

Table A1. Average Marshallian price and expenditure elasticities over all households (Continued)

Demand for food group	With respect to price of group					
	13	14	15	16	17	18
1. grains, 0 star	0.268	-0.123	-0.180	-0.081	0.026	0.131
	(0.087)	(0.059)	(0.068)	(0.097)	(0.127)	(0.092)
2. grains, 1-3 star	0.222	0.037	0.128	-0.249	-0.410	-0.061
	(0.054)	(0.036)	(0.038)	(0.051)	(0.101)	(0.056)
3. vegetables, 0 star	-0.096	0.202	-0.468	-0.368	0.131	0.211
	(0.090)	(0.061)	(0.084)	(0.102)	(0.144)	(0.094)
4. vegetables, 1-3 star	-0.009	-0.142	-0.181	0.091	0.120	0.283
	(0.079)	(0.043)	(0.046)	(0.073)	(0.115)	(0.077)
5. fruit, 0 star	0.039	-0.076	-0.129	-0.603	0.102	0.153
	(0.111)	(0.080)	(0.112)	(0.159)	(0.162)	(0.111)
6. fruit, 1-3 star	0.059	0.133	-0.295	0.220	-0.760	0.398
	(0.064)	(0.035)	(0.048)	(0.068)	(0.112)	(0.063)
7. milk products, 0 star	-0.100	-0.010	0.093	-0.121	-1.280	0.136
	(0.074)	(0.037)	(0.040)	(0.057)	(0.142)	(0.065)
8. milk products, 1-3 star	-0.136	-0.026	-0.204	0.118	0.142	-0.302
	(0.075)	(0.057)	(0.080)	(0.109)	(0.119)	(0.084)
9. meat and protein, 0 star	-0.440	-0.019	-0.023	-0.203	-0.166	-0.094
	(0.055)	(0.029)	(0.036)	(0.051)	(0.085)	(0.047)
10. meat and protein, 1-3 star	-0.068	-0.036	-0.048	-0.223	0.079	-0.030
	(0.018)	(0.018)	(0.031)	(0.032)	(0.030)	(0.023)
11. prepared meals, 0 star	-0.017	0.004	-0.185	0.266	0.350	0.048
	(0.059)	(0.039)	(0.048)	(0.067)	(0.104)	(0.061)
12. prepared meals, 1-3 star	-0.362	-0.005	-0.162	-0.129	0.053	-0.006
	(0.067)	(0.048)	(0.055)	(0.075)	(0.112)	(0.067)
13. fats and oils, 0 star	**-1.700**	-0.094	-0.050	-0.176	0.190	-0.495
	(0.138)	(0.050)	(0.052)	(0.080)	(0.169)	(0.093)
14. fats and oils, 1-3 star	-0.142	**-1.738**	0.287	-0.110	0.396	-0.453
	(0.075)	(0.086)	(0.072)	(0.097)	(0.119)	(0.081)
15. beverages, 0 star	-0.025	0.087	**-1.902**	-0.085	-0.097	0.248
	(0.024)	(0.022)	(0.066)	(0.043)	(0.041)	(0.029)
16. beverages, 1-3 star	-0.085	-0.034	-0.100	**-1.733**	-0.243	-0.241
	(0.035)	(0.030)	(0.042)	(0.088)	(0.052)	(0.043)
17. snacks, 0 star	0.082	0.109	-0.079	-0.205	**-0.544**	-0.070
	(0.068)	(0.033)	(0.036)	(0.046)	(0.151)	(0.054)

Table A1. Average Marshallian price and expenditure elasticities over all households (Continued)

Demand for food group	With respect to price of group 19	20	21	Expenditure elasticity
1. grains, 0 star	-0.712	-0.138	0.912	1.229
	(0.189)	(0.115)	(0.317)	(0.158)
2. grains, 1-3 star	-0.808	0.194	1.609	0.929
	(0.116)	(0.071)	(0.187)	(0.081)
3. vegetables, 0 star	-0.427	0.482	2.114	1.506
	(0.210)	(0.127)	(0.335)	(0.171)
4. vegetables, 1-3 star	0.254	-0.507	0.157	1.113
	(0.148)	(0.092)	(0.218)	(0.114)
5. fruit, 0 star	-0.657	0.701	0.592	1.252
	(0.264)	(0.165)	(0.551)	(0.311)
6. fruit, 1-3 star	-0.950	-0.355	2.006	1.278
	(0.153)	(0.081)	(0.264)	(0.121)
7. milk products, 0 star	0.588	-0.095	1.707	0.720
	(0.144)	(0.076)	(0.212)	(0.110)
8. milk products, 1-3 star	-0.426	-0.312	1.354	1.338
	(0.205)	(0.110)	(0.306)	(0.170)
9. meat and protein, 0 star	-0.178	0.304	1.659	0.918
	(0.102)	(0.063)	(0.204)	(0.084)
10. meat and protein, 1-3 star	0.191	0.224	1.856	1.039
	(0.072)	(0.037)	(0.187)	(0.070)
11. prepared meals, 0 star	-0.077	0.251	1.527	1.208
	(0.132)	(0.080)	(0.242)	(0.115)
12. prepared meals, 1-3 star	-0.314	-0.372	2.404	1.139
	(0.168)	(0.084)	(0.286)	(0.122)
13. fats and oils, 0 star	0.475	0.466	1.674	1.091
	(0.185)	(0.111)	(0.310)	(0.150)
14. fats and oils, 1-3 star	0.221	-0.451	0.580	1.471
	(0.189)	(0.114)	(0.320)	(0.156)
15. beverages, 0 star	0.183	-0.108	1.346	1.067
	(0.085)	(0.042)	(0.208)	(0.080)
16. beverages, 1-3 star	0.010	0.254	1.573	1.172
	(0.099)	(0.051)	(0.189)	(0.086)
17. snacks, 0 star	0.029	-0.317	1.092	0.993
	(0.111)	(0.074)	(0.181)	(0.089)

Table A1. Average Marshallian price and expenditure elasticities over all households (Continued)

Demand for food group	With respect to price of group					
	1	2	3	4	5	6
18. snacks, 1-3 star	0.104	-0.079	0.107	0.443	0.087	0.590
	(0.064)	(0.071)	(0.049)	(0.113)	(0.064)	(0.091)
19. FAFH, 0 star	-0.077	-0.158	-0.030	0.077	-0.058	-0.201
	(0.019)	(0.022)	(0.016)	(0.032)	(0.022)	(0.031)
20. FAFH, 1-3 star	-0.038	0.088	0.101	-0.309	0.166	-0.208
	(0.031)	(0.035)	(0.026)	(0.053)	(0.038)	(0.045)
21. numeraire	0.013	0.036	0.024	0.008	0.011	0.059
	(0.003)	(0.004)	(0.003)	(0.005)	(0.004)	(0.006)

Table A1. Average Marshallian price and expenditure elasticities over all households (Continued)

Demand for food group	With respect to price of group					
	7	8	9	10	11	12
18. snacks, 1-3 star	0.215	-0.189	-0.235	-0.075	0.089	-0.008
	(0.103)	(0.053)	(0.119)	(0.056)	(0.112)	(0.076)
19. FAFH, 0 star	0.136	-0.037	-0.069	0.084	-0.005	-0.047
	(0.032)	(0.019)	(0.038)	(0.026)	(0.035)	(0.028)
20. FAFH, 1-3 star	-0.083	-0.083	0.300	0.213	0.187	-0.167
	(0.047)	(0.028)	(0.062)	(0.036)	(0.057)	(0.038)
21. numeraire	0.045	0.019	0.074	0.086	0.059	0.051
	(0.004)	(0.003)	(0.007)	(0.008)	(0.006)	(0.005)

Table A1. Average Marshallian price and expenditure elasticities over all households (Continued)

Demand for food group	With respect to price of group					
	13	14	15	16	17	18
18. snacks, 1-3 star	-0.472	-0.297	0.510	-0.495	-0.163	**-2.312**
	(0.088)	(0.053)	(0.062)	(0.092)	(0.130)	(0.137)
19. FAFH, 0 star	0.070	0.029	0.071	-0.004	0.016	-0.090
	(0.026)	(0.018)	(0.026)	(0.031)	(0.040)	(0.025)
20. FAFH, 1-3 star	0.176	-0.114	-0.092	0.212	-0.303	0.209
	(0.041)	(0.029)	(0.035)	(0.043)	(0.068)	(0.041)
21. numeraire	0.032	0.013	0.054	0.065	0.049	0.023
	(0.004)	(0.003)	(0.006)	(0.007)	(0.007)	(0.004)

Table A1. Average Marshallian price and expenditure elasticities over all households (Continued)

Demand for food group	With respect to price of group 19	20	21	Expenditure elasticity
18. snacks, 1-3 star	-0.606	0.530	1.233	0.978
	(0.170)	(0.107)	(0.258)	(0.139)
19. FAFH, 0 star	**-0.777**	-0.161	0.351	0.905
	(0.076)	(0.038)	(0.112)	(0.051)
20. FAFH, 1-3 star	-0.459	**-0.880**	-0.184	1.198
	(0.101)	(0.078)	(0.151)	(0.073)
21. numeraire	0.038	0.001	**-1.725**	0.975
	(0.013)	(0.006)	(0.051)	(0.015)

Notes: Standard errors in parentheses. Bold face numbers are own-price elasticities.