Regressive Effects

Causes and Consequences of Selective Consumption Taxation

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Abstract

This study provides a systematic analysis of selective consumption tax policy. We detail both the motivations behind selective consumption taxes and the policy's shortcomings. Empirically, we explore how consumption of 12 goods—alcohol, cigarettes, fast food, items sold at vending machines, purchases of food away from home, cookies, cakes, chips, candy, donuts, bacon, and carbonated soft drinks—varies across the income distribution by calculating the goods' income-expenditure elasticities. Income has the greatest effect on expenditures for alcohol. A 1 percentage point increase in income (approximately $428 at the mean) translates into a 0.314 percentage point increase in spending on alcoholic beverages (approximately $1 annually at the mean). Income has the smallest influence on tobacco expenditures (0.007) and donut expenditures (−0.009). We conclude from this evidence that any tax on such goods is regressive.

JEL codes: D12, H24, I18

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1. Introduction

On the surface, public policy is intended to improve people's lives. This being the case, a benevolent policy analyst will want to find opportunities to achieve social welfare improvement with few (or no) offsetting negative effects. Recently, behavioral economics research, animated by the impulse to mitigate the social costs of poor or unhealthy consumption choices, has drawn attention to expanding the set of policy tools for modifying consumer behavior, such as by reconfiguring the "choice architecture" or changing consumers' default options (Thaler and Sunstein 2008). Nevertheless, imposing selective excise (per unit) or sales (ad valorem) taxes on targeted goods remains the most popular policy tool for reaching social welfare goals at all levels of government.

Behavioral economics emerged not long after activists began to raise concerns about the adverse health consequences of certain behaviors not included in the list of "sinful" behaviors traditionally regulated by government—smoking, drinking, gambling, and prostitution.[1] Among these behaviors is the consumption of junk food, defined as calorie-dense, prepared food items containing large amounts of fat, sugar, or salt, among other less healthy ingredients. Given medical evidence that consuming junk food contributes to obesity, heart disease, and type 2

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[1] Taxes on alcohol nowadays are low enough that many people have not stopped drinking, whereas increasingly cities and states set tobacco taxes at levels high enough to stop smoking altogether. In reality, however, these high taxes have led to cross-border shopping and the emergence of robust black markets in cigarettes (Hoffer, Shughart, and Thomas 2014). Hoffer, Shughart, and Thomas (2014) describe the tradeoff between tax revenues and modern prohibitionist impulses, which, of course, work at cross-purposes. See Shughart (1997) for an analysis of traditional "sin taxes."

diabetes, and given policymakers' stated desire to reduce the consumption of less healthy foods, behavioral economists have proposed policies aimed at informing consumers about the connections between poor diets and negative health outcomes or changing the choice architecture by placing healthier substitutes in more visible locations. In the context of behavioral economic theory, such "nudges" are forms of soft paternalism.[2] Although providing nutritional information and rearranging the architecture of choice may influence consumers' purchasing decisions, such policies do not generate additional revenue for the public sector. A policy of hard paternalism, by contrast, involves selectively imposing taxes on goods that have fallen into disfavor, thereby explicitly changing the relative prices of so-called good and bad food options.[3] Extending the selective tax policy on cigarettes, alcohol, and gambling to foods that are high in empty calories, salt, sugar, and fat obviously expands the number of items subject to this public policy of hard paternalism.

A growing list of academic studies recommends imposing new (or higher) excise taxes on unhealthy foods (Battle and Brownell 1997; Brownell et al. 2009; Chriqui et al. 2008; Duffey et al. 2010; Jacobson and Brownell 2000; Malik et al. 2010). At the same time, other scholars conclude that the social welfare benefits of selectively taxing disfavored goods are very small (Kuchler, Tegene, and Harris 2005; Fletcher, Frisvold, and Tefft 2010a, 2010b). Such contributors to the literature clearly do not favor selective consumption taxes as a first-best policy option (Fletcher, Frisvold, and Tefft 2014; Hoffer, Shughart, and Thomas 2014).

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[2] To illustrate, Sacks et al. (2011) suggest that three "trigger warning" labels—red, yellow, and green, like traffic lights—be affixed to product packages, in-store displays, and advertising materials. The colors correspond to high, moderate, and low levels of implicated food ingredients, as categorized by the US Food and Drug Administration. Another behaviorist option would be to place racks displaying snack food at the back of the store rather than at or near the checkout lines.

[3] The focus of this paper is on the growing number of items included in that category, and the justification for defining some goods as disfavored is secondary.

More work is needed to compare the studies that claim large benefits from selective consumption taxes with those that underscore the costs and unintended consequences of such policies. An important question we explore in this paper is whether the predicted reduction in the consumption of politically disfavored goods that is caused by selectively higher taxes can be counted as a dollar-for-dollar benefit to the individual consumer and society as a whole.[4] We argue that, to the extent that consumption of disfavored goods continues after a selective tax is imposed or increased (as it will do, even as tax-ridden prices rise), the projected benefits of improved health cannot be fully realized. The main effect of taxing some purchases at differentially higher rates is that some consumers' discretionary budgets shrink. As a result of tax-imposed cuts in their discretionary budgets, households must reduce their expenditures on all budgeted consumption items, whether taxed or untaxed. That reduction in household expenditures is spread over all income-normal goods, including luxuries, which may include healthier foods.[5] One downside is that selective excise or sales taxes are regressive—as are all consumption taxes—meaning that the tax burden falls more heavily on low-income households.

To quantify the regressive effects of selective taxation, we calculated income-expenditure elasticities for 12 goods—alcohol, cigarettes, fast food, items sold at vending machines, purchases of food away from home, cookies, cakes, chips, candy, donuts, bacon, and carbonated soft drinks—using household demographic and expenditure data from the Consumer Expenditure Surveys conducted by the Bureau of Labor Statistics from 2009 through 2012. Our results reveal

[4] As we discuss later in this paper, the benefit is limited in that behavior does not change very much and expenditures are not tied to the revenue raised.
[5] A good that is income normal is one for which demand rises when income rises, all other things, including relative prices, remaining constant. *Luxuries* are defined as goods for which increases in income, *ceteris paribus*, trigger more than proportional increases in consumer purchases.

little evidence of correlation between household incomes and expenditures on tax-disfavored goods. When we combine those results with other measures of (own-) price and income elasticities reported in the existing academic literature, we conclude that selective consumption taxes are likely to be regressive, mainly because purchases of disfavored goods constitute larger shares of the budgets of low-income households than of high-income households.

We begin our investigation in the next section by reviewing the literature on consumption taxes that target socially and politically disfavored goods. We present our model in section 3 and report our empirical results in section 4. We conclude our investigation by suggesting alternatives to selective taxes (e.g., information provision, expansion of access to healthier foods, and improved handling of issues related to habit formation and supply-chain management) that address more directly the substitution between snack foods and other, perhaps healthier, consumption alternatives.

2. To Tax or Not to Tax? Some Background

On the surface, taxes on less healthy food items are extraordinarily attractive policy tools. As the after-tax price of the less healthy good rises, consumers will reduce their purchases of that good and allocate more of their budgets to other (untaxed) goods that have relatively lower prices and are considered reasonably good substitutes for the taxed item. From a social engineering perspective, the response is even better if consumers substitute healthier alternatives for the taxed good. Hence, by imposing the appropriate tax rate on those less healthy alternatives, in principle society can shift consumption patterns in ways that improve public health outcomes and also raise additional revenues. Those revenues could even pay for existing or expanded public health care services for individuals suffering the ill effects of bad diets.[6] But those ideal outcomes rarely materialize in an imperfect world. In the following section, we review the academic literature that identifies both the benefits and the costs of selective consumption tax policies to provide background and identify how our empirical contribution on regressive effects fits within this literature.

Arguments for Selective Consumption Taxes

The primary argument favoring selective taxes relies on the substitution effect in the theory of consumer demand. Selective taxes predictably increase the market prices of the targeted goods. Other things being the same, the quantities of the taxed goods consumers buy will fall and the quantities of untaxed or less taxed goods they buy will rise. The important question addressed more fully in this paper is, how big will these changes be? In any case, because the consumption of goods such as sugar-sweetened beverages, fast food, vending machine items, pizza, and cigarettes, among others, has been tied to negative health outcomes (e.g., weight gain, obesity, type 2 diabetes, and lung diseases, including cancer), any reduction in consumption is considered socially beneficial. Policies that deliver on that goal, such as selective consumption taxes, are aimed at promoting healthier lifestyle choices.

Brownell et al. (2009) estimate the effects of a tax of one cent per ounce on sugar-sweetened beverages. They calculate a reduction of about 20 kilocalories[7] per day for drinkers of sugar-sweetened beverages after the tax is imposed. In addition to the benefits of these behavioral changes, proponents of the selective taxation of disfavored goods consider the

[6] The growing role of government in the US health care system may be a major motivator of these tax proposals. With more taxpayer financing of health insurance and health care, unhealthy lifestyle choices arguably impose a burden on the public health care budget. Tax revenue earmarking is discussed in more detail in a later section.
[7] The term *Calories* is often used in place of kilocalories, for example, in Food and Drug Administration–approved nutrition labels.

resulting tax revenues to be a significant policy benefit. The estimated increases in revenue from imposing a new consumption tax or raising an existing one tend to be very large. Brownell et al. (2009) project that a federal excise tax of one cent per ounce on sugar-sweetened beverages would generate approximately $14.9 billion in new revenues every year.[8]

Arguments against Selective Consumption Taxes

Selective sales and excise taxes have been criticized on a number of grounds. We condense the critiques into three broad categories: (a) selective taxes do very little to curb consumption or improve health outcomes by, for example, reducing obesity rates; (b) granting government the power to selectively tax products reduces the welfare of consumers and producers; and (c) the burden of selective consumption taxes is not trivial and falls most heavily on low-income households (that is, such taxes are regressive, thereby violating two normative principles of public finance known as horizontal and vertical tax equity).[9]

Why do selective taxes do little to reduce consumption of the targeted goods? Basic economics, of course, predicts that purchases of any good will fall if the price of that good increases for any reason, including the imposition of a new tax or increase of an existing one. The magnitude of the effect for any tax policy, however, depends on whether consumers can switch from the taxed good to an alternative consumption good. The degree to which this substitution occurs is reflected in the price elasticity of demand. The more responsive the good is to changes in its own price, other things being the same, the more elastic the demand for it; the

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[8] Note that the revenue raised by any tax is a transfer of income from the private to the public sector; that transfer is hardly seen as a "benefit" by the payers of the tax.

[9] *Horizontal tax equity* refers to the idea that households in the same income bracket should bear the same tax burden. *Vertical tax equity* refers to the idea that taxes should rise as incomes rise. Selective consumption taxes violate the first principle because tax burdens vary not by income but by consumption choices; they violate the second principle because tax burdens fall as income increases.

less responsive the good is, the more inelastic the demand. Disfavored goods generally are goods for which demand is price inelastic.[10]

Summaries of the relevant literature, including meta-analyses of multiple empirical studies, report elasticity estimates for many of the goods targeted by selective sales or excise taxes. Gallet (2007), for example, finds the median own-price elasticity for alcohol to be –0.497. Gallet and List (2003) report a median price elasticity estimate for cigarettes of –0.40. According to Andreyeva, Long, and Brownell (2010), the median price elasticity estimates are –0.81 for food eaten away from home, –0.79 for soft drinks, and –0.34 for sweets and sugars.[11] In the case of an elasticity of –0.34 for sweets, for example, we would expect a tax that increases consumer prices by 10 percent to reduce consumption of sweets by approximately 3.4 percent.

Consumption, thus, is very persistent for all those targeted goods. The quantities demanded decline, as theory predicts, but not by much, thus explaining why a tax-ridden price increase has a less than proportional effect on purchases and, hence, on the adverse health outcomes associated with consumption. Thus, the goal of behavioral modification through taxation is muted.

In contrast, price-inelastic demand means that selectively imposing a new tax on such a good or increasing an existing one will generate more tax revenue. The increase in tax revenue may explain why consumption taxes are popular both among the politicians who support them (more revenue will be available for spending) and among consumers who do not buy the taxed goods and thus will not see their own tax bills rise.

[10] Holding all else equal, the elasticity of demand for a good is computed as the percentage change in quantity demanded divided by the percentage change in the good's own price that prompted a change in the quantity demanded (in the direction opposite the change in price). Demand is said to be inelastic whenever the percentage change in quantity demanded is smaller than the corresponding percentage change in price, meaning that the price elasticity coefficient is less than one in absolute value.

[11] These estimates are all less than one in absolute value. The closer an elasticity estimate is to one, the closer it is to the statement that a 1 percent increase in price leads to a 1 percent reduction in purchases of the item in question.

The consumption of tax-disfavored goods persists in part because the search for alternative goods to replace the taxed ones can be costly.[12] The pro-tax argument rests on the conjecture that consumers who are faced with a higher tax (and a higher purchase price) will substitute healthier foods for snack foods (e.g., switch from potato chips to apple slices). That reaction, of course, requires those healthier substitutes to be known and readily available to the consumers affected by the tax. If, for any reason, the healthier substitute good is priced much higher or is considered a poor substitute for the taxed good, consumers are unlikely to change their marketplace behavior enough to produce a noticeable effect on health outcomes.[13]

Furthermore, not all tax-driven substitutions will create the intended health benefits. Dharmasena and Capps (2012, 672 fn. 2) suggest that low to moderate tax rates do not change behavior in the way that Brownell et al. (2009) describe. In response to a selective tax on carbonated soft drinks, for instance, consumers may well switch to fruit juices that contain similarly high levels of sugar. Hence, the predicted reductions in body weight from such a tax will be smaller than Brownell et al. lead us to expect.[14] Dharmasena and Capps's results suggest that taxing a particular class of beverages becomes complex, and policymakers must therefore consider the demand interactions between the various beverages households consume.

For selective consumption taxes to promote reductions in body weight, not only must consumers substitute away from the taxed items, but the substitutes those consumers choose must also contain significantly fewer calories. A number of empirical studies of substitution

[12] Indeed, the elasticity of demand for any good depends critically on the number of available substitutes for that good. Goods for which many options are available tend to have more elastic demand than do goods with few substitutes. The demand for insulin is considerably less elastic than the demand for gasoline sold at the corner service station, for example, if other stations are located nearby.

[13] We expect that one of the reasons the demand curves for soda, candy, potato chips, and fast food are price inelastic is that consumers do not know of or cannot find many good substitutes for them.

[14] Dharmasena and Capps (2012) estimate that a soda tax of one cent per ounce would lead to a reduction in average body weight over one year of between 1.54 and 2.55 pounds, as opposed to Brownell et al.'s (2009) estimate of 2.10 to 3.21 pounds.

suggest that when consumers stop buying tax-disfavored goods, they simply replace the calories given up with an alternative form.

Fletcher, Frisvold, and Tefft (2010a) find that although increases in soft drink tax rates reduce soda consumption among children, those reductions do not influence total caloric intake because children increase their consumption of other high-calorie beverages, such as chocolate milk. Fletcher, Frisvold, and Tefft (2010b) report similar results for adults. Fletcher, Frisvold, and Tefft (2014) conclude that evidence from the academic literature clearly indicates that small taxes on soft drinks do not have detectible effects on consumers' weight.[15] Fletcher, Frisvold, and Tefft (2014, 13) then explore the effects of large taxes on soft drinks and again find tax proponents' arguments to be lacking:

> Together, our results cast serious doubt on the assumptions that proponents of large soda taxes make on its likely impacts on population weight. Together with evidence of important substitution patterns in response to soda taxes that offset any caloric reductions in soda consumption (Fletcher et al., 2010a), our results suggest that fundamental changes to policy proposals relying on large soda taxes to be a key component in reducing population weight are required.

Kuchler, Tegene, and Harris (2005) explore the effects of price increases on a slightly broader category of tax-disfavored goods and report similar findings. Allowing for an extremely conservative assumption of zero food substitution, they estimate that a 20 percent tax on potato chips would result in a reduction of 830 calories per person per year, which translates into the loss of slightly less than one-fourth of one pound of body weight.

Schroeter, Lusk, and Tyner (2008) model the effects of income changes and selective consumption taxes on weight gain. They conclude that, despite a seemingly logical application of the relationship between household income, taxes, consumption, and weight—fast food

[15] Fletcher, Frisvold, and Tefft (2014) define *large taxes* as taxes measured by changes in the top or bottom quartile of the distribution of tax changes and *small taxes* as taxes measured by changes in the second or third quartile of the distribution of tax changes.

consumption rises with income, fast food is more calorie dense and higher in fat than food consumed at home, and taxes on fast food reduce fast food consumption as well as body weight—taxing food eaten away from home could actually increase weight. The authors find that a 10 percent tax on food away from home would increase body weight by approximately 0.196 percent. Their finding results from the fact that consumers substitute food away from home with food consumed at home (especially dairy foods). The combination of substituted calories and added food preparation time more than offsets the reduction in calories consumed away from home.[16]

The structures of many American cities also deter the substitution of healthy foods for less healthy foods. Many people simply lack functional access to healthier diet alternatives. According to the Economic Research Service of the US Department of Agriculture, about 2.3 million families (or 2.2 percent of all US households) live more than one mile away from a supermarket and do not own a car (ERS 2009). Areas that lack access to a full range of food choices have been called *food deserts* (Walker, Keane, and Burke 2010).[17] Food deserts are associated with lower-income neighborhoods. In many urban areas, especially those that lack good public transportation options, a trip to a supermarket can be difficult and can significantly increase the final (full) cost of alternative consumption choices.

Studies have found that wealthy areas—that is, *food oases*—have, on average, three times as many supermarkets as poorer areas. Moreover, grocery stores in African American communities are usually smaller and have fewer aisles and food departments (Morland et al.

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[16] Yaniv, Rosin, and Tobol (2009) discuss how restricting choices changes the way in which individuals use their scarce time budgets. Time spent cooking substitutes for time spent doing other things, such as exercising. Hence, the net effect of a tax on food eaten away from home may not be positive if it prompts consumers both to eat less fast food and to spend less time at the gym.

[17] *Food desert* is defined in various studies by distance to a grocery store, density of grocery store options in a zip code, or travel time necessary to get to and from a grocery store.

2002). Given this vast difference in access to healthy food, it is important for policymakers to think about the impact that increasing food taxes will have on those who have fewer choices and are therefore less able to substitute in favor of healthier alternatives.

Shortcomings of the Social Engineering Approach to Selective Tax Policy

In addition to the failure to fully evaluate the behavioral consequences of selective consumption taxes, major shortcomings exist in governmental attempts to promote healthier lifestyles through social engineering. The policy limits fall into seven categories.

First, government intervention cannot be justified on traditional grounds of economic efficiency. Hoffer, Shughart, and Thomas (2013, 2014) and Browning (1999) point out that the health care budget externalities supposedly associated with poor diets are not externalities in the traditional Pigouvian "market failure" sense. Although moral hazard can intensify in situations where individuals do not bear the full costs of their own choices, such as consumption decisions that impair health (Pauly 1968), evidence is weak for the theory that people become obese because taxpayers will pay for some of the consequences of gaining too much weight (Kelly and Markowitz 2009).

Second, tax revenues cannot be counted fully as a policy benefit. Tax receipts are transfers to the public sector; those transfers reduce producer and consumer surplus both directly and indirectly. All taxes other than taxes levied as lump sums (e.g., poll or head taxes) create excess burdens (deadweight welfare losses), such that the public sector's revenue gains are more than offset by the private sector's losses. Moreover, although the proponents of selective consumption taxes may claim that the revenue will be used to pay for existing or new health care spending, the political reality is that the link between revenue and spending is indirect, if it exists at all, even if the taxes are earmarked for specific line items in the public budget.[18]

Chriqui et al. (2008) and Jacobson and Brownell (2000) note that none of the nearly $1 billion in revenues generated annually by state taxes on soft drinks, snack foods, candy, and other less healthy food items actually has been spent on health care programs or healthier food subsidies. Hoffer, Shughart, and Thomas (2014) add that the time lag between tax receipts and expenditures on health outcomes related to food consumption supports the belief that current budget shortfalls, not the expectation of higher future public health care costs, are the real motivator behind proposals to selectively tax the ingredients in less healthy food choices. Health care costs compete alongside any other budget expenditure unless specific earmarks are put in place. Even when tax earmarks are in place, tax revenues may be diverted, as happened with the Highway Trust Fund and motor fuel taxes (Wagner 1991).[19] It is therefore unlikely that revenues from new selective consumption taxes would be used to combat obesity.

Third, policymakers possess imperfect knowledge of individual preferences and the ways that individuals adjust to changes in relative prices (Hayek 1945; Rizzo 2009). The absence of perfect information leads to imperfect public policies. Selective taxation also is a blunt policy instrument: it penalizes both moderate and immoderate consumers of the taxed item (Wagner 1997).

[18] Hoffer, Shughart, and Thomas (2014) note that disfavored taxes have risen precisely at the time of historical increases in federal and state budget deficits. Hoffer and Pellillo (2012) report that less than 5 percent of the $206 billion in additional state revenues from the tobacco industry's Master Settlement Agreement with US state governments actually was spent on antismoking programs. Even if taxes are earmarked for particular spending categories, the revenue side of the public budget is largely fungible; thus, very little of the revenue sticks to its intended target (Crowley and Hoffer 2012).

[19] This conclusion follows from the equimarginal principle of economic theory. Just as consumers maximize total utility by selecting a mix of goods and services such that the marginal utility per dollar spent is the same across all elements of the consumption bundle, politicians maximize political support by allocating the public budget across all programs such that the marginal vote-buying benefit per dollar spent is the same. At least some of the revenue windfall from a new tax, therefore, will be allocated to other spending programs for which the marginal political benefit is higher than the one for which taxes are dedicated.

Fourth, any tax policy necessarily imposes a single vision of the desired policy outcome on everyone, disproportionately affecting those who have alternative views of what is desirable and those who simply have different budget priorities. This result is known as the social choice problem (Arrow 1951). Consumers of disfavored goods currently are revealing their preferences for consuming those goods, and they are unlikely to change their minds simply because politicians extract taxes from them. By definition, any tax levied on—or forced substitution away from—individuals' chosen "ideal points" reduces consumer welfare, at least in the short run.[20] Unless taxes change underlying preferences, they will not work. This problem is found in all but a very long-run analysis.

Fifth, Hoffer, Shughart, and Thomas (2014) summarize the public choice dilemma surrounding selective tax policies. Selective taxation elicits rent-seeking by individuals, and some groups win in their aim of shifting tax burdens to others. Which particular food items will be defined as junk and subjected to selective taxes and which will be excluded from the junk food tax base? Will the fructose in orange juice be a favored sugar while the cane sugar or high-fructose corn syrup in carbonated soft drinks is disfavored? These definitions matter when labeling mandated by the Food and Drug Administration steers consumers to foods that are less healthy alternatives to what they would otherwise be eating, such as products with excessive trans fats (Remig et al. 2010). Minger (2014) describes how the US Department of Agriculture's Food Pyramid, which was used for nearly two decades to teach nutrition in almost all US public schools, was by and large constructed by special interest groups.

[20] In addition to differences in consumers' tastes and preferences, tax-disfavored foods tend to contain preservatives, which help extend their shelf life, thus reducing sellers' inventory costs and increasing convenience for consumers (Monteiro 2009).

When firms find it easier to influence politicians and policy outcomes than to influence the market process, lobbying and campaign contributions (influence peddling) predictably become more salient than does remaining alert to consumers' tastes and preferences (Peltzman 1976).[21] Rinaldi (2010, 368) identifies the slippery slope of selective taxation:

> Many behavioral choices involve costs borne by society. All high-caloric foods can be tied to obesity. If soda is taxed, should this tax also be applied to all "fast food," confections, or portion size? Why limit it to food? Should we not tax all behaviors linked to health care expenditures? Why not deter gun and motorcycle ownership or sedentary lifestyle[s] through taxation? How parental should government be?

Sixth, the unintended consequences of a policy can negate its intended effects (Dharmasena and Capps 2012). Because no single market choice is fully disconnected from other choices, distortions in one market that are caused, for example, by imposing a tax on that market, spill over to many other markets, including markets in which substitutes for and complements to the taxed items are bought and sold. Moreover, because of the income effect of a tax-induced change in relative prices, the policy may affect every other item in consumers' budgets (Lipsey and Lancaster 1956).

The last reason to question policy effects, and the focus of the rest of the paper, is the fact that selective consumption taxes are regressive. As discussed earlier, the demand for many disfavored goods is price-inelastic. Hence, other things being the same, an after-tax price increase of, for example, 10 percent leads to a less (in many cases, substantially less) than 10 percent reduction in purchases of that good. Given that the consumption of snack food and other disfavored items is quite unresponsive to changes in price, many consumers of those goods will continue to buy them (in modestly smaller quantities) rather than switch to substitutes. Such

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[21] The distinction between directly productive and directly unproductive activities in the economy was developed by Bhagwati (1982). Baumol (1990) focuses on rewarding unproductive entrepreneurs who seek political rents rather than market profits. Directly unproductive activities are the same thing as rent-seeking behavior, terminology introduced to the literature by Tullock (1967) and Krueger (1974).

persistence in consumption means that the chief consequence of a selective tax is to reduce households' discretionary budgets. Smaller discretionary budgets cause households to cut their expenditures on all other income-normal goods, including items such as organic, low-fat, and low-preservative foods, which tend to be more expensive (Durack, Alonso-Gomez, and Wilkinson 2008).

If lower-income households consume relatively more disfavored goods than higher-income households, selective taxes will disproportionately burden the former. Lower-income households then are forced to spend far larger percentages of their budgets on the selectively taxed items. The available empirical evidence supports that conclusion. Farrelly, Nonnemaker, and Watson (2012) calculate that spending on cigarettes increased from 11.6 percent to 23.6 percent of disposable income for consumers who did not quit smoking after New York City raised its excise tax on cigarettes. Sharma et al. (2014), who estimated the effects of a 20 percent sales tax on sugar-sweetened beverages, find that the percentage reduction in the budgets of lower-income households would be three times greater than the budget impact for higher-income households.

3. Data and Method

In our empirical analysis, we rely on pooled microdata from the Bureau of Labor Statistics (BLS) Consumer Expenditure (CE) Surveys for 2009–2012. The surveys are composed of two parts—a personal interview and a diary. We exploit the underused but far more detailed diary section of the CE dataset for this analysis so as to more thoroughly explore the effects of income on consumption behavior.

We combined expenditure (EXPN) and family (FMLY) files from the diary survey. The FMLY files contain information about each household's demographics.[22] The EXPN files record household expenditures for a consecutive two-week period on the basis of direct out-of-pocket spending. The CE Survey then codes the expenditure data into more than 500 categories. We identified several goods that are targets of selective taxation within the reported categories. These include (as coded in the BLS dataset) alcohol; tobacco; candy and gum (candy); soft drinks (cola); potato chips (chips); cakes and cupcakes (cake); cookies; donuts and other sweet rolls (donuts); and bacon.

We also constructed three dependent variables to capture complete meals purchased and consumed outside the home: vending, fast food, and food away. *Vending* captures spending on food and drink items at such machines; *fast food* measures expenditures at fast food restaurants; and *food away* sums all spending on meals prepared and eaten outside the home, minus vending machine and fast food purchases. Several of our variables consist of the sums of multiple BLS categories (e.g., vending is the sum of eight disaggregated vending purchase categories in the diary dataset). Table 1 (page 44) provides definitions of the variables used in our empirical analysis.

Given that the CE Survey information is reported for two-week periods, we annualized the data following the procedure of Kornrich and Furstenberg (2013). We organized the expenditure information by household and multiplied the within-category variables by 26 to estimate households' yearly expenditures on each categorical item.[23] This approach allows a

[22] These data, user files, and additional information and documentation are publicly available and can be accessed through the BLS website: http://www.bls.gov/cex/pumdhome.htm.

[23] This method for organizing the dataset likely overestimates snack food consumption for survey participants during abnormally high candy consumption periods (e.g., Halloween or Easter), but it likewise underestimates less healthy food consumption during periods of the year when less income is allocated to such purchases. As long as the survey is representative of the entire population across all years, however, such within-year variation cancels out in aggregating the data. In our empirical analysis, we additionally include control variables for when and where the diaries were completed and, as mentioned, drop extreme outliers.

more direct match with our primary variable of interest, household income, which is reported in annual after-tax dollars. After we dropped extreme outliers—observations more than three standard deviations away from the mean—our sample size was 20,040 households.[24] The summary statistics are reported in table 2 (page 46).

Average expenditures on alcohol (including beer, wine, and distilled spirits) totaled about $260 per household per year. Tobacco expenditures averaged $130 per household, and spending on food away from home (FAFH) averaged about $1,770 annually. Within the FAFH category, households spent about $731 on fast food and $19 at vending machines on average per year. Households spent approximately $52 on candy and gum, $56 on cola, $80 on potato chips, $21 on cakes and cupcakes, $35 on cookies, $15 on doughnuts and sweet rolls, and $23 on bacon. About 9 percent of the households in the sample received food stamps (indicated by a dummy variable), and 61 percent had some college education. Average household income (after taxes, including transfer payments) over the four years was about $42,788, and the average household size was 2.4 persons.

Our focus was identifying empirically *who* consumes tax-targeted less healthy foods. Specifically, we wanted to determine how spending on tax-disfavored goods varies across the income distribution. Owing to the aforementioned consumption persistence, we hypothesized that, given revealed tastes and preferences, lower-income households would purchase only marginally smaller quantities of such goods than households with higher incomes. Thus, we expected income to have a zero or marginally positive effect on consumption. To test this

[24] A total of 7,185 observations were dropped. An overwhelming majority of the observations that were dropped were households with large expenditures in a single category. For example, one household spent an annualized $20,091.24 on alcohol in 2012. The unfiltered mean alcohol expenditure in 2012 was $442.73, with a standard deviation of $1,110.22. Dropping these observations does not significantly affect the empirical results. We report estimates of ordinary least squares regressions that include the outliers in appendix B.

hypothesis, we began our empirical analysis with a pooled panel ordinary least squares (OLS) regression with random effects.

$$y_f = \alpha + \beta_1 income + \beta_2 food\ stamps + \beta_3 income \times food\ stamps + \gamma X + \mu. \qquad (1)$$

We estimated equation 1 for each food and beverage category separately; y_f represents spending in a given category for each household (cross-sectional, spanning over four years). As spelled out in table 1, several explanatory variables enter the X matrix.

The primary independent variables of interest are household income, food stamps, and their interaction. We were specifically interested in the behavior of lower-income households, so we selected a functional form that includes income, including that of all households in the dataset, and a food stamp dummy variable, which is set equal to 1 if a household earns an income small enough to qualify for the federal food stamp program (now called the Supplemental Nutrition Assistance Program, or SNAP) and 0 otherwise.[25]

The food stamp dummy variable allows us to determine whether lower-income households that receive food stamps behave differently from higher-income households that do not. The interaction term is a novel contribution to the literature insofar as it allows us to explore behavior within the subset of food stamp recipients. Most notably, we ask whether income-expenditure elasticities differ for lower-income households compared with higher-income households.

Because of the prevalence of dummy variables on the right-hand side of equation 1, we calculate income-expenditure elasticities at the variable means (and medians) rather than using

[25] The eligibility threshold for SNAP in 2012 was a monthly income of $1,245 for a household of one. Detailed information regarding SNAP can be found on the US Department of Agriculture's website at http://www.fns.usda.gov/snap/eligibility.

coefficients from a log-log model. The income-elasticity calculation is shown in equation 2, where the bars represent the data means (or medians).[26]

$$\varepsilon_{income} = (\beta_1 + \beta_3 \times food\ stamps)\frac{\$42{,}788}{\overline{y_f}}. \tag{2}$$

The income-expenditure model offers many advantages over traditional income-quantity elasticity (commonly known as *income elasticity*) or own-price elasticity (commonly known as *price elasticity*), but it also introduces other interpretative restrictions. The most notable limitation of the model specification in equation 1 is that when total expenditure is used as the dependent variable, the effects of price and quantity are combined and thus inseparable. That is, the income-expenditure model cannot disentangle a policy change's effects on price from its effects on quantity, for instance, following the imposition of a tax.

However, the most attractive feature of the model is that it supplies a direct measure of changes in household spending as market prices and quantities move in opposite directions according to the law of demand. The model provides a direct estimate of expenditures and the factors that influence those expenditures, which explains why the model was so popular in the early literature that explored the determinants of tax revenue (Fox and Campbell 1984; Groves and Kahn 1952) and food expenditures (Byrne, Capps, and Saha 1996; McCracken and Brandt 1987; Yen 1993).

Marginal expenditure effects resulting from price changes usually can be inferred from price elasticity estimates. Also, marginal quantity effects resulting from income changes can be inferred from income elasticity estimates. But the income-expenditure elasticity model provides

[26] The income elasticity estimates are calculated using the conditional estimates from equation 1, so equation 2 will only approximate the estimates presented in the empirical tables.

the most direct way of gauging how total expenditures will vary in response to price changes over the income distribution.

We also use total expenditures rather than quantities because the former absorbs quality changes that may not be encompassed by traditional estimates of income elasticity. For example, a sizable range of qualities and prices exists in any measure of alcohol consumption. A box of wine may sell for a price roughly equal to the minimum hourly wage, whereas a rare vintage can easily sell for thousands of dollars per bottle. A measure of the quantity of wine consumed as income varies will be biased if it does not account for differences in product quality.

The income-expenditure model in equation 1 captures such variations in quality, price, and quantity in a single measure. Hence, the empirical results on which we focus most of our discussion will be the income elasticity estimates. The elasticity coefficients computed according to equation 2 can be interpreted as follows. If an individual is not on food stamps ($food\ stamps = 0$), a 1 percent increase in income will lead to an increase in expenditures of $\beta_1 \times \left(\$42{,}788/\overline{y_f}\right)$ on the dependent variable, y_f, where β_1 is the coefficient estimated by the OLS regression. Average annual household income was \$42,788 in our full sample. If an individual is on food stamps, a 1 percent increase in income will lead to a $(\beta_1 + \beta_3) \times \left(\$42{,}788/\overline{y_f}\right)$ increase in expenditures on the dependent variable.

Thus, the β_3 coefficient tells us whether the expenditures of low-income households (those receiving food stamps) and those of high-income households differ statistically. Income elasticities should be positive for income-normal goods and negative for inferior goods. We assume that all consumption goods we examine empirically are income-normal goods, so that $\beta_1 > 0$. A positive coefficient on β_3 indicates that, within the food stamp recipient population, an increase in income leads to increases in consumption (or, alternatively, that the income elasticity of demand for food stamp recipients will be larger in absolute value than it is for higher-income households).

For an individual household, we hypothesized earlier that the unexplained variation in expenditures among our 12 food and beverage expenditure categories would be linked somehow (e.g., sugary foods and drinks are more or less good substitutes for one another; sugar-sweetened beverages are complementary to fast food). If that is the case, we can estimate all the regressions jointly using a seemingly unrelated regression (SUR) model. Zellner (1962) is the seminal work on SUR models. Zellner shows that the SUR model can provide sizable gains in coefficient-estimating efficiency by accounting for the unobservable error that is present among all the dependent variable estimates.[27]

Beyond links in the error terms by SUR, a majority of our expenditure observations are zero. Because of the large number of observations taking values of zero, we also estimate a Tobit model. The Tobit technique, introduced by Tobin (1958), uses all the observations in the dataset, both at a limiting value (usually zero) and above the limiting value, to estimate a regression line.[28] The Tobit model is particularly useful in our analysis because it can be used both to determine changes in the probability of an observation being nonzero and to quantify changes in the value of the dependent variable if expenditures are above zero (McDonald and Moffitt 1980).

In a cross-sectional analysis, the Tobit model estimates both the quantity responses of households actively consuming (*conditional quantity elasticities*) and the participation adjustments of exit-entry households (*market participation elasticities*) (McCracken and Brandt 1987). The effect of a change in an independent variable, X_i, on $E(Y_i/X_i)$ in elasticity form is

[27] The SUR model and estimation equations are presented in appendix A.
[28] The Tobit model and estimation equations are presented in appendix A.

$$\varepsilon_i = \frac{\partial F\left(\frac{\beta' X_i}{\sigma}\right)}{\partial X_i} \frac{X_i}{F\left(\frac{\beta' X_i}{\sigma}\right)} + \frac{\partial E(Y_i^*|X_i)}{\partial X_i} \frac{X_i}{E(Y_i^*|X_i)}, \tag{3}$$

where $F(\cdot)$ is the standard normal density function. The first product is the elasticity of the probability of consumption. The second product is the elasticity of expected consumption for consuming households (McCracken and Brandt 1987). All marginal effects and elasticities were calculated at the means.

Although the Tobit model can resolve the problem of a large percentage of zero-expenditure observations, its underlying assumptions are quite restrictive. For example, the Tobit model requires that variables determining the (conditional) consumption levels also determine the (unconditional) decision to consume. As an alternative to the Tobit model, Cragg (1971) proposed a double-hurdle model. The double-hurdle model integrates (a) the probit (binary) model to determine the decision to consume and (b) a truncated normal model to estimate the effects for conditional ($y > 0$) consumption (Burke 2009). By allowing the conditional and unconditional estimates to be determined by different mechanisms, the double-hurdle model may provide more accurate estimates:

$$f(w, y|x_1, x_2) =$$

$$\{1 - \Phi(x_1, y)\}^{1(\omega=0)} \times$$

$$\left[\Phi(x_1 y)(2\pi)^{-(1/2)\sigma^{-1}} \exp\{-(y - x_2\beta)^2/2\sigma^2\}/\Phi(x_2\beta/y)\right]^{1(\omega=1)}, \tag{4}$$

where w is a binary indicator equal to 1 if y is positive and 0 otherwise.[29]

[29] In Cragg's model, the probability of $y > 0$ and the value of y, given $y > 0$, are determined by different mechanisms (the vectors γ and β, respectively). Additionally, no restrictions are imposed on the elements of x_1 and x_2, implying that each decision may be determined by separate explanatory variables. Also, the Tobit model is nested within Cragg's alternative because if $x_1 = x_2$ and $\gamma = \beta/\sigma$, the models become identical (Burke 2009).

4. Results

Tables 3 and 4 present the OLS results. These estimates highlight the basic relationship between income and our 12 dependent variables. For all of them except tobacco, cakes, donuts, and bacon, increases in household income are correlated with near-zero increases in expenditures. The coefficient estimates are exceptionally small, the largest being 0.012 on fast food. Thus, a $1 increase in income is associated with about a one-cent increase in expenditures on fast food.

The estimated coefficient on food stamps in table 3 (page 47) is negative and significant for alcohol and the three FAFH variables, but interestingly, the food stamp coefficient is positive and significant for tobacco and carbonated soft drinks. That finding suggests that households on food stamps may spend absolutely more on tobacco and soft drinks than do higher-income households, rather than just relatively more as fractions of their total after-tax budgets.

The interaction between food stamp receipt and household income is either economically or statistically insignificant for all disfavored goods in our dataset. Income changes evidently do not affect food stamp recipients' spending in ways that are significantly different from how changes in income influence the behaviors of households not receiving food stamps.

Larger households spend more on all disfavored goods except alcoholic beverages. We had expected households with more children or other dependents to spend more on all items in our sample, including tax-targeted goods. The negative coefficient on alcohol may be driven by the fact that a larger number of individuals in a household increases the demand for time spent at home, resulting in fewer opportunities for consuming alcohol at home or for frequenting bars and restaurants where beer, wine, and distilled spirits tend to be more expensive than when purchased for home consumption. In any case, our evidence suggests that having children is not a reason for drinking more at home.

Black households consume less of all disfavored goods except bacon than white households do. Hispanic households similarly consume less of all goods except cola and FAFH than their white counterparts.

Table 4 (page 48) presents the OLS estimates of income-expenditure elasticity. Alcohol expenditure reveals a positive income elasticity of 0.385. This elasticity is less than the median income elasticity of 0.499 reported by Gallet (2007) and underscores the conclusion that alcohol is income-expenditure inelastic. Income has no marginal effect on expenditures for food stamp recipients, because the coefficient on the interaction term is not statistically different from zero. The interaction term likewise has a statistically insignificant coefficient for most of the other expenditure categories considered. A 1 percentage point increase in income (approximately \$428 at the mean) translates to a 0.385 percentage point increase in spending on alcoholic beverages (approximately \$1 annually at the mean).

An increase in expenditures of \$1 may seem small economically, relative to a \$428 income gain—accounting for only 0.23 percent of the corresponding household budget increase—precisely because the increase in alcohol expenditures is estimated to be quite small. However, the same mathematics can be applied to budget reductions. Hence, a \$428 income loss would lead to only a \$1 reduction in alcohol expenditures. Thus, as incomes get smaller and smaller, alcohol expenditures remain fairly persistent. And alcohol has the largest income-expenditure elasticity of any of the goods we investigated. Expenditures on other tax-disfavored goods are even less responsive to changes in income.

Spending on tobacco, cakes, donuts, and bacon shows no statistically significant relationship with household incomes. Figure 1 (page 49) plots the tobacco expenditure and income data, along with the fitted regression line. Total expenditures on tobacco are slightly higher, on average, at lower income levels. Such expenditures appear to increase moderately at annual incomes up to about $50,000 and to decrease gradually at incomes exceeding $50,000 per year. However, the slope of the fitted line is so small over the relevant range—varying from about $300 to $400 per household across the entire income distribution—that no significant statistical relationship is evident.

The lack of a statistically significant relationship between household income and expenditures on tobacco is quite interesting, but it represents a finding that is not all that surprising. Existing smokers' behavior changes little with respect to taxation (Farrelly, Nonnemaker, and Watson 2012). As household incomes grow larger and larger, any smoker would have difficulty keeping pace by increasing his or her smoking expenditures proportionately.[30] Unlike wine sales, for which exceptionally rare and high-quality vintages can carry large price tags, a very high-end, luxurious cigarette market does not exist.

Our three categories of meals consumed away from home—FAFH purchases from vending machines, fast food restaurants, and other establishments—returned positive income elasticity estimates that range from 0.212 (vending) to 0.295 (food away). Our estimate of income elasticity of food away from home of 0.263 is consistent with the estimate of 0.24 reported in McCracken and Brandt (1987) and 0.20 reported in Byrne, Capps, and Saha (1996).

These results are, once again, not too surprising. It may be difficult for food expenditures to account for substantial (and larger) fractions of high-income household budgets. To be more precise, the relatively broad category of FAFH encompasses fancy restaurants, where scaling up spending is easier than scaling up spending on potato chips, for example. In addition, higher-income households (where at least one person is likely to be employed) face higher opportunity

[30] It is possible that, as incomes grow larger, average tobacco expenditures would go up because more people think they can afford to smoke, which would make this result somewhat surprising.

costs in preparing time-intensive, high-quality meals eaten at home. We therefore would expect higher-income households to be more willing to pay to have meals prepared for them at restaurants.

We found the income-expenditure elasticity estimates for potato and corn chips, candy, cookies, and cola to be positive but economically small; the coefficients range from 0.042 (cola) to 0.132 (chips). The implication of these small coefficients is exactly the same as it was for spending on FAFH. Higher-income households spend much smaller fractions of their budgets on cola and chips than do low-income households (any expenditure-income elasticity less than 1.0 indicates a reduction in budget expenditures at higher income levels).[31] Spending on chips, candy, cookies, and cola is not proportional at higher household incomes, but people with low incomes evidently benefit from their consumption choices beyond basic nutritional values.

The elasticity estimates for cakes, donuts, and bacon are not statistically different from zero. The OLS estimates reported in table 5 (page 50) support our conclusion that no statistical relationship exists between household incomes and expenditures on those three food items. The elasticity results from our SUR model are presented in table 6 (page 51). Tables containing the corresponding coefficient estimates and their standard errors can be found in appendix A. The SUR coefficients are identical to the OLS estimates, but the increase in model efficiency (smaller standard errors) results in one notable change. The income-expenditure elasticity estimate on cake, 0.036, becomes (marginally) statistically significant at the 10 percent level. We can therefore conclude more confidently that increases in household income are associated with marginal increases in expenditures on the items in the cake category.

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[31] This finding supports Engel's Law. Zimmerman (1932, 80) provides a direct translation of Ernst Engel's writing (Engel's Law): "The poorer is a family, the greater is the proportion of the total outgo which must be used for food."

Table 7 (page 52) presents the elasticity estimates from the Tobit model. (The coefficient estimates and standard errors can be found in appendix table A3.) The Tobit results are broadly consistent with the OLS results discussed earlier. The market participation (unconditional) elasticity estimates represent the likelihood of an individual consuming the items included in the various dependent variables. Owing to the large number of zero-expenditure observations in our dataset, a majority of the unconditional elasticity estimates approximate the OLS elasticity estimates in table 4. For most of the (actual or potential) selectively taxed goods, income has a small, but positive, effect on household consumption spending.

We highlight a few notable differences between the Tobit and OLS elasticity estimates. Household income has a statistically significant and negative effect on participation in the market for tobacco, which is consistent with other evidence. The interaction term (food stamp participation × income) is positive and significant for alcohol, suggesting that individuals on food stamps are more likely than individuals above the food stamp income threshold to become alcohol consumers if their household income increases. Conversely, the food stamp income elasticity estimate for donuts is negative and significant.

The conditional quantity elasticity estimates identify the effect of household income on expenditures only for individuals who consume the good in question. The marginal (conditional) effects of household income on spending are substantially smaller than the market participation (unconditional) effects of income on consumption. This finding supports the results of McCracken and Brandt (1987). However, all our FAFH and fast food income-expenditure elasticity estimates exceed the FAFH estimates from that same study.

These results from the Tobit estimation broadly support our hypothesis that selective tax-targeted expenditures are very unresponsive to household incomes, especially for individuals who already consume such goods. These findings support the literature (mostly focusing on the purchases of a single good), which finds that consumption behavior is remarkably persistent through time.

Table 8 (pages 53–54) presents our estimates of the double-hurdle model. In hurdle 1, Cragg's double-hurdle model examines binary changes in the dependent variable (consuming or not consuming the good in question). Hurdle 2 examines the effects on spending if the household already purchases the good. The output of a Cragg model generates hurdle 1 and hurdle 2 estimates. As with the Tobit model, we are able to extract both the probabilities of being above the consumption threshold and the marginal effects on the dependent variable, given that purchases indeed exceed the threshold. As before, we are most interested in the effects of income and the interaction between income and eligibility for food stamps.

Similar to the Tobit results, the tier 1 Cragg effects of income and its interaction with food stamp eligibility are positive and significant for tobacco spending. The indirect tier 2 effects for household income and tobacco purchases are neither statistically nor economically salient. In contrast, the tier 1 and tier 2 income coefficients are positive and significant for alcoholic beverages, implying that as household income increases, the probability of buying beer, wine, and distilled spirits increases (the coefficient is quite small, however). For a household already consuming alcohol, the effect is larger. For a household receiving food stamps, though, the relationship is negative.

Again, elasticities are of interest insofar as we can calculate how percentage changes in income affect percentage changes in the consumption of the goods at hand. Elasticities, which represent the change in the unconditional expected value of the dependent variable resulting from a change in an independent variable, are calculated at the mean household income. The interaction term estimates the average partial effect.

Table 9 (page 55) reports the elasticity estimates from Cragg's double-hurdle model. For food consumed away from home, a 1 percent increase in household income produces a 0.13 percent increase in spending. All our elasticity estimates are positive, except those for donuts. The largest income elasticity coefficients are for food eaten away from home and for spending on alcohol, tobacco, vending machine purchases, and fast food. All interaction term elasticities are smaller than the corresponding income elasticities, thus indicating that households that do not receive food stamps are far less responsive to income increases than households that do not qualify for such taxpayer-financed benefits.

5. Policy Discussion

The empirical results reported in this paper support the conclusion that the social welfare costs of selective sales and excise taxes are large and that the benefits of such policies are small. That conclusion follows from two empirical observations. First, selective consumption taxes are quite regressive and therefore violate the principle of vertical tax equity because the tax burden becomes lighter as household incomes increase.[32] Second, the purchased quantities of all consumption items considered are remarkably unresponsive to changes in their own prices, including price changes caused by imposing new selective sales or excise taxes or raising existing tax rates.

These conclusions admittedly are drawn from consumers' observed behavioral responses in the short run. A longer time horizon allows consumers to search for and take advantage of

[32] For a recent and independent confirmation of this conclusion, see Snowden (2013).

substitutes for the items subject to selective taxation. As economic theory teaches, the demand for any good is more elastic in the long run than in the short run. (Indeed, that relationship is so important that it often is referred to as the second law of demand.) Excise taxes on cigarettes illustrate the point. For current smokers, the income effects of such taxes are dramatic in the short run, doubling (from 11.6 to 23.6 percent) the fraction of disposable household income that smokers in the lowest income bracket spend on cigarettes. In the longer term, though, fewer people—especially young people—may begin to smoke in the first place (Farrelly, Nonnemaker, and Watson 2012).

Focusing solely on selective taxation's effects on consumption in the long run (plus limiting the analysis to a single disfavored good, such as cigarettes) overlooks the second- and higher-order consequences of a tax policy that is aimed at improving public health outcomes by reducing smoking. Among those higher-order consequences is the aforementioned income effect of imposing taxes selectively on cigarettes, snack food, and other disfavored goods. Individuals who continue to purchase those items after a new tax has been levied (or an existing tax is raised) see declines in their disposable income available for spending on other goods, thereby making it more difficult to climb out of poverty. Stuck in poverty, those households also are unable to adopt healthier diets or change their behaviors in the ways desired by the supporters of selective consumption taxes.

Farrelly, Nonnemaker, and Watson (2012) conclude, as we do, that cigarette purchases are not very responsive to changes in income and that tobacco taxes impose their heaviest burdens on households in the lowest income category. Cigarette consumption has been declining steadily in the United States ever since the release of the US Surgeon General's 1964 report documenting links between smoking and lung cancer. Over the same time horizon, the US federal government and most US states imposed and later increased—in some cases dramatically—excise taxes on cigarettes. Although selective cigarette taxes undoubtedly contributed to the secular decline in smoking, they do not tell the whole story. A range of other policy tools has been introduced over the past five decades to discourage cigarette consumption (e.g., educational campaigns in nearly every school in the country, warning label requirements for cigarette packages, advertising bans, public smoking bans, and stricter enforcement of the minimum age for purchasing cigarettes).

Harris, Balsa, and Triunfo (2014) use a quasi-experimental study design to estimate the effects of a variety of antismoking policies targeting pregnant women in Uruguay. The policies studied include the establishment of units at health centers to treat nicotine dependence, a comprehensive tobacco control law banning nearly all cigarette advertising, a series of rotating warning pictograms on every cigarette pack, limits on multiple presentations to consumers of the same cigarette brand, expansion of the required pictograms to 80 percent of the front and back of each pack, and increased cigarette taxes (and retail prices). Harris, Balsa, and Triunfo found that, although both price and nonprice policies caused less smoking, the nonprice policies were far more effective in discouraging cigarette consumption. Indeed, taxes and smoking cessation showed very little relationship.

Our evidence reveals that the links between selective taxes and consumption of alcohol, sugary drinks, snack food, and other elements of poor diets also are weak. As such, selective consumption taxes are unlikely to slow—and certainly will not reverse—the ongoing obesity epidemic. Action is not necessarily required, because one of the effects of a rising income is the ability to engage in healthier behavior. If policy is necessary to achieve desirable social aims, advocates should not ignore alternatives such as (a) reconfiguring the food supply chain to make healthier options more readily available, especially in low-income neighborhoods; (b) educating people about healthier diets;[33] and (c) promoting and supporting good eating habits if individuals try to make healthier choices. But bad habits such as smoking, drinking, and going on sugar binges are hard to break.

Another policy option is to subsidize the purchase of more healthful substitutes for snack food. Policies could thereby promote drinking milk or diet sodas rather than sugar-sweetened beverages, for example (French et al. 1997; Horgen and Brownell 1997; Schroeter, Lusk, and Tyner 2008; Herman et al. 2008). But just as proposals to selectively tax less healthy food items trigger lobbying by producers that want to avoid being tax targets (Hoffer, Shughart, and Thomas 2013, 2014), proposals to subsidize healthier foods likewise will elicit lobbying to get on the list of subsidy recipients.

Evidence shows not only that the existence of farmers' markets in cities and towns expands the availability of fresh fruits and vegetables as substitutes for less healthy foods, but also that prices in local retail grocery stores fall as a result (Larsen and Gilliland 2009). The introduction of healthier alternatives into areas where none have been available previously can go a long way toward making the demands for less healthy foods more elastic in the intermediate and longer runs.

Reger et al. (1998) supply evidence that educational campaigns can be an extraordinarily cheap means of nudging consumers into healthier choices. Their "1% or Less" campaign spent seven weeks in Clarksburg, West Virginia, encouraging consumers to switch from higher- to

[33] Information provision, as mentioned earlier, is a form of soft libertarian paternalism that "nudges" consumers into making "better" choices (Thaler and Sunstein 2008). Unlike taxes, nudges do not explicitly change relative prices. But placing racks of candy bars and snack food at the back of the store rather than at the checkout lane ("changing the choice architecture") may limit the options available to consumers and preclude experimentation and opportunities to learn about the ability of different goods to satisfy their wants.

lower-fat milk.[34] The campaign spent $60,000 on community-based education and advertising. After the campaign ended, the market share of low-fat milk had risen from 18 percent to 41 percent and persisted at elevated levels for a full year. According to Jacobson and Brownell (2000), a health-conscious advertising effort targeting 200,000 people costs about the same as a single coronary bypass operation.[35]

Finally, a variety of other policy options that are at the discretion of governments, nonprofit organizations, and even for-profit organizations can support individuals who decide to make healthier choices, rather than punish those making less healthy choices. Public and private support groups, a wide range of commitment devices, and even targeted subsidies can be effective in the right scenario. Herman et al. (2008) document the powerful effect of a subsidy for fruits and vegetables. The study showed an increase of 1.4 servings of consumed fruits and vegetables with a farmer's market subsidy and an increase of 0.8 servings with a supermarket subsidy over the duration of the study. This increase persisted for six months after the subsidy ceased.

Ultimately, we think that true long-term change will come from the formation of better habits through better nutritional education. In the case of public policies on consumer choices, rewards simply outperform punishments. As people become wealthier, they may eat more. However, individuals can afford to be concerned about morbidity and mortality only after they have become wealthy enough to address more immediate priorities. Taxing away disposable incomes may make it more difficult for individuals to make long-run health a priority. It is unfortunately true that public policies aimed at improving welfare by selectively

[34] An interesting debate persists regarding the actual weight-loss effectiveness of consuming reduced-fat milk (0 to 2 percent fat) compared with whole-fat milk (Ludwig and Willett 2013).
[35] In contrast, schoolchildren nationwide are in open rebellion against initiatives to introduce healthier alternatives into public school lunch programs that are financed in part by the US Department of Agriculture. Athletes, in particular, complain of caloric starvation (Zanteson 2013).

taxing and differentially raising the prices of snack food and other less healthy choices will increase food insecurity, lead to greater income inequality, and place a heavier burden on the least well off in society.

7. Summary

In this paper, we have argued that selective sales and excise taxes are not the first-best policy interventions for promoting healthier consumption choices. The existing literature has shown that the consumption of tax-disfavored goods (alcohol, cigarettes, carbonated soft drinks, candy, chips, and so on) is unresponsive to tax-ridden changes in relative prices. We supply additional evidence supporting that conclusion by asking whether purchases of those goods vary across the income distribution and, if so, whether such taxes have disproportionate impacts on lower-income households. They do.

We report evidence that higher household incomes are weakly correlated with increases in the purchases of the goods in question. A 10 percent increase in income for households receiving food stamps led to changes in consumption of between −0.03 percent (donuts) and 0.08 percent (tobacco). Consumption of the same goods by households not eligible for food stamps was found to be far more responsive to changes in income. For households not receiving food stamps, purchases of alcohol and vending machine purchases revealed the largest income-expenditure elasticities, at 0.305 and 0.231, respectively.

These findings suggest that lower-income households are far less responsive than their higher-income counterparts to taxes that promote paternalistic goals ostensibly aimed at promoting healthier diets and other lifestyle choices. Any consumption tax that is selectively levied on snack food, as broadly defined, forces lower-income households to spend disproportionately more of their budgets on the food and drink options deemed to be bad for the households that continue to buy them. One explanation for this finding is that higher incomes supply wider ranges of choices. Combined with the demographic characteristics of low-income neighborhoods, which offer few healthier substitutes for fast food, the burden of selective consumption taxes on poor people is differentially heavy.

Research on diet choices and eating habits suggests that education about the link between diet and health outcomes and access to healthier alternatives are more effective than selective consumption taxes at reducing spending on disfavored goods. Imposing sales and excise taxes selectively on alcohol, tobacco, and snack food is not the first-best policy response to the current obesity epidemic or to any other perceived public health care challenge.

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Table 1. Variable Descriptions

Variable	Description
Dependent variables	
Alcohol	Alcoholic beverage expenditures (in dollars, multiplied by 26)
Food away	Food away from home expenditures minus fast food expenditures and minus expenditures at vending machines (in dollars, multiplied by 26)
Fast food	Fast food expenditures (in dollars, multiplied by 26)
Tobacco	Tobacco products and smoking supplies expenditures (in dollars, multiplied by 26)
Vending	Vending machine expenditures
Candy	Candy and chewing gum expenditures (in dollars, multiplied by 26)
Soda	Soft drink expenditures (in dollars, multiplied by 26)
Chips	Potato chips and other snacks expenditures (in dollars, multiplied by 26)
Cake	Cake and cupcake expenditures (in dollars, multiplied by 26)
Cookies	Cookies, excluding refrigerated dough expenditures (in dollars, multiplied by 26)
Donuts	Donut, sweet roll, and coffee cake expenditures (in dollars, multiplied by 26)
Bacon	Bacon expenditures (in dollars, multiplied by 26)
Independent variables	
Age of children	0 = no children 1 = all children < 6 2 = oldest child between 6 and 11, and ≥ 1 child < 6 3 = all children between 6 and 11 4 = oldest child between 12 and 17, and ≥ 1 child < 12 5 = all children between 12 and 17 6 = oldest child > 17, and ≥ 1 child < 17 7 = all children > 17
Education	1 if ≥ 1 year of college, 0 otherwise
Household size	Number of members in consumer unit (household)
Income	Annual household income after taxes during the past 12 months (in dollars)
Food stamps	1 if household received food stamps in past month, 0 otherwise
Male	1 if male, 0 otherwise

continued on next page

Variable	Description
Married	1 if married, 0 otherwise
Population size *i*	Pop0 = 1 if population ≤ 0.3299 million, 0 otherwise Pop1 = 1 if population ≥ 0.33 million and ≤ 1.19 million, 0 otherwise Pop2 = 1 if population ≥ 1.2 million and ≤ 4 million, 0 otherwise Pop3 = 1 if population ≥ 4 million, 0 otherwise
Quarter *i*	1 if recorded in January–March, 0 otherwise 1 if recorded in April–June, 0 otherwise 1 if recorded in July–September, 0 otherwise 1 if recorded in October–December, 0 otherwise
Race *i*	1 if white, 0 otherwise 1 if African American or black, 0 otherwise 1 if Hispanic, 0 otherwise 1 if other race, 0 otherwise
Region *i*	1 if Northeast, 0 otherwise 1 if Midwest, 0 otherwise 1 if South, 0 otherwise 1 if West, 0 otherwise
Urban	1 if household is in an urban area, 0 otherwise

Table 2. Descriptive Statistics

Variable	Mean	Standard deviation	Minimum	Maximum
Alcohol	260.2	566.13	0	3,355.3
Food away	1,770.4	1,983.68	0	11,650.6
Fast food	731.9	881.77	0	4117.1
Tobacco	129.7	394.32	0	2510.8
Vending	19.2	61.94	0	552.5
Candy	51.9	85.75	0	489.3
Cola	56.2	89.22	0	451.9
Chips	79.8	112.10	0	606.8
Cakes	21.3	57.12	0	434.5
Cookies	35.5	63.54	0	340.3
Donuts	15.1	38.72	0	208.5
Bacon	22.9	52.35	0	261.0
Gym	53.1	317.78	0	4,237.5
Age of children	1.6	2.45	0	7
College	0.6	0.48	0	1
Household size	2.4	1.41	1	10
Income	42,787.7	42,503.57	−375	247,100
Food stamps	0.1	0.28	0	1
Male	0.5	0.49	0	1
Married	0.5	0.49	0	1
Pop1	0.1	0.23	0	1
Pop2	0.2	0.43	0	1
Pop3	0.4	0.47	0	1
Q2	0.3	0.44	0	1
Q3	0.2	0.43	0	1
Q4	0.2	0.41	0	1
Black	0.1	0.33	0	1
Hispanic	0.1	0.33	0	1
Other race	0.1	0.24	0	1
Northeast	0.2	0.39	0	1
Midwest	0.2	0.42	0	1
West	0.2	0.40	0	1
Urban	0.9	0.22	0	1

Table 3. OLS Expenditure Estimates

	Alcohol	Tobacco	Vending	Fast food	Food away	Cola
Income	0.002***	0.000	0.000***	0.004***	0.012***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Food stamps	−28.535**	75.820***	−5.558***	−207.365***	−521.419***	10.610***
	(12.797)	(15.622)	(2.106)	(27.227)	(48.676)	(3.109)
Income × food stamps	−0.000	0.000	0.000**	0.001	−0.001	−0.000
	(0.001)	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)
Age of children	−4.281**	4.213***	−0.080	5.393*	−0.821	1.429***
	(1.861)	(1.502)	(0.233)	(3.164)	(6.856)	(0.344)
College	86.767***	−58.111***	3.057***	148.763***	434.184***	−3.752***
	(7.785)	(6.408)	(0.942)	(12.599)	(26.577)	(1.350)
Household size	−16.037***	9.735***	2.691***	84.470***	81.846***	7.648***
	(3.502)	(2.960)	(0.505)	(6.560)	(13.389)	(0.690)
Male	77.160***	33.113***	1.347	72.301***	199.088***	2.703**
	(8.175)	(5.712)	(0.890)	(12.255)	(26.630)	(1.268)
Married	−5.046	−36.444***	−3.341***	−0.303	267.670***	6.976***
	(9.371)	(6.870)	(1.082)	(14.440)	(31.565)	(1.527)
Pop1	38.623**	−16.375	6.174***	119.248***	327.535***	11.382***
	(17.138)	(13.425)	(2.259)	(26.780)	(60.425)	(3.112)
Pop2	44.290***	−24.971***	−2.946**	47.812***	157.424***	0.911
	(10.402)	(7.879)	(1.199)	(15.764)	(33.927)	(1.736)
Pop3	54.180***	−44.934***	−4.646***	89.581***	275.227***	−0.518
	(10.531)	(7.471)	(1.174)	(15.502)	(33.438)	(1.621)
Black	−117.579***	−68.957***	−0.558	−7.187	−329.665***	−15.062***
	(9.361)	(8.234)	(1.240)	(18.067)	(35.040)	(1.771)
Hispanic	−55.242***	−102.025***	5.057***	56.441***	−62.665	−0.424
	(11.168)	(7.605)	(1.515)	(20.581)	(41.067)	(2.052)
Other race	−121.025***	−38.463***	2.595	−27.843	−6.239	−19.271***
	(15.490)	(9.671)	(2.024)	(27.187)	(62.532)	(2.364)
Urban	27.462*	−7.344	−2.241	22.366	78.773	−10.029***
	(15.787)	(15.589)	(2.279)	(25.927)	(51.337)	(3.317)
Constant	78.807***	191.393***	6.458**	181.290***	519.660***	43.640***
	(18.618)	(17.540)	(2.577)	(30.879)	(63.537)	(3.771)
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,040	20,040	20,040	20,040	20,040	20,040
R^2	0.069	0.027	0.014	0.104	0.165	0.045

Note: Robust standard errors are in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

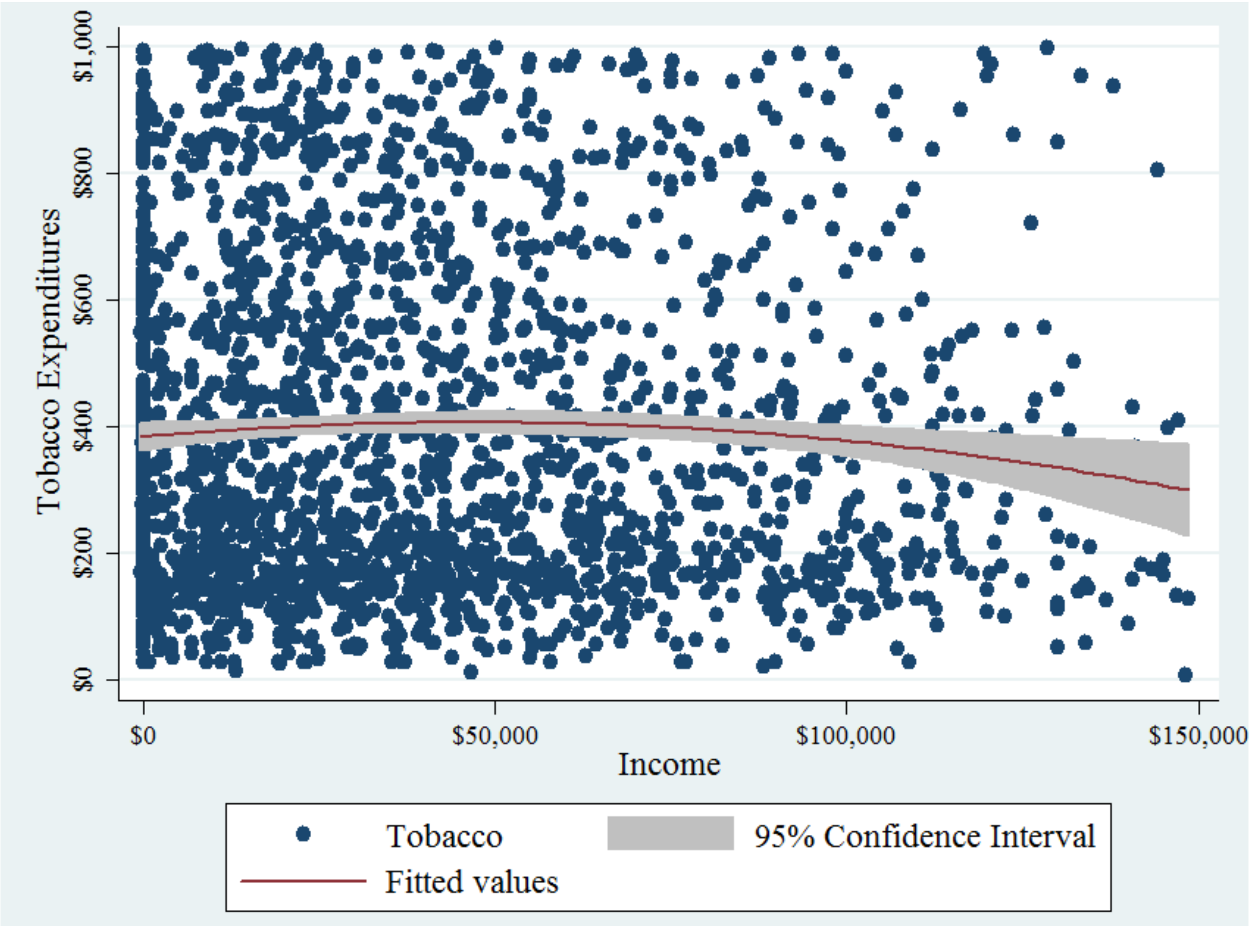
Table 4. OLS Mean Elasticities

	Alcohol	Tobacco	Vending	Fast food	Food away	Cola	Chips	Cakes	Cookies	Candy	Donuts	Bacon
Income	0.385***	0.032	0.212***	0.238***	0.295***	0.042***	0.132***	0.036	0.061***	0.105***	−0.028	0.017
	(0.019)	(0.020)	(0.026)	(0.010)	(0.010)	(0.013)	(0.012)	(0.023)	(0.016)	(0.014)	(0.022)	(0.019)
Income × food stamps	−0.000	0.007	0.024**	0.003	−0.001	−0.002	−0.004	−0.004	−0.002	−0.000	−0.009	0.005
	(0.004)	(0.008)	(0.010)	(0.003)	(0.002)	(0.004)	(0.003)	(0.007)	(0.005)	(0.004)	(0.006)	(0.006)

Note: Robust standard errors are in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1. Relationship between Tobacco Expenditure and Household Income



Source: Bureau of Labor Statistics Consumer Expenditure Surveys for 2009–2012.

Table 5. OLS Expenditure Estimates

	Chips	Cakes	Cookies	Candy	Donuts	Bacon
Income	0.000*** (0.000)	0.000 (0.000)	0.000*** (0.000)	0.000*** (0.000)	−0.000 (0.000)	0.000 (0.000)
Food stamps	4.389 (3.534)	0.715 (1.990)	0.491 (2.364)	0.561 (2.895)	2.084 (1.349)	1.142 (2.020)
Income × food stamps	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)
Age of children	2.066*** (0.425)	0.636*** (0.230)	0.153 (0.240)	0.862*** (0.328)	0.349** (0.151)	0.691*** (0.211)
College	7.165*** (1.610)	−1.261 (0.871)	−0.429 (0.946)	3.435*** (1.253)	−1.805*** (0.600)	−3.147*** (0.811)
Household size	12.460*** (0.889)	2.974*** (0.460)	5.855*** (0.516)	5.660*** (0.658)	2.276*** (0.309)	2.847*** (0.420)
Male	−3.126** (1.553)	−0.221 (0.819)	−2.071** (0.902)	−4.884*** (1.208)	−0.201 (0.557)	0.125 (0.751)
Married	17.735*** (1.827)	4.439*** (1.008)	8.425*** (1.099)	12.425*** (1.452)	3.484*** (0.671)	5.021*** (0.927)
Pop1	7.380** (3.612)	0.912 (1.827)	1.238 (1.947)	−1.102 (2.590)	0.430 (1.201)	1.724 (1.708)
Pop2	2.545 (2.128)	3.913*** (1.070)	1.566 (1.188)	1.295 (1.681)	1.097 (0.736)	0.313 (1.002)
Pop3	−0.910 (2.017)	5.587*** (1.060)	4.798*** (1.179)	0.160 (1.615)	2.236*** (0.733)	1.817* (0.967)
Black	−25.130*** (2.077)	−5.315*** (1.180)	−7.135*** (1.283)	−15.856*** (1.590)	−5.203*** (0.765)	1.077 (1.180)
Hispanic	−22.729*** (2.401)	−5.070*** (1.293)	−8.599*** (1.383)	−17.772*** (1.803)	−1.964** (0.909)	−2.859** (1.205)
Other race	−29.393*** (3.112)	−4.765*** (1.700)	−9.363*** (1.858)	−16.802*** (2.480)	−5.357*** (1.034)	−5.920*** (1.447)
Urban	−6.688* (3.820)	−1.416 (1.910)	−2.789 (2.237)	0.253 (2.947)	−0.296 (1.331)	−3.744** (1.870)
Constant	39.095*** (4.388)	11.160*** (2.281)	20.620*** (2.587)	30.810*** (3.389)	9.638*** (1.554)	15.544*** (2.153)
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,040	20,040	20,040	20,040	20,040	20,040
R^2	0.087	0.018	0.038	0.048	0.020	0.020

Note: Robust standard errors are in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6. SUR Elasticity Estimates

	Income elasticities	Income × food stamp elasticities
Alcohol	0.385***	−0.000
	(0.017)	(0.005)
Tobacco	0.032	0.007
	(0.024)	(0.007)
Vending	0.212***	0.024***
	(0.025)	(0.007)
Fast food	0.238***	0.003
	(0.009)	(0.003)
Food away	0.295***	−0.001
	(0.008)	(0.002)
Cola	0.042***	−0.002
	(0.012)	(0.004)
Chips	0.132***	−0.004
	(0.011)	(0.003)
Cake	0.036*	−0.004
	(0.021)	(0.006)
Cookies	0.061***	−0.002
	(0.014)	(0.004)
Candy	0.105***	−0.000
	(0.013)	(0.004)
Donuts	−0.028	−0.009
	(0.020)	(0.006)
Bacon	0.017	0.005
	(0.018)	(0.005)
Observations	20,040	20,040

Note: Robust standard errors are in parentheses. Unlike the OLS elasticities, which are estimated independently, the SUR elasticities are estimated conditionally on the common error term, *U*. Therefore, we present all the SUR elasticities in a single column rather than as separate columns.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7. Tobit Elasticity Estimates

	Alcohol	Tobacco	Vending	Fast food	Food away	Cola	Chips	Cakes	Cookies	Candy	Donuts	Bacon
Market participation (unconditional) elasticity estimates												
Income	0.345***	0.051**	0.216***	0.216***	0.260***	0.033***	0.113***	0.023	0.049***	0.080***	−0.033	0.015
	(0.015)	(0.021)	(0.020)	(0.009)	(0.009)	(0.012)	(0.011)	(0.021)	(0.015)	(0.013)	(0.022)	(0.020)
Income × food stamps	0.009**	0.000	0.015***	0.006*	0.004	−0.003	−0.005	−0.007	−0.002	−0.002	−0.010*	0.002
	(0.005)	(0.005)	(0.006)	(0.003)	(0.002)	(0.003)	(0.003)	(0.006)	(0.004)	(0.004)	(0.006)	(0.005)
Conditional quantity elasticity												
Income	0.090***	0.010**	0.043***	0.103***	0.141***	0.011***	0.043***	0.005	0.013***	0.026***	−0.007	0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Income × food stamps	0.002**	0.000	0.003***	0.003*	0.002	−0.001	−0.002	−0.002	−0.000	−0.001	−0.002*	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	20,040	20,040	20,040	20,040	20,040	20,040		20,040	20,040	20,040	20,040	20,040

Note: Robust standard errors are in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8. Cragg Double-Hurdle Model

Panel A

	Alcohol	Tobacco	Vending	Fast food	Food away	Cola
Hurdle 1						
Income	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000** (0.000)
Food stamps	−0.213*** (0.054)	0.381*** (0.051)	−0.147*** (0.057)	−0.249*** (0.048)	−0.351*** (0.050)	0.221*** (0.046)
Income × food stamps	0.000 (0.000)	0.000 (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000** (0.000)	0.000 (0.000)
College	0.281*** (0.021)	−0.184*** (0.023)	0.155*** (0.024)	0.259*** (0.020)	0.313*** (0.022)	−0.068*** (0.020)
Male	0.176*** (0.019)	0.143*** (0.022)	−0.002 (0.022)	0.073*** (0.020)	0.065*** (0.022)	0.036* (0.018)
Married	−0.021 (0.021)	−0.090*** (0.023)	0.012 (0.023)	0.042** (0.021)	0.072*** (0.023)	0.205*** (0.019)
Urban	0.130*** (0.048)	−0.067 (0.048)	−0.099** (0.050)	0.004 (0.045)	−0.053 (0.050)	−0.085** (0.043)
Constant	−1.146*** (0.055)	−0.738*** (0.056)	−1.188*** (0.058)	0.041 (0.052)	0.425*** (0.057)	−0.233*** (0.050)
Hurdle 2						
Income	0.007*** (0.001)	−0.001 (0.001)	0.002* (0.001)	0.010*** (0.001)	0.032*** (0.002)	0.000*** (0.000)
Food stamps	−831.298** (386.407)	−153.270 (174.906)	29.749 (169.256)	−1,142.744*** (183.218)	−6,502.047*** (574.063)	8.931 (11.081)
Income × food stamps	0.008 (0.010)	0.008 (0.006)	0.007 (0.004)	0.014*** (0.004)	0.062*** (0.011)	0.000 (0.000)
College	303.239*** (114.023)	−358.550*** (87.172)	−141.780* (82.635)	390.757*** (65.182)	1,727.659*** (158.618)	−4.180 (4.821)
Male	520.468*** (97.685)	90.253 (82.379)	118.581 (74.564)	235.720*** (56.435)	856.094*** (127.274)	1.225 (4.567)
Married	−136.688 (97.365)	−149.046* (87.057)	−119.009 (78.637)	429.025*** (62.185)	1,831.920*** (149.100)	24.757*** (4.919)
Urban	−111.582 (257.540)	165.424 (161.543)	48.152 (149.516)	193.540 (152.023)	771.960** (349.248)	−24.004** (9.674)
Constant	−2,156.501*** (401.321)	−356.488 (240.560)	−1,924.490*** (709.929)	−2,666.694*** (235.273)	−8,242.523*** (581.678)	36.836*** (12.512)
Sigma constant	1,596.914*** (65.129)	1,208.419*** (52.216)	448.925*** (73.406)	1,661.847*** (35.969)	3,772.236*** (79.958)	138.370*** (2.483)
Observations	20,040	20,040	20,040	20,040	20,040	20,040
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Population size fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Race fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B

	Chips	Cakes	Cookies	Candy	Donuts	Bacon
Hurdle 1						
Income	0.000***	0.000	0.000***	0.000***	−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Food stamps	0.113**	0.091*	0.040	0.066	0.153***	0.067
	(0.046)	(0.055)	(0.048)	(0.047)	(0.055)	(0.052)
Income × food stamps	−0.000	−0.000	0.000	0.000	−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
College	0.039**	−0.078***	−0.060***	0.005	−0.074***	−0.115***
	(0.020)	(0.023)	(0.020)	(0.020)	(0.023)	(0.022)
Male	−0.071***	−0.028	−0.092***	−0.109***	−0.043*	−0.040*
	(0.018)	(0.022)	(0.019)	(0.019)	(0.022)	(0.021)
Married	0.308***	0.207***	0.290***	0.254***	0.237***	0.232***
	(0.019)	(0.023)	(0.020)	(0.020)	(0.023)	(0.023)
Urban	−0.049	−0.052	−0.039	0.010	0.003	−0.106**
	(0.043)	(0.051)	(0.044)	(0.043)	(0.051)	(0.048)
Constant	−0.173***	−1.083***	−0.583***	−0.368***	−1.116***	−0.997***
	(0.050)	(0.058)	(0.051)	(0.050)	(0.059)	(0.056)
Hurdle 2						
Income	0.001***	0.000**	0.000***	0.000***	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Food stamps	0.239	−12.226	2.019	−10.500	−4.533	1.399
	(14.173)	(10.703)	(5.707)	(13.618)	(4.550)	(4.176)
Income × food stamps	0.001*	0.000	0.000	0.001*	−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
College	22.718***	8.585**	6.440***	18.074***	−1.766	1.956
	(5.728)	(4.343)	(2.358)	(5.428)	(1.834)	(1.751)
Male	−3.166	2.283	3.890*	−5.324	3.527**	6.096***
	(5.221)	(4.142)	(2.218)	(5.003)	(1.767)	(1.697)
Married	62.150***	10.554**	13.540***	39.234***	3.636*	3.790**
	(5.835)	(4.443)	(2.370)	(5.453)	(1.881)	(1.787)
Urban	−15.599	0.246	−6.925	−3.837	−2.700	−0.261
	(11.553)	(9.694)	(5.025)	(11.291)	(4.019)	(3.648)
Constant	−23.373	74.597***	83.664***	−11.594	88.785***	116.011***
	(15.355)	(11.384)	(5.901)	(14.725)	(4.662)	(4.401)
Sigma constant	169.124***	94.192***	73.098***	141.619***	45.521***	48.731***
	(2.861)	(1.922)	(0.973)	(2.769)	(0.692)	(0.621)
Observations	20,040	20,040	20,040	20,040	20,040	20,040
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Population size fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Race fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors are in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9. Cragg Double-Hurdle Mean Total Elasticities

	Alcohol	Tobacco	Vending	Fast food	Food away	Cola	Chips	Cakes	Cookies	Candy	Donuts	Bacon
Income	0.305***	0.022***	0.231***	0.149***	0.127***	0.050***	0.106***	0.055***	0.074***	0.093***	−0.005***	0.034***
	(0.105)	(0.006)	(0.064)	(0.022)	(0.032)	(0.008)	(0.019)	(0.013)	(0.013)	(0.020)	(0.002)	(0.006)
Income × food stamps	0.007***	0.008***	0.022***	0.007***	0.005***	0.003***	0.002***	0.004***	0.004***	0.004***	−0.003***	0.007***
	(0.003)	(0.003)	(0.007)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Note: Robust standard errors are in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix A: Empirical Robustness Analysis

Table A1. OLS Median Elasticities

	Alcohol	Tobacco	Vending	Fast food	Food away	Cola	Chips	Cakes	Cookies	Candy	Donuts	Bacon
Income	0.318	0.029	0.184**	0.199***	0.258	0.036***	0.123	0.031	0.051***	0.090***	−0.025	0.014
	(23.231)	(1.339)	(0.075)	(0.009)	(0.861)	(0.011)	(0.084)	(0.020)	(0.014)	(0.018)	(0.038)	(0.016)
Observations	20,040	20,040	20,040	20,040	20,040	20,040	20,040	20,040	20,040	20,040	20,040	20,040

Note: Robust standard errors are in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The basic SUR model is

$$
\begin{aligned}
y_1 &= \beta_1' x_1 + \mu_1 \\
&\vdots \\
y_{12} &= \beta_{13}' x_{13} + \mu_{13},
\end{aligned}
\tag{A1}
$$

where $y_i (i = 1 \ldots 12)$ is the dependent expenditure variable from each regression, $\beta' x_i (i = 1 \ldots 12)$ is the vector of all independent variables and their coefficients from each regression, and $\mu_i (i = 1 \ldots 12)$ is the error term from each regression. By stacking notation, the SUR model can be more easily represented as

$$Y = \tilde{X}\beta + U, \tag{A2}$$

where $Y = [y_1 \ldots y_{13}]'$, $\tilde{X} = diag[x_1 \ldots x_{13}]$, a block diagonal matrix with $x_1 \ldots x_{13}$ on its diagonal, $\beta = [\beta_1 \ldots \beta_{13}]'$, and $U = [\mu_1 \ldots \mu_{13}]'$.

The OLS estimate β thus becomes

$$\varepsilon_{i\ Income} = \left(\beta_{i\ Income} + \beta_{i\ FoodStamps \times Income} \times food\ stamps\right) \frac{\overline{Income}}{\bar{Y}}. \tag{A3}$$

Table A2. SUR Results

Panel A

	Alcohol	Tobacco	Vending	Fast food	Food away	Cola
Income	0.002***	0.000	0.000***	0.004***	0.012***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Food stamps	−28.535	75.820***	−5.558**	−207.365***	−521.419***	10.610***
	(19.907)	(14.181)	(2.242)	(30.429)	(66.087)	(3.178)
Income × food stamps	−0.000	0.000	0.000***	0.001	−0.001	−0.000
	(0.001)	(0.000)	(0.000)	(0.001)	(0.002)	(0.000)
Age of children	−4.281**	4.213***	−0.080	5.393*	−0.821	1.429***
	(1.981)	(1.411)	(0.223)	(3.028)	(6.577)	(0.316)
College	86.767***	−58.111***	3.057***	148.763***	434.184***	−3.752***
	(8.410)	(5.991)	(0.947)	(12.855)	(27.919)	(1.343)
Household size	−16.037***	9.735***	2.691***	84.470***	81.846***	7.648***
	(3.952)	(2.815)	(0.445)	(6.041)	(13.121)	(0.631)
Male	77.160***	33.113***	1.347	72.301***	199.088***	2.703**
	(7.921)	(5.642)	(0.892)	(12.107)	(26.295)	(1.265)
Married	−5.046	−36.444***	−3.341***	−0.303	267.670***	6.976***
	(9.262)	(6.598)	(1.043)	(14.157)	(30.746)	(1.479)
Pop1	38.623**	−16.375	6.174***	119.248***	327.535***	11.382***
	(17.996)	(12.819)	(2.027)	(27.507)	(59.741)	(2.873)
Pop2	44.290***	−24.971***	−2.946**	47.812***	157.424***	0.911
	(10.689)	(7.614)	(1.204)	(16.338)	(35.484)	(1.706)
Pop3	54.180***	−44.934***	−4.646***	89.581***	275.227***	−0.518
	(10.323)	(7.354)	(1.163)	(15.779)	(34.270)	(1.648)
Black	−117.579***	−68.957***	−0.558	−7.187	−329.665***	−15.062***
	(12.229)	(8.712)	(1.377)	(18.693)	(40.598)	(1.952)
Hispanic	−55.242***	−102.025***	5.057***	56.441***	−62.665	−0.424
	(12.612)	(8.985)	(1.420)	(19.278)	(41.870)	(2.014)
Other race	−121.025***	−38.463***	2.595	−27.843	−6.239	−19.271***
	27.462	−7.344	−2.241	22.366	78.773	(2.623)
Urban	(18.585)	(13.239)	(2.093)	(28.407)	(61.696)	−10.029***
	(16.431)	(11.705)	(1.850)	(25.115)	(54.547)	(2.967)
Constant	78.807***	191.393***	6.458***	181.290***	519.660***	43.640***
	(21.899)	(15.600)	(2.466)	(33.473)	(72.698)	(3.496)
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,040	20,040	20,040	20,040	20,040	20,040
R^2	0.069	0.027	0.014	0.104	0.165	0.045

Panel B

	Chips	Cakes	Cookies	Candy	Donuts	Bacon
Income	0.000***	0.000*	0.000***	0.000***	−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Food stamps	4.389	0.715	0.491	0.561	2.084	1.142
	(3.904)	(2.063)	(2.272)	(3.050)	(1.397)	(1.889)
Income × food stamps	−0.000	−0.000	−0.000	−0.000	−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age of children	2.066***	0.636***	0.153	0.862***	0.349**	0.691***
	(0.389)	(0.205)	(0.226)	(0.304)	(0.139)	(0.188)
College	7.165***	−1.261	−0.429	3.435***	−1.805***	−3.147***
	(1.649)	(0.872)	(0.960)	(1.289)	(0.590)	(0.798)
Household size	12.460***	2.974***	5.855***	5.660***	2.276***	2.847***
	(0.775)	(0.410)	(0.451)	(0.606)	(0.277)	(0.375)
Male	−3.126**	−0.221	−2.071**	−4.884***	−0.201	0.125
	(1.553)	(0.821)	(0.904)	(1.214)	(0.556)	(0.752)
Married	17.735***	4.439***	8.425***	12.425***	3.484***	5.021***
	(1.816)	(0.960)	(1.057)	(1.419)	(0.650)	(0.879)
Pop1	7.380**	0.912	1.238	−1.102	0.430	1.724
	(3.529)	(1.865)	(2.054)	(2.757)	(1.263)	(1.708)
Pop2	2.545	3.913***	1.566	1.295	1.097	0.313
	(2.096)	(1.108)	(1.220)	(1.638)	(0.750)	(1.014)
Pop3	−0.910	5.587***	4.798***	0.160	2.236***	1.817*
	(2.025)	(1.070)	(1.178)	(1.582)	(0.725)	(0.980)
Black	−25.130***	−5.315***	−7.135***	−15.856***	−5.203***	1.077
	(2.398)	(1.268)	(1.396)	(1.874)	(0.858)	(1.160)
Hispanic	−22.729***	−5.070***	−8.599***	−17.772***	−1.964**	−2.859**
	(2.473)	(1.307)	(1.439)	(1.932)	(0.885)	(1.197)
Other race	−29.393***	−4.765***	−9.363***	−16.802***	−5.357***	−5.920***
	(3.222)	(1.703)	(1.875)	(2.517)	(1.153)	(1.559)
Urban	−6.688*	−1.416	−2.789	0.253	−0.296	−3.744**
	(3.645)	(1.926)	(2.121)	(2.847)	(1.305)	(1.763)
Constant	39.095***	11.160***	20.620***	30.810***	9.638***	15.544***
	(4.295)	(2.270)	(2.499)	(3.355)	(1.537)	(2.078)
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,040	20,040	20,040	20,040	20,040	20,040
R^2	0.087	0.018	0.038	0.048	0.020	0.020

Note: Robust standard errors are in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Our Tobit model takes the following form:

$$y_i = X_i'\beta + e_i \qquad \text{if } X_i'\beta + e_i > 0$$

$$y_i = 0 \qquad \text{if } X_i'\beta + e_i \leq 0, \qquad i = 1, \dots, N, \tag{A4}$$

where N is the number of households, y_i represent the less healthy expenditures for household i, β is a vector of unknown coefficients, X_i is our vector of independent variables, and e_i is an independently distributed error term.

Although the Tobit parameter estimates, similar to OLS, can provide some useful information, we are more interested in the marginal effects and elasticities. With Tobit analysis in a cross-sectional dataset, we estimate the effects of income on market participation (unconditional elasticities) and expenditures for households that are actively consuming (conditional elasticities), following McCracken and Brandt (1987). The following relationships are[36]

$$E(Y_i|X_i) = F\left(\frac{\beta' X_i}{\sigma}\right)(\beta' X_i) + \sigma f\left(\frac{\beta' X_i}{\sigma}\right)$$

$$E(Y_i^*|X_i) = E(Y_i|X_i, Y_i > 0)$$

$$= (\beta' X_i) + \frac{\sigma f\left(\frac{\beta' X_i}{\sigma}\right)}{F\left(\frac{\beta' X_i}{\sigma}\right)}, \tag{A5}$$

where $f(\cdot)$ is the standard normal distribution function.

[36] For more detailed information about the Tobit model, see McCracken and Brandt (1987) and McDonald and Moffitt (1980).

Table A3. Tobit Regression Estimates

Panel A

	Alcohol	Tobacco	Vending	Fast food	Food away	Cola
Income	0.006***	0.001**	0.001***	0.005***	0.014***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Food stamps	−279.666***	472.652***	−33.922***	−345.751***	−877.009***	28.784***
	(64.254)	(64.645)	(11.937)	(44.181)	(77.670)	(6.362)
Income × food stamps	0.004**	0.000	0.001***	0.003*	0.005	−0.000
	(0.002)	(0.002)	(0.000)	(0.002)	(0.003)	(0.000)
Age of children	−10.954*	20.287***	0.442	7.428*	−1.942	3.288***
	(5.999)	(7.421)	(1.109)	(4.229)	(8.313)	(0.666)
College	340.522***	−280.829***	29.459***	243.002***	593.475***	−9.085***
	(25.755)	(32.428)	(5.019)	(17.859)	(33.324)	(2.903)
Household size	−62.913***	62.451***	13.354***	107.700***	98.765***	17.625***
	(12.348)	(14.478)	(2.185)	(8.611)	(16.326)	(1.290)
Male	238.753***	206.072***	3.382	101.567***	237.262***	6.829**
	(23.337)	(30.487)	(4.582)	(16.666)	(31.952)	(2.759)
Married	26.155	−198.322***	−13.259**	−2.496	298.389***	16.653***
	(27.863)	(36.046)	(5.386)	(19.646)	(38.063)	(3.203)
Pop1	178.075***	−69.906	39.272***	190.223***	424.566***	19.702***
	(52.927)	(66.955)	(9.674)	(35.250)	(70.334)	(6.254)
Pop2	166.669***	−118.059***	−12.750**	49.058**	149.303***	−1.464
	(31.061)	(40.056)	(6.162)	(21.903)	(41.569)	(3.734)
Pop3	143.155***	−247.376***	−27.613***	96.795***	279.439***	−3.798
	(30.845)	(40.138)	(6.092)	(21.424)	(40.604)	(3.569)
Black	−397.926***	−270.544***	5.476	−14.230	−409.042***	−26.640***
	(38.529)	(47.889)	(7.061)	(25.749)	(45.997)	(4.196)
Hispanic	−111.652***	−507.931***	32.029***	82.529***	−51.843	4.310
	(36.980)	(53.223)	(7.225)	(27.538)	(50.381)	(4.174)
Other race	−381.981***	−197.742***	9.840	−53.757	−48.088	−50.443***
	(50.728)	(66.416)	(9.718)	(36.210)	(73.000)	(6.224)
Urban	146.564**	−63.416	−18.523*	26.500	56.925	−17.983***
	(58.970)	(64.549)	(10.439)	(37.565)	(65.226)	(6.366)
Constant	−1,337.060***	−1,138.000***	−281.437***	−244.337***	25.384	−57.264***
	(69.108)	(80.629)	(13.455)	(44.610)	(80.319)	(7.610)
Sigma constant	1,281.988***	1,437.070***	218.439***	1,091.111***	2,129.851***	165.717***
	(13.929)	(18.999)	(3.693)	(7.975)	(17.422)	(1.421)
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,040	20,040	20,040	20,040	20,040	

Panel B

	Chips	Cakes	Cookies	Candy	Donuts	Bacon
Income	0.000***	0.000	0.000***	0.000***	−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Food stamps	11.797*	13.373	2.727	4.729	19.396**	9.522
	(6.956)	(11.513)	(7.069)	(6.975)	(8.071)	(9.492)
Income × food stamps	−0.000	−0.000	−0.000	−0.000	−0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age of children	3.868***	3.664***	0.800	1.920***	2.125***	3.403***
	(0.693)	(1.094)	(0.660)	(0.672)	(0.785)	(0.939)
College	11.880***	−13.444***	−5.364*	5.261*	−11.323***	−19.697***
	(2.974)	(4.815)	(2.883)	(2.868)	(3.487)	(4.111)
Household size	21.471***	16.808***	16.449***	13.880***	12.414***	13.704***
	(1.422)	(2.122)	(1.300)	(1.314)	(1.506)	(1.811)
Male	−8.164***	−3.680	−9.939***	−14.598***	−4.331	−3.988
	(2.813)	(4.563)	(2.736)	(2.718)	(3.296)	(3.908)
Married	35.396***	27.977***	28.185***	28.684***	23.480***	29.771***
	(3.272)	(5.350)	(3.195)	(3.184)	(3.836)	(4.588)
Pop1	14.264**	4.989	4.002	−0.818	−1.303	6.456
	(6.436)	(10.693)	(6.259)	(6.200)	(7.739)	(8.988)
Pop2	3.157	22.963***	4.791	4.192	5.276	0.862
	(3.798)	(6.219)	(3.700)	(3.669)	(4.460)	(5.303)
Pop3	−1.638	30.705***	12.776***	1.833	10.183**	7.760
	(3.635)	(5.967)	(3.551)	(3.549)	(4.298)	(5.065)
Black	−43.557***	−29.080***	−21.145***	−36.207***	−33.983***	6.591
	(4.310)	(7.195)	(4.272)	(4.172)	(5.412)	(5.977)
Hispanic	−41.639***	−31.269***	−22.358***	−38.646***	−12.748**	−15.260**
	(4.570)	(7.380)	(4.346)	(4.371)	(5.180)	(6.209)
Other race	−60.210***	−34.740***	−32.690***	−46.050***	−35.069***	−37.657***
	(6.348)	(10.274)	(6.076)	(6.170)	(7.400)	(8.804)
Urban	−11.043*	−10.697	−7.586	0.437	−0.161	−19.353**
	(6.481)	(10.476)	(6.394)	(6.368)	(7.594)	(8.693)
Constant	−58.809***	−258.054***	−108.200***	−78.041***	−184.921***	−203.905***
	(7.740)	(12.922)	(7.655)	(7.576)	(9.254)	(10.754)
Sigma constant	175.489***	217.693***	153.763***	162.459***	155.827***	192.424***
	(1.513)	(2.597)	(1.313)	(1.501)	(1.422)	(1.583)
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,040	20,040	20,040	20,040	20,040	

Note: Robust standard errors are in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix B: Unfiltered Regression Analysis with 2012 Data

Table B1. Unfiltered 2012 Data Summary Statistics

Variable	Mean	Standard deviation	Minimum	Maximum
Alcoholic beverages	442.73	1,110.22	0.00	20,091.24
Black	0.12	0.33	0.00	1.00
Child age	1.70	2.48	0.00	7.00
College	0.64	0.48	0.00	1.00
Family size	2.51	1.45	1.00	12.00
Income after taxes	52,039.01	62,306.64	−118,436.00	797,691.00
Fast food	991.93	1,337.21	0.00	30,824.56
Food away from home	2,348.30	2,955.78	0.00	37,939.46
Food stamps	0.10	0.30	0.00	1.00
Hispanic	0.13	0.33	0.00	1.00
Male	0.46	0.50	0.00	1.00
Married	0.52	0.50	0.00	1.00
Midwest	0.23	0.42	0.00	1.00
Northeast	0.19	0.39	0.00	1.00
South	0.35	0.48	0.00	1.00
Other race	0.07	0.25	0.00	1.00
White	0.81	0.39	0.00	1.00
Pop0	0.34	0.48	0.00	1.00
Pop1	0.06	0.24	0.00	1.00
Pop2	0.24	0.43	0.00	1.00
Pop3	0.36	0.48	0.00	1.00
Vending	0.19	0.39	0.00	1.00
Q1	0.29	0.45	0.00	1.00
Q2	0.26	0.44	0.00	1.00
Q3	0.24	0.43	0.00	1.00
Q4	0.22	0.41	0.00	1.00
Tobacco	219.43	725.30	0.00	10,093.72
Candy	81.95	167.34	0.00	2,780.18
Cola	75.72	141.97	0.00	2,143.96
Chips	114.34	182.11	0.00	3,002.48
Cakes	35.54	114.74	0.00	2,600.00
Cookies	50.94	101.60	0.00	2,123.42
Donuts	24.96	69.51	0.00	1,166.62
Bacon	33.72	87.64	0.00	2,060.22
Urban	0.95	0.22	0.00	1.00
West	0.22	0.41	0.00	1.00

Table B2. Alcohol and Smoking Expenditures, 2012, Including Outliers

	Alcohol	ε	Smoking	ε
Income	0.003***	0.299***	−0.000	−0.028
	(0.000)	(0.028)	(0.000)	(0.036)
Food stamps	−30.640	−0.007	−13.451	−0.006
	(64.486)	(0.014)	(42.709)	(0.019)
Income × food stamps	−0.002	−0.008	0.007***	0.067***
	(0.002)	(0.010)	(0.001)	(0.013)
Age of children	−15.310**	−0.059**	17.407***	0.135***
	(6.568)	(0.025)	(4.350)	(0.034)
College	173.097***	0.250***	−119.857***	−0.349***
	(28.814)	(0.042)	(19.083)	(0.057)
Household size	−27.796**	−0.157**	−5.496	−0.063
	(12.796)	(0.073)	(8.475)	(0.097)
Male	65.235**	0.068**	62.510***	0.132***
	(26.638)	(0.028)	(17.642)	(0.038)
Married	96.477***	0.112***	11.407	0.027
	(30.922)	(0.036)	(20.480)	(0.048)
Pop1	26.123	0.004	5.081	0.001
	(59.304)	(0.008)	(39.277)	(0.011)
Pop2	64.267*	0.034*	−24.107	−0.026
	(36.367)	(0.020)	(24.086)	(0.026)
Pop3	96.109***	0.078***	−40.386*	−0.066*
	(34.868)	(0.028)	(23.093)	(0.038)
Black	−188.851***	−0.053***	−124.985***	−0.071***
	(42.073)	(0.012)	(27.865)	(0.016)
Hispanic	−58.092	−0.017	−195.156***	−0.114***
	(42.532)	(0.012)	(28.169)	(0.017)
Other race	−199.349***	−0.030***	−77.716**	−0.024**
	(53.992)	(0.008)	(35.759)	(0.011)
Urban	148.020**	0.318**	−23.812	−0.103
	(63.470)	(0.137)	(42.036)	(0.182)
Constant	−6.437		328.338***	
	(70.566)		(46.736)	
Regional dummies	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes
Observations	6,904	6,904	6,904	6,904
R^2	0.056		0.030	

Note: Robust standard errors are in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B3. OLS Results Using 2012 Data, Including Outliers

Panel A

	Candy	ε	Donuts	ε	Cookies	ε	Cake	ε
Income	0.000***	0.112***	0.000	0.042	0.000***	0.119***	0.000***	0.098***
	(0.000)	(0.022)	(0.000)	(0.030)	(0.000)	(0.022)	(0.000)	(0.036)
Food stamps	8.151	0.010	−3.092	−0.012	0.900	0.002	−2.680	−0.007
	(9.725)	(0.012)	(4.102)	(0.016)	(5.937)	(0.011)	(6.778)	(0.019)
Income × food stamps	−0.000	−0.003	0.000**	0.022**	−0.000	−0.003	0.000	0.010
	(0.000)	(0.008)	(0.000)	(0.011)	(0.000)	(0.008)	(0.000)	(0.013)
Age of children	1.366	0.028	0.274	0.019	−0.508	−0.017	0.553	0.026
	(0.990)	(0.021)	(0.418)	(0.028)	(0.605)	(0.020)	(0.690)	(0.033)
College	10.938**	0.085**	−3.049*	−0.078*	−2.707	−0.034	1.116	0.020
	(4.345)	(0.034)	(1.833)	(0.047)	(2.653)	(0.033)	(3.029)	(0.054)
Household size	13.038***	0.399***	5.111***	0.513***	10.437***	0.513***	9.187***	0.648***
	(1.930)	(0.060)	(0.814)	(0.083)	(1.178)	(0.059)	(1.345)	(0.098)
Male	−11.171***	−0.063***	0.331	0.006	−2.810	−0.026	1.451	0.019
	(4.017)	(0.023)	(1.694)	(0.032)	(2.453)	(0.022)	(2.800)	(0.037)
Married	21.513***	0.135***	4.168**	0.086**	11.217***	0.114***	2.591	0.038
	(4.663)	(0.030)	(1.967)	(0.041)	(2.847)	(0.029)	(3.250)	(0.047)
Pop1	0.551	0.000	6.841*	0.017*	5.916	0.007	6.374	0.011
	(8.943)	(0.007)	(3.772)	(0.009)	(5.460)	(0.006)	(6.234)	(0.011)
Pop2	0.989	0.003	5.326**	0.051**	0.751	0.003	7.428*	0.050*
	(5.484)	(0.016)	(2.313)	(0.022)	(3.348)	(0.016)	(3.823)	(0.026)
Pop3	7.712	0.034	7.259***	0.104***	7.542**	0.053**	10.812***	0.109***
	(5.258)	(0.023)	(2.218)	(0.032)	(3.210)	(0.023)	(3.665)	(0.037)
Black	−26.968***	−0.041***	−6.629**	−0.033**	−9.048**	−0.022**	−11.539***	−0.041***
	(6.345)	(0.010)	(2.676)	(0.013)	(3.874)	(0.010)	(4.422)	(0.016)
Hispanic	−33.121***	−0.052***	−2.724	−0.014	−12.614***	−0.032***	−9.470**	−0.034**
	(6.414)	(0.010)	(2.705)	(0.014)	(3.916)	(0.010)	(4.471)	(0.016)
Other race	−13.506*	−0.011*	−3.193	−0.009	−9.302*	−0.012*	−7.080	−0.013
	(8.142)	(0.007)	(3.434)	(0.009)	(4.971)	(0.007)	(5.675)	(0.011)
Urban	−9.741	−0.113	1.144	0.044	1.886	0.035	6.672	0.178
	(9.572)	(0.111)	(4.037)	(0.154)	(5.844)	(0.109)	(6.672)	(0.178)
Constant	33.725***		3.721		14.041**		−2.612	
	(10.642)		(4.488)		(6.497)		(7.418)	
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,904	6,904	6,904	6,904	6,904	6,904	6,904	6,904
R^2	0.055		0.026		0.045		0.024	

Panel B

	Cola	ε	Bacon	ε	Chips	ε
Income	0.000 (0.000)	0.012 (0.020)	0.000** (0.000)	0.068** (0.029)	0.000*** (0.000)	0.109*** (0.017)
Food stamps	10.883 (8.250)	0.014 (0.011)	4.370 (5.188)	0.013 (0.015)	7.941 (10.243)	0.007 (0.009)
Income × food stamps	0.000 (0.000)	0.005 (0.007)	−0.000 (0.000)	−0.009 (0.010)	−0.001* (0.000)	−0.012* (0.006)
Age of children	2.982*** (0.840)	0.067*** (0.019)	0.919* (0.528)	0.046* (0.027)	4.544*** (1.043)	0.068*** (0.016)
College	−10.460*** (3.686)	−0.088*** (0.031)	−2.522 (2.318)	−0.048 (0.044)	14.127*** (4.577)	0.079*** (0.026)
Household size	13.172*** (1.637)	0.436*** (0.055)	5.081*** (1.030)	0.378*** (0.077)	27.038*** (2.033)	0.593*** (0.046)
Male	−3.623 (3.408)	−0.022 (0.021)	0.902 (2.143)	0.012 (0.030)	−4.123 (4.231)	−0.017 (0.017)
Married	17.369*** (3.956)	0.118*** (0.027)	8.075*** (2.488)	0.124*** (0.038)	24.944*** (4.912)	0.113*** (0.022)
Pop1	17.063** (7.587)	0.014** (0.006)	6.400 (4.771)	0.011 (0.009)	7.233 (9.420)	0.004 (0.005)
Pop2	1.191 (4.653)	0.004 (0.015)	2.978 (2.926)	0.021 (0.021)	−4.474 (5.777)	−0.009 (0.012)
Pop3	−0.040 (4.461)	−0.000 (0.021)	2.548 (2.805)	0.027 (0.030)	−2.788 (5.538)	−0.009 (0.017)
Black	−28.327*** (5.383)	−0.047*** (0.009)	3.155 (3.385)	0.012 (0.013)	−41.441*** (6.683)	−0.045*** (0.007)
Hispanic	−11.609** (5.442)	−0.020** (0.009)	−3.193 (3.422)	−0.012 (0.013)	−41.131*** (6.756)	−0.046*** (0.008)
Other race	−35.577*** (6.908)	−0.032*** (0.006)	−8.748** (4.344)	−0.017** (0.009)	−42.429*** (8.576)	−0.025*** (0.005)
Urban	−8.524 (8.120)	−0.107 (0.102)	−9.962* (5.106)	−0.281* (0.144)	4.078 (10.082)	0.034 (0.084)
Constant	52.131*** (9.028)		23.969*** (5.677)		9.763 (11.209)	
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,904	6,904	6,904	6,904	6,904	6,904
R^2	0.055		0.020		0.115	

Panel C

	Vending	ε	Food away	ε
Income	0.000***	0.115***	0.012***	0.263***
	(0.000)	(0.023)	(0.001)	(0.013)
Food stamps	−0.065***	−0.034***	−828.580***	−0.035***
	(0.023)	(0.012)	(161.835)	(0.007)
Income × food stamps	0.000***	0.025***	−0.000	−0.000
	(0.000)	(0.008)	(0.005)	(0.005)
Age of children	0.000	0.000	3.517	0.003
	(0.002)	(0.021)	(16.483)	(0.012)
College	0.030***	0.103***	544.586***	0.148***
	(0.010)	(0.035)	(72.311)	(0.020)
Household size	0.012***	0.162***	173.694***	0.185***
	(0.005)	(0.061)	(32.113)	(0.034)
Male	−0.016*	−0.039*	142.369**	0.028**
	(0.010)	(0.024)	(66.851)	(0.013)
Married	−0.007	−0.020	423.209***	0.093***
	(0.011)	(0.030)	(77.602)	(0.017)
Pop1	0.054**	0.017**	630.901***	0.016***
	(0.021)	(0.007)	(148.831)	(0.004)
Pop2	−0.006	−0.008	293.125***	0.030***
	(0.013)	(0.016)	(91.267)	(0.009)
Pop3	−0.033***	−0.062***	521.579***	0.080***
	(0.013)	(0.024)	(87.505)	(0.013)
Black	−0.025*	−0.017*	−369.366***	−0.020***
	(0.015)	(0.010)	(105.586)	(0.006)
Hispanic	0.041***	0.028***	−22.911	−0.001
	(0.015)	(0.010)	(106.738)	(0.006)
Other race	−0.027	−0.010	−21.663	−0.001
	(0.019)	(0.007)	(135.500)	(0.004)
Urban	0.009	0.044	−60.564	−0.025
	(0.023)	(0.115)	(159.285)	(0.064)
Constant	0.094***		402.014**	
	(0.025)		(177.094)	
Regional dummies	Yes	Yes	Yes	Yes
Quarterly dummies	Yes	Yes	Yes	Yes
Observations	6,904	6,904	6,904	6,904
R^2	0.023		0.161	

Note: Robust standard errors are in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.