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Research Report

BMI/Obesity and consumers' price sensitivity: Implications for food tax policies

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Abstract

We examine the relationship between BMI and food purchase behavior using a unique dataset that links individual-level food purchases to health data. We find that individuals with higher BMI are significantly more sensitive to price changes in vice categories but do not show similar sensitivity in comparable nonvice categories. We rely on past literature that defines and identifies vice categories as those that are tempting and purchased impulsively. We explore the effectiveness of a 10% price increase on vice food categories, a hypothetical policy similar in spirit to a fat tax or sugar tax. We predict that such a tax would substantially reduce consumption of these foods, and would be particularly effective in reducing consumption by individuals with higher BMI.

Keywords: obesity and BMI, health outcome, scanner data, markets and health, soda tax

Significance Statement

This article contributes to the discussion on obesity by examining the connection between BMI and food purchasing habits, with emphasis on how consumers respond to price fluctuations. By linking unique health data to detailed individual-level food choices, our research reveals that individuals with higher BMI display significantly more sensitivity to price variations in vice-food categories compared to those with lower BMI. Following past literature, we identify vice categories as those that are tempting and purchased impulsively. Importantly, this relationship between price sensitivity and BMI does not extend to non-vice categories. We find that the predicted impact of taxes on vice foods is large in magnitude and increasing for individuals higher on the BMI spectrum.

Introduction

Soda and sugar-sweetened beverage taxes, implemented by over 50 countries and by at least seven US localities,[a] and fat or junk-food taxes,[b] tried by at least two countries and by the Navajo Nation in the United States of America, could be particularly effective (or ineffective) at improving health if unhealthy individuals were especially responsive (or unresponsive) to price increases in unhealthy foods (31–37). Consider the condition of obesity in the Unites States of America, where the incidence rate has now risen to 41.9%.[c] If obese Americans were shown to be more responsive to price changes, a soda tax applied uniformly to all consumers would indirectly reduce consumption to a greater extent for those with obesity. Conversely, if consumers with obesity were less responsive to price changes, the opposite effect might occur. This paper delves into an empirical exploration of this question. We hypothesize that individuals across the entire body weight spectrum exhibit the same sensitivity to price changes. Testing this hypothesis, our results reject it and find that taxes on unhealthy foods can be particularly effective in reducing consumption among individuals living with obesity.

Even though diet and obesity are inextricably linked, a key challenge in empirically examining the relationship between dietary choices and obesity is the relative absence of longitudinal data linking consumer's food purchase behavior to his/her health outcomes. For example, while the National Health and Nutrition Examination Survey (NHANES) can link health outcomes and dietary choices, it does so for only single cross-sections, and food purchase information is based on recall, rather than observation.[d] While a few studies (e.g. (38–40)) do rely on longitudinal data to link health and dietary choices, they study different questions entirely. Only Okrent and Sweitzer (41), in their ongoing work, and concurrent work by Zhen et al. (42) investigate the question of price responsiveness, but with a different focus, approach, and data (in the case of Zhen et al. (42)). In contrast to our work, neither

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Okrent and Sweitzer (41) nor Zhen et al. (42) conduct systematic comparisons between vice and nonvice goods. Furthermore, while Zhen et al. (42) find price sensitivity is greatest in low-income obese consumers, we find no interaction between income, obesity and price sensitivity to be significant. We believe that some of the differences in our findings may be attributed to disparities in the data employed. Additionally, we employ highly flexible functional forms in pinning down the demand curves, which contrasts their approach.[e]

To explore how price sensitivity varies across Body Mass Index (BMI) or different obesity brackets, we follow previous research in classifying foods into "vice" and "nonvice" categories. Vice categories refer to unhealthy products that consumers tend to purchase impulsively and later regret (43–45). Examples of vice categories we include in our analysis are ice cream, potato chips, and cookies. Our empirical results suggest the demand for vice categories is different for individuals living with obesity and for those living without. To better examine this relationship, we estimate flexible demand curves for 10 representative vice product categories and 10 nonvice categories. The categories are chosen to reflect a wide range of characteristics, such as storability, and whether a product is frozen or perishable. We allow both the level and slope of demand for vice/nonvice product categories to depend on an individual's BMI. We find that, when considering vice foods collectively, individuals with obesity exhibit a significantly greater level of demand and price sensitivity compared to those without. This finding contrasts with the results obtained for the nonvice categories, where individuals with higher BMI show no discernible difference in price sensitivity compared to those with lower BMI.

It is notable that the magnitude of the difference in price sensitivity for vice foods between individuals living with obese and nonobese status is substantial. To demonstrate the economic significance of the differences in price sensitivities across BMI brackets, we perform a simple exercise that forecasts the impact of a 10% price increase, a hypothetical policy similar in spirit to a fat tax or sugar tax, for all 10 vice categories and our result suggests large effects of such a tax or price increase, relative to baseline levels of consumption for individuals who are higher on the BMI spectrum. Overall, our results suggest that taxes, especially those targeted at sugar-sweetened beverages, will decrease consumption for both high and low BMI individuals.

Results

Matching detailed individual-level food purchase data to the individual's characteristics, including self-reported height and weight, we investigate how obesity status (as measured by BMI) relates to consumers' price sensitivity for vice and comparable nonvice products categories. As discussed in detail in Section "Materials and Methods", we focus on households with a single member across all our analysis. We include 10 vice categories, and 10 nonvice categories in our analysis. To select categories, we primarily utilize survey results from Thomas et al. (45) which rank food categories in terms of how tempting and unhealthy consumers see them, along with survey results ranking product category healthiness by health experts from Oster (43). Our selection procedure begins with the top 20 rated vice categories from Thomas et al. (45) and the top 25 rated virtue categories from their survey. We note that the categories listed in the Thomas et al. (45) paper do not correspond exactly to the category definitions used by NielsenIQ. Because of this mismatch, where possible we find the closest matching NielsenIQ product category. From this set of categories, we focus on categories with a substantial number of purchases, allowing us to reliably estimate a demand curve, and where the classification is consistent with that in Oster (43). To the former point, we include a category when (i) there is a sufficiently large percentage of purchases where store price data are available and (ii) if a regression of a category purchase indicator on price, along with a set of household, store and time fixed effects, generates a negative and statistically significant price coefficient. We provide additional detail on our selection procedure in the Supplemental Appendix.

We take two approaches to measuring price sensitivity: first, we estimate nonparametric demand curves for each product category. In this approach, we flexibly estimate both the level and slope of demand for different levels of price conditional on a rich set of demographic, individual, and store-level observables. Second, we estimate parametric demand curves. This approach allows us to control more finely for individual and store characteristics, although it imposes stronger restrictions on the functional relationship between quantity purchased and price. Our findings, discussed in the next two sections, are robust to both approaches.

Nonparametric demand curve estimates

In Figures 1 and 2, we plot nonparametric demand estimates for the vice and nonvice product categories conditional on obesity status (BMI being above or below 30). Our measure of the category-level price is computed as the weighted average of the price per ounce of all UPCs in each category based on weekly store level sales and store (we discuss why, and provide evidence that, our price measure is robust to endogeneity concerns in the next section). The weights correspond to the share of units of each UPC sold in the store in a given week. We estimate demand using household-level trip data, where each observation is a store visit. The price variable is merged in from the NielsenIQretail panel using the store identifier where the household trip occurred; thus, the price faced by the household during the visit, and is observed even if the household purchases no UPCs in a category.

To estimate demand flexibly, for each category we bin the product's price per ounce into deciles, and for each decile we regress the category-level volume purchased during a trip on an indicator for whether the individual is obese or not, and a rich set of fixed effects.[f] For each category, each dot in Figures 1 and 2 shows the estimated category-level volume purchased in a trip at a given price decile, and the solid colors lines show the line of best fit through all deciles.[g] To compute the estimated purchase volumes for obese and nonobese individuals, we predict the purchase volume at the modal values of the fixed effects, and only vary the inclusion of the obesity coefficient. The analysis thus controls for differences in observable characteristics that may be correlated with obesity. The error bars around the estimated purchase volumes for obese individuals show 95% confidence bounds around the estimated effect of obesity on demand. The estimated demand functions suggest three important patterns: First, individuals living with obesity have higher demand for vice categories. Second, for at least half of vice categories, the slopes of the demand curves for obese individuals are flatter than those for the nonobese, suggesting individuals with higher BMI have higher demand elasticities in these categories.[h] Third, for nonvice categories, there are generally no statistically significant differences between consumers with different obesity status.[i] Eggs and fresh packaged salads show higher levels of demand, but no differences in slope.

Parametric regression analysis of price sensitivity

In this section, we present our second approach to estimating demand, which uses a regression with individual, store, and time-specific fixed effects.[j] Our baseline regression specifications are

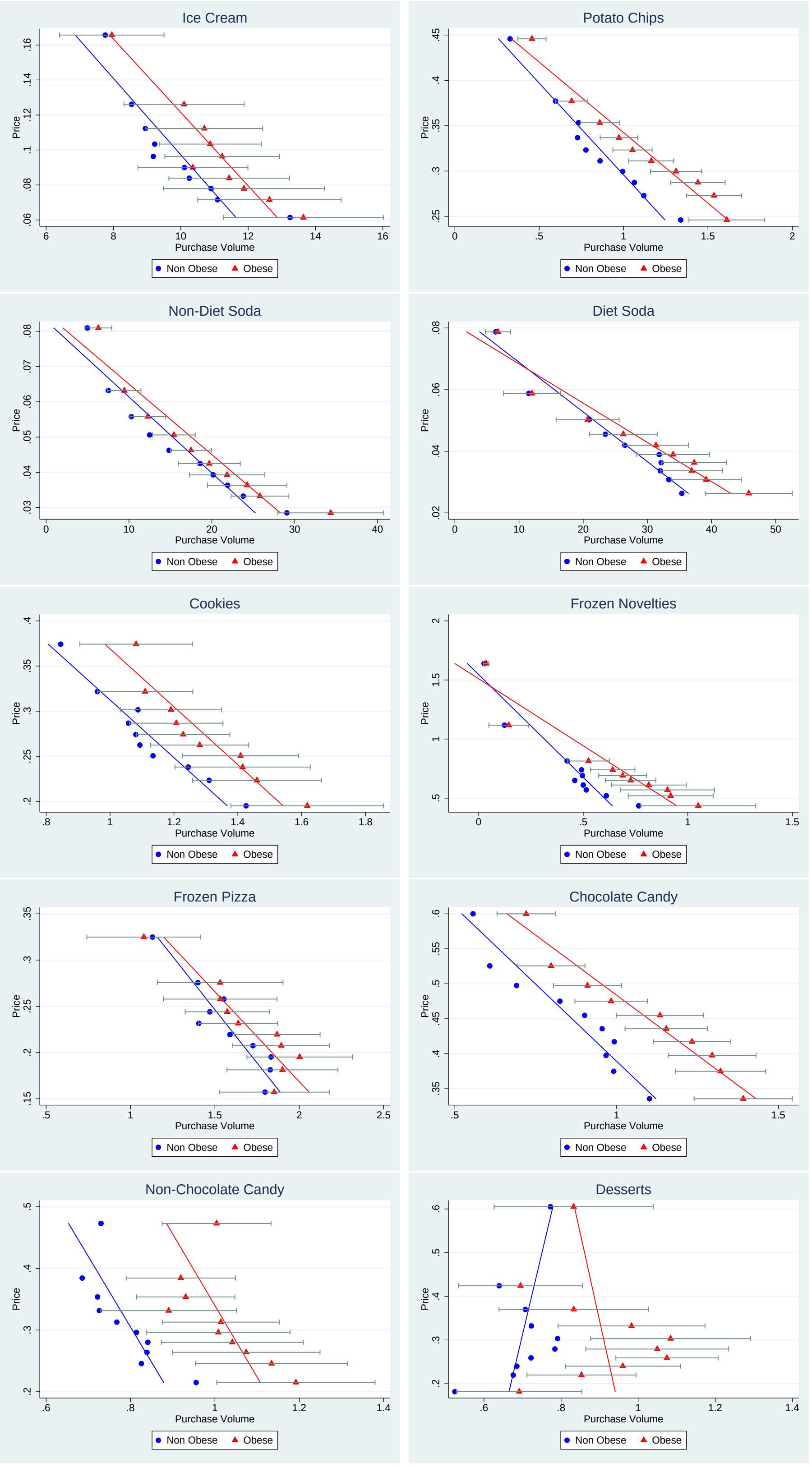

Fig. 1. Nonparametric estimates of demand curves for 10 vice categories.

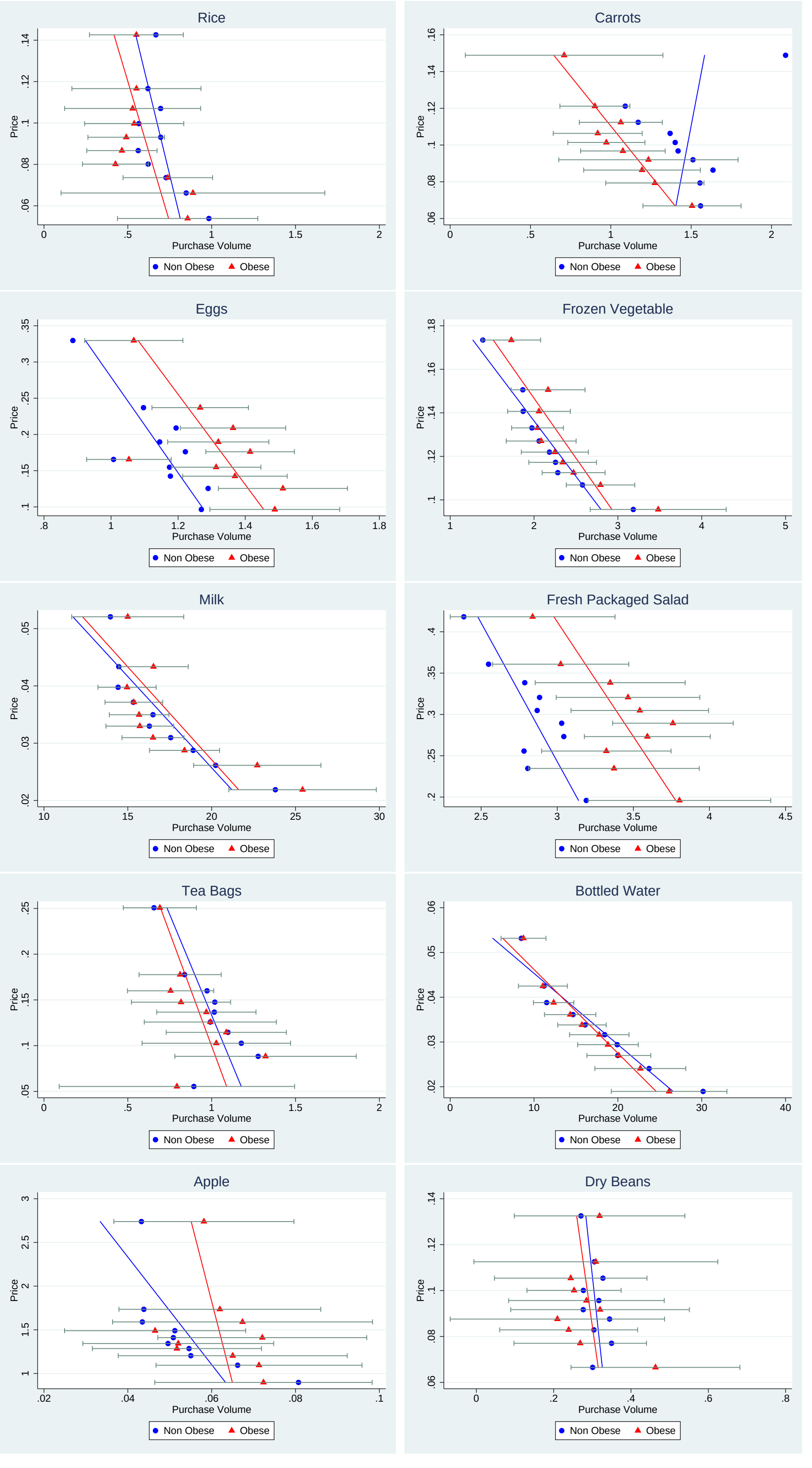

Fig. 2. Nonparametric estimates of demand curves for 10 nonvice categories.

based on Eq. 1 below:

$$\begin{aligned} y_{ijt} &= \beta_{1j} Inventory_{ijt} + \beta_{2j} BMI_{it} + \beta_{3j} \log(p_{ijt}) + \beta_4 \log(p_{ijt}) \times BMI_{it} \\ &+ \beta_{5j} Income_{it} + \beta_{6j} Income_{it} \times \log(p_{ijt}) \\ &+ \beta_7 Income_{it} \times \log(p_{ijt}) \times BMI_{it} + \alpha_{ij} + \gamma_{s(i,t)j} + \delta_{jT(t)} + \epsilon_{ijt}. \end{aligned} \quad (1)$$

The dependent variable in our main specification is the volume of all UPCs purchased in a category j by individual i, during a shopping trip indexed by t.[k] $Inventory_{ijt}$ represents individual i's imputed inventory for product category j at the time of trip t. It is used to control for potential stockpiling behavior.[l] BMI_{it} measures the individual's BMI at the time of trip t, and $Income_{it}$ is an indicator variable for whether a consumer is low income at the time of trip t. In addition to controlling for an individual-product category specific effect α_{ij}, we also include a week-product category fixed effect, $\delta_{jT(t)}$, to control for holiday effects, and a store fixed effect $\gamma_{s(i,t)j}$, which controls for whether an individual i shops at store s in trip t for product category j.[m] As was the case with the construction of demand curves in the previous subsection, the category-level price, p_{ijt}, is measured as the weighted average of the prices of all UPCs in category j that are offered in the store where the individual shops during trip t.[n] Prices are measured in price per ounce, and the weights used in averaging correspond to the share of units of each UPC sold in the store in a given week. We use a share-weighted average price in order to capture the fact that larger share brands may be more important in determining a consumer's purchase decision, reducing measurement error in the price variable.

The use of the weighted average price raises a potential endogeneity concern: the share weights could be functions of unobservables. In our preferred specification, we include store fixed effect to capture store-specific unobservables such as the positioning of category captain brands in better places on the store shelf, as well as the time controls to capture time-varying unobservables.

To understand how BMI and price sensitivity jointly affect purchases across all categories in the aggregate, we restrict β_4 and β_7 to be the same across all categories. We also present model estimates in SI Appendix Tables SI-29 and SI-30, where we allow these coefficients to vary across categories, in order to understand for which categories the effects are biggest. We present estimates using the logarithm of price as our preferred specification, since the logarithm of price should be more robust to aggregation across categories; if prices across categories differ by a particular percentage due to differences in package sizes (for example), this will factor out of the logarithm and be absorbed in the category-level fixed effects.

A partial set of results from estimation of Eq. 1 are shown in Table 1. Each of the specifications shows the estimated coefficients of interest, the BMI and price interaction, as well as the three-way interaction between price, BMI, and the low-income indicator, with different sets of store fixed effects. Our main coefficient of interest is the interaction between price and BMI, β_4. Focusing on the first row of Table 1, it is notable that this interaction is negative and statistically significant at the 1% level, indicating that individuals with higher BMI are more sensitive to price changes in vice categories in the aggregate. We find strongly significant and negative results even if we control for the specific store fixed effect, suggesting that the endogeneity bias arising from store level differences in promotional strategies does not seem to be a large concern.[o] In SI Appendix Tables SI-13 and SI-14, we present additional results with different levels of retailer fixed effects including channel, parent company, retailer, and store, and find the magnitudes of the main coefficients of interest are relatively insensitive to how the store fixed effects are defined, providing further support for the exogeneity of the price variable.[p] Table 2 shows a similar set of regressions for the nonvice categories, and shows that the interaction between BMI and price is insignificant. The lack of statistical significance of the price-BMI interaction in these regressions suggests that in nonvice categories, there is no difference in price sensitivity between individuals living with and without obesity. Interestingly, in both specifications we do not find a significant three-way interaction between price, BMI and the income indicator. This suggests that the BMI and price sensitivity relationship does not depend on income. In the category-by-category-level results (see SI Appendix Table SI-29), we find that for vice categories the estimated coefficients on the BMI and price interaction are almost always negative in sign, and in half of the 10 vice categories this interaction is statistically significant at a level of at least 10%. For nonvice categories, we do not find systematic patterns in the interaction between price sensitivity and BMI: estimated coefficients vary in sign, and are seldom significant (see SI Appendix Table SI-30).[q]

Table 1. Price and BMI interaction coefficients from purchase quantity regression, vice categories.

Regressor	(1)	(2)
Log(*Price*) × BMI	−0.1293976***	−0.0944423***
	(0.0348613)	(0.0272648)
Log(*Price*) × BMI × Low Income	−0.0181202	−0.0048351
	(0.0186061)	(0.0187061)
Category × Week	×	×
Category × Household	×	×
Category × Store		×

Notes: An observation in this regression an individual shopping trip in one of the 10 vice categories. The dependent variable is purchase volume in ounces within the 10 categories. Price is measured in dollars per ounce, and we use the logarithm of the price in this regression. All regressions include category-individual fixed effects, category-week fixed effect, and category-store(channel, parent company, retailer) fixed effect. The standard errors are two-way clustered at the category and individual level. *** indicates at 1% levels.

Overall, the results of the parametric demand estimation are consistent with those of the nonparametric demand approach: individuals with higher BMI are more price sensitive in vice categories, but they are not more price sensitive in the comparable nonvice categories. In SI Appendix Section "Robustness of Main Results", we present a number of robustness exercises to deal with potential concerns about data and model specification. One such concern is that the dependent variable, volume, may be skewed as it is zero for many trips. To deal with this, in SI Appendix Table SI-17 through SI-20 we present model estimates where we transform the dependent variable using an inverse hyperbolic sine transformation following Burbidge et al. (46). Our findings are robust to this transformation of the dependent variable. In SI Appendix Tables SI-21 through SI-24, we show our findings are robust to defining the dependent variable is an indicator for purchase within the category. In SI Appendix Tables SI-25 through SI-28, we show our findings are also robust to the definition of price (in levels rather than logarithms) and obesity (as an indicator rather than using BMI).

Discussion

In our work, we document that individuals who are higher on the BMI spectrum are more sensitive to price changes in vice product categories, but there is no evidence for such an interaction in

Table 2. Price and BMI interaction coefficients from purchase quantity regression, nonvice Categories.

Regressor	(1)	(2)
Log(*Price*) × BMI	−0.0041223	0.013274
	(0.0241068)	(0.0241572)
Log(*Price*) × Low Income × BMI	0.0028487	−0.0008988
	(0.0105941)	(0.0110346)
Category × Week	×	×
Category × Household	×	×
Category × Store		×

Notes: An observation in this regression an individual shopping trip in one of the 10 nonvice categories. The dependent variable is purchase volume in ounces within the 10 categories. Price is measured in dollars per ounce and we use the logarithm of the price in this regression. All regressions include category-individual fixed effects, category-week fixed effect, and category-store(channel, parent company, retailer) fixed effect. The standard errors are two-way clustered at the category and individual level.

nonvice categories. Our working hypothesis prior to performing our analysis was that we would find no significant differences in price sensitivity between higher and lower BMI individuals. Our results indicate that this is indeed the case for nonvice product categories, but we find that for vice categories, individuals with higher BMI appear to be more sensitive to price changes. We believe this finding will be of interest to both academics who conduct research on food demand, as well as policymakers interested in the differential effects of taxes on demand for unhealthy foods. We leave an investigation of the behavioral drivers of the relationship between BMI and price sensitivity to future research, as there may be a number of different factors at play. For example, there is some lab work suggesting that advertising and promotions in vice categories may be more salient to individuals with lower inhibition, and may be correlated with future weight gain (47, 48). An implication of this work is that it is possible that price changes in these categories (which are often advertised, especially if a product is discounted) could be more salient to consumers with higher BMI, which would be consistent with our findings. Future work could test whether price sensitivity differences, in addition to advertising, across product type and BMI can be replicated in lab setting.

Additional and related avenues for future research could involve investigating whether other types of interventions (e.g. information provision) can also interact with category-level demand and obesity status. We have conducted some preliminary investigation along these lines. One relates to the possibility that information may moderate the BMI-price sensitivity relationship we recover. We have conducted some preliminary work along these lines by estimating regressions similar to Eq. 1 with additional proxies for whether a consumer may have additional information about healthy eating interacted with BMI and price, to see if information provision may moderate the BMI-price sensitivity relationship. Our proxies rely on survey questions that ask individuals if they have been diagnosed with an obesity-related health condition, which would result in a conversation with their health provider about healthy eating. We do not find systematic evidence supporting such moderating effects: the three-way interaction terms we estimate are insignificant. This suggests that having more information about may not be as effective.

Turning to policy implications, our findings have important implications for existing and proposed policies such as soda taxes and taxes on other unhealthy products. The effectiveness of these different strategies will be a function of consumer's responsiveness. With respect to taxation, earlier work has shown mixed

Table 3. The effect of 10% price increase on purchase volume, level (first number) and percentage (third number), compared to baseline consumption (second number).

	Healthy	Overweight	Obese	Extreme Obese
NonDiet Soda				
Change (OZ)	−1.696	−1.72	−1.763	−1.847
Baseline (OZ)	9.146	9.516	9.764	10.672
Change (%)	−18.545	−18.069	−18.06	−17.305
Frozen Novelties				
Change (OZ)	−0.0226	−0.029	−0.039	−0.057
Baseline (OZ)	0.237	0.251	0.294	0.446
Change (%)	−9.546	−11.689	−13.247	−12.855
Chocolate Candy				
Change (OZ)	−0.07	−0.08	−0.098	−0.126
Baseline (OZ)	0.54	0.611	0.689	0.822
Change (%)	−13.16	−13.532	−14.223	−15.363
Potato Chips				
Change (OZ)	−0.073	−0.077	−0.084	−0.096
Baseline (OZ)	0.465	0.529	0.605	0.801
Change (%)	−15.667	−14.634	−13.83	−11.936
Ice Cream				
Change (OZ)	−0.785	−0.743	−0.693	−0.599
Baseline (OZ)	6.391	7.908	7.903	9.456
Change (%)	−12.275	−9.397	−8.767	−6.334
Diet Soda				
Change (OZ)	−2	−2.37	−2.854	−3.754
Baseline (OZ)	11.847	12.516	14.408	21.902
Change (%)	−16.88	−18.934	−19.812	−17.139
Non−Chocolate Candy				
Change (OZ)	−0.025	−0.029	−0.033	−0.042
Baseline (OZ)	0.523	0.558	0.645	0.796
Change (%)	−4.802	−5.114	−5.158	−5.285
Cookies				
Change (OZ)	−0.079	−0.086	−0.096	−0.115
Baseline (OZ)	0.698	0.827	0.848	1.025
Change (%)	−11.327	−10.433	−11.347	−11.184
Frozen Pizza				
Change (OZ)	−0.072	−0.085	−0.103	−0.136
Baseline (OZ)	0.706	0.767	0.775	0.969
Change (%)	−10.225	−11.105	−13.282	−14.046
Desserts				
Change (OZ)	−0.026	−0.026	−0.027	−0.027
Baseline (OZ)	0.421	0.487	0.542	0.664
Change (%)	−6.241	−5.409	−4.882	−4.111

Notes: The first row for each category is the predicted change in volume purchased from a 10% price increase, while the second shows the overall average volume purchased per trip in that category. The third row in each category shows the percentage change in volume purchased for that category.

effectiveness of such policies (9, 49–54). Our finding that individuals living with obesity are more sensitive to price changes in vice categories suggests that taxation of such goods will result in greater consumption reductions for these individuals. While our results do not predict the full range of consumer responses from a tax (such as substitution to other unhealthy products), our findings do suggest that taxes on unhealthy products could be particularly effective in reducing consumption by higher BMI individuals.

To demonstrate that such policies may be effective, we conduct analysis to quantify the impact of a 10% price increase in the vice categories we analyze. To conduct this analysis, we use the previously discussed category-level regressions presented in Eq. 1, We present the main estimated coefficients from this set of regressions in SI Appendix Table SI-29 We used the regression coefficients to predict the impact of a 10% price increase in each product category across four BMI brackets in Table 3 (we leave out the underweight group since it is only about 1% of the population).[r] For each category in the table, we present the predicted change in trip-level consumption in ounces (the first row titled "Change (OZ)"), the baseline level of trip-level consumption in ounces (the second row), and the predicted percentage change in trip-level consumption (third row). The exercise predicts large effects of such a tax or price increase, relative to baseline levels of consumption. Looking at the absolute changes in consumption, the predicted effects are generally increasing for individuals who are higher on the BMI spectrum; the only exception is the ice cream category. We note, however, that for the ice cream category such a tax would decrease purchase incidence more for individuals with higher BMI, so the different implication in this category (relative to the implication of the purchase incidence model) seems to be driven by different quantity responses. In percentage terms, the effects are usually increasing, except in the soda categories. The difference between the absolute and percentage changes for soda seems to be driven by the higher base levels of consumption for individuals who are higher on the BMI spectrum. Overall, our results suggest that taxes, especially those targeted at sugar-sweetened beverages, will decrease consumption for both high and low BMI individuals. Since the absolute effects are larger for higher BMI individuals, and the absolute reduction in consumption should correlated to larger reductions in calories, we would expect such taxes to proportionately curb obesity among individuals who are already obese, relative to preventing obesity among individuals who are not. The latter effect we would still expect to be significant, though, give the large effect sizes across all BMI spectrum.

We note that while a 10% price per ounce tax was one of the first soda taxes proposed (55), most current taxes on sodas and sugar-sweetened beverages imposed by US cities are set between 1 and 2 cents per once, which could generate even larger reductions since these tax rates are effectively much higher than 10%. We caution that such an interpretation of our exercise sidesteps a number of potentially important complications. In particular, in response to a price increase of these vice categories, individuals may substitute to other unhealthy goods. A complete analysis of the effect of such a tax would require us to estimate a category-level demand model that would allow elasticities of substitution to depend on individual characteristics, including obesity. Such an exercise is beyond the scope of this paper. In the presence of such substitution effects, our measured effect of the policy is likely an upper bound. Nevertheless, our exercise suggests that if substitution effects are small, then levying such a tax on vice categories could potentially be an effective approach to curbing growth in obesity.

Materials and methods

The data

Our analysis makes use of three datasets: the NielsenIQ Homescan Consumer Panel, the NielsenIQ Retail Scanner data, and the Circana MedProfiler survey which is a health survey that we link to the NielsenIQ Homescan Consumer Panel data. The NielsenIQ Homescan panel tracks the purchases of a panel of households across the United States of America. Households in the panel scan receipts from their shopping trips at grocery, drug, and related retailers, and thus the household panel data records all UPCs purchased in a given trip to a store. In our analyses, a unit of observation is a household-trip-category. UPC characteristics are provided in a product dictionary file, which includes both the UPC category as well as UPC volume; this file is merged into the household-trip data so the UPC-level data can be aggregated to the trip level. Category level volume is therefore the sum of volumes of all UPCs purchased by a household in a given trip for a given category. The Medprofiler survey is a large-scale survey that is administered by Circana to all Homescan panelists. The survey includes a broad range of health-related questions, which collect information about an individual's weight and height, eating/exercise habits, as well as different kinds of health conditions. The Medprofiler data that were available to us covers the years 2010 through 2015. About three quarters of Homescan households complete the Medprofiler survey: The number of households in the Homescan panel, and those who are in the Medprofiler data, are shown in the first two columns of Table 4. The NielsenIQ Retail Scanner data track all weekly, UPC level quantities sold and prices for a panel of stores that provide their data to NielsenIQ (quantity sold is for all customers who shop in the store, not just Homescan panelists). The retail data are used to construct the category-level prices that consumers are exposed to. As we discuss in the body of the paper, for each store, week and category we construct category-level weighted average prices from these data. The weights are the within store purchase shares (in units) for each UPC in a given week. The averages are taken across all UPCs that are designated to be within a given NielsenIQ product category. These average prices are merged into the consumer panel data at the trip level, using the trip's store identifier.

Table 4. Number of households by year and subsample of homescan and medprofiler.

Year	Homescan # of Households	1 Person Homescan # of Households	Medprofiler # of Households	1 Person Medprofiler # of Households
2010	60,658	15,483	38,750	8,009
2011	62,092	15,859	48,701	9,534
2012	60,538	15,303	39,651	8,570
2013	61,097	15,615	47,040	10,574
2014	61,557	15,703	41,573	9,828
2015	61,380	15,424	45,264	9,942
2016	63,150	15,375	41,163	9,470

Sample selection

In our paper, we limit the sample in our analysis to one-person households who complete the Medprofiler survey. We take this approach for several reasons. First, the Homescan data do not identify which member of the household is shopping in a given trip, so by restricting the sample to one-member households, we know that the shopper in the household will be the one who consumes the goods purchased. Even though our sample is limited to one person households, as can be seen in the third column of Table 4, we still retain about 8–10,000 households every year. Second, to check if our sample is representative or not, we compare single person households to the entire Medprofiler sample in terms of the distributions of several key observable demographic variables, in SI Appendix Tables SI-4 through SI-10. The tables show that the households are similar in many variables, outside income, gender and age. In our regressions, we either include these variables as controls, or include household fixed effects, to help deal with any sample selection concerns.

An additional sample restriction we make in the empirical analysis for this paper, is to only include individuals who are below 65 years old, but above 20 years old. We make this restriction for three reasons: (i), the BMI calculation may not be a good indicator of health for the elderly and young adults (56–58). In particular, the BMI guidance is different for elder adults.[s] (ii), an individual's

Table 5. Distribution of BMI brackets (person-year level), by medprofiler sample.

BMI Bracket	BMI Ranges	Medprofiler Percent household-years	1 Person Medprofiler Percent household-years
Underweight	<18.5	1.79	1.71
Healthy	18.5–24.9	28.39	27.61
Overweight	25–29.9	33.64	32.16
Obese	30–39.9	28.44	29.36
Extremely Obese	≥ 40	7.74	9.16

lifestyle may change significantly after the age of 65, when most people in the US retire.[t] Retired individuals may exhibit substantially different behavior than those who are working. (iii), our data oversample individuals above the age of 65, and including these individuals may skew our results if their behavior is substantially different from the general population. Excluding the elderly reduces our sample size by 29%. The number of households included in our sample after these exclusions is roughly 7,000.

Data description

A comparison of the distribution of BMI, one of our main variables of interest, between the entire Medprofiler dataset and one person households is shown in Table 5. The BMI is defined as an individual's body mass, measured in kilograms, divided by the square of the individual's height, measured in meters. It is a commonly used measure of obesity in clinical practice.[u] Individuals are typically classified into one of five BMI brackets, which are shown in the first column of the table. The second column shows the BMI cutoffs used to assign an individual to a particular bracket. An important takeaway from the table is that the BMI distribution presented in the table is very similar the population distribution of BMI in the United States of America during this period (59). Although individual weight is self-reported, the fact that BMI as measured in the survey mimics the nationwide distribution of BMI suggests that there are not systematic biases in how individuals report their weight. Additionally, SI Appendix Figures 3 and 4 show the distributions of weight in pounds, as well as BMI, for individuals over 20 years old for both samples. These figures also make it clear that the BMI distributions are similar for the one person and entire Medprofiler samples.

Notes

[a] The literature on sugar-sweetened beverage taxes is extensive. Their effectiveness has been studied in and out of the United States of America. Fletcher et al. (1, 2), Dharmasena and Capps (3), Finkelstein et al. (4), Goryakin et al. (5), Paarlberg et al. (6), Cornelsen and Smith (7), Cawley et al. (8), Seiler et al. (9) have delved deep in the US finding mixed results. While Andreyeva et al. (10), Zhen et al. (11), Colchero et al. (12), Barrientos- Gutierrez et al. (13), Nakamura et al. (14), Alsukait et al. (15), Teng et al. (16), Phonsuk et al. (17), Zhang et al. (18), Chatelan et al. (19) explore effects outside the US and finding some evidence in support of these taxes.

[b] A number of studies, including but not limited to Creighton (20), Allais et al. (21), Tiffin and Arnoult (22), Cawley (23), Jensen and Smed (24), Gustavsen and Rickertsen (25), Bødker et al. (26), Hernández-F et al. (27), Krishnamoorthy et al. (28), Le Bodo et al. (29), Aguilar et al. (30), have also looked into taxes levied on fat or other junk-foods.

[c] https://www.cdc.gov/obesity/data/adult.html

[d] https://www.cdc.gov/nchs/nhanes/index.htm

[e] When comparing our findings to those presented in Zhen et al. (42), certain similarities and substantial differences emerge. While our conclusions regarding the effectiveness of a price increase or tax exhibit some consistency with Zhen et al. (42), we encounter notable disparities in results concerning price sensitivity, income, and obesity.

For instance, in our research, we uncover evidence suggesting that consumers with obesity respond more significantly to price discounts in unhealthy food categories, which contradicts the findings of Zhen et al. (42). Moreover, while Zhen et al. (42) indicate that non-obese consumers exhibit greater price elasticity than obese consumers in fruits and vegetables, our analysis reveals no evidence of such distinctions in packaged fresh salads, apples, or carrots.

We attribute these differences to both the data utilized and the methodology employed. Zhen et al. (42) relied on a 7-day survey of household purchases conducted between April 2012 and January 2013, whereas our investigation is based on continuous food purchases made by households from 2010 to 2015, complemented by self-reported annual height and weight data for the same households. The extended timeframe of our data, coupled with our flexible demand modeling approach, enables us to control for a comprehensive set of individual and store fixed effects, effectively addressing unobserved consumer and store variations. Methodologically, the analyses in both Okrent and Sweitzer (41) and Zhen et al. (42) rely on expenditure-share based demand models (the Almost Ideal Demand System and Exact Affine Stone Index, respectively), and do not include household or store fixed effects as we do.

[f] The volume purchased in a category may be zero during a trip if the household purchases no UPCs in the corresponding category. The fixed effects capture age, income, occupation, ethnicity, education, county code, gender, Hispanic origin, and the identifier of the store the consumer shopped at.

[g] We also replicate Figures 1 and 2 using an indicator for purchase of a product in the category as the dependent variable, and find similar results. The graphs are shown in Supplemental Appendix Figures 5 and 6.

[h] Visually, there are differences in slope for ice cream, potato chips, diet soda, frozen novelties, frozen pizza, and chocolate candy. In the next section, we will statistically test whether the demand curves' slopes are different both in the aggregate and on a category-by-category basis. One of the lines of best fit through the demand for baked desserts looks to be increasing; however, this seems to be due to idiosyncratic demand estimates at the top and bottom price deciles. The demand estimates below this decile appear more consistent with a decreasing relationship between price and quantity.

[i] Again, for the carrots category the lines of best fit seems to suggest a counterintuitive relationship between price and quantity, but this seems to be due to the estimated demand for the highest price decile being substantially higher than the rest of the sample for non obese individuals.

[j] As discussed in details in the next section, our analysis is based on one-member households.

[k] This volume will be zero if the individual purchases no UPCs in the category during the trip.

[l] To measure inventory, we assume a constant daily consumption rate within a category. We compute the consumption rate as the total quantity, in ounces, that the individual purchases over the time she is observed, and divide by the total number of days over which we observe purchases. Inventory at the beginning of day t is measured as total quantity purchased prior to that day minus total consumption. An individual's inventory at the beginning of the sample will be absorbed by their fixed effect.

[m] We code store fixed effects using NielsenIQ 's store identifier, which is disaggregated.
[n] In the NielsenIQ store data, prices are measured at the weekly level.
[o] We also find that the coefficient on the price variable, β_{3j}, is similar in magnitude when comparing the specification with store fixed effects to that without, which provides additional evidence that price endogeneity is not a severe concern.
[p] The NielsenIQ store code is the finest level of detail regarding the store classification, as it is a code that uniquely identifies a particular retail location. The retailer code is a unique identifier for a store's retail chain, while the parent company identifier identifies the corporation which owns a retailer. Channel captures the broad category of the retailer, e.g. grocery, drug or mass merchandizer.
[q] This null results for nonvice categories also holds when purchase incidence is used as the dependent variable.
[r] To be clear, for each individual in the data, we predict the impact of the price increase conditional on both their income status and BMI, since we allow price sensitivity to vary with both demographic factors. Including income is important because if lower income people are more inelastic in certain categories, it could mitigate the impact of a price increase on obese individuals, negating some of the benefits of a price cut. Income effects like this are found in the context of soda taxes in Seiler et al. (9).
[s] https://thegeriatricdietitian.com/bmi-in-the-elderly/
[t] About 70% of the US population aged 65 or above is retired, see https://www.bls.gov/opub/btn/volume-4/people-who-are-not-in-the-labor-force-why-arent-they-working.htm.
[u] According to the US Center for Disease Control, "The correlation between the BMI and body fatness is fairly strong", and "The accuracy of BMI as an indicator of body fatness also appears to be higher in persons with higher levels of BMI and body fatness" (https://www.cdc.gov/healthyweight/assessing/bmi/adult_bmi/index.html, retreived on 2021 November 11).

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Supplementary Material

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Author Contributions

Y.B., M.O., E.W. and E.J. designed research; Y.B. and M.O. performed research; and Y.B., M.O., E.W., and E.J. wrote the paper.

Previous presentation

These results were previously presented at Marketing Science(2017), UTD FORMS (2019), Industrial Organization and the Food Industry(2019), BIOMS (2019).

Data Availability

Our dataset is constructed using NielsenIQ's Homescan Consumer Panel, the NielsenIQ Retail Scanner data, and the Circana MedProfiler Survey. These datasets are available to researchers who sign the appropriate confidentiality agreements with NielsenIQ and Circana. The authors can provide replication code to researchers who have been approved for access to the data.

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https://www.ers.usda.gov/topics/food-markets-prices/food-prices-expenditures-and-establishments/using-proprietary-data/

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