## Exploring Strategies to Promote a Healthier Food Environment

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# Exploring Strategies to Promote a Healthier Food Environment 

Sophia V. Hua

A dissertation submitted to the Department of Nutrition in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the subject of Population Health Sciences

(Track: Public Health Nutrition)

Harvard University

Boston, Massachusetts

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# Strategies to Promote a Healthier Food Environment 


#### Abstract

Excess weight, which affects over 70\% of the population in the United States, has been associated with a plethora of chronic diseases, including diabetes, cardiovascular disease, some cancers, and mortality. As posited by the ecological model of behavior change, our environment shapes the way we behave, so to change behavior requires changing the ecology in which we live. Therefore, the three papers that make up this dissertation explores various strategies to promote a healthier food environment.

In paper 1, we asked how beverages with child-directed marketing compare to beverages without such marketing with respect to front-of-package claims and nutrient profile. We found that sugary fruit drinks with child-directed marketing were more likely to show front-of-package micronutrient claims ( $\mathrm{OR}=2.1,95 \% \mathrm{Cl}=1.5,3.1$ ) and contained more vitamin C (18.5\% daily value, $95 \% \mathrm{Cl}=1.6,35.5$ ) than fruit drinks without child-directed marketing. These results suggest that beverages companies may be fortifying their sugary beverages with vitamin C in order to market their beverages with micronutrient claims. We put forth a series of recommendations to change the marketing landscape.

In paper 2, we examine whether beverage taxes influence beverage prices and consumer behavior by studying the impact of the Philadelphia beverage tax in one of the largest longitudinal studies of beverage taxes to date. Our results showed that the average


price of taxed beverages in Philadelphia increased by 1.6 cents-per-ounce ( $95 \% \mathrm{Cl}: 1.1,2.0$; 28.7\% increase; 107\% pass-through) compared to Baltimore in the year after the beverage tax. This change in price led to loyalty cardholders in Philadelphia purchasing 6.8 ounces ( $95 \% \mathrm{Cl}:-7.3,-6.2$ ) fewer of taxed beverages per transaction compared to Baltimore post-tax. Both the price and volume of nontaxed beverages in Philadelphia compared to Baltimore did not significantly differ after the beverage tax was implemented. This study provides strong evidence at the individual-level that beverage taxes can alter consumer behavior.

In paper 3, we studied whether nudges on restaurant menus can influence which portion sizes diners select in an online randomized controlled experiment. We found that regardless of pricing scheme, participants were more likely to select a reduced portion entrée if we named the smaller portion "Standard" or "Just Right" compared to leaving it blank. We show evidence of an effective low-cost strategy to promote selection of lower-calorie smaller portions when dining out. Restaurants can potentially benefit from such a menu change by not only reducing food waste, but also expanding their customer base to include those who seek healthier alternatives when dining out.

Together, these papers make the argument that there are many tools we can use to change our environment. Although no single action can solve the issue of excess weight, better beverage packaging regulations, beverage taxes in more cities, and menu changes in chain restaurants can help ensure that people are making healthy choices at every stage of life.

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## Dedication

I would not have completed my PhD without the incredible support from my parents, my godparents, my siblings, and my partner. I dedicate this dissertation to them.

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Figure 3.4 Predicted probabilities for choosing the smaller portion by pricing scheme in an online randomized controlled ordering trial ( $n=2,205$ )

# Paper 1: Child-Directed Marketing, Health Claims, and Nutrients in Popular Beverages 

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#### Abstract

Introduction: Fruit drinks are a major source of added sugar in children's diets. This study describes the associations between front-of-package child-directed marketing (i.e., sports, fantasy, or child-directed imagery; child-directed text) and (1) health-related claims and (2) nutrient content of fruit drinks, $100 \%$ juices, and flavored waters.

Methods: Beverage purchase data from a national sample of 1,048 households with children aged 0-5 years were linked with front-of-package label and nutrition data to conduct a content analysis on fruit drinks ( $n=510$ ), 100\% juices ( $n=337$ ), and non-carbonated flavored waters $(n=40)$ in 2019-2020. Unstratified and stratified regression models assessed the differences in the prevalence of claims (macronutrient, micronutrient, natural/healthy, and fruit and juice), non-nutritive sweeteners, and nutrient content (calories, total sugar, and percent daily value of vitamin C) between drinks with and those without child-directed marketing in 2021.

Results: Fruit drinks with child-directed marketing were more likely to show front-of-package micronutrient claims ( $\mathrm{OR}=2.1,95 \% \mathrm{Cl}=1.5,3.1$ ) and contained more vitamin C ( $18.5 \%$ daily value, $95 \% \mathrm{Cl}=1.6,35.5$ ) than fruit drinks without child-directed marketing. $100 \%$ juices with child-directed marketing contained less vitamin C ( $35.6 \%$ daily value, $95 \% \mathrm{CI}=57.5,13.8$ ) and 3.0 ( $95 \% \mathrm{Cl}=5.5,0.4$ ) fewer grams of sugar than $100 \%$ juices without child-directed marketing. Flavored waters with child-directed marketing contained less vitamin C ( $37.9 \%$ daily value, $95 \%$ $\mathrm{Cl}=68.1,7.6$ ) than flavored waters without child-directed marketing.

Conclusions: The combination of child-directed marketing with health-related claims may mislead parents into believing that fruit drinks are healthy and appealing to their children, highlighting the need for government regulation of sugary drink marketing.


## INTRODUCTION

Research has shown that marketing is effective in influencing children's choice and intake, and that marketing of unhealthy foods can lead to overconsumption ${ }^{1}$ and contribute to childhood obesity, which currently impacts 1 in 5 children in the U.S. ${ }^{2,3}$ In the U.S., food and beverage companies spend approximately $\$ 1$ billion advertising products to children aged <12 years, many of which are high in calories and added sugar. ${ }^{4}$ Children are particularly susceptible to marketing as they do not understand the persuasive intent of such tactics, ${ }^{5-7}$ and busy parents are susceptible to the "pester power" of their children. ${ }^{8,9}$ As such, there have been efforts to restrict marketing toward children. Internationally, Chile's Law of Food Labeling and Advertising put into place a series of regulations requiring a warning label and limiting the use of child-directed marketing techniques such as cartoons on products that contain added sugar, sodium, or saturated fat, and exceed recommended thresholds for calories, sodium, total sugar, or saturated fat. ${ }^{10}$ Many more countries—including Mexico and Taiwan—have federally mandated restrictions on the types of foods that can be advertised on children's TV networks. ${ }^{10}$ In the U.S., though, such efforts have been mostly voluntary and unsuccessful. ${ }^{11}$

Despite industry-led pledges to advertise healthier products to children, ${ }^{12,13}$ children continue to see advertisements for foods of poor nutritional quality. ${ }^{14-17}$ One of the main products advertised to children in the U.S. are sugar-sweetened beverages (SSBs), the number one source of added sugars in the American diet. ${ }^{18}$ Some of the most commonly consumed SSBs among children aged <8 years are fruit drinks, defined as fruit-flavored drinks that contain $<100 \%$ juice with or without added sugars or nonnutritive sweeteners (NNSs), ${ }^{19-22}$ and are not recommended for young children. ${ }^{23}$ Unlike fruit drinks, which include diluted juices, $100 \%$ juices
do not contain added sweeteners, but excessive consumption can still lead to weight gain. ${ }^{23-25}$ Thus, the Dietary Guidelines for Americans 2020-2025 and the American Academy of Pediatrics recommend limiting 100\% juices to children, but national averages suggest children currently consume more than the recommended amount. ${ }^{18,23,26}$ Consumption of flavored waters, which may contain added sugars and NNSs, has also increased from 2006 to 2017 among U.S. children. ${ }^{27}$

Perhaps the biggest industry pledge in the U.S. toward healthier marketing for children is the Children's Food and Beverage Advertising Initiative, but it does not cover marketing on product packaging and labeling. ${ }^{12}$ Currently, popular beverages for children such as fruit drinks may have product packaging that leads to confusion about the drinks' healthfulness. For instance, claims related to fruit/juice (e.g., "fruit drink") and nutrition (e.g., "100\% Vitamin C") are highly prevalent on fruit drink front-of-package (FOP) labels. These claims may be misleading because they often appear on drinks with high levels of added sugar, thus falsely implying that they are healthy. ${ }^{28-33}$ Additionally, labeling guidelines are not conducive to parents' understanding of whether the beverages they are purchasing contain added sweeteners, because NNSs do not have to be listed on the Nutrition Facts Panel or declared on the FOP. ${ }^{34}$ Their disclosure is only mandated on the back-of-package ingredients list. In 2016, the U.S. Food and Drug Administration issued a redesign of the Nutrition Facts Panel to include both total and added sugar, but not NNSs. ${ }^{35}$ Furthermore, these beverages feature childdirected marketing, which can include spokes-characters, bright colors, and games, all of which have been shown to influence children's dietary intake and are not proactively regulated by the Federal Trade Commission despite falling under its purview. ${ }^{36,37}$

The association between child-directed marketing and the nutritional profile of beverages is not well explored in the U.S. In 2014, the Rudd Center for Food Policy and Obesity published a report detailing that children's drinks in the U.S. had fewer calories than other similar beverages that were not marketed to children, likely because of the greater use of NNSs in children's products. ${ }^{38}$ Outside of the U.S., researchers in Chile found that beverages with child-directed marketing had more total sugar and calories than beverages without. ${ }^{39}$ CruzCasarrubias et al. ${ }^{40}$ found similar results in an assessment of sugary drinks in Mexico: Beverages with child-directed marketing had higher levels of sugar and saturated fats than beverages without such marketing. These beverage results are consistent with several other studies that focused on foods, suggesting an overall association between products with child-directed marketing and less healthy nutrient profiles. ${ }^{41-44}$

Though past studies have examined the relationship between FOP claims on fruit drinks and their nutritional profile, ${ }^{30}$ few if any studies have assessed the relationship between the nutrient profile of fruit-flavored drinks (i.e., fruit drinks, $100 \%$ juices, and non-carbonated flavored waters) and FOP child-directed marketing. As efforts to regulate child-directed marketing in the U.S. have been stymied, ${ }^{11}$ it is important to understand how such marketing tactics are associated with the healthfulness of products marketed to children given the lack of regulation in this sphere. It is particularly important to understand the marketing and nutrient profile of products that are purchased by families with young children to better inform government action. Thus, the objectives of this paper are to examine the association between the presence of child-directed FOP marketing on fruit drinks, $100 \%$ juice, and non-carbonated
flavored waters purchased by households with young children and: (1) the presence of healthrelated claims and non-nutritive sweeteners and (2) the nutritional profile of these beverages.

## METHODS

A content analysis of FOP marketing on fruit drinks, 100\% juices, and non-carbonated flavored waters purchased by households with young children was conducted using previously described methods. ${ }^{29}$ To identify beverages purchased by households with young children, 2 data sources were used. The first was acquisition data from households with children aged 0-5 years from the U.S. Department of Agriculture's National Household Food Acquisition and Purchase Survey ( $n=748$ households with children aged $0-5$ years of 4,826 total households) collected in 2012-2013. To complement these national data with newer purchasing information, loyalty card-linked sales data from households with children aged 0-5 years with loyalty cards at a large, Northeast supermarket chain in 2016-2017 ( $n=300$ ) were also used. Using two data sets created an expanded time window for the sample and captured changes in FOP labels as well as trends in new products. These data sets were appended, and beverages with duplicate Universal Product Codes (unique identifiers for each product) were removed. The remaining observations were merged by Universal Product Code with Label Insight data, which contains detailed package and nutrition information for each purchased beverage, as well as details about when the information was collected. ${ }^{45}$ The final sample was restricted to unique fruit drinks ( $n=510$ ), $100 \%$ juices ( $n=337$ ), and non-carbonated flavored waters ( $n=40$ ) that were purchased by households with children aged 0-5 years and had package information in Label Insight (Figure 1.1). Despite the differences in time periods that the data were collected, the distribution of the beverage types between the two data sets was similar.

Figure 1.1 Examples of fruit drinks, $100 \%$ juices, and non-carbonated flavored waters with and without child-directed marketing in our sample ( $n=887$ ).

| Wruit drinks <br> ( $\mathrm{n}=510$ ) | Without child-directed <br> marketing | With child-directed marketing |
| :--- | :---: | :---: | :---: |

## Measures

The FOP child-directed marketing and health-related claims were captured using a codebook adapted from a previous study on beverage FOP marketing. ${ }^{39}$ Child-directed marketing was defined as child-directed imagery (e.g., anthropomorphized animals), sports or fantasy imagery, or child-directed text (e.g., exaggerated fonts or flavors such as "Polar Blast"). Health-related claims included macronutrient claims (any claims that included fat, sugar, protein, or calories), micronutrient claims (any claims regarding vitamins, minerals, probiotics, and antioxidants), healthy/natural claims (any claims about being healthy or natural), and fruit and juice claims (any claims that the product contains fruits, vegetables, or juice). Two coders were trained and independently coded a random sample of $20 \%$ of the products to assess interrater reliability. After removing variables with $<80 \%$ inter-rater reliability ( $n=7$ ) and removing ( $n=4$ ) or revising variables for clarity ( $n=9$ ), the codebook was updated, and the remaining $80 \%$ of the products were split and coded independently in 2019-2020. The codebook is available upon request.

Beverage nutrition information was captured by Label Insight between 2012 and 2020. NNSs were sweeteners that did not contain calories, such as stevia and aspartame. For beverages missing calories ( $n=13,1.5 \%$ ) and total sugar ( $n=56,6.3 \%$ ) information, the authors rechecked the Nutrition Facts Panel on the Label Insight website, and if the amount still could not be identified, the manufacturer's website was used. For beverages missing vitamin C information ( $n=200,22.5 \%$ ), a multistep approach was used in which the next step was followed if the previous step was unsuccessful: (1) rechecked the Nutrition Facts Panel on the Label Insight website; (2) assigned 0\% daily value (\% DV) vitamin C to products that contained
no juice or ascorbic acid, or had a disclaimer that the item was "not a significant source of vitamin C"; (3) referred to the manufacturer's website; and (4) referred to the U.S. Department of Agriculture FoodData Central website. ${ }^{46}$ These steps resulted in complete nutrition information for all beverages in the sample ( $n=887$ ).

## Statistical Analysis

Logistic regression models were used to assess the association between the presence of FOP child-directed marketing (independent variable, yes/no) and the presence of NNSs and four different categories of FOP health-related claims (macronutrient, micronutrient, healthy/natural, fruit and juice; dependent variables, yes/no). First, analyses were performed across all beverages controlling for beverage type. No other covariates were included. For the model predicting the presence of NNSs, $100 \%$ juices were not included as they do not contain NNSs. Second, models were stratified by drink type to examine beverage-specific associations. Stratified results for fruit drinks and 100\% juices are reported; because of limited statistical power to analyze non-carbonated flavored waters owing to the small number of these beverages in the data set, these exploratory results are presented in Appendix Tables 1.1 and

## 1.2.

Linear regression models were used to assess the association between the presence of FOP child-directed marketing (independent variable, yes/no) and the nutritional profile of the beverages (dependent variables), stratified by beverage type. Three nutrients were examined: calories per package serving, grams of total sugar per package serving, and \% DV of vitamin C per package serving. Sugar and vitamin C were chosen as outcome measures because claims
about vitamin C and sugar are common on fruit drinks. ${ }^{30}$ All statistical tests were conducted in Stata, version 16.1 in 2021.

## RESULTS

The total sample included 510 fruit drinks, 337 100\% juices, and 40 non-carbonated flavored waters. Among fruit drinks, approximately $45 \%$ had child-directed marketing, and similar percentages had macronutrient claims, micronutrient claims, fruit and juice claims, and NNSs. Among 100\% juices, 16.3\% had child-directed marketing, 52\% had micronutrient claims, and $98 \%$ had fruit and juice claims. Similar to fruit drinks, $45 \%$ of non-carbonated flavored waters had child-directed marketing, though $80 \%$ had macronutrient claims and $97.5 \%$ had healthy/natural claims. Additionally, 80\% of non-carbonated flavored waters had NNSs. Fruit drinks contained an average of 71.5 calories and 16.6 grams of total sugar, and $100 \%$ juices had an average of 115.7 calories and 24.9 grams of total sugar. Non-carbonated flavored waters had the least number of calories and sugar on average at 21.0 and 5.4 grams, respectively. With respect to vitamin C content, 100\% juices had the most ( $92.6 \%$ DV), followed by fruit drinks ( $46.8 \% \mathrm{DV}$ ) and non-carbonated flavored waters (31.4\% DV) (Table 1.1).

Table 1.1 Presence of Child-Directed Marketing, Mean Nutrient Content, and Prevalence of Claims by Beverage Type ${ }^{\text {a }}$

| Variable | Fruit drinks ${ }^{\text {a }}$ $n=510$ | $\begin{gathered} \text { 100\% Juices }{ }^{\text {a }} \\ \mathrm{n}=337 \end{gathered}$ | Non-carbonated flavored waters ${ }^{\text {a }}$ $n=40$ |
| :---: | :---: | :---: | :---: |
| Presence of child-directed marketing, \% (n) | 44.5 (227) | 16.0 (54) | 45.0 (18) |
| Calories, mean (SD) | 71.5 (55.1) | 115.7 (41.6) | 21.0 (37.1) |
| Sugar (g), mean (SD) | 16.6 (13.1) | 24.9 (8.9) | 5.4 (9.9) |
| Vitamin C \% daily value, mean (SD) | 46.8 (97.4) | 92.6 (75.9) | 31.4 (50.2) |
| Presence of non-nutritive sweeteners, \% (n) | 47.1 (240) | 0 (0) | 80.0 (32) |
| Presence of macronutrient claim, \% (n) | 49.0 (250) | 44.8 (151) | 80.0 (32) |
| Presence of micronutrient claim, \% (n) | 47.3 (241) | 51.9 (175) | 57.5 (23) |
| Presence of healthy/natural claim, \% (n) | 62.4 (318) | 72.7 (245) | 97.5 (39) |
| Presence of fruit and juice claim, \% (n) | 47.3 (241) | 97.6 (329) | 5.0 (2) |

${ }^{a}$ Fruit drinks were defined as: fruit-flavored drinks, frozen and liquid concentrates, and powdered mixes with less than $100 \%$ fruit juice and with or without added sugars or nonnutritive sweeteners; 100\% juices were defined as: 100\% fruit juice or fruit/vegetable juice blends, or coconut water with no added sugars or non-nutritive sweeteners; non-carbonated flavored waters were defined as: non-carbonated drinks with water in the statement of identity and with added fruit flavors, with or without added sugars or non-nutritive sweeteners.

The presence of FOP child-directed marketing was associated with increased odds of having macronutrient claims ( $\mathrm{OR}=1.4,95 \% \mathrm{Cl}=1.1,1.9$ ), micronutrient claims ( $\mathrm{OR}=1.5,95 \%$ $\mathrm{Cl}=1.1,2.0$ ), and natural or healthy claims ( $\mathrm{OR}=1.5,95 \% \mathrm{Cl}=1.1,2.0$ ), and decreased odds of having fruit and juice claims ( $\mathrm{OR}=0.6,95 \% \mathrm{Cl}=0.4,0.8$ ) after controlling for drink type. After stratifying by drink type, one main association persisted: Compared with fruit drinks without child-directed marketing, those with child-directed marketing had more than twice the odds of having micronutrient claims ( $\mathrm{OR}=2.1,95 \% \mathrm{Cl}=1.5,3.1$ ). No other stratified associations between health-related claims and presence of child-directed marketing were significant (Table 1.2 and Appendix Table 1.1).

Table 1.2 Odds ${ }^{\text {a }}$ of Claims and Child-Directed Marketing ${ }^{\mathrm{b}}$ on Beverage Labels, Before and After Beverage Type Stratification ${ }^{\text {c }}$

| Health-related claim | Beverages with child-directed marketing (All beverages $\mathrm{n}=299$; fruit drinks $\mathrm{n}=227$; 100\% juice=54) vs control (All beverages $\mathrm{n}=588$; fruit drinks $\mathrm{n}=283$; $100 \%$ juice $\mathrm{n}=283$ ) |
| :---: | :---: |
|  | OR (95\% CI) |
| All beverages ( $\mathrm{n}=888)^{\text {c }}$ |  |
| Macronutrient claims | 1.4 (1.1, 1.9)* |
| Micronutrient claims | 1.5 (1.1, 2.0)** |
| Natural or healthy claims | 1.5 (1.1, 2.0)* |
| Fruit and juice claims | $0.6(0.4,0.8)^{* * *}$ |
| Presence of non-nutritive sweeteners ${ }^{\text {e }}$ | $1.2(0.8,1.6)$ |
| Fruit drinks ( $\mathrm{n}=510$ ) |  |
| Macronutrient claims | 1.3 (0.9, 1.9) |
| Micronutrient claims | 2.1 (1.5, 3.1)*** |
| Natural or healthy claims | 1.4 (1.0, 2.1) |
| Fruit and juice claims | 0.9 (0.6, 1.2) |
| Presence of non-nutritive sweeteners | 1.0 (0.7, 1.5) |
| 100\% juice ( $\mathrm{n}=337$ ) |  |
| Macronutrient claims | 1.0 (0.5, 1.8) |
| Micronutrient claims | 0.7 (0.4, 1.3) |
| Natural or healthy claims | 1.2 (0.6, 2.4) |
| Fruit and juice claims | 1.3 (0.2, 11.2) |
| Presence of non-nutritive sweeteners | $-^{f}$ |

Note: Boldface indicates statistical significance ( ${ }^{*} p<0.05 ;{ }^{* *} p<0.01 ;{ }^{* * *} p<0.001$ ).
${ }^{\text {a }}$ Logistic regression models used to analyze data.
${ }^{\text {b }}$ Child-directed marketing is defined as containing: child-directed text and imagery, including image of a child, adult, animal, anthropomorphized ingredient/object; sports or fantasy imagery; or child-directed text, including use of unconventional or exaggerated fonts, indication of an extreme experience or taste (i.e., made up flavors), claims related to enjoyment or fun, and words that reference children.
 waters ( $\mathrm{n}=40$ ).
${ }^{d}$ Control group includes beverages without child-directed marketing.
${ }^{e}$ Only fruit drinks and non-carbonated flavored waters were included in the unstratified model predicting the presence of non-nutritive sweeteners as $100 \%$ juices by definition cannot contain non-nutritive sweeteners; $n=847$ ).
${ }^{f} 100 \%$ juices do not contain non-nutritive sweeteners.

Using linear regression to examine nutrient content, fruit drinks with child-directed marketing were associated with an absolute $18.5 \%(95 \% \mathrm{Cl}=1.6,35.5)$ greater \% DV of vitamin C than fruit drinks without child-directed marketing. There was no association between total sugar and presence of child-directed marketing. Conversely, the presence of child-directed marketing on $100 \%$ juices was associated with 3.0 ( $95 \% \mathrm{Cl}=-5.5,-0.4$ ) fewer grams of total sugar and an absolute $35.6 \%(95 \% \mathrm{Cl}=-57.5,-13.8$ ] lower \% DV of vitamin C when compared with the same beverage types without child-directed marketing. There was no association between calorie content and the presence of child-directed marketing in either beverage types. In exploratory analyses of flavored waters, similar patterns to $100 \%$ juice were found with regard to the examined nutrients (Table 1.3 and Appendix Table 1.2).

Table 1.3 Nutrient Analysis ${ }^{a}$ for Fruit Drinks ( $n=510$ ) and $100 \%$ Juices ( $n=337$ ) With and Without Child-Directed Marketing ${ }^{\text {b }}$

| Variable | Beverages with children-directed marketing (fruit drinks $\mathrm{n}=227$; $100 \%$ juice=54) vs control ${ }^{\text {c }}$ (fruit drinks $\mathrm{n}=283$; 100\% juice $\mathrm{n}=283$ ) |
| :---: | :---: |
|  | $\beta$ (95\% CI) |
| Fruit drinks ( $\mathrm{n}=510$ ) |  |
| Calories (kcal) | -3.8 (-13.5, 5.8) |
| Total sugar (g) | -1.0 (-3.3, 1.3) |
| Vitamin C (\% DV) | 18.5 (1.6, 35.5)* |
| 100\% juice ( $\mathrm{n}=337$ ) |  |
| Calories (kcal) | -7.5 (-19.7, 4.6) |
| Total sugar (g) | -3.0 (-5.5, -0.4)* |
| Vitamin C (\% DV) | -35.6 (-57.5, -13.8)** |

Note: Boldface indicates statistical significance *p<0.05; **p<0.01; ***p<0.001).
${ }^{\text {a }}$ Linear regression models used to analyze the data.
${ }^{\text {b }}$ Child-directed marketing is defined as containing: child-directed text and imagery, including image of a child, adult, animal, anthropomorphized ingredient/object; sports or fantasy imagery; or child-directed text, including use of unconventional or exaggerated fonts, indication of an extreme experience or taste (i.e., made up flavors), claims related to enjoyment or fun, and words that reference children.
${ }^{\text {c Control }}$ group includes beverages without child-directed marketing.

## DISCUSSION

In a sample of 887 fruit drinks, $100 \%$ juices, and non-carbonated flavored waters purchased by households with children aged 0-5 years, FOP child-directed marketing on fruit drinks was associated with more than twice the odds of having micronutrient claims and higher levels of vitamin C. Child-directed marketing on $100 \%$ juices, on the other hand, was associated with nearly 35 percentage points less vitamin C based on \% DV and 3 fewer grams of total sugar than $100 \%$ juices without child-directed marketing.

In this sample, $>85 \%$ of fruit drinks with any vitamin C had the nutrient fortified, suggesting that companies fortify fruit drinks with vitamin $C$ as a marketing ploy to attract parents. In a study done on the effects of food fortification, researchers showed that vitamin
fortification may increase purchasing. ${ }^{47}$ Currently, the Food and Drug Administration does not condone the fortification of unhealthy snacks or carbonated beverages. ${ }^{48}$ In light of the findings in this study, policymakers at the Food and Drug Administration should focus on updating this regulation to also include non-carbonated beverages as such marketing tactics may mislead parents into thinking that sugary fruit drinks are a healthy choice that their children will enjoy. Although vitamin C is an essential micronutrient, it is one in which children are not deficient in the U.S. ${ }^{49}$ Thus, these sugary drinks, which have been linked to excess weight gain and dental caries, have a health halo despite containing added sugar and excess calories. ${ }^{50,51}$

In 2012, the Federal Trade Commission published a review of the industry's youthdirected marketing expenditures and activities. ${ }^{52}$ The Federal Trade Commission concluded the study with suggestions on how to strengthen the marketing landscape, including setting nutrition standards for the types of foods and beverages that can be marketed to children and expanding the definition of marketing to include all forms of promotion; however, until such recommendations are codified, the marketing landscape will not change in a substantial way. In the absence of government regulations, industry self-regulation is unlikely to fix the problem. As the Children's Food and Beverage Advertising Initiative does not cover marketing on package labels, ${ }^{12}$ for instance, children continue to see many junk food ads on packaging. ${ }^{16,17}$

A previous study in Mexico analyzing SSBs found that those with child-directed marketing were significantly more likely to have more total sugar than SSBs without childdirected marketing. ${ }^{40}$ Similarly, Stoltze and colleagues ${ }^{39}$ analyzed a sample that included water, juices, SSBs, and dairy and found that beverages with child-directed marketing have approximately 15 more calories and 1 additional gram of added sugar per 100 mL serving when
compared with beverages without child-directed marketing. Unlike these two studies, the analyses performed in this paper were stratified by beverage type and used package serving sizes, and found that the presence of child-directed marketing on any fruit-flavored beverage had no association with calories and on $100 \%$ juice was associated with fewer grams of sugar. Similar to the study conducted in Mexico, ${ }^{39}$ the present analysis also assessed total sugars because products' added sugars information was not available for the time period. Though added sugars are a major health concern, excessive total sugar in a child's diet is also inadvisable. As such, experts recommend limiting even the natural sugars found in $100 \%$ juice. ${ }^{23}$

Other ingredients to consider are NNSs, which experts do not recommend for young children, ${ }^{53}$ and parents wish to avoid. ${ }^{54,55}$ Although this study found no association between the presence of child-directed marketing and the use of NNSs, nearly half of the fruit drinks and $80 \%$ of the non-carbonated flavored waters in this sample contained NNSs. The high prevalence of NNSs in this sample reflects a trend of increasing NNS consumption. ${ }^{56,57}$

This study had several strengths. First, this study expanded upon an earlier study conducted by the Rudd Center on children's drinks to include a nutrient content analysis with vitamin C. ${ }^{38}$ Models included stratification by beverage type, which enabled detailed recommendations for specific sugary drink categories. Second, this sample is representative of beverages purchased by U.S. households with young children and thus represents what parents see at the supermarket.

## Limitations

This study also had several limitations. First, the FOP marketing information used in this content analysis was collected between 2012 and 2017. It is possible that some packaging may
have been redesigned. Furthermore, as Label Insight does not provide historical data on beverage labels, the exact sales date could not be matched to the date the package information was collected. To address this, the authors reviewed news articles about food and beverage package redesign from 2012 to 2020 on Packaging Digest, ${ }^{58}$ and none of the beverages included in this study had undergone a redesign during the included timeframe. In addition, Label Insight re-indexes their database weekly, and a vast majority of the $10,000+$ weekly label submissions are from the brands themselves. Taken together, there is confidence that the reviewed labels have not undergone a major redesign. Second, this study does not address consumption of fruit-flavored beverages, only purchases. Third, some beverages were missing data for calories (1.5\%), total sugar (6.3\%), and vitamin C (22.5\%). However, information for all three nutrients was readily available through other reliable sources. Fourth, added sugar content could not be examined because nutrient data were collected prior to the implementation of the new Nutrition Facts Panel, which requires information about added sugars. Future research should examine the relationships between FOP child-directed marketing, health-related claims, and nutrition on a wider variety of foods and beverages consumed by young children using updated package information.

## CONCLUSION

Fruit drinks with FOP child-directed marketing were more likely to show micronutrient claims and contain more vitamin C than fruit drinks without child-directed marketing. This combination of marketing elements may mislead parents into believing that these sugary drinks are not only healthy, but also appropriate for and appealing to their children. Greater
regulation is needed for FOP beverage marketing on sugary drinks, particularly ones that contain child-directed marketing.

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## REFERENCES

1. Hall KD, Ayuketah A, Brychta R, et al. Ultra-processed diets cause excess calorie intake and weight gain: an inpatient randomized controlled trial of ad libitum food intake [published correction appears in Cell Metab. 2019;30(1):226] [published correction appears in Cell Metab. 2020;32(4):690]. Cell Metab. 2019;30(1):226. https://doi.org/10.1016/i.cmet.2019.05.020.
2. Harris JL, Pomeranz JL, Lobstein T, Brownell KD. A crisis in the marketplace: how food marketing contributes to childhood obesity and what can be done. Annu Rev Public Health. 2009;30:211-225. https://doi.org/10.1146/annurev.publhealth.031308.100304.
3. Childhood obesity facts. Centers for Disease Control and Prevention. https://www.cdc.gov/obesity/data/childhood.html. Updated 2019. Accessed September 26, 2020.
4. Federal Trade Commission. A review of food marketing to children and adolescents. Washington, DC: Federal Trade Commission; 2012.
https://www.ftc.gov/sites/default/files/documents/reports/reviewfood-marketing-children-and-adolescents-follow-report/121221foodmarketingreport.pdf. Published December. Accessed August 5, 2021.
5. Sadeghirad B, Duhaney T, Motaghipisheh S, Campbell NR, Johnston BC. Influence of unhealthy food and beverage marketing on children's dietary intake and preference: a systematic review and meta-analysis of randomized trials [published correction appears in Obes Rev. 2020;21(2):e12984]. Obes Rev. 2016;17(10):945-959. https://doi.org/10.1111/obr.12445.
6. Kunkel D, Wilcox BL, Cantor J, Palmer E, Linn S, Dowrick P. Report of the APA task force on advertising and children. Washington, DC: American Psychological Association, 2004. https://www.apa.org/pi/ families/resources/advertising-children.pdf. Published February 20. Accessed February 22, 2022.
7. Hastings G, Stead M, McDermott $L$, et al. Review of Research on the Effects of Food Promotion to Children. London, United Kingdom: Food Standards Agency; 2003. https://www.researchgate.net/publication/242490173_Review_Of_Research_On_The_ Effects_Of_Food_Promotion_To_Children. Accessed March 29, 2022.
8. Papoutsi GS, Nayga RM, Lazaridis P, Drichoutis AC. Fat tax, subsidy or both? The role of information and children's pester power in food choice. J Econ Behav Organ. 2015;117:196-208. https://doi.org/10.1016/i.jebo.2015.06.011.
9. McDermott L, O’Sullivan T, Stead M, Hastings G. International food advertising, pester power and its effects. Int J Advert. 2006;25(4):513-539.
https://doi.org/10.1080/02650487.2006.11072986.
10. Taillie LS, Busey E, Stoltze FM, Dillman Carpentier FR. Governmental policies to reduce unhealthy food marketing to children. Nutr Rev. 2019;77(11):787-816. https://doi.org/10.1093/nutrit/nuz021.
11. Fleming-Milici F, Harris JL. Food marketing to children in the United States: can industry voluntarily do the right thing for children's health? Physiol Behav. 2020;227:113139. https://doi.org/10.1016/i.physbeh.2020.113139.
12. Children's food and beverage advertising initiative. BBB National Programs; 2021. https://bbbprograms.org/programs/all-programs/cfbai.
13. Disney to cut junk food ads on kids' television. Center for Science in the Public Interest; 2012.
https://web.archive.org/web/20210515133203/https://www.cspinet.org/new/2012060 51.html.
14. Powell LM, Schermbeck RM, Chaloupka FJ. Nutritional content of food and beverage products in television advertisements seen on children's programming. Child Obes. 2013;9(6):524-531. https://doi.org/10.1089/chi.2013.0072.
15. Kunkel DL, Castonguay JS, Filer CR. Evaluating industry self-regulation of food marketing to children. Am J Prev Med. 2015;49(2):181-187. https://doi.org/10.1016/i.amepre.2015.01.027.
16. Abbasi J. Junk food ads reach children despite food industry self-regulation. JAMA. 2017;317(23):2359-2361. https://doi.org/10.1001/jama.2017.4653.
17. Frazier WC, Harris JL. Trends in television food advertising to young people: 2017 update. Hartford, CT: UConn Rudd Center for Food Policy \& Obesity, 2018. https://uconnruddcenter.org/wpcontent/uploads/sites/2909/2020/09/TVAdTrends2018_Final.pdf. Published May. Accessed August 24, 2021.
18. 2020-2025 edition. Dietary Guidelines for Americans. www.Dietary-Guidelines.gov. Updated December 2020. Accessed May 24, 2021.
19. Pomeranz JL, Harris JL. Children's fruit "juice" drinks and FDA regulations: opportunities to increase transparency and support public health. Am J Public Health. 2020;110(6):871-880. https://doi.org/10.2105/AJPH.2020.305621.
20. Kay MC, Welker EB, Jacquier EF, Story MT. Beverage consumption patterns among infants and young children (0-47.9 months): data from the Feeding Infants and Toddlers Study, 2016. Nutrients. 2018;10(7):825. https://doi.org/10.3390/nu10070825.
21. Bailey RL, Fulgoni VL, Cowan AE, Gaine PC. Sources of added sugars in young children, adolescents, and adults with low and high intakes of added sugars. Nutrients. 2018;10(1):102. https://doi.org/10.3390/nu10010102.
22. Fulgoni VL 3rd, Quann EE. National trends in beverage consumption in children from birth to 5 years: analysis of NHANES across three decades. Nutr J. 2012;11:92. https://doi.org/10.1186/1475-2891-11-92.
23. Heyman MB, Abrams SA. Section on Gastroenterology, Hepatology, and Nutrition, Committee on Nutrition. Fruit juice in infants, children, and adolescents: current recommendations. Pediatrics. 2017;139(6):e20170967. https://doi.org/10.1542/peds.2017-0967.
24. Auerbach BJ, Wolf FM, Hikida A, et al. Fruit juice and change in BMI: a meta-analysis. Pediatrics. 2017;139(4):e20162454. https://doi.org/10.1542/peds.2016-2454.
25. Auerbach BJ, Dibey S, Vallila-Buchman P, Kratz M, Krieger J. Review of $100 \%$ fruit juice and chronic health conditions: implications for sugar-sweetened beverage policy. Adv Nutr. 2018;9(2):78-85. https://doi.org/10.1093/advances/nmx006.
26. Nicklas T, O'Neil C, Fulgoni VL IIII. Consumption of $100 \%$ fruit juice is associated with better nutrient intake and diet quality but not with weight status in children: NHANES 2007-2010. Int J Child Health Nutr. 2015;4(2):112-121. https://doi.org/10.6000/19294247.2015.04.02.7.
27. Choi YY, Andreyeva T, Fleming-Milici F, Harris JLU. S. households' children's drink purchases: 2006-2017 trends and associations with marketing. Am J Prev Med. 2022;62(1):9-17. https://doi.org/10.1016/j.amepre.2021.06.013.
28. Sütterlin B, Siegrist M. Simply adding the word "fruit" makes sugar healthier: the misleading effect of symbolic information on the perceived healthiness of food. Appetite. 2015;95:252-261. https://doi.org/10.1016/i.appet.2015.07.011.
29. Musicus AA, Hua SV, Moran AJ, et al. Front-of-package claims \& imagery on fruitflavored drinks and exposure by household demographics. Appetite. 2022;171:105902. https://doi.org/10.1016/i.appet.2021.105902.
30. Duffy EW, Hall MG, Dillman Carpentier FR, et al. Nutrition claims on fruit drinks are inconsistent indicators of nutritional profile: a content analysis of fruit drinks purchased
by households with young children. J Acad Nutr Diet. 2021;121(1):36-46 e4. https://doi.org/10.1016/i.jand.2020.08.009.
31. Moran AJ, Roberto CA. Health warning labels correct parents' misperceptions about sugary drink options. Am J Prev Med. 2018;55(2): e19-e27. https://doi.org/10.1016/j.amepre.2018.04.018.
32. Munsell CR, Harris JL, Sarda V, Schwartz MB. Parents' beliefs about the healthfulness of sugary drink options: opportunities to address misperceptions. Public Health Nutr. 2016;19(1):46-54. https://doi.org/10.1017/S1368980015000397.
33. Welsh JA, Healy SK, Vos MB. Parental perceptions of healthy beverage alternatives to sugar-sweetened beverages. FASEB J. 2013;27(suppl1). 232.3-232.3. https://doi.org/10.1096/fasebj.27.1 supplement.232.3.
34. Harris JL, Pomeranz JL. Misperceptions about added sugar, non-nutritive sweeteners and juice in popular children's drinks: experimental and cross-sectional study with U.S. parents of young children (1-5 years). Pediatr Obes. 2021;16(10):e12791. https://doi.org/10.1111/ijpo.12791.
35. Changes to the nutrition facts label. U.S. Food and Drug Administration. https://www.fda.gov/food/food-labeling-nutrition/changes-nutrition-facts-label. Updated 2021. Accessed December 5, 2021.
36. Cairns G, Angus K, Hastings G, Caraher M. Systematic reviews of the evidence on the nature, extent and effects of food marketing to children. A retrospective summary. Appetite. 2013;62:209-215. https://doi.org/10.1016/j.appet.2012.04.017.
37. Story M, French S. Food advertising and marketing directed at children and adolescents in the U.S. Int J Behav Nutr Phys Act. 2004;1(1):3. https://doi.org/10.1186/1479-5868-13.
38. Harris JL, Schwartz MB, LoDolce M, et al. Sugary Drink FACTS 2014: some progress but much room for improvement in marketing to youth. Hartford, CT: UConn Rudd Center for Food Policy \& Obesity, November 2014. https://www.sugarydrinkfacts.org/resources/SugaryDrinkFACTS_Report.pdf. Published November. Accessed December 1, 2021.
39. Mediano Stoltze F, Barker JO, Kanter R, et al. Prevalence of child-directed and general audience marketing strategies on the front of beverage packaging: the case of Chile. Public Health Nutr. 2018;21(3):454-464. https://doi.org/10.1017/S1368980017002671.
40. Cruz-Casarrubias C, Tolentino-Mayo L, Nieto C, Theodore FL, Monterrubio-Flores E. Use of advertising strategies to target children in sugar-sweetened beverages packaging in

Mexico and the nutritional quality of those beverages. Pediatr Obes. 2021;16(2):e12710. https://doi.org/10.1111/ijpo. 12710.
41. Luisa Machado M, Mello Rodrigues V, Bagolin do Nascimento A, Dean M, Medeiros Rataichesck Fiates G. Nutritional composition of Brazilian food products marketed to children. Nutrients. 2019;11(6):1214. https://doi.org/10.3390/nu11061214.
42. Lavrisa Z, Pravst I. Marketing of foods to children through food packaging is almost exclusively linked to unhealthy foods. Nutrients. 2019;11(5):1128. https://doi.org/10.3390/nu11051128.
43. Lapierre MA, Brown AM, Houtzer HV, Thomas TJ. Child-directed and nutrition-focused marketing cues on food packaging: links to nutritional content. Public Health Nutr. 2017;20(5):765-773. https://doi.org/10.1017/S1368980016002317.
44. Elliott C. Tracking kids' food: comparing the nutritional value and marketing appeals of child-targeted supermarket products over time. Nutrients. 2019;11(8):1850. https://doi.org/10.3390/nu11081850.
45. Label Insight. www.labelinsight.com. Accessed January 27, 2020 to May 5, 2020.
46. FoodData Central. USDA U.S. Department of Agriculture Agricultural Research Service. https://fdc.nal.usda.gov/. Updated 2019. Accessed October 2020.
47. Verrill L, Wood D, Cates S, Lando A, Zhang Y. Vitamin-fortified snack food may lead consumers to make poor dietary decisions. J Acad Nutr Diet. 2017;117(3):376-385. https://doi.org/10.1016/i.jand.2016.10.008.
48. U.S. Food and Drug Administration. Questions and answers on FDA's fortification Policy.: guidance for industry. Silver Spring, MD: U.S: Food and Drug Administration; 2015. https://www.fda.gov/media/94563/download.
49. Vitamin C. NIH, Office of Dietary Supplements. https://ods.od.nih.gov/factsheets/VitaminC-HealthProfessional/\#en19. Updated March 26, 2021. Accessed May 1, 2021.
50. Chi DL, Scott JM. Added sugar and dental caries in children: a scientific update and future steps. Dent Clin North Am. 2019;63(1):17-33. https://doi.org/10.1016/i.cden.2018.08.003.
51. Hu FB. Resolved: there is sufficient scientific evidence that decreasing sugar-sweetened beverage consumption will reduce the prevalence of obesity and obesity-related diseases. Obes Rev. 2013;14(8):606-619. https://doi.org/10.1111/obr. 12040.
52. Marketing food to children and adolescents: a review of industry expenditures, activities, and self-regulation. Washington, DC: Federal Trade Commission, July 2008. https://www.ftc.gov/sites/default/files/documents/reports/marketing-food-children-and-adolescents-reviewindustry-expenditures-activities-and-selfregulation/p064504foodmktingreport.pdf. Published July. Accessed April 26, 2021.
53. Lott M, Callahan E, Welker Duffy E, Story M, Daniels S. Healthy beverage consumption in early childhood: recommendations from key national health and nutrition organizations. Consensus statement. Princeton, NJ: Healthy eating research, Robert Wood Johnson Foundation, September 2019. https://healthyeatingresearch.org/wp-content/uploads/2019/09/HER-HealthyBeverage-ConsensusStatement.pdf. Published September. Accessed December 6, 2021.
54. Sylvetsky AC, Greenberg M, Zhao X, Rother KI. What parents think about giving nonnutritive sweeteners to their children: a pilot study. Int J Pediatr. 2014;2014:819872. https://doi.org/10.1155/2014/819872.
55. Smith MA, Wells MH, Scarbecz M, Vinall CV, Woods MA. Parents' preferences and perceptions of their children's consumption of sugar and non-nutritive sugar substitutes. Pediatr Dent. 2019;41(2):119-128.
56. Sylvetsky AC, Welsh JA, Brown RJ, Vos MB. Low-calorie sweetener consumption is increasing in the United States. Am J Clin Nutr. 2012;96(3):640-646. https://doi.org/10.3945/ajen.112.034751.
57. Sylvetsky AC, Jin Y, Clark EJ, Welsh JA, Rother KI, Talegawkar SA. Consumption of lowcalorie sweeteners among children and adults in the United States. J Acad Nutr Diet. 2017;117(3):441-448 e2. https://doi.org/10.1016/i.jand.2016.11.004.
58. Packaging Digest. https://www.packagingdigest.com/. Accessed March 2020.

# Paper 2: Longitudinal Study on the Impact of the Philadelphia Beverage Tax on Prices and Purchasing 

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#### Abstract

Background: Policymakers are increasingly interested in sweetened beverage taxes as a way to reduce sweetened beverage purchases and generate revenue. A number of studies have evaluated the influence of beverage taxes on purchases, but few have used person-level longitudinal data. The aim of this study was to estimate the influence of Philadelphia's sweetened beverage tax on beverage prices and purchases made in a national pharmacy chain. Methods: We analyzed longitudinal beverage point-of-sale data from 313,582 loyalty cards from a national pharmacy chain before and after the implementation of Philadelphia's 1.5 cent per oz. tax on sugar- and artificially-sweetened beverages on January 1, 2017. To analyze the change in mean price-per-ounce for taxed and nontaxed beverages, we used generalized linear models comparing Philadelphia (intervention) to Baltimore (comparison city) before and after the tax (January 1, 2015 through December 31, 2017). We used multilevel models to analyze the change in cardholder's mean volume (ounces) of taxed and nontaxed beverages purchased per transaction.

Results: Average prices of taxed beverages in Philadelphia increased by 1.6 cents-per-ounce ( $95 \% \mathrm{CI}$ : 1.1, 2.0; $28.7 \%$ increase; $107 \%$ pass-through) compared to Baltimore in the year after the beverage tax. This price increase varied across taxed beverages types. Prices of nontaxed beverages saw no changes in Philadelphia compared to Baltimore post-tax ( 0.1 cents-per-ounce [ $95 \% \mathrm{CI}:-0.1,0.4]$ ). Loyalty cardholders in Philadelphia purchased 6.8 ounces ( $95 \% \mathrm{Cl}:-7.3,-6.2$ ) fewer of taxed beverages per transaction compared to Baltimore from before to after implementation of the beverage tax. The volume purchased of nontaxed beverages in


Philadelphia compared to Baltimore did not significantly differ after the beverage tax was implemented.

Conclusion: The Philadelphia beverage tax led to significant price increases for taxed beverages, which in turn led to a $7.6 \%$ decline in taxed beverage purchases at a national pharmacy chain. This longitudinal study contributes to a growing literature demonstrating sustained reductions in taxed beverage sales following beverage excise taxes. Cities should consider such taxes to reduce purchases of sugary drinks.

## INTRODUCTION

Consuming sugary drinks is associated with excess weight gain, diabetes, and cardiovascular disease, among many other negative health outcomes. ${ }^{1-4}$ Americans eat an average of 68 grams of added sugar a day, ${ }^{5}$ which is greater than the upper limit of $\sim 50$ grams that the Dietary Guidelines for Americans 2020-2025 recommends for an adult on a 2000 calorie diet. ${ }^{6}$ One of the biggest sources of added sugars in the American diet comes from sugary drinks. ${ }^{6}$ As such, there have been efforts to reduce the amount of sugary drinks Americans consume, using methods such as portion limits, excise taxes, healthier default beverages on kid's menus, and traffic light labeling signage. ${ }^{7-11}$

There has been increasing momentum and political feasibility for beverage taxes in the U.S. since 2014, when Berkeley, CA passed the nation's first sugar-sweetened beverage (SSB) tax. ${ }^{12}$ In 2016, Philadelphia, PA followed suit, and several other U.S. cities thereafter. ${ }^{13}$ This paper will focus on the Philadelphia beverage tax, a 1.5 cent-per-ounce excise tax on artificiallyand sugar-sweetened beverages that was implemented on January 1, 2017. ${ }^{14}$

The beverage industry has pushed back against beverage taxes, ${ }^{15}$ claiming that with decreased purchasing, stores would lose profit and be forced to lay off employees. However, studies have shown that unemployment rates did not change after the Philadelphia beverage tax was implemented. ${ }^{16-18}$ While qualitative studies conducted with beverage retailers have uncovered general discontent around beverage taxes, the same retailers ultimately reported that their sales did not change. ${ }^{19}$

Studies examining the impact of beverage taxes on prices have consistently shown that a large portion of beverage excise taxes are passed on from the beverage distributors (the
entities that actually pay the tax to the city) to retailers and finally to consumers. ${ }^{10,20-22}$ In Berkeley, chain supermarkets saw complete pass-through of the tax-i.e., the cost of the tax was completely passed onto the consumers-though pharmacies only saw partial passthrough; ${ }^{20}$ on the other hand, supermarkets in Philadelphia saw partial pass-through while pharmacies and small, independent stores saw complete pass-through. ${ }^{10,21}$ As prices of taxed beverages have gone up, sales have correspondingly declined, as demonstrated by studies in Berkeley, Philadelphia, and Seattle. ${ }^{10,20-22}$ Understanding the extent of a decline in sales is important because it may predict the amount of reduced consumption, which would define the amount of health benefit for those who drink fewer sugary drinks after the tax.

While studies have consistently shown an increase in the price of taxed beverages and a subsequent population-level decline in sales, what is less well-studied is how individuals respond to the tax. In two longitudinal studies (i.e., following the same people over time) conducted in Philadelphia using receipt collection or surveys, one found no statistically significant changes in purchases of taxed beverages, ${ }^{11}$ while another found decreases in selfreported consumption of soda among adults. ${ }^{23}$ Researchers in Mexico also found sustained declines in self-reported consumption of taxed beverages in a longitudinal design. ${ }^{24}$ However, results from self-report surveys and receipt collection may be limited by measurement error, sampling, or participant forgetting to submit all receipts.

Building off those previous longitudinal evaluations of beverages taxes, this study uses objectively collected sales data to investigate how the Philadelphia beverage tax impacted the prices and purchasing of beverages in a large, national pharmacy chain among consumers whose individual purchases were linked by their loyalty cards.

## METHODS

A national pharmacy chain provided complete scanner data for all beverages sold from January 1, 2015 through December 31, 2017 for Philadelphia (intervention city with a beverage tax), Baltimore (comparison city without a tax), and Providence (comparison city without a tax). The data are card-level beverage dollar sales, volume, and price information for all SKUs ("stock keeping units" representing distinct items for sale) from the stores. Unique loyalty card numbers linked purchases over this three-year period either to individual loyalty card owners, or to store locations (for purchases made without an individual loyalty card).

Beverages were classified into two broad categories: taxed and nontaxed. Beverages subject to the Philadelphia beverage tax included soda, diet soda, fruit drinks, iced tea \& lemonade, sweetened sparkling water, sports drinks, sweetened coffee, and energy drinks. The nontaxed beverages included regular water, unsweetened sparkling water, fruit juice, milk, and unsweetened coffee. Analyses of taxed beverages as a category additionally included milk alternatives and other taxed beverages. Analyses of nontaxed beverages as a category additionally included milk alternatives, energy drinks, flavored waters, iced tea or lemonade, sports drinks, and other nontaxed beverages.

Our two primary outcomes were: 1) change in mean weighted beverage price-per-ounce for taxed beverages using SKU-within-store-level data weighted by volume sold at baseline (captures pass-through of the tax), and 2) change in mean volume (ounce) of taxed beverages purchased per transaction.

We created parallel trend graphs for average price-per-ounce and for total volume sold among the following beverage groups: all taxed beverages, all nontaxed beverages, soda, diet
soda, fruit drinks, iced tea \& lemonade, sparkling water (taxed and nontaxed separately), sports drinks, coffee (taxed and nontaxed separately), regular water, fruit juice, and milk. These graphs showed that both Baltimore and Providence were acceptable controls for Philadelphia; we chose to compare Philadelphia with Baltimore in our primary models because Baltimore is more similar with regard to demographic variables and had more units of observations. We ran sensitivity analyses with Providence as the comparison city.

Both analyses excluded the following transactions from the $16,796,831$ original transactions in Philadelphia and Baltimore: products that were not beverages ( $\mathrm{n}=2,819$ transactions; 0.02\%), beverages which we were unable to locate online ( $n=169,251$ transactions; 1.0\%), beverages whose tax status could not be determined ( $n=239,989$ transactions; 1.4\%), return transactions (i.e., store credits, $n=26,372 ; 0.2 \%$ ), beverages for which beverage size ( $n=8,796$ transactions; $0.05 \%$ ) or volume ( $n=18,970$ transactions; $0.1 \%$ ) information was missing, and beverage concentrates ( $n=36,873$ transactions; $0.2 \%$ ) as their volumes are very different from the typical beverage.

For the price-per-ounce analyses, we also excluded energy drink ( $n=930,393 ; 5.7 \%$ ) and coffee ( $n=337,909 ; 2.2 \%$ ) transactions as these beverage types have a higher price-per-ounce than other beverages, which would have skewed the price results had we included them in the overall analysis. Mean prices were weighted using pre-tax volume sold by each SKU in each store to estimate the effective impact of price changes on consumers, not just the average price change across the menu of available products. Therefore, we additionally excluded transactions for SKUs that did not appear in both the pre- and post-tax period ( $n=476,095$ transactions;
$3.2 \%$ ) leaving $14,558,160$ transactions which were aggregated to the week by store by SKU level ( $N=2,646,098$ ).

For the volume purchased analyses, we dropped purchases not associated with an individual loyalty card ( $n=5,104,360 ; 31.3 \%$ ) and purchases from loyalty card IDs that did not appear in both time periods ( $n=3,315,160 ; 29.6 \%$ ), leaving 7,883,037 transactions from 313,582 unique cardholders.

## Analytic Models

We used generalized linear models to analyze the change in mean weighted price-perounce for beverages. Our primary models included store ID, city, tax period, and the interaction of city and tax period (the difference-in-differences [DID] estimate). Data were clustered at the SKU level and weighted by the pre-tax volume sold by SKU and store ID.

To analyze the change in mean volume (ounces) of beverages purchased per card per transaction, we used cross-classified mixed models to account for imperfect nesting of loyalty cardholders and stores. In other words, loyalty cardholders were able to make purchases from multiple stores. Our primary models included city, tax period, the interaction of the city and tax period (DID estimate), and random intercepts for the store ID and loyalty card ID.

We used Holm-Bonferroni's method to adjust $p$-values within families of outcomes (total taxed beverages [1 test], taxed beverage subcategories [8 tests], total nontaxed beverages [1 test], and nontaxed beverage subcategories [ 5 tests]). We ran sensitivity analyses on our models to include covariates for yearly quarters and store zip code-level percent below
the poverty line (as determined by the store's zip code from the 2019 American Community Survey). ${ }^{25}$

## RESULTS

Price Outcome

Data came from 48 unique stores of this chain retail pharmacy in Philadelphia and 27 in Baltimore. There were 1,078 unique beverage SKUs that were purchased from the same store pre and post-tax. Price analyses compared prices across the 104 weeks pre- and 52 weeks posttax. At baseline, prices in Philadelphia and Baltimore were fairly comparable: taxed beverages were 6.7 and 6.5 cents-per-ounce, respectively, and nontaxed beverages were 8.6 cents-perounce in both cities (see Table 2.1).
Table 2.1 Difference-in-difference regression results for changes in beverage price-per-ounce following implementation of a beverage tax in Philadelphia compared to Baltimore (Baltimore = reference city).

|  | Philadelphia |  | Baltimore |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Pre-tax Mean (SD) cents-per-ounce | Post-tax Mean (SD) cents-per-ounce | Pre-tax Mean (SD) cents-per-ounce | Post-tax <br> Mean (SD) cents-per-ounce | $\qquad$ | $p$ $v^{2}{ }^{\text {a }}{ }^{\text {a }}$ | Percent passthrough ${ }^{\text {b }}$ |
| Taxed Beverages ${ }^{\text {c }}$ $(n=1,799,963)^{d}$ | 6.7 (5.0) | 8.2 (5.2) | 6.5 (4.5) | 6.7 (4.5) | $\begin{gathered} \hline 1.6 \\ (1.1,2.0) \\ \hline \end{gathered}$ | <. 001 | 106.7 |
| $\begin{array}{r} \text { Soda } \\ (n=447,118) \end{array}$ | 5.8 (4.0) | 7.3 (4.0) | 5.6 (3.9) | 5.8 (3.9) | $\begin{gathered} 1.4 \\ (1.1,1.8) \end{gathered}$ | <. 001 | 93.3 |
| $\begin{array}{r} \text { Iced Tea \& } \\ \text { Lemonade } \\ (\mathrm{n}=411,840) \\ \hline \end{array}$ | 6.0 (3.5) | 6.9 (3.4) | 6.0 (3.3) | 6.3 (3.4) | $\begin{gathered} 0.9 \\ (0.7,1.1) \end{gathered}$ | <. 001 | 60.0 |
| Fruit Drinks $(n=289,643)$ | 8.0 (5.4) | 8.8 (5.1) | 7.6 (5.1) | 7.3 (4.6) | $\begin{gathered} 0.8 \\ (0.6,1.0) \\ \hline \end{gathered}$ | <. 001 | 53.3 |
| Sports Drinks $(n=267,331)$ | 7.0 (2.3) | 9.0 (2.3) | 7.1 (2.1) | 7.6 (2.1) | $\begin{gathered} 1.8 \\ (1.5,2.2) \end{gathered}$ | <. 001 | 120.0 |
| $\begin{array}{r} \text { Diet Soda } \\ (\mathrm{n}=223,129) \\ \hline \end{array}$ | 5.1 (3.4) | 6.6 (3.6) | 5.3 (3.5) | 5.6 (3.4) | $\begin{gathered} 1.4 \\ (1.0,1.8) \\ \hline \end{gathered}$ | <. 001 | 93.3 |
| Sparkling Water ( $\mathrm{n}=125,332$ ) | 5.9 (5.4) | 7.9 (6.5) | 5.6 (4.8) | 5.5 (5.1) | $\begin{gathered} 1.5 \\ (1.2,1.8) \\ \hline \end{gathered}$ | <. 001 | 100.0 |
| $\begin{array}{r} \text { Coffee } \\ (\mathrm{n}=62,643) \end{array}$ | 20.8 (4.2) | 23.2 (4.4) | 20.4 (4.0) | 21.3 (4.1) | $\begin{gathered} 1.2 \\ (0.9,1.5) \end{gathered}$ | <. 001 | 80.0 |
| Energy Drinks $(n=231,614)$ | 19.5 (5.8) | 21.6 (5.3) | 19.4 (6.0) | 21.2 (6.6) | $\begin{gathered} 0.2 \\ (-0.5,0.8) \end{gathered}$ | . 589 | 13.3 |
| Nontaxed Beverages ${ }^{\text {e }}$ ( $\mathrm{n}=846,135$ ) | 8.6 (7.7) | 8.7 (7.2) | 8.6 (7.9) | 8.6 (7.3) | $\begin{gathered} 0.1 \\ (-0.1,0.4) \end{gathered}$ | . 363 | N/A |
| Regular Water ( $n=318,455$ ) | 4.8 (2.8) | 5.3 (3.1) | 4.8 (2.8) | 5.2 (3.1) | $\begin{gathered} -0.002 \\ (-0.1,0.1) \end{gathered}$ | . 974 | N/A |

Table 2.1 Difference-in-difference regression results for changes in beverage price-per-ounce following implementation of a beverage tax in Philadelphia compared to Baltimore (Baltimore = reference city) (Continued).

|  | Philadelphia |  | Baltimore |  | Weighted DID estimate(95\% CI) | $\begin{gathered} p- \\ \text { value }^{\text {a }} \end{gathered}$ | Percent passthrough ${ }^{\text {b }}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $\begin{gathered} \text { Pre-tax } \\ \text { Mean (SD) } \\ \text { cents-per-ounce } \end{gathered}$ | Post-tax <br> Mean (SD) cents-per-ounce | $\begin{gathered} \text { Pre-tax } \\ \text { Mean (SD) } \\ \text { cents-per-ounce } \end{gathered}$ | Post-tax <br> Mean (SD) cents-per-ounce |  |  |  |
| $\begin{array}{r} \text { Fruit Juice } \\ (\mathrm{n}=267,705) \\ \hline \end{array}$ | 14.5 (9.8) | 14.3 (8.7) | 14.9 (10.6) | 14.7 (9.4) | $\begin{gathered} 0.2 \\ (-0.3,0.6) \\ \hline \end{gathered}$ | . 519 | N/A |
| $\begin{array}{r} \text { Milk } \\ (\mathrm{n}=144,939) \end{array}$ | 6.1 (4.1) | 6.4 (4.1) | 6.6 (4.3) | 6.8 (4.8) | $\begin{gathered} 0.04 \\ (-0.1,0.1) \\ \hline \end{gathered}$ | . 429 | N/A |
| Sparkling Water ( $\mathrm{n}=79,865$ ) | 6.2 (3.6) | 6.9 (6.1) | 6.3 (2.9) | 6.1 (2.9) | $\begin{gathered} 0.5 \\ (0.1,1.0) \end{gathered}$ | <. 05 | N/A |
| $\begin{array}{r} \text { Coffee } \\ (n=19,815) \end{array}$ | 24.0 (8.6) | 26.9 (8.3) | 24.5 (9.1) | 28.2 (10.4) | $\begin{gathered} -1.7 \\ (-3.5,0.1) \end{gathered}$ | . 061 | N/A |

[^0] models include store ID
${ }^{\text {a }}$ Bolded values indicate statistical significance after applying the Holm-Bonferroni correction for multiple testing on families of outcome (total taxed beverages [1 test], taxed beverage subcategories [8 tests], total nontaxed beverages [1 test], nontaxed
${ }^{\text {b }}$ The percent pass-through was calculated for taxed beverages as the difference-in-differences point estimate divided by 1.5 cents/oz.
coverall taxed category does not sum up to the composite categories because it also includes milk alternatives and other taxed beverages. It does not include taxed coffees and energy drinks as the price-per-ounce is much higher than the other beverages. ${ }^{d}$ Ns represent the number of unique week by store ID by SKU combinations over 104 weeks pre-tax and 52 weeks post-tax. In total, there were 1,078 unique SKUs in this dataset across 75 unique stores.
${ }^{e}$ Overall nontaxed category does not sum up to the composite categories because it also includes milk alternatives, flavored waters, iced tea or lemonade, sports drinks, and other nontaxed beverages. It does not include nontaxed coffees as the price-per-ounce is much higher than the other beverages.

Prices of taxed beverages in Philadelphia increased by 1.6 cents-per-ounce ( $95 \% \mathrm{CI}$ : 1.1, 2.0; $28.7 \%$ increase; $107 \%$ pass-through) compared to Baltimore after the beverage tax was implemented. This increase in price varied among taxed beverages, ranging from a 0.8 cents-per-ounce ( $95 \% \mathrm{Cl}: 0.6,1.0 ; 53 \%$ pass-through) increase among fruit drinks to a 1.8 cents-perounce ( $95 \%$ CI: 1.5, 2.2; 120\% pass-through) increase among sports drinks. Prices of nontaxed beverages did not change between Philadelphia compared to Baltimore post-tax for all nontaxed beverages combined ( 0.1 cents-per-ounce [ $95 \% \mathrm{CI}:-0.1,0.4]$ ), and for each nontaxed beverage subcategory (Table 2.1).

We ran sensitivity analyses to additionally include covariates for yearly quarters and store zip code-level percent below the poverty line to the primary models (Appendix Table 2.1). We additionally ran sensitivity analyses with Providence as the comparison city for Philadelphia (Appendix Table 2.2). Results for all sensitivity analyses were similar to the primary analyses.

## Volume Outcome

The volume analysis dataset included data from 231,065 unique cardholders in Philadelphia who made beverage purchases in both the pre- and post-tax period, while in Baltimore there were data from 82,517 unique cardholders who made purchases in both the pre- and post-tax period. Across both cities, we analyzed 3,634,736 taxed and 2,443,752 nontaxed daily beverage transactions for changes in volume purchased at the individual level. At baseline, individual cardholders purchased fewer ounces of taxed beverages per transaction in Philadelphia relative to Baltimore (73 and 91 ounces, respectively) and more ounces of nontaxed beverages (142 and 129 ounces; see Table 2.2).
Table 2.2 Difference-in-difference regression results ${ }^{\text {a }}$ for individual-level changes in volume of beverages purchased among
purchasers of beverages both pre- and post-tax, following implementation of a beverage tax in Philadelphia compared to Baltimore

|  | Philadelphia |  | Baltimore |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Pre-tax <br> Mean (SD) <br> ounces purchased | Post-tax <br> Mean (SD) <br> ounces purchased | Pre-tax <br> Mean (SD) <br> ounces purchased | Post-tax <br> Mean (SD) ounces purchased | DID estimate (95\% CI) | $\begin{gathered} p- \\ \text { value }^{\text {b }} \end{gathered}$ |
| Taxed Beverages ${ }^{\text {c }}$ $(n=3,634,736)^{d}$ | 73.0 (118.0) | 59.1 (102.9) | 90.8 (148.1) | 81.5 (144.6) | $\begin{gathered} -6.8 \\ (-7.3,-6.2) \end{gathered}$ | <. 001 |
| $\begin{array}{r} \text { Soda } \\ (\mathrm{n}=995,966) \\ \hline \end{array}$ | 95.5 (145.7) | 75.3 (137.2) | 120.4 (175.7) | 103.4 (149.6) | $\begin{gathered} -7.4 \\ (-8.5,-6.3) \\ \hline \end{gathered}$ | <. 001 |
| Iced Tea \& Lemonade ( $\mathrm{n}=983,266$ ) | 54.5 (79.5) | 47.2 (62.6) | 53.3 (78.8) | 56.2 (99.6) | $\begin{gathered} -8.3 \\ (-8.9,-7.6) \end{gathered}$ | <. 001 |
| Fruit Drinks ( $\mathrm{n}=551,722$ ) | 49.2 (71.4) | 42.4 (57.9) | 50.5 (76.4) | 55.3 (123.0) | $\begin{gathered} -8.3 \\ (-9.1,-7.5) \end{gathered}$ | <. 001 |
| Sports Drinks $(n=448,602)$ | 43.1 (35.4) | 39.4 (26.8) | 43.8 (34.6) | 42.5 (31.1) | $\begin{gathered} -2.8 \\ (-3.4,-2.3) \end{gathered}$ | <. 001 |
| $\begin{array}{r} \text { Diet Soda } \\ (n=487,937) \end{array}$ | 96.3 (122.8) | 75.9 (94.7) | 122.5 (157.4) | 102.1 (134.0) | $\begin{gathered} -3.2 \\ (-4.5,-1.8) \end{gathered}$ | <. 001 |
| Sparkling Water $(n=283,874)$ | 54.2 (65.1) | 51.6 (64.5) | 45.6 (54.7) | 46.5 (55.3) | $\begin{gathered} -2.6 \\ (-3.7,-1.6) \\ \hline \end{gathered}$ | <. 001 |
| $\begin{array}{r} \text { Coffee } \\ (n=100,391) \\ \hline \end{array}$ | 18.5 (12.4) | 17.0 (10.0) | 19.7 (15.9) | 19.7 (13.9) | $\begin{gathered} -1.2 \\ (-1.5,-0.8) \\ \hline \end{gathered}$ | <. 001 |
| Energy Drinks ( $\mathrm{n}=345,044$ ) | 21.4 (14.9) | 20.8 (14.3) | 21.0 (14.4) | 21.0 (12.7) | $\begin{gathered} -0.5 \\ (-0.7,-0.3) \\ \hline \end{gathered}$ | <. 001 |
| Nontaxed Beverages ${ }^{\text {e }}$ $(n=2,443,752)$ | 142.3 (250.0) | 134.0 (243.0) | 129.4 (228.1) | 118.7 (222.8) | $\begin{gathered} 0.5 \\ (-1.0,2.0) \\ \hline \end{gathered}$ | . 494 |
| Regular Water $(n=1,108,582)$ | 227.0 (342.1) | 206.3 (334.0) | 203.4 (316.5) | 177.6 (307.4) | $\begin{gathered} 3.5 \\ (0.7,6.4) \end{gathered}$ | <. 05 |

Table 2.2 Difference-in-difference regression results ${ }^{\text {a }}$ for individual-level changes in volume of beverages purchased among
purchasers of beverages both pre- and post-tax, following implementation of a beverage tax in Philadelphia compared to Baltimore
(Baltimore = reference city) (Continued).

|  | Philadelphia |  | Baltimore |  |
| :---: | :---: | :---: | :---: | :---: |
|  | Pre-tax <br> Mean (SD) <br> ounces purchased | Post-tax <br> Mean (SD) ounces purchased | Pre-tax <br> Mean (SD) ounces purchased | Po Mea our pur |
| $\begin{array}{r} \text { Fruit Juice } \\ (\mathrm{n}=426,901) \end{array}$ | 37.4 (34.0) | 39.1 (32.6) | 38.6 (51.6) | 39.3 |
| $\begin{array}{r} \text { Milk } \\ (\mathrm{n}=773,300) \\ \hline \end{array}$ | 86.9 (57.7) | 85.4 (56.8) | 90.8 (88.7) | 83.2 |
| Sparkling Water $(n=210,764)$ | 44.5 (39.9) | 50.3 (42.0) | 39.2 (36.9) | 49 |
| $\begin{array}{r} \text { Coffee } \\ (n=46,915) \end{array}$ | 12.9 (8.4) | 12.7 (8.4) | 12.7 (7.1) | 12 |

Note. Mean ounces purchased are raw means per card, per transaction. Regression models only include cardholder IDs that had beverage transactions in both the pre- and post- tax periods. ${ }^{\text {a }}$ Cross-classified mixed models were used to analyze the data
${ }^{\text {b }}$ Bolded values indicate statistical significance after applying the Holm-Bonferroni correction for multiple testing on families of outcome (total taxed beverages [1 test], taxed beverage subcategories [ 8 tests], total nontaxed beverages [1 test], nontaxed beverage subcategories [ 5 tests]
${ }^{\text {co }}$ ( ${ }^{\prime}$ verall taxed category does not sum up to the composite categories because it also includes milk alternatives and other taxed beverages.
${ }^{\mathrm{d}}$ Ns represent the number of unique transactions over 104 weeks pre-tax and 52 weeks post-tax.
${ }^{e}$ Overall nontaxed category does not sum up to the composite categories because it also includes milk alternatives, energy drinks, flavored waters, iced tea or lemonade, sports drinks, and other nontaxed beverages.

Loyalty cardholders in Philadelphia purchased 6.8 ounces ( $95 \% \mathrm{CI}:-7.3,-6.2$ ) fewer of taxed beverages per transaction compared to Baltimore from before to after implementation of the beverage tax. This decline in cardholders' purchases of taxed beverages in Philadelphia was seen across all categories of taxed beverages. These decreases ranged from 0.5 ounces ( $95 \% \mathrm{Cl}$ : $-0.7,-0.3$ ) for energy drinks to 8.3 ounces for both fruit drinks ( $95 \% \mathrm{CI}:-9.1,-7.5$ ) and iced teas and lemonades ( $95 \% \mathrm{CI}:-8.9,-7.6$; Table 2.2). There was no difference between cities from before to after the tax in cardholders' purchases of nontaxed beverages; however, there were differences by individual nontaxed beverage categories. Cardholders purchased more regular water and milk (regular water: 3.5 ounces [ $95 \% \mathrm{Cl}: 0.7,6.4$ ]; milk: 2.5 ounces [ $95 \% \mathrm{CI}: 1.9,3.0$ ]), and less nontaxed sparkling water ( -1.7 ounces $[95 \% \mathrm{CI}:-2.7,-0.6]$ ) in Philadelphia compared to Baltimore post-tax (Table 2.2).

We ran sensitivity analyses to include covariates for yearly quarters and store zip codelevel percent below the poverty line to the primary models (Appendix Table 2.3). We additionally ran sensitivity analyses with Providence as the comparison city for Philadelphia (Appendix Table 2.4). Results for all sensitivity analyses were similar to the primary analyses.

## DISCUSSION

The 1.5 cents-per-ounce Philadelphia beverage tax on sweetened beverages led to a 1.6 cents-per-ounce increase in the price of taxed beverages which subsequently led to cardholders buying nearly 7 ounces less of taxed beverages per transaction in a national pharmacy chain. The price increase of taxed beverages represents a $107 \%$ pass-through of the tax onto consumers and a $29 \%$ increase in price in Philadelphia compared to Baltimore post-tax. Our
study showed that beverage taxes work as predicted and can lead to decreased consumption of sugary drinks.

While the Philadelphia beverage tax was passed as a method to raise money for citywide initiatives such as universal pre-K, ${ }^{26}$ beverages taxes are also a strong public health tool to decrease purchasing and potentially consumption of sugary drinks. ${ }^{21,23,27-31}$ Our findings showed that the tax was completely passed on to consumers in the pharmacy retail setting, which contrasts with how the tax was passed on in supermarkets, mass merchandise stores, gas stations, and independent corner stores. ${ }^{10,21,23}$ The effect of such pass-through-whether complete or not-was that consumers purchased fewer sugary drinks in Philadelphia, and the amount of cross-border shopping to buy taxed beverages did not completely offset that decrease. ${ }^{10,23}$

Similar to results in Berkeley, CA, ${ }^{20}$ our results showed a relative increase in purchased volume of milk and water post-tax in Philadelphia compared to Baltimore; however, this was the result of a smaller decrease in purchases in Philadelphia in the post-tax period compared to a larger decrease in purchases of these products in Baltimore. Thus, it is unclear whether consumers were necessarily substituting to these healthier beverages due to the tax. In line with a study by Roberto et al., ${ }^{10}$ we found no statistically significant increases in overall nontaxed beverage purchases, which suggests that in general, customers were not substituting to nontaxed beverages when in the store. Notably, total purchased volume of taxed and nontaxed beverages in both cities declined, driven by decreases in sodas, diet sodas, water, and milk. These findings reflect an overall national trend of decreased beverage consumption. ${ }^{32}$

Our results, in the context of other studies that have been done in Philadelphia which showed decreased purchasing of taxed beverages in other retail settings, suggest that Philadelphia consumers were actually purchasing fewer sugary beverages as a result of the tax. Importantly, a study by Grummon and colleagues showed that consumers were not substituting to other unhealthy items, such as sugary sweets or salty snacks. ${ }^{33}$ Despite a decrease in purchasing, the tax revenue from the first half of the implementation year was still nearly $\$ 40$ million, thus generating substantial revenue for city initiatives. ${ }^{34}$

## Strengths and Limitations

This study has several strengths. It is the first to use point-of-sale data in conjunction with loyalty card numbers to evaluate the impact of the Philadelphia beverage tax using scanner data over time. Prior studies relied on self-report surveys and receipt collection methods, both of which are prone to measurement and human error. ${ }^{11,23}$ Second, it is the largest longitudinal study to date to study the beverage tax in Philadelphia. Our sample size, with hundreds of thousands of participants, is much larger than prior longitudinal studies, and this enabled us to clearly show how the beverage tax impacted those who reside and work in Philadelphia over time. Finally, our data allowed us to understand how consumers' individual behaviors changed over time rather than just how store-level sales changed. Store-level patterns may mask important individual-level patterns. Given these strengths, we are confident that among the same people over time, the volume purchased of taxed beverages decreased in Philadelphia as a result of the tax.

This study has several limitations. First, we were only able to assess how this one particular chain handled the beverage tax, and how customers for this chain reacted. However, this national chain had 48 unique stores in Philadelphia included in the dataset, and 231,065 unique loyalty cardholders who visited the store at least once in both the pre- and post-tax period. Second, we were only able to examine purchase patterns, not patterns of consumption. However, there is a strong relationship between purchasing and consumption, so given that other analyses have found declines in purchases across other retail settings, it is unlikely that the declines in purchasing detailed in this study did not lead to declines in consumption. This is especially true because studies have found that the amount of cross-border shopping was not enough to offset the decrease in purchased taxed volume in Philadelphia. ${ }^{10}$ Finally, given that our study only included stores from one national pharmacy chain, our ability to understand whether customers were going to supermarkets, mass merchandise stores, or other big box stores to make their taxed beverage purchases was limited. Other studies in other retail settings, however, support the overall conclusion that the beverage tax in Philadelphia resulted in decreased purchases of taxed beverages. ${ }^{10}$

## CONCLUSION

The beverage tax in Philadelphia worked exactly as economic models predicted: prices increased on taxed beverages leading to a decrease in purchased volume of those same beverages. This study adds to the pool of literature demonstrating the efficacy of beverage taxes in reducing purchasing, and likely consumption, of sweetened beverages. Several additional localities are currently considering their own beverage taxes; this study provides
evidence that a tax is not only a good way to raise revenue for city initiatives to benefit all, but also a strong public health tool reducing purchases of sweetened beverages.

## REFERENCES

1. Malik VS, Schulze MB, Hu FB. Intake of sugar-sweetened beverages and weight gain: a systematic review. Am J Clin Nutr. Aug 2006;84(2):274-88. doi:10.1093/ajcn/84.1.274
2. Malik VS, Popkin BM, Bray GA, Despres JP, Willett WC, Hu FB. Sugar-sweetened beverages and risk of metabolic syndrome and type 2 diabetes: a meta-analysis. Diabetes Care. Nov 2010;33(11):2477-83. doi:10.2337/dc10-1079
3. Malik VS, Hu FB. Sugar-Sweetened Beverages and Cardiometabolic Health: An Update of the Evidence. Nutrients. Aug 8 2019;11(8)doi:10.3390/nu11081840
4. Hu FB. Resolved: there is sufficient scientific evidence that decreasing sugar-sweetened beverage consumption will reduce the prevalence of obesity and obesity-related diseases. Obes Rev. Aug 2013;14(8):606-19. doi:10.1111/obr. 12040
5. What We Eat In America, NHANES 2017-2018. 2021. Accessed July 6, 2021. https://www.ars.usda.gov/ARSUserFiles/80400530/pdf/FPED/tables 14 FPED 1718.pdf
6. Dietary Guidelines for Americans, 2020-2025. 2020. Accessed May 24, 2021. DietaryGuidelines.gov.
7. Kansagra SM, Kennelly MO, Nonas CA, et al. Reducing sugary drink consumption: New York City's approach. Am J Public Health. Apr 2015;105(4):e61-4. doi:10.2105/AJPH.2014.302497
8. Thorndike AN, Sonnenberg L, Riis J, Barraclough S, Levy DE. A 2-phase labeling and choice architecture intervention to improve healthy food and beverage choices. Am J Public Health. Mar 2012;102(3):527-33. doi:10.2105/AJPH.2011.300391
9. Ritchie LD, Lessard L, Harpainter P, et al. Restaurant kids' meal beverage offerings before and after implementation of healthy default beverage policy statewide in California compared with citywide in Wilmington, Delaware. Public Health Nutr. Apr 12 2021:1-11. doi:10.1017/S1368980021001245
10. Roberto CA, Lawman HG, LeVasseur MT, et al. Association of a Beverage Tax on SugarSweetened and Artificially Sweetened Beverages With Changes in Beverage Prices and Sales at Chain Retailers in a Large Urban Setting. JAMA. May 14 2019;321(18):17991810. doi:10.1001/jama.2019.4249
11. Lawman HG, Bleich SN, Yan J, et al. One-year changes in sugar-sweetened beverage consumers' purchases following implementation of a beverage tax: a longitudinal quasiexperiment. Am J Clin Nutr. Sep 1 2020;112(3):644-651. doi:10.1093/ajcn/nqaa158
12. Imposing a General Tax on the Distribution of Sugar-Sweetened Beverage Products, Ordinance No. 7,388-N.S., City of Berkeley (2014). November 4, 1014. Accessed July 6, 2021.
https://www.cityofberkeley.info/uploadedFiles/Health Human Services/Level 3 Public Health/SSB\%20Tax\%20Ordinance\%207,388-N.S..pdf
13. Soda Taxes. Urban Institute. Updated 2021. Accessed July 6, 2021, https://www.urban.org/policy-centers/cross-center-initiatives/state-and-local-finance-initiative/state-and-local-backgrounders/soda-taxes
14. Payments, assistance \& taxes. City of Philadelphia. Updated September 20, 2019. Accessed October 15, 2019, https://www.phila.gov/services/payments-assistance-taxes/business-taxes/philadelphia-beverage-tax/
15. Big Soda vs. Public Health (2017 Edition) Center for Science in the Public Interest. Updated 2017. Accessed September 25, 2020, https://cspinet.org/resource/big-soda-vs-public-health-2017-edition
16. Powell LM, Wada R, Persky JJ, Chaloupka FJ. Employment impact of sugar-sweetened beverage taxes. Am J Public Health. Apr 2014;104(4):672-7. doi:10.2105/AJPH.2013.301630
17. Marinello S, Leider J, Pugach O, Powell LM. The impact of the Philadelphia beverage tax on employment: A synthetic control analysis. Econ Hum Biol. Jan 2021;40:100939. doi:10.1016/j.ehb.2020.100939
18. Lawman HG, Bleich SN, Yan J, LeVasseur MT, Mitra N, Roberto CA. Unemployment claims in Philadelphia one year after implementation of the sweetened beverage tax. PLoS One. 2019;14(3):e0213218. doi:10.1371/journal.pone. 0213218
19. Ponce J, Yuan H, Schillinger D, et al. Retailer perspectives on sugar-sweetened beverage taxes in the California Bay Area. Prev Med Rep. Sep 2020;19:101129. doi:10.1016/j.pmedr.2020.101129
20. Silver LD, Ng SW, Ryan-Ibarra S, et al. Changes in prices, sales, consumer spending, and beverage consumption one year after a tax on sugar-sweetened beverages in Berkeley, California, US: A before-and-after study. PLoS Med. Apr 2017;14(4):e1002283. doi:10.1371/journal.pmed. 1002283
21. Bleich SN, Lawman HG, LeVasseur MT, et al. The Association Of A Sweetened Beverage Tax With Changes In Beverage Prices And Purchases At Independent Stores. Health Aff (Millwood). Jul 2020;39(7):1130-1139. doi:10.1377/hlthaff.2019.01058
22. Powell LM, Leider J. The impact of Seattle's Sweetened Beverage Tax on beverage prices and volume sold. Econ Hum Biol. May 2020;37:100856. doi:10.1016/j.ehb.2020.100856
23. Cawley J, Frisvold D, Hill A, Jones D. The impact of the Philadelphia beverage tax on purchases and consumption by adults and children. J Health Econ. Sep 2019;67:102225. doi:10.1016/j.jhealeco.2019.102225
24. Sanchez-Romero LM, Canto-Osorio F, Gonzalez-Morales R, et al. Association between tax on sugar sweetened beverages and soft drink consumption in adults in Mexico: open cohort longitudinal analysis of Health Workers Cohort Study. BMJ. May 6 2020;369:m1311. doi:10.1136/bmj.m1311
25. American Community Survey 5-Year Data (2009-2019). United States Census Bureau. Accessed June 29, 2021, https://www.census.gov/data/developers/data-sets/acsSyear.html
26. Purtle J, Langellier B, Le-Scherban F. A Case Study of the Philadelphia Sugar-Sweetened Beverage Tax Policymaking Process: Implications for Policy Development and Advocacy. J Public Health Manag Pract. Jan/Feb 2018;24(1):4-8. doi:10.1097/PHH. 0000000000000563
27. Cawley J, Frisvold D, Hill A, Jones D. Oakland's sugar-sweetened beverage tax: Impacts on prices, purchases and consumption by adults and children. Econ Hum Biol. May 2020;37:100865. doi:10.1016/j.ehb.2020.100865
28. Zhong Y, Auchincloss AH, Lee BK, McKenna RM, Langellier BA. Sugar-Sweetened and Diet Beverage Consumption in Philadelphia One Year after the Beverage Tax. Int J Environ Res Public Health. Feb 19 2020;17(4)doi:10.3390/ijerph17041336
29. Lee MM, Falbe J, Schillinger D, Basu S, McCulloch CE, Madsen KA. Sugar-Sweetened Beverage Consumption 3 Years After the Berkeley, California, Sugar-Sweetened Beverage Tax. Am J Public Health. Apr 2019;109(4):637-639. doi:10.2105/AJPH.2019.304971
30. Edmondson EK, Roberto CA, Gregory EF, Mitra N, Virudachalam S. Association of a Sweetened Beverage Tax With Soda Consumption in High School Students. JAMA Pediatr. Dec 1 2021;175(12):1261-1268. doi:10.1001/jamapediatrics.2021.3991
31. Cawley J, Frisvold D, Jones D. The impact of sugar-sweetened beverage taxes on purchases: Evidence from four city-level taxes in the United States. Health Econ. Oct 2020;29(10):1289-1306. doi:10.1002/hec. 4141
32. Bleich SN, Vercammen KA, Koma JW, Li Z. Trends in Beverage Consumption Among Children and Adults, 2003-2014. Obesity (Silver Spring). Feb 2018;26(2):432-441. doi:10.1002/oby. 22056
33. Grummon AH, Roberto CA, Lawman HG, et al. Purchases of Non-taxed Foods, Beverages, and Alcohol in a Longitudinal Cohort after Implementation of the Philadelphia Beverage Tax. J Nutr. Dec 15 2021;doi:10.1093/jn/nxab421
34. Rhynhart R. Data Release: Beverage Tax Revenue and Expenditures. 2019. Accessed October 15, 2019. https://controller.phila.gov/philadelphia-audits/data-release-beverage-tax/\#fn1

# Paper 3: Naming Matters: Nudging toward Smaller Portions in an Online Randomized Controlled Trial 

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#### Abstract

Objective: To test whether portion-size descriptions on menus and different pricing strategies influence selection of smaller portion sizes.

Methods: In 2021, we conducted an online simulated menu-ordering study, randomizing 2,205 U.S. adults to view one of four portion-size descriptions (Reduced/Larger portion): 1) no label/"Large" (control); 2) "Standard"/"Large"; 3) "Just Right"/"Large"; 4) no label/"Hearty". Participants were also randomized to either linear (50\% and 100\% of pricing for reduced size and larger size) or non-linear pricing ( $70 \%$ and $100 \%$ of pricing for reduced and larger size) ( $4 \times 2$ factorial design). They viewed two menus and ordered an entrée from each. Logistic regression models analyzed whether the interventions increased the likelihood of choosing a reduced portion.

Results: Regardless of pricing scheme, participants in the "Standard/Large" condition selected reduced portions by 10 ( $95 \% \mathrm{Cl}: 0.04,0.16$ ) and 12 ( $95 \% \mathrm{Cl}: 0.07,0.18$ ) percentage points more than those in the control condition (fast-casual and full-service, respectively). Selection of reduced portions in the "Just Right"/"Large" condition increased by $9(95 \% \mathrm{CI}: 0.04,0.15)$ and 8 ( $95 \% \mathrm{Cl}: 0.02,0.14$ ) percentage points.

Conclusion: Portion-size descriptions on menus, even with non-linear pricing, is a low-cost strategy to promote choice of lower-calorie smaller portions when dining out.


## INTRODUCTION

Portion sizes for foods and beverages in the U.S. have increased over time, and this parallels an increase in dining out. ${ }^{1-3}$ When served large portions, people consume in excess without realizing it, and in the restaurant setting, this means consuming more foods that tend to be higher in calories, sodium, and saturated fats than foods cooked at home. ${ }^{4,5}$ Excess weight and obesity are driven in part by larger portion sizes, which contribute to overeating and have reset norms around reasonable serving sizes. ${ }^{6-8}$

Developing low-cost interventions to guide consumers to choose smaller portions has the potential to help people stay within calorie recommendations and potentially shift perceived norms about portion sizes towards appropriate servings to support a healthy, active life. Hollands et al. found that portion size reduction has the potential to reduce average daily energy consumption among adults by up to $16 \%$, and Zlatevska et al. found that doubling portions may increase consumption by up to $39 \%{ }^{6,9}$ Studies have shown that when people are served less food, they will eat less without necessarily feeling less sated. ${ }^{10-12}$ However, it is still unclear whether compensation for these calories occurs later in the day. ${ }^{12,13}$ In one of the few studies conducted in a real-world setting, nearly one third of consumers in a Chinese take-out restaurant opted to receive reduced side dish portions for the same cost as the regular portions. ${ }^{14}$ Downsizing a part of their meal led people to consume fewer calories and did not lead to overconsumption of other portions of the meal.

Current restaurant pricing strategies also play an important role in encouraging the selection of large portions when dining out. ${ }^{15}$ Many restaurants use "non-linear pricing," in which the price per ounce is cheaper as the portion size increases, thus incentivizing customers
to order larger sizes. ${ }^{16}$ This is in contrast to linear pricing, in which the price per ounce stays the same regardless of size. Despite models suggesting that non-linear pricing should increase the ordering of larger-sized meals, ${ }^{16}$ the few experimental studies that have examined the effects of linear and non-linear pricing on portion size choice have found no significant effects. ${ }^{17-19} \mathrm{~A}$ study by John et al. showed that pricing scheme did not interact with beverage menu type (in this case, a menu with three sizes of beverages or a menu with the larger sizes split into two cups such that a 32 -ounce drink was presented as 216 -ounce drinks). ${ }^{20}$ Because the restaurant industry operates on thin margins, it is important to understand how portion size reduction interventions may interact with non-linear and linear pricing schemes.

Social norms theory posits that people incorrectly believe that behaviors of others are not aligned with their own when that is not the case. ${ }^{21}$ As a result, interventions that aim to correct that misperception can encourage healthier behavior. By calling the larger of two sizes "Hearty" on a restaurant menu, for instance, we hope to portray the larger size as "larger than average," thus steering consumers toward the smaller size. Similarly, by calling the smaller size "Standard" or "Just Right," we hope consumers will perceive the reduced portion as the "normal" size, or what others are choosing to eat.

In recognition of the role large portions play in promoting overconsumption of unhealthy foods, New York City attempted and failed in 2013 to implement a cap on the size of sugary drink portions. ${ }^{22}$ This highlights a need to explore low-cost portion size reduction strategies that restaurants can voluntarily implement. Therefore, the goal of this study was to test the effects of manipulating portion-size descriptions on fast-casual and full-service
restaurant menus on consumers' choice of reduced portions. The study also examined if the portion-size description manipulation was dependent on non-linear or linear pricing schemes. We hypothesized that describing a reduced portion entrée as "Standard" size or "Just Right" (compared to having no description) or describing the larger portion entrée as "Hearty" would increase the odds of customers choosing the smaller portion size, regardless of whether linear or non-linear pricing was used.

## METHODS

We conducted a pre-registered (AsPredicted \#72850) online randomized controlled experiment with a $4 \times 2$ factorial design. Data were collected September-October 2021. This study was determined exempt by the Harvard T.H. Chan School of Public Health Institutional Review Board. The sample consisted of U.S. adults who spoke English and reported eating out or ordering from a restaurant at least twice in the past four weeks. Participants were recruited to take an online survey by Dynata, a research firm with an online panel of U.S. consumers. Participants were invited to take a survey about consumer preferences when dining out. Quotas were used to recruit a sample with an educational attainment that aligned with the U.S. distribution according to the 2020 Census. ${ }^{23}$ In total, 2,785 participants were randomized and completed the survey. Participants were excluded from primary analyses if they met the following pre-specified criteria: 1) completed the survey in less than one-third of the median completion time ( $\mathrm{n}=23$ ); or 2 ) did not pass the attention check question asking, "What month are we were in now?" ( $n=404$ ). Although not pre-specified, we further excluded participants from the primary analyses if they omitted race $(n=5), B M I(n=58)$, or numeracy ( $n=40$ ) information, or had a reported $\mathrm{BMI}<13 \mathrm{~kg} / \mathrm{m} 2(\mathrm{n}=50)$. Since our secondary analyses controlled
for these demographic variables, excluding those missing the relevant information allowed our sample size to be the same for both primary and secondary analyses. The final analytic sample included 2,205 participants (See Figure 3.1 for CONSORT diagram).
Figure 3.1 CONSORT diagram for an online randomized controlled experiment examining selection of a reduced portion on a menu with two portion sizes on a fast-casual menu and a full-service restaurant menu in the presence of different portion size descriptors


Participants were randomized to see one of eight sets of menus, with each set including a menu inspired by a fast-casual restaurant (e.g., Panera) and a menu inspired by a full-service chain restaurant (e.g., TGI Fridays), shown in a random order (Figure 3.2). We reviewed existing restaurant menus to come up with plausible menu items for the study. All menu items were labeled with their calorie content as required by national law. Each menu showed entrées available in two sizes: a reduced portion and a larger portion. The calorie contents for the larger entrées were modeled after standard sizes in restaurants, and the reduced-portion entrees had half as many calories. The mean number of calories per order in the fast-casual menu assuming the side salad was 100 calories and the beverage was 0 calories was 515 calories; in the fullservice menu, it was 620 calories. Participants were randomized to see menu sets with one of four pairs of portion-size descriptors (reduced portion and larger portion): no label and "Large"; "Standard" and "Large"; "Just Right" and "Large"; and no label and "Hearty". The no label and "Large" condition was the control based on the labeling used at several popular chain restaurants that offer multiple entrée sizes. ${ }^{24,25}$ Participants were additionally randomized to one of two pricing conditions: linear pricing (i.e., the reduced portion was $50 \%$ of the larger entrée's price) and non-linear pricing (i.e., the reduced portion was $70 \%$ of the larger entrée's price). The larger entrée prices were held constant while the reduced portion entrée prices changed.
Figure 3.2: Sample fast-casual and full-service chain restaurant menus that participants saw in an online randomized controlled

| Delaxe CROWD PLEASERS |  |
| :---: | :---: |
| Served with fresh side salad (or warm bread roll for salad options) and beverage of choice |  |
| 2,000 calories a day is used for general nutrition advice, but calorie needs vary. |  |
| SLOW ROASTED TRI-TIP Tri-tip in a peppered BBQ sauce with secret spice rub. Served with |  |
| roasted asparagus and a baked potato. | SANTA FE SALAD Crisped romaine, pickled red |
| Standard: \$7.50 (705 cal) \| Large: \$15.00 (1410 | onions, fire-roasted red peppers, pepper jack cheese, avocado, sweet corn, crispy corn tortilla strips, spiced black beans. Dressed with tomato salsa ranch (V) <br> Standard: $\mathbf{\$ 7 . 7 5}$ ( $\mathbf{5 2 0} \mathbf{c a l )}$ \| Large: $\mathbf{\$ 1 5 . 5 0 ( 1 0 4 0 ~ c a l )}$ |
|  | CHOPPED COBB SALAD Crispy romaine, slowroasted chicken, bacon, chopped egg, avocado, tomatoes, chives, crumbled bleu cheese. Dressed with house made signature ranch. <br> Standard: $\mathbf{\$ 6 . 1 5 ( 4 0 5 ~ c a l )}$ \| Large: $\$ 12.30(810 \mathrm{cal})$ |
| SWEET GLAZED TOFU "STEAKS" Grilled tofu marinated in a sweet chill glaze. Served with sautéed vegetables and long grain rice (V) <br> Standard: $\mathbf{\$ 6 . 6 5}$ ( $\mathbf{4 6 0} \mathbf{c a l}$ ) \| Large: $\$ 13.30(920 \mathrm{cal})$ | NEW ORLEANS JAMBALAYA Blackened chicken breast, sautéed shrimp, andouille sausage, and vegetable medley in a Cajun-spiced broth. |
| DEEP DISH FOUR-CHEESE ZITI Baked blend of parmesan, mozzarella, provolone, and ricotta mixed with pasta and marinara (V) | Served over rice pilaf. Standard: $\$ 9.95$ (665 cal) \| Large: $\$ 19.90$ ( 1330 cal ) |
| Standard: $\mathbf{\$ 8 . 4 0} \mathbf{( 7 0 0} \mathrm{cal})$ \| Large: $\mathbf{\$ 1 6 . 8 0} \mathbf{( 1 4 0 0} \mathrm{cal})$ |  |
| ITALIAN VEGETABLE PENNE slow roasted zucchini, asparagus, red peppers, and carrots tossed with penne and marinara sauce (V) Standard: $\mathbf{\$ 6 . 6 5}$ ( $\mathbf{3 5 0} \mathbf{~ c a l )}$ \| Large: $\$ 13.30(700 \mathrm{cal})$ |  |
| PULLED PORK PITA TACOS slow roasted pulled pork, crispy red onions, avocado crema, pineapple slaw, tomatoes, served on grilled pita. Topped with cilantro and three-cheese blend |  |
| Standard: \$6.50 ( 480 cal ) \| Large: $\mathbf{\$ 1 3 . 0 0}(960 \mathrm{cal})$ |  |
| CHIPOTLE CAULIFLOWER PITA TACOS | SPICY PEANUT CHICKEN WITH SOBA |
| Chipotle roasted cauliflower, avocado crema, pickled red onions, spiced black beans, tomatoes, served on grilled pita. Topped with cilantro and cotija | NOODLES Stir fried chicken breast with broccoli and carrots doused in a spicy peanut sesame sauce. Served over soba noodles. |
| Standard: \$6.50 (400 cal) \| Large: \$13.00 (960 cal) | Standard: \$7.95 (520 cal) \| Large: \$15.90 (1040 cal) |

experiment

| Served with fresh side salad (or warm bread roll for salad options) and beverage of choice |  |  |
| :---: | :---: | :---: |
| 2,000 calories a day is used for general nutrition advice, but calorie needs vary. |  |  |
| SPECIALTY SALADS \& SOUPS | Standard | Large |
| SOUTHWEST CHILI LIME RANCH SALAD WITH CHICKEN | \$5.75 | \$11.50 |
| Chicken raised without antibiotics, romaine, black bean \& corn salsa, fresh cilantro, and tortilla crisps in chili lime ranch. Topped with feta, avocado, and grilled chicken | 400 cal | 800 cal |
| KALE AND SWEET HONEY PECAN SALAD (V) |  |  |
| Tender kale, sliced grape tomatoes, roasted carrots, seasoned chickpeas, and sweet honey-glazed pecans in a creamy garlic dressing. Topped with mozzarella balls and quinoa. | $\$ 5.45$ $445 \mathrm{cal}$ | $\begin{aligned} & \$ 10.90 \\ & 890 \text { cal } \end{aligned}$ |
| TOMATO BASIL BISQUE | \$3.40 | \$6.80 |
| Rich and zesty tomato soup with cream, sherry, basil and garlic | 300 cal | 600 cal |
| BOWLS AND NOODLES |  |  |
|  | Standard | Large |
| MEDITERRANEAN BOWL WITH CHICKEN |  |  |
| Lime brown rice and quinoa, chicken raised without antibiotics, spinach, red grape tomatoes, Kalamata olives, diced cucumbers, hummus, lemon tahini sauce. Topped with feta. | $\begin{aligned} & \$ 5.45 \\ & 350 \mathrm{cal} \end{aligned}$ | $\begin{aligned} & \$ 10.90 \\ & 700 \mathrm{cal} \end{aligned}$ |
| PESTO TOFU QUINOA BOWL (V) | \$5.30 | \$10.60 |
| Lemon quinoa mixed with kale, grilled tofu steaks, spinach, roasted grape tomatoes, diced cucumbers, basil pesto sauce. Topped with feta and fresh herbs. | 320 cal | 640 cal |
| GRILLED ORANGE CHICKEN LO MEIN | \$4.90 |  |
| Lo mein noodles in orange sauce with grilled chicken, snap peas, napa and red cabbage topped with green onions, black sesame seeds and cilantro | 490 cal | 980 cal |
| JAPANESE PAN NOODLES WITH TOFU |  |  |
| Caramelized udon noodles in sweet soy sauce, broccoli, mushrooms and carrots | $\begin{aligned} & \$ 4.90 \\ & 435 \mathrm{cal} \end{aligned}$ | $\begin{aligned} & \$ 9.80 \\ & 870 \mathrm{cal} \end{aligned}$ |
| topped win black sesame seeds and clantro. Topped wh miso marnated toru |  |  |
| MAC \& CHEESE | \$4.50 | \$9.00 |
| Tender elbow pasta in a blend of rich cheeses including our tangy Vermont white cheddar cheese sauce | 475 cal | 950 cal |
| PIZZAS |  |  |
| FOUR CHEESE FLATBREAD PIZZA (V) | Standard | Large $\$ 9.30$ |
| Fresh mozzarella, grated parmesan, feta crumbles, and Fontina with garlic flavored cream sauce on our flatbread | 465 cal | 930 cal |
| PEPPERONI FLATBREAD PIZZA (V) | \$4.65 | \$9.30 |
| Pepperoni, fresh mozzarella, and Fontina with tomato bell pepper sauce on our flatbread | 475 cal | 950 cal |

After providing informed consent, participants viewed the two menus one at a time, and were instructed to imagine they were eating out on a typical night and to order one entrée from each menu. Participants clicked on the menu item they wanted to select, similar to how they might for an online ordering platform. Participants were then asked questions about their menu choices, followed by a series of demographic questions, and a 3-question, validated numeracy scale. ${ }^{26}$ (See Appendix Table 3.1 for the survey.) We measured numeracy because the only indicator that the reduced portion was half the size of the larger portion was the calorie labels, so we wanted to control for numeracy in the analyses if it was not balanced across conditions.

The primary outcome was a dichotomous variable indicating whether or not a participant chose a reduced portion entrée from each restaurant menu (fast-casual and fullservice chain).

## Data Analysis

Analyses were conducted separately for the fast-casual and full-service restaurant menus because portion sizes are usually larger in full-service restaurants. Primary analyses used logistic regression models to assess how naming and pricing affected choice of a reduced portion entrée. Each model contained a categorical variable for portion-size-description condition (reference=control), a binary variable for pricing condition (non-linear vs. linear), and an interaction between the two variables. The interactions were not significant in any model, so they were removed from the final models. We tested for differences across conditions by demographic variables such as age and gender identity (ANOVA for continuous variables,

Kruskal-Wallis H tests for categorical). Because conditions were randomized, demographic variables were balanced across conditions, so our primary analyses did not control for other variables. Sensitivity analyses were performed on the full sample without any of the exclusions based on time to completion, accuracy of attention check answer, or missing information.

We conducted secondary analyses to develop more precise estimates and to demonstrate that our results were not due to confounding. We adjusted for age (categorical by decade; 18- and 19-year-olds were included in the <30 group), gender identity (categorical; female, male, other), BMI (categorical; underweight, normal weight, overweight, obese), race (categorical; White, Black, other), numeracy (categorical; score of 0-3 depending on number of accurate answers), and educational attainment (categorical; less than high school, high school/GED, some college, 2-year/Associate degree, 4-year degree, graduate degree), in addition to price and portion size variables.

In exploratory analyses, we also tested for effect modification of the portion description by educational attainment and numeracy as both have been found to affect the efficacy of nutrition labels. ${ }^{27}$ Not only did we want to test whether these factors could similarly affect the efficacy of portion-size descriptors, but we also wanted to statistically control for both variables if they were not balanced across conditions. Odds ratios and predicted probabilities are presented. With a sample size of 2200 , we would have $80 \%$ power to detect an odds ratio of 1.3 ( $\alpha=0.05$, two tailed). ${ }^{14}$ All analyses were conducted using Stata version 17 (StataCorp LLC, College Station, TX).

## RESULTS

In the final analytic sample ( $n=2,205$ ), the average age was 59.1 years, $53.0 \%$ identified as being female, and the majority of participants identified as White (82.5\%). Participants had an average BMI in the overweight category $\left(28.0 \mathrm{~kg} / \mathrm{m}^{2}\right)$. These variables did not differ by condition. See Table 3.1.
Table 3.1 Demographics of participants ( $n=2,205$ ) by menu condition in an online randomized controlled experiment

|  | Linear Pricing ( $\mathrm{n}=1,097$ ) |  |  |  | Non-Linear Pricing ( $\mathrm{n}=1,108$ ) |  |  |  | $p$-value |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | no label and "Large" $\mathrm{n}=265$ | $\begin{gathered} \text { "Standard" } \\ \text { and } \\ \text { "Large" } \\ \mathrm{n}=282 \\ \hline \end{gathered}$ | "Just Right" and "Large" $\mathrm{n}=281$ | no label and "Hearty" $\mathrm{n}=269$ | no label and "Large" $\mathrm{n}=278$ | "Standard" and "Large" $\mathrm{n}=278$ | "Just Right" and "Large" $\mathrm{n}=286$ | no label and "Hearty" $\mathrm{n}=266$ |  |
| Age, mean (SD) | 59.5 (18.2) | 59.6 (18.1) | 59.2 (17.9) | 57.9 (19.1) | 59.6 (18.8) | 58.1 (18.2) | 59.6 (18.3) | 58.9 (17.9) | 0.89 ${ }^{\text {a }}$ |
| Gender Identity, $\mathrm{n}(\%)$ |  |  |  |  |  |  |  |  | $0.93{ }^{\text {b }}$ |
| Female | 148 (55.9) | 148 (52.5) | 150 (53.4) | 136 (50.5) | 148 (53.2) | 155 (55.8) | 145 (50.7) | 138 (51.9) |  |
| Male | 116 (43.8) | 130 (46.1) | 130 (46.3) | 132 (49.1) | 129 (46.4) | 121 (43.5) | 138 (48.3) | 127 (47.7) |  |
| Other | 1 (0.4) | 4 (1.4) | 1 (0.4) | 1 (0.4) | 1 (0.4) | 2 (0.7) | 3 (1.1) | 1 (0.4) |  |
| Race, n (\%) |  |  |  |  |  |  |  |  | $0.98{ }^{\text {b }}$ |
| Black | 27 (10.2) | 33 (11.7) | 30 (10.7) | 32 (11.9) | 29 (10.4) | 36 (13.0) | 36 (12.6) | 34 (12.8) |  |
| White | 221 (83.4) | 230 (81.6) | 236 (84.0) | 219 (81.4) | 229 (82.4) | 226 (81.3) | 239 (83.6) | 220 (82.7) |  |
| Other ${ }^{\text {c }}$ | 17 (6.4) | 19 (6.7) | 15 (5.3) | 18 (6.7) | 20 (7.2) | 16 (5.8) | 11 (3.9) | 12 (4.5) |  |
| $\mathrm{BMI}(\mathrm{~kg} / \mathrm{m} 2),$ mean (SD) | 27.8 (6.2) | 28.2 (6.8) | 27.7 (9.0) | 27.8 (6.4) | 27.7 (6.2) | 28.0 (6.4) | 28.2 (6.9) | 28.8 (7.5) | $0.56{ }^{\text {a }}$ |
| Educational Attainment, n(\%) |  |  |  |  |  |  |  |  | $0.72{ }^{\text {b }}$ |
| Less than HS | 18 (6.8) | 26 (9.2) | 29 (10.3) | 24 (8.9) | 28 (10.1) | 24 (8.6) | 27 (9.4) | 26 (9.8) |  |
| $\begin{array}{r} \text { High } \\ \text { school/GED } \end{array}$ | 80 (30.2) | 80 (28.4) | 79 (28.1) | 68 (25.3) | 87 (31.3) | 81 (29.1) | 84 (29.4) | 74 (27.8) |  |
| Some college | 55 (20.8) | 43 (15.3) | 50 (17.8) | 53 (19.7) | 50 (18.0) | 35 (12.6) | 46 (16.1) | 53 (19.9) |  |
| 2-yr/Associate | 32 (12.1) | 34 (12.1) | 19 (6.8) | 33 (12.3) | 24 (8.6) | 36 (13.0) | 27 (9.4) | 27 (10.2) |  |
| 4-yr/University | 56 (21.1) | 59 (20.9) | 60 (21.4) | 56 (20.8) | 59 (21.2) | 65 (23.4) | 71 (24.8) | 58 (21.8) |  |
| Graduate | 24 (9.1) | 40 (14.2) | 44 (15.7) | 35 (13.0) | 30 (10.8) | 37 (13.3) | 31 (10.8) | 28 (10.5) |  |


${ }^{\text {b }}$ Kruskal-Wallis H test used to test for significant differences among conditions
Includes American Indian, Asian, and Native Hawaiian

For the fast-casual menu, holding pricing condition constant, the predicted probability of participants in the control condition (no label and "Large") choosing the reduced portion was $55 \%$ ( $95 \%$ CI: $0.51,0.59$ ). Participants who viewed a menu that referred to the smaller portion as "Standard" and the larger portion as "Large" had 1.5 ( $95 \%$ CI: 1.2, 2.0) times the odds—or an increase of 10 percentage points in predicted probability ( $95 \% \mathrm{Cl}: 0.04,0.16$ ) -of choosing the smaller size compared to the control condition. Participants who viewed the "'Just Right' and 'Large'" menu had 1.5 ( $95 \% \mathrm{Cl}: 1.2,1.9$ ) times the odds and an increase of 9 percentage points ( $95 \% \mathrm{CI}: 0.04,0.15$ ) of choosing the smaller portion size. The menu that displayed the name of the larger portion as "Hearty" while keeping the smaller portion unlabeled was not associated with increased odds of choosing a smaller portion ( $\mathrm{OR}=1.0$ [ $95 \% \mathrm{Cl}: 0.8,1.3$ ]) compared to the control. See Figure 3.3 and Appendix Table 3.2.
Figure 3.3 Predicted probabilities ${ }^{a}$ for choosing the smaller portion by portion size descriptors in an online randomized controlled ordering trial $(n=2,205)$

${ }^{a}$ Logistic regression models controlled for pricing scheme (linear vs. nonlinear pricing)

For the full-service menu, similar patterns existed (Figure 3.3). Those who viewed the "'Standard' and 'Large'" labels on the menu had 1.7 ( $95 \% \mathrm{Cl}: 1.3,2.2$ ) times the odds and an increase of 12 percentage points ( $95 \% \mathrm{Cl}: 0.07,0.18$ ) of choosing a reduced portion entrée, and those who viewed the "'Just Right' and 'Large'" labeled menu had 1.4 (95\% CI: 1.1, 1.8) times the odds and an increase of 8 percentage points ( $95 \% \mathrm{Cl}: 0.02,0.14$ ) of ordering a reduced portion entrée as compared to the control. As with the fast-casual menus, the odds of consumers choosing a reduced portion entrée when viewing the "no label and 'Hearty"" menu ( $\mathrm{OR}=1.0$ [ $95 \% \mathrm{Cl}: 0.8,1.2]$ ) did not statistically differ from the control menu.

For the fast-casual menu, holding portion-size descriptors constant, customers had 1.2 ( $95 \% \mathrm{CI}: 1.0,1.5$ ) times the odds of ordering a reduced portion entrée with non-linear pricing compared to linear pricing. For the full-service menu, the odds of choosing a reduced portion entrée did not differ between linear and non-linear pricing ( $O R=1.1$ [ $95 \% \mathrm{CI}: 0.9,1.3$ ]) (Figure 3.4). Results of sensitivity analyses with all participants who completed the survey (ignoring exclusion criteria) were similar to the primary models (Appendix Table 3.3).

Figure 3.4 Predicted probabilities ${ }^{\text {a }}$ for choosing the smaller portion by pricing scheme in an online randomized controlled ordering trial ( $n=2,205$ )

** $p<0.01$
${ }^{\text {a }}$ Logistic regression models controlled for portion size descriptors (4 levels: no label and "Large"; "Standard" and "Large"; "Just Right" and "Large"; and no label and "Hearty"

We ran exploratory analyses examining effect modification of the portion description by education and numeracy. For the full-service menu, compared to participants with a high school degree, participants with "some college" or a "4-year degree" were significantly more likely to order reduced portions when nudged to do so in the "no label and 'Hearty'" condition compared to the control "no label and 'Large'" condition (OR = 2.7 [ $95 \% \mathrm{CI}: 1.3,5.8$ ]; OR = 2.7 [ $95 \% \mathrm{CI}: 1.3,5.6$ ], respectively). No other significant education or numeracy interactions with portion-size descriptors were observed for portion size choice on either restaurant menu.

In secondary models which took the primary analyses' models and additionally controlled for demographic characteristics, results were generally similar across both menus. (Appendix Table 3.4).

## DISCUSSION

Our study found that naming the smaller portion "Standard" or "Just Right" on menus with two different-sized entrées increased the predicted probability of participants choosing reduced portion entrées by 8-12\% in an online hypothetical restaurant setting. Non-linear pricing increased the predicted probability of selection of reduced portions in the fast-casual setting, though it did not impact selection of reduced portions in the full-service setting, keeping portion names constant. The impact of the portion-size descriptors did not differ by level of pricing.

Our results suggest that it is possible to nudge consumers to select smaller portion sizes by labeling them as "Standard" or "Just Right." Unexpectedly, referring to the larger size as "Hearty"—which was meant to connote "larger than average"—did not alter the odds of ordering a smaller size compared to the control condition. However, it is possible that in our study, "Hearty" did not properly convey how much bigger the larger size was, although all menus did have calorie counts that reflected that the larger size had twice as many calories as the smaller size. It is also possible that simply naming the smaller size anything at all prompted participants to order that size, as the control condition and "no label and 'Hearty"' did not label the smaller size. Currently, restaurants like Chipotle and Blaze only describe the larger size (such as our control condition), , ${ }^{24,25}$ so if merely adding a description for the smaller size can increase selection, then the strategy merits further exploration.

Despite the influence of price on restaurant choices, ${ }^{15}$ we found that, holding portionsize descriptors constant, there were no differences in the odds of selecting reduced portions between linear and non-linear pricing in the full-service setting. Surprisingly, in the fast-casual setting, non-linearly priced menus compared to the linearly priced menus increased selection of reduced portions. This meant that participants were willing to pay more for a smaller portion. Even though reduced portions were more expensive in the non-linear price conditions, participants may have been using price instead of calories as a proxy for size. As a result, when they viewed prices that were only slightly lower than the larger size, they may have assumed the size of the portion would also be slightly smaller instead of half the size.

Consistent with our results, research on the effect of linear and non-linear pricing on ordering decisions has been counterintuitive, with studies showing that behavior is not affected by the type of pricing used. ${ }^{17,18,20,28,29}$ Although we did not find interactions between portionsize descriptors and pricing, it will be important for future research to examine interactions between pricing and item naming in real-world settings, and how such interventions impact restaurants' bottom line.

We did find that those with higher educational attainment had increased odds of ordering reduced portions in the full-service setting when they viewed the no label and "Hearty" compared to the control no label and "Large", even though this condition did not have an effect in our primary analyses. These results highlight the importance of testing seemingly similar wording, especially when viewed through a health equity lens. Implementing "no label and 'Hearty'" portion naming could potentially widen health disparities among lower- and higher-educated populations. Given that effect modification by education was not apparent in
the "'Standard' and 'Large'" condition, and this intervention arm had the greatest ordering of reduced portions, the "'Standard' and 'Large'" wording has the most promise for overall effectiveness and for equal effectiveness across educational levels, and thus should be tested under real-world conditions as a next research step.

Groups that oppose public health measures such as beverage taxes and portion size caps for sugary beverages use the argument that such measures turn cities and other localities into a "nanny state." ${ }^{30}$ It is therefore important that public health officials propose interventions like the one in this experiment that can preempt that argument-one in which consumers can still order the larger size. Restaurants can voluntarily alter their menus with this low-cost intervention to improve the health of their customers, preserve consumer choice, reduce food waste, and potentially profit from an expanded customer market.

## Strengths and Limitations

This study had several strengths. It was the first study to examine the efficacy of changing the description of reduced portion entrées to nudge consumers toward smaller portion sizes when dining out. It is also one of the few studies to assess the impact of pricing on ordering reduced sizes. It considered the importance of linear versus non-linear pricing when using these nudges to address whether such nudges would work in the context of non-linear pricing, which is often used in the restaurant industry. Finally, we used a randomized, controlled design with a large sample size.

Our study also had several limitations. First, as this was an online hypothetical study testing a single exposure to mock menus, it may not reflect repeated ordering behavior from a
real restaurant menu using real money. However, we only recruited participants who indicated that they either ate out or ordered online at least twice in the past four weeks, suggesting familiarity with both dining out and/or using an online platform to order. The menus were modeled after real menus. In addition, the calories ordered in hypothetical scenarios are often in line with calories ordered in real world studies. ${ }^{31,32}$ Second, we did not measure consumption. It is possible that participants who ordered the larger size in this study did not intend to finish the entire entrée as one meal, in which case, the portion size consumed may have been appropriate, though we know that people typically overeat with larger portions. ${ }^{6}$ Third, despite attempts to recruit a racially diverse sample, over $80 \%$ of our participants identified as White, limiting the generalizability of our results to other important demographic groups. Fourth, this intervention did not account for dietary quality, though reducing caloric intake is another important aspect of chronic disease prevention. ${ }^{33}$ Finally, the average age of our participants was relatively high (59 years) compared to the median age of the U.S. population, limiting generalizability to other age groups. Future studies should assess the effects of repeated ordering from menus with modified portion-size descriptors and linear/nonlinear pricing schemes in real-world restaurant settings. It will also be important to test these interventions on populations with diverse sociodemographic characteristics.

## CONCLUSION

Portions sizes of foods and beverages have grown in the U.S., as has the prevalence of overweight and obesity. To reverse such societal norms will require not only policies targeting larger portions, but also time for such norms to change. Innovative strategies are needed to combat the consumption of excess calories. This study demonstrated that describing reduced
portion sizes on restaurant menus as "Standard" or "Just Right" could encourage consumers to choose smaller portion sizes, which has the potential to reduce caloric intake. Given the frequency with which Americans eat restaurant foods, our experiment provides a novel strategy to encourage people to eat smaller portions without taking away their choice.

## REFERENCES

1. Elitzak H, Okrent A. New U.S. food expenditure estimates find food-away-from-home spending Is higher than previous estimates. 2018. https://www.ers.usda.gov/amber-waves/2018/november/new-us-food-expenditure-estimates-find-food-away-from-home-spending-is-higher-than-previous-estimates/
2. Young LR, Nestle M. Portion Sizes of Ultra-Processed Foods in the United States, 2002 to 2021. Am J Public Health. Dec 2021;111(12):2223-2226. doi:10.2105/AJPH.2021.306513
3. Piernas C, Popkin BM. Food portion patterns and trends among U.S. children and the relationship to total eating occasion size, 1977-2006. J Nutr. Jun 2011;141(6):1159-64. doi:10.3945/jn.111.138727
4. Livingstone MB, Pourshahidi LK. Portion size and obesity. Adv Nutr. Nov 2014;5(6):829-34. doi:10.3945/an.114.007104
5. Bezerra IN, Curioni C, Sichieri R. Association between eating out of home and body weight. Nutr Rev. Feb 2012;70(2):65-79. doi:10.1111/j.1753-4887.2011.00459.x
6. Hollands GJ, Shemilt I, Marteau TM, et al. Portion, package or tableware size for changing selection and consumption of food, alcohol and tobacco. Cochrane Database Syst Rev. Sep 14 2015;(9):CD011045. doi:10.1002/14651858.CD011045.pub2
7. Geier $A B$, Rozin P, Doros G. Unit bias. A new heuristic that helps explain the effect of portion size on food intake. Psychol Sci. Jun 2006;17(6):521-5. doi:10.1111/j.14679280.2006.01738.x
8. Marteau TM, Hollands GJ, Shemilt I, Jebb SA. Downsizing: policy options to reduce portion sizes to help tackle obesity. BMJ. Dec 2 2015;351:h5863. doi:10.1136/bmj.h5863
9. Zlatevska N, Dubelaar C, Holden SS. Sizing up the Effect of Portion Size on Consumption: A Meta-Analytic Review. Journal of Marketing. 2014/05/01 2014;78(3):140-154. doi:10.1509/jm.12.0303
10. Levitsky D, Agaronnik N, Zhong W, Morace C, Barre L, Michael JJ. Reducing an entree portion size does not affect the amount of dessert consumed. Appetite. Aug 1 2020;151:104684. doi:10.1016/j.appet.2020.104684
11. Reinders MJ, Huitink M, Dijkstra SC, Maaskant AJ, Heijnen J. Menu-engineering in restaurants - adapting portion sizes on plates to enhance vegetable consumption: a real-life experiment. Int J Behav Nutr Phys Act. Dec 25 2017;14(1):41. doi:10.1186/s12966-017-0496-9
12. Vermote $M$, Versele $V$, Stok $M$, et al. The effect of a portion size intervention on French fries consumption, plate waste, satiety and compensatory caloric intake: an on-campus restaurant experiment. Nutrition Journal. 2018;17
13. Sim AY, Cheon BK. Influence of impending healthy food consumption on snacking: Nudging vs. compensatory behaviour. Physiol Behav. Jan 1 2019;198:48-56.
doi:10.1016/j.physbeh.2018.10.010
14. Schwartz J, Riis J, Elbel B, Ariely D. Inviting consumers to downsize fast-food portions significantly reduces calorie consumption. Health Aff (Millwood). Feb 2012;31(2):399-407. doi:10.1377/hlthaff.2011.0224
15. Hua SV, Sterner-Stein K, Barg FK, et al. A Qualitative Study of Parents With Children 6 to 12 Years Old: Use of Restaurant Calorie Labels to Inform the Development of a Messaging Campaign. J Acad Nutr Diet. Nov 2020;120(11):1884-1892 e4.
doi:10.1016/j.jand.2020.05.018
16. Dobson PW, Gerstner E. For a Few Cents More: Why Supersize Unhealthy Food? Marketing Science. 2010/07/01 2010;29(4):770-778. doi:10.1287/mksc.1100.0558
17. Haws KL, Liu PJ. Half-size me? How calorie and price information influence ordering on restaurant menus with both half and full entree portion sizes. Appetite. Feb 1 2016;97:12737. doi:10.1016/j.appet.2015.11.031
18. Harnack LJ, French SA, Oakes JM, Story MT, Jeffery RW, Rydell SA. Effects of calorie labeling and value size pricing on fast food meal choices: results from an experimental trial. Int J Behav Nutr Phys Act. Dec 5 2008;5:63. doi:10.1186/1479-5868-5-63
19. John LK, Donnelly GE, Roberto CA. Psychologically Informed Implementations of SugaryDrink Portion Limits. Psychol Sci. May 2017;28(5):620-629. doi:10.1177/0956797617692041
20. John LK, Donnelly GE, Roberto CA. Using Behavioral Science To Inform Policies Limiting Sugary-Drink Portions: Reply to Wilson and Stolarz-Fantino (2018). Psychol Sci. Jul 2019;30(7):1103-1105. doi:10.1177/0956797619851731
21. Berkowitz AD. An Overview of the Social Norms Approach. Accessed May 6, 2022, http://alanberkowitz.com/articles/social\ norms\ approach-short.pdf
22. Kansagra SM, Kennelly MO, Nonas CA, et al. Reducing sugary drink consumption: New York City's approach. Am J Public Health. Apr 2015;105(4):e61-4. doi:10.2105/AJPH.2014.302497
23. Educational Attainment in the United States: 2020. United States Census Bureau. Accessed Dec. 10, 2021, https://www.census.gov/data/tables/2020/demo/educational-attainment/cps-detailed-tables.html
24. Chipotle. Accessed Janurary 28, 2021, https://www.chipotle.com/
25. Blaze Pizza. Accessed Janurary 28, 2021, https://www.blazepizza.com/
26. Schwartz LM, Woloshin S, Black WC, Welch HG. The role of numeracy in understanding the benefit of screening mammography. Ann Intern Med. Dec 1 1997;127(11):966-72. doi:10.7326/0003-4819-127-11-199712010-00003
27. Hess R, Visschers VH, Siegrist M. The role of health-related, motivational and sociodemographic aspects in predicting food label use: a comprehensive study. Public Health Nutr. Mar 2012;15(3):407-14. doi:10.1017/S136898001100156X
28. Haws KL, Liu PJ, Dallas SK, Cawley J, Roberto CA. Any Size for a Dollar: The Effect of Any-Size-Same-Price Versus Standard Pricing on Beverage Size Choices. Journal of Consumer Psychology. 2019;30(2):392-401. doi:https://doi.org/10.1002/jcpy. 1129
29. Ito K. Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing. American Economic Review. 2014;104(2):537-63. doi:10.1257/aer.104.2.537
30. Bateman-House A, Bayer R, Colgrove J, Fairchild AL, McMahon CE. Free to Consume? AntiPaternalism and the Politics of New York City's Soda Cap Saga. Public Health Ethics. 2018;11(1):45-53. doi:10.1093/phe/phw046
31. Musicus AA, Hua SV, Schwartz MB, et al. Messages Promoting Healthy Kids' Meals: An Online RCT. Am J Prev Med. May 2021;60(5):674-683. doi:10.1016/j.amepre.2020.11.012
32. Tandon PS, Zhou C, Chan NL, et al. The impact of menu labeling on fast-food purchases for children and parents. Am J Prev Med. Oct 2011;41(4):434-8.
doi:10.1016/j.amepre.2011.06.033
33. Guth E. Counting Calories as an Approach to Achieve Weight Control. JAMA. Jan 16 2018;319(3):225-226. doi:10.1001/jama.2017.21355

## Paper Appendices

## Paper 1 Appendix

Appendix Table 1.1 Odds ${ }^{\text {a }}$ of Claims and Child-Directed Marketing ${ }^{b}$ on Beverage Labels for NonCarbonated (NC) Flavored Waters ( $\mathrm{n}=40$ )

| NC flavored waters $(\mathbf{n}=\mathbf{4 0})$ | Beverages with children-directed marketing <br> $(\mathbf{n}=\mathbf{1 8 )}$ vs controlc $\mathbf{( n = 2 2 )}$ <br> OR (95\% CI) |
| :--- | :---: |
| Macronutrient claims | $7.9(0.9,72.1)$ |
| Micronutrient claims $^{\text {Natural or healthy claims }}{ }^{\text {d }}$ | $0.6(0.2,2.0)$ |
| Fruit and juice claims $^{d}$ | $0.8(0.0, \mathrm{inf})$ |
| Presence of non-nutritive sweeteners $^{\text {d }}$ | $3.1(0.2, \mathrm{inf})$ |

Note: Boldface indicates statistical significance ( ${ }^{*} p<0.05 ;{ }^{* *} p<0.01 ;{ }^{* * *} p<0.001$ ).
${ }^{\text {a }}$ Logistic regression models used to analyze the data.
${ }^{\text {b }}$ Child-directed marketing is defined as containing: child-directed text and imagery, including image of a child, adult, animal, anthropomorphized ingredient/object; sports or fantasy imagery; or child-directed text, including use of unconventional or exaggerated fonts, indication of an extreme experience or taste (i.e., made up flavors), claims related to enjoyment or fun, and words that reference children.
${ }^{\text {c Control group includes beverages without child-directed marketing. }}$
${ }^{\text {d}}$ Due to small sample size, exact logistic regression was used.

Appendix Table 1.2 Nutrient Analysis ${ }^{\text {a }}$ for Non-Carbonated Flavored Waters (NC Flavored Waters) ( $n=40$ ) With and Without Child-Directed Marketing ${ }^{\text {b }}$

| NC flavored waters ( $\mathbf{n}=\mathbf{4 0}$ ) | Beverages with children-directed <br> $(\mathbf{n}=\mathbf{1 8})$ vs control ${ }^{\text {c }}(\mathbf{n}=\mathbf{2 2}$ <br> $\beta(95 \% ~ C I)$ |
| :--- | :---: |
| Calories (kcal) | $-3.8(-28.0,20.3)$ |
| Total sugar (g) | $-1.2(-7.7,5.2)$ |
| Vitamin C (\% DV) | $\mathbf{- 3 7 . 9 ( - 6 8 . 1 , - 7 . 6 ) ^ { * }}$ |

Note: Boldface indicates statistical significance ( ${ }^{*} p<0.05 ;{ }^{* *} p<0.01 ;{ }^{* * *} p<0.001$ ).
${ }^{\text {a }}$ Linear regression models used to analyze the data.
${ }^{\text {b }}$ Child-directed marketing is defined as containing: child-directed text and imagery, including image of a child, adult, animal, anthropomorphized ingredient/object; sports or fantasy imagery; or child-directed text, including use of unconventional or exaggerated fonts, indication of an extreme experience or taste (i.e., made up flavors), claims related to enjoyment or fun, and words that reference children.
${ }^{\text {c Control group includes beverages without child-directed marketing. }}$
Paper 2 Appendix
Appendix Table 2.1 Difference-in-difference regression results for changes in beverage price-per-ounce following implementation of a beverage tax in Philadelphia compared to Baltimore (reference city) controlling for store ID, yearly quarters, and poverty.

|  | Philadelphia |  | Baltimore |  | Weighted DID estimate(95\% CI) | $\begin{gathered} p- \\ \text { value }^{\text {a }} \end{gathered}$ | Percent passthrough ${ }^{\text {b }}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Pre-tax <br> Mean (SD) cents-per-ounce | Post-tax <br> Mean (SD) cents-per-ounce | Pre-tax <br> Mean (SD) cents-per-ounce | Post-tax <br> Mean (SD) cents-per-ounce |  |  |  |
| Taxed Beverages ${ }^{\text {c }}$ $(\mathrm{n}=1,769,331)^{\mathrm{d}}$ | 6.7 (5.0) | 8.2 (5.2) | 6.4 (4.5) | 6.7 (4.5) | $\begin{gathered} 1.6 \\ (1.1,2.0) \\ \hline \end{gathered}$ | <. 001 | 106.7 |
| $\begin{array}{r} \text { Soda } \\ (\mathrm{n}=439,834) \end{array}$ | 5.8 (4.0) | 7.3 (4.0) | 5.6 (4.0) | 5.8 (3.9) | $\begin{gathered} 1.4 \\ (1.1,1.7) \\ \hline \end{gathered}$ | <. 001 | 93.3 |
| $\begin{array}{r} \hline \text { Iced Tea \& } \\ \text { Lemonade } \\ (\mathrm{n}=404,144) \\ \hline \end{array}$ | 6.0 (3.5) | 6.9 (3.4) | 6.0 (3.3) | 6.3 (3.4) | $\begin{gathered} 0.9 \\ (0.7,1.1) \end{gathered}$ | <. 001 | 60.0 |
| Fruit Drinks $(n=284,624)$ | 8.0 (5.4) | 8.8 (5.1) | 7.6 (5.0) | 7.3 (4.6) | $\begin{gathered} 0.8 \\ (0.6,1.0) \\ \hline \end{gathered}$ | <. 001 | 53.3 |
| Sports Drinks $(n=262,835)$ | 7.0 (2.3) | 9.0 (2.3) | 7.1 (2.1) | 7.6 (2.1) | $\begin{gathered} 1.8 \\ (1.5,2.2) \\ \hline \end{gathered}$ | <. 001 | 120.0 |
| $\begin{array}{r} \text { Diet Soda } \\ (n=219,423) \\ \hline \end{array}$ | 5.1 (3.4) | 6.6 (3.6) | 5.3 (3.5) | 5.7 (3.4) | $\begin{gathered} 1.5 \\ (1.1,1.9) \\ \hline \end{gathered}$ | <. 001 | 100.0 |
| Sparkling Water $(n=123,298)$ | 5.9 (5.4) | 7.9 (6.5) | 5.6 (4.7) | 5.4 (4.9) | $\begin{gathered} 1.5 \\ (1.2,1.8) \\ \hline \end{gathered}$ | <. 001 | 100.0 |
| $\begin{array}{r} \text { Coffee } \\ (n=61,368) \end{array}$ | 20.8 (4.2) | 23.2 (4.4) | 20.4 (4.0) | 21.3 (4.1) | $\begin{gathered} 1.1 \\ (0.8,1.4) \end{gathered}$ | <. 001 | 73.3 |
| Energy Drinks ( $n=227,767$ ) | 19.5 (5.8) | 21.6 (5.3) | 19.5 (6.0) | 21.2 (6.6) | $\begin{gathered} 0.2 \\ (-0.4,0.8) \end{gathered}$ | . 514 | N/A |

Appendix Table 2.1 Difference-in-difference regression results for changes in beverage price-per-ounce following implementation of a beverage tax in Philadelphia compared to Baltimore (reference city) controlling for store ID, yearly quarters, and poverty (Continued).

|  | Philadelphia |  | Baltimore |  | Weighted |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |

Note. Mean prices are the mean cents-per-ounce per beverage product (SKU), per store, per week. Covariates in all regression models include store ID, yearly quarters, and store zip code-level percent below the poverty line.
${ }^{\text {ab Bolded values indicate statistical significance after applying the Holm-Bonferroni correction for multiple testing on families of }}$
outcome (total taxed beverages [1 test], taxed beverage subcategories [ 8 tests], total nontaxed beverages [1 test], nontaxed beverage subcategories [ 5 tests]
${ }^{\text {b }}$ The percent pass-through was calculated for taxed beverages as the difference-in-differences point estimate divided by 1.5 cents/oz.
${ }^{\text {conerall taxed category does not sum up to the composite categories because it also includes milk alternatives and other taxed }}$ beverages. It does not include taxed coffees and energy drinks as the price-per-ounce is much higher than the other beverages.
${ }^{\mathrm{d}} \mathrm{N}$ s represent the number of unique week by store ID by SKU combinations over 104 weeks pre-tax and 52 weeks post-tax. In total, there were 1,078 unique SKUs in this dataset across 75 unique stores.
${ }^{\text {e }}$ Overall nontaxed category does not sum up to the composite categories because it also includes milk alternatives, flavored waters, iced tea or lemonade, sports drinks, and other nontaxed beverages. It does not include nontaxed coffees as the price-per-ounce is much higher than the other beverages.
Appendix Table 2.2 Difference-in-difference regression results for changes in beverage price-per-ounce following implementation of a beverage tax in Philadelphia compared to Providence (Providence = reference city).

|  | Philadelphia |  | Providence |  | $\begin{gathered} \text { Weighted } \\ \text { DID estimate } \\ (95 \% \mathrm{CI}) \\ \hline \end{gathered}$ | $p$ value ${ }^{\text {a }}$ | Percent passthrough ${ }^{\text {b }}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Pre-tax <br> Mean (SD) cents-per-ounce | Post-tax <br> Mean (SD) cents-per-ounce | Pre-tax <br> Mean (SD) cents-per-ounce | Post-tax <br> Mean (SD) cents-per-ounce |  |  |  |
| Taxed Beverages ${ }^{\text {c }}$ $(n=1,441,700)^{d}$ | 6.8 (5.0) | 8.2 (5.2) | 7.3 (5.6) | 7.5 (5.7) | $\begin{gathered} 1.4 \\ (1.0,1.7) \\ \hline \end{gathered}$ | <. 001 | 93.3 |
| $\begin{array}{r} \text { Soda } \\ (\mathrm{n}=337,777) \\ \hline \end{array}$ | 5.8 (4.0) | 7.3 (4.0) | 6.1 (4.1) | 6.2 (3.8) | $\begin{gathered} 1.4 \\ (1.1,1.7) \\ \hline \end{gathered}$ | <. 001 | 93.3 |
| Iced Tea \& Lemonade $(n=308,701)$ | 6.0 (3.5) | 6.9 (3.4) | 6.6 (4.3) | 6.8 (4.7) | $\begin{gathered} 0.9 \\ (0.7,1.1) \end{gathered}$ | <. 001 | 60.0 |
| Fruit Drinks $(n=231,200)$ | 8.0 (5.5) | 8.8 (5.1) | 8.1 (5.7) | 8.1 (5.4) | $\begin{gathered} 0.4 \\ (-0.4,1.1) \end{gathered}$ | . 372 | 26.7 |
| Sports Drinks $(n=230,888)$ | 7.0 (2.3) | 9.0 (2.3) | 7.1 (2.3) | 7.5 (2.2) | $\begin{gathered} 1.9 \\ (1.6,2.2) \\ \hline \end{gathered}$ | <. 001 | 126.7 |
| $\begin{array}{r} \text { Diet Soda } \\ (\mathrm{n}=185,704) \\ \hline \end{array}$ | 5.1 (3.4) | 6.6 (3.6) | 5.6 (3.6) | 5.8 (3.4) | $\begin{gathered} 1.4 \\ (1.1,1.7) \end{gathered}$ | <. 001 | 93.3 |
| Sparkling Water ( $n=111,153$ ) | 5.9 (5.4) | 7.9 (6.5) | 6.6 (6.1) | 6.3 (5.9) | $\begin{gathered} 1.4 \\ (1.1,1.7) \end{gathered}$ | <. 001 | 93.3 |
| $\begin{array}{r} \text { Coffee } \\ (n=50,434) \end{array}$ | 20.8 (4.2) | 23.2 (4.4) | 20.8 (4.1) | 21.4 (4.1) | $\begin{gathered} 1.5 \\ (1.3,1.6) \\ \hline \end{gathered}$ | <. 001 | 100.0 |
| Energy Drinks ( $\mathrm{n}=200,477$ ) | 19.5 (5.8) | 21.6 (5.3) | 19.2 (5.8) | 19.9 (5.8) | $\begin{gathered} 1.4 \\ (1.0,1.8) \\ \hline \end{gathered}$ | <. 001 | 93.3 |
| Nontaxed Beverages ${ }^{\text {e }}$ ( $\mathrm{n}=728,160$ ) | 8.6 (7.8) | 8.7 (7.2) | 9.1 (8.3) | 9.4 (7.7) | $\begin{gathered} -0.5 \\ (-1.5,0.5) \end{gathered}$ | . 307 | N/A |
| Regular Water $(n=265,580)$ | 4.8 (2.8) | 5.3 (3.1) | 4.8 (2.8) | 5.4 (3.0) | $\begin{gathered} -0.1 \\ (-0.3,0.02) \end{gathered}$ | . 097 | N/A |

Appendix Table 2.2 Difference-in-difference regression results for changes in beverage price-per-ounce following implementation of a beverage tax in Philadelphia compared to Providence (Providence = reference city) (Continued)

|  | Philadelphia |  | Providence |  | Weighted DID estimate(95\% CI) | $\begin{gathered} p- \\ \text { value }^{\mathrm{a}} \end{gathered}$ | Percent passthrough ${ }^{\text {b }}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Pre-tax Mean (SD) cents-per-ounce | Post-tax <br> Mean (SD) cents-per-ounce | Pre-tax Mean (SD) cents-per-ounce | Post-tax <br> Mean (SD) cents-per-ounce |  |  |  |
| $\begin{array}{r} \text { Fruit Juice } \\ (n=236,541) \\ \hline \end{array}$ | 14.6 (9.8) | 14.3 (8.7) | 15.7 (10.4) | 15.3 (9.3) | $\begin{gathered} 0.2 \\ (-0.5,0.8) \end{gathered}$ | . 624 | N/A |
| $\begin{array}{r} \text { Milk } \\ (n=120,213) \end{array}$ | 6.0 (4.0) | 6.4 (4.1) | 6.2 (4.5) | 7.3 (4.9) | $\begin{gathered} -0.005 \\ (-0.1,0.1) \end{gathered}$ | . 934 | N/A |
| Sparkling Water $(n=77,972)$ | 6.2 (3.6) | 6.9 (6.1) | 5.8 (2.4) | 6.1 (2.8) | $\begin{gathered} 0.03 \\ (-0.4,0.5) \end{gathered}$ | . 886 | N/A |
| $\begin{array}{r} \text { Coffee } \\ (n=17,242) \end{array}$ | 24.0 (8.6) | 26.9 (8.3) | 23.3 (8.3) | 25.4 (8.5) | $\begin{gathered} 1.1 \\ (-0.7,2.9) \end{gathered}$ | . 215 | N/A |

Note. Mean prices are the mean cents-per-ounce per beverage product (SKU), per store, per week. Covariates in all regression models include store ID
${ }^{\text {a Bolded values indicate statistical significance after applying the Holm-Bonferroni correction for multiple testing on families of }}$ outcome (total taxed beverages [1 test], taxed beverage subcategories [8 tests], total nontaxed beverages [1 test], nontaxed
${ }^{\text {b }}$ The percent pass-through was calculated for taxed beverages as the difference-in-differences point estimate divided by 1.5 cents/oz.
coverall taxed category does not sum up to the composite categories because it also includes milk alternatives and other taxed beverages. It does not include taxed coffees and energy drinks as the price-per-ounce is much higher than the other beverages. ${ }^{d}$ Ns represent the number of unique week by store ID by SKU combinations over 104 weeks pre-tax and 52 weeks post-tax. ${ }^{e}$ Overall nontaxed category does not sum up to the composite categories because it also includes milk alternatives, flavored waters, iced tea or lemonade, sports drinks, and other nontaxed beverages. It does not include nontaxed coffees as the price-per-ounce is much higher than the other beverages.
Appendix Table 2.3 Difference-in-difference regression results for individual-level changes in volume of beverages purchased among purchasers of beverages both pre- and post-tax, following implementation of a beverage tax in Philadelphia compared to Baltimore (Baltimore = reference city) controlling for yearly quarters, and poverty.

|  | Philadelphia |  | Baltimore |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Pre-tax <br> Mean (SD) <br> ounces purchased | Post-tax <br> Mean (SD) ounces purchased | Pre-tax <br> Mean (SD) <br> ounces purchased | Post-tax <br> Mean (SD) ounces purchased | Adjusted ${ }^{\text {a }}$ DID estimate (95\% CI) | $p$-value ${ }^{\text {b }}$ |
| Taxed Beverages ${ }^{\text {c }}$ $(n=3582799)^{d}$ | 73.0 (118.0) | 59.1 (102.9) | 98.8 (148.1) | 81.5 (144.6) | $\begin{gathered} -6.5 \\ (-7.0,-5.9) \\ \hline \end{gathered}$ | <. 001 |
| $\begin{array}{r} \text { Soda } \\ (\mathrm{n}=981,503) \end{array}$ | 95.5 (145.7) | 75.3 (137.2) | 120.4 (175.7) | 103.4 (149.6) | $\begin{gathered} -7.0 \\ (-8.1,-5.8) \\ \hline \end{gathered}$ | <. 001 |
| Iced Tea \& Lemonade $(n=968,646)$ | 54.5 (79.5) | 47.2 (62.6) | 53.3 (78.8) | 56.2 (99.6) | $\begin{gathered} -8.3 \\ (-9.0,-7.7) \\ \hline \end{gathered}$ | <. 001 |
| Fruit Drinks ( $n=541,626$ ) | 49.2 (71.4) | 42.4 (57.9) | 50.5 (76.4) | 55.3 (123.0) | $\begin{gathered} -8.5 \\ (-9.3,-7.6) \end{gathered}$ | <. 001 |
| Sports Drinks $(n=442,942)$ | 43.1 (35.4) | 39.4 (26.8) | 43.8 (34.6) | 42.5 (31.1) | $\begin{gathered} -2.6 \\ (-3.1,-2.1) \end{gathered}$ | <. 001 |
| $\begin{array}{r} \text { Diet Soda } \\ (n=481,112) \end{array}$ | 96.3 (122.8) | 75.9 (94.7) | 122.5 (157.4) | 102.1 (134.0) | $\begin{gathered} -2.6 \\ (-4.0,-1.3) \end{gathered}$ | <. 001 |
| Sparkling Water $(\mathrm{n}=280,944)$ | 54.2 (65.1) | 51.6 (64.5) | 45.6 (54.7) | 46.5 (55.3) | $\begin{gathered} -2.7 \\ (-3.8,-1.6) \\ \hline \end{gathered}$ | <. 001 |
| $\begin{array}{r} \text { Coffee } \\ (\mathrm{n}=98,528) \end{array}$ | 18.5 (12.4) | 17.0 (10.0) | 19.7 (15.9) | 19.7 (13.9) | $\begin{gathered} -1.2 \\ (-1.5,-0.8) \end{gathered}$ | <. 001 |
| Energy Drinks ( $n=339,537$ ) | 21.4 (14.9) | 20.8 (14.3) | 21.0 (14.4) | 21.0 (12.7) | $\begin{gathered} -0.5 \\ (-0.7,-0.2) \\ \hline \end{gathered}$ | <. 001 |
| Nontaxed Beverages ${ }^{\text {e }}$ $(n=2415620)$ | 142.3 (250.0) | 134.0 (243.0) | 129.4 (228.1) | 118.7 (222.8) | $\begin{gathered} 1.8 \\ (0.2,3.3) \\ \hline \end{gathered}$ | <. 05 |
| Regular Water $(n=1,099,099)$ | 227.0 (342.1) | 206.3 (334.0) | 203.4 (316.5) | 177.6 (307.4) | $\begin{gathered} 5.4 \\ (2.5,8.4) \end{gathered}$ | <. 001 |

Appendix Table 2.3 Difference-in-difference regression results for individual-level changes in volume of beverages purchased among purchasers of beverages both pre- and post-tax, following implementation of a beverage tax in Philadelphia compared to Baltimore (Baltimore = reference city) controlling for yearly quarters, and poverty (Continued).

|  | Philadelphia |  | Baltimore |  | $\begin{gathered} \text { Adjusted }^{\text {a }} \\ \text { DID estimate } \\ (95 \% \mathrm{CI}) \\ \hline \end{gathered}$ | $p$-value ${ }^{\text {b }}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Pre-tax <br> Mean (SD) <br> ounces purchased | Post-tax <br> Mean (SD) <br> ounces purchased | Pre-tax <br> Mean (SD) <br> ounces purchased | Post-tax <br> Mean (SD) <br> ounces purchased |  |  |
| $\begin{array}{r} \text { Fruit Juice } \\ (\mathrm{n}=420,505) \end{array}$ | 37.4 (34.0) | 39.1 (32.6) | 38.6 (51.6) | 39.3 (49.1) | $\begin{gathered} 0.4 \\ (-0.2,0.9) \end{gathered}$ | . 22 |
| $\begin{array}{r} \text { Milk } \\ (\mathrm{n}=761,829) \\ \hline \end{array}$ | 86.9 (57.7) | 85.4 (56.8) | 90.8 (88.7) | 83.2 (74.9) | $\begin{gathered} 2.7 \\ (2.1,3.3) \\ \hline \end{gathered}$ | <. 001 |
| Sparkling Water $(n=208,990)$ | 44.5 (39.9) | 50.3 (42.0) | 39.2 (36.9) | 49.2 (44.3) | $\begin{gathered} -1.7 \\ (-2.8,-0.6) \\ \hline \end{gathered}$ | <. 01 |
| $\begin{array}{r} \text { Coffee } \\ (n=46,287) \end{array}$ | 12.9 (8.4) | 12.7 (8.4) | 12.7 (7.1) | 12.8 (7.6) | $\begin{gathered} -0.4 \\ (-0.8,0.09) \\ \hline \end{gathered}$ | . 11 | Note. Mean ounces purchased are raw means per card, per transaction. Regression models only include cardholder IDs that had

beverage transactions in both the pre- and post- tax periods. ${ }^{\text {a B Bolded values indicate statistical significance after applying the Holm-Bonferroni correction for multiple testing on families of }}$ outcome (total taxed beverages [1 test], taxed beverage subcategories [ 8 tests], total nontaxed beverages [1 test], nontaxed

$$
\text { ancor } \mathrm{c}
$$

${ }^{\text {b }}$ Covariates included store ID, yearly quarters, and store zip code-level percent below the poverty line.
${ }^{\text {c Overall taxed category does not sum up to the composite categories because it also includes milk alternatives and other taxed }}$ beverages.
${ }^{\mathrm{d}}$ Ns represent the number of unique transactions over 104 weeks pre-tax and 52 weeks post-tax.
${ }^{\text {e Overall }}$ nontaxed category does not sum up to the composite categories because it also includes milk alternatives, energy drinks, flavored waters, iced tea or lemonade, sports drinks, and other nontaxed beverages
Appendix Table 2.4 Difference-in-difference regression results ${ }^{a}$ for individual-level changes in volume of beverages purchased among purchasers of beverages both pre- and post-tax, following implementation of a beverage tax in Philadelphia compared to Providence (Providence = reference city).

|  | Philadelphia |  | Providence |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Pre-tax <br> Mean (SD) <br> ounces purchased | Post-tax <br> Mean (SD) <br> ounces purchased | Pre-tax <br> Mean (SD) <br> ounces purchased | Post-tax <br> Mean (SD) <br> ounces purchased | $\begin{gathered} \text { DID estimate } \\ (95 \% \mathrm{CI}) \\ \hline \end{gathered}$ | $\begin{gathered} p- \\ \text { value }^{\text {b }} \end{gathered}$ |
| Taxed Beverages ${ }^{\text {c }}$ $(n=3,196,535)^{\text {d }}$ | 73.0 (118.0) | 59.1 (103.0) | 63.0 (118.4) | 60.4 (103.7) | $\begin{gathered} -7.3 \\ (-7.9,-6.6) \\ \hline \end{gathered}$ | <. 001 |
| $\begin{array}{r} \text { Soda } \\ (\mathrm{n}=794,474) \\ \hline \end{array}$ | 95.5 (145.7) | 75.3 (137.3) | 95.3 (197.2) | 86.0 (170.6) | $\begin{gathered} -7.0 \\ (-8.7,-5.3) \\ \hline \end{gathered}$ | <. 001 |
| Iced Tea \& Lemonade $(n=832,865)$ | 54.6 (79.5) | 47.2 (62.6) | 42.4 (44.5) | 44.2 (42.5) | $\begin{gathered} -7.4 \\ (-8.2,-6.4) \end{gathered}$ | <. 001 |
| Fruit Drinks $(n=470,717)$ | 49.2 (71.4) | 42.5 (58.1) | 43.8 (46.9) | 45.3 (44.8) | $\begin{gathered} -6.0 \\ (-6.9,-5.1) \\ \hline \end{gathered}$ | <. 001 |
| Sports Drinks $(n=436,738)$ | 43.1 (35.4) | 39.4 (26.7) | 40.6 (30.4) | 42.0 (31.3) | $\begin{gathered} -3.8 \\ (-4.3,-3.3) \\ \hline \end{gathered}$ | <. 001 |
| $\begin{array}{r} \text { Diet Soda } \\ (n=431,595) \end{array}$ | 96.32 (122.9) | 76.0 (94.7) | 80.9 (109.1) | 74.6 (99.9) | $\begin{gathered} -8.6 \\ (-10.1,-7.0) \end{gathered}$ | <. 001 |
| Sparkling Water $(n=277,255)$ | 54.2 (65.1) | 51.6 (64.5) | 40.2 (44.8) | 42.5 (48.3) | $\begin{gathered} -2.5 \\ (-3.6,-1.4) \\ \hline \end{gathered}$ | <. 001 |
| $\begin{array}{r} \text { Coffee } \\ (\mathrm{n}=90,614) \\ \hline \end{array}$ | 18.5 (12.4) | 17.0 (10.0) | 17.6 (10.2) | 17.8 (10.9) | $\begin{gathered} -1.5 \\ (-1.9,-1.2) \\ \hline \end{gathered}$ | <. 001 |
| Energy Drinks $(n=329,276)$ | 21.4 (14.9) | 20.8 (14.4) | 20.9 (13.7) | 20.9 (13.8) | $\begin{gathered} -0.5 \\ (-0.8,-0.3) \\ \hline \end{gathered}$ | <. 001 |
| Nontaxed Beverages ${ }^{\text {e }}$ $(n=2,388,308)$ | 142.3 (249.9) | 134.1 (243.1) | 133.4 (232.1) | 123.6 (222.9) | $\begin{gathered} 1.2 \\ (-0.4,2.7) \\ \hline \end{gathered}$ | . 137 |
| Regular Water $(n=1,075,972)$ | 227.1 (341.9) | 206.4 (334.1) | 212.7 (330.2) | 194.6 (320.5) | $\begin{gathered} -0.9 \\ (-4.0,2.2) \end{gathered}$ | . 574 |

Appendix Table 2.4 Difference-in-difference regression results ${ }^{\text {a }}$ for individual-level changes in volume of beverages purchased among purchasers of beverages both pre- and post-tax, following implementation of a beverage tax in Philadelphia compared to Providence (Providence = reference city) (Continued).

|  | Philadelphia |  | Providence |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Pre-tax <br> Mean (SD) ounces purchased | Post-tax <br> Mean (SD) ounces purchased | Pre-tax <br> Mean (SD) ounces purchased | Post-tax <br> Mean (SD) ounces purchased | DID estimate (95\% CI) | $\begin{gathered} p- \\ \text { value } \end{gathered}$ |
| $\begin{array}{r} \text { Fruit Juice } \\ (\mathrm{n}=407,713) \end{array}$ | 37.4 (34.0) | 39.1 (32.6) | 37.0 (33.7) | 36.1 (28.6) | $\begin{gathered} 2.2 \\ (1.6,2.8) \end{gathered}$ | <. 001 |
| $\begin{array}{r} \text { Milk } \\ (\mathrm{n}=765,588) \end{array}$ | 87.0 (57.7) | 85.4 (56.8) | 93.6 (64.5) | 89.4 (63.5) | $\begin{gathered} 0.2 \\ (-0.3,0.7) \\ \hline \end{gathered}$ | . 429 |
| Sparkling Water $(n=218,413)$ | 44.5 (39.9) | 50.3 (42.0) | 40.5 (36.6) | 44.7 (40.0) | $\begin{gathered} 0.2 \\ (-0.7,1.2) \\ \hline \end{gathered}$ | . 618 |
| $\begin{array}{r} \text { Coffee } \\ (\mathrm{n}=44,405) \end{array}$ | 12.9 (8.5) | 12.7 (8.4) | 12.6 (7.1) | 13.1 (6.7) | $\begin{gathered} -0.9 \\ (-1.4,-0.5) \end{gathered}$ | <. 001 |

Note. Mean ounces purchased are raw means per card, per transaction. Regression models only include cardholder IDs that had beverage transactions in both the pre- and post- tax periods.
${ }^{\text {a Cross-classified mixed models with random intercepts for store ID and card ID were used }}$
${ }^{\text {b }}$ Bolded values indicate statistical significance after applying the Holm-Bonferroni correction for multiple testing on families of
outcome (total taxed beverages [1 test], taxed beverage subcategories [8 tests], total nontaxed beverages [1 test], nontaxed beverage subcategories [5 tests]
'Overall taxed category does not sum up to the composite categories because it also includes milk alternatives and other taxed beverages.
${ }^{\mathrm{d}}$ Ns represent the number of unique transactions over 104 weeks pre-tax and 52 weeks post-tax.
${ }^{\text {e O O }}$ verall nontaxed category does not sum up to the composite categories because it also includes milk alternatives, energy drinks, flavored waters, iced tea or lemonade, sports drinks, and other nontaxed beverages

## Paper 3 Appendix

## Appendix Table 3.1 Survey

Q1.1 By clicking the arrow, you will start this research survey hosted by Harvard researchers to learn about consumer preferences when dining out. To be eligible, you need to be 18 or older and speak English. Further inquiries should be directed to Sophia at svh085@g.harvard.edu.

Q1.2 In the past four weeks, how often did you eat out at a restaurant and/or order food online (either on a website or using an app)?Never/once in the past four weeks2-4 times in the past four weeks

More than once a week

## Survey ends if participant selects "Never/once in the past four weeks"

Q1.3 Do you currently live in the United States of America?

Yes

No

Survey ends if participant selects "No"

Appendix Table 3.1 Survey (Continued).
Q2.1 Welcome to our study!
You are being asked to take part in a research study.

This research is being conducted to learn about consumer preferences when dining out at or ordering from restaurants. You are being asked to participate in this research because you had indicated that you occasionally eat out/order from restaurants.

Your participation in this study is voluntary and you may withdraw your participation at any time for any reason.

If you take part in this study, you will be asked to take a short, 8-10 minute survey during which time no identifiable information will be collected. Specifically, you will be asked a number of questions about what you would order when dining out (you will be shown two menus) and then a series of simple questions about you.

The possible risks of participating in this study include breach of confidentiality. However, we will not be collecting identifiable information, so your answers cannot be linked back to you. Furthermore, the data will be stored in a password protected file.

There are no direct benefits to you from your taking part in this research. However, the information we get from this data can potentially help make the dining experience better for the general population.

You can decline to participate in any part of this study for any reason and can end your participation at any time.

If you have any questions about this study, you can contact Sophia at svh085@g.harvard.edu.

Thank you again for your time and participation. As we will not be collecting your name or email, please either save this webpage or take a screenshot if you would like a copy of this consent language.

Q2.2 Please choose one.I have read the above statements and give my consent to take part in this research.
No, I do not give consent.
Survey ends if participant selects "No"

Appendix Table 3.1 Survey (Continued).
Q2.3 What is your highest level of education?
Less than high school
High school/GED
Some college2 year degree/associate's degree

College/university degree (4 years)Graduate degree

Q3.1 You are about to view two different menus on the next two screens. For each one, imagine you are about to spend your own money for dinner at the restaurant on a typical night out.

Q4.1 Imagine you are about to spend your own money to order dinner from a fast casual restaurant similar to Panera or Chipotle. Please browse the menu below and select 1 entrée you would like to order by clicking on its price. To unselect, click the price a second time.

For ease of viewing, we only list entrée items from the menu. Assume any item can be modified to accommodate any dietary restriction. Items marked (V) are specifically vegetarian.

## Randomized to one of eight conditions

Q4.2 Imagine you are about to spend your own money to order dinner from a full-service restaurant similar to Olive Garden or Applebee's. Please browse the menu below and select 1 entrée you would like to order by clicking on its price. To unselect, click the price a second time.

For ease of viewing, we only list entrée items from the menu. Assume any item can be modified to accommodate any dietary restriction. Items marked (V) are specifically vegetarian.

## Randomized to one of eight conditions

Appendix Table 3.1 Survey (Continued).
Q5.1
For one of the dinners, the entrée you selected was:
[display what participant selected]

Please check the one or two most important reasons why you made that selection.It was a healthy choice.The entrée sounded delicious.It was a good value.The calories seemed right for me.I wanted to treat myself.The portion size seemed right for me.Other (please explain):

Appendix Table 3.1 Survey (Continued).
Q5.2 For the other dinner, the entrée you selected was:
[display what participant selected]

Please check the one or two most important reasons why you made that selection.


It was a healthy choice.The entrée sounded delicious.It was a good value.The calories seemed right for me.I wanted to treat myself.The portion size seemed right for me.Other (please explain):

## Appendix Table 3.1 Survey (Continued).

Q5.3 On at least one of the menus, you ordered the larger of two entrée sizes. In general, when you look at menus with different portion sizes, do you usually order the larger portion?YesNo

## Display Q5.4 if participant selected "yes" to Q5.3.

Q5.4 You selected that you usually order the larger of two portions. What might persuade you to order the smaller size?If it's cheaperIf I'm not that hungryIf I'm going to order more than one item (such as an appetizer or dessert)If the size of the smaller item is enough to fill me upOther (please explain):

Q6.1 What is your age?

Q6.2 What is your gender identity?

Male

FemaleNon-binary

TransgenderOther

## Appendix Table 3.1 Survey (Continued).

Q6.3 What is your total annual household income before taxes?Less than (not including) \$25,000
Between \$25,000 and \$49,999Between \$50,000 and \$74,999Between \$75,000 and \$99,999Between \$100,000 and \$124,999Greater than \$125,000

Q6.4 What is your height in feet and inches?
Q6.5 What is your weight in pounds?

Q6.6 Are you Hispanic?YesNo

Appendix Table 3.1 Survey (Continued).

Q6.7 What is your race? Check all that apply.


WhiteBlack or African American
$\square$ American Indian or Alaska Native


AsianNative Hawaiian or Pacific IslanderOther

## Appendix Table 3.1 Survey (Continued).

Q6.8 What month are we in now?JanuaryFebruaryMarchAprilMayJuneJulyAugustSeptemberOctoberNovemberDecember

Q6.9 Do you have any dietary restrictions? Check all that apply.


NoVegetarian


VeganGluten-freeLactose intolerant

Appendix Table 3.1 Survey (Continued).
$\square$ Other

Q6.10 Do you have any food allergies?YesNo

Q7.1 Lastly, we're going to ask you a few questions to understand how you think about numbers. Please answer the following questions.

Q7.2 Imagine that we flip a fair coin 1,000 times. What is your best guess about how many times the coin would come up heads in 1,000 flips?

Q7.3 In the BIG BUCKS LOTTERY, the chance of winning a $\$ 10$ prize is $1 \%$. What is your best guess about how many people would win a $\$ 10$ prize if 1,000 people each buy a single ticket to BIG BUCKS?

Q7.4 In ACME PUBLISHING SWEEPSTAKES, the chance of winning a car is 1 in 1,000 . What percent of tickets to ACME PUBLISHING SWEEPSTAKES win a car? Please do not include the percent sign in your answer below.
Appendix Table 3.2 Predicted probabilities and odds ${ }^{\text {a,b }}$ of selecting a reduced portion on a menu with two portion sizes on a fastcasual menu and a full-service restaurant menu in the presence of different portion size descriptors in an online randomized controlled experiment $(n=2,205)$
Appendix Table 3.3 Sensitivity analyses - predicted probabilities and odds ${ }^{\text {a,b }}$ of selecting a reduced portion on a menu with two portion sizes on a fast-casual menu and a full-service restaurant menu in the presence of different portion size descriptors in an online randomized controlled experiment without exclusions based on time to survey completion, accuracy of attention check answer, and missing information for race, BMI, or numeracy score ( $\mathrm{n}=2,785$ )

| $\begin{array}{c}\text { Predicted Probability } \\ (95 \% ~ C I)\end{array}$ | $\begin{array}{c}\text { Absolute Difference in } \\ \text { Predicted Probability (95\% CI) }\end{array}$ | $\begin{array}{c}\text { Odds Ratio } \\ (95 \% ~ C I)\end{array}$ |
| :---: | :---: | :---: |


| Fast-Casual Restaurant Menu |  |  |  |
| :---: | :---: | :---: | :---: |
| Descriptor |  |  |  |
| no label and "Large" (Control) | 0.54 (0.50, 0.58) | Ref | Ref |
| "Standard" and "Large" | 0.65 (0.62, 0.69) | 0.11 (0.06, 0.16)*** | 1.6 (1.3, 2.0)*** |
| "Just Right" and "Large" | 0.64 (0.61, 0.68) | 0.10 (0.05, 0.15)*** | 1.5 (1.2, 1.9)*** |
| no label and "Hearty" | 0.57 (0.53, 0.60) | 0.02 (-0.03, 0.08) | 1.1 (0.9, 1.4) |
| Pricing |  |  |  |
| Linear | 0.58 (0.55, 0.60) | Ref | Ref |
| Non-Linear | 0.62 (0.60, 0.65) | 0.05 (0.01, 0.08)* | 1.2 (1.0, 1.4)* |
| Full-Service Restaurant Menu |  |  |  |
| Descriptor |  |  |  |
| no label and "Large" (Control) | 0.55 (0.51, 0.59) | Ref | Ref |
| "Standard" and "Large" | 0.67 (0.64, 0.71) | 0.12 (0.07, 0.17)*** | 1.7 (1.4, 2.1)*** |
| "Just Right" and "Large" | 0.65 (0.61, 0.69) | 0.10 (0.05, 0.15)*** | 1.5 (1.2, 1.9)*** |
| no label and "Hearty" | 0.54 (0.50, 0.57) | -0.01 (-0.06, 0.04) | 1.0 (0.8, 1.2) |
| Pricing |  |  |  |
| Linear | 0.60 (0.57, 0.62) | Ref | Ref |
| Non-Linear | 0.61 (0.58, 0.64) | 0.01 (-0.02, 0.05) | 1.1 (0.9, 1.2) |

atogistic regression models included naming condition and pricing scheme (non-linear vs. linear pricing) ${ }^{\mathrm{b}}$ Bolded indicates statistical significance: ${ }^{*} p<0.05 ;{ }^{* *} p<0.01 ;{ }^{* * *} p<0.001$
Appendix Table 3.4 Predicted probabilities and odds ${ }^{\mathrm{a}, \mathrm{b}}$ of selecting a reduced portion on a menu with two portion sizes on a fastcasual menu and a full-service restaurant menu in the presence of different portion size descriptors in an online randomized controlled experiment ( $n=2,205$ ) by demographic variables

|  | Fast-casual ( $\mathrm{n}=2,205$ ) |  |  | Full-service ( $\mathrm{n}=2,205$ ) |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Predicted Probability (95\% $\mathrm{Cl})$ | Absolute Difference in Predicted Probability (95\% CI) | Odds Ratio (95\% $\mathrm{Cl})$ | Predicted Probability (95\% CI) | Absolute Difference in Predicted Probability (95\% CI) | Odds Ratio (95\% <br> $\mathrm{Cl})$ |
| Age |  |  |  |  |  |  |
| $\geq 18$ to <30 | 0.58 (0.50, 0.65) | Ref | Ref | 0.50 (0.42, 0.58) | Ref | Ref |
| $\geq 30$ to <40 | 0.46 (0.39, 0.53) | -0.12 (-0.21, -0.02)* | 0.6 (0.4, 0.9)* | 0.44 (0.37, 0.50) | -0.06 (-0.16, 0.03) | $0.8(0.5,1.1)$ |
| $\geq 40$ to <50 | 0.50 (0.42, 0.58) | -0.08 (-0.18, 0.03) | $0.7(0.5,1.1)$ | 0.54 (0.46, 0.62) | 0.04 (-0.06, 0.15) | $1.2(0.8,1.8)$ |
| $\geq 50$ to <60 | 0.52 (0.44, 0.59) | -0.06 (-0.17, 0.05) | 0.8 (0.5, 1.2) | $0.54(0.46,0.61)$ | 0.03 (-0.07, 0.14) | $1.2(0.8,1.8)$ |
| $\geq 60$ to <70 | 0.63 (0.58, 0.67) | 0.05 (-0.04, 0.14) | 1.2 (0.8, 1.8) | 0.68 (0.64, 0.72) | 0.18 (0.09, 0.27)*** | 2.1 (1.5, 3.1)*** |
| $\geq 70$ to $<80$ | 0.69 (0.65, 0.73) | 0.11 (0.02, 0.20)* | 1.6 (1.1, 2.4)* | 0.72 (0.69, 0.76) | 0.22 (0.13, 0.31)*** | 2.6 (1.8, 3.8) ${ }^{* * *}$ |
| 80+ | 0.65 (0.56, 0.73) | 0.07 (-0.05, 0.19) | 1.3 (0.8, 2.2) | 0.71 (0.63, 0.80) | 0.21 (0.10, 0.33)*** | 2.5 (1.5, 4.2)*** |
| Gender Identity |  |  |  |  |  |  |
| Female | 0.67 (0.64, 0.70) | Ref | Ref | 0.69 (0.66, 0.72) | Ref | Ref |
| Male | 0.53 (0.50, 0.56) | -0.14 (-0.19, -0.10)*** | 0.5 (0.5, 0.7)*** | 0.56 (0.52, 0.59) | -0.14 (-0.18, -0.09)*** | 0.6 (0.5, 0.7)*** |
| Other | 0.56 (0.29, 0.83) | -0.11 (-0.39, 0.16) | 0.6 (0.2, 1.9) | 0.78 (0.58, 0.99) | 0.09 (-0.12, 0.30) | 1.6 (0.5, 5.4) |
| Race |  |  |  |  |  |  |
| White | 0.61 (0.59, 0.64) | Ref | Ref | 0.64 (0.61, 0.66) | Ref | Ref |
| Black | 0.61 (0.54, 0.68) | -0.004 (-0.08, 0.07) | 1.0 (0.7, 1.3) | 0.63 (0.57, 0.70) | -0.003 (-0.07, 0.07) | 1.0 (0.7, 1.3) |
| Other | 0.55 (0.46, 0.64) | -0.06 (-0.16, 0.03) | 0.8 (0.5, 1.1) | 0.60 (0.51, 0.69) | -0.04 (-0.13, 0.06) | 0.9 (0.6, 1.3) |
| BMI |  |  |  |  |  |  |
| Underweight | 0.68 (0.56, 0.79) | 0.02 (-0.11, 0.13) | 1.1 (0.6, 1.9) | 0.62 (0.50, 0.75) | -0.06 (-0.19, 0.07) | 0.8 (0.4, 1.3) |
| Normal weight | 0.66 (0.63, 0.70) | Ref | Ref | 0.68 (0.65, 0.72) | Ref | Ref |

Appendix Table 3.4 Predicted probabilities and odds ${ }^{\text {a,b }}$ of selecting a reduced portion on a menu with two portion sizes on a fastcasual menu and a full-service restaurant menu in the presence of different portion size descriptors in an online randomized controlled experiment ( $n=2,205$ ) by demographic variables (Continued).

|  | Fast-casual ( $\mathrm{n}=2,205$ ) |  |  | Full-service ( $\mathrm{n}=2,205$ ) |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Predicted Probability (95\% $\mathrm{Cl})$ | Absolute Difference in Predicted Probability (95\% CI) | Odds Ratio (95\% CI) | Predicted Probability (95\% $\mathrm{Cl})$ | Absolute Difference in Predicted Probability (95\% CI) | Odds Ratio (95\% $\mathrm{Cl})$ |
| Overweight | 0.59 (0.55, 0.63) | $-0.07(-0.13,-0.02)^{* *}$ | $0.7(0.6,0.9)^{* *}$ | 0.61 (0.58, 0.65) | -0.07 (-0.12, -0.02)* | $0.7(0.6,0.9) *$ |
| Obese | 0.56 (0.52, 0.60) | $-0.10(-0.15,-0.05)^{* * *}$ | $0.7(0.5,0.8) * * *$ | 0.60 (0.56, 0.64) | $-0.08(-0.13,-0.03) * *$ | $0.7(0.6,0.9) * *$ |
| Educ Attainment |  |  |  |  |  |  |
| Less than HS | 0.53 (0.45, 0.61) | -0.10 (-0.19, -0.01)* | 0.7 (0.5, 0.9)* | 0.63 (0.55, 0.70) | -0.02 (-0.11, 0.06) | 0.9 (0.6, 1.3) |
| High school/GED | 0.63 (0.59, 0.67) | Ref | Ref | 0.65 (0.61, 0.69) | Ref | Ref |
| Some college | 0.60 (0.55, 0.65) | -0.03 (-0.09, 0.04) | 0.9 (0.7, 1.2) | 0.61 (0.56, 0.67) | -0.04 (-0.10, 0.03) | $0.9(0.6,1.1)$ |
| 2-yr/Associate | 0.59 (0.53, 0.66) | -0.04 (-0.11, 0.04) | $0.9(0.6,1.2)$ | 0.63 (0.57, 0.69) | -0.02 (-0.10, 0.06) | $0.9(0.7,1.3)$ |
| 4-yr/University | 0.60 (0.56, 0.65) | -0.03 (-0.09, 0.04) | $0.9(0.7,1.2)$ | 0.64 (0.60, 0.69) | -0.01 (-0.07, 0.05) | 1.0 (0.7, 1.3) |
| Graduate | 0.65 (0.59, 0.71) | 0.02 (-0.05, 0.09) | $1.1(0.8,1.5)$ | 0.61 (0.55, 0.67) | -0.04 (-0.12, 0.04) | 0.8 (0.6, 1.2) |
| Numeracy |  |  |  |  |  |  |
| 0/3 correct | 0.62 (0.57, 0.67) | Ref | Ref | 0.61 (0.55, 0.66) | Ref | Ref |
| 1/3 correct | 0.63 (0.59, 0.67) | 0.01 (-0.05, 0.07) | 1.0 (0.8, 1.3) | 0.62 (0.58, 0.66) | $0.02(-0.05,0.08)$ | $1.1(0.8,1.4)$ |
| 2/3 correct | 0.59 (0.55, 0.63) | -0.03 (-0.10, 0.03) | $0.9(0.7,1.1)$ | 0.65 (0.61, 0.69) | 0.04 (-0.02, 0.11) | 1.2 (0.9, 1.6) |
| 3/3 correct | 0.58 (0.53, 0.64) | -0.04 (-0.12, 0.04) | 0.8 (0.6, 1.2) | 0.65 (0.60, 0.71) | 0.05 (-0.03, 0.13) | 1.2 (0.9, 1.7) | ${ }^{2}$ Multivariate logistic regression models included the following covariates: age (decades), gender identity, BMI (underweight, normal weight, overweight, obese), race (White, Black, other), educational attainment (less than high school, high school/GED, some college, 2-year degree/Associate's, college/university degree, graduate degree), numeracy (score of 0-3 based on number of correct answers to a 3-question numeracy scale), pricing scheme (non-linear vs. linear pricing) ${ }^{\text {b }}$ Bolded indicates statistical significance: ${ }^{*} p<0.05 ;{ }^{* *} p<0.01$; ${ }^{* * *} p<0.001$


[^0]:    Note. Mean prices are the mean cents-per-ounce per beverage product (SKU), per store, per week. Covariates in all regression

