The Impact of Soda Taxes: Pass-through, Tax Avoidance, and Nutritional Effects*

Stephan Seiler Stanford University

Anna Tuchman Northwestern University

Song Yao University of Minnesota

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We analyze the impact of a tax on sweetened beverages, often referred to as a "soda tax," using a unique data-set of prices, quantities sold and nutritional information across several thousand taxed and untaxed beverages for a large set of stores in Philadelphia and its surrounding area. We find that the tax is passed through at an average rate of 97%, leading to a 40% price increase. Demand in the taxed area decreases by 46% in response to the tax. There is no significant substitution to untaxed beverages (water and natural juices), but there is a large amount of cross-shopping to stores outside of Philadelphia. After taking into account cross-shopping, the total demand reduction is equal to only 22%. We do not detect a significant reduction in calorie and sugar intake.

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1 Introduction

The US has the highest rate of obesity among all developed countries (OECD (2017)). According to the CDC, 36% of Americans are clinically obese and another third of Americans are overweight (Ogden et al. (2015)). The increasing prevalence of obesity in the US has become a serious public health concern because obesity has been linked to adverse health outcomes, including heart disease, type 2 diabetes, stroke, and certain cancers. The high obesity rate also imposes a great economic burden. In 2008, the CDC estimated the annual medical cost of obesity in the U.S. was $147 billion (CDC (2016)).

The taxation of specific products in order to combat obesity and other health related issues has recently gained in popularity. One particularly popular example of such a "sin tax" are taxes on sugar-sweetened beverages (SSBs). SSBs have been singled out for taxation because research has shown that sugary drinks are the single largest source of added sugar in the average American's diet (National Cancer Institute (2018)). Mexico implemented a nationwide tax of 1 peso (5 cents USD) per liter on SSBs in 2014. In the United States, similar taxes have been implemented at the local level. Berkeley, CA, was the first municipality to implement a 1 cent-per-ounce tax in March 2015. More recently, other cities and counties have implemented similar taxes, including Philadelphia, PA, Cook County, IL (covering Chicago and most of its suburbs)[1], San Francisco, CA, Boulder, CO, and Seattle, WA. In the case of Philadelphia and Cook County, not just sugar sweetened beverages, but all beverages with *any* added sweetener are taxed. Several other cities (e.g., Washington, D.C., New York City, and Portland, OR) have contemplated introducing similar taxes, and hence understanding their impact is important when considering whether and how to implement such taxes.

To fully understand the impact of an SSB tax, we need to analyze its impact on various adjustment margins. SSB taxes tend to be levied at the distributor level, and they apply to a subset of products within a larger class of substitutable products. Thus, there are several potential impediments for the tax to achieve its goals of improving nutritional intake and generating tax revenue. First, the tax constitutes a change in the wholesale price of retailers and is not necessarily passed through to consumers. Second, consumers might engage in tax avoidance, substituting away from taxed products by choosing to buy taxed beverages from stores outside the taxed zone, or substituting to other untaxed beverages. The overall impact of the tax on nutritional intake as well as the ability to generate revenue crucially depends on these various margins of adjustment. Therefore, in order to paint a complete picture of the impact of the tax we need to study price and demand response for taxed products, as well as substitutes in geographic and product space.

In this paper we use the case of Philadelphia as a test-bed for understanding the impact of a tax on sweetened beverages. Philadelphia presents a particularly rich setting to study a sweetened beverages tax, because it is a large and demographically diverse city that is served by many different types of stores and chains. We base our analysis on a unique panel dataset that covers sales of

[1] The Cook County, IL tax went into effect in August 2017 and was repealed four months later in December 2017.

thousands of taxed and untaxed beverages at several hundred stores, ranging from small convenience stores to wholesale clubs. We complement these data on store/product-level prices and quantities sold, with local demographic information and hand-coded product-level nutritional information. We rely on a difference-in-differences framework that compares changes before and after the tax took effect in Philadelphia relative to a control group of stores outside of Philadelphia (we only include stores located at least 6 miles outside Philadelphia in the control group).[2]

Several key findings emerge from our analysis: (1) The tax is passed through at an average rate of 97% which corresponds to a 40% price increase. Pass-through is remarkably similar across different types of stores, chains and products. (2) The large increase in prices leads to a 46% reduction in the quantity purchased of taxed beverages in Philadelphia. However, a little over half of this reduction is offset by an increase in quantity purchased at stores up to 6 miles outside of the city border. After taking into account cross-shopping, we find that net sales of taxed beverages only fell by 22%. We find no significant change in quantity or prices of untaxed beverages (water and natural juices). (3) We are not able to detect a significant change in calorie and sugar intake once we take consumers' cross-shopping into account. (4) Finally, we find that purchase quantity decreases less in low income (and high obesity) neighborhoods. This suggests that low income consumers either reduce their consumption of taxed beverages less or they are less likely to engage in cross-shopping.

We draw several lessons about the effectiveness of local sweetened-beverage taxes from these analyses. First, the tax was less effective at reducing consumption of unhealthy products due to leakage through cross-shopping. Second, in terms of revenue generation, the tax was only partly effective due to consumers substituting to stores outside of Philadelphia. Third, low income households are less likely to engage in cross-shopping, and instead are more likely to continue to purchase taxed products at a higher price at stores in Philadelphia. The lower propensity for low income households to avoid the tax through cross-shopping leads to a relatively larger tax burden for those households. In summary, the tax does not lead to a shift in consumption towards healthier products, it affects low income households more severely, and it is limited in its ability to raise revenue.

Furthermore, although not the primary focus of the paper, it is noteworthy that there are significant pricing rigidities at the chain/geography level that lead to an imperfect response to changes in demand. This is consistent with recent work on supermarket price setting (e.g., Hitsch et al. (2017) and DellaVigna and Gentzkow (2017)). Most notably, despite large increases in demand at stores just outside the city border, we do not observe an increase in prices at those stores.

Our work contributes to the growing body of research that seeks to evaluate the effects of soda taxes on consumption decisions, firm pricing, and consumer health. A first set of papers that is relevant to our analysis are studies that use structural models and pre-tax data to predict the impact of a (hypothetical) soda tax using counterfactual simulations. Using this approach, Wang (2015) simulates a 1 cent-per-oz tax on regular soda and predicts that, assuming full pass-through,

[2]We provide evidence that this distance threshold is appropriate later in the paper.

high-income households reduce their consumption by 7.6%, while low-income households reduce consumption by 9.7%. Kifer (2015) predicts a 140% pass-through rate for a 2 cents-per-oz soda tax, which leads to a drop in demand of 75%. Using a panel dataset of on-the-go soda consumption in the UK, Dubois et al. (2017) estimate a demand model and simulate the impact of a 1.2 cents-per-oz (25 pence-per-liter) tax. They predict a pass-through rate of 140% and a drop in consumption of between 11% and 15%.[3] They also find that people who consume sugar heavily are the least likely to reduce soda consumption. Compared to these studies, we find a lower pass-through rate in our data, which suggests that retailers were hesitant to raise prices by more than the taxed amount. On the demand-side, we analyze substitution to both untaxed products and untaxed stores. We find that cross-shopping is an important margin of substitution that these papers do not model.

A second set of studies analyzes the impact of soda taxes after their implementation. Various papers study such taxes outside of the United States, where taxes have been implemented at the national level. Using pricing data only, Berardi et al. (2016), Bergman and Hansen (2017) and Grogger (2015) measure beverage prices after the implementation of soda taxes in France, Denmark, and Mexico, respectively. All papers find significant tax pass-through for taxed products. Bergman and Hansen (2017) find that the Danish tax pass-through rate increases with a store's distance to the Germany border, potentially because of a strategic reaction to cross-border shopping behavior. Relying on both price and quantity data, Aguilar et al. (2016), and Colchero et al. (2017) investigate the effects of SSB taxes in Mexico. They find that taxed categories witness considerable price hikes and reduction in demand, while untaxed categories also see moderate price increases, possibly due to consumer substitution to untaxed beverages. Notably, Aguilar et al. (2016) argue that the long-term health consequences of the tax remain unclear because people switch to untaxed yet unhealthy beverages, and the high-calorie intake may offset the reduction in sugary drinks consumption. Relative to the more localized taxes in the US, the national implementation of these taxes makes inference more difficult because there is no obvious control group of stores that are unaffected by the tax.

Within the US context, the most well-studied tax is the one implemented in Berkeley in 2014. Cawley and Frisvold (2015) and Falbe et al. (2015) measure the change in beverage prices after the implementation of the Berkeley soda tax. They find that pass-through rates range from 40% to nearly 70%. Due to data availability, these studies only focus on the (manually collected) prices of a small set of products. Bollinger and Sexton (2018) use retailer scanner data to measure both the changes in price and quantity sales that can be attributed to the tax. Bollinger and Sexton (2018) find that stores of different chains only have limited or moderate pass-through of the tax. For stores that increase SSB prices, the reduction in demand is mostly offset by more purchases right outside the city of Berkeley. Using scanner data and household panel data, Rojas and Wang (2017) also find the impact of the Berkeley soda tax on price and consumption to be limited. More recently, several studies have focused on the soda taxes in Philadelphia and Boulder, CO. Cawley

[3]The predicted reduction in consumption is much lower than Kifer (2015), potentially because Dubois et al. (2017) focus on "on-the-go" beverages, which have small pack-sizes and lower overall price levels. We find that demand is less price elastic for small pack-size products than large pack-size ones.

et al. (2018b) and Cawley et al. (2018a) manually collect price and product assortment information for a sample of products and stores in Philadelphia and Boulder. The studies find that the prices of taxed products increase considerably, implying tax pass-through rates of 100% and 75% in the two cities, respectively. Cawley et al. (2018c) further survey households in Philadelphia and show evidence of reduced consumption of soda in the city.

Similar to Bollinger and Sexton (2018), we rely on detailed retailer scanner data on prices and quantities. However, relative to the Berkeley-centric studies, our data from Philadelphia allows us to explore certain aspects of a soda tax in more detail. First, our data contains 357 stores from 11 different chains in Philadelphia (compared to 7 stores from 2 chains in Bollinger and Sexton (2018)'s analysis of Berkeley's tax). Second, Philadelphia is a much larger and demographically diverse city. Both aspects together allow us to explore heterogeneity across stores, chains and consumer demographics in more detail. These dimensions of heterogeneity are of first order importance with regards to understanding the impact of the tax. Specifically, we can assess the impact on consumption as a function of pre-tax obesity rates and quantify the financial burden of the tax across the income spectrum. Furthermore, Philadelphia represents a more relevant test-bed for studying soda taxes due to the fact that its demographic composition is closer to the US average. Berkeley is a small city of 113,000 residents, of whom only 36% are either overweight or obese (BMI$\geq$25).[4] In contrast, 68% of Philadelphia's 1.5 million residents are considered overweight or obese (CDC (2013)) and hence, Philadelphia's obesity rate is more representative of the prevalence of obesity in the US in general.

The rest of this paper is organized as follows. In section 2 we provide additional details on the tax's implementation, and in section 3 we describe the data and provide descriptive statistics. Section 4 presents the empirical approach and provides results for the impact of the tax on prices and quantities of taxed and untaxed products, on cross-shopping behavior and on nutritional intake. Section 5 provides a set of additional results and robustness checks. Section 6 concludes.

2 Institutional Context

In March 2016, Philadelphia Mayor Jim Kenney proposed a tax of 3 cents-per-ounce on sweetened beverages. After months of debate around the proposal, a scaled-down version of the tax was voted on by the Philadelphia City Council in June 2016, and approved with a vote of 13-4. A tax of 1.5 cents-per-ounce went into effect on January 1, 2017. According to a spokeswoman for the Mayor, Kenney's primary reason for proposing the tax was to raise tax revenue, but she noted that the tax could also bring health benefits if it reduces the consumption of sweetened beverages (Esterl (2016)). In Philadelphia, pre-implementation projections predicted that the tax would raise $92 million in tax revenue in 2017.[5] In practice, the city collected $79 million in 2017, falling short of

[4] City of Berkeley, "Health Status Report", City of Berkeley Public Health Division (2013). https://www.cityofberkeley.info/Health_Human_Services/Public_Health/2013_Health_Status_Report.aspx, accessed on January 20, 2018.

[5] The funds are earmarked to go to pre-K education programs, community schools, and improvements to parks, libraries, and recreation centers.

the projection.

In terms of implementation, the tax is structured as a tax of 1.5 cents-per-ounce, which, for example, amounts to a tax of \$1.01 on a 2-liter bottle. In our data, the average pre-tax price of a 2-liter of soda in Philadelphia is \$1.56, thus the tax is equal to almost two-thirds of the pre-tax price of this product. It is important to note that the tax is levied on distributors, not directly on consumers. Thus, the extent to which the tax is felt by consumers depends on how much of the tax is passed through the supply chain. Finally, Philadelphia's tax applies to both sugar-sweetened and artificially-sweetened beverages. Thus, both diet and regular soft drinks are taxed, as well as pre-sweetened coffee and tea drinks, sports drinks, energy drinks, and non-100% fruit drinks that contain a caloric sweetener or non-nutritive sweetener.[6]

The decision to tax artificially sweetened beverages might seem surprising. From a health perspective, if the goal is to reduce calories consumed, taxing diet drinks that are a close substitute to sugar-sweetened beverages could be counter-productive. In the case of Philadelphia, the Mayor's office has acknowledged that the primary purpose of the tax is to raise tax revenue, and hence it is likely that the decision to include artificially-sweetened drinks was driven by financial motivations. It is also important to note that many other municipalities that introduced similar taxes (several Bay Area cities, Boulder, CO, and Seattle, WA) only tax drinks with caloric sweeteners.

3 Data

We analyze retail sales data collected by IRI, a large market-research firm. We supplement this data with nutrition information on products and demographic data. Each of these datasets is described in more detail below.

3.1 Data sources

Retail Sales Data The sales data covers the period from January 2015 through September 2018 and contains information on prices and quantity sold at the UPC/store/week-level. We obtained data for all beverage categories, including untaxed beverages, which constitute potential substitutes. We exclude alcoholic beverages from our analysis. We focus our analysis on stores located in the city of Philadelphia and the four 3-digit zip codes that surround Philadelphia. We observe the location and the chain affiliation for each store.[7] We restrict our analysis to stores that entered the panel before January 1, 2016 and were tracked through at least December 31, 2017. We focus our

[6]Examples of caloric sweeteners include cane sugar, high fructose corn syrup, and honey. Examples of non-nutritive sweeteners include stevia, aspartame, sucralose, or saccharin. Drinks that are exempt from the tax include alcoholic beverages, beverages that are 100% juice, and drinks that are more than 50% milk by volume.

[7]For most stores, we observe the exact street address of each store and the exact chain affiliation. For the remaining stores we only observe the location at the 5-digit zip-code level and the retailer type (Mass Merchant, Dollar Store, or Convenience Store). For the latter set of stores, we assume that they are located at the centroid of their zip-code. We ran robustness checks which exclude stores with noisy location information for all regressions that involve distance variables and found results to be similar in all cases. When performing analysis at the chain level, we treat the unidentified mass merchants, dollar stores, and convenience stores as separate groups. We anonymize the chain affiliation per the request of our data provider.

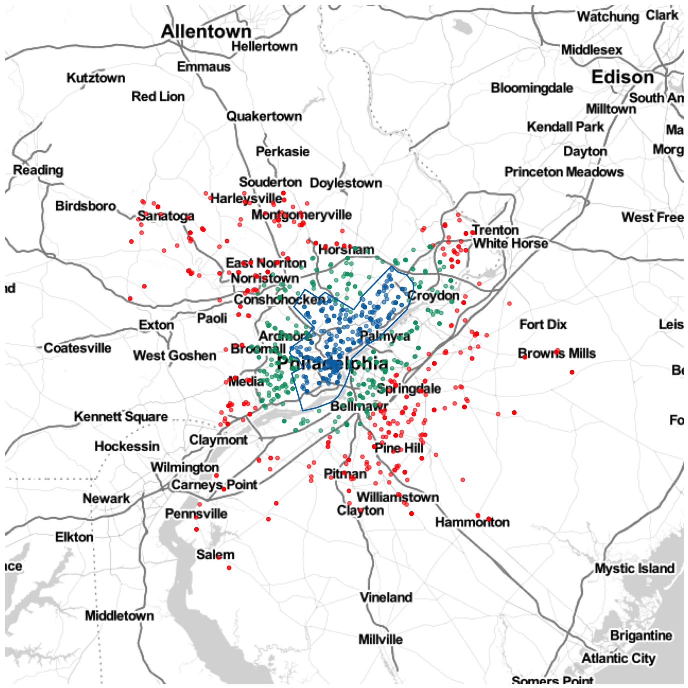

Figure 1: Stores Within and Outside of Philadelphia

analysis on the 11 chains / groups of stores that operate stores both within the city and outside of the city. Our final dataset includes 357 stores located in Philadelphia and 870 stores located in the surrounding area around Philadelphia. Panel B of Table 1 lists the types of stores (grocery stores, drugstores, etc.) covered in our data and the number of locations observed for each chain. Figure 1 shows the geographic location of all stores. Philadelphia stores are shown in blue, while stores 0-6 miles outside the city limits are shown in green and stores more than 6 miles outside the city are shown in red. More detailed descriptive statistics are provided in the next section.

At the most granular level, the data records sales at the UPC/store/week-level. Across all stores and weeks, we observe a total of 17,582 individual UPCs due to the fact that many products are sold in various pack-sizes and flavors. In our empirical analysis, we consider two levels of aggregation. We first define a product to be a brand/diet-status/pack-size combination, and we aggregate the UPC-level data up to this level, calculating total units sold and quantity weighted prices at the product/store/week level. Thus, different flavors of the same brand (such as Cherry Coke and Vanilla Coke) are aggregated together.[8] After dropping infrequently purchased products for which prices are often missing, we are left with a total of 861 products (489 taxed and 372 untaxed). In Appendix A, we analyze the product-level data to determine whether there are systematic differences in how the tax affected the price and sales of individual products.

For our main analysis, we further aggregate the data from the product/store/week-level to the tax-status/store/week-level. That is, we compute total quantity sold and average price separately

[8]Different flavors of the same brand are typically priced uniformly and hence little information is lost when aggregating prices at this level.

for all taxed products and all untaxed products. We also analyze individual categories (such as soda, energy drinks, water, etc.) within the taxed/untaxed groups of products and report results whenever there are meaningful differences across categories. We compute tax-status/store/week-level prices as a weighted average of product-level prices, where the weights are equal to market shares (in terms of total ounces sold) of products at each store in the pre-tax period. Total volume sold is obtained by aggregating product/store/week-level volume up to the tax-status/store/week-level.

Demographic Data We supplement the store-level sales data with highly localized demographic data. These data allow us to determine the demographics of each store's catchment area and explore whether the response to the tax varies as a function of local population characteristics. We obtained data on median household income from the Census Bureau's 2011-2015 American Community Survey (ACS), and data on obesity rates from the CDC.[9] Both datasets vary at the census tract level.[10] We focus on these two sociodemographic measures because i) past work suggests that income may be correlated with price sensitivity and preference for sweetened beverages (Wang (2015)) and ii) because obesity data allows us to analyze whether the consumers who could reap the largest health benefits from reducing consumption actually do so. We assign demographic profiles to individual stores by calculating average income and obesity rates in each store's catchment area. To this end, we identify all census tracts that are within 1 mile of each store in our data, and calculate (population-weighted) average demographics for each store.[11]

Ingredient and Nutrition Data Finally, we manually collect ingredient and nutrition information on all taxed and untaxed products contained in the retail sales data.[12] For each product, we search for the list of ingredients and the nutrition facts label on the manufacturer and retailers' websites, and we record the total sugars and calories for each UPC in the data. This data serves two purposes. First, the retail sales data does not have a field that indicates whether each product is subject to Philadelphia's tax. We use the ingredients list to determine the taxed status of each product. Second, we use the nutrition data to evaluate the overall effect of the tax on sugar and calorie consumption.

[9]The CDC reports model-based estimates of obesity rates at the census tract level as part of their 500 Cities Project. Further detail on the CDC's methodology is available in their report, "500 Cities Project: Local Data for Better Health. Philadelphia, PA. 2014." (CDC/NCCDPHP/DPH/ESB (2016)). Obesity data is only available for census tracts within the city of Philadelphia. We do not observe data for tracts in our control regions.

[10]There are 384 census tracts in the city of Philadelphia. Census tracts cover on average 4,000 people, with individual census tracts ranging between 2,500 and 8,000 inhabitants.

[11]We also experiment with 2, 3, and 4 mile radii when computing store demographics, and find results to be similar.

[12]We are not able to locate nutrition information for all products in the data. Private label products are especially challenging because we do not observe the name of the private label brand. We drop products from our analysis if we are unable to obtain their ingredients list in order to confirm whether they are subject to the tax (such products make up less than 2% market share). If we can confirm a product's taxed status, but are not able to find its exact nutrition information, we fill in the nutrition information for that product with the average across similar products produced by the same brand (such imputation is necessary for products that make up 4.8% market share).

3.2 Descriptive Statistics

Panel A in Table 1 provides descriptive statistics on the categories included in our data. As described earlier, despite the fact that the tax is often referred to as a "soda tax," it applies to all beverages that contain added sugar or an artificial sweetener (such as diet Mountain Dew made with sucralose and diet Snapple Peach Tea made with aspartame). We report market-shares based on pre-tax sales in ounces in the first row of panel A. Among taxed products, soda makes up about one-third of all purchases, followed by juice and tea/coffee. Energy drinks, sports drinks and taxed water (e.g., sweetened "Vitamin Water") make up a smaller market-share. We provide a list of sample brands in each category at the bottom of Panel A. Notably, the three larger taxed categories are similar in terms of pricing and nutritional content. Sports drinks and taxed water are healthier and more expensive. Energy drinks are significantly more expensive.

There are two types of beverages that are not taxed. Out of those two, pure water constitutes the bulk of purchases in the pre-tax period. The second category is natural juices.[13] They make up only 11% of sales, but are notable due to the fact that they contain similar amounts of sugar and more calories relative to taxed juices. In terms of overall market-share, untaxed products are purchased slightly more frequently than taxed beverages.

Panel B in Table 1 describes the characteristics of different stores in our sample. These can broadly be divided into grocery stores, mass merchants, drugstores and convenience stores. Two residual types of stores with smaller market shares are dollar stores and a wholesale club chain. Each row in the table indicates an anonymized chain belonging to one of these categories of stores. As mentioned previously, the categories "other mass merchants," convenience stores, and dollar stores pool together stores with different chain affiliations and independent stores. The first two columns in the table report counts of stores within and outside the city of Philadelphia. The third column displays the average weekly volume per store of taxed beverages in the pre-tax period,[14] and the fourth column reports total market-share. Grocery stores, mass merchants and the wholesale club all sell a relatively large volume on a per store basis, and despite the fact that there are relatively few of these store locations, these retail formats account for over two-thirds of purchase volumes. Drugstores, dollar stores and convenience stores sell a much lower volume per store. Due to the relatively larger number of stores, they jointly account for about 30% of sales. Finally, the average price per ounce is significantly higher in the smaller stores, largely due to the fact that they tend to sell smaller pack-sizes which are significantly more expensive on a per-unit basis. We illustrate this in the final two columns of panel B. These show that the price for the same product, in this case a 2L bottle of a popular soda brand, only differs marginally across stores, but the smaller stores tend to sell smaller pack-sizes.[15]

Finally, panel C in Table 1 summarizes the variation in local demographics for the stores in

[13] Juice products from concentrate are included in this untaxed category as long as the sugar content is comparable to freshly extracted juice and there is no added sweetener.

[14] Relative volume differences and market-shares across chains / types of stores are similar for untaxed products.

[15] Many beverages are priced in a highly non-linear way. For example, a 2 liter (67.6 oz) bottle of Coca-Cola is often sold at the identical (or only marginally different) price as a 20 oz bottle.

Panel A: Category-Level	*Taxed Categories*						*Untaxed Categories*	
Market Share	0.457						0.543	
	Soda	Taxed Juice	Tea / Coffee	Sports Drinks	Taxed Water	Energy Drinks	Pure Water	Natural Juice
Market Share (Within Taxed / Untaxed Categories)	0.352	0.256	0.224	0.108	0.031	0.030	0.891	0.109
Price: Cents/Oz	3.71	3.50	3.74	4.53	5.13	19.32	1.35	6.37
Grams Sugar/Oz	2.65	2.71	2.33	1.62	0.71	2.22	0	2.98
Calories/Oz	9.95	10.99	9.81	6.45	2.64	9.14	0	13.87
Brands	Coke, Pepsi, Sprite	Ocean Spray, Minute Maid	Lipton, Snapple, Starbucks	Gatorade, Powerade	Glaceau Vitamin Water, Propel	Red Bull, Monster	Deer Park, Fiji	Tropicana, Naked Juice

Panel B: Store-Level	#Stores Inside Phil.	#Stores Outside Phil.	Ave Weekly Volume (Oz) Per Store	Phil. Market Share		Average Price/Oz	Pre-Tax Price/Oz Soda 2L	Median Pack-Size (Oz)
Grocery A	15	46	377,774	0.13		3.53	2.52	59
Grocery B	1	38	781,050	0.02		3.27	2.35	48
Grocery C	16	32	1,035,115	0.38	0.53	3.10	2.47	51
Mass Merchant M	6	21	223,869	0.03		4.10	2.16	46
Other Mass Merchants	5	28	920,248	0.11	0.14	3.19	1.97	59
Drugstore X	45	128	29,536	0.03		5.15	2.42	20
Drugstore Y	80	122	15,436	0.03		5.79	2.40	23
Drugstore Z	17	51	42,265	0.02	0.08	5.30	2.99	20
Convenience St.	116	324	72,619	0.19		8.02	2.69	18
Wholesale Club W	2	8	717,375	0.03		3.46	1.94	192
Dollar Stores	54	72	29,721	0.04		3.25	2.20	32
All Stores	357	870	122,409					

Panel C: Demographics	N	Min	Median	Mean	Max
Median Household Income ($1,000s)	357	20.0	41.9	44.1	76.2
Obesity Rate	357	0.20	0.28	0.29	0.42

Table 1: **Descriptive Statistics.**

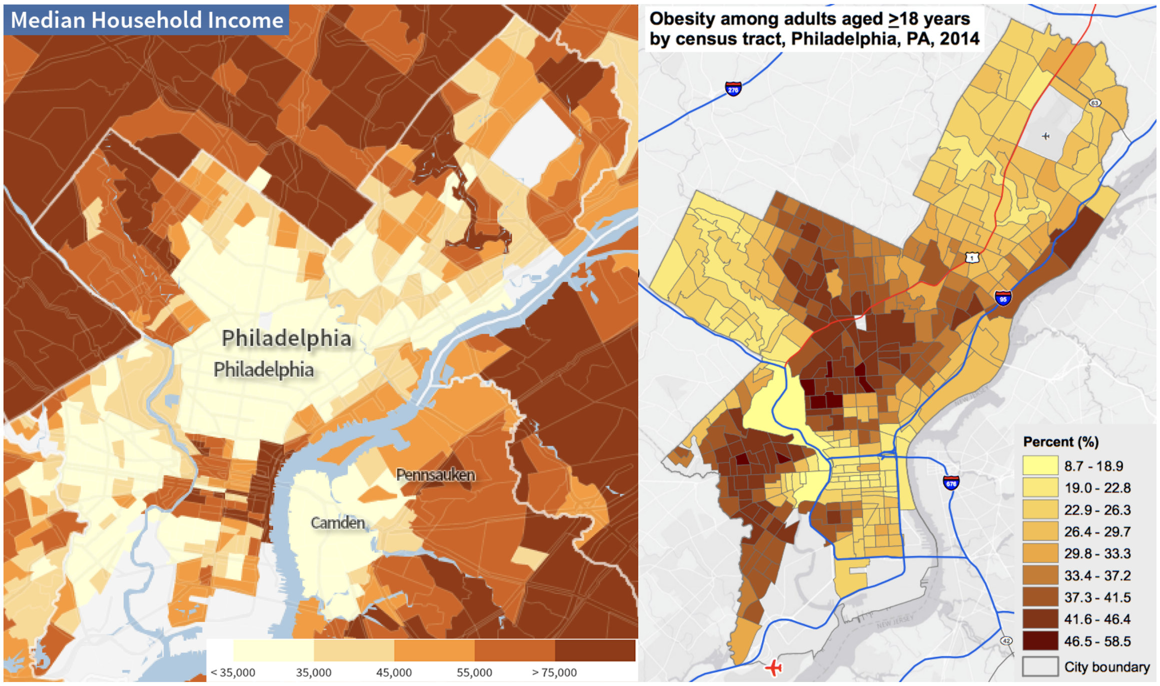

Figure 2: Variation in Income and Obesity Rates in Philadelphia

Philadelphia. There is significant variation in income and obesity rates, and these two measures are highly correlated (corr = -0.8). We provide some graphical evidence for this negative correlation in Figure 2.[16] North Philadelphia and West Philadelphia are lower income neighborhoods that have a higher obesity prevalence, while Center City, Manayunk, Chestnut Hill, and Northeast Philadelphia are higher income neighborhoods that have lower obesity rates. In Section A of the appendix we show that most chains are present in neighborhoods with different income levels and obesity rates.

Descriptive Graphical Evidence: Impact of the Tax on Price and Quantity Sold of 2L Bottles of a Popular Soda Brand As a precursor to the more systematic empirical analysis below, we illustrate the effect of the tax on price and quantity sold for one of the most popular products in our sample: a 2L-bottle of a popular soda brand. The top graph in Figure 3, plots the average weekly unit prices of the product at stores in Philadelphia and surrounding stores outside Philadelphia from January 2015 to September 2018. The product was priced at a similar level both within and outside the city before January 2017, and the weekly price series appear to be highly correlated. When the tax went into effect on January 1, 2017, the average price in the city increased dramatically, while the price remained at a lower level outside the city. Correspondingly, the bottom graph of Figure 3 depicts the average weekly unit sales of the same product at stores in Philadelphia and outside the city. The weekly unit sales inside and outside Philadelphia followed parallel trends over time before the tax. After January 1, 2017, unit sales experienced a substantial

[16] Map Source: CDC/NCCDPHP/DPH/ESB (2016).

Figure 3: Unit Price and Sales of 2L Bottles of a Popular Soda Brand

drop inside the city.[17]

4 Estimation and Results

Our key identification strategy is a difference-in-differences approach that compares the change in various outcome measures at stores in Philadelphia against stores in the surrounding 3 digit zip codes. In all regressions (unless stated otherwise), we only include stores that are located more than 6 miles away from the city limits in the control group (see Figure 1). This is to ensure that

[17]The bottom graph in Figure 3 seems to indicate that the week-on-week variation in sales decreases in the post-tax period. We explore this pattern further in Section 5.3.

the control group is not affected by the treatment, for example through price competition or cross-shopping behavior. We later show that 6 miles constitutes an appropriate choice of distance (see column (2) in Table 5). Our choice of control group has two advantages. First, the control group stores are relatively close to the city of Philadelphia and hence likely to experience similar demand shocks. Second, choosing stores from a nearby area assures that the chain affiliations of stores in the city are represented in the control group. In many of our specifications, this allows us to use stores of the same chain outside of Philadelphia as a control group for stores of the same chain in the city.

Formally, we estimate regressions based on the following general structure:

$$y_{st} = \alpha(Philly_s \times AfterTax_t) + \gamma_s + \delta_t + \varepsilon_{st}, \tag{1}$$

where the unit of observation is a store/week (s,t) combination. γ_s and δ_t are store and week fixed effects and ε_{st} denotes the regression error. $Philly_s$ denotes a dummy that is equal to one if store s is located in Philadelphia and $AfterTax_t$ is a dummy that is equal to one for any week after the tax went into effect. The difference-in-differences coefficient α is the main coefficient of interest. y_{st} denotes various outcome variables such as price, quantity sold, etc.

We also explore heterogeneity in the impact of the tax along various dimensions such as chain identity, local demographics and the competitive environment. To this end, we implement the following regression framework:

$$\begin{aligned} y_{st} \quad = \quad & \tilde{\alpha_0}(Philly_s \times AfterTax_t) + (Philly_s \times AfterTax_t \times \mathbf{X}_s)'\tilde{\boldsymbol{\alpha}}_1 \\ & + (AfterTax_t \times \mathbf{X}_s)'\tilde{\boldsymbol{\beta}} + \tilde{\gamma}_s + \tilde{\delta}_t + \tilde{\varepsilon}_{st}, \end{aligned} \tag{2}$$

where $\tilde{\gamma}_s$ and $\tilde{\delta}_t$ are store and week fixed effects and $\tilde{\varepsilon}_{st}$ denotes the regression error. The vector $\mathbf{X}_s$ denotes a set of store characteristics and $\tilde{\boldsymbol{\beta}}$ denotes a vector of coefficients capturing the change in the outcome in stores outside of Philadelphia after the tax took effect as function of $\mathbf{X}_s$. The vector $\tilde{\boldsymbol{\alpha}}_\mathbf{1}$ captures the differential change in the outcome in Philadelphia stores relative to stores outside of the city as a function of $\mathbf{X}_s$. The coefficient $\tilde{\alpha_0}$ denotes the baseline, i.e. un-interacted, difference-in-differences estimate.[18] We cluster standard errors two-way at the store and the week level in all regressions. We later (see Section 5.5) show robustness to higher levels of clustering both along the geographical dimension and along the time dimension.

Finally, we note that there is a brief adjustment period during which price pass-through and the quantity decrease are slightly lower. After the first 4 months, the impact of the tax does not vary over time for any of the outcomes we analyze below. We analyze these dynamic adjustment patterns in detail in Section 5.1. In our main regressions below, we omit the first four months after the tax went into effect in order to focus on the impact of the tax after the initial adjustment

[18] In some specifications below we include an exhaustive set of dummies along a specific dimension and hence no $\tilde{\alpha_0}$ term is included. Also, note that the estimation equation does not include "un-interacted" $\mathbf{X}_s$ terms because we include a full set of store dummies.

period.

We first analyze the impact of the tax on prices and quantities sold of taxed products. We then turn to analyzing potential substitution to other untaxed beverages. In particular, we analyze quantity changes of untaxed beverages and purchases at stores outside of Philadelphia which are not subject to the tax.

4.1 Price Reaction and Pass-through

In order to measure pass-through we use price/oz at store s in week t as the outcome measure. The difference-in-differences coefficient in this regression denotes the estimated change in the price per ounce due to the tax. Remember that the tax is equal to 1.5 cents per ounce. Hence, a coefficient of 1.5 would correspond to full pass-through and dividing the coefficient by 1.5 yields the percentage pass-through rate. All results below are based on the average price for all taxed products. We later return to the results for soda specifically, which is the largest category among taxed beverages. Results from the base specification in equation (1) are reported in column (1) of Table 2 and show an average pass-through of 1.45 cents per oz, corresponding to a 97% average pass-through rate.

We next explore heterogeneity by allowing the pass-through coefficient to differ along various dimensions. In column (2) of Table 2, we report results from a regression that includes interactions of the after-tax dummy times the Philadelphia dummy with a full set of of chain dummies for the 11 different chains / groups of stores in our sample.[19] We find pass-through rates to be remarkably consistent across chains. Apart from two exceptions, the increase in price per ounce lies between 1.16 and 1.78 (77% and 119% pass-through). Mass Merchant M and Drugstore Z have significantly smaller pass-through rates. We return to those two exceptions in more detail below. However, the two chains jointly make up less than 5% of market share and hence are not the primary focus of our analysis. Column (3) shows the same regression using the log of price per ounce as the dependent variable. The pass-through rate documented in column (2) translates into a 30-40% price increase in most stores. The price increase in percentage terms is somewhat lower in convenience stores and drugstores, despite a similar pass-through rate. This is because those retail formats tend to sell smaller pack-sizes, which on average have a higher price per ounce (see the last column in Table 1, Panel B). We note that due to large coefficient values in the log-specifications in columns (3) - (6), it is necessary to apply the transformation $\exp(coefficient) - 1$ to obtain the percentage change. When discussing percentage results in the paper, we always apply this transformation.[20]

In the remaining columns of Table 2, we explore other factors that may drive within-chain variation in pass-through. In column (4) we investigate whether the competitive environment affects pass-through. In our context, the strongest competition for stores in Philadelphia originates from stores outside of the city. These stores are not subject to the tax and, as we show later,

[19]To simplify exposition, we do not report the coefficient vector $\tilde{\boldsymbol{\beta}}$ pertaining to $(AfterTax_t \times \mathbf{X}'_s)$ terms for any of the regressions in column (2) - (6) of Table 2.

[20]For example, the estimated effect for Grocery A in column (3) corresponds to a 37.3% change: $\exp(0.317) - 1 = 37.3\%$.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent			Log	Log	Log	Log
Variable	Price/Oz	Price/Oz	Price/Oz	Price/Oz	Price/Oz	Price/Oz
Philadelphia × AfterTax	1.449***					
	(0.022)					
Grocery A		1.355***	0.317***	0.319***	0.332***	0.308***
× Philadelphia × AfterTax		(0.018)	(0.008)	(0.012)	(0.009)	(0.008)
Grocery B		1.290***	0.320***	0.324***	0.330***	0.311***
× Philadelphia × AfterTax		(0.003)	(0.001)	(0.014)	(0.003)	(0.002)
Grocery C		1.780***	0.442***	0.444***	0.450***	0.424***
× Philadelphia × AfterTax		(0.051)	(0.011)	(0.013)	(0.012)	(0.012)
Mass Merchant M		0.655***	0.144***	0.145***	0.156***	0.131***
× Philadelphia × AfterTax		(0.122)	(0.027)	(0.029)	(0.027)	(0.029)
Other Mass Merchants		1.155***	0.308***	0.310***	0.319***	0.295***
× Philadelphia × AfterTax		(0.011)	(0.005)	(0.009)	(0.006)	(0.005)
Drugstore X		1.492***	0.258***	0.260***	0.271***	0.247***
× Philadelphia × AfterTax		(0.038)	(0.009)	(0.011)	(0.010)	(0.009)
Drugstore Y		1.377***	0.216***	0.218***	0.226***	0.200***
× Philadelphia × AfterTax		(0.025)	(0.006)	(0.009)	(0.007)	(0.007)
Drugstore Z		0.342***	0.062***	0.064***	0.072***	0.048***
× Philadelphia × AfterTax		(0.031)	(0.006)	(0.010)	(0.007)	(0.007)
Wholesale Club		1.398***	0.336***	0.339***	0.346***	0.326***
× Philadelphia × AfterTax		(0.013)	(0.003)	(0.012)	(0.005)	(0.006)
Dollar Stores		1.557***	0.389***	0.391***	0.396***	0.369***
× Philadelphia × AfterTax		(0.032)	(0.007)	(0.011)	(0.007)	(0.010)
Convenience Stores		1.626***	0.183***	0.185***	0.194***	0.170***
× Philadelphia × AfterTax		(0.032)	(0.003)	(0.009)	(0.006)	(0.004)
Distance (in Miles) to Border				-0.001		
× Philadelphia × AfterTax				(0.003)		
Income					-0.024***	
× Philadelphia × AfterTax					(0.009)	
Obesity Rate						0.033***
× Philadelphia × AfterTax						(0.009)
$(AfterTax_t \times \mathbf{X}_s)'$ Interactions	n/a	Yes	Yes	Yes	Yes	Yes
Store FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	144,700	144,700	144,700	144,700	144,700	144,700
Stores	832	832	832	832	832	832
Weeks	176	176	176	176	176	176

Table 2: **Impact on Prices / Pass-through Rate Estimates.** Interactions with an after-tax dummy (the $(AfterTax_t \times \mathbf{X}'_s)$ term) are included in columns (2) - (5), but not reported separately. One exception is column (5). We have no obesity data outside of Philadelphia and hence no (Obesity × AfterTax) term is included.

they do not adjust prices after the tax. As a simple measure of competition, we therefore include distance to the city border (with the appropriate interactions) in the regression. We find that the distance to the border does not predict a differential price reaction, and the estimated coefficient is small in magnitude. The effect remains small and insignificant when we estimate the regression without chain interactions. We conclude that competitive pressure does not affect pass-through.

In the final two columns of Table 2 we investigate whether income and obesity rates in the store's catchment area (1 mile radius around the store) are predictive of pass-through. To facilitate interpretation we use re-scaled versions of the income and obesity variables that range from 0 to 1 across all stores in Philadelphia. We find that prices increase more in low income and high obesity areas.[21] Hence, from a health policy point of view one might be encouraged by the higher increase in high obesity area. On the other hand, the differential price increase leads to a higher financial burden for low income households. Further, although both coefficients are significant, they are relatively small in magnitude.[22]

In summary, we find that the primary predictor of pass-through is chain identity, whereas the competitive environment does not predict differential pass-through and local demographics explain a small part of the variation in pass-through across store locations.

Soda Results Table A5 in the appendix replicates the results reported above, but uses the price for soda rather than all taxed products as the dependent variable. Results are largely very similar. The average price increase is equal to 1.449 for soda versus 1.459 for all taxed products.

Two noticeable differences concern the two smaller chains that showed limited pass-through for all taxed products. Mass Merchant M experiences a price increase of 0.655 for all taxed products and 1.441 for soda. This is due to the fact that stores belonging to this chain did not increase prices for any taxed category other than soda. Results for all other taxed categories all show zero pass-through. Similarly, Drugstore Z experiences a larger price increase for soda relative to other categories. Even the increase for soda is only equal to 0.935 in the case of this chain.

With regards to the competition variable as well as demographic interactions, we find results to be similar to the ones obtained for all taxed products. However, the coefficients on both demographic variables are insignificant when using soda prices. Nevertheless, both coefficients are similar in magnitude to and not statistically different from the corresponding coefficients based on all taxed products.

Product-level Results The analysis thus far has been at the store-week level. In Appendix B, we explore heterogeneity in pass-through across different kinds of products. We study differences in pass-through across brands, pack sizes, and diet versus sugar-sweetened drinks. The only significant difference in pass-through along these dimensions is a significantly lower pass-through rate for

[21] We re-iterate that income and obesity are strongly negatively correlated (correlation coefficient of -0.8) and hence when we include both variables, estimates become noisier. We obtain a coefficient (standard error) of 0.009 (0.015) for income and 0.039 (0.016) for obesity when including both variables.

[22] The standard deviation of the re-scaled income (obesity) variable is equal to 0.26 (0.27). Hence a one standard deviation shift in either variable leads to a change in the price adjustment of less than 1%.

private label products relative to national brands. This is consistent with the fact that private label products are on average cheaper than name brands, and demand for private labels tends to be more elastic. We find no evidence for differences in pass-through across pack sizes. We note, however, that due to non-linear pricing across pack-sizes, an identical pass-through rate leads to a larger percentage increase in price for large pack-sizes. Finally, we find that the tax is passed through in a similar way to diet and sugar-sweetened drinks.

4.2 Quantity Reaction

We now turn to analyzing changes in quantity sold after the tax. As in the previous section, we use the framework outlined in equations (1) and (2), but use quantity sold (measured in ounces) as the dependent variable. The first column of Table 3 shows an average decrease of 56,000 ounces per store in the total volume of taxed beverages that were sold in Philadelphia. This effect is large in magnitude and constitutes a 46% reduction relative to the average pre-tax level of weekly sales of 122,000 ounces per store (see panel B in Table 1).

There is notable heterogeneity in this effect across chains. In columns (2) and (3) we report results using total quantity and the logarithm of total quantity as the dependent variable, respectively. The chains which sold large quantities prior to the tax, namely grocery stores, mass merchants and the wholesale club, all experience dramatic decreases in sales of 41% to 69%.[23] Among the smaller volume chains, only dollar stores experience a similar decrease. Drugstores and convenience stores instead experience a more modest decrease or no decrease in volume sold. Looking at the patterns documented in panel B of Table 1 and the price results in Table 2, there are two likely explanations for this pattern. First, price increased less in percentage terms at drugstores and convenience stores due to a higher pre-tax price level. Second, those stores tend to sell smaller pack-sizes which are more likely to be impulse purchases, and hence consumers might be less price sensitive for such purchases.

Finally, we singled out Mass Merchant M and Drugstore Z in the previous section because those two chains are characterized by significantly lower price increases. Consistent with this pattern, we find that Mass Merchant M experiences no quantity decrease, and quantity sold actually increases at Drugstore Z. This increase is likely due to the fact that Drugstore Z has the lowest pass-through rate of all stores, and hence becomes relatively more attractive to consumers after the tax goes into effect.

Next, we turn to the competitive environment and find that distance to the city border does not have a significant impact on quantity changes (see column (4)). We return to this finding in more detail in the next section when we analyze whether consumers engage in cross-shopping behavior by driving to stores outside of the city which are unaffected by the tax.

Results based on interactions with income and obesity rates are reported in columns (5) and (6). We find that quantity decreases more in high income areas, whereas obesity rates do not

[23] As mentioned before, we apply the transformation $\exp(coefficient) - 1$ to translate the regression coefficients into percentage changes.

Dependent Variable	(1) Ounces Sold	(2) Ounces Sold	(3) Log Ounces	(4) Log Ounces	(5) Log Ounces	(6) Log Ounces
Philadelphia × AfterTax	-56,192***					
	(9,740)					
Grocery A		-207,363***	-0.733***	-0.747***	-0.652***	-0.725***
× Philadelphia × AfterTax		(34,502)	(0.068)	(0.077)	(0.077)	(0.070)
Grocery B		-369,605***	-0.674***	-0.700***	-0.609***	-0.665***
× Philadelphia × AfterTax		(9,753)	(0.011)	(0.062)	(0.027)	(0.015)
Grocery C		-728,854***	-1.173***	-1.187***	-1.111***	-1.157***
× Philadelphia × AfterTax		(82,272)	(0.068)	(0.070)	(0.071)	(0.074)
Mass Merchant M		-23,083	-0.110	-0.121	-0.033	-0.098
× Philadelphia × AfterTax		(24,797)	(0.109)	(0.119)	(0.112)	(0.110)
Other Mass Merchants		-406,541***	-0.529***	-0.544***	-0.461***	-0.518***
× Philadelphia × AfterTax		(65,340)	(0.078)	(0.087)	(0.080)	(0.080)
Drugstore X		-7,899***	-0.290***	-0.304***	-0.212***	-0.280***
× Philadelphia × AfterTax		(1,232)	(0.041)	(0.054)	(0.048)	(0.043)
Drugstore Y		-610***	-0.002	-0.015	0.063	0.013
× Philadelphia × AfterTax		(202)	(0.034)	(0.048)	(0.041)	(0.039)
Drugstore Z		26,169***	0.558***	0.542***	0.621***	0.570***
× Philadelphia × AfterTax		(4,310)	(0.079)	(0.088)	(0.080)	(0.083)
Wholesale Club		-423,042***	-0.878***	-0.899***	-0.796***	-0.869***
× Philadelphia × AfterTax		(35,987)	(0.062)	(0.079)	(0.074)	(0.061)
Dollar Stores		-16,234***	-0.568***	-0.583***	-0.519***	-0.550***
× Philadelphia × AfterTax		(1,669)	(0.034)	(0.048)	(0.038)	(0.040)
Convenience Stores		-7,131***	-0.108***	-0.122***	-0.035	-0.096***
× Philadelphia × AfterTax		(1,530)	(0.019)	(0.037)	(0.034)	(0.023)
Distance (in Miles) to Border				0.006		
× Philadelphia × AfterTax				(0.014)		
Income					-0.106**	
× Philadelphia × AfterTax					(0.044)	
Obesity Rate						-0.030
× Philadelphia × AfterTax						(0.041)
$(AfterTax_t \times X_s)'$ Interactions	n/a	Yes	Yes	Yes	Yes	Yes
Store FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	144,700	144,700	144,700	144,700	144,700	144,700
Stores	832	832	832	832	832	832
Weeks	176	176	176	176	176	176

Table 3: **Impact on Quantity Sold.** Interactions with an after-tax dummy (the $(AfterTax_t \times \mathbf{X}_s')$ term) are included in columns (2) - (5), but not reported separately. One exception is column (5). We have no obesity data outside of Philadelphia and hence no (Obesity × AfterTax) term is included.

predict a differential quantity response. The relationship between income and changes in quantity is relatively large in magnitude. This specification shows that quantity decreases by approximately 10% more in the highest income area relative to the lowest income area. The direction of the correlation with income is surprising because we would expect high income households to be less price sensitive (all else equal), and hence reduce consumption less after the tax. Moreover, we saw in Table 3 that prices increased somewhat less in high income areas, and hence this should lead to a lower quantity reaction. One possible explanation is that high income households have easier access to transport, and thus are able to avoid the tax by driving to stores outside of the city. This finding suggests that lower income households bear a relatively higher financial burden because they continue to purchase a larger quantity of taxed products than wealthier households. We return to this point after presenting the cross-shopping results in the next section.

Soda Results In Table A6 in the appendix we present results from the quantity regression for the soda category. Results are very similar with regards to overall effect magnitude and patterns of heterogeneity along various dimensions. The only meaningful difference is a larger quantity reaction for Mass Merchant M in the soda category. This finding is consistent with the earlier finding that Mass Merchant M only increased prices for soda but not for other taxed categories.

Product-level Results In Appendix B, we further explore heterogeneity in quantity response across products. Notably, we find that large pack sizes ($\geq$ 60 ounces) see a larger reduction in sales than small pack sizes ($<$ 60 ounces). Further, we find that sales of diet drinks decrease 15% more than sales of sugar-sweetened drinks in response to the tax. These two facts provide a deeper understanding of what types of purchases and consumers are most responsive to the tax policy. Large pack-sizes are more likely to be purchased in advance for future consumption, whereas small bottles are more likely to be purchased for immediate, on-the-go consumption. In addition, diet soda is more popular among older, high income consumers, whereas regular soda is on average more popular among young, low-income, non-white consumers (Mendes (2013); Wang (2015)). This is in line with the previous finding that quantity decreases less at stores in low income areas.

4.3 Pricing and Demand for Untaxed Beverages

So far we have documented that the tax was passed-through to retail prices to a large extent and that the quantity of taxed beverages sold in Philadelphia decreased by 46%. We now turn to analyzing whether consumers substitute to other products in reaction to the tax-induced price increase. In our context, there are two possible channels for substitution. First, consumers might substitute to other untaxed beverages, namely water or natural juices. Among those two alternatives, water constitutes a healthier alternative, whereas this is less clear for natural juices that tend to contain more calories than most taxed beverages. Second, consumers might drive outside of the city border to purchase sweetened beverages at stores that are not subject to the tax.

	All Untaxed Beverages				Water		
	(1)	(2)	(3)	(4)	(5)	(6)	
Dependent Variable	Ounces Sold	Ounces Sold	Price/Oz	Price/Oz	Ounces Sold	Price/Oz	Average Pre-Tax Volume
Philadelphia × AfterTax	-4,521		0.063***		-4,940	0.024**	Untaxed: 146,017
	(7,118)		(0.010)		(6,569)	(0.010)	Water: 130,472
Grocery A		20,730		0.003			Chain-specific Vol.:
× Phil. × AfterTax		(17,194)		(0.006)			324,645
Grocery B		59,912***		-0.001			
× Phil. × AfterTax		(6,443)		(0.002)			1,336,881
Grocery C		-54,012		-0.005			
× Phil. × AfterTax		(44,679)		(0.007)			1,490,350
Mass Merchant M		-9,572		0.049***			
× Phil. × AfterTax		(8,900)		(0.018)			259,547
Other Mass Merch.		5,466		0.020*			
× Phil. × AfterTax		(154,735)		(0.011)			1,032,948
Drugstore X		-3,760**		0.213***			
× Phil. × AfterTax		(1495)		(0.024)			42,034
Drugstore Y		3,718***		0.043**			
× Phil. × AfterTax		(960)		(0.021)			13,505
Drugstore Z		2,321		-0.023***			
× Phil. × AfterTax		(1,952)		(0.008)			56,027
Wholesale Club		455,134*		0.026***			
× Phil. × AfterTax		(252,216)		(0.007)			3,440,038
Dollar Stores		-660		0.088***			
× Phil. × AfterTax		(795)		(0.014)			15,263
Convenience Stores		160		0.018			
× Phil. × AfterTax		(659)		(0.024)			31,123
$(AfterTax_t \times \mathbf{X}_s')$ Interact.	Yes	Yes	Yes	Yes	Yes	Yes	
Store FE	Yes	Yes	Yes	Yes	Yes	Yes	
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	
Observations	144,209	144,209	144,209	144,209	143,931	143,931	
Stores	829	829	829	829	827	827	
Weeks	176	176	176	176	176	176	

Table 4: **Price and Quantity Reaction of Untaxed Beverages.**

Substitution to Untaxed Beverages We first turn to demand for untaxed beverages as a potential channel of substitution. We use the same regression framework as in the case of prices and quantities of taxed products. Specifically, columns (1) and (2) of Table 4 are identical to the specifications in columns (1) and (2) of Table 3, but now total quantity sold of *untaxed* beverages is used as the dependent variable. The simple difference-in-differences estimate in column (1) shows a decrease of 4,521 ounces in the average store in Philadelphia. The effect is statistically insignificant and small in magnitude. Relative to the average pre-tax volume of untaxed beverages of 146,000 (reported in the right-most column of Table 4), the decrease constitutes a 3.1% change in demand. We analyze heterogeneity in demand for untaxed beverages in column (2). While some coefficients are significant, we observe decreases and increases across the various chains that are generally small in magnitude relative to the pre-tax volume of untaxed beverages (reported in the final column of Table 4) and the change in volume of *taxed* beverages at each respective chain (see column 2 in Table 3).[24]

In columns (3) and (4) of Table 4 we replicate the same analysis using price per ounce of untaxed beverages as the dependent variable. These products are not subject to the tax, so prices for these products should not increase as a direct result of the tax. However, if the tax leads to changes in the elasticity of demand for untaxed beverages, then retailers might choose to adjust their prices for untaxed products as well. We find that on average prices increase slightly by 0.063 cents/oz. While statistically significant, this effect is small in magnitude. In comparison, the price for taxed beverages went up by 1.45 cents/oz for taxed beverages (see column (1) of Table 2). Column (4) shows that some chains experience price increases of up to 0.21 cents/oz, potentially in anticipation of consumers substituting to untaxed beverages. However, most chain-specific effects are small in magnitude and statistically insignificant.[25]

In columns (5) and (6) we report the average quantity and price effect for the water category in isolation. As reported earlier, water makes up the bulk of untaxed beverage sales and also constitutes the healthiest beverage option. Therefore, changes in water consumption are of particular interest. We find that results for water are very similar to the results based on all untaxed beverages. Demand does not change significantly and the estimated change is small in magnitude. The increase in water prices is statistically significant, but small in magnitude.

Cross-shopping Next, we explore whether consumers chose to drive outside of Philadelphia to purchase at stores that were not subject to the tax. In order to analyze the extent of cross-shopping at stores outside of Philadelphia, we employ the basic framework laid out in equation (1). However, rather than excluding stores within 6 miles of the city border, we now include those stores and estimate separate treatment effects for them. Thus, we continue to treat stores more

[24]For example, the average pre-tax volume sold of untaxed beverages at Grocery B stores is equal to 1,336,881. The 59,912 ounces increase therefore constitutes a 4.5% change. In contrast, stores of this chain experienced a 370,000/780,000=47% decline in sales of taxed beverages.

[25]The observed increase in the price of untaxed products could come from two different sources. First, retailers might be optimally adjusting their prices to reflect changes in the elasticity of demand for untaxed products. Second, it is possible that some retailers mistakenly applied the tax to some products that are not intended to be taxed. For example, a January 6, 2017, interview with ShopRite, a major grocery chain, vice president Karen Meleta in *Philadelphia* magazine acknowledged that some products (including plain mineral water and a natural lime juice) had been mislabeled (Fiorillo (2017)). In the article, Meleta explains that "we literally had to go through all of our drink products by hand to determine which ones would be subject to the tax. It's very confusing and complicated. If you read the original regulations, where there was some confusion was that the original regulation actually says that caloric sweeteners may also include sugars from concentrated fruits or vegetable juices that are in excess of what would be expected from fruits or vegetables. [...] We reached out to the city and asked how were were [sic] supposed to calculate this. How do we know if something has been reconstituted to its original sweetness level?"

Dependent Variable	(1) Ounces Sold Taxed Beverages	(2) Ounces Sold Taxed Beverages	(3) Ounces Sold Taxed Beverages	(4) Price Per Oz Taxed Beverages	(5) Ounces Sold Untaxed Beverages	# Stores in Geogr. Area
Philadelphia * After Tax	-56,193***	-56,797***		1.449***	-4,481	357
	(9,740)	(9,774)		(0.022)	(7,111)	
0-2 Miles Inside			-48,922***			113
City Border * After Tax			(16,638)			
>2 Miles Inside			-59,600***			244
City Border * After Tax			(11,706)			
0-2 Miles Outside	63,650***	63,046***	63,650***	-0.022**	6,323	106
City Border * After Tax	(20,733)	(20,748)	(20,733)	(0.011)	(7,610)	
2-4 Miles Outside	18,364***	17,760**	18,364***	0.006	4,648	140
City Border * After Tax	(7,031)	(7,081)	(7,031)	(0.011)	(9,472)	
4-6 Miles Outside	8,640**	8,036*	8,640**	0.002	19,877	149
City Border * After Tax	(4,196)	(4,259)	(4,196)	(0.009)	(16,274)	
6-8 Miles Outside		2,790				118
City Border * After Tax		(3,711)				
8-10 Miles Outside		-5,995*				103
City Border * After Tax		(3,044)				
Store FE	Yes	Yes	Yes	Yes	Yes	
Week FE	Yes	Yes	Yes	Yes	Yes	
Change in Aggregate	-9,456**					
Quantity (Unit: 1,000 Ounces)	(4,358)					
Change in % of Pre-tax Volume in	-0.216**					
Philadelphia **w/ Cross-Shopping**	(0.100)					
Change in % of Pre-tax Volume in	-0.459***					
Philadelphia **w/o Cross-Shopping**	(0.080)					
Observations	213,499	213,499	213,499	213,499	212,556	
Stores	1,227	1,227	1,227	1,227	1,221	
Weeks	176	176	176	176	194	

Table 5: **Quantity and Price Reaction in Stores Near the City Border.**

than 6 miles outside of the city as the control group, and we estimate separate treatment effects for stores in Philadelphia and stores near the city boundary.

We first estimate a regression that allows for separate effects within 0-2, 2-4 and 4-6 miles outside of the city. Results from this regression are reported in the first column of Table 5 and show that quantity sold increases significantly for stores up to 6 miles outside of the city limits. Compared to the decrease of 56,000 ounces of taxed beverages at the average store in Philadelphia, we find an even larger increase of 64,000 ounces/store in stores up to 2 miles away from the city. Stores up to 4 and 6 miles outside of Philadelphia experienced smaller increases in sales. Though not shown, we also estimated a regression with 1-mile distance bands and found an even larger increase of 182,000 ounces in stores up to 1 mile outside of the city. Figure 4 presents a graphical

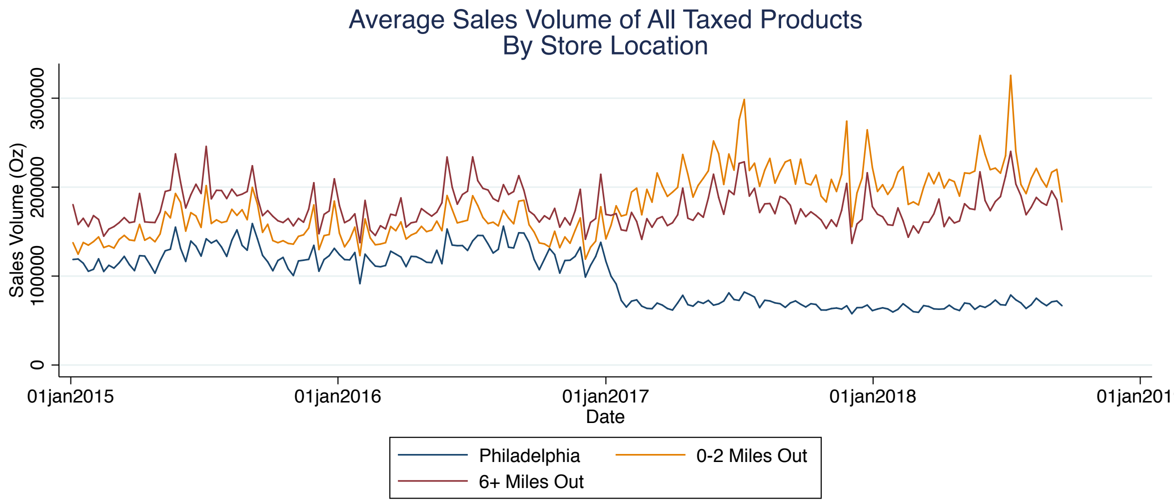

Figure 4: **Taxed Beverage Sales in Philadelphia and Surrounding Area Stores Over Time.**

representation of the regression in column (1) and shows how sales in the 0-2 miles band near the city increase relative to stores more than 6 miles away, whereas sales in stores in Philadelphia decrease. To avoid clutter, we do not show the two curves for stores 2-4 and 4-6 miles outside of the city.

Due to the fact that the number of stores varies across geographical areas (see the last column of Table 5), we need to weigh the different coefficients in column (1) appropriately in order to assess the aggregate change in quantity. In the lower panel of Table 5 we report the total weekly decrease in quantity in Philadelphia and stores less than 6 miles outside of the city, which is equal to 9.5 million ounces and constitutes a 22% decrease relative to the total volume sold in Philadelphia prior to the tax. The effect is statistically significant at the 5% level.[26] Notably (as reported earlier), when focusing on stores in Philadelphia only, we find a much larger decrease in quantity of 46%. The difference between the "Philadelphia only" and "Philadelphia plus 6 miles outside" percentage decrease is statistically significant. Therefore, to measure the aggregate quantity change correctly, it is important to account for cross-shopping behavior.

We next probe whether stores further than 6 miles outside of Philadelphia also experience an increase in quantity by adding 2 additional separate terms for stores 6-8 and 8-10 miles outside of the city, respectively. Stores that are located more than 10 miles away from the city limit serve as the control group. Results from this regression are reported in column (2) of Table 5 and show that there is no significant increase in quantity at stores further than 6 miles away from the city border.[27] These estimates provide evidence that stores more than 6 miles away from the city constitute a

[26] In an earlier working paper version, we found an effect that was significant only at the 10% level (but similar in magnitude to the effect reported above). The key difference is that we now omit the first four months of the tax from our analysis (due to the fact that patterns during this adjustment period are slightly different from the longer run impact of the tax).

[27] The 8-10 mile coefficient is significant only at the 10% level and has a negative sign.

valid control group that is not indirectly affected by the tax due to cross-shopping.

In column (3) we test whether there are differences in quantity changes *within* Philadelphia depending on the distance of the store to the city limits. We add separate terms for in-city stores that are less than 2 miles and more than 2 miles away from the border, but find the two coefficients not to be different from each other. This finding is consistent with the insignificant "distance to the border" effect reported in column (4) of Table 3. Thus, it appears that consumers engage in cross-shopping regardless of their proximity to the border. We also note that the shape of the Philadelphia city limits is such that among all stores in Philadelphia, the furthest distance to the border is equal to only 4.37 miles.

In column (4) we assess whether prices react differently in areas within a specific distance of the city. Interestingly, we find that prices at stores within 0-6 miles outside of Philadelphia remain almost unchanged despite the large increase in quantity sold in those geographic areas. In fact, in stores within 2 miles we find a small, but statistically significant, decrease in prices. We also find that sales of untaxed products do not change at stores near the city border (see column (5)).

Finally, we investigate whether we can detect patterns suggesting that different income groups are more or less likely to engage in cross-shopping. To this end, we analyze heterogeneity in the demand increase at stores outside of the city border as a function of the income level of nearby census tracts *inside* Philadelphia. If high income consumers are more likely to travel to stores outside of Philadelphia, we should see a larger increase in demand at border stores near high income areas in Philadelphia. We run such a test by adding interactions of the border store dummies with income in nearby areas in Philadelphia (and the post-tax dummy). We find that higher income in nearby areas in Philadelphia leads to a larger increase in demand at border stores. However, in most specifications, the interaction effects are not statistically significant, most likely due to a lack of sufficient power to identify such effects.[28]

4.4 Nutritional Intake

To analyze nutritional intake we calculate the total number of calories and grams of sugar sold (via beverage sales) at the store/week-level. Both variables are obtained by simply adding up calories and sugar across all beverage products sold in a given store/week. Hence, we intentionally do not distinguish between taxed and untaxed categories because we want to analyze changes in total calories and grams of sugar from all beverage sales. However, as our earlier findings indicate, most of the change in nutritional intake will come from taxed products because demand for untaxed products remained largely unchanged.

[28]Specifically, we run a regression that replicates column (1) in Table 5, but add two interaction terms for the 0-2 mile and 2-4 mile distance bands of border stores with the income level in nearby areas in Philadelphia (and the post-tax dummy). We compute this income variable by calculating the average of the median income level at all census tracts in Philadelphia that are within 4 miles of the store. The coefficients on both interaction terms are positive, but not statistically significant. We then split the distance bands more finely into 0-1, 1-2, 2-4, and 4-6 mile bands and include interactions of the three closest bands with the income level in nearby areas in Philadelphia (and the post-tax dummy). In that specification, we find the coefficient on the interaction term for stores in the 0-1 mile distance band to be statistically significant at the 5% level.

Dependent Variable	(1) Calories	(2) Calories	(3) Grams of Sugar	(4) Grams of Sugar	# Stores in Geogr. Area
Sample	Excluding Stores 0-6 Miles Outside Phil.	All Stores	Excluding Stores 0-6 Miles Outside Phil.	All Stores	
Average Pre-Tax Calories / Sugar	1,389,424		342,807		
Philadelphia * After Tax	-523,225***	-523,176***	-132,143***	-132,129***	357
	(95,929)	(95,942)	(24,312)	(24,315)	
0-2 Miles Outside		636,965***		166,074***	106
City Border * After Tax		(204,747)		(53,314)	
2-4 Miles Outside		192,558***		50,600***	140
City Border * After Tax		(68,390)		(18,026)	
4-6 Miles Outside		93,293**		24,572**	149
City Border * After Tax		(42,894)		(11,086)	
Store FE	Yes	Yes	Yes	Yes	
Week FE	Yes	Yes	Yes	Yes	
Change in Aggregate Quantity		-78,396*		-18,821*	
(Unit: 1,000 Calories / Grams of Sugar)		(42939)		(10,979)	
Change in % of Pre-tax Volume in		-0.158*		-0.154*	
Philadelphia **w/ Cross-Shopping**		(0.086)		(0.090)	
Change in % of Pre-tax Volume in		-0.376***		-0.385***	
Philadelphia **w/o Cross-Shopping**		(0.069)		(0.071)	
Observations	144,700	213,499	144,700	213,499	
Stores	832	1,227	832	1,227	
Weeks	176	176	176	176	

Table 6: **Impact on Nutritional Intake.**

We analyze the impact of the tax on nutritional intake in Table 6. We first estimate our base specification (see equation (1)), which excludes stores within 6 miles of the city border, using total calories as the dependent variable. This regression shows that calories (in beverages) sold at stores in Philadelphia decreased by about 38% relative to pre-tax levels. However, once we use the full sample of stores and account for cross-shopping, we find that the decrease drops to 16% and is not statistically significant at the 5% level (column (2) is based on the same specification as column (1) in Table 5). Results analyzing the impact on total grams of sugar sold are presented in columns (3) and (4) of Table 6. The patterns for sugar are very similar to the calorie results. We observe a large decrease in Philadelphia, which is offset to a large extent by an increase in stores near the city. After taking cross-shopping into account, the change in grams of sugar consumed is not statistically significant at the 5% level.

The reason why the nutritional regressions differ from the earlier cross-shopping regression based on quantity sold is due to the fact that there is variation in nutritional content within the category of taxed products. Therefore, if the decrease in quantity is driven predominantly by a decrease in healthier variants of taxed products, the percentage decrease in calories and sugar will be lower than the raw quantity decrease. We documented earlier (see Section 4.2 and Appendix B) that diet products experienced a larger decrease in quantity relative to sugar-sweetened variants. It is this heterogeneity in the response to the tax (and potentially other compositional changes in the demand for taxed beverages) that leads to a smaller percentage reduction in calorie and sugar intake that is not significant at the 5% level.

4.5 Summary of results

The analysis in the preceding sections demonstrated that the tax on sweetened beverages was passed through at a rate of 77-119% in almost all stores. As a consequence, demand decreased dramatically in many stores in Philadelphia. We find that consumers do not switch to other untaxed beverages, but demand increases strongly in stores just outside the city boundary. The latter channel of substitution largely offsets the decrease in demand for taxed products in the city.

Nutritional Intake When taking cross-shopping into account, we find that nutritional intake in terms of total calories and grams of sugar from beverages does not change significantly. This establishes our first key finding: the tax did not improve nutritional intake by encouraging consumers to substitute to healthier beverages.

Tax Revenue Second, we find that tax revenue is substantially reduced by the fact that consumers engage in cross-shopping. The 46% reduction in quantity sold of taxed beverages leads to an equivalent percentage reduction in tax revenue relative to the case where consumers continue to consume at pre-tax levels. Hence, any projection of tax revenue for a local sweetened-beverage tax of this kind needs to take the extent of consumers' cross-shopping behavior into account.

Welfare and Distributional Effects Finally, although we do not conduct a formal welfare analysis, we glean several implications for welfare from our analysis. First, consumers are able to partially avoid the financial burden of the tax by driving to stores outside of the city. Furthermore, high income consumers are more likely to engage in such cross-shopping, possibly due to the fact that their transport costs are lower. While we cannot track consumers of different income levels individually, several patterns indicate differences in access to transport. First, we find that quantity decreases more in stores that are located in high income areas (see column (5) of Table 3). This finding seems surprising given that we would expect lower income consumers to be more price sensitive. However, we also find that the primary channel of substitution is to stores outside of the city. Hence, geographic substitution being more costly for low income households could be an alternative driver for the lack of quantity response in low income areas. Second, we find that there is a larger reduction in *diet* beverage sales (in Philadelphia), which tend to be consumed by higher income customers (Mendes (2013), Wang (2015)). Based on these findings, we conclude that the tax imposes a disproportionate burden on low-income households.

5 Additional Results and Robustness Checks

In this section we provide a set of additional results as well as robustness checks for the main results presented earlier.

5.1 Dynamics

In our main analysis the post-tax period comprises May 2017 to September 2018. We omitted the first four months after the tax was introduced due to the fact that there is some adjustment period in which prices and quantities differ from their long-run values. In this section, we decompose the impact of the tax over time and assess any changes in our key outcome measures that evolve over the course of the post-tax period.

Dynamic adjustment patterns could occur because it takes retailers and consumers some time to adjust their behavior in response to the tax. Furthermore, consumers might engage in tax avoidance via cross-shopping immediately after the tax goes into effect but find it inconvenient to do so in the long-run. Fortunately, the relatively long post-tax period observed in our data provides us with ample opportunity to test for dynamic adjustments. To investigate the importance of changes in the impact of the tax over time, we categorize the post-tax data into four time periods: January to April of 2017, May to August of 2017, September to December of 2017, and January 2018 to September 2018 (the end of our sample period). We then re-estimate several of our main regressions, allowing for different treatment effects in the four post-tax time periods. Table 7 reports the results of these analyses. For ease of comparison, in columns (1), (3), (5), and (7) we replicate the results in column (1) of Tables 2, 3, 4, and 5 respectively.

In column (2), we test for changes in the pass-through rate over time. Besides the interaction of the Philadelphia dummy with the after-tax dummy, we now add further interactions of the Philadelphia dummy with dummies for the time-periods January-April of 2017, May-August of 2017, and September-December of 2017. Accordingly, the Philadelphia times after-tax coefficient now captures the long-run impact of the tax on prices for the final period of our sample from January to September 2018. The other three interaction terms capture differences in short-term price adjustments relative to the long-run pass-through rate. The interaction term of January-April of 2017 is equal to -0.31 and significant, which indicates that the pass-through rate was at a slightly lower level during the first 4 months after the tax.[29] In comparison, the interaction terms for May-August and September-December of 2017 are small in magnitude and not significantly different from the pass-through rate in 2018, which implies that pass-through remained stable after May 2017.

The remaining columns present similar specifications regarding the impact of the tax on quantity sales of taxed products, quantity sales of untaxed products, and cross-shopping behavior. In all cases we find that the difference in the treatment effects in May-December of 2017 relative to the long-run outcome are small in magnitude and not statistically significant, whereas outcomes in the

[29] We also investigate the pass-through for each of the first 6 months separately, and obtain the same conclusion.

first four months of the tax differ moderately from long-run outcomes.[30] We conclude that after a brief adjustment period of 4 months, prices and quantities sold stabilized and show no sign of further adjustments between May 2017 and September 2018.

5.2 Cross-shopping and Basket-level Effects

One salient pattern in our data is the large degree of substitution of sweetened beverage sales from stores in Philadelphia to stores just outside the city border. Such tax avoidance due to cross-shopping behavior reduces the city's ability to raise tax revenue. Furthermore, it is possible that consumers who shift their sweetened beverage purchases to stores outside of the city also start purchasing other (non-taxed) products outside of Philadelphia. Thomassen et al. (2017) highlight the importance of such basket-level substitution effects.[31]

In order to assess the importance of basket-level substitution effects, we study purchase patterns for milk in Philadelphia, as well as in border stores. We choose this category because milk is one of the most frequently purchased consumer packaged goods categories and not a direct substitute or complement to sweetened beverages. Because we are not able to obtain data across an exhaustive set of categories in all stores, we treat milk as a stand-in for other items in a consumer's basket. We use the same specification as in our cross-shopping regression (see column (1) of Table 5), but use milk sales as the dependent variable. We start by examining all types of stores in Philadelphia, and find that store-level demand for milk decreases by a small amount of 1,100 ounces per week relative to an average pre-tax level of 58,870 ounces per week. The effect is not statistically significant.[32] In line with this finding, we also find no evidence that milk sales at stores near the city border experience a change in demand.[33]

If we focus only on grocery stores, where consumers might be more likely to engage in cross-shopping, we find a statistically significant substitution effect. However, even for this subset of stores, the effect is small in magnitude and corresponds to a substitution of 5% of milk sales from grocery stores in Philadelphia to grocery stores just outside the city. Based on these findings, we conclude that consumers substitute only to a very limited extent other parts of their basket to stores just outside the city.

[30] The one exception are the cross-shopping effects, where we find estimates for the various distance bands outside of Philadelphia to not be significant for either of the two time periods just after the tax went into effect. A few individual coefficient in this regression are significant. However, we run a set of joint significance tests of the three distance band coefficients in each time-period and find that in all cases we cannot reject that the three coefficients are equal to zero.

[31] If consumers purchase other products outside of the city, this would lead to lower purchases across a wider range of products beyond the sweetened beverage category and, hence, lower overall sales tax revenue in Philadelphia.

[32] We also find no price adjustment for milk both inside and outside the city.

[33] The changes in average weekly milk sales in the 0-2 mile, 2-4 mile, and 4-6 mile distance bands are 1,553 ounces, -1,131 ounces, and -336 ounces, respectively, and none of these estimates are statistically significant at the 5% level.

	Taxed Products				Untaxed Products		Cross-shopping	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	Price/Oz	Price/Oz	Ounces Sold	Ounces Sold	Ounces Sold	Ounces Sold	Ounces Sold	Ounces Sold
Philadelphia	1.449***	1.451***	-56,192***	-55,612***	-4,521	-5,437	-56,193***	-55,612***
× AfterTax	(0.022)	(0.025)	(9,740)	(10,162)	(7,118)	(7,041)	(9,740)	(10,163)
Philadelphia		-0.309***		18,982***		3,847		18,982***
× Jan-April 2017		(0.064)		(5,145)		(4,097)		(5,150)
Philadelphia		-0.002		-6,230		4,990		-6,230
× May-Aug 2017		(0.020)		(4,791)		(3,184)		(4,817)
Philadelphia		-0.008		3,537		-929		3,537
× Sept-Dec 2017		(0.015)		(4,661)		(3,270)		(4,704)
0-2 Miles Outside							63,650***	61,787***
× AfterTax							(20,733)	(20,164)
0-2 Miles Outside								-12,196
× Jan-April 2017								(8,007)
0-2 Miles Outside								2,846
× May-Aug 2017								(2,498)
0-2 Miles Outside								4,736***
× Sept-Dec 2017								(1,818)
2-4 Miles Outside							18,364***	17,017**
× AfterTax							(7,031)	(6,664)
2-4 Miles Outside								-2,538
× Jan-April 2017								(3,187)
2-4 Miles Outside								3,029
× May-Aug 2017								(2,575)
2-4 Miles Outside								2,544**
× Sept-Dec 2017								(1,017)
4-6 Miles Outside							8,640**	7,819*
× AfterTax							(4,196)	(4,267)
4-6 Miles Outside								1,334
× Jan-April 2017								(2,739)
4-6 Miles Outside								2,800
× May-Aug 2017								(2,944)
4-6 Miles Outside								617
× Sept-Dec 2017								(1,778)
Store FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	144,700	159,676	144,700	159,676	144,209	159,131	213,499	235,585
Stores	832	832	832	832	832	832	1,227	1,227
Weeks	176	194	176	194	176	194	176	194

Table 7: **Dynamics of Impacts on Price, Quantity, and Cross-Shopping.** Column (1), (3), (5), and (7) replicate earlier results and are based on a sample that excludes the first four months after the tax was introduced.

5.3 Volatility of Purchases and Changes in Price Sensitivity

Figure 3 presented earlier shows that in the case of 2 liter bottles of a popular soda brand, purchase volume decreases in Philadelphia relative to the control group. Furthermore, the volatility of sales in stores in Philadelphia also decreases markedly after the tax goes into effect. In this section, we show that this pattern occurs for taxed beverages more broadly, and it is driven by the fact that the most price sensitive consumers start to engage in cross-shopping after the tax went into effect. Therefore, the set of consumers that continues to purchase taxed beverages in Philadelphia after the tax constitutes a selected set of less price sensitive consumers. Those price insensitive consumers react less to temporal movements in price, and therefore the volatility in sales decreases.

We first turn to analyzing the change in volatility across all taxed beverages. To this end, we compute the variance of sales for each store/product combination separately for the pre- and post-tax period. We find that in Philadelphia, the standard deviation of sales decreased by more than 50%, falling from 1,270 to 443, whereas in control stores outside of the city (excluding the buffer zone), the variance of sales decreased only slightly from 1,206 to 1,130. We also note that during the same time, the volatility of price movements actually remained constant in Philadelphia and outside of the city. This suggests that the nature of demand changed in a way that led to a decrease in the volatility of sales over time.

In order to assess the cause of this change more directly, we estimate the average product-level elasticity separately for the pre-/post-tax period and for stores inside and outside of the city. We estimate the elasticity by regressing (at the product level) log quantity on log price, store/product-pair fixed effects, and week fixed effects. We find that the product-level elasticity of demand dropped from -2.00 to -1.23 at stores in Philadelphia, whereas at control group stores it decreased by a more modest amount from -2.21 to -1.87. We therefore conclude that consumers that continue to purchase taxed beverages in Philadelphia are less price sensitive than the average pre-tax consumer that purchased in Philadelphia. This pattern is consistent with the idea that the consumers that start to engage in cross-shopping are the most price sensitive consumers. Hence, consumers that continue to purchase sweetened beverages in Philadelphia will tend to be less price sensitive.

5.4 Robustness Check: Parallel Time Trends

Our difference-in-differences approach to estimating the impact of the tax relies on the assumption that the treatment and control groups would follow the same time trend in the absence of treatment. Because we have data for multiple time periods before and after treatment, we are able to control for differential time trends flexibly while still estimating the treatment effect of the tax. We do so by including a third-order polynomial time trend interacted with the Philadelphia dummy variable in several of our main regressions. (In all regressions, we control for a "baseline" time-trend using a full set of week fixed effects). In the majority of specifications, we find that the differential time trend variables are jointly insignificant and the estimated coefficients of interest do not change significantly when including the additional time-trend controls. For example, when including time-trend controls in the regressions reported in column (1) of Tables 2, 3, and 4, we find p-values of 0.50, 0.16, and 0.33 for a test of joint significance of the differential time-trend variables.[34] We conclude that the similarity of time-trends in the treatment and control groups before and after the tax is implemented supports the parallel trends assumption underlying our identification strategy.

5.5 Robustness Check: Clustering

In our main specification we use two-way clustering at the store- and week-level. As an additional robustness check, we explore the sensitivity of our results to clustering at a higher level of aggregation. Table A4 in the appendix reports results for our main specifications, when clustering standard errors at the store and *month* level. In columns (1), (3), (5), and (7) we replicate our earlier results with store/week clustering and the remaining columns show results when using a higher level of clustering. Across all four regressions, standard errors only change minimally. In most cases they are slightly larger when clustering at the month level, but not uniformly so (see for instance the three distance band coefficients in the cross-shopping regression). We also probed robustness to clustering at the county rather than the store level (not reported in the table). We find that county level clustering (combined with either week- or month-level clustering) leads to lower standard errors in almost all regressions.

6 Conclusion

We use detailed supermarket scanner data from a large set of stores in Philadelphia to evaluate the impact of a sweetened beverage tax on nutritional intake and consumer welfare. Our findings suggest that the tax was almost fully passed through at most stores. While there is some decreasein the aggregate consumption of taxed beverages, the magnitude of the decrease is reduced considerably because consumers avoid the tax by cross-shopping. As a consequence, the reform does not lead to an improvement in terms of the consumption of healthier beverages, it has little impact on nutritional intake, and it is limited in its ability to raise revenue. Finally, it imposes a relatively larger financial burden on low income / high obesity households that are less likely to engage in cross-shopping at stores outside of the city.

These results relate to a broader discussion about the optimal design of policies that are intended to encourage changes in consumer behavior. First, our results suggest that consumers have strong preferences for taxed beverages relative to healthier alternatives, and these preferences are not easily altered. Our data spans almost two years after the tax, and we don't find evidence that cross-shopping decreases over time (see Figure 4), so it is therefore unlikely to be a short-term effect. Second, our analysis shows that in order to be effective, taxes must be imposed in a way that makes them hard to evade. Highly localized taxes make it relatively easy for consumers to seek

[34]The main coefficients of interest with and without time-trend controls are not statistically significantly different from each other for any of the three pairs of regressions.

alternatives.[35] This kind of tax evasion behavior has been documented for other kinds of local taxes as well, including cigarette and liquor taxes (Barker et al. (2016); Beard et al. (1997)). Finally, while we would expect low income households to generally be more price sensitive, our results also show that low income consumers are less likely to avoid the tax through cross-shopping. The latter effect is so strong that it leads to a lower reduction in quantity (for the same price increase) in low income areas in Philadelphia. Generally, taxes on grocery items tend to be regressive due to the fact that such goods constitute a larger share of expenditure for low income households (Bureau of Labor Statistics (2015); Wilson et al. (2016)). The differential behavior with regards to tax avoidance that we document constitutes an additional driver that makes the tax regressive. Hence, fully understanding the impact of the tax across the income spectrum is important to correctly quantify distributional consequences.

[35]From a policy-design perspective, imposing a tax at the national level makes it harder for consumers to avoid the tax. In such settings, consumers may be more likely to substitute to untaxed products within the taxed zone. This is consistent with Aguilar et al. (2016)'s finding that consumers in Mexico switched to untaxed yet unhealthy beverages that are high in calories.

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A Additional Store Descriptive Statistics

Figure A1 shows a map of Philadelphia stores, color-coded by retail format. The map shows that the stores in our sample are geographically dispersed. Table A1 summarizes the within and across-chain variation in demographics. First, looking at the average income across chains shows that Grocery A and Drugstore X stores are on average located in higher-income neighborhoods, while Grocery C and Dollar stores tend to be located in lower-income neighborhoods. Second, the chain-specific standard deviations tend to be only slightly smaller than the standard deviations across all stores. Therefore, we are able to analyze the impact of demographics based on the variation in demographics within stores of the same chain.

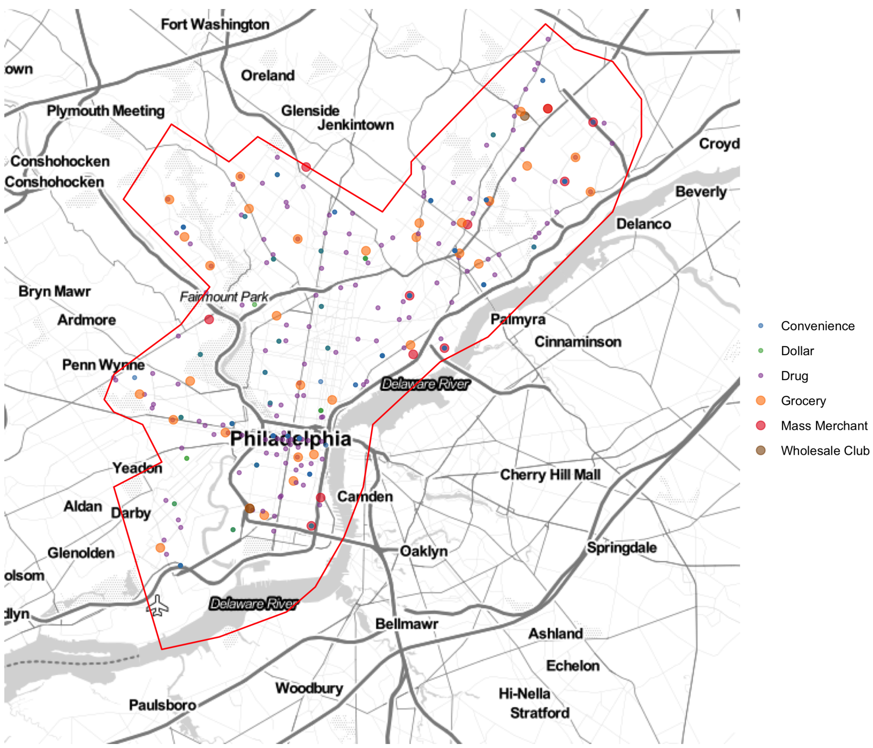

Figure A1: Philadelphia Stores by Retail Format

B Product-level Analysis

The unit of observation in our main analysis is a store/week combination. In this appendix, we carry out a similar analysis at the store/**product**/week level in order to explore whether pass-through and quantity response vary systematically across products. As defined in Section 3 above, we consider a product to be a brand/diet-status/pack-size combination. For instance a 20 ounce bottle of diet Coke is a product in our dataset. Different flavors of a given product (such as cherry coke or vanilla coke), are aggregated and not treated as separate products.

	# Stores in Phil.	Median Income ($1,000s) Mean	Std. Dev	Obesity Rate Mean	Std. Dev
Grocery A	15	53.7	11.7	0.26	0.03
Grocery B	1	41.6	-	0.26	-
Grocery C	16	37.9	11.2	0.32	0.06
Mass Merchant M	6	47.7	7.7	0.28	0.05
Other Mass Merchants	5	45.8	10.5	0.28	0.04
Drugstore X	45	50.9	14.5	0.27	0.05
Drugstore Y	80	43.2	14.7	0.30	0.06
Drugstore Z	17	44.0	15.6	0.29	0.07
Convenience St.	116	45.2	14.6	0.28	0.06
Wholesale Club W	2	41.4	7.8	0.27	0.05
Dollar Stores	54	36.1	11.8	0.33	0.05
All Stores	357	44.1	14.5	0.29	0.06

Table A1: **Within and Across-Chain Variation in Demographics.**

We explore heterogeneity in the impact of the tax along various product-level dimensions: product category, private label vs national brand, package size, and diet status. Table A2 summarizes the variation in characteristics across the 477 different taxed products that are sold in Philadelphia stores.[36] Soda products account for 35% of the pre-tax volume sales of taxed products, while taxed juices (26%) and tea and coffee drinks (22%) are the next largest categories of taxed products. Although the majority of products in the data are national brands, 8% of pre-tax sales volume is for private label products. Next, we consider the package size of different products. We classify products that have 60 or more ounces as large pack-sizes. With this classification, roughly 50% of products are considered large, but large products account for almost two-thirds of total volume sales. Finally, we split products based on whether they are sugar-sweetened or artificially sweetened (diet). Diet products account for 12% of the pre-tax sales volume of taxed products.

We employ a regression framework similar to the one outlined in equations (1) and (2). However, now the unit of observation is a store/product/week combination. Due to this more granular data, we control for fixed effects at the store/product-pair level and the week level. All regressions reported below include chain interaction terms in addition to interactions between product-characteristic dummy variables and the Philadelphia and AfterTax dummies. We cluster standard errors at both the store and brand level in all regressions.

[36]The regressions reported in Table A3 include observations for an additional 43 products that were only sold in stores in the control group. Our results are robust to restricting the sample to the set of 456 products that were sold in both Philadelphia and the control group.

	# Products	Market Share
Product Category		
Soda	165	35.1%
Taxed Juice	139	25.6%
Tea and Coffee	76	22.4%
Sports Drinks	21	10.8%
Taxed Water	29	3.1%
Energy Drinks	47	3.0%
Brand		
National Brand	416	91.6%
Private Label	61	8.4%
Pack Size		
Small ($<$ 60 oz)	238	33.6%
Large ($\geq$ 60 oz)	239	66.4%
Sweetener		
Sugar-Sweetened	345	87.7%
Artificially Sweetened (Diet)	132	12.3%
All Taxed Products	477	100%

Table A2: **Description of product-level data.** The first column records the count of products with each product characteristic. The second column records the fraction of pre-tax volume sales that came from products with each characteristic.

B.1 Pass-through

We start by analyzing price pass-through. We report regressions using price per ounce as the dependent variable for all taxed products and for soda only in columns (1) and (2) of Table A3. In these regressions, the omitted category is small pack-sizes of sugar-sweetened, national brand soda, and each coefficient in the table represents the difference between average pass-through for products with the focal characteristic and this omitted category. The results for all taxed products and soda are very consistent. The negative coefficient on the private label interaction term indicates that private label products have significantly lower pass-through than national brands. Average pass-through for national brands is 1.45 cents per oz, so pass-through for private label products is about 25% lower. This is consistent with the fact that private label products are on average cheaper than name brands, and demand for private labels tends to be more elastic. Next, we examine whether average pass-through differs as a function of package size. Beverage prices tend to exhibit quantity-discounts, which means that full-pass through would result in a larger percent increase in price for large pack sizes relative to small pack sizes. To avoid very large price increases on large pack sizes, retailers may pass less of the tax through to consumers. Looking at columns

	(1)	(2)	(3)	(4)
Dependent Variable	Price Per Oz All Taxed	Price Per Oz Soda	Log Ounces All Taxed	Log Ounces Soda
Private Label	-0.381***	-0.400***	0.144*	0.226
	(0.097)	(0.128)	(0.084)	(0.240)
Large Pack Size (>= 60 oz)	-0.074	-0.062	-0.403***	-0.549***
	(0.049)	(0.072)	(0.067)	(0.095)
Diet	-0.075	-0.023	-0.156***	-0.176**
	(0.091)	(0.025)	(0.042)	(0.067)
Tea and Coffee	-0.010		-0.190**	
	(0.114)		(0.086)	
Taxed Juice	-0.166***		-0.095	
	(0.056)		(0.080)	
Energy Drinks	-0.070		-0.109**	
	(0.187)		(0.051)	
Sports Drinks	0.099*		-0.189	
	(0.059)		(0.133)	
Taxed Water	-0.057		-0.382***	
	(0.074)		(0.066)	
Chain Interactions	Yes	Yes	Yes	Yes
Product Char. × ($AfterTax_t$)	Yes	Yes	Yes	Yes
Product-Store FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Observations	10,767,100	5,226,940	10,767,100	5,226,940
Stores	832	832	832	832
Weeks	176	176	176	176
Products	520	179	520	179

Table A3: **Product-Level Regressions: Pass-Through and Impact on Quantity Sold.** Chain dummy interactions with a Philadelphia dummy and an after-tax dummy, as well as interactions of product characteristic and chain dummies with an after-tax dummy, are included in all regressions. Standard errors are clustered at the store, brand, and week levels.

(1) and (2), we find only directional evidence that pass-through is lower on large pack sizes.[37] We also test whether pass-through is higher for diet products, and we find no significant difference between pass-through for sugar- and artificially-sweetened drinks. Finally, column (1) shows that pass-through for taxed juices is significantly lower than pass-through for soda, and pass-through for sports drinks is marginally significantly higher. All other product categories experience similar pass-through to soda.

[37] In a variant of column (2), we test for differences between the three most popular pack-sizes that make up about 60% of soda sales: 20oz bottles, 2 liter bottles and 12 packs of 12oz cans. In this regression, pass-through is 0.22 cents per ounce smaller for 2 liter bottles relative to the other two pack sizes and this difference is significant at the 1% level.

B.2 Quantity-Response

Having documented that there is significant heterogeneity in pass-through across products, we next explore whether demand responds for some types of products more than others. To this end, we estimate the same set of regressions as in the previous section, using log sales in ounces as the dependent variable.

Columns (3) and (4) of Table A3 document the observed heterogeneity in quantity response for all taxed products and soda products, respectively. In the previous section, we saw that pass-through on private label products was smaller than on name brands. Here, we explore whether the demand response differs for private label products relative to name brands. Although prices for private label products did not increase as much as prices for name brands, consumers who buy private label are often very price sensitive, so these two forces may net out. Overall, columns (3) and (4) show that the demand response for private label products is similar to the response for national brands. In columns (3) and (4), we also test whether large pack sizes experience a larger reduction in sales than small pack sizes. We find that averaging across all taxed products, sales of large pack sizes in Philadelphia decrease by an additional 33% relative to the reduction in sales for small pack sizes. This is true despite the fact that pass-through on a per-oz basis was similar for large pack sizes and small package sizes.[38] The difference in the reduction between large and small pack sizes is even larger within the soda category (column (4)). The larger reduction in large pack-size products relative to small pack-size products is consistent with our hypothesis that consumers engage in cross-shopping behavior for large-volume trips, whereas purchases of smaller products are more impulse buys for on-the-go consumption, and therefore consumers do not plan ahead to make these purchases outside of the city. Columns (3) and (4) also explore whether the quantity response is similar for diet and regular drinks and show that sales of diet drinks fall by more than sales of regular drinks. Finally, column (3) shows that sales of tea and coffee drinks, energy drinks, and taxed waters decrease even more than soda sales.

C Chain-Specific Rigidities in Pass-Through and Quantity Response

In this Appendix, we further investigate pass-through for Drugstore Z and Mass Merchant M, the chains that do not come close to fully passing the tax through to consumers. Figures A2 and A3 graphically depict the pass-through of the tax over time for these two chains. The first panel in Figure A2 seems to indicate that Drugstore Z stores did not pass the tax through on soda products at all for the first approximately four months of 2017, but they did pass a substantial fraction of the tax through beginning in May 2017. The subsequent panels in Figure A2 show that Drugstore Z stores did not pass the tax through on other taxed products.

[38] Although pass-through on a per-oz basis is similar for large and small pack sizes, the pre-tax average price per oz of large pack sizes is lower because of quantity discounts, so the observed change in price as a percent of the pre-tax price is actually quite large, relative to smaller package sizes.

Turning to Mass Merchant M, Figure A3 visually shows that Mass Merchant M stores immediately passed the tax through on soda products, but there is little evidence of pass-through on any other taxed product categories. Visually, it appears that Mass Merchant M may have made small increases to the price of tea and coffee products in Philadelphia stores beginning in 2018, a full year after the tax went into effect.

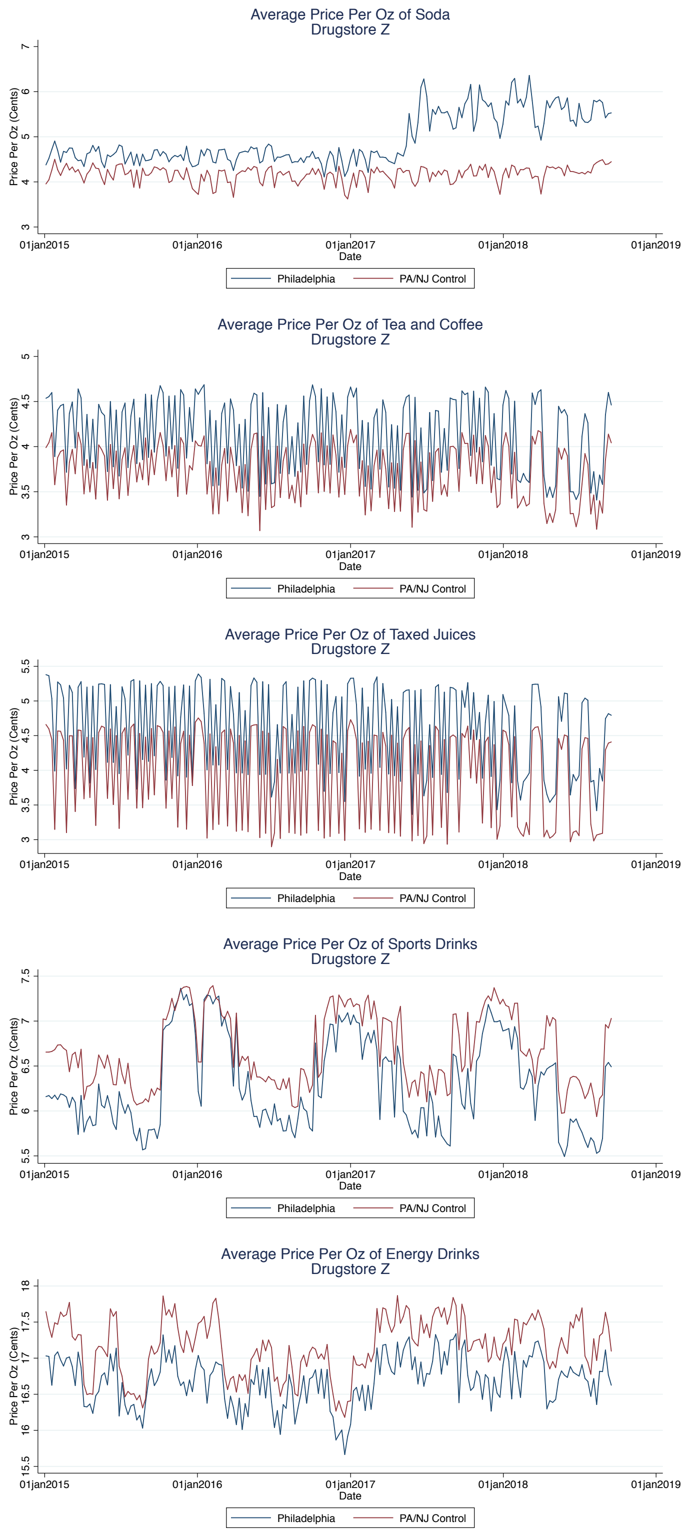

Figure A2: Pass-Through Over Time at Drugstore Z

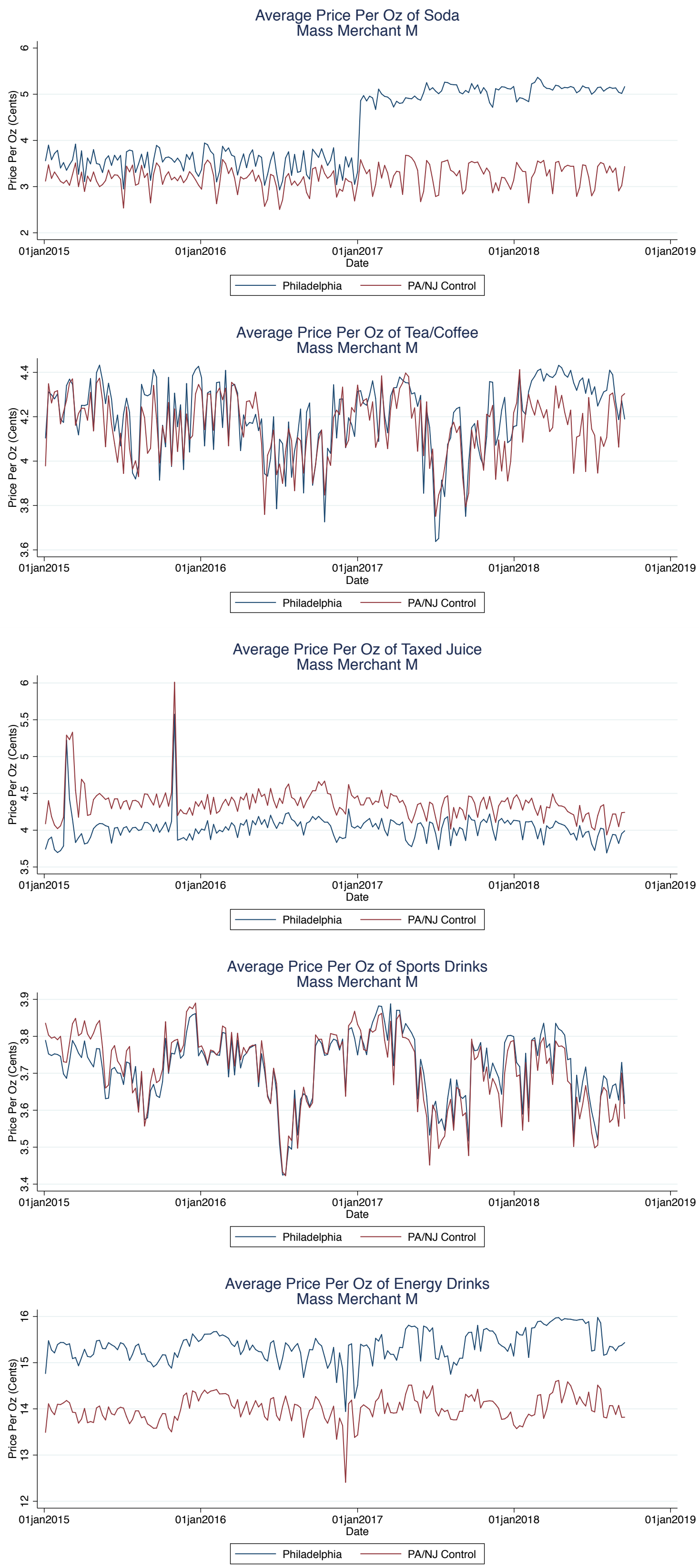

Figure A3: Pass-Through Over Time at Mass Merchant M

D Additional Tables

	Taxed Products				Untaxed Products		Cross-shopping	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	Price/Oz	Price/Oz	Ounces Sold	Ounces Sold	Ounces Sold	Ounces Sold	Ounces Sold	Ounces Sold
Clustering	Store and Week	Store and Month	Store and Week	Store and Month	Store and Week	Store and Month	Store and Week	Store and Month
Philadelphia	1.449***	1.449***	-56,192***	-56,192***	-4,521	-4,521	-56,193***	-56,193***
× After Tax	(0.022)	(0.024)	(9,740)	(9,865)	(7,118)	(7,063)	(9,740)	(9,864)
0-2 Miles Outside							63,650***	63,650***
City × After Tax							(20,733)	(20,706)
2-4 Miles Outside							18,364***	18,364**
City × After Tax							(7,031)	(7,022)
4-6 Miles Outside							8,640**	8,640**
City × After Tax							(4,196)	(4,166)
Store FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	144,700	144,700	144,700	144,700	144,209	144,700	213,499	213,499
Stores	832	832	832	832	832	832	1,227	1,227
Weeks	176	176	176	176	176	176	176	176
Months	-	41	-	41	-	41	-	41

Table A4: **Robustness Check: Store/Month Clustering.**

Dependent Variable	(1) Price/Oz	(2) Price/Oz	(3) Log Price/Oz	(4) Log Price/Oz	(5) Log Price/Oz	(6) Log Price/Oz
Philadelphia × AfterTax	1.459***					
	(0.020)					
Grocery A		1.308***	0.344***	0.340***	0.351***	0.342***
× Philadelphia × AfterTax		(0.025)	(0.010)	(0.015)	(0.012)	(0.010)
Grocery B		1.518***	0.414***	0.406***	0.417***	0.411***
× Philadelphia × AfterTax		(0.004)	(0.001)	(0.021)	(0.005)	(0.004)
Grocery C		1.838***	0.466***	0.462***	0.469***	0.461***
× Philadelphia × AfterTax		(0.055)	(0.015)	(0.019)	(0.017)	(0.017)
Mass Merchant M		1.441***	0.318***	0.315***	0.323***	0.314***
× Philadelphia × AfterTax		(0.270)	(0.061)	(0.064)	(0.061)	(0.060)
Mass Merchant N		1.084***	0.303***	0.298***	0.308***	0.299***
× Philadelphia × AfterTax		(0.029)	(0.008)	(0.015)	(0.009)	(0.009)
Drugstore X		1.536***	0.300***	0.296***	0.306***	0.297***
× Philadelphia × AfterTax		(0.039)	(0.012)	(0.016)	(0.014)	(0.013)
Drugstore Y		1.321***	0.250***	0.246***	0.254***	0.245***
× Philadelphia × AfterTax		(0.020)	(0.007)	(0.012)	(0.009)	(0.009)
Drugstore Z		0.935***	0.179***	0.174***	0.183***	0.174***
× Philadelphia × AfterTax		(0.068)	(0.008)	(0.015)	(0.010)	(0.010)
Wholesale Club		1.411***	0.439***	0.433***	0.442***	0.436***
× Philadelphia × AfterTax		(0.073)	(0.009)	(0.019)	(0.010)	(0.009)
Dollar Stores		1.456***	0.360***	0.355***	0.362***	0.353***
× Philadelphia × AfterTax		(0.042)	(0.012)	(0.017)	(0.012)	(0.016)
Convenience Stores		1.602***	0.197***	0.193***	0.202***	0.193***
× Philadelphia × AfterTax		(0.025)	(0.005)	(0.013)	(0.007)	(0.007)
Distance (in Miles) to Border				0.002		
× Philadelphia × AfterTax				(0.005)		
Income					-0.013	
× Philadelphia × AfterTax					(0.012)	
Obesity Rate						0.010
× Philadelphia × AfterTax						(0.014)
($AfterTax_t \times \mathbf{X}'_s$) Interactions	n/a	Yes	Yes	Yes	Yes	Yes
Store FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	144,700	144,700	144,700	144,700	144,700	144,700
Stores	832	832	832	832	832	832
Weeks	176	176	176	176	176	176

Table A5: **Impact on Prices / Pass-through Rate Estimates for the Soda Category.** Interactions with an after-tax dummy (the ($AfterTax_t \times \mathbf{X}'_s$) term) are included in columns (2) - (5), but not reported separately. One exception is column (5). We have no obesity data outside of Philadelphia and hence no (Obesity × AfterTax) term is included.

Dependent Variable	(1) Ounces Sold	(2) Ounces Sold	(3) Log Ounces	(4) Log Ounces	(5) Log Ounces	(6) Log Ounces
Philadelphia × AfterTax	-18,713***					
	(-3,909)					
Grocery A		-103,199***	-0.810***	-0.818***	-0.671***	-0.826***
× Philadelphia × AfterTax		(-18,693)	(0.080)	(0.092)	(0.091)	(0.083)
Grocery B		-163,577***	-0.891***	-0.906***	-0.787***	-0.909***
× Philadelphia × AfterTax		(-5,162)	(0.012)	(0.079)	(0.030)	(0.018)
Grocery C		-237,319***	-1.024***	-1.032***	-0.928***	-1.057***
× Philadelphia × AfterTax		(-42,436)	(0.087)	(0.092)	(0.088)	(0.093)
Mass Merchant M		-33,289	-0.554**	-0.560**	-0.427*	-0.578***
× Philadelphia × AfterTax		(-20,205)	(0.222)	(0.236)	(0.225)	(0.211)
Mass Merchant N		-130,308***	-0.492***	-0.501***	-0.378***	-0.515***
× Philadelphia × AfterTax		(-26,802)	(0.104)	(0.116)	(0.105)	(0.106)
Drugstore X		-2,692***	-0.229***	-0.237***	-0.098*	-0.250***
× Philadelphia × AfterTax		(-779)	(0.047)	(0.063)	(0.055)	(0.052)
Drugstore Y		-427***	0.004	-0.004	0.110**	-0.026
× Philadelphia × AfterTax		(-146)	(0.038)	(0.057)	(0.048)	(0.045)
Drugstore Z		16,053***	0.701***	0.692***	0.806***	0.676***
× Philadelphia × AfterTax		(-3,048)	(0.104)	(0.116)	(0.101)	(0.106)
Wholesale Club		-73,161***	-0.802***	-0.814***	-0.679***	-0.821***
× Philadelphia × AfterTax		(-6,733)	(0.065)	(0.090)	(0.083)	(0.067)
Dollar Stores		-8,085***	-0.416***	-0.425***	-0.338***	-0.453***
× Philadelphia × AfterTax		(-1,349)	(0.039)	(0.059)	(0.044)	(0.049)
Convenience Stores		385	-0.024	-0.033	0.094**	-0.048*
× Philadelphia × AfterTax		(-322)	(0.021)	(0.048)	(0.039)	(0.027)
Distance (in Miles) to Border				0.003		
× Philadelphia × AfterTax				(0.018)		
Income					-0.202***	
× Philadelphia × AfterTax					(0.053)	
Obesity Rate						0.062
× Philadelphia × AfterTax						(0.052)
($AfterTax_t \times \mathbf{X}'_s$) Interactions	n/a	Yes	Yes	Yes	Yes	Yes
Store FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	144,700	144,700	144,700	144,700	144,700	144,700
Stores	832	832	832	832	832	832
Weeks	176	176	176	176	176	176

Table A6: **Impact on Quantity Sold for the Soda Category.** Interactions with an after-tax dummy (the ($AfterTax_t \times \mathbf{X}'_s$) term) are included in columns (2) - (5), but not reported separately. One exception is column (5). We have no obesity data outside of Philadelphia and hence no (Obesity × AfterTax) term is included.