Substitution Patterns and Welfare Implications of Local Taxation: Empirical Analysis of a Soda Tax

Jiawei Chen and Colin Reinhardt and Saad Andalib Syed Shah*
University of California, Irvine

September 2022

Abstract

We present a structural choice model that incorporates households' geographic and product substitution for studying the effects of localized taxation policies. Using detailed retail and household data pertaining to Philadelphia's soda tax, we estimate the choice model linking households' demographic characteristics and proximity to the city border to their tax avoidance behavior—switching from taxed to untaxed products or from Philadelphia to non-Philadelphia stores. We find that the inclusion of travel time is vital for modeling households' heterogeneous responses, with an extra minute of travel time to reach the untaxed region equivalent to adding 47¢ to the product price. Taking into account travel costs and the switch to less preferred products, Philadelphia households on average incur a loss in consumer surplus more than twice the amount of tax paid, with low-income households bearing the largest burden.

JEL: D04, D12, H23, H26, L66. *Keywords:* demand estimation, substitution patterns, consumer heterogeneity, local taxation, policy evaluation.

1 Introduction

Governments of all types levy "sin taxes"—excise taxes imposed on certain goods deemed harmful to society and individuals—with the dual, and oftentimes competing, motives of curbing consumption and raising tax revenue. Examples include taxes on tobacco, alcohol, gambling, drugs[1], junk foods[2], etc. The present study designs a model to evaluate the effects of an increasingly popular category of sin taxes—"soda taxes", which are imposed on sugar-sweetened beverages

*Chen: jiaweic@uci.edu. Reinhardt: creinha1@uci.edu. Syed Shah: ssyedsha@uci.edu. We are grateful for comments and suggestions received at several seminar and conference presentations. Researchers' own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researchers and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

[1]Such as legal marijuana (Hollenbeck and Uetake, 2021).

[2]See for example Yazzie et al. (2020).

(SSBs)—by paying particular attention to both cross-border shopping (geographic substitution) and switching to alternative products (product substitution) as forms of tax avoidance.

We focus on the SSB tax implemented in the US city of Philadelphia. Philadelphia provides a set of conditions that benefits researchers interested in the effects of SSB taxation. First, Philadelphia is demographically diverse, particularly in terms of income distribution, which allows researchers to better understand the heterogeneous effects of the taxation on the city's rich and poor households. Second, Philadelphia is a large urban center with a substantial set of retail-level and household-level data available. Finally, the city of Philadelphia is both expansive and surrounded by a large suburban population, which provides an ideal setting for studying the effects of geographic and product substitution.

The difference between geographic and product substitution is an important one. For a local government collecting tax revenue, geographic substitution hurts local businesses and lowers tax revenue as consumers take their SSB purchase and with it their grocery shopping to other locations, whereas product substitution leaves consumers' purchases in the same location. For public health agencies, geographic substitution defeats the purpose of the tax as consumers continue to buy unhealthy products and only change where they buy them, whereas product substitution achieves exactly the health objective of the tax by diverting consumption from unhealthy products to healthier ones. A good understanding of the relation between and the magnitudes of geographic and product substitution is then an important prerequisite for sound policymaking, for local governments and public health agencies alike.

Besides SSB taxation, analogous scenarios featuring such tension between geographic and product substitution apply to many policies implemented by states, counties, or cities, including all kinds of sin taxes collected at the local level, other types of local taxes and regulations[3], local subsidies for certain products such as healthy foods and gasoline[4], and even restrictions on abortion imposed by various US states[5]. By providing a structural empirical analysis of a local policy that decomposes consumers' heterogeneous substitution responses along the dimensions of geographic and product substitution, this paper offers new insights as well as a useful approach for

[3] Such as gasoline taxes at the state level and local amusement taxes (Breslow, 2019).

[4] A local subsidy not only induces local consumers to switch from unsubsidized products to subsidized ones, but also incentivizes consumers in other locations to travel to the subsidized location in pursuit of lower prices. For example, when the subsidized gasoline prices in Mexico are noticeably lower than the prices in the US, many US drivers cross the border into Mexico to fill their tanks, leading to a gasoline shortage and temporary suspension of the gasoline subsidy in Mexico's US border region (Garrison and Barrera, 2022).

[5] In states where abortion restrictions are in place, a woman may face a choice among getting an abortion at an out-of-state clinic, switching to an alternative method such as abortion medication by mail, and the "outside option" of using none of the above and giving birth instead. In such cases, the cost associated with traveling out of state to obtain an abortion plays a significant role in determining the woman's ultimate choice.

related policy studies in local taxation, subsidy, and regulation.

The primary goals of this study are then twofold: to estimate consumers' geographic and product substitution as well as welfare changes resulting from an SSB tax, and to provide an empirical framework by which one can evaluate the effects of local taxation or related policies taking into account consumers' multifaceted and heterogeneous substitution patterns.

To quantify the effects of Philadelphia's SSB tax on consumers' product and location choices and their welfare, we construct and estimate a model of consumer demand in the random coefficients nested logit (RCNL) framework (e.g., Grigolon and Verboven (2014), Miller and Weinberg (2017), and Miravete et al. (2018)) using a combination of retail and household data. The random coefficients approach allows rich modeling of heterogeneity in consumer tastes and travel costs, while the nested structure is particularly suited to our analysis of consumers' substitution across beverage categories ("nests"). Aggregate-level retail data lacks the information needed to track individual households' heterogeneous responses to the tax, but measures the aggregate effect of the tax with far less noise and provides a reliable method by which one can account for endogenous variables. Micro-level household data covers only a small subset of all households, but provides an accurate measure of consumer heterogeneity and responsiveness to travel costs. Our empirical approach combines the strengths of the above elements and incorporates the two kinds of data in an internally consistent way.

In estimation, we follow an approach suggested in Grieco et al. (2022) to recover mean utility and unobserved demand shocks while accounting for heterogeneous tastes and cross-border shopping.[6] Our results include estimates of mean responses to SSB taxation and travel time as well as heterogeneous parameters related to preference and substitution. To the best of our knowledge, this paper is the first study that estimates an RCNL model using a combination of aggregate-level and micro-level data.[7]

Several key findings emerge from our analysis. (1) Our demand estimates show that travel time to the alternative region plays a key role in determining households' willingness to cross-border shop, the effectiveness of the taxation, and changes in consumer surplus. On average an extra minute of travel time to reach a store in the alternative region is equivalent to adding 47¢ to the product price. (2) We obtain households' substitution patterns in response to the SSB tax that clearly show both geographic and product substitution are substantial. For each category of Philadelphia SSBs, we quantify to what extent households switch their purchases to a store

[6]Several other papers have used similar methods combining retail and household data, including Goolsbee and Petrin (2004), Chintagunta and Dubé (2005), Tuchman (2019), and Murry and Zhou (2020).

[7]In our estimation process, we found that the inclusion of household data, rather than relying solely on retail data, greatly facilitates the estimation of the RCNL model, particularly the estimation of the nesting parameter (compared to using moment conditions derived from aggregate-level data).

outside Philadelphia, to an untaxed product in Philadelphia, and to the outside option of no purchase, respectively. (3) We find the SSB tax to be highly regressive. When measured as a percentage of annual income, low-income Philadelphia households on average incur a loss of consumer surplus 4.8 times as large as their high-income counterparts'. (4) Sugar intake from beverages drops significantly for Philadelphia households, by 38% and 35% for high- and low-income households, respectively, attesting to the substantial public health benefit of the tax. (5) Accounting for households' heterogeneous preferences and substitution patterns, we find 3.14¢ per ounce to be the revenue-maximizing tax rate. Compared to this rate, the current tax rate of 1.5¢ per ounce results in 90% of the tax revenue, 72% of the reduction in Philadelphia SSB volume sales, and 68% of the loss in consumer surplus.

As of July 2022, excluding Cook County in the state of Illinois and the Navajo Nation, all SSB taxes in the US have been implemented at the city level. Given the relatively small area of taxation, these SSB taxation policies are especially vulnerable to tax avoidance behavior in the form of cross-border shopping. Roberto et al. (2019) compare pre- and post-taxation SSB sales in and around Philadelphia, concluding that 24% of the decrease in Philadelphia SSB sales due to the SSB tax is offset by an increase in sales in the surrounding region. Similarly, Seiler et al. (2021) find evidence of cross-border shopping by Philadelphia households to the city's surrounding region, indicating that such behavior offsets 52% of the sales reduction resulting from the city's SSB tax. In the general market for food products, cross-border shopping as a response to sales taxes has been observed in the District of Columbia (Fisher, 1980) and West Virginia (Tosun and Skidmore, 2007), among others.

Literature pertaining to both aggregate-level data (e.g., Thomadsen (2005), Davis (2006), and Houde (2012)) and micro-level data (e.g., McFadden et al. (1977), Capps et al. (2003), Bayer et al. (2007), and Burda et al. (2008)) finds that distance plays an important role in determining product choices. In terms of cross-border shopping, Harding et al. (2012) show that the distance to a lower-tax border affects the pass-through rates of state cigarette taxes, suggesting that consumers engage in cross-state purchasing, which pushes the burden of taxation backwards onto the factors of production. Chandra et al. (2014) find that longer driving distances strongly disincentivize shopping across the US-Canadian border in search of cheaper alternatives. Cross-border shopping as a function of geographic distance has also been identified in Denmark (Bygvrå, 2009) and Norway (Friberg et al., 2018). Our analysis builds upon the idea that distance plays a large role in inhibiting cross-border shopping, and applies it to the policy evaluation of Philadelphia's SSB tax. Our modeling of travel time as a measure of distance within an RCNL model provides a novel approach for incorporating heterogeneous cross-locational substitution patterns into the analysis of consumer choices.

Through the inclusion of geographic and product substitution of beverages in a choice modeling structure, our paper also contributes to the expanding set of SSB taxation literature. Prior works that have considered Philadelphia's SSB tax as well as cross-border shopping, such as Roberto et al. (2019) and Seiler et al. (2021), have used either retail-level or household-level data but not both and have relied on reduced form estimation techniques. We complement those existing works by using both retail-level and household-level data to estimate consumer behavior and aggregate responsiveness to taxation and by conducting counterfactual analyses based on structural estimation results. In the context of structural modeling, Kifer (2015), Wang (2015), Allcott et al. (2019) and Dubois et al. (2020) have used pre-taxation data to predict the effects of hypothetical SSB taxes. We take a different approach by studying the actual implementation of an SSB tax, incorporating both retail-level and household-level data, and accounting for the effects of geographic substitution.

The remainder of this paper proceeds as follows. In Section 2, we introduce background information about the Philadelphia SSB tax. We describe our data sources and provide detailed information about the products and market in Section 3. Section 4 details the discrete choice model of demand that incorporates both the retail and household data. In Section 5, we discuss model identification and estimation. Section 6 presents the results of our demand estimation. We discuss the effects of the taxation on prices, market shares and consumption in Section 7. Changes in consumer surplus and the heterogeneous impact of the taxation by household income level are discussed in Section 8. Section 9 derives the revenue-maximizing tax rate and explores the effects of alternative taxation schemes. Section 10 concludes.

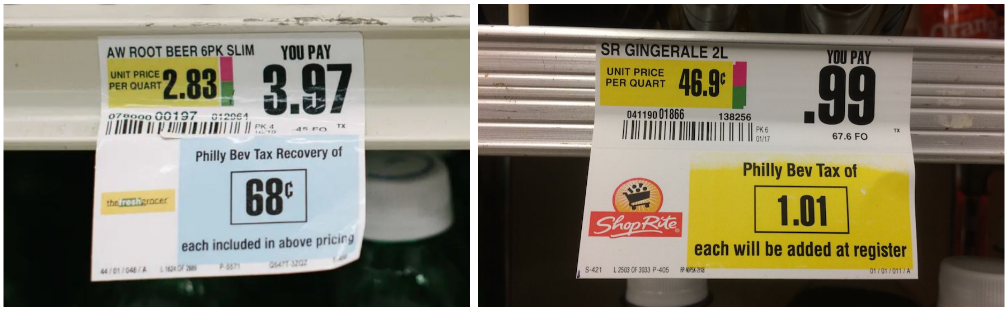
2 Philadelphia Soda Tax

On June 16th, 2016, Philadelphia became the second US city to pass an SSB tax, after Berkeley. Initially proposed as a 3¢-per-ounce tax on all sugar-sweetened sodas, the measure garnered widespread support.[8] Supporters of the proposal, such as the American Medical Association, American Heart Association, and other medical groups, argued that such a tax would combat the twin epidemics of obesity and heart disease. Philadelphia ranks as one of the worst cities in the US in terms of type 2 diabetes, heart disease, and obesity. City mayor Jim Kenney predicted the tax would raise $400 million over five years, which would be used to fund universal pre-kindergarten, job creation, and development projects.

Opponents of the proposal claimed that the measure would disproportionately affect the least fortunate. The American Beverage Association, a lobbying group formed of beverage manufac-

[8] In the context of beverages, the term *ounce* is a measure of volume and means fluid ounce.

Figure 1: Grocery Store Price Tags Indicating Amount of SSB Tax



turers and distributors, pushed newspaper, radio and television ads condemning the proposal as regressive—burdening the city's poorest with the largest share of the tax. Interest in the measure was so high that Democratic primary candidates Hilary Clinton and Bernie Sanders weighed in with their opinions for and against the measure, respectively. After months of negotiation, a compromise was reached.

Passing with a city council vote of 13-to-4, the final draft required distributors to pay a 1.5¢-per-ounce tax on all sugar-/artificially sweetened beverages, with the law becoming effective on January 1st, 2017.[9] Thus, the tax applies to not only beverages sweetened with sugar but also diet beverages containing artificial sweeteners. While it may seem surprising to tax artificially sweetened beverages, given that artificial sweeteners have virtually no calories and that diet beverages (beverages with few or no calories) are generally considered healthier alternatives, the city council included diet beverages in the tax to make up for lost revenue as a result of decreasing the tax from the proposed 3¢ per ounce to the actual 1.5¢ per ounce. Most other soda taxes (in Berkeley, CA, Boulder, CO, Seattle, WA, etc.) tax only products with added caloric sweeteners, thus excluding diet beverages. In this paper, we use the term *SSB* to denote a sugar-/artificially sweetened beverage, corresponding to the coverage of Philadelphia's soda tax. Figure 1 illustrates store-level responses to the taxation policy by retailers. The figure shows that the retailers display the amount of SSB tax prominently, contributing to the issue of tax salience, which we discuss in Section 6.

3 Data

In this section, we describe the data used in our estimation.

[9]The tax is levied on distributors, and so the price increase observed by consumers is subject to a pass-through rate.

3.1 Retail Data

Our retail dataset, from Nielsen through the Kilts Center for Marketing at The University of Chicago Booth School of Business, covers the 4-year period from January 1st, 2015 to December 31st, 2018 (Philadelphia's SSB tax took effect at the midpoint of this period on January 1st, 2017). The dataset contains store-level information detailing weekly price and quantity sold at the Universal Product Code (UPC) level. For each store in the dataset, we observe a store identifier, retailer identifier, retailer type as well as the store's ZIP Code prefix (a ZIP Code prefix is the first three digits of a 5-digit ZIP Code). Stores contained within the six ZIP Code prefixes in and around Philadelphia (080, 081, 189, 190, 191, 194) are considered in our analysis. We apply further restrictions by only considering stores that maintained a presence throughout the period of the dataset, whose ZIP Code could be approximated via the household-level data (as detailed later), and whose approximated ZIP Code fell within 8 miles of the nearest ZIP Code in Philadelphia.[10]

Seiler et al. (2021) suggest that cross-border shopping in response to the Philadelphia SSB tax occurs in the region immediately surrounding the city. They find that post SSB taxation, there is a positive, statistically significant increase in SSB sales in stores located 0-6 miles from Philadelphia's border, but not in stores more than 6 miles from the border. Given that the primary purpose of our work is to evaluate the effect of SSB taxation on cross-border shopping and avoidance behavior, we define our market similarly. In practice, we define our market to be the collection of the ZIP Codes in Philadelphia and the surrounding 8-mile band ("city + 8 miles"), where we use the wider 8-mile band to account for the fact that our retail dataset does not provide exact store locations. Appendix A1 shows that sales in stores beyond the 8-mile band surrounding the city do not experience an increase in SSB sales following the implementation of the SSB tax. Our final retail dataset contains 218 stores: 111 stores in Philadelphia and 107 in the surrounding region.[11]

In our retail data, we observe 7,805 UPCs pertaining to eight beverage categories: Carbonated Soft Drinks, Juice, Sports Drinks, Energy Drinks, Coffee, Tea, Flavored Water and Pure Water. All beverage categories, excluding Pure Water, contain both taxed and untaxed products. For each UPC, we have information concerning brand, pack size, container ounces, and flavor (many

[10] Nielsen data provides ZIP Code information according to the United States Postal Service (USPS) designation. We match these USPS ZIP Codes to their corresponding ZIP Code Tabulation Areas (ZCTAs) as defined in 2016 according to the US Census Bureau. UDSMapper.org, funded by the American Academy of Family Physicians, provides the most up-to-date conversion of USPS ZIP Codes to their corresponding ZCTAs. ZCTA centroids and distances for 2016 are provided by the NBER ZIP Code Distance Database.

[11] In our retail dataset we observe 31 grocery stores, 171 drug stores, and 16 discount stores, which comprise 54%, 30%, and 16% of our observed unit sales, respectively.

UPCs relate to variations in pack size and container ounces). We rely on the USDA FoodData Central database along with several food nutrition API services[12] to collect information pertaining to ingredients, sugar content, and caloric value (sugar content and caloric value are reported per a 100ml serving size). Among the UPCs we observe, we remove infrequently purchased items and consider only the 5,259 UPCs whose brand has greater than 0.5% market share in any of the eight beverage categories; such UPCs account for 97.5% of all unit sales.

We then aggregate the UPCs into products, where each product is a brand/SSB status/category/diet status/size combination.[13] SSB status is an indicator denoting the presence of added sugar or artificial sweeteners—these products are subject to the SSB tax if they are sold in Philadelphia. Diet status indicates those products marketed as "diet", "light", "reduced calories", etc. To allow for heterogeneous responsiveness to the tax by product size, we create three size categories in which all products fall: small, for products whose pack size $\times$ container ounces is less than or equal to 20oz; medium, greater than 20oz but less than or equal to 80oz; and large, greater than 80oz. Each size category accounts for roughly a third of all unit sales. In total there are 567 products, of which 377 are SSBs and the other 190 are non-SSBs. Prices are adjusted for inflation.[14]

We use the term *location* to denote Philadelphia or non-Philadelphia (the 8-mile band surrounding Philadelphia). For computational reasons, we aggregate our data from the store-week level to the location-month level; the aggregation over time also helps reduce the potential bias in demand estimation stemming from households' stockpiling behavior (see for example Miller and Weinberg (2017)). In our demand model, to be specified in the next section, we define an alternative in households' monthly choice set to be a product-location combination. Correspondingly, total unit sales, quantity-weighted price, sugar content, and caloric value are considered at the product-location-month level. If every product is available in every location in every month, there would be $567 \times 2 \times 12 \times 4 = 54,432$ observations at the product-location-month level. In reality, not all products are available in both locations every month, and as a result our retail dataset has a smaller number of observations, at 41,464.

Table 1 provides retail data descriptive statistics, broken down by beverage category and SSB status. We note that we do not account for beverage sales at non-retailer vendors such as restaurants, fast-food outlets, and theaters, as such vendors are not covered in our data.

[12] world.openfoodfacts.org, chompthis.com, edamam.com, foodrepo.org and nutritionix.com.

[13] Flavor variations for the same product are aggregated together. Such variations typically have uniform price and similar sugar content and caloric values.

[14] We adjust for inflation by expressing prices as their December 2018 dollar values using the Consumer Price Index for All Urban Consumers (CPI-U).

Table 1: Retail Data Descriptive Statistics[a]

Category	Number of Products	Market Share in Beverages	Price	Sugar[b] (g/100ml)	Calories (cal/100ml)
Carbonated Soft Drinks	**160**	**36.48%**			
SSB	114	32.6%	$2.20	7.43	27.84
Non-SSB	46	3.88%	$2.13	0.03	0.14
Coffee	**37**	**1.76%**			
SSB	25	1.64%	$2.96	8.13	54.48
Non-SSB	12	0.12%	$3.89	0.10	5.26
Energy Drinks	**40**	**4.63%**			
SSB	38	4.63%	$2.73	6.64	28.03
Non-SSB	2	<0.01%	$1.76	2.93	14.69
Flavored Water	**32**	**2.57%**			
SSB	27	2.5%	$1.52	2.9	10.95
Non-SSB	5	0.07%	$1.37	0.13	0.68
Juice	**145**	**20.25%**			
SSB	87	9.38	$2.16	8.37	35.91
Non-SSB	58	10.87	$3.26	9.69	46.99
Pure Water	**45**	**12.07%**			
SSB	0	0%	–	–	–
Non-SSB	45	12.07%	$2.70	0	0
Sports Drinks	**27**	**8.63%**			
SSB	23	8.57%	$1.81	4.76	18.66
Non-SSB	4	0.06%	$1.10	0	0
Tea	**81**	**13.53%**			
SSB	63	13.01%	$2.04	5.98	25.63
Non-SSB	18	0.52%	$2.24	0.08	0.32

[a]Price, Sugar and Calories are presented as quantity-weighted averages.

[b]Sugar present in non-SSB products is the result of natural processes and is not considered added.

3.2 Household Data

Nielsen provides household purchase data for a sample of US households. Beverage purchases, information pertaining to the number of shopping trips, a household's ZIP Code of residence, and other household demographic data are recorded. The purchase data reports the price paid, number of units purchased, and product UPC. When available, store identifier, retailer identifier, retailer type and store location information are provided. As with the retail data, store location

Table 2: Household Distribution by Location and Income Status

Income Status	Households by Location		
	All	Philadelphia	Non-Philadelphia
High-Income	659,923	267,727	392,196
Low-Income	535,749	327,112	208,637
Total	**1,195,672**	**594,839**	**600,833**

information is provided as a 3-digit ZIP Code prefix.

Between 2015 and 2018, there were 866 households recorded in the Nielsen data who lived within the 153 ZIP Codes pertaining to our market.[15] Over the course of these 4 years, these households recorded 212,301 purchase opportunities (i.e., store trips) with 68,442 beverage purchases. With the provided household demographic information, we differentiate between low- and high-income households. Specifically, we create an indicator variable for the 365 households whose annual income falls below $50,000—we provide reasoning for this choice of cutoff in the next subsection. We focus on income as a demographic variable of interest since (1) opponents of the taxation policy argued that low-income individuals would be most negatively affected by the policy, and (2) prior works suggest that low income is correlated with a higher price sensitivity and a greater preference for sugary beverages.

3.3 ZIP Codes

We define our market as the 153 ZIP Codes either within Philadelphia or whose centroid is outside Philadelphia but within 8 miles of the nearest Philadelphia ZIP Code centroid; 46 ZIP Codes exist within Philadelphia while the other 107 are in the surrounding 8-mile band. ZIP Code-specific demographic data pertaining to the number of households and the percentage of households whose annual income is below $50,000 is collected from the 2018 5-Year American Community Survey (ACS).[16] We consider those households whose annual income is below $50,000 to be "Low-Income" for the purposes of this study (as also observed in Miravete et al. (2018)). Table 2 provides the household distribution by location and income status. The table shows that the two locations have roughly the same number of households, with Philadelphia having more low-income households and non-Philadelphia having more high-income ones.

Rather than using straight-line distance to account for location substitution in our model,

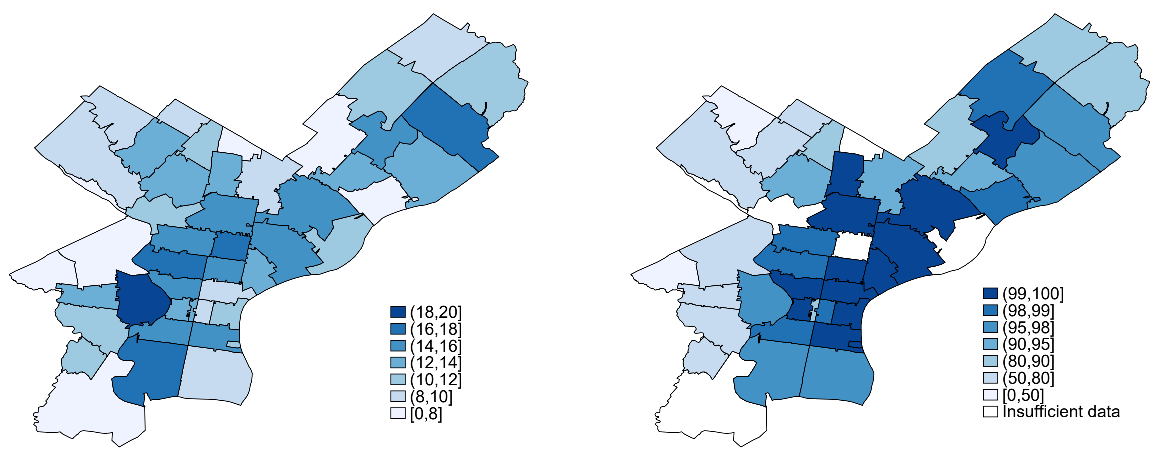
[15] Of these 866 households, 211 were tracked for all 4 years. Nationally, Nielsen records a household attrition rate of about 40% each year. Our estimation uses all the 866 households.

[16] Both the Nielsen data and the ACS report household income in ranges, and the range cutoffs in the two data sources match only at the $50,000 mark.

we rely on travel time as provided by the Google Maps API service. For each Philadelphia ZIP Code, we find the minimum travel time to drive to a non-Philadelphia ZIP Code, and vice versa.[17] We rely on travel time rather than distance to account for location substitution for two reasons: (1) ZIP Code distances do not account for road and highway placements which can greatly alter consumers' willingness to cross-border shop, and (2) Philadelphia is home to many rivers and bridges which would remain unaccounted for if distance was the metric considered. Furthermore, driving is by far the most popular mode of transportation in and around Philadelphia (see for example Duchneskie (2016)), giving support to calculating travel time based on driving as an approximation.

Figure 2 presents some model-free, suggestive evidence of the importance of travel time. Panel (a) shows, for each Philadelphia ZIP Code, the minimum travel time to a non-Philadelphia ZIP Code. Panel (b) shows, for each Philadelphia ZIP Code, the percentage of beverage purchases made by the ZIP Code's households that are recorded in a store within their home location (Philadelphia). A comparison of the two panels suggests these two variables are positively correlated (a longer travel time to the alternative location is associated with a higher percentage of beverage purchases in the home location), and calculation shows these two variables have a correlation coefficient of 0.53.

Figure 2: Travel Time and Beverage Purchases



(a) Travel time (minutes) to alternative location for Phil. ZIP Codes; affected by not only distance but also roads, highways, rivers, bridges, etc.

(b) Percentage of beverage purchases in home location by Phil. households, as observed in the household dataset.

[17] Travel time between two ZIP Codes is defined as the average time required to drive from one ZIP Code centroid to the other. Using ZIP Code centroids for the calculation is analogous to how ZCTA distances are calculated.

3.4 Store Location

As detailed above, the retail dataset does not provide stores' exact locations or full 5-digit ZIP Codes. Instead, we are provided with the stores' 3-digit ZIP Code prefixes (corresponding to the first three digits of the ZIP Codes). There are six ZIP Code prefixes in and around Philadelphia. Among them, two are entirely within our market: 191 is the ZIP Code prefix for Philadelphia, and 081 corresponds to a region of New Jersey that is entirely within the 8-mile band surrounding Philadelphia. Stores located within the ZIP Code prefixes of 080, 189, 190 and 194 have their locations approximated to determine whether they fall within any of the ZIP Codes pertaining to our market, as follows.

To approximate store locations, we rely on a method similar to that proposed in DellaVigna and Gentzkow (2019) and Goldin et al. (2022). For each store, we observe in the household data the ZIP Codes of residence for the households who make purchasing trips to the store. We then take the store's location to be the average of the centroids of these ZIP Codes, weighted by the total number of trips to the store originating from each of these ZIP Code during the pre-taxation period.[18] In the data, only retailers of the types "Grocery", "Discount Store", and "Drug Store" have unique identifying information that allows for this location approximation. Thus, our final retail and household dataset only considers stores of these types to remain consistent.

4 Model

In modeling the demand for beverages as a function of product and household characteristics incorporating consumer heterogeneity and demographic information, we follow the literature on discrete choice demand estimation with retail data (Berry et al. (1995) (BLP), Nevo (2000), etc.), and supplement the traditional method with household data in a process similar to that described in Goolsbee and Petrin (2004), Murry and Zhou (2020), and Grieco et al. (2022).[19] This allows us to leverage the benefits of both datasets: the retail data measures responses to the SSB tax with far less noise and allows for a reliable method by which one can account for price endogeneity, while the household data provides a more accurate estimation of heterogeneous parameters, substitution patterns, and responsiveness to travel time. The model we propose utilizes the retail and household data in an internally consistent way.

[18]Centroid locations are given as latitude and longitude. We first convert the centroids to polar coordinates, calculate the weighted average, then convert back to latitude and longitude. There is a slight error introduced, as this conversion assumes a perfectly spherical earth, however given the relative closeness of locations this error is minimal.

[19]Another method is the micro-BLP estimator (Berry et al., 2004). Grieco et al. (2022) suggest that the use of micro-moment conditions, as described in Berry et al. (2004), induces an additional cost in efficiency relative to a share constrained micro likelihood estimator, the type of estimator applied in this paper.

4.1 Demand Specification

Consider household i in month t. The household chooses one of the available beverage options ($j = 1, \ldots, J_t$) or the outside option of no purchase ($j = 0$), where a beverage option is defined as a product-location combination.[20] Household i's indirect utility from choosing beverage option j in month t is given by

$$\begin{aligned} u_{ijt} =& x'_{jt}\beta_i + \alpha_i p_{jt} + h'_{jt}\gamma + \mathbb{1}(A_j \neq A_{z_i})(\phi_i Q_{z_i}) + \xi_{jt} + \bar{\epsilon}_{ijt}, \\ & \text{where } i = 1, \ldots, H_t,\ j = 1, \ldots, J_t,\ t = 1, \ldots, T, \text{ and } z_i = 1, \ldots, Z. \end{aligned} \tag{1}$$

x_{jt} is an $n_1 \times 1$ vector of option j's characteristics in month t, including a constant, Philadelphia dummy variable, category dummy variables, brand dummy variables, sugar content, caloric value, etc. (the full specification is given later in Section 6). p_{jt} denotes the retail price for option j in month t. The $n_2 \times 1$ vector h_{jt} contains categorical time trends and month fixed effects. Our month fixed effects are not year-specific; rather, they capture seasonal variation in beverage sales. z_i denotes household i's ZIP Code of residence. A_j and A_{z_i} are indicator variables signifying if option j and ZIP Code z_i are in the Philadelphia location, respectively. Q_{z_i} is the minimum travel time for a household living in ZIP Code z_i to drive to the alternative location (Philadelphia or non-Philadelphia), in which z_i is not located. ξ_{jt} denotes unobserved quality, and $\bar{\epsilon}_{ijt}$ denotes unobserved idiosyncratic preferences. The indirect utility from choosing the outside option excluding $\bar{\epsilon}_{i0t}$ is normalized to 0.

We characterize household i by a d-vector of demographic attributes D_i, including low-income (below \$50,000) and location (non-Philadelphia). We model unobserved household preference heterogeneity through the use of the multivariate normal distribution. Households' preferences for price, beverage option characteristics, and travel time are as follows:

$$\begin{pmatrix} \alpha_i \\ \beta_i \\ \phi_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \\ \phi \end{pmatrix} + \Pi D_i + \Sigma v_i, \ \ v_i \sim \mathcal{N}(\mathbf{0}, \mathbf{I}_{n_1+2}), \tag{2}$$

where Π is an $(n_1 + 2) \times d$ matrix that measures the impact of observable demographic attributes on preferences, while Σ is an $(n_1 + 2) \times (n_1 + 2)$ matrix that captures the covariance of unobserved household preferences. In our study we estimate only the variance of unobserved household preferences, and therefore we restrict $\Sigma_{hk} = 0\ \forall h \neq k$.

Given the specification in Eq. (2), the indirect utility in Eq. (1) excluding $\bar{\epsilon}_{ijt}$ can be decomposed into its common and idiosyncratic components, δ_{jt} and μ_{ijt}, respectively, where

$$\begin{aligned} \delta_{jt} &= x'_{jt}\beta + \alpha p_{jt} + h'_{jt}\gamma + \xi_{jt}, \text{ and} \\ \mu_{ijt} &= \left[x'_{jt}, p_{jt}, \mathbb{1}(A_j \neq A_{z_i})Q_{z_i}\right](\Pi D_i + \Sigma v_i) + \mathbb{1}(A_j \neq A_{z_i})(\phi Q_{z_i}). \end{aligned} \tag{3}$$

[20] Product availability varies month to month. Similar to Miravete et al. (2018), if no sales are observed for a beverage option during a specific month, then we assume that option is not present in households' choice set for that month.

We assume that unobserved idiosyncratic preferences for beverage options, $\bar{\epsilon}_{ijt}$, are correlated within the same beverage category. In our data we observe eight beverage categories (coffee, carbonated soft drinks, energy drinks, flavored water, juice, pure water, sports drinks, and tea), and the outside option of no purchase is defined to be category zero. Thus $\bar{\epsilon}_{ijt}$ follows the distributional assumption of a one-level nested logit model and can be decomposed into

$$\bar{\epsilon}_{ijt} = \zeta_{igt} + (1-\rho)\epsilon_{ijt}, \tag{4}$$

where ϵ_{ijt} is i.i.d. extreme value, $\rho \in [0,1]$ is the nesting parameter, $g \in \{0,1,\ldots,8\}$ is the category that option j belongs to, and ζ_{igt} has a (unique) distribution such that $\bar{\epsilon}_{ijt}$ is distributed extreme value. The nesting parameter ρ measures the correlation in preferences across beverages within the same category. Perfect within-nest substitution is obtained if ρ equals one, while as ρ goes to zero, the model reduces to the standard random coefficients logit specification.

The probability of household i choosing option j belonging to category g in month t is then

$$\pi_{ijt} = \frac{\exp\Big((\delta_{jt} + \mu_{ijt})/(1-\rho)\Big)}{\exp\Big(I_{igt}/(1-\rho)\Big)} \times \frac{\exp\big(I_{igt}\big)}{\exp\big(I_{it}\big)}, \tag{5}$$

where the "inclusive values" I_{igt} and I_{it} are given by

$$I_{igt} = (1-\rho)\log \sum_{j\in\mathcal{J}_{gt}} \exp\Big(\frac{\delta_{jt} + \mu_{ijt}}{1-\rho}\Big) \tag{6}$$

with $\mathcal{J}_{gt}$ denoting the set of beverage options in category g in month t, and

$$I_{it} = \log\Big(1 + \sum_{g=1}^{8} \exp\Big(I_{igt}\Big)\Big). \tag{7}$$

4.2 Household Choice Probabilities

In the household dataset, for each household i and each month $t \in \mathcal{T}_i$ during which household i is in the data, we observe the household's O_{it} purchase opportunities (i.e., store trips). During each opportunity, the household chooses one of the available beverage options or the outside option of no purchase.[21] Integrating over the distribution of unobserved household attributes, denoted $F_v(v_i)$, the density of household i's observed sequence of choices is given by

$$L_i(Y_i|x,p,h,Q_{z_i},D_i;\delta,\Theta) = \int \prod_{t\in\mathcal{T}_i} \prod_{o=1}^{O_{it}} \prod_{j=0}^{J_t} [\pi_{ijt}(x_t,p_t,h_t,Q_{z_i},D_i,\delta_t,\Theta,v_i)]^{y_{ijot}}\, dF_v(v_i), \tag{8}$$

where $\delta_t = (\delta_{1t},\ldots,\delta_{J_t t})'$, $x_t = (x'_{1t},\ldots,x'_{J_t t})'$, $p_t = (p_{1t},\ldots,p_{J_t t})'$, and $h_t = (h'_{1t},\ldots,h'_{J_t t})'$.

[21]We assume that the number of purchase opportunities is independent of observable or unobservable individual characteristics. Such an assumption is necessary for our estimation to be tractable under the BLP framework, and is one innately imposed by researchers working solely with retail data (i.e., Berry et al. (1995), Nevo (2000), etc.).

We summarize the model's heterogeneous taste, travel time, and nesting parameters as $\Theta = (\Pi, \Sigma, \phi, \rho)$, and use Y_i to denote the observed sequence of household i's choices, where $y_{ijot} = 1$ if household i chooses beverage option j during purchase opportunity o in month t.

4.3 Retail Market Shares

At the retail level, we use M_t to denote the market size in month t, i.e., the total number of purchase opportunities experienced that month, obtained as the total number of households in the market multiplied by the average number of grocery store trips per household in that month as observed in the household data. We assume a continuum of purchase opportunities of mass M_t, and the household data is assumed to be a finite sample drawn from it.[22]

Consider the set of household-specific characteristics that lead to the purchase of beverage option j in month t, $\{(D_i, z_i, v_i, \bar{\epsilon}_{ijt}) | u_{ijt} \geq u_{ikt} \; \forall k = 0, 1, \ldots, J_t\}$. The distribution of $\bar{\epsilon}_{ijt}$ is extreme value as given in Eq. (4), which leads to household choice probabilities π_{ijt} given in Eq. (5). The distribution of v_i is multivariate normal as given in Eq. (2), and the distributions of z_i and $D_i|z_i$ are obtained from the ACS. Integrating over the distributions of v_i, z_i, and $D_i|z_i$, we obtain the predicted market share for beverage option j in month t as

$$s_{jt} = \int_{v_i} \int_{z_i} \int_{D_i} \pi_{ijt}(x_t, p_t, h_t, Q_{z_i}, D_i, \delta_t, \Theta, v_i) dF_D(D_i|z_i) dF_z(z_i) dF_v(v_i). \tag{9}$$

In assuming a continuum of households, as is routine in the literature, and conditioning on ξ, through δ, the market share in Eq. (9) is deterministic, and the aggregate demand for beverage option j is obtained as $M_t s_{jt}$.

5 Identification and Estimation

Our objective is to estimate the parameters α, β, γ, Π, Σ, ϕ, and ρ. While we are not necessarily interested in the value of δ per se, it is required to recover the mean taste parameters α, β, and γ. Thus, our estimation proceeds with two steps. First, we maximize a likelihood function using the retail and household data. This identifies all the parameters except those derived from the mean utility. Next, to estimate α, β, and γ, we use a two-stage least squares (TSLS) regression and instrument p_{jt} with a Hausman style instrument (as seen in Nevo (2001)) to control for correlation with the error term ξ_{jt}.[23]

[22] Appendix A2 provides details about the case of multiple purchases during a single trip.

[23] We calculate the average price of each product across all US stores in the Nielsen data, excluding those in the Philadelphia designated market area (DMA) which contains the market of our demand model, and use this average to instrument the price in our model.

5.1 Maximum Likelihood

In the first stage of our estimation, for any candidate values of Θ and δ, the density of a household's choice history is given by Eq. (8), and the corresponding log-likelihood of the household data is

$$\mathcal{L}(Y;\delta,\Theta) = \sum_{i=1}^{H} log[L_i(Y_i|x,p,h,Q_{z_i},D_i;\delta,\Theta)]. \tag{10}$$

In theory it is possible to estimate δ directly via maximum likelihood solely with the household-level data; practically, however, this is computationally infeasible considering the large number of beverage options available. Instead, we rely upon the work of Berry (1994) who shows that for any given value of Θ, there exists a unique vector of δ such that the predicted market shares from Eq. (9), s_{jt}, exactly match those observed in the retail data, S_{jt}. Consequently, given the retail market shares, we can treat δ as a known function of Θ.[24] Appendix A3 shows in more detail how a unique vector of δ is obtained from our retail data.

Thereby, the log-likelihood of the household-level data shown in Eq. (10) can be re-written as

$$\mathcal{L}(Y;\Theta) = \sum_{i=1}^{H} log[L_i(Y_i|x,p,h,Q_{z_i},D_i,\delta(\Theta);\Theta)], \tag{11}$$

where $\delta(\Theta)$ is given by the one-to-one contraction mapping from the retail market share constraint. In performing the contraction mapping, we evaluate the integrals of Eq. (9) by Monte Carlo simulation with 4000 Halton draws from the distributions of v, z, and $D|z$ (i.e., 4000 simulated households). Similarly, we use a separate set of 100 Halton draws from the distribution of v when evaluating the integral in Eq. (8).[25] Our estimation proceeds by searching for the value of Θ that maximizes Eq. (11).[26] Finally, we obtain robust standard errors for Θ by sandwiching the covariance of the household-level gradient between the inverted Hessian at the optimum of the likelihood function.[27]

[24] By assuming the aggregate market shares are derived from a continuum of households, the asymptotic variance of the shares is zero. Grieco et al. (2022) shows that this assumption has a cost in terms of both efficiency and inference, unless the household sample size is negligibly small when compared to the size of the market population. This is similar to the efficiency loss of the standard micro-BLP (Berry et al., 2004). In our model $H/N = 0.00072$, where $H = 866$ is the size of the household dataset and $N = 1,195,672$ is the population of households in and around Philadelphia from which those 866 households were drawn; accordingly, the efficiency loss should be minimal. Furthermore, to use a mixed data likelihood estimator as suggested in Grieco et al. (2022) would be too computationally burdensome, as each δ_{jt} must be treated as a parameter of interest in the likelihood estimation.

[25] Results from Train (1999) show simulation variance with 100 Halton draws to be lower than 1000 random draws in a mixed logit application.

[26] Our tolerance for the contraction mapping step is set to $.5e^{-12}$. For the likelihood maximization algorithm, we set a tolerance of $2e^{-10}$ and provide computed numerical gradients. We consider several randomized starting values when proceeding with the maximization algorithm to rule out local minima.

[27] See Train (2009), p. 201.

5.2 Mean Utility Coefficients

Given $\hat{\delta}$ resulting from the optimal $\hat{\Theta}$ in the maximum likelihood step, we use the fact that $\delta_{jt} = x'_{jt}\beta + \alpha p_{jt} + h'_{jt}\gamma + \xi_{jt}$ to determine our mean utility parameters. We proceed with a TSLS regression relying upon Hausman style instruments, as there is reason to believe p_{jt} may be correlated with the error term ξ_{jt}. Standard errors for $(\hat{\alpha}, \hat{\beta}, \hat{\gamma})$ are calculated using a two-stage bootstrap procedure where the first stage captures the estimation error from the maximum likelihood step and the second stage captures the typical sampling error. Specifically, we begin by first taking 1000 draws from the asymptotic distribution of Θ. Next, for each draw, Θ_d, we find its corresponding vector $\delta(\Theta_d)$. We then draw with replacement from the sample $\{(\delta_{11}(\Theta_d), x_{11}, p_{11}, h_{11}), \ldots, (\delta_{J_T T}(\Theta_d), x_{J_T T}, p_{J_T T}, h_{J_T T})\}$ to create a bootstrapped dataset (of a size equal to the original sample). Given this bootstrapped sample, we then perform the TSLS regression to estimate $(\alpha^*_d, \beta^*_d, \gamma^*_d)$. From the distribution of $(\alpha^*_d, \beta^*_d, \gamma^*_d)$, we find the standard errors of our mean utility parameters.

6 Demand Estimates

Table 3 presents the demand estimates of our preferred specification of the RCNL model using the two-step procedure outlined above.[28] To avoid perfect collinearity, we have dropped the category pure water, the brand Aquafina, the size small, and the month of December. On average, consumer valuations for beverages decrease with calories, but increase with sugar content. Excluding juices and flavored water, beverages that contain added sweeteners display a comparative increase in demand. We also observe that consumer valuations decrease with price, conforming to the law of demand.

Tax Salience Considering the price tags displayed in Figure 1, where the per-unit price and tax amount are displayed independently and prominently, and the publicity surrounding the SSB tax, we hypothesize that consumer responsiveness to the taxation policy is greater than that arising solely from a change in price. In fact, Acton et al. (2022) find an increase in perceived costs of SSBs and taxation awareness in countries where a national SSB tax has been implemented.

We therefore include the variable "tax amount", which provides a quantity-weighted dollar value of the SSB tax to be paid for each Philadelphia beverage option. Similar to Li et al. (2014), who examine gasoline taxes, our negative and significant coefficient for tax amount shows con-

[28] We considered a three-level nested logit model (Train, 2009) with the choice between beverages and the outside option at the highest level and the choices of beverage category and beverage option at subsequent nodes; however such a model did not improve model fit.

Table 3: RCNL Demand Estimates[a]

	Mean	Standard	Demographic Interactions (Π)	
	(α, β, ϕ)	Deviation (Σ)	Low-Income	Non-Phil.
Price	-0.285***	0.010***	-0.006	
	(0.024)	(0.008)	(0.013)	
Calories	-0.011***			
	(0.001)			
Sugar	0.021***	0.051***	0.009	
	(0.004)	(0.004)	(0.006)	
Diet	-0.393***		-0.009	
	(0.039)		(0.042)	
Medium	0.546***		-0.161***	
	(0.054)		(0.062)	
Large	0.964***	0.235***	-0.222***	
	(0.082)	(0.029)	(0.084)	
Tax Amount	-0.157***		0.020	
	(0.029)		(0.055)	
Tax Saving	0.012			
	(0.008)			
SSB × Carb. Soft Drinks	0.224***	0.705***		
	(0.024)	(0.040)		
SSB × Coffee	0.556***			
	(0.048)			
SSB × Energy Drinks	0.580***			
	(0.065)			
SSB × Flavored Water	0.042			
	(0.085)			
SSB × Juice	-0.263***	0.242***		
	(0.024)	(0.030)		
SSB × Sports Drinks	0.798***			
	(0.081)			
SSB × Tea	0.571***			
	(0.048)			
Philadelphia	-0.378***	0.428***		0.754***
	(0.064)	(0.045)		(0.203)
Constant	-4.781***	0.988***	0.877***	
	(0.200)	(0.045)	(0.226)	
Travel Time	-0.127***	0.047***	0.021**	
	(0.014)	(0.007)	(0.010)	
Category Nesting (ρ)	0.685***			
	(0.024)			
Category FEs	Y	N	Y	N
Category Time Trends	Y	N	N	N
Month FEs	Y	N	N	N
Brand FEs	Y	N	N	N

***p<.01, **p<.05, *p<.1

[a]Standard errors are reported in parentheses. Estimates of Category FEs and corresponding Low-Income interactions are provided in Appendix A4.

sumer responsiveness to the taxation policy is greater than what the price increase per se suggests. This points to the existence of a tax salience effect, whereby consumers exhibit heightened awareness of and aversion to a highly visible tax, given the extensive media coverage of the tax and retailers' eagerness to inform consumers of the source of such price increases (Figure 1). Our estimation results show that on average, the tax salience effect increases consumers' disutility from a price increase due to the tax by $0.157/0.285 = 55\%$.

Likewise, we include the variable "tax saving" which provides, for non-Philadelphia beverage options, their SSB tax amount if sold in Philadelphia. Although only statistically significant at the 85% confidence level, the coefficient for tax saving suggests a small but positive increase in demand for products in the non-Philadelphia location whose counterparts in Philadelphia are subject to the tax. We can interpret this increase in demand as a result of psychological gains from purchasing a product at a lower price than at the alternative location.

Demographic Interactions We also allow for variation in consumer valuations across observed demographic characteristics including income and location, presented in columns 4 and 5 of Table 3. The estimation of Π reveals significant differences in consumer valuations for beverage options. For instance, compared to high-income households, low-income households have higher valuations for inside options except for medium- and large-sized tea products (based on the estimates for low-income interactions with constant, sizes, and category fixed effects, the last of which reported in Appendix A4). The disutility from travel time is greater for high-income households, consistent with prior transportation research (e.g., Hymel et al. (2010)) which suggests that high-income households have a higher valuation of their time. Finally, allowing non-Philadelphia households to experience a heterogeneous response to Philadelphia beverage options allows for differing intercepts when considering willingness to cross-border shop.

Random Coefficients and Nesting Parameter We include in our model a rich set of random coefficient parameters (Σ), all of which exhibit statistical significance and sensible results. For instance, the relatively large standard deviation of the random coefficient on sugar content suggests that only 66% of high-income households and 72% of low-income households experience an increase in utility from higher sugar content. The nesting parameter ρ is estimated very precisely, and implies that consumers show a strong correlation across beverages within the same category. To corroborate this point, consider the price elasticity of demand.

Price and Travel Time Elasticities Table 4 provides the price elasticity of demand for all households, reporting own- and cross-elasticities averaged at the category-location level, location level,

Table 4: Price Elasticity of Demand for All Households

Average Level	**Own-Elasticity**	**Cross-Elasticity**			
		Same Category			All Bev. Options
		All Bev. Options	Same Location	Different Location	
Phil. Bev. Options	-2.0910	0.0115	0.0195	0.0035	0.0017
Carbonated Soft Drinks	-1.9999	0.0050	0.0083	0.0017	0.0016
Coffee	-2.6384	0.0446	0.0778	0.0120	0.0020
Energy Drinks	-2.0163	0.0200	0.0348	0.0053	0.0017
Flavored Water	-1.7985	0.0248	0.0411	0.0081	0.0012
Juice	-2.3227	0.0063	0.0106	0.0019	0.0019
Pure Water	-1.9250	0.0201	0.0344	0.0057	0.0019
Sports Drinks	-1.8850	0.0266	0.0452	0.0084	0.0015
Tea	-1.9713	0.0084	0.0141	0.0028	0.0015
Non-Phil. Bev. Options	-2.0225	0.0120	0.0212	0.0028	0.0018
Carbonated Soft Drinks	-1.8685	0.0052	0.0092	0.0011	0.0017
Coffee	-2.6511	0.0482	0.0841	0.0118	0.0022
Energy Drinks	-2.1000	0.0203	0.0342	0.0063	0.0017
Flavored Water	-1.7104	0.0255	0.0461	0.0054	0.0013
Juice	-2.2776	0.0067	0.0120	0.0014	0.0020
Pure Water	-1.9100	0.0214	0.0377	0.0052	0.0020
Sports Drinks	-1.7606	0.0250	0.0442	0.0057	0.0014
Tea	-1.8698	0.0092	0.0165	0.0018	0.0016
All Bev. Options	-2.0564	0.0117	0.0203	0.0031	0.0017

and all beverage options level. Cross-elasticities of demand are reported for beverage options from the same category, same category and same location, same category and different location, and all beverage options. Estimates for the own-elasticity of demand show that households have elastic demand for beverages, with the elasticity ranging from -1.71 to -2.65. Considering the cross-elasticity of demand, we see that it is higher between beverages in the same category, and furthermore it is higher between beverages in the same category and same location when compared to beverages in the same category but different locations. These results delineate a clear order of preference in terms of substitution.

Turning to the travel time elasticity of locational demand, the estimates in Table 5 provide the percentage changes in quantity demanded for beverage options in a household's home and alternative locations, respectively, given a 1% increase in travel time needed to reach the alternative location. These estimates are found by first taking, for each simulated household/beverage option/month combination, 100 draws from the distribution of $\bar{\epsilon}_{ijt}$. Next, the change in choice of beverage location is found by comparing beverage choices given a 1% increase in travel time and

Table 5: Travel Time Elasticity of Locational Demand

	Phil. Households	**Non-Phil. Households**
Phil. Bev. Options	0.14	-1.75
Non-Phil. Bev. Options	-1.36	0.14

holding draws from the distribution of $\bar{\epsilon}_{ijt}$ constant. Finally, the change in locational demand is averaged across simulated households at the location level. These results provide a picture of households who are elastic in travel responsiveness, willing to decrease their propensity to shop in the alternative location when faced with increased travel time.

Cost of Traveling Lastly, consider the cost of traveling to a grocery store. Taking the average of the ratio of travel time responsiveness to price responsiveness across all simulated households, we find that on average an extra minute of travel time to reach the store is equivalent to adding \$0.47 to the product price.[29] Note that our travel time variable measures the time needed to travel *to* a store in the alternative location, so purchasing at a store 10 minutes away would involve a 20-minute round trip. Also note that the per-minute cost of travel includes not only the cost of time but also the cost of fuel. Other factors such as the depreciation of the car are not significant for the relatively short trips of grocery shopping.

To obtain a back-of-the-envelope figure for the value of time based on the above estimate, consider driving to a store 10 minutes away and coming back. Assuming a speed of 30 miles per hour, a fuel efficiency of 25 miles per gallon, and a gasoline price of \$2.53 per gallon (the average gasoline price in the Philadelphia area in May 2017 (U.S. Bureau of Labor Statistics, 2017)), the fuel cost for the 20-minute round trip is approximately $(30 \times 20/60)/25 \times 2.53 = \$1.01$. Consequently, the value of the 20 minutes spent is approximately $0.47 \times 10 - 1.01 = \$3.69$, implying a value of time equal to $3.69 \times 60/20 = \$11.07$ per hour. This figure falls in the same range as the US Government's practice of valuing people's time between 1/3 and 1/2 of the wage rate based on research in transportation and recreational demand (Goldszmidt et al., 2020). Workers in the Philadelphia area had an average hourly wage of \$26.41 in May 2017 (U.S. Bureau of Labor Statistics, 2018), implying a value of time at $26.41/3 = \$8.80$ per hour using the 1/3 factor and $26.41/2 = \$13.21$ per hour using the 1/2 factor.[30]

[29] Both price and travel time have random coefficients, and so directly taking the ratio of the mean coefficient for travel time to the mean coefficient for price would give an inaccurate figure, as the ratio of averages differs from the average of ratios.

[30] Goldszmidt et al. (2020) find a higher value of time at \$19 per hour using natural field experiments with the ridesharing company Lyft. One possible reason for the difference between our estimate and that of Goldszmidt et al. (2020) is that Lyft passengers considered in their study may differ from the household sample in our data.

7 Pass-Through, Substitution Patterns, and Consumption Changes

In the remainder of this paper, we study the effects of Philadelphia's SSB tax by using our demand estimates to evaluate various counterfactual scenarios. Comparing the outcome under taxation to the counterfactual scenario of no tax, this section examines consumers' substitution patterns and consumption changes brought about by the tax, while the next section analyzes the welfare implications and regressivity of the tax. Then in Section 9 we consider the effects of alternative tax rates, alternative tax coverages, and changes in travel time.

As an input for conducting the counterfactual analyses, we first estimate the pass-through rate of the SSB tax.

7.1 Pass-Through Rate

Since we do not estimate the supply side of the market, when conducting counterfactual analyses involving changes in the SSB tax, we need to make an assumption about prices under the counterfactual scenarios. To that end, we follow the literature on SSB taxation and estimate a pass-through rate of the tax for constructing counterfactual prices.

Studying Philadelphia's SSB tax, several authors have conducted various analyses on this topic. Cawley et al. (2018) and Roberto et al. (2019) find pass-through rates of 55% and 68%, respectively, while Bleich et al. (2020) and Cawley et al. (2020) find higher pass-through rates of 120% and 105%, respectively. More recently, Seiler et al. (2021) find a pass-through rate of 97%, relying upon their finding that the region more than 6 miles away from Philadelphia does not exhibit an increase in SSB sales in response to Philadelphia's SSB tax. They proceed by treating this region as their control: it is close enough to Philadelphia to experience similar marketing and demand shocks while uninfluenced by cross-border shopping. Similarly, our Appendix A1 demonstrates that the stores present in the Nielsen data that are located in ZIP Codes 8+ miles from Philadelphia do not exhibit a positive SSB sales response to Philadelphia's SSB tax.

We progress with the estimation of the pass-through rate as observed in Seiler et al. (2021), treating the stores 8+ miles from Philadelphia yet still within the surrounding 3-digit ZIP Code prefixes (see Subsection 3.1) as the control group for the per-ounce price of SSBs. When performing the pass-through rate analysis, we work with quantity-weighted per-ounce prices at the product-store-week level (similar to Roberto et al. (2019) and Cawley et al. (2020)) rather than aggregating per-ounce prices to the SSB status-store-week level (as in Seiler et al. (2021)), and we obtain category-level estimates of the pass-through rate rather than an average across all categories.

Additionally, the value of time may vary across different types of activities.

Specifically, for each of the seven categories containing SSBs, we regress price observed at the product-store-week level on the interaction Post-Tax × Philadelphia as well as store fixed effects and their interactions with the diet, medium, and large dummy variables, week fixed effects, and additional product characteristics including sugar and caloric content. Detailed results are reported in Appendix A5. The interaction Post-Tax × Philadelphia provides the mean increase in SSB prices in Philadelphia compared to the control group. We find category-level price increases ranging from 1.09¢ per ounce (tea) to 1.59¢ per ounce (energy drinks), corresponding to pass-through rates of 72.7% to 106% of the 1.5¢-per-ounce tax rate. A Wald test rejects ($p < .01$) the null hypothesis of the same pass-through rate across the seven categories containing SSBs. Differences across category-level pass-through rates likely arise from a combination of factors including different price elasticities on the demand side and different levels of competition on the supply side. Furthermore, our category-level estimates fall within the range observed in prior research (e.g., Cawley et al. (2018), Roberto et al. (2019), Bleich et al. (2020), Cawley et al. (2020), and Seiler et al. (2021)).

Our estimation contributes to the expanding literature of tax pass-through and serves as an input for our policy evaluation. For the remainder of this study, we assume category-level pass-through rates equal to those obtained here when performing counterfactual analyses.

7.2 Substitution Patterns

As our first counterfactual of interest, we examine how the SSB tax induces categorical and locational substitution. To perform this analysis, similar to how we found travel time elasticity, we simulate 100 draws from the distribution of $\bar{\epsilon}_{ijt}$ for each combination of simulated household i, beverage option j, and post-taxation month $t = 25, \ldots, 48$ (January 2017 to December 2018). We then determine product-level utility with and without the SSB tax holding the $\bar{\epsilon}_{ijt}$ draws constant. That is, product-level utility takes the form

$$u_{ijt}^{\text{with tax}} = \delta_{jt}^{\text{with tax}} + \mu_{ijt}^{\text{with tax}} + \bar{\epsilon}_{ijt}, \text{ and} \tag{12}$$

$$u_{ijt}^{\text{without tax}} = \delta_{jt}^{\text{without tax}} + \mu_{ijt}^{\text{without tax}} + \bar{\epsilon}_{ijt}. \tag{13}$$

Thus, beverage choice with and without the tax is given by the maximal value of the utilities found in Eqs. (12) and (13), respectively.

In both equations, the coefficients are the estimated coefficients from our demand estimation, and the household and beverage option characteristics are the observed characteristics. In Eq. (12), the prices are the observed prices, while in Eq. (13), for each SSB sold in Philadelphia, the tax amount calculated according the relevant pass-through rate is subtracted from the observed

Table 6: Model Predicted Substitution Patterns

Choice W/o Tax		Top Four Choices With Tax							
Phil. SSBs		**1st Choice**		**2nd Choice**		**3rd Choice**		**4th Choice**	
Carb.	(43.30%)	P Carb. S	(66.78%)	NP Carb. S	(13.07%)	Outside Op.	(12.46%)	P Carb. NS	(4.45%)
Coffee	(2.21%)	P Coffee S	(90.90%)	Outside Op.	(3.90%)	NP Coffee S	(2.91%)	P Coffee NS	(1.67%)
Energy	(6.65%)	P Energy S	(90.58%)	Outside Op.	(4.86%)	NP Energy S	(3.92%)	P Water NS	(0.45%)
Flav.	(2.52%)	P Flav. S	(83.51%)	Outside Op.	(7.17%)	NP Flav. S	(6.71%)	P Flav. NS	(1.26%)
Juice	(18.67%)	P Juice S	(61.38%)	P Juice NS	(18.97%)	Outside Op.	(8.63%)	NP Juice S	(6.12%)
Sports	(7.75%)	P Sports S	(73.27%)	Outside Op.	(12.09%)	NP Sports S	(12.05%)	P Water NS	(1.04%)
Tea	(18.91%)	P Tea S	(69.79%)	Outside Op.	(13.53%)	NP Tea S	(11.75%)	P Tea NS	(1.72%)

P, NP, S, and NS denote Philadelphia, non-Philadelphia, SSB, and non-SSB, respectively.

price to obtain the counterfactual price in the no-tax scenario, and the variables "tax amount" and "tax saving" are set to zero for all beverage options.

Holding $\bar{\epsilon}_{ijt}$ to be the same between the two equations when examining beverage choices with and without the tax allows us to isolate the effects of the tax on households' beverage choices. In comparison, tracking how the households in our household dataset actually change their choices from the pre-taxation period to the post-taxation period would not paint an accurate picture of the tax-induced substitution patterns, because households' idiosyncratic preferences $\bar{\epsilon}_{ijt}$, product availability, and demand shocks all have changed between the two periods. Likewise, relying on the retail data would not allow us to track how households switch from one category to another and/or from one location to the other as a result of the tax.

We report our findings in Table 6. The first column of the table provides the category market shares for Philadelphia SSBs under the counterfactual scenario of no taxation, averaged across the 24 post-taxation months. The next four columns provide the first, second, third and fourth location $\times$ category $\times$ SSB status choices with taxation, given the household would have chosen the leftmost item of that row without taxation. For example, without taxation, sweetened carbonated soft drinks would have made up 43.3% of the market share for Philadelphia SSBs; with taxation, 66.78% of the households who would have chosen sweetened Philadelphia carbonated soft drinks continue to choose sweetened Philadelphia carbonated soft drinks (no substitution), 13.07% choose sweetened carbonated soft drinks in the non-Philadelphia location (geographic substitution), 12.46% choose the outside option (consumption reduction), and 4.45% choose non-sweetened carbonated soft drinks in Philadelphia (product substitution). Information like this can be particularly useful to policymakers for understanding people's behavior patterns in response to the implementation of a policy.

As expected, for all SSB categories, the primary choice with taxation remains the same as that without. We observe that the categories of Philadelphia SSBs that are the most responsive to

Table 7: Simulated Market Shares by SSB Status, Size, and Location

SSB Status × Size × Bev. Location	Without Tax	With Tax	Difference	% Change
Philadelphia Bev. Options				
Non-SSB × Small	0.63%	0.80%	+0.17	26.97%
Non-SSB × Medium	1.27%	1.59%	+0.32	25.27%
Non-SSB × Large	1.06%	1.20%	+0.13	12.46%
SSB × Small	3.03%	3.48%	+0.45	15.01%
SSB × Medium	4.36%	3.10%	-1.26	-28.88%
SSB × Large	2.89%	0.67%	-2.22	-76.75%
Non-Philadelphia Bev. Options				
Non-SSB × Small	0.63%	0.64%	+0.01	2.33%
Non-SSB × Medium	1.89%	1.94%	+0.05	2.37%
Non-SSB × Large	1.70%	1.71%	+0.01	0.87%
SSB × Small	3.08%	3.26%	+0.18	5.69%
SSB × Medium	5.42%	5.85%	+0.42	7.80%
SSB × Large	3.08%	3.50%	+0.42	13.67%
Outside Option	70.96%	72.26%	+1.30	1.84%

taxation are juice, carbonated soft drinks, tea, and sports drinks, as measured by the proportion of households who switch away. Excluding carbonated soft drinks and juice, the primary choice of substitution is the outside option, followed by the same category of SSBs in the alternative location. For Philadelphia SSBs, the proportion of households who transfer their consumption to the same category of SSBs in the alternative location is almost as large as those who switch to the outside option, or, in the case of carbonated soft drinks, larger. This provides clear evidence towards a willingness to cross-border shop in the presence of an SSB tax.

The Philadelphia SSB categories of coffee and energy drinks retain the greatest proportion of original consumers. We hypothesize that this pattern is due to the heterogeneous interaction of taxation policy with product size. Coffee and energy drink products are primarily sold in small, single serving containers with relatively high per-ounce prices; thus, the price increase due to the tax is proportionally smaller than those observed in other categories, where products on average come in larger sizes with lower per-ounce prices.

Supportive evidence is provided in Table 7, which displays simulated market shares for SSBs and non-SSBs by size and location with and without taxation. Unlike Table 6, for Table 7 we do not need to keep track of how each simulated household switches from one choice to another in response to the tax, and so the market shares reported in Table 7 are found by averaging the choice probabilities of the original 4000 Halton draws across the 24 post-taxation months without directly simulating product choices. The "without tax" counterfactual is conducted with the effect of taxation removed from the individual-level utility.

From Table 7 we observe that the effect of the SSB tax is heterogeneously distributed among differently sized SSBs. The tax increases the market share of small Philadelphia SSBs while decreasing the market shares of medium and large Philadelphia SSBs, with large Philadelphia SSBs seeing the biggest drop. SSBs in the non-Philadelphia location experience an increase in market share regardless of size; so do non-SSBs in Philadelphia. These are intuitive results. Consider Philadelphia SSBs, which are subject to the SSB tax. Compared to small products, large products are typically sold at a "quantity discount" and have a lower per-ounce price. Consequently, the SSB tax—levied at 1.5¢ per ounce—results in proportionally larger price increases for large products, thereby having a more negative impact on large products' market shares. Some of the market share that leaves large Philadelphia SSBs goes to small Philadelphia SSBs due to their proportionally smaller price increases and relatively high substitutability, giving rise to an increase in the market share of small Philadelphia SSBs.

7.3 Effects of SSB Tax on Beverage Consumption

We now consider the effects of Philadelphia's SSB tax on households' beverage consumption as well as their cross-border shopping and tax avoidance behavior. For each simulated household in each post-taxation month, we compute the household's expected consumption (in ounces) of Philadelphia SSBs, Philadelphia non-SSBs, non-Philadelphia SSBs, and non-Philadelphia non-SSBs, respectively, based on the model predicted choice probabilities and adjusting the amounts to account for the expected numbers of products and units purchased per trip and the expected number of trips in that month. We then sum over the 24 post-taxation months and compute the average per household over all households, Philadelphia households, and non-Philadelphia households, respectively.[31] We do this twice, without tax and with tax, respectively, and then calculate the differences. The results are reported in Table 8.

Turning first to Table 8's estimates pertaining to the average across all households in both locations, our counterfactual simulation shows that Philadelphia's SSB tax reduces an average household's purchase of Philadelphia SSBs by 55%. 23% ($= 509/2,219$) of this reduction is offset by an increase in the purchase of non-Philadelphia SSBs, leading to a net reduction equal to 42% of the purchase of Philadelphia SSBs in the no-tax scenario. Of course, considering only the average household does not provide a full picture. Instead, a primary benefit of our structural estimation using a combination of retail and household data is the ability to explore how the taxation policy affects households' behavior conditional on the location of their residence.

[31] The same procedure for computing the expected amount for each simulated household and then averaging across simulated households is used in subsequent analyses when we compute the average amount of tax paid, loss in consumer surplus, and sugar and caloric consumption.

Table 8: Average Beverage Consumption per Household[a]

SSB Status × Bev. Location	Without Tax	With Tax	Difference	% Change
All Households				
Philadelphia Bev. Options				
Non-SSB	2,158	2,428	+270	12.51%
SSB	4,026	1,807	-2,219	-55.12%
Non-Philadelphia Bev. Options				
Non-SSB	3,332	3,364	+32	0.96%
SSB	4,600	5,109	+509	11.07%
Philadelphia Households				
Philadelphia Bev. Options				
Non-SSB	3,827	4,341	+514	13.45%
SSB	7,097	3,306	-3,791	-53.42%
Non-Philadelphia Bev. Options				
Non-SSB	770	824	+54	7.11%
SSB	1,009	1,483	+474	47.00%
Non-Philadelphia Households				
Philadelphia Bev. Options				
Non-SSB	521	551	+30	5.69%
SSB	1,012	335	-677	-66.85%
Non-Philadelphia Bev. Options				
Non-SSB	5,846	5,856	+10	0.17%
SSB	8,124	8,668	+544	6.69%

[a] In ounces; aggregate amount over the post-taxation period January 2017 to December 2018.

As expected, Philadelphia households on the whole favor Philadelphia beverage options. In the case without taxation, 88% of Philadelphia households' SSB purchase is for SSBs sold within the city limits. The implementation of the SSB tax reduces their purchase of Philadelphia SSBs by 53% and increases their purchase of non-Philadelphia SSBs by 47%. Since Philadelphia households' purchase of non-Philadelphia SSBs without taxation is relatively small, a 47% increase in their non-Philadelphia purchase offsets only 13% of the reduction in their Philadelphia purchase. When considering the change in SSB purchase in the two locations combined, Philadelphia households experience an average reduction of 41%.

As observed with Philadelphia households, non-Philadelphia households also prefer beverage options in their home location. In the case without taxation, the purchase of Philadelphia SSBs accounts for only 11% of non-Philadelphia households' SSB purchase. Furthermore, non-Philadelphia households are more responsive to the SSB tax, reducing their purchase of Philadelphia SSBs by 67% in response to the tax and offsetting 80% of this reduction through an increase in non-Philadelphia SSB purchase. This is an intuitive result, as non-Philadelphia households already live in a region without taxation and travel carries an inherent cost. When considering non-Philadelphia households' SSB purchase in the two locations combined, we find that the tax leads to a drop of only 1.5%.

Finally, from Table 2 we know that non-Philadelphia households comprise 50.25% of all households in our market, and from Table 8 we find that relative to Philadelphia households, non-Philadelphia households display a greater tendency to transfer their SSB purchase from Philadelphia to the surrounding region in response to the SSB tax. It is then not surprising that a majority (54%) of the increase in the purchase of non-Philadelphia SSBs comes from non-Philadelphia households avoiding the taxed region rather than cross-border shopping by Philadelphia households. Prior studies of SSB taxation typically consider the increase in SSB sales in the surrounding untaxed region to be a result of cross-border shopping by residents of the taxed region. Our results shed light on the multiple sources of such an increase and suggest that SSB taxation may be more effective than previously thought, if we consider that the tax's intended target is those households residing within the city limits.

Two prior papers, Roberto et al. (2019) and Seiler et al. (2021), also use retail scanner data to examine the SSB tax and sales of SSBs in and around Philadelphia. There exist several similarities and dissimilarities between our works. In particular, our counterfactual simulation finds a decrease in volume sales of Philadelphia SSBs greater than that suggested by either prior paper. Roberto et al. (2019) find that volume sales of Philadelphia taxed beverages decline by 51% after the taxation policy and that 24% of this reduction is offset by an increase in volume sales in the surrounding region for a net reduction of 38%, while Seiler et al. (2021) find a decrease of 46% in volume sales of Philadelphia taxed beverages, with 52% of this reduction offset by an increase in volume sales in the surrounding region for a net reduction of 22%. In comparison, we find that the SSB tax results in a 55% reduction in volume sales of Philadelphia taxed beverages, with an increase in volume sales in the surrounding region offsetting 23% of this reduction for a net reduction of 42%.

Differences in the estimated impact of the SSB tax can result from a multitude of factors. Firstly, to the best of our knowledge, our paper is the first to analyze the effects of an SSB tax in a structural context where geographic substitution plays a primary role in determining consumers' choices. The works of Roberto et al. (2019), Cawley et al. (2020), and Seiler et al. (2021), among others, employ reduced form estimations that consider the change from pre-taxation to post-taxation SSB volume sales. Using a structural model, we complement prior works by forming our counterfactual estimation directly on the post-taxation months and incorporating the presence of shocks unrelated to changes in tax policy; thus, we model purchase as it would have been in the post-taxation period barring the presence of taxation. Secondly, both Roberto et al. (2019)

Table 9: Average Tax Paid and Loss in Consumer Surplus per Household[a]

	All Households	Phil. Households	Non-Phil. Households
Tax Paid	\$27.10	\$49.59	\$5.04
ΔCS	-\$55.83	-\$106.32	-\$6.27

[a]Aggregate amount over the post-taxation period January 2017 to December 2018.

and Seiler et al. (2021) use data obtained from IRI whereas our data is provided by Nielsen; differences in the retail stores covered by the different data sources can contribute to differences in the expected outcome. Finally, to more accurately account for households' heterogeneous responsiveness, we rely upon both retail and household data, which is another potential source for differing results between our work and those of others.

8 Welfare Implications

In this section, we consider the welfare effects of the SSB tax for consumers shopping at grocery stores, drug stores, and discount stores, including the amount of tax paid by households, the change in their consumer surplus, and the effects on their sugar and caloric consumption. We first present our findings at the location level and later, when focusing on the regressivity of the SSB tax, consider them at the income status $\times$ location level.

8.1 Welfare Effects by Household Location

We begin by evaluating the average amount of tax paid and loss in consumer surplus per household during the 24 post-taxation months, where the loss in consumer surplus is the difference between the expected utility (the "inclusive value" I_{it} in Eq. (7)) without and with taxation, divided by the household's marginal utility of money α_i. Table 9 presents our findings averaged across all households, Philadelphia households, and non-Philadelphia households, respectively.

As expected with local taxation, households paying the most taxes are those living within the city limits, with an average Philadelphia household paying over 9 times that of an average non-Philadelphia household. This difference follows from non-Philadelphia households' lower demand for Philadelphia SSBs (as discussed in Subsection 7.3) and the fact that they can purchase in the untaxed location without incurring travel costs.

For households in both locations, the expected loss in consumer surplus is noticeably greater than the expected amount of tax paid, but the ratio is heterogeneous across household locations. While an average non-Philadelphia household experiences a loss of consumer surplus equal to 124% of their tax amount, an average Philadelphia household's loss of consumer surplus is 214%

of their tax amount. The discrepancy in this ratio between the two locations arises primarily from the difference in how costly geographic substitution is. Switching from Philadelphia SSBs to non-Philadelphia SSBs in response to the tax necessitates traveling for Philadelphia households but not for non-Philadelphia households, and therefore Philadelphia households incur a larger proportion of their consumer surplus loss in the form of travel costs as opposed to tax paid.

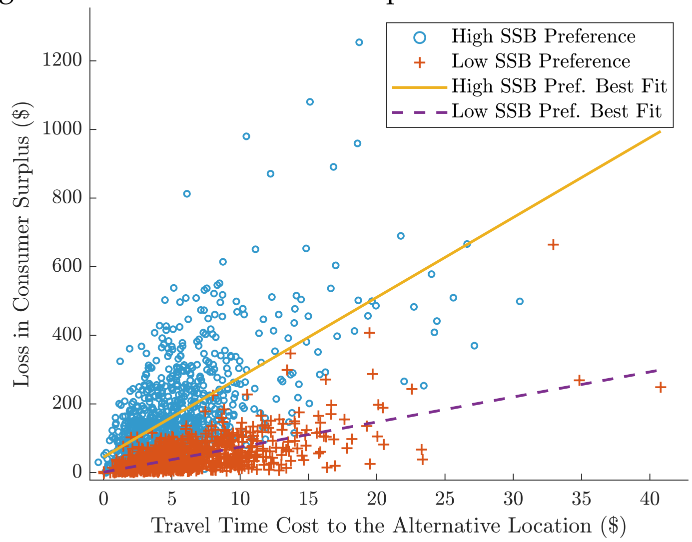
Even among Philadelphia households, there is a large degree of heterogeneity in terms of travel costs, which depend on households' proximity to the city border. In addition, another factor impacting households' welfare changes is their preference for SSBs. Figure 3 illustrates how these two factors interact and jointly influence Philadelphia households' loss of consumer surplus resulting from the SSB tax. The figure presents a scatter plot of Philadelphia households' loss in consumer surplus versus their travel time cost to reach the alternative location (equal to a household's travel time to reach the non-Philadelphia location times its marginal disutility of travel time and divided by its marginal utility of money). It shows that across all Philadelphia households, the magnitude of a household's consumer surplus loss increases in the household's travel time cost. Moreover, an increase in travel time cost is particularly detrimental for households with a high preference for SSBs, as they are more "attached" to SSBs and therefore more likely to engage in cross-border shopping to purchase SSBs. In Figure 3, among low SSB preference households the line of best fit has a slope of 7.3, whereas among high SSB preference households the slope is much higher at 23.3, implying that a $1 increase in travel time cost leads to a $23.3 increase in consumer surplus loss (recall that the consumer surplus loss is the aggregate amount over the 24 post-taxation months).[32] These results thus shed light on the intricate relation between geographic and product substitution as well as the SSB tax's heterogeneous welfare implications for different types of households.

All is not bad for those consumers of SSBs, as we consider how the taxation policy reduces sugar and caloric consumption—a side benefit of the SSB tax, whose stated primary goal is to generate tax revenue. According to the US Center for Disease Control and Prevention, SSBs are the leading source of added sugars in the American diet, and frequent consumption of sugary drinks is associated with obesity, type 2 diabetes, heart disease, and kidney diseases, among a plethora of other negative health effects.[33] Table 10 presents the change in sugar and caloric consumption from beverages during the 24 post-taxation months, averaged across all households, Philadelphia households, and non-Philadelphia households, respectively.

[32]High SSB preference households are defined as those Philadelphia households whose average utility derived from SSBs, in the simulation without taxation, is greater than the median for Philadelphia households. The rest are low SSB preference households.

[33]See https://www.cdc.gov/nutrition/data-statistics/sugar-sweetened-beverages-intake.html.

Figure 3: Loss in Consumer Surplus vs. Travel Time Cost[a]



[a]For simulated Philadelphia households. High SSB preference households are those whose average utility derived from SSBs, in the simulation without taxation, is greater than the median for Philadelphia households. The rest are low SSB preference households.

Table 10: Average Sugar and Caloric Consumption from Beverages per Household[a]

	Without Tax	**With Tax**	**Difference**	**% Change**
All Households				
Sugar (g)	20,080	16,483	-3,597	-17.91%
Calories (cal)	81,822	67,774	-14,048	-17.17%
Philadelphia Households				
Sugar (g)	19,148	12,252	-6,896	-36.01%
Calories (cal)	77,212	50,192	-27,020	-34.99%
Non-Philadelphia Households				
Sugar (g)	20,995	20,636	-359	-1.71%
Calories (cal)	86,345	85,030	-1,315	-1.52%

[a]Aggregate amount over the post-taxation period January 2017 to December 2018.

We find that, for an average household living in Philadelphia and the surrounding region, there is an expected reduction in the consumption of sugar by 18%. This effect is strongest for Philadelphia households, who have an average reduction of 36%, whereas non-Philadelphia households—who are not the targeted population of the SSB tax—experience an average reduction of 1.7%. To put this reduction in context, we consider the expected caloric reduction. For Philadelphia households, the implementation of the SSB tax translates to a decrease in caloric intake equal to 27,020 calories—approximately 13.5 days' worth of caloric intake (under a 2,000-

calories-a-day diet). The sizeable reduction in sugar and caloric consumption among Philadelphia households attests to the substantial public health benefits of the SSB tax. Note that our results only consider the decrease in sugar and caloric consumption from beverages purchased at grocery stores, discount stores, and drug stores; overall reduction will be larger when considering other avenues of purchase. Also note that our analysis does not consider substitution to sugary non-beverage alternatives.

8.2 Differences between High- and Low-Income Households

We now consider to what extent households with different income status differ in their amount of tax paid, loss of consumer surplus, and reduction in sugar and caloric consumption. This will in turn inform us about the degree to which the taxation policy exhibits regressive tendencies, which is particularly relevant in this context, as a primary concern for opponents of Philadelphia's SSB tax was its potential impact on the city's poor—households who, as found in past studies, generally display a greater demand for SSBs, the products to be taxed.

From our structural setup, there are several mechanisms by which low-income households may react differently to the implementation of an SSB tax. First, we know from our model estimates reported in Table 3 that low-income households display a greater demand for inside options excluding medium- and large-sized tea products. Second, our results suggest that low-income households incur less disutility in regard to travel, which may result in a greater willingness to cross-border shop. Finally, price sensitivity may differ between those with means and those without.

Price Elasticity of Demand We begin by considering price elasticity of demand by income status. Table 11 presents our findings. Unlike in Table 4, here we consider own- and cross-elasticities of demand averaged only at the "all beverage options" level to highlight the differences between high- and low-income households in terms of their responsiveness to price increases. As before, cross-elasticities of demand are reported for beverage options from the same category, same category and same location, same category and different location, and all beverage options.

We find that low-income households display a greater price sensitivity than high-income households, with respect to both own-elasticity and cross-elasticities. For example, low-income households' own-elasticity of demand is 21% greater than high-income households'. This finding is intuitive, as one would expect those with less income to display a greater sensitivity to changes in price. However, despite their greater price sensitivity, regardless of location low-income households still display a greater preference for SSBs under taxation, as demonstrated by Table 12.

Table 11: Price Elasticity of Demand by Income Status

Average Level	**Own-Elasticity**	**Cross-Elasticity**			
		Same Category			All Bev. Options
		All Bev. Options	Same Location	Different Location	
High-Income					
All Bev. Options	-1.8820	0.0101	0.0179	0.0023	0.0015
Low-Income					
All Bev. Options	-2.2696	0.0138	0.0233	0.0042	0.0020

Table 12: Average SSB Consumption per Household, by Location and Income Status[a]

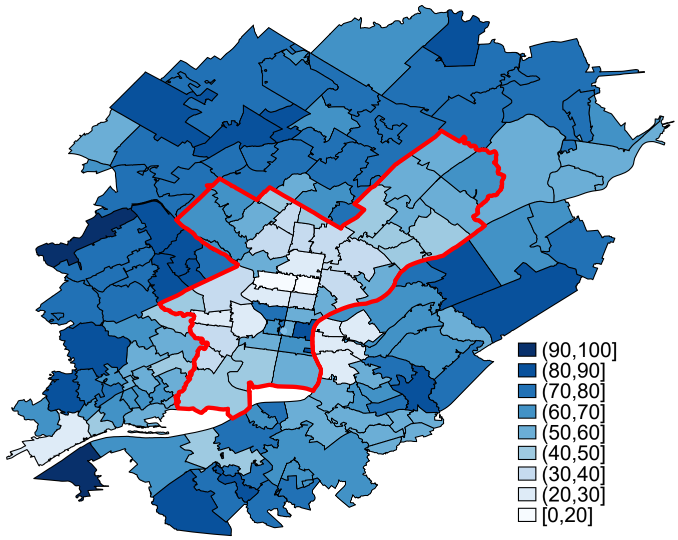
Income Status × SSB Location	**Without Tax**	**With Tax**	**Difference**	**% Change**
Philadelphia Households				
High-Income				
Philadelphia SSBs	7,030	3,148	-3,882	-55.22%
Non-Philadelphia SSBs	745	1,192	+447	59.95%
Low-Income				
Philadelphia SSBs	7,152	3,434	-3,718	-51.98%
Non-Philadelphia SSBs	1,223	1,719	+496	40.59%
Non-Philadelphia Households				
High-Income				
Philadelphia SSBs	768	220	-548	-71.41%
Non-Philadelphia SSBs	8,059	8,559	+500	6.20%
Low-Income				
Philadelphia SSBs	1,468	552	-916	-62.41%
Non-Philadelphia SSBs	8,246	8,871	+626	7.59%

[a]In ounces; aggregate amount over the post-taxation period January 2017 to December 2018.

SSB Consumption Table 12 shows that low-income households are less responsive to the taxation policy than high-income households. Regardless of household location, low-income households reduce their consumption of Philadelphia SSBs at a lower rate. Among Philadelphia households, low-income households reduce their consumption of Philadelphia SSBs by 52% in response to the tax, 3 percentage points lower than their high-income counterparts. Among non-Philadelphia households, the two types of households exhibit an even greater discrepancy in their responses, with low-income households reducing their consumption of Philadelphia SSBs by 62% in response to the tax, 9 percentage points lower than their high-income counterparts.

High- and low-income households' geographic distribution may go towards explaining the discrepancies between their responses. Figure 4 shows the percentage of high-income house-

Figure 4: Percentage of High-Income Households by ZIP Code[a]



[a]The city of Philadelphia is the area outlined in red.

holds for each ZIP Code in and around Philadelphia. From the figure, we observe that within Philadelphia, low-income households tend to live near the city center, while outside Philadelphia, low-income households tend to live near the city border. Therefore, when the tax is in effect, among Philadelphia households, low-income households find it more costly to cross-border shop in the non-Philadelphia location since their travel costs would be higher, while among non-Philadelphia households, high-income households find it more beneficial to avoid cross-border shopping in Philadelphia since their saving of travel costs would be higher. Such a pattern therefore offers an explanation for the greater tendency among low-income households in both locations to continue buying Philadelphia SSBs under taxation.

Amount of Tax Paid and Loss in Consumer Surplus Following directly from the differences in purchasing behavior, we consider the differences between high- and low-income households in the amount of tax paid and loss in consumer surplus. Table 13 presents these results.

We find that low-income households bear the largest tax burden. Within Philadelphia, low-income households pay 9% more taxes than their high-income counterparts, while outside Philadelphia, low-income households pay an astounding 152% more taxes than their high-income counterparts. Among Philadelphia households, the difference in tax paid arises primarily from the pattern that low-income households have a greater preference for SSBs and tend to purchase more SSBs with or without taxation. Among non-Philadelphia households, in addition to

Table 13: Average Tax Paid and Loss in Consumer Surplus per Household, by Location and Income Status[a]

	All Households	Phil. Households	Non-Phil. Households
High-Income			
Tax Paid	\$21.01	\$47.22	\$3.29
ΔCS	-\$45.29	-\$108.26	-\$2.71
Low-Income			
Tax Paid	\$34.55	\$51.51	\$8.28
ΔCS	-\$68.71	-\$104.75	-\$12.89

[a] Aggregate amount over the post-taxation period January 2017 to December 2018.

the greater preference for SSBs displayed by low-income households, another factor that contributes to the difference in tax paid is a household's home location. As shown in Figure 4, outside Philadelphia, low-income households tend to live close to the city border; their proximity to Philadelphia coupled with their lower disutility from travel time (as found in Table 3) contributes to their much larger purchase of Philadelphia SSBs, with or without taxation, than their high-income counterparts (as shown in Table 12). This, in turn, is the primary driver behind the difference in the amount of tax paid between high- and low-income non-Philadelphia households.

This border proximity also helps explain the significantly larger loss in consumer surplus observed for low-income non-Philadelphia households. For them, compared to their high-income counterparts who tend to live farther away from the city and have a lower preference for SSBs, Philadelphia SSBs are more likely to be the most preferred among all options in their choice set when there is no tax, and therefore the imposition of a tax on Philadelphia SSBs has a more negative impact on their consumer surplus. As supporting evidence, Table 12 shows that in response to the tax, low-income non-Philadelphia households on average reduce their Philadelphia SSB purchase by 916 ounces, much higher than the reduction of 548 ounces by their high-income counterparts; in other words, the distortion to the optimal consumption is greater for low-income non-Philadelphia households than for their high-income counterparts.

Interestingly, we find that low-income Philadelphia households experience a smaller loss in consumer surplus compared to their high-income counterparts, although the difference is not large (\$104.75 vs. \$108.26). Relative to high-income Philadelphia households, low-income Philadelphia households have a greater preference for SSBs, which tends to exacerbate their loss in consumer surplus, but at the same time, as we discuss below, they incur lower travel costs associated with cross-border shopping, which alleviates their loss in consumer surplus. Our simulation shows that despite living closer to the city center, due to their lower disutility from travel time, low-income Philadelphia households' expected cost of travel to the region outside Philadelphia is \$5.27, lower than the \$6.08 for high-income Philadelphia households, indicating that cross-border shopping is less costly for low-income Philadelphia households. Supporting evidence is provided by Table 12, which shows that, with and without taxation, low-income Philadelphia households exhibit a greater tendency to cross-border shop in the non-Philadelphia location, relative to their high-income counterparts.

Regressivity of the SSB Tax Although low-income Philadelphia households on average incur a loss of consumer surplus similar to that for their high-income counterparts, the large income difference between these two groups of households needs to be taken into account when assessing the regressivity of the SSB tax.[34] According to data from the 2018 ACS, the average annual income for low-income Philadelphia households is \$22,783, whereas their high-income counterparts have a much higher average of \$112,380.[35] These numbers, together with the loss-in-consumer-surplus numbers reported in Table 13, show that when measured as a percentage of annual income, low-income Philadelphia households on average incur a loss of consumer surplus 4.8 times as large as their high-income counterparts', suggesting that the tax is highly regressive. Similarly, among those living outside the city limits, low-income households have an average annual income of \$26,440, whereas high-income households have a much higher average of \$131,974. Therefore, when measured as a percentage of annual income, low-income non-Philadelphia households again incur a much larger loss of consumer surplus than their high-income counterparts. These findings highlight the regressive nature of the SSB tax: those that bear the greatest burden from the tax are those with the least means.

Changes in Sugar and Caloric Consumption Lastly, we consider changes in sugar and caloric consumption from beverages for high- and low-income households by home location. We find that among Philadelphia households, high-income households on average consume less sugar and fewer calories and experience a greater percentage reduction in their consumption, while among non-Philadelphia households, high-income households on average consume less sugar

[34]Due to the unavailability of joint income and household size data at the ZIP Code level in the ACS, we are not accounting for household size in our model. Research suggests households with less income generally have higher birth rates (Balbo et al., 2013). As such, this would only exacerbate the difference in income per capita between the two types of households, and therefore our estimate of the regressivity of the tax is likely an underestimate.

[35]We fit a generalized beta distribution of the second kind (GB2) to the grouped income data from the 2018 ACS (Jorda et al. (2021) show that GB2 is particularly suitable for modeling income distributions). We then compute the average incomes according to the fitted GB2 distribution. We do this for Philadelphia households and non-Philadelphia households, respectively.

and fewer calories but experience a smaller percentage reduction in their consumption. Detailed results are reported and discussed in Appendix A6.

9 Alternative Scenarios

We examine several alternative scenarios to further our understanding of Philadelphia's SSB tax. We first vary the tax rate to identify the one that maximizes the tax revenue. We then examine the changes in sugar and caloric consumption, consumer surplus, and the revenue-maximizing tax rate if diet products are not subject to taxation (as in the original proposal of the Philadelphia SSB tax). We also explore the impact of taxation on SSB consumption and consumer surplus if not only Philadelphia but also its surrounding region are subject to the same tax (as would be the case if the tax is implemented in a broader region, for instance as a national tax). Lastly, we consider how changes in travel time (resulting from improved roads, for example) would affect SSB consumption and cross-border shopping behavior.

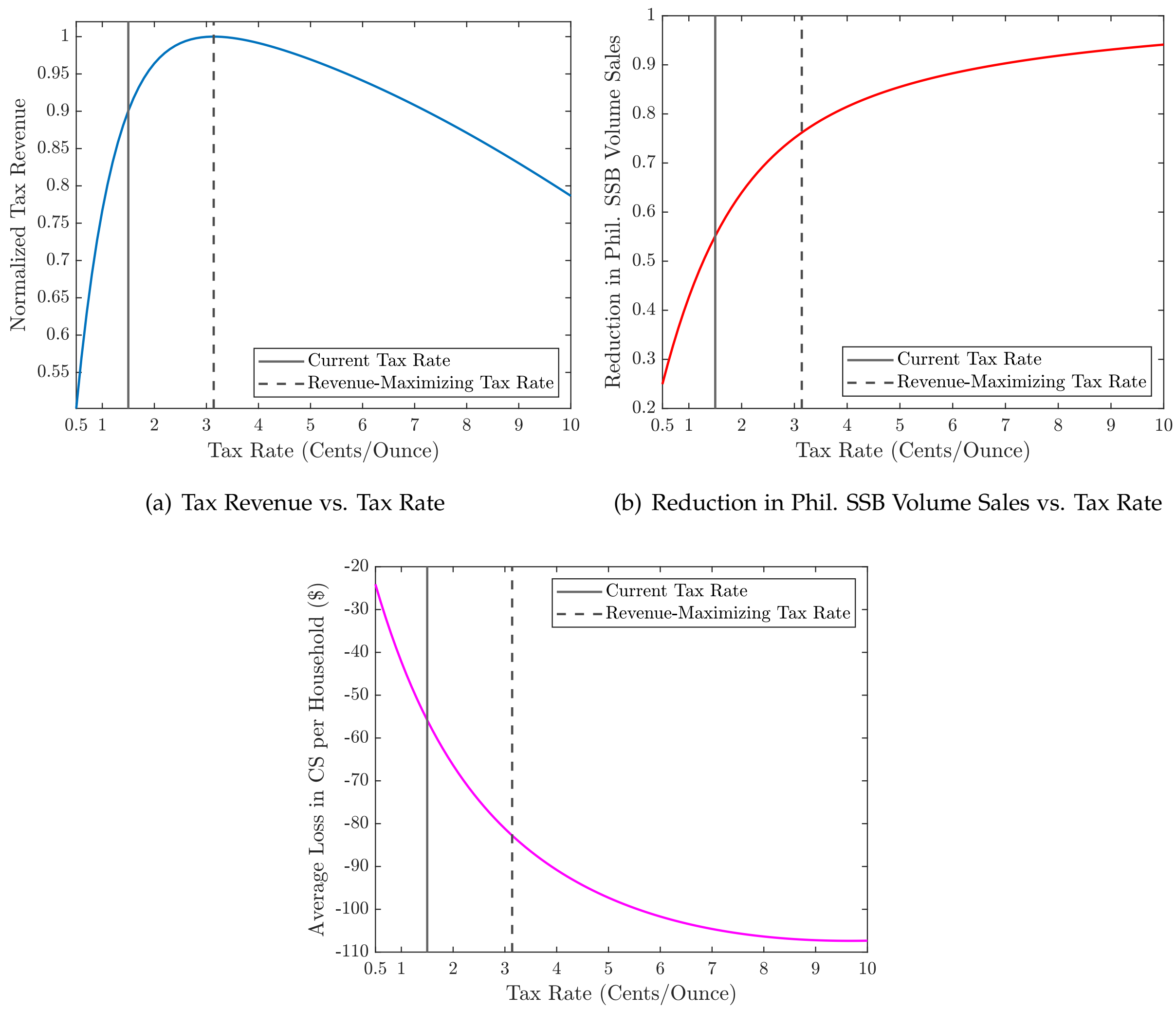
9.1 Revenue-Maximizing Tax Rate

Here we use our estimates of beverage demand and taxation responses to predict outcomes under counterfactual tax rates. To simplify analysis, when computing prices under counterfactual tax rates, we maintain the category-level pass-through rates found earlier. This assumption of a constant pass-through rate is not beyond that observed in prior literature (Allcott et al. (2019) and Seiler et al. (2021)). Unlike prior works, our counterfactual estimates of demand responsiveness to taxation account for consumer heterogeneity in terms of beverage preferences, travel costs, and locational and categorical substitution.

Given any hypothetical tax rate and the corresponding beverage prices computed according to the category-level pass-through rates, we calculate the average amount of SSB tax payment per household during the 24 post-taxation months for each income status/location combination. We use these averages and the demographic distribution of households provided in Table 2 to obtain the total tax revenue in each income status/location combination. Summing over the four income status/location combinations provides the total tax revenue for the given tax rate. We also compute the reduction in Philadelphia SSB volume sales and average loss in consumer surplus per household during the 24 post-taxation months in a similar fashion. Figure 5 plots those three variables against the tax rate.

We obtain a revenue-maximizing tax rate of 3.14¢ per ounce—much closer to the initially proposed tax rate of 3¢ per ounce than the current tax rate of 1.5¢ per ounce. We find that the current tax rate generates a revenue of $32.5 million during the 24 post-taxation months, which

Figure 5: Tax Revenue, SSB Volume Sales, and Consumer Surplus: Alternative Tax Rates



(a) Tax Revenue vs. Tax Rate

(b) Reduction in Phil. SSB Volume Sales vs. Tax Rate

(c) Average Loss in CS per Household vs. Tax Rate

Notes: Tax revenue is normalized relative to the maximum, and reduction in Philadelphia SSB volume sales is normalized relative to the volume sales without tax.

equals 90% of the $36.1 million that would be generated at the revenue-maximizing tax rate, whereas the initially proposed tax rate of 3¢ per ounce would generate a revenue more than 99% of the maximal revenue. We note that these revenue figures account for revenue generated at the stores in our sample, namely grocery stores, discount stores, and drug stores; we do not consider revenue from other sources such as supercenters, gas stations, and dollar stores, nor non-retailer locations such as restaurants, fast-food outlets, and theaters.

With respect to SSB volume sales, under the revenue-maximizing tax rate, there would be a 76% reduction in Philadelphia SSB volume sales, 29% of which would be offset by an increase in the volume sales in the surrounding region, for a net reduction of 54%; under the current tax rate, those figures are noticeably smaller at 55%, 23%, and 42%, respectively. The larger reduction in SSB sales associated with the revenue-maximizing tax rate would be an added benefit for those lawmakers and public health advocates concerned with the consumption of products that contribute to unhealthy lifestyles. However, such a large reduction in SSB sales could be damaging to retailers located in Philadelphia, especially since consumers may take not only their SSB purchase but also their grocery shopping altogether to stores outside Philadelphia.

Furthermore, we find that the revenue-maximizing tax rate demonstrates even bigger regressive tendencies, with 60% of the tax revenue generated coming from low-income households, compared to 57% under the current tax rate. Additionally, the revenue-maximizing tax rate would lead to an average consumer surplus loss of $82.77, constituting a 48% increase when compared to the current tax rate's average loss of $55.83.

Differences between the revenue-maximizing tax rate found in our work and those found in other research likely arise from differences in the structure of the demand curve. Of particular note is Seiler et al. (2021), who found a revenue-maximizing SSB tax rate of 1.63¢ per ounce for Philadelphia, when assuming a linear demand curve. Our findings, however, are derived from our demand estimates based on the RCNL modeling structure. We contend that our higher revenue-maximizing tax rate is driven primarily by the persistent consumption of Philadelphia SSBs from a subset of Philadelphia households who lack inexpensive substitutes for SSBs within their home region, many of these households experiencing large travel costs and high SSB preferences. This pattern leads to such households' low price sensitivity with respect to Philadelphia SSBs, which in turn gives rise to a higher figure for the revenue-maximizing tax rate.

In terms of structural modeling, Allcott et al. (2019) consider the optimal SSB tax rate for a government with preferences for wealth redistribution. They determine an optimal tax rate between 1¢ and 2.1¢ per ounce. In contrast to their findings, our analysis is concerned with the revenue-maximizing tax rate rather than the socially optimal tax rate. Furthermore, they focus on a national SSB tax imposed on sugar-sweetened beverages only, whereas our analysis is concerned with the city of Philadelphia and includes diet products containing artificial sweeteners. A more appropriate comparison between our work and Allcott et al. (2019) is found in Appendix A7.1, where we report a revenue-maximizing tax rate of 2.33¢ per ounce under the assumption that diet products are excluded from the tax.

9.2 Additional Counterfactuals

Next we consider three additional counterfactual scenarios. Detailed results are reported and discussed in Appendix A7; here we summarize the main findings.

We find that removing diet products from the tax (Appendix A7.1) induces a greater reduction in households' sugar and caloric consumption, reduces households' loss in consumer surplus, and lowers the revenue-maximizing tax rate. The main intuition here is that sugary beverages and their diet counterparts are good substitutes for some households, therefore when diet products are excluded from the tax, these households are able to switch from sugary beverages to their diet counterparts in order to avoid the tax, rather than having to travel for cross-border shopping or switch to less substitutable products.

We also consider a counterfactual in which the tax is levied upon both Philadelphia and its surrounding region (Appendix A7.2), and a counterfactual in which the travel time experienced by all households is varied proportionally from 50% to 200% of the baseline (Appendix A7.3). Results from those counterfactuals indicate that a taxation policy's geographic coverage as well as households' travel costs have significant impact on households' responses and the consumption and welfare outcomes.

Together, our counterfactual analyses show that policymakers need to pay careful attention to the scope of the tax—in terms of product and geographic coverage—as well as households' cross-border shopping behavior when designing taxation policies.

10 Conclusion

In this work, we employ a structural modeling framework that combines both retail and household data to study the relationship between local taxation and households' tax avoidance behavior including cross-border shopping and product substitution, focusing on Philadelphia's SSB tax.

We find that travel time to the untaxed region surrounding Philadelphia plays an important role in determining households' substitution patterns. In response to the implementation of an SSB tax, our results quantify households' reduction in the consumption of taxed beverages in Philadelphia and their willingness to seek untaxed products in locales beyond the city border. Accounting for household location, we find that a majority 54% of the rise in SSB sales in the surrounding region is due to an avoidance of Philadelphia SSBs by those residing in the surrounding region, rather than cross-border shopping by Philadelphia households. We also show that price responsiveness alone does not fully account for observed consumer behavior; instead, we provide evidence that tax salience has a noticeable impact on consumer demand, particularly in highly publicized and politicized taxes such as the SSB tax our work studies.

Our model and estimation allow for heterogeneous consumer behavior based on their demographic characteristics and proximity to the city border. Taking into account consumers' heterogeneous responses to the tax, we show that the current tax rate 1.5¢ per ounce is well below the revenue-maximizing tax rate 3.14¢ per ounce. Our results suggest that, without readily available substitutes and facing large travel costs associated with cross-border shopping, a subset of Philadelphia households are persistent in their consumption of Philadelphia SSBs, willing to pay the higher prices resulting from the tax. Their low price sensitivity with respect to Philadelphia SSBs is a main factor behind the high revenue-maximizing tax rate.

Based on our demand estimates, we calculate the average amount of tax paid and the average loss in consumer surplus for households at different locations and different income levels. Taking into account travel costs and the switch to less preferred products, Philadelphia households on average incur a loss in consumer surplus more than twice the amount of tax paid, with low-income households bearing the largest burden. When measured as a percentage of annual income, low-income Philadelphia households on average incur a loss of consumer surplus 4.8 times as large as their high-income counterparts', suggesting that the tax is highly regressive.

These findings are especially relevant for governmental entities weighing the benefits of a revenue-generating, healthy-habit-inducing tax against the drawbacks of a strongly regressive taxation policy. Additionally, through counterfactual analyses in which we vary the geographic coverage of the tax as well as travel times to the alternative region, we provide supportive evidence for the notion that policymakers must carefully consider geographic coverage and geographic substitution when assessing the effects of local policies.

Lastly, our model's applicability extends beyond the context studied in this work. Any local tax or subsidy susceptible to cross-border shopping offers an opportunity for study under our framework, which facilitates rich modeling and sensible estimation of individuals' heterogeneous travel costs and substitution patterns, as well as the policy's potentially vastly different welfare implications for different individuals.

References

Acton, Rachel B, Lana Vanderlee, Jean Adams, Sharon I Kirkpatrick, Lilia S Pedraza, Gary Sacks, Christine M White, Martin White, and David Hammond. 2022. "Tax awareness and perceived cost of sugar-sweetened beverages in four countries between 2017 and 2019: findings from the international food policy study." *International Journal of Behavioral Nutrition and Physical Activity* 19 (1): 1–18.

Allcott, Hunt, Benjamin B Lockwood, and Dmitry Taubinsky. 2019. "Regressive sin taxes, with an application to the optimal soda tax." *The Quarterly Journal of Economics* 134 (3): 1557–1626.

Balbo, Nicoletta, Francesco C Billari, and Melinda Mills. 2013. "Fertility in advanced societies: A review of research." *European Journal of Population/Revue europeenne de demographie* 29 (1): 1–38.

Bayer, Patrick, Fernando Ferreira, and Robert McMillan. 2007. "A Unified Framework for Measuring Preferences for Schools and Neighborhoods." *Journal of Political Economy* 115 (4): 588–638.

Berry, Steven, James Levinsohn, and Ariel Pakes. 1995. "Automobile Prices in Market Equilibrium." *Econometrica* 63 (4): 841–890.

Berry, Steven, James Levinsohn, and Ariel Pakes. 2004. "Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Car Market." *Journal of Political Economy* 112 (1): 68–105.

Berry, Steven T. 1994. "Estimating Discrete-Choice Models of Product Differentiation." *The RAND Journal of Economics* 25 (2): 242–262.

Bleich, Sara N, Hannah G Lawman, Michael T LeVasseur, Jiali Yan, Nandita Mitra, Caitlin M Lowery, Ana Peterhans, Sophia Hua, Laura A Gibson, and Christina A Roberto. 2020. "The Association Of A Sweetened Beverage Tax With Changes In Beverage Prices And Purchases At Independent Stores." *Health Affairs* 39 (7): 1130–1139.

Breslow, Samantha K. 2019. "Chicago and Cook County Amusement Tax." *The National Law Review* IX (114). https://www.natlawreview.com/article/chicago-and-cook-county-amusement-tax.

Burda, Martin, Matthew Harding, and Jerry Hausman. 2008. "A Bayesian mixed logit–probit model for multinomial choice." *Journal of Econometrics* 147 (2): 232–246, Estimating demand systems and measuring consumer preferences.

Bygvrå, Susanne. 2009. "Distance and cross-border shopping for alcohol – evidence from Danes' cross-border shopping 1986–2003." *Nordic Studies on Alcohol and Drugs* 26 (2): 141–163.

Capps, Cory, David Dranove, and Mark Satterthwaite. 2003. "Competition and Market Power in Option Demand Markets." *The RAND Journal of Economics* 34 (4): 737–763.

Cawley, John, and David Frisvold. 2015. "The Incidence of Taxes on Sugar-Sweetened Beverages: The Case of Berkeley, California." Working Paper 21465, National Bureau of Economic Research.

Cawley, John, David Frisvold, Anna Hill, and David Jones. 2020. "The impact of the Philadelphia beverage tax on prices and product availability." *Journal of Policy Analysis and Management* 39 (3): 605–628.

Cawley, John, Barton Willage, and David Frisvold. 2018. "Pass-through of a tax on sugar-sweetened beverages at the Philadelphia International Airport." *JAMA* 319 (3): 305–306.

Chandra, Ambarish, Keith Head, and Mariano Tappata. 2014. "The Economics of Cross-Border Travel." *The Review of Economics and Statistics* 96 (4): 648–661.

Chintagunta, Pradeep K., and Jean-Pierre Dubé. 2005. "Estimating a Stockkeeping-Unit-Level Brand Choice Model That Combines Household Panel Data and Store Data." *Journal of Marketing Research* 42 (3): 368–379.

Davis, Peter. 2006. "Spatial Competition in Retail Markets: Movie Theaters." *The RAND Journal of Economics* 37 (4): 964–982.

DellaVigna, Stefano, and Matthew Gentzkow. 2019. "Uniform Pricing in U.S. Retail Chains." *The Quarterly Journal of Economics* 134 (4): 2011–2084.

Dubois, Pierre, Rachel Griffith, and Martin O'Connell. 2020. "How Well Targeted Are Soda Taxes?" *American Economic Review* 110 (11): 3661–3704.

Duchneskie, John. 2016. "Philly's daily commute: How do your habits compare?." *The Philadelphia Inquirer*. https://www.inquirer.com/philly/business/transportation/405506645.html.

Fisher, Ronald C. 1980. "Local Sales Taxes: Tax Rate Differentials, Sales Loss, and Revenue Estimation." *Public Finance Quarterly* 8 (2): 171–188.

Friberg, Richard, Frode Steen, and Simen A. Ulsaker. 2018. "Hump-shaped cross-price effects and the extensive margin in cross-border shopping." Discussion Paper Series in Economics 20/2019, Norwegian School of Economics.

Garrison, Cassandra, and Adriana Barrera. 2022. "Mexico suspends gasoline subsidy as U.S. drivers cross border for deals." *Reuters*. https://www.reuters.com/world/americas/mexico-suspends-subsidy-gasoline-border-region-with-us-2022-04-02/.

Goldin, Jacob, Tatiana Homonoff, and Katherine Meckel. 2022. "Issuance and Incidence: SNAP Benefit Cycles and Grocery Prices." *American Economic Journal: Economic Policy* 14 (1): 152–78.

Goldszmidt, Ariel, John A. List, Robert D. Metcalfe, Ian Muir, V. Kerry Smith, and Jenny Wang. 2020. "The Value of Time in the United States: Estimates from Nationwide Natural Field Experiments." Working Paper 28208, National Bureau of Economic Research.

Goolsbee, Austan, and Amil Petrin. 2004. "The Consumer Gains from Direct Broadcast Satellites and the Competition with Cable TV." *Econometrica* 72 (2): 351–381.

Grieco, Paul LE, Charles Murry, Joris Pinkse, and Stephan Sagl. 2022. "Conformant and Efficient Estimation of Discrete Choice Demand Models." working paper, The Pennsylvania State University.

Grigolon, Laura, and Frank Verboven. 2014. "Nested Logit or Random Coefficients Logit? A

Comparison of Alternative Discrete Choice Models of Product Differentiation." *The Review of Economics and Statistics* 96 (5): 916–935.

Harding, Matthew, Ephraim Leibtag, and Michael F. Lovenheim. 2012. "The Heterogeneous Geographic and Socioeconomic Incidence of Cigarette Taxes: Evidence from Nielsen Homescan Data." *American Economic Journal: Economic Policy* 4 (4): 169–98.

Hollenbeck, Brett, and Kosuke Uetake. 2021. "Taxation and Market Power in the Legal Marijuana Industry." *The RAND Journal of Economics* 52 (3): 559–595.

Houde, Jean-François. 2012. "Spatial Differentiation and Vertical Mergers in Retail Markets for Gasoline." *American Economic Review* 102 (5): 2147–82.

Hymel, Kent, Kenneth Small, and Kurt Van Dender. 2010. "Induced demand and rebound effects in road transport." *Transportation Research Part B: Methodological* 44 1220–1241.

Jorda, Vanesa, José María Sarabia, and Markus Jäntti. 2021. "Inequality measurement with grouped data: Parametric and non-parametric methods." *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 184 (3): 964–984.

Kifer, Avigail. 2015. "The Incidence of a Soda Tax, in Pennies and Pounds." Working Paper 1-017, Kilts Center for Marketing at Chicago Booth – Nielsen Dataset Paper Series.

Li, Shanjun, Joshua Linn, and Erich Muehlegger. 2014. "Gasoline Taxes and Consumer Behavior." *American Economic Journal: Economic Policy* 6 (4): 302–342.

McFadden, Daniel, Antti Talvitie, and Associates. 1977. *Demand Model Estimation and Validation*. Institute of Transportation Studies, Berkeley CA.

Miller, Nathan H., and Matthew C. Weinberg. 2017. "Understanding the Price Effects of the MillerCoors Joint Venture." *Econometrica* 85 (6): 1763–1791.

Miravete, Eugenio J., Katja Seim, and Jeff Thurk. 2018. "Market Power and the Laffer Curve." *Econometrica* 86 (5): 1651–1687.

Murry, Charles, and Yiyi Zhou. 2020. "Consumer Search and Automobile Dealer Colocation." *Management Science* 66 (5): 1909–1934.

Nevo, Aviv. 2000. "A Practitioner's Guide to Estimation of Random-Coefficients Logit Models of Demand." *Journal of Economics & Management Strategy* 9 (4): 513–548.

Nevo, Aviv. 2001. "Measuring Market Power in the Ready-to-Eat Cereal Industry." *Econometrica* 69 (2): 307–342.

Roberto, Christina A., Hannah G. Lawman, Michael T. LeVasseur, Nandita Mitra, Ana Peterhans, Bradley Herring, and Sara N. Bleich. 2019. "Association of a Beverage Tax on Sugar-Sweetened and Artificially Sweetened Beverages With Changes in Beverage Prices and Sales at Chain Retailers in a Large Urban Setting." *JAMA* 321 (18): 1799–1810.

Seiler, Stephan, Anna Tuchman, and Song Yao. 2021. "The Impact of Soda Taxes: Pass-Through, Tax Avoidance, and Nutritional Effects." *Journal of Marketing Research* 58 (1): 22–49.

Thomadsen, Raphael. 2005. "The Effect of Ownership Structure on Price in Geographically Differentiated Industries." *RAND Journal of Economics* 36 908–929.

Tosun, Mehmet, and Mark Skidmore. 2007. "Cross-Border Shopping and the Sales Tax: An Examination of Food Purchases in West Virginia." *Topics in Economic Analysis & Policy* 7 1877–1877.

Train, Kenneth. 1999. "Halton sequences for mixed logit." working paper, Department of Economics, UC Berkeley.

Train, Kenneth E. 2009. *Discrete choice methods with simulation*. Cambridge university press.

Tuchman, Anna E. 2019. "Advertising and Demand for Addictive Goods: The Effects of E-Cigarette Advertising." *Marketing Science* 38 (6): 994–1022.

U.S. Bureau of Labor Statistics. 2017. "Average Energy Prices, Philadelphia-Wilmington-Atlantic City – May 2017." News release.

U.S. Bureau of Labor Statistics. 2018. "Occupational Employment and Wages in Philadelphia-Camden-Wilmington – May 2017." News release.

Wang, Ao. 2021. "A BLP Demand Model of Product-Level Market Shares with Complementarity." The Warwick Economics Research Paper Series (TWERPS) 1351, University of Warwick.

Wang, Emily Yucai. 2015. "The impact of soda taxes on consumer welfare: implications of storability and taste heterogeneity." *The RAND Journal of Economics* 46 (2): 409–441.

Yazzie, Del, Kristen Tallis, Caleigh Curley, Priscilla R. Sanderson, Regina Eddie, Timothy K. Behrens et al. 2020. "The Navajo Nation Healthy Diné Nation Act: A Two Percent Tax on Foods of Minimal-to-No Nutritious Value, 2015–2019." *Preventing Chronic Disease* 17:200038.

Online Appendix

A1 SSB Sales in Stores 8+ Miles from Philadelphia

To assess the exclusion of stores beyond the 8-mile band surrounding Philadelphia, we examine SSB sales in stores within the 3-digit ZIP Code prefixes (080, 181, 189, 190, 191, 192 and 194) pertaining to Philadelphia and its surrounding region. Specifically, we estimate the impact of the SSB tax on SSB sales within Philadelphia, 0-8 miles from Philadelphia, and 8-10 miles from Philadelphia, respectively. In addition to the 218 stores in the "city + 8 miles" region referenced in Section 3.1, we also observe the sales of 25 stores 8-10 miles from the city, and 93 stores 10+ miles from the city which we use as the control group for this analysis. SSB sales are aggregated at the store-week level for estimation purposes.

Results in Table A1 provide evidence that stores 8-10 miles from the city border are not affected by cross-border shopping, as their SSB sales do not demonstrate a positive response to the Philadelphia SSB tax. The variable "Post-Tax × (8-10 miles from Philadelphia)" has a negative coefficient, inconsistent with what would be expected if the taxation induced cross-border shopping in this region. Seiler et al. (2021, p. 35) report a similar finding.

Table A1: Regression of SSB Volume Sales[a]

Dependent Variable: SSB Weekly Volume Sales (in Ounces)	
Post-Tax × Philadelphia	-51626.97***
	(1629.77)
Post-Tax × (0-8 miles from Philadelphia)	10256.10***
	(1643.79)
Post-Tax × (8-10 miles from Philadelphia)	-15138.82***
	(2612.22)
Store FEs	Y
Week FEs	Y
Observations	103,503
Weeks	209

***p<.01, **p<.05, *p<.1

[a]Robust standard errors are reported in parentheses. SSB sales are aggregated at the store-week level.

A2 Multiple Purchases During a Single Trip

During some observed purchase opportunities, households buy multiple units of the same product or choose to purchase multiple different products. However, in our retail data, information pertaining to individual-level purchase variety and amounts is unavailable—we only observe aggregate store sales. To make our model tractable under a discrete choice framework, and to reconcile with the retail data, a couple of assumptions are required. In the case where we observe multiple distinct product purchases during a single trip, we treat them as arising from multiple purchase opportunities. Furthermore, when focusing on household purchases, we follow the example of Tuchman (2019) and consider purchase incidence—whether at least one unit was purchased—instead of purchase quantity.

Current literature involving the purchase of multiple units or multiple products under the BLP framework considers bundling units of the same, or different, goods together as a sort of composite product (e.g., Wang (2021)). This approach would be computationally infeasible in our case given the large number of beverage products. As such, our rationalizations described above (1) simplify our estimation, (2) make the model tractable under the BLP framework, and (3) are simply following those innately made by researchers working solely with retail data (i.e., Berry et al. (1995), Nevo (2000), etc.).

A3 Estimation Procedure During the Retail Data Step

Provided a candidate draw of Θ, for each month $t = 1, \ldots, T$ we need to solve for $\delta_t = (\delta_{1t}, \ldots, \delta_{J_t t})'$ such that

$$s_{jt}(\delta_t; \Theta) = S_{jt}, \text{ for } j = 1, \ldots, J_t, \tag{A1}$$

where $s_{jt}(\cdot)$ are the predicted retail market shares from Eq. (9) and S_{jt} are the observed retail market shares. In solving this system of equations, we require two steps.

We start by calculating the left-hand side of (A1). In practice, we rely upon Monte Carlo integration where Equation (9) is approximated by

$$s_{jt}(\delta_t; \Theta) = \frac{1}{R} \sum_{r=1}^{R} \pi_{rjt}(x_t, p_t, h_t, Q_{z_r}, D_r, \delta_t, \Theta, v_r). \tag{A2}$$

Each simulated household $r = 1, \ldots, R$ is represented by Halton draws of v_r, z_r, and D_r from the distributions of v, z, and $D|z$, respectively. We draw $R = 4000$ simulated households to compute Eq. (A2).

Next, to obtain δ_t, we must invert our system of equations (A1). For the RCNL model, this system of equations is non-linear and is solved numerically. Grigolon and Verboven (2014) provides the contraction mapping algorithm for the random coefficients logit model with nesting parameters. In the case of a one-level nested model, the algorithm iteratively solves

$$\begin{aligned} &\delta_t^{k+1} \equiv \ \delta_t^k + (1-\rho)[\ln(S_t) - \ln(s_t(\delta_t^k;\Theta))],\ k = 1, 2, \ldots, \\ &\text{where } S_t = (S_{1t}, \ldots, S_{J_t t})' \text{ and } s_t = (s_{1t}, \ldots, s_{J_t t})', \end{aligned} \tag{A3}$$

until the relative difference between δ_t^{k+1} and δ_t^k is less than our tolerance of .5e^{-12}. Once the inversion has been completed for each $t = 1, \ldots, T$, a unique $\delta(\Theta)$ has been obtained, and we proceed to the evaluation of our household-level log-likelihood.

A4 Category Fixed Effects

Table A2 provides estimates for the category fixed effects not reported in the RCNL Demand Estimates table found in Section 6. The first column of Table A2 provides the variable of interest, followed by the mean utility and low-income interaction, respectively. The category pure water was dropped to avoid perfect collinearity.

Table A2: RCNL Demand Estimates - Category Fixed Effects[a]

	Mean Utility	**Low-Income Interaction**
Carb. Soft Dr.	0.42**	-0.18
	(0.11)	(0.18)
Coffee	-1.82***	-0.40
	(0.18)	(0.31)
Energy Dr.	-2.45***	1.26***
	(0.29)	(0.35)
Flav. Water	-1.45***	-0.25
	(0.17)	(0.27)
Juice	0.85***	-0.58***
	(0.11)	(0.20)
Sports Dr.	-1.73***	-0.34
	(0.23)	(0.22)
Tea	-0.22*	-0.72***
	(0.12)	(0.20)

***p<.01, **p<.05, *p<.1

[a]Robust standard errors are reported in parentheses.

Table A3: Pass-Through Rate of SSB Tax, by Category

	Dependent Variable: SSB Per-Ounce Price (in Cents)						
	Carb. Soft Dr.	Coffee	Energy Dr.	Flav. Water	Juice	Sports Dr.	Tea
Post-Tax × Philadelphia	1.221***	1.201***	1.590***	1.239***	1.173***	1.250***	1.091***
	(0.004)	(0.048)	(0.029)	(0.056)	(0.012)	(0.011)	(0.011)
Product Characteristics	Y	Y	Y	Y	Y	Y	Y
Store FEs	Y	Y	Y	Y	Y	Y	Y
Store FEs × Diet/Med./Large	Y	Y	Y	Y	Y	Y	Y
Week FEs	Y	Y	Y	Y	Y	Y	Y
Observations	2,150,691	142,320	550,246	162,800	844,697	268,785	777,840
Stores	229	229	229	229	229	229	229
Weeks	209	209	209	209	209	209	209
Products	114	25	38	27	87	23	63

***p<.01, **p<.05, *p<.1

There are 111 stores in Philadelphia and 118 in the region more than 8 miles from Philadelphia. The 209 weeks span the 4-year period from 2015 to 2018. In total, 377 products across seven categories are subject to the SSB tax if sold in Philadelphia. Prices are aggregated to the product-store-week level for estimation purposes. For the regression in each category, we also include store fixed effects and their interactions with the diet, medium, and large dummy variables, week fixed effects, and additional product characteristics including sugar and caloric content. Standard errors are reported in parentheses and clustered at the product-store-week level.

A5 Category-Level Pass-Through Rates

To estimate category-level pass-through rates, for each of the seven categories containing SSBs, we regress price observed at the product-store-week level on the interaction Post-Tax × Philadelphia as well as store fixed effects and their interactions with the diet, medium, and large dummy variables, week fixed effects, and additional product characteristics including sugar and caloric content. Table A3 presents our results.

A6 Changes in Sugar and Caloric Consumption for High- and Low-Income Households

Table A4 reports changes in sugar and caloric consumption from beverages for high- and low-income households by home location. We find that among Philadelphia households, high-income households on average consume less sugar and fewer calories and experience a greater percentage reduction in their consumption. The pattern is different for non-Philadelphia households, where high-income households on average consume less sugar and fewer calories but experience a smaller percentage reduction in their consumption. Differences in the outcomes in response to

Table A4: Average Sugar and Caloric Consumption from Beverages per Household, by Location and Income Status[a]

	Without Tax	With Tax	Difference	% Change
Philadelphia Households				
High-Income				
Sugar (g)	17,953	11,144	-6,809	-37.93%
Calories (cal)	73,062	46,096	-26,966	-36.91%
Low-Income				
Sugar (g)	20,118	13,152	-6,966	-34.63%
Calories (cal)	80,579	53,515	-27,064	-33.59%
Non-Philadelphia Households				
High-Income				
Sugar (g)	19,826	19,655	-171	-0.86%
Calories (cal)	82,488	81,908	-580	-0.70%
Low-Income				
Sugar (g)	23,167	22,458	-709	-3.06%
Calories (cal)	93,513	90,832	-2,681	-2.87%

[a] Aggregate amount over the post-taxation period January 2017 to December 2018.

the taxation are best explained by Table 12, where we observe that, in terms of the total volume of Philadelphia and non-Philadelphia SSBs consumed, low-income Philadelphia households are less responsive to the tax compared to their high-income counterparts, but the opposite is true for low-income non-Philadelphia households, who experience a larger volume reduction in SSB consumption—and therefore a larger reduction in sugar and caloric consumption—compared to their high-income counterparts.

A7 Additional Counterfactual Analyses

Here we report the results from three additional counterfactual analyses.

A7.1 No Taxation on Diet Products

We now analyze the counterfactual policy in which diet products are not subject to the SSB tax—as was originally proposed. The Philadelphia City Council has specified that their SSB taxation policy is first and foremost a revenue-generating scheme; generally, however, taxes imposed on sweetened beverages are designed to reduce consumption, as in the case of Berkeley, CA, Boulder, CO, and Seattle, WA, among others. Thus, except for Philadelphia, diet products are normally excluded from SSB taxation, being regarded as healthier alternatives to sugary products. We are therefore interested in how a policy under which diet products remain untaxed in Philadelphia would change households' consumption and welfare as well as the revenue-maximizing tax rate.

As before, we consider average sugar and caloric consumption from beverages per household during the 24 post-taxation months. We find that under the alternative policy, Philadelphia households would on average reduce their sugar intake by 40%, greater than the 36% reduction under the current policy. They would experience an average reduction of 29,358 calories—approximately 14.7 days' worth of caloric intake, a 9% increase compared to the 13.5 days under the current policy. These results show that from a public health perspective, leaving diet products untaxed is more beneficial by inducing a greater reduction in households' sugar and caloric consumption.

With respect to changes in consumer surplus, the alternative policy would leave households better off when compared to the current policy. Among Philadelphia households, we find an average consumer surplus loss of $80.95 and $80.09 for low- and high-income households, respectively, noticeably smaller than the $104.75 and $108.26 under the current policy (Table 13). Sugary beverages and their diet counterparts are good substitutes for some households, therefore when diet products are excluded from the tax, these households are able to switch from sugary beverages to their diet counterparts in order to avoid the tax, rather than having to travel for cross-border shopping or switch to less substitutable products, and thus households' average loss in consumer surplus is reduced.

In addition to lessening the loss in consumer surplus, the alternative policy also has an impact on the revenue-maximizing tax rate. The greater availability of untaxed substitutes in the form of diet products leads to households' higher price sensitivity with respect to sugary beverages, and we find that the revenue-maximizing tax rate falls from 3.14¢ per ounce under the current policy to 2.33¢ per ounce under the alternative policy. The tax revenue generated under the respective revenue-maximizing tax rate falls from $32.5 million to $24.6 million.

We note that our revenue-maximizing tax rate of 2.33¢ per ounce under the alternative policy is similar to the 2¢-per-ounce SSB tax rate in Boulder, CO, where the SSB tax includes only those products with added sugar, thus excluding diet products. Our revenue-maximizing tax rate falls slightly above the range of optimal tax rates found by Allcott et al. (2019), who study a national tax imposed on sugar-sweetened beverages only and determine an optimal tax rate between 1¢ and 2.1¢ per ounce. Different from our setting, their optimal tax rate is derived from a model interested in government redistribution of wealth.

A7.2 Both Locations Taxed

Next, we turn to our counterfactual analysis regarding the changes in SSB consumption and consumer surplus if the tax is levied upon both Philadelphia and its surrounding region. This counterfactual scenario can be interpreted as a national or multi-state SSB taxation policy (the region surrounding Philadelphia includes elements of both the state of Pennsylvania and the state of New Jersey), which removes Philadelphia households' ability to avoid taxation by cross-border shopping in the surrounding region. To create our counterfactual, for each beverage option sold in the non-Philadelphia location, we calculate the tax amount based on the tax rate, adjust the price accordingly based on the relevant pass-through rate, and set the variable "tax saving" to zero.

Results pertaining to the effects of this alternative tax coverage on households' beverage consumption are presented in Table A5. We observe that, given the widened tax coverage, non-Philadelphia households now experience a reduction in SSB consumption similar to those living in Philadelphia. Interestingly yet intuitively, Philadelphia households' consumption of Philadelphia SSBs becomes less responsive to the levying of an SSB tax: they reduce their consumption of Philadelphia SSBs by 3,553 ounces when both locations are taxed, compared to 3,791 ounces (Table 8) when the tax covers Philadelphia only. This result is primarily driven by Philadelphia households who have strong preference for SSBs: when the widened tax coverage removes their ability to avoid taxation through cross-border shopping, they instead continue to purchase SSBs in their home location, willing to pay the higher prices. Additionally, Philadelphia households' purchase of non-Philadelphia SSBs decreases by 496 ounces, compared to an increase of 474 ounces when the tax covers Philadelphia only.

The removal of households' ability to exploit the geographic nature of local taxation policies has a direct impact on households' loss of consumer surplus. Under the widened tax coverage, the loss in consumer surplus for low- and high-income Philadelphia households is $128.35 and $123.93, respectively, representing an increase of 23% and 14% when compared to the current tax coverage (Table 13). With cross-border shopping no longer a viable strategy for tax avoidance, a lower disutility from travel time no longer benefits low-income Philadelphia households as much, and their loss of consumer surplus is now greater than their high-income counterparts'. Finally, among non-Philadelphia households, we find a loss of consumer surplus in the amount of $149.20 for low-income households and $141.38 for high-income households when both locations are taxed.

Table A5: Average Beverage Consumption per Household: Both Locations Taxed[a]

SSB Status × Bev. Location	Without Tax	With Tax	Difference	% Change
All Households				
Philadelphia Bev. Options				
Non-SSB	2,158	2,486	+328	15.17%
SSB	4,027	2,012	-2,015	-50.04%
Non-Philadelphia Bev. Options				
Non-SSB	3,332	3,881	+549	16.49%
SSB	4,600	2,286	-2,314	-50.30%
Philadelphia Households				
Philadelphia Bev. Options				
Non-SSB	3,827	4,404	+577	15.09%
SSB	7,097	3,544	-3,553	-50.06%
Non-Philadelphia Bev. Options				
Non-SSB	770	887	+117	15.29%
SSB	1,009	513	-496	-49.20%
Non-Philadelphia Households				
Philadelphia Bev. Options				
Non-SSB	521	603	+82	15.70%
SSB	1,012	507	-505	-49.88%
Non-Philadelphia Bev. Options				
Non-SSB	5,846	6,819	+973	16.64%
SSB	8,124	4,027	-4,097	-50.44%

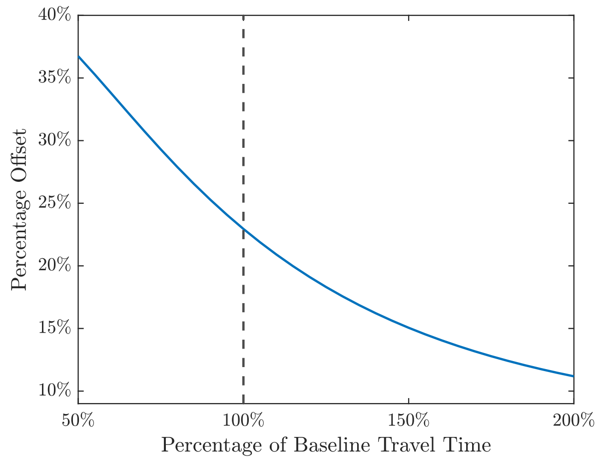
[a] In ounces; aggregate amount over the post-taxation period January 2017 to December 2018.

A7.3 Travel Time Changes

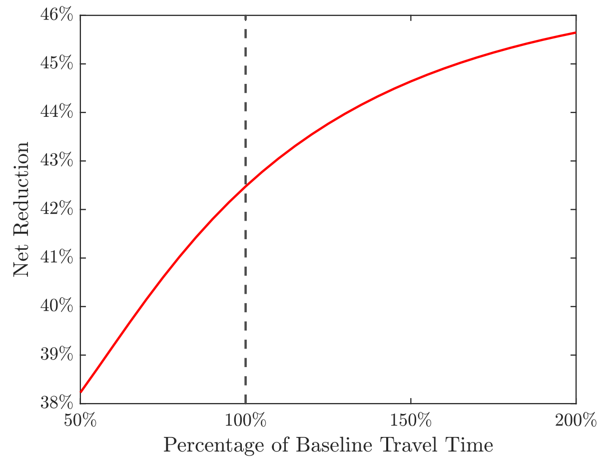
We now consider how changes in travel time affect both the willingness to cross-border shop and expected consumer surplus under the current taxation policy. This counterfactual provides an analysis of the effects of increased ease of transportation, for example due to improved roads, reduced traffic, better traffic control, etc. We calculate households' consumption of beverages while proportionally varying the travel time experienced by all households. Our findings are shown in Figure A1, with travel time being varied from 50% to 200% of the baseline. The figure presents the percentage of the decrease in Philadelphia SSB consumption that is offset by an increase in non-Philadelphia SSB consumption, the net reduction in SSB consumption—after accounting for the offset—as a percentage of Philadelphia SSB consumption in the no-tax scenario, and the expected loss of consumer surplus for Philadelphia households.

Travel time plays a large role in determining the degree to which households cross-border shop. When travel time is halved, we find that 37% of the reduction in Philadelphia SSB consumption due to taxation is offset by an increase in non-Philadelphia SSB consumption. However,

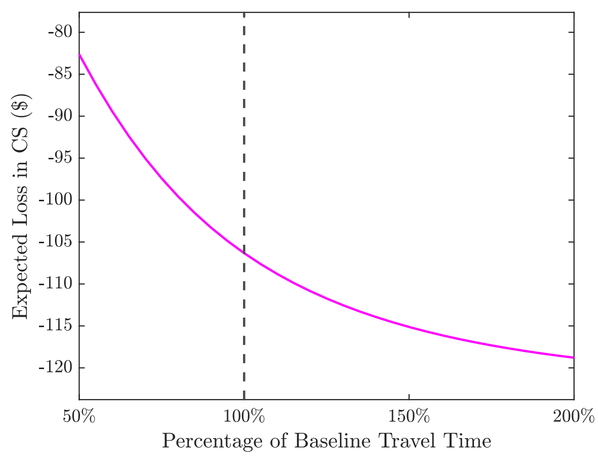
Figure A1: SSB Consumption and Consumer Surplus: Changes in Travel Time



(a) Percentage of Phil. SSB Reduction Offset



(b) Net Reduction in SSB Consumption



(c) Phil. Household Expected Loss in CS

Notes: The percentage of Philadelphia SSB reduction offset (Panel a) measures the percentage of the decrease in Philadelphia SSB consumption that is offset by an increase in non-Philadelphia SSB consumption. The net reduction in SSB consumption (Panel b) measures the net reduction—after accounting for the offset—as a percentage of Philadelphia SSB consumption in the no-tax scenario.

when travel time is doubled, only 11% of the reduction is offset. As such, travel time ties directly into the net effect of SSB taxation on the consumption of taxed products. When travel time is halved, the net reduction in SSB consumption equals 38% of Philadelphia SSB consumption in the no-tax scenario. In comparison, when travel time is doubled, we find a net reduction of 46%. At this point, few Philadelphia households engage in cross-border shopping; instead, much of the rise in non-Philadelphia SSB consumption is driven by non-Philadelphia households, for whom purchasing in the non-Philadelphia location does not involve travel costs.

Our findings provide supporting evidence towards the effectiveness, or lack thereof, of SSB taxation policies in regions of differing sizes. For instance, Cawley and Frisvold (2015) suggest that one possible reason the SSB tax pass-through rate found in Berkeley is so low compared to other localities is consumers' ability to evade city-level taxes through cross-border shopping. Berkeley's land area is only 10.4 square miles (compared to Philadelphia's 134 square miles), and the authors note that the average US consumer travels 5.2 miles when shopping for groceries. As such, we would expect Berkeley residents to act similarly to Philadelphia households residing minutes from the city border. Comparatively, residents of large cities may experience longer travel time when seeking to cross-border shop and therefore, as our findings suggest, their rate of tax avoidance by cross-border shopping may be significantly smaller.

Finally, travel time and the ease of cross-border shopping have a direct impact on the loss in consumer surplus resulting from SSB taxation. We focus on Philadelphia households' expected change in consumer surplus, as they reside in the taxed region and experience the greatest change in utility resulting from a change in the ease of travel. As expected, a lower travel time directly implies a smaller loss of consumer surplus associated with SSB taxation, as increased ease of travel allows for greater tax avoidance behavior. When travel time is increased from 50% to 200% of the baseline, an average Philadelphia household's expected loss in consumer surplus increases by 43.8% from \$82.6 to \$118.8, compared to \$106.3 at the baseline. While an increase in the ease of travel is beneficial for consumers, from the perspective of the Philadelphia government, providing for methods by which households can more easily access the untaxed region is contrary to the stated revenue-maximizing intentions of its SSB taxation.