Research Group on Human Capital
Working Paper Series

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Working Paper No. 22-01

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March 2022

Groupe de recherche sur le
CAPITAL HUMAIN
ESG UQÀM

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Estimating consumer preferences for different beverages using the BLP approach

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Abstract

The overconsumption of sugar is a significant problem in many jurisdictions, and one possible method to remedy this problem is the taxation of sugar-sweetened beverages (SSBs). To be able to implement an optimal tax, it is important to know the preferences and price sensitivity of consumers. This article therefore estimates the price elasticity of demand for different beverages in Quebec, using the Berry, Levinsohn and Pakes (BLP) random parameter logistic demand model, combined with Nielsen data from 2010 to 2016 and the 2016 Canadian Census. The results suggest that the average consumer prefers high-calorie beverages containing fruits and vegetables, and the estimated price elasticities are between -4.40 (energy drinks) and -1.59 (regular soft drinks). As a result, consumers of energy drinks appear to reduce their consumption the most in the face of rising prices, whereas consumers of soft drinks will decrease their consumption the least. However, at a general level, the implementation of a tax on SSBs in Quebec should generate a significant reduction in consumption.

Keywords: sugar-sweetened beverages, price elasticity of demand, BLP, taxation
JEL codes: I12, I18, D12, H23

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1. Introduction

Overweight problems represent a heavy burden on society. According to the OECD, one in four people is obese, and 56% of the population is overweight (OECD, 2019a). At the national level, obesity is associated with a loss of gross domestic product of 3.3% (OECD, 2019b). One intervention being considered to reduce obesity is the reduction of sugar consumption. Indeed, a large proportion of the population consumes excessive amounts of sugar, and a large part of this overconsumption comes from the consumption of sugar-sweetened beverages (SSBs).

To combat over-consumption of sugar, one possible policy intervention that could be used is the taxation of sugar-sweetened beverages (SSBs). Taxation can facilitate the reduction of sugar consumption by targeting sugary drinks. Nine American cities and more than forty countries have already implemented a tax on SSBs (Global Food Research Program (GFRP), 2020).[1] However, in order to have an idea of the magnitude and design of an optimal tax on SSBs, we first need to have valid estimates of the own-price and cross-price elasticities of SSBs and other types of beverages. The majority of the literature only estimates own-price elasticity across SSBs, without differentiating the effects between different types of SSBs or documenting the cross-price elasticities with other beverage options.[2] However, there are potentially differences in elasticities between different drinks and substitution between different beverages, which would influence the choice of an optimal form of taxation.

This article estimates the own-price and cross-price elasticities of demand for different beverages using scanner data on food purchases made in department stores and grocery chains in the province of Quebec, Canada's second largest province. Purchases made in these stores represent around 86% of all food purchases[3] from 2010 to 2016. We also combine these data

[1] Appendix A contains a table summarizing the levels of taxation of sugar-sweetened beverages observed in different countries around the world, as well as the dates of implementation of these taxes.

[2] Allcott et al. (2019a) jointly estimates the own-price elasticity of SSBs, and also the cross-price elasticities of SSBs with other sin food categories. Drinks are grouped into three categories: SSBs, diet drinks and fruit juices, while other healthier choices are not included.

[3] We use data from Statistics Canada: Table 20-10-0008-02, Retail trade sales by industry (x 1,000).

with socioeconomic data from the 2016 Canadian Census. Our combined data sets allow us to estimate a simple linear demand model, as well as our main specification: a random parameter logistic demand model (BLP) proposed by Berry, Levinsohn and Pakes (Berry et al., 1995), on the purchase shares of 11 categories of beverages. The BLP model allows us to obtain the own-price and cross-price elasticities for each category of beverages, while controlling for the endogeneity of prices and heterogeneous tastes of the consumers for beverage characteristics. While price sensitivity is likely to vary between individual countries and across different socioeconomic and cultural groups within a jurisdiction, we believe our analysis highlights two important and general features that should be accounted for when designing a sugar-sweetened beverage tax. First, our results show that linear models typically used in many published articles are not appropriate and fail to account for the endogeneity of prices. Second, our results clearly highlight that the price elasticity varies across beverage types and that consumers substitute across types within SSBs. The design of taxation therefore needs to take this reality into account to help reduce sugar consumption.

Our results also suggest that consumers of energy drinks react more strongly to a change in price, while consumers of soft drinks react the least to a change in price. The price elasticity of demand for energy drinks is -4.40, compared to -1.59 and -1.72 for regular and diet soft drinks. The demand for some other sugar-sweetened beverages such as flavoured milks and soy drinks is strongly affected by a price variation, with elasticities of about -3.50 for these drinks. Our results also show that the average consumer prefers a high-calorie beverage containing fruits or vegetables. Finally, our results suggest that lower-income households are more sensitive to a price change. Since they consume a larger share of SSBs, they are therefore likely to see their overall consumption fall more in both absolute and proportional terms.

This article is divided into six sections. Section 2 provides a review of empirical studies dealing with the impact of sugar consumption on health and the effects of taxation and the price of sugar-sweetened beverages on consumption. Section 3 describes the data used in this article, while the empirical methodology is described in section 4 and the results are presented in section 5. Finally, a conclusion is provided in section 6.

2. Background

In this section, we first present a brief overview of the literature on the association between sugar consumption and health. We then present the literature that estimates the price elasticities of SSBs and the impact of the taxation of SSBs on consumption, as well as a discussion of the heterogeneity of preferences across consumers.

2.1. Association between sugar consumption and health

The link between consumption of SSBs[4] and health problems has been shown in many studies, including but not limited to, type 2 diabetes (Imamura et al., 2015; Malik et al., 2010), heart problems (Xi et al., 2015), metabolic syndrome (Malik et al., 2010), overweight (Pan and Hu, 2011), and tooth decay (Bernabé et al., 2014). These problems generate important medical costs and influence overall productivity (OECD, 2019b). In countries where medical assistance is universally covered, the associated medical costs of SSBs are not only paid by the consumer, but shared among all taxpayers. Given the mounting evidence against SSBs, it appears important to educate the population on the health risks surrounding the consumption of these drinks and limit their consumption.

2.2. Estimates of price elasticities

A meta-analysis on estimates of own-price elasticities of demand for SSBs in a number of American cities, Mexico, Chile, and Barbados finds that they vary greatly from one place to another, ranging between -0.35 and -9.95 for a weighted average of -1.36 (Pan American Health Organization (PAHO), 2020). Two American literature reviews find slightly lower average estimates: Powell et al. (2013) finds -1.21 (with a range of -3.87 to -0.71) and Andreyeva et al. (2010) finds -0.79 (with a range of -1.24 to -0.33). A number of recent studies have estimated own-price elasticities of demand for SSBs using the Almost Ideal Demand System and find elasticities of -1.06

[4]The US Centers for Disease Control and Prevention (Centers for Disease Control and Prevention, 2021) define SSBs as including "regular soda (not sugar-free), fruit drinks, sports drinks, energy drinks, sweetened waters, and coffee and tea beverages with added sugars". The Institut national de santé publique du Québec (Durette et al., 2017), meanwhile, provides an alternative definition of "sweetened drinks" (*boissons sucrées*) that additionally includes artificially-sweetened drinks such as diet soft drinks. As a general rule of thumb, the definition of the CDC seems to prevail in the literature cited.

to -1.37 for a few Latin American countries (Colchero et al., 2015; Guerrero-López et al., 2017; Paraje, 2016). Finally, a recent study using US data at the consumer level estimates a price elasticity of -1.37 jointly for all SSBs using an instrumental variable approach (Allcott et al., 2019a). Together, theses findings suggest that price sensitivity varies from one region to another. These differences across jurisdictions possibly represent different preferences for SSBs, but also differences in access to other beverage options and the use of different estimation methods.

While the BLP method is more advantageous because it uses a flexible demand system and considers the heterogeneous preferences of consumers as well as the endogeneity of prices, few studies use the BLP method. To our knowledge, only two studies, using French and American data respectively, exploit the BLP approach but focus on differentiation across brands rather than types of drinks: Bonnet and Réquillart (2013) estimate a price elasticity of -3.46 for SSBs, whereas Lopez and Fantuzzi (2012) find elasticities for individual drinks that range from -3 to -10, but with an overall elasticity of -0.58 for caloric drinks and -0.42 for diet drinks.

2.3. SSB taxation

The literature on SSB taxation also provides evidence of sensitivity of consumers to price variations. A number of studies have shown that taxation of SSBs has led to a reduction in the consumption of SSBs in favour of less sugary drinks (Falbe et al., 2016; Colchero et al., 2016; Berardi et al., 2016). However, the magnitude of the decrease varies greatly from place to place. The taxation of SSBs has reduced sales by 21 to 38% in places such as Philadelphia (Roberto et al., 2019), Seattle (Powell and Leider, 2020), and in Cook County, Illinois (Powell et al., 2020). On the other hand, several other cities and countries saw a much smaller decrease in sales of SSBs after the implementation of a tax, ranging from 0 to 9% (Colchero et al., 2016, 2017; Alvarado et al., 2019; Nakamura et al., 2018; Silver et al., 2017; Cawley et al., 2020).

This literature also shows that to optimize the impact of the tax, it is preferable for it to cover a large geographical area to avoid a transfer of purchases outside the area covered by the tax (Bollinger and Sexton, 2018; Seiler et al., 2021). Also, the positive impact is greater when the tax is applied on the amount of sugar contained in a drink (Bonnet and Réquillart, 2013; Allcott et al., 2019b), rather than on the amount of liquid. When designed in this way, the level of taxation is more strongly related to the harmful factor of the drink, i.e. sugar, and the effect on consumption is more directly proportional to the amount of sugar consumed. This allows for a better transition towards pure fruit juices (Sharma et al., 2014), diet soft drinks (Allcott et al., 2019a), and even bottled water (Colchero et al., 2016), while also encouraging a downward adjustment by the beverage industry in the amount of sugar contained in drinks.

2.4. Heterogeneous preferences

Finally, heterogeneous preferences have been documented for SSBs. For example, in the United States, people with low incomes ($10,000 or less) consume twice as much of SSBs as those with incomes above $100,000 (Allcott et al., 2019a). While individual preferences for SSBs differ by income, these preferences do not seem to be driven by income per se (Allcott et al., 2019a). Thus, the observed differences in SSB consumption are attributable to differences in preferences (or knowledge), and implementing a tax could help to redress this in a progressive way. Allcott et al. (2019a) finds that improving consumers' nutritional knowledge and self-control could decrease Americans' consumption of SSBs by 31% to 37%. Other studies have also found that the effects of an SSB tax tend to be greater for people with low income: their consumption appears to decrease by around 20% with the introduction of a tax of only 1 cent (± 0.3) per ounce (Colchero et al., 2016; Falbe et al., 2016). Allcott et al. (2019a) provide additional evidence on the differential impact of SSBs taxation across the income distribution. Given these findings, in our analysis, we assess the variation in price sensitivity between low- and high-income households.

3. Description of the data

3.1. Data sources

To estimate the price elasticity of demand for various categories of beverages, we use data from Nielsen as well as micro data from the 2016 Canadian Census.

Our Nielsen data covers food and drink purchases made in the three largest grocery chains and in big box stores in Quebec, Canada's second largest province. Convenience store sales are therefore not included, which represents a limitation of our data which we will discuss later.[5] Purchases made in stores included in Nielsen represent around 86% of all food purchases[6] from 2010 to 2016. We have annual data, aggregated at the store level, covering the period from 2010 to 2016. The location of each store in the Nielsen database can be determined using its forward sortation area (FSA), a geographic area representing a neighbourhood, municipality, or region. The FSA corresponds to the first three characters of a Canadian postal code, and there are over 1,600 FSAs in Canada, for an average of 23,000 individuals per FSA. The number of stores present in our data each year varies from 592 in 2010-11 to 854 in 2015-16; this variation is explained by the expansion of Nielsen's coverage area and by the opening and closing of certain stores.

We have combined the Nielsen data with micro data from the 2016 Canadian Census, specifically the data from the long-form Census questionnaire. About 20% of the Canadian population was randomly selected to complete the long-form questionnaire, and the response rate for Quebec in 2016 was 97.6%. The Census therefore constitutes a large sample of the Canadian population, which makes it possible to calculate statistics representative of small geographic areas such as FSAs. The long-form census contains a wide variety of socio-economic information, which we discuss below.

3.2. Variables

The Nielsen data contains the aggregate annual sales for a very wide variety of products for each participating store. For beverages, we have the

[5] This limitation is, however, not unusual in the literature that estimate demand systems for various products; see, for example, the samples of stores from certain categories in Weinberg and Hosken (2013), or one of the classic early applications of the BLP method, Nevo (2001), who uses data on cereal sales in a random sample of supermarkets.

[6] We use data from Statistics Canada: Table 20-10-0008-02, Retail trade sales by industry (x 1,000).

total annual sales amount in constant 2021 dollars, and the total number of kilograms these sales represent. The value of purchases was calculated from the total sum of purchases, in kilograms or dollars, made in big box stores and supermarkets. To simplify the analysis, the values in kilograms were converted to litres using the conversion factor provided by Nielsen (1.0022407 kilogram is equivalent to 1 litre). Frozen drinks were adjusted by quadrupling their weight before being converted to litres. Powdered drinks were removed from the sample due to the large variation in the amounts of powder and liquid needed to reconstitute these drinks.

As can be seen in Table 1, regular and diet soft drinks are the cheapest beverage options ($1.04 and $1.00 per litre respectively) just after still bottled water ($0.45 per litre). Soft drinks are also among the most purchased drinks (25.5%) between still water (21.3%) and milk (27.5%). Energy drinks are by far the most expensive ($7.45 per litre), but their share of sales (0.28%) is certainly not representative of total consumption since this type of drink is more often bought in convenience stores rather than supermarkets. Fruit drinks and fruit juices are similarly priced ($1.92 and $1.94 per litre respectively), but fruit juices are much more popular (15.3% of sales versus 2.7% for fruit drinks). As for soy and other milks and flavoured milks, they are among the most expensive drinks ($2.54 and $2.51 per litre) and the least popular (1.72% and 1.30% of sales).

We have also added data on some additional beverage characteristics to the Nielsen data. For each category of beverage, the following characteristics were added: the number of calories, the sugar and sodium content, the percentage of the recommended daily value of calcium and vitamin A, and a binary variable indicating the presence of fruit or vegetables in the drink. Each characteristic added represents an average of the Nutrition Facts label of the most popular drinks or comes from Statistics Canada. Table 2 represents a summary of the characteristics of our categories of drinks.

From the micro Census data, we use household information such as visible minority status, the presence of children, and household total income. We also use one variable measured at the individual level, namely education. Finally, the average is calculated by FSA for each of the characteristics. For example, the income variable represents the percentage of low-income households in an FSA. The education variable represents the percentage of people who did not obtain a high school diploma or an equivalency diploma in an FSA. The Census data was then merged with Nielsen data at the level of each FSA.

Table 1: Summary statistics of Nielsen data

Drinks	Average price (cents/L)	Average volume sold (L)	Sales share
Soft drinks	104.15 (8.03)	245,324 (154,785)	17.50%
Diet soft drinks	100.07 (6.67)	112,204 (59,522)	8.00%
Energy drinks	744.57 (63.39)	3,908 (1,806)	0.28%
Fruit beverages	191.89 (26.70)	37,904 (26,098)	2.70%
Flavored milk	251.41 (28.80)	18,161 (9,362)	1.30%
Soy and other	254.47 (10.30)	24,141 (18,700)	1.72%
Real juices	194.01 (12.45)	214,264 (102,762)	15.28%
Vegetable juices	223.82 (16.42)	31,178 (14,291)	2.22%
Milk	203.83 (8.54)	386,237 (142,828)	27.55%
Flat water	44.68 (1.29)	299,117 (207,268)	21.33%
Carbonated water	166.99 (17.34)	29,651 (16,704)	2.11%

Note: () = Standard deviation.
Source: Authors' calculations based on Nielsen data.

Table 3 provides summary statistics on our Census variables, showing that 6.4% of households in our reference population have a low income, 13.9% associate themselves with a visible minority, 35.8% have children at home, and 35.6% of the individuals in our reference population have less than a high school diploma.

For the BLP estimation, we need to have a sample of randomly drawn individuals from each market (which is an FSA in a year), but we accessed the confidential Census data in a QICSS (Quebec Interuniversity Center for Social Statistics) data laboratory, from which it is illegal to export individual observations. Therefore, we exported the means and a correlation matrix for each FSA, which is sufficient to characterize the joint distribution of our four binary household characteristics. We then used the user-written Stata command `rbinary` to simulate 100 random observations for our correlated binary variables for each market.

Table 2: Characteristics of beverages added to Nielsen data

Per litre	Sugar (g)	Calories	Calcium (%)	Vitamin A (%)	Sodium (mg)	Contain fruits or vegetables
Soft drinks	112	440	2.8	0	76	No
Diet soft drinks	0	0	3.6	0	0.4	No
Energy drinks	104	468	0	0	0.4	No
Fruit beverages	108	420	0	0	96	No
Flavored milk	100	640	100	60	720	No
Soya and others	36	400	108	32	200	No
Real juices	124	508	28	2.4	20	Yes
Vegetable juices	34	200	12	200	1452	Yes
Milk	44	520	120	60	440	No
Carbonated water	0	0	0.4	0	28	No

Note: The first 5 columns represent information calculated by the authors from Nutrition Facts labels of the most popular drinks in each category or from Statistics Canada; the sources of these data are available upon request.

Table 3: Summary statistics on characteristics of Quebec households

Household caracteristics	Mean	SD
Low income	0.06	0.05
Less than high school diploma	0.36	0.07
Kids at home	0.36	0.10
Visible minority	0.14	0.14

Note: Each variable is binary; low-income status represents a household income below the low-income cut-off (LICO-AT).
Source: Authors' calculations using microdata from the 2016 Canadian Census.

4. Methodology

The objective of this article is to estimate the price elasticity of demand for each beverage and the cross-price elasticities. First of all, it is important to specify a demand function for beverages that will allow us to measure the consumer's reaction to a price change. In addition, the demand for SSBs is part of the demand for beverages in a broad sense, which means that it is an integral part of a system of equations which depend on the price and the heterogeneous preferences of consumers for these different drinks. With aggregated data (like our Nielsen data) and a discrete choice of products (a limited number of purchase options in a category), the best method available in the literature on the economics of industrial organization is the Berry-Levinsohn-Pakes (BLP) method. To explain how the BLP estimator works, and how it allows us to obtain the price elasticity of demand we are looking for, we have separated this section into two subsections. First, we present a linear model which will make it possible to calculate preliminary estimates and to validate the results of the BLP model. Second, we define the BLP model.

4.1. Linear model

In this subsection, we present the linear model. The Nielsen data provides us with the volumes and selling prices of various beverages sold in stores. By taking the logarithm of these variables and performing a simple regression, it is possible to estimate a linear model and obtain what could be perceived as price elasticities of demand for various drinks. In reality, the linear model will not provide us with an exact estimate of the price elasticities, because the price is an endogenous result of the equilibrium in the market, and because of the potential for division bias if the volume is measured with an error (due to the existence of other stores outside of our sample, for example). To estimate the price elasticity of demand, we need to distinguish the demand from the supply equation, which cannot be achieved with a simple linear model. We need a more structured approach such as the BLP model which corrects for both limitations using instrumental variables. Nonetheless, since other papers use the linear approach, to benchmark our results and show the large differences between estimates from a linear model and a BLP model, we start by estimating the following linear model:

$$v_{tb} = c + (p_{tb} \times D_b)X_1 + educ_t X_2 + child_t X_3 + minority_t X_4 + income_t X_5 + \epsilon_t, \quad (1)$$

where v represents the logarithm of the total volume of sales in litres, c is the constant, p is the logarithm of the price per litre sold (adjusted for inflation), D is a binary variable for each type of beverage b, *educ* represents the ratio of the population not having completed a high school diploma or equivalency, *child* represents the ratio of households with children of all ages, *minority* represents the ratio of visible minority households, and *income* represents the ratio of low income households, all calculated for market t (which is an FSA in a given year).

$p_{tb} \times D_b$ represents an interaction between the price and the binary variable identifying the beverage. This allows individual price elasticities to be obtained for each category of beverages, instead of just an overall price elasticity.

4.2. The BLP model of demand

In this subsection, we will specify a model of the demand for beverages. Our presentation closely follows that of Nevo (2001). To begin, suppose that we observe $t = 1, ..., T$ markets each having $i = 1, ..., I_t$ consumers who buy $j = 0, 1, ..., J_t$ products (in this case, different drinks). The definition of the market usually depends on the data. Here, we have annual data aggregated at the store level, but we further aggregate the data at the level of an FSA in order to obtain a larger sector in which there may be more than one store. Thus, a market is an FSA, representing a neighbourhood, municipality, or region, for a given year.

The indirect utility of consumer i for a beverage j in a market t is given by:

$$u_{ijt} = x_j \beta_i - \alpha_i p_{jt} + \xi_j + \Delta\xi_{jt} + \epsilon_{ijt}, \quad (2)$$

where x_j is a vector of dimension K of observable characteristics of a product, p_{jt} is the price of product j in market t, ξ_j is the provincial mean of the unobservable characteristics of a product, $\Delta\xi_{jt}$ is the FSA-specific deviation from the mean, and ϵ_{ijt} is the error term which has zero mean. Product $j = 0$ is the "outside good" or base category for which utility is normalized to $u_{i0t} = \epsilon_{i0t}$.

In our case, the observable characteristics are the variables specifying the composition of a beverage, for example the amount of sugar, the number of calories, the presence of vitamin A, etc. The unobservable characteristics are consumer preferences for certain types of drinks at a given price.

The distribution of consumer taste parameters is modelled to follow a multivariate normal distribution with a conditional mean depending on demographic variables and estimated parameters. This is represented by:

$$\begin{bmatrix}\alpha_i \\ \beta_i\end{bmatrix} = \begin{bmatrix}\alpha \\ \beta\end{bmatrix} + \Pi D_i + \Sigma v_i, \qquad v_i \sim N(0, I_{K+1}), \tag{3}$$

where K is the length of the vector of observable characteristics, Π is a $(K+1) \times d$ matrix of coefficients which measure the changes in taste according to the d socio-demographic characteristics, D_i is a $d \times 1$ vector of socio-demographic variables, $\sum$ is a matrix in row echelon form, and v_i are additional unobservable characteristics. This specification allows consumer characteristics to include "observable" demographic characteristics (D_i) and additional "unobservable" characteristics (v_i).

By combining equations (2) and (3), it is possible to obtain the following equation for indirect utility:

$$u_{ijt} = \delta_{jt}(x_j, p_{jt}, \xi_j, \Delta\xi_{jt}; \theta_1) + \mu_{ijt}(x_j, p_{jt}, v_i, D_i; \theta_2) + \epsilon_{ijt} \tag{4}$$

where $\delta_{jt} = x_j\beta - \alpha p_{jt} + \xi_j + \Delta\xi_{jt}$ represents the average utility and $\mu_{ijt} + \epsilon_{ijt} = [-p_{jt}, x_j]' \cdot (\Pi D_i + \Sigma v_i) + \epsilon_{ijt}$ captures the effects of random coefficients. The vector $\theta_1 = (\alpha, \beta)$ contains the linear parameters, while the vector $\theta_2 = (vec(\Pi), vec(\Sigma))$ contains the nonlinear parameters.

We assume that a consumer will buy a unit of the product that allows them to obtain the highest possible utility. This implies that a set of unobserved variables influence the choice of a product j in a market t. The set of consumers that buy product j in market t can be written as:

$$A_{jt}(x_{.t}, p_{.t}, \xi_{.t}; \theta) = \{(D_i, v_i, \epsilon_{.t}) | u_{ijt} \geq u_{imt} \quad \forall \quad m = 0, 1, ..., J\}$$

where $x_{.t}$ is the matrix of observed characteristics of all beverages, $\xi_{.t}$ is a $J \times 1$ vector of unobserved characteristics of beverages, $p_{.t}$ is a $J \times 1$ vector of beverage prices, and θ is a vector that includes all the parameters of the model.

This allows us to write the market share of drink j based on the average utility levels of all $J + 1$ drinks, which gives us an integral over the mass of consumers in the region A_{jt}:

$$s_{jt}(x, p_t, \delta_t; \theta_2) = \int_{A_{jt}} dP^*(D, v, \epsilon) = \int_{A_{jt}} dP^*_{\epsilon}(\epsilon) dP^*_{v}(v) dP^*_{D}(D) \tag{5}$$

where P^* represents the population distribution function. The second equality is a consequence of the assumption of independence of D, v and ϵ. Even if only aggregate market share data is observed, the model can be estimated by choosing parameters that minimize the distance between the predicted shares from equation (5) and the observed shares. However, the equation above allows us to estimate the demand for only one type of beverage. This is why we use the BLP model since it nests several such models and it allows flexible estimation of own-price and cross-price elasticities.

The own-price and cross-price elasticities of beverage sales are obtained from:

$$e_{jkt} = \begin{cases} -\frac{p_{jt}}{s_{jt}} \int \alpha_i Pr_{ijt}(1 - Pr_{ijt}) dF(D_i, v_i) & \text{if } j = k \\ \frac{p_{kt}}{s_{jt}} \int \alpha_i Pr_{ijt} Pr_{ikt} dF(D_i, v_i) & \text{if } j \neq k \end{cases} \tag{6}$$

The integrals are approximated by Monte Carlo simulations.

For the creation of the instruments for prices, we follow the work of Hausman (1996) and Nevo (2000a,b, 2001). We create three categories of instruments: first, we add a dummy variable for each category of beverage. Second, we use the regional annual average price (excluding the FSA instrumented) of each beverage category for each of the six years contained in the data. Third, we create two more instrument groups following the recommendation of Dubé et al. (2012): we square each average price instrument, and also add interactions between them and the beverage categories.

Finally, we can estimate the demand equations using the BLP estimator. This nested fixed point algorithm consists of two loops. An internal loop maps the contractions of the market to determine the consumer's utility, and an external loop estimates a non-linear GMM specification making it possible to obtain the matrix of own-price and cross-price elasticities.

5. Results

This section is divided into two parts. First, we calculate preliminary estimates using a linear model. Second, we present results based on the BLP model.

5.1. Linear model

This subsection contains the estimates of the linear model, where the dependent variable is the logarithm of the quantity sold (in litres) and the principal explanatory variable is the logarithm of the price per litre for a given beverage. In order to clearly distinguish the link between the price and the quantity sold of each beverage, we interact the logarithm of the price with a binary variable identifying beverage type. This approach allows us to obtain an approximation of the price elasticity of demand for each beverage category.

In Table 4, columns (1) to (3) only include drinks whose consumption should be limited according to the Institut national de santé publique du Québec. In columns (4) to (6), we also include all other categories of beverages. Columns (1) and (4) do not include any control variables, while columns (2) and (5) include socioeconomic variables calculated at the FSA level: the percentage of people without a high school diploma or equivalency, the percentage of households where there is at least one child, the percentage of people from visible minorities, and finally the percentage of households with low income. Finally, columns (3) and (6) also include FSA fixed-effects.

The results presented in column (1) of Table 4 suggest that the price elasticity of demand varies from -3.00 for diet soft drinks to -2.59 for energy drinks. Thus, at first glance, consumers of diet soft drinks seem more sensitive to a price variation than consumers of energy drinks. In addition, the demand for diet soft drinks appears to be more elastic than the demand for regular soft drinks. The results imply that if the price of diet soft drinks increased by 1 percent, the quantity sold would decrease by 3 percent, while if the price of regular soft drinks increased by 1 percent, the quantity sold would decrease by 2.8 percent. The difference is small, but significant: with a confidence level of 99%, we easily reject the null hypothesis of equality of the coefficients. The addition of control variables in column 2 very slightly reduces the size of the coefficients in absolute value, while adding FSA fixed-effects leads to higher price elasticities for all beverage types.

Table 4: Estimated price elasticities of beverages using linear model

Log volume (litre)	(1)	(2)	(3)	(4)	(5)	(6)
Log soft drinks price / litre	-2.8044***	-2.7795***	-3.3790***	-2.2217***	-2.2578***	-2.5098***
	(0.0339)	(0.0338)	(0.0782)	(0.0224)	(0.0218)	(0.0575)
Log diet soft drinks price / litre	-2.9997***	-2.9746***	-3.5712***	-2.4109***	-2.4473***	-2.6964***
	(0.0342)	(0.0342)	(0.0783)	(0.0226)	(0.0221)	(0.0576)
Log energy drinks price / litre	-2.5891***	-2.5718***	-3.2485***	-2.1826***	-2.2078***	-2.5387***
	(0.0236)	(0.0236)	(0.0742)	(0.0156)	(0.0152)	(0.0556)
Log fruit beverages price / litre	-2.8471***	-2.8250***	-3.4548***	-2.3338***	-2.3653***	-2.6485***
	(0.0298)	(0.0298)	(0.07642)	(0.0197)	(0.0192)	(0.0567)
Log milk price / litre				-1.8266***	-1.8580***	-2.1435***
				(0.0195)	(0.0190)	(0.0566)
Log flavoured milks price / litre				-2.3408***	-2.3709***	-2.6648***
				(0.0188)	(0.0183)	(0.0564)
Log vegetable juices price / litre				-2.2810***	-2.3119***	-2.6013***
				(0.0192)	(0.0187)	(0.0565)
Log water price / litre				-2.7028***	-2.7476***	-2.9375***
				(0.0278)	(0.0271)	(0.0596)
Log carbonated water price / litre				-2.4453***	-2.4778***	-2.7536***
				(0.0204)	(0.0198)	(0.0567)
Log soy and other price / litre				-2.3099***	-2.3400***	-2.6348***
				(0.0187)	(0.0183)	(0.0564)
Log real juices price / litre				-1.9738***	-2.0056***	-2.2886***
				(0.0198)	(0.0193)	(0.0567)
Ratio of people with less than high school diploma		1.4837***	1.2571***		2.5774***	0.7849***
		(0.0802)	(0.0864)		(0.0507)	(0.0668)
Ratio of households with children		0.9169***	0.0961		1.2108***	0.0538
		(0.0679)	(0.0727)		(0.0429)	(0.0562)
Ratio of visible minorities		-1.2052***	-0.6083		-1.1769***	-0.6701***
		(0.0873)	(0.0928)		(0.0552)	(0.0715)
Ratio of low income households		4.6108***	1.5497***		5.3533***	1.2620***
		(0.2549)	(0.2696)		(0.1608)	(0.2079)
Constant	24.7351***	23.2212***	23.4768***	22.1194***	20.0274***	21.1090***
	(0.1517)	(0.1636)	(0.1506)	(0.1001)	(0.1048)	(0.0953)
Number of observations	18 180	18 180	18 180	49 995	49 995	49 995
Adjusted R^2	0.861	0.865	0.898	0.811	0.825	0.863
FSA fixed effects	no	no	yes	no	no	yes

Notes: *Significative at 10%, **Significative at 5%, ***Significative at 1%. Standard deviations are shown in parentheses. The first two columns only include observations for the first four categories of beverages.
Source: Authors' calculations using Nielsen data and 2016 Canadian Census microdata.

The addition of the other beverages to the model slightly modifies the estimated coefficients (columns 4 to 6). The coefficients for soft drinks (diet or regular), energy drinks and fruit beverages vary between -2.21 and -2.45 in column 5, a decrease of more than 15% compared to the estimates without the control variables in column 1. However, a price change continues to generate a greater change in the quantity sold for diet soft drinks (-2.45) than for regular soft drinks (-2.26) or energy drinks (-2.21) in column 5. We note that the price elasticity is lower for plain milk (-1.86) and fruit juices (-2.00), but comparable for flavoured milks (-2.37) and vegetable juices (-2.32), and even higher for still water (-2.75).

These elasticities seem to be realistic compared to the estimates reported in the literature. Indeed, a study carried out in France using the BLP method estimates a price elasticity of demand of -3.46 for regular soft drinks, iced teas and fruit drinks (Bonnet and Réquillart, 2013), while US data suggests instead a price elasticity of the order of -1.04 for regular soft drinks using the Exact Affine Stone Index (EASI) demand system (Zhen et al., 2013). This difference by country could be partly due to methodological differences, but also to different preferences within the population.

Of course, this type of model draws a regression line through a cloud of points, each point of which reflects an equilibrium between supply and demand. This line is therefore neither representative of demand nor of supply. To estimate the consumer's reaction to a price change, we need to estimate the demand equation which requires a more structured model as discussed above. We now take the BLP approach in order to better estimate the demand for SSBs.

5.2. BLP Model

This subsection presents the estimates for the BLP model described in section 4.2. To estimate this model, several product characteristics are included: the amount of sugar (in grams), the number of calories (per litre), the amount of sodium (per litre), the presence or absence of fruits or vegetables (binary variable), and the percentages of the recommended daily values of calcium and vitamin A (both per litre). The BLP method requires that one category be defined as the "outside good", or the base category in comparison to which preferences are estimated for the other drinks, and we use flat water as our base category.

The BLP model makes it possible to estimate the consumers' preferences over the different characteristics of the product, and to see if these preferences vary according to the characteristics of the households in the market. Thus, Table 5 presents the average marginal utility (top panel) of the different characteristics of the drinks, and the variation in consumer preferences over the price per litre according to different socio-demographic characteristics of the consumer (bottom panel). Finally, the standard deviation (σ) of the random price coefficient (at the bottom) captures the effects of unobserved demographic variables. This table presents the results from two models: in model 1, we include all four of our demographic variables, whereas in model 2 only the low-income variable is included. We will discuss this further below. As discussed at the end of section 3, our observations for the socio-demographic variables are actually random draws from the joint distribution of our variables at the level of each FSA, rather than random draws directly from the Census samples, given that it was impossible to extract individual observations from the confidential data laboratory in which we were working with the Census data.

First of all, in Table 5, we see that the consumer's utility decreases with the price (the average marginal utility is negative), which was expected. The results presented in the top panel also suggest that household utility increases if the drink contains fruits or vegetables or contains a higher amount of calories. This means that households prefer drinks with fruits or vegetables and having a higher calorie content. The marginal utility attributed to the presence of fruit or vegetables is very high. We also note that, all things being equal, the marginal utility of consumers decreases with the amount of sugar, sodium, calcium, and vitamin A. It goes without saying that drinks containing fruits or vegetables also contain sugar, calcium, sodium, and vitamins in varying amounts. In addition, the amounts of vitamins and calcium in drinks containing fruits or vegetables are on average different from those observed for other types of drinks. Thus, the marginal utility of each characteristic should be compared with the marginal utility of whether or not to include fruits or vegetables. In summary, consumers prefer a lower price and drinks that contain fruits or vegetables, but less sugar, sodium, calcium, and vitamin A.

The bottom panel, concerning the interactions between socio-demographic variables and price, reveals that low-income households are more sensitive to price (model 2), but that when other socio-demographic characteristics are included (model 1), they appear less sensitive to price (positive deviation from the average). It is important to note that education and visible minority status are strongly correlated with income, so that in model 1 the coefficient

Table 5: Estimation of consumer preferences in BLP model

	Average marginal utility ($-\alpha, \beta$)	
	model 1	model 2
Constant	1.3428***	1.2541***
	(0.0267)	(0.0241)
Price (¢/litre)	-0.0147***	-0.0199***
	(0.0001)	(0.0001)
Sugar (g/litre)	-0.1683***	-0.1663***
	(0.0015)	(0.0016)
Calories (cal./litre)	0.0450***	0.0445***
	(0.0004)	(0.0004)
Sodium (mg/litre)	-0.0016***	-0.0016***
	(0.0001)	(0.0001)
Fruits or vegetables (yes vs no)	2.9599***	2.9342***
	(0.0290)	(0.0304)
Calcium (%/litre)	-0.3899***	-0.3846***
	(0.0036)	(0.0038)
Vitamin A (%/litre)	-0.0102***	-0.0098***
	(0.0008)	(0.0008)
Interactions of price and	Interaction coefficient	
demographic variables	model 1	model 2
Low income	0.0025**	-0.0028***
	(0.0002)	(0.0003)
Less than high school	-0.0089***	
diploma	(0.0003)	
Presence of children	-0.0030***	
	(0.0001)	
Visible minorities	-0.0051***	
	(0.0002)	
Standard deviation	0.0046***	0.0062***
	(0.0001)	(0.0001)
N	18 660	18 660

Notes: * Significative at 10%, ** Significative at 5%, *** Significative at 1%. Standard deviations are shown in parentheses, and year fixed effects are included in both estimations (but not presented in the table). The second panel of the table presents the Π coefficients for the effect of socio-demographic characteristics on the effect of the price, and the third panel presents the standard deviation of the random component of the coefficient on price. When we include the interactions for all variables (and not just the price), the results are very similar.
Source: Authors' calculations using Nielsen data and 2016 Canadian Census microdata.

on income must be interpreted as the effect of income holding fixed the other demographic variables. Thus, if we include only the low income variable in the model (model 2), we see that the interaction coefficient is -0.0028, which suggests that in general, low-income households are more likely to decrease their beverage consumption following a price increase. Since their total consumption of SSBs is higher, the decrease in SSB consumption in absolute value will be greater for low-income households. On the other hand, since the consumption of all consumers will decrease, it is possible that low-income households will still pay a larger share of the overall tax revenues. Thus, to mitigate the potential regressivity of the tax, it will be important to dedicate a portion of the tax revenues to investments benefitting these people (Allcott et al., 2019a), and to monitor the benefits for their health and well-being.

In addition, Model 1 allows us to anticipate which low-income consumers will be most at risk of a decrease in welfare following the imposition of a tax. To fully understand the effect of a price variation on a group compared to the average, it is necessary to combine the interaction coefficients of the bottom panel. We know that on average low-income people will react more strongly (model 2), but among these people there are differences in preferences. To identify the reaction of different groups, one must calculate their net interaction coefficient by summing the coefficients corresponding to the characteristics of the person. For example, a person with low income but having children will not be much more price sensitive than the average (0.0025-0.0030 = -0.0005). On the other hand, a person with a low income and not having a high school diploma will be more sensitive to the price than the average (0.0025-0.0089 = -0.0064). A person with low income, children and no high school diploma will react even more strongly (0.0025-0.0089-0.0030 = -0.0094). Finally, people from visible minorities also react more strongly to price changes. In summary, this model makes it possible to anticipate that people with low income, but having no children, not coming from a visible minority and having at least a high school diploma, will be the people who will react the least to a price change. This group will therefore be at a disadvantage compared to the others since their consumption will become proportionally higher and their health benefit smaller. Given their consumption, they will pay a larger share of the tax and in this sense may be less well-off following the implementation of the tax.

To summarize the results so far, the average consumer prefers to buy a high-calorie beverage that contains fruits or vegetables. Low-income households are more sensitive to price changes (model 2), and people with a low level of education (less than a high school diploma), from visible minorities or with children are also more sensitive to price changes (model 1). This heterogeneity in consumer preferences is not specific to a particular beverage; instead, it informs us about consumer preferences for beverages in general.

Having estimated the BLP model, it is now possible to estimate the price elasticities of demand for our various beverages. Table 6 contains the own-price and cross-price elasticities of the different types of beverages.[7] A price elasticity measures the percentage change in quantity demanded as a result of a 1 percent change in the product's price. The higher the elasticity in absolute value, the greater the price sensitivity. A cross-price elasticity measures the percentage change in the quantity demanded of good A when the price of good B changes by 1 percent. If the cross-price elasticity is positive, then goods A and B are substitutes, which means that good A can easily replace good B. In this case, if the price of good B increases, then the quantity demanded of good A will increase. The BLP model does not restrict the elasticities to be similar across markets, which here are the FSAs. However, since all products are beverages and the estimated elasticities represent the average of the elasticities across the FSAs, then it may not be surprising that the cross-price elasticities are similar across products. Additionally, for computational simplicity, we only allow the coefficient on price to be heterogeneous, and it has been frequently found in the empirical literature that uses BLP that cross-price elasticities for a change in price of one product are similar across products when the heterogeneity in coefficients is limited, as we find in Table 6.[8] On the other hand, the variation in cross-price elasticities that does exist goes in a logical direction – diet soft drinks are the most substituable with regular soft drinks and vice versa – and cross-price elasticities do vary significantly for changes in price of different drinks.

[7]Element $\{i, j\}$ of Table 6 represents the percentage change in demand for product i following a percentage change in the price of product j.

[8]This issue is mentioned by both Berry et al. (1999) and Vincent (2015), and the latter paper points out that cross-price elasticities would be identical across products in a logit model with homogeneous preferences. The empirical application in Vincent (2015) shows a tendency towards similar cross-price elasticities across products (page 873), and even Nevo (2001), who permits more parameter heterogeneity than we do, presents cross-price elasticities that are generally quite similar across products (page 331). Lopez and Fantuzzi (2012) are able to generate more variation in cross-price elasticities by interacting almost all preference parameters with demographic characteristics, but they have far fewer markets than in our data, making for a much lower computational burden.

Table 6: Estimates of price elasticities based on the BLP model

	Soft drinks	Diet soft drinks	Milk	Flavored milk	Energy drinks	Vegetable juices	Carbonated water	Fruit beverages	Soy and other	Real juices
Soft drinks	**-1.5850**	0.1599	0.9270	0.0446	0.0084	0.0762	0.0627	0.0777	0.0633	0.4792
Diet soft drinks	0.3568	**-1.7157**	0.9261	0.0442	0.0081	0.0759	0.0630	0.0776	0.0628	0.4791
Milk	0.2753	0.1231	**-2.2195**	0.0500	0.0195	0.0801	0.0570	0.0755	0.0716	0.4710
Flavored milk	0.2417	0.1073	0.9052	**-3.4863**	0.0282	0.0798	0.0533	0.0733	0.0733	0.4564
Energy drinks	0.0674	0.0288	0.5158	0.0403	**-4.3991**	0.0518	0.0228	0.0387	0.0567	0.2429
Vegetable juices	0.2610	0.1165	0.9239	0.0508	0.0230	**-3.2477**	0.0556	0.0746	0.0726	0.4661
Carbonated water	0.3029	0.1362	0.9357	0.0484	0.0146	0.0792	**-2.7011**	0.0767	0.0684	0.4776
Fruit beverages	0.2844	0.1270	0.9261	0.0497	0.0187	0.0795	0.0572	**-2.9428**8	0.0707	0.4715
Soy and other	0.2392	0.1063	0.9105	0.0516	0.0281	0.0800	0.0534	0.0730	**-3.4996**	0.4563
Real juices	0.2831	0.1264	0.9300	0.0498	0.0183	0.0798	0.0575	0.0769	0.0708	**-2.5806**

Note: The `blp` command in Stata solves for the matrix of elasticities for a given market; we modified the code to solve for the matrix of elasticities for all markets and calculate the averages of each elasticity across all markets, which are presented in this table.
Source: Authors' calculations using Nielsen data and 2016 Canadian Census microdata.

Table 6 reveals that the price elasticities vary from beverage to beverage, and are between -1.59 (for regular soft drinks) and -4.40 (for energy drinks). These estimates differ from those obtained with the linear model presented above. It is quite normal that the price elasticities obtained with the naive model are different, because the endogeneity of the price generally biases the coefficient towards zero, whereas the BLP model corrects this bias and considers the preferences of consumers according to their characteristics. Thus, for certain beverages, the consumer reacts more strongly to a price variation than the estimates of the linear model would suggest, while for others they react less strongly. The BLP model suggests that consumers of energy drinks (-4.40), flavoured milk (-3.49), and soy drinks (-3.50) are much more sensitive to price changes than consumers of regular (-1.59) or diet (-1.72) soft drinks, or plain milk (-2.22). This finding suggests that taxation could generate a significant reduction in the consumption of SSBs other than carbonated drinks. Indeed, the consumption of soft drinks seems to be noticeably less sensitive to price variations.

This significant variation in elasticities for different types of drinks highlights the importance of thinking about the different possible forms that taxation of sugar-sweetened beverages could take. Given the higher prices per litre of flavoured milks, fruit beverages, and particularly energy drinks, and their relatively large elasticities, a tax as a percentage of the price would be likely to reduce the consumption of such drinks and redirect consumption towards lower priced items such as soft drinks. A tax per unit of volume or per gram of sugar would be relatively more effective in reducing the consumption of regular soft drinks.

When we compare our results with those of the literature, it seems that the variation in the quantity of beverages demanded by Quebec consumers following a price change is somewhere in between the ones observed among American consumers (-1.31 (Allcott et al., 2019a)) and among French consumers (-3.46 (Bonnet and Réquillart, 2013), (Labrecque et al., 2006)): the price elasticities for Quebec consumers vary between -1.59 and -4.40.

Our results for energy drinks suggest a strong consumer reaction to price changes. It is important to remember here that the Nielsen data that we use to estimate consumer responses do not include sales in convenience stores. As shown in Table 1, energy drinks are particularly expensive, with an average price per litre that is twice the price of flavoured milks, the second most expensive drink in Quebec. Table 1 also reveals that energy drinks represent a very small share of the total volume of grocery store sales. Capps and Hanselman (2012) report that only 10% of energy drink sales occur in grocery stores in the United States. It is very likely that sales of energy drinks are much greater in convenience stores than in grocery stores in Quebec as well.

Thus, it is possible that the price elasticity of demand for energy drinks is lower than what we have estimated since convenience store purchases are made more impulsively. On the other hand, since energy drinks are mainly consumed by young consumers, whose budget constraints are much more restrictive, it is possible that their price elasticity is stronger. It is impossible for us to predict the direction of the bias. Capps and Hanselman (2012) suggests a much lower price elasticity, varying between -1.5 and -1.8, for energy drinks consumed in a grocery store near the Texas A&M University campus. However, the authors do not use an approach that permits them to distinguish supply from demand; instead, they estimate a simple linear model that is comparable to our linear model. If we compare the results of our linear model with those of Capps and Hanselman (2012) we notice that they are similar, but unfortunately this approach is not valid. Given that we have data on purchases in big-box stores and the three largest supermarket chains in Quebec, we believe that our estimates should be accurate for the type of people who buy drinks in large stores, particularly if the elasticity of substitution between supermarkets and convenience stores is small.

To summarize, our results show that taxation could help reduce the consumption of SSBs, as has been demonstrated by other studies, but that a naive linear model provides inaccurate estimates of the consumers' response to price changes. It further shows that price elasticities vary across different types of beverages, and in order to design an optimal tax to reduce the consumption of sugar in the form of beverages it is essential to understand how consumers substitute their consumption from one good to another. Our results clearly highlight that a tax as a percentage of the price would be less effective than a tax on the grams of sugar. It also shows that low-income households react more strongly to price changes on average, but within this group certain individuals would likely not react as strongly.

6. Conclusion

The main objective of this article was to determine own-price and cross-price sensitivity of consumers of sugar-sweetened beverages, especially soft drinks (diet or regular), fruit drinks and energy drinks. More precisely, we sought to estimate the price elasticity of demand for sugar-sweetened beverages and the cross-price elasticity of demand.

In a preliminary analysis, we presented a portrait of the prices and consumption of various non-alcoholic beverages in Quebec using our Nielsen data. We showed that soft drinks are the cheapest drinks available on the market (just after plain water), and thus the most accessible products for low income households. Soft drinks are the second most consumed beverage after milk in Quebec, which can also be seen in data from the Surveys of Household Spending from Statistics Canada. As mentioned, the medical literature shows that these products have harmful effects on long-term health which consumers may or may not account for when making their consumption decision.

To assess the potential effects of taxation on the consumption of SSBs, we estimated a demand model using data from both Nielsen and the 2016 Canadian Census. More specifically, we estimated the Berry-Levinsohn-Pakes (BLP) model to determine consumer preferences for non-alcoholic beverages. The results suggest that the average consumer prefers a high-calorie beverage containing fruits or vegetables. In addition, our results suggest that the demand for energy drinks is the most sensitive to price changes, while the demand for soft drinks is the least impacted by price variations. Indeed, the price elasticity of demand for energy drinks is -4.40 compared to -1.59 and -1.72 for regular and diet soft drinks. The demand for sweetened drinks such as flavoured milks and soy drinks is strongly affected by price changes, with elasticities of about -3.50. Thus, the price elasticity of demand for sugar-sweetened beverages in Quebec generally seems to be between that of the United States (-1.37 (Allcott et al., 2019a)) and that of France (-3.46 (Bonnet and Réquillart, 2013)), but is closer to the United States given the high volume of soft drink consumption.

Our results suggest that, on average, low-income households react more strongly to price changes, so their health benefit could be relatively greater. We also note that the reduction in consumption due to a tax would be greater for families with children. Thus, it is possible that this form of taxation has positive intergenerational effects since future generations may become less inclined to consume sugar-sweetened beverages if raised in households not consuming such products. However, there are differences in preferences among low-income households. Finally, as some individuals may not change their consumption, it cannot be denied that some people will be disadvantaged by the implementation of a tax: they will have a lower disposable income after beverage consumption and will not receive the benefit of greater health from reduced SSB consumption. Tax revenues from SSBs will therefore need to be allocated in a way that prevents taxation from becoming regressive. Investing in lower income neighborhoods in programs that are beneficial to those living there would be a sensible approach. In Philadelphia, the money from the tax has been used to fund access to preschool for the city's children (Allcott et al., 2019a). Also, the tax revenue could be used to fund, for example, a quality food assistance program in disadvantaged schools, access to clean water, or programs that promote physical activity. The objective would be to use a portion of the tax revenue for a program that has a clear benefit to low-income people.

Our study has certain limitations. We only have the total annual sales amount and the average price of items for each store in each year from 2010-11 to 2015-16. If we had access to weekly data, we would have had more variation to use to analyze consumption habits. For example, to study consumer behaviour when the prices of sugar-sweetened beverages vary, we could have exploited variations in purchase volumes during promotional campaigns. In addition, the data that we use in the estimation of price elasticities do not include sales in convenience stores or vending machines. The price per litre is probably higher for such purchases. Nonetheless, the approach chosen is designed to use aggregate market data and can therefore be trusted to represent the price sensitivity of purchases made in these stores.

To conclude, this article suggests that the implementation of a tax on sugar-sweetened beverages would reduce the consumption of these drinks and could promote product reformulation towards less sugary options. Since the reaction of some low-income households to a price change is weaker, part of the tax revenues should be reinvested in programs that benefit these people.

7. Acknowledgements

The analysis presented in this paper was conducted at the Quebec Interuniversity Centre for Social Statistics which is part of the Canadian Research Data Centre Network (CRDCN). The services and activities provided by the QICSS are made possible by the financial or in-kind support of the Social Sciences and Humanities Research Council (SSHRC), the Canadian Institutes of Health Research (CIHR), the Canada Foundation for Innovation (CFI), Statistics Canada, the Fonds de recherche du Québec - Société et culture (FRQSC), the Fonds de recherche du Québec - Santé (FRQS) and the Quebec universities. The views expressed in this paper are those of the authors, and not necessarily those of the CRDCN or its partners. Declarations of interest: none.

Appendix A. Summary of types of taxation on sugar-sweetened beverages elsewhere in the world

Where	Tax type	Amount of tax	Beverage types	Starting year
USA				
Seattle San Francisco Albany Berkeley Oakland Philadelphia Boulder Navajo Nation	Excise tax	Between 1 and 2 cents per ounce	All sweetened drinks except: - Diet soft drinks - Real juices - Milk products	2015, 2017 and 2018
Central America				
Barbados Dominica Panama	Excise tax	7 to 10 %	All beverages with sugar added	2015 and 2019
South America				
Chile Peru	Value-added	10 to 25 %	All beverages with sugar added	2014 and 2019
Europe				
Belgium Latvia Saint-Helena	Excise tax (cents per litre)	Between 8.1 and 103 cents per litre	All beverages with sugar added (mostly soft drinks)	2014 and 2016
United Kingdom Ireland France Portugal Norway Finland Hungary	Cents per litre	Between 10 and 39 cents per litre	All beverages with added sugar or artificial sugar	1981, 2011, 2012, 2017 and 2018
Asia				
Maldives Philippines Malaysia Brunei	Cents per litre	Between 10 and 218 cents per litre	All beverages with added sugar or artificial sugar	2017 and 2018
Pacific Islands				
Samoa French Polynesia Palau Fiji Tonga Vanuatu	Cents per litre	Between 16 and 60 cents per litre	All beverages with sugar added (mostly soft drinks)	1984, 2002, 2003, 2016 and 2017
Middle East				
Saudi Arabia Bahrain Qatar Oman United Arab Emirates	Excise tax	50 % and 100 %	All beverages with sugar added (mostly soft drinks) [50 %] and energy drinks [100%]	2017 and 2019
Africa				
Morocco Seychelles	Cents per litre	Between 2 and 21 cents per litre	All beverages with sugar added	2019

Note: All prices are in US dollars.
Source: The data come from the Global Food Research Program (GFRP) (2020).

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