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The Incidence of Soft-Drink Taxes on Consumer Prices and Welfare: Evidence from the French Soda Tax *

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Abstract

The impact and acceptability of soft-drink taxes depend crucially on their incidence on consumer prices and welfare across socio-economic groups and markets. We use Kantar Worldpanel homescan data to analyse the incidence of the 2012 French soda tax on Exact Price Indices (EPI) measuring consumer welfare from the availability and consumption of Sugar-Sweetened Beverages (SSB) and Non-Calorically Sweetened Beverages (NCSB) at a local geographical level. The soda tax has had significant, similar but small impacts on the EPI of SSB and NCSB (+4%), corresponding to an aggregate pass-through of about 39%. Tax incidence was slightly higher for low-income and high-consuming households. Retailers set higher pass-throughs in low-income, less-competitive and smaller markets. They did not change their product assortments. The lack of horizontal competition in low-income markets had a sizeable effect on tax regressivity. Finally, the negative income gradient in tax incidence was offset by a positive gradient in expected health benefits.

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1 Introduction

The worldwide rise in obesity and diabetes has prompted public-health officials to pay particular attention to sugar intake from Sugar-Sweetened Beverages (SSB).[1] Epidemiological analyses clearly show that high SSB consumption is associated with greater risks of obesity and diabetes, especially for children (Malik et al., 2013). The taxation of SSB is thus viewed as a means of decreasing SSB consumption by increasing prices, and is therefore expected to yield considerable population-health benefits at zero cost to public finances (Le Bodo et al., 2017). The behavioural impacts of soft-drink taxes depend not only on the price elasticity of SSB consumption, but also on the impact of the tax on consumer prices. A tax is unlikely to be shifted 1:1 onto equilibrium prices due to changes in consumer behaviour on the demand side and producer and retailer marketing-mix decisions on the supply side. We here use homescan panel data to propose an ex-post evaluation of the pass-through of the French soda tax on SSB prices and its incidence on consumer welfare, with a particular focus on heterogeneity across sociodemographic groups and markets.

The French soda tax is a new tax passed in November 2011, and implemented on the 1st of January 2012. It is a unit excise tax of 0.0716 Euro/Litre on the producer price. This corresponds to about 11 cents for a 1.5-litre bottle or 2.4 cents for a 33-centilitre can. Under full pass-through onto consumer prices, the latter should have increased by about 10% on average. The tax is levied on manufacturers or importers of SSB (soft drinks and nectars) *and* Non-Calorically Sweetened Beverages (NCSB). NCSB were included at the end of a political process that started in August 2011, when the government announced the creation of a SSB tax to fight children obesity. After several rounds of discussions between the government, the parliament and the industry, an agreement was reached. The original public-health motivation for the tax — fighting obesity — became secondary, and the legal text focussed on a fiscal motivation : raising revenue for Social Security and the farming sector. NCSB were included in the fiscal basis as a "voluntary" contribution of the beverage industry to Social Security.

We estimate the impact of the tax on SSB and NCSB prices using six years of nationally-representative homescan data provided by Kantar Worldpanel (2008-2013).[2] Our dependent variables of interest are local Exact Price Indices (EPI) for SBB and NCSB. They are constructed from local price series and the estimation of nested Constant Elasticity of Substitutions (CES) demand functions for product varieties, following recent methodological advances in trade and spatial economics (Broda and Weinstein, 2006, 2010; Handbury and Weinstein, 2014; Redding and Weinstein, 2016). They are also adjusted for consumer and retailer heterogeneity, so that we abstract from welfare changes reflecting differences in preferences for products or store formats across households: our analysis focusses on representative households present across heterogeneous markets.

We have two motivations for using these local EPI. First, working on a price index for SSB rather than on separate price series of product varieties is all the more important as the crucial margin for public-health policies is the quantity of SSB that is purchased by households. As shown below, and in an ex-ante study of the soft-drink market by Bonnet and Réquillart (2013b), substitution between SSB varieties is unlikely to produce variations in sugar intake. The key health benefits are obtained through substitutions towards outside options, such as NCSB or Naturally Sweetened Beverages (NSB, *e.g.* pure fruit juices).[3] The National Statistics office

[1]See the Harvard School of Public Health: `https://www.hsph.harvard.edu/nutritionsource/sugary-drinks-fact-sheet/`; and the World Health Organization: `http://www.who.int/elena/titles/ssbs_childhood_obesity/en/`.

[2]About 75% of SSB purchases in France are made in stores for home consumption, according to the *Syndicat National des Boissons Rafraichissantes*, the beverage business federation.

[3]We are however aware that the health benefits of artificially-sweetened beverages have been debated in the public-health literature, *e.g.* Borges et al. (2017).

(INSEE) provides a national Consumer Price Index for an aggregated beverage category that includes both taxed products (SSB and NCSB) and untaxed products (fruit juices, syrups). Hence, this index cannot be used for evaluating the impact of the tax. Our EPI are tailored to provide an exact measure of the impact of the soft-drink tax on consumer welfare from SSB and from NCSB, under transparent assumptions regarding the structure of consumer preferences. They do not only account for consumer substitution between varieties, but also for variations in the availability of products across local markets and time. This is potentially an important issue in the identification of the welfare impact of taxation, as product availability has been shown to be important for consumer welfare in modern economies, and producers and retailers may react to taxation by narrowing or broadening their product portfolio.

A second motivation is that differences in local market structures may generate heterogeneity in the distribution of the tax burden across socioeconomic groups. One common argument against soft-drink taxes is that they are regressive, as low-income households spend more on soft-drinks. However, it may also be the case that they are more likely to purchase in markets whose structure (*e.g.* fewer retailers) is conducive to higher pass-through of the tax onto consumer prices. The pass-through depends on the determinants of equilibrium prices and is always below 100% under perfect competition.[4] Some models of imperfect competition and horizontal competition between differentiated products predict overshifting in the excise tax when demand is highly convex (Anderson et al., 2001; Delipalla and Keen, 1992; Tyagi, 1999).[5] Hong and Li (2017) show that introducing a vertical market structure with non-integrated manufacturers and retailers changes the pass-through analysis. As the tax is borne by producers, it pushes wholesale prices upwards. There is then a double mark-up adjustment, by producers and retailers, which mechanically reduces the pass-through. This implies that we may see incomplete pass-through for the EPI of both SSB and NCSB, and no overshifting of the tax. In the end, the combination of horizontal competition and vertical market structure will produce heterogeneous pass-through rates across local markets. As we conduct our analysis at the level of local markets, which differ by population and competitive structure, we can analyze how competition and socioeconomic characteristics jointly explain the regressivity of soft-drink taxes.

We estimate the impact of the tax on the EPI, using a before-after approach that controls for the confounding shock on the cost of sugar, which is a key input in the production of SSB. This shock came from a revision in the EU quota in October 2011, which was politically unrelated to the soda tax, but generated a sharp rise in the producer price of sugar between October 2011 and March 2012. As other unobserved macro-shocks may still affect our policy estimate of interest, we also apply a difference-in-difference design that uses changes in the EPI of water as a counterfactual. This is a good counterfactual, as water is not in the sweetened-beverage market, but their prices are affected by the same production costs as SSB prices (except for sugar).

Our two identification strategies produce the same results. Taking the before-after estimates, the tax increased the price of SSB by about 4.1%, corresponding to a tax incidence of 39.1%. The pass-through rate

[4]Under perfect competition with no product differentiation, the pass-through rate ρ is a direct function of the elasticities of demand and supply, η_D and η_S, so that $\rho = \frac{\eta_S}{\eta_S - \eta_D}$ is a measure of the incidence of the tax on consumer welfare for an infinitesimal variation in the excise unit tax with an exact price measure (Fullerton and Metcalf, 2002; Weyl and Fabinger, 2013). In this setting, the more elastic the demand is, the lower is ρ.

[5]When demand is highly convex, each additional marginal price increase produces increasingly large reductions in demand. In this case, a profit-maximizing firm has to raise its price by more than the increase in the marginal cost from the tax in order to maintain the equality between marginal revenue and marginal cost. Intuitively, the profit loss from a fall in demand is offset by a higher markup on each unit sold, which is possible due to the market power of suppliers.

for NCSB is very similar at 39.0%. We then consider tax incidence across markets and consumer groups. We find that the effect of the tax on consumer prices is slightly higher for low-income households and high-consumption households. We find no evidence of sizeable border effects, but considerable spatial heterogeneity, in line with the theoretical prediction that tax incidence depends on market structure and the costs faced by retailers/producers. As expected, tax incidence falls with retailer competition and market size. In addition, conditional on local market structure, initial prices are higher but tax incidence is lower in high-income markets. Consequently, consumer welfare was more affected by the tax in less-affluent areas, so that the tax was regressive only in poorer markets. However, combining the estimated price changes with estimates of demand elasticities by market segments reveals that the income gradient in consumer (private) welfare should be compared to an inverse income gradient in expected health benefits, contributing to private and social welfare.

Our results lead to revise downward previous estimates from two published studies on SSB taxes in France. In an ex-ante evaluation study, Bonnet and Réquillart (2013) exploit the 2002-2005 Kantar Worldpanel homescan data to fit an Industrial Organization model of the market. They predict an over-shifting of excise taxes for soft-drinks, *i.e.* a tax incidence higher than 100%. The discrepancy between this prediction and our main result may come from the limited ability of their supply-side model to capture specific strategic motivations that influence producers' and retailers' decisions in the context of singular tax reforms. The soda tax is not merely a shock on equilibrium prices. The analysis of the policy process leading to its adoption reveal that it has been perceived by producers as a structural change in the regulation of the French food market and a threat for brand reputation (Le Bodo et al., 2017).

An ex-post evaluation study by Berardi et al. (2016) exploits extracts of shopping prices collected between August 2011 and June 2012 from the online sites of about 1,800 drive outlets. It concludes that the tax was fully shifted onto SSB prices after six months. There are however three important difference between their study and ours. First, online shopping prices lack representativeness, as compared to the Kantar Worldpanel data, which cover all outlets formats and provide price quotes that are representative of purchases made by French. Berardi et al. also work on store-level product prices weigthed by fixed market shares that are inferred from national-level data. They cannot account for consumer substitutions between varieties and for variations in product availability. Second, their empirical analysis does control neither for variations in sugar prices nor for month-of-the-year (seasonal) effects. Third, they assume a priori that the extent of the pass-through has to be evaluated by comparing the price levels in June 2012 with those observed in December 2011. Our own event study indeed suggests that the pass-through was complete after three months, which is consistent with the fact that the mandatory end of yearly negotiations between retailers and producers was March. The rise in prices over the second quarter 2012 was due to a seasonal effect, which Berardi et al. (2016) could not control for due to the limited time window covered by their data.

Our research contributes to two strands of literature. First, the default pass-through applied in most health-econometric simulation analyses of nutritional taxes is 100% (Nordström and Thunström, 2009; Allais et al., 2010; Dharmasena and Capps, 2012; Finkelstein et al., 2013; Etilé and Sharma, 2015; Harding and Lovenheim, 2017). Our pass-through rates are much lower, in line with recent ex-post evaluation work on the Berkeley soda tax, which finds tax incidence rates of between 22% and 47% (Falbe et al., 2015; Cawley and Frisvold, 2017). Overall, our findings underlines the importance of accounting for supply-side reactions and uncertainty in pass-through when simulating the impact of nutritional taxes. Second, understanding and identifying the incidence of taxes and their pass-through rates is a critical research question in public economics and industrial organization. Existing analyses have notably focussed on the impact of taxes on consumer prices and their progressivity, as measured by the relative burden of the tax falling on different income groups (Fullerton and Metcalf, 2002).[6] Our research adds to the tax incidence literature by showing that soft-drink taxes are regressive because low-income consumers, endowed with higher preferences for soft drinks, are also more likely to live in markets with less competition. Our findings illustrate that supply- and demand-side factors simultaneously determine the distributional impacts of the tax. It also confirms that the interaction of vertical and horizontal market structure is important for understanding cost pass-through (Hong and Li, 2017).

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 then presents the main assumptions regarding consumer preferences, and the derivation of the formula for the nested-CES Exact Price Index for aggregate consumption, and analyses its evolution over time. The details of the construction of the index appear in the Appendices. Section 4 sets out the identification strategies and presents national-level analyses of the incidence on EPI. Section 5 analyses the behavioural responses on the demand and supply sides by examining the heterogeneity of tax incidence across consumer segments and markets. Section 6 then weighs up tax-incidence concerns with behavioural and health effectiveness. Last, Section 7 concludes.

2 Data

We construct our local price indices from 2008-2013 household panel homescan data collected by Kantar Worldpanel (KWP) over the 2008-2013 period. There are 43,379 distinct households over the whole period, with each household remaining in the sample for three years on average. In each year, between 21,000 and 22,500 sampled households produce between 1 and 1.1 million purchases of non-alcoholic beverages. Each annual sample is nationally representative of the French population in the corresponding year.

2.1 Local markets

We first delineate local market areas, since we want to construct local prices that account for spatial and time variations in non-alcoholic beverage prices and the set of products available to consumers. To this end, we assign each household to a "living zone" according to the city code of the place of residence. A living zone is defined by the French National Statistics Office (INSEE) as the smallest territory where inhabitants have access to everyday facilities and services, including stores.[7] These living zones are consumer catchment areas from the perspective of retailers. A local market will be defined as the combination of the time period and the living zone.

We retain living zones where at least 10 households are observed over the whole period, to ensure the statistical representativeness of the price indices. This leaves us with 263 living zones, out of a total of 1,633 in France. We essentially lose rural living zones. Almost 250,000 purchases of non-alcoholic beverages per year are recorded over 2008-2013, on average, in the remaining areas. Table 1 sets out some household descriptive

[6] Several studies have already documented the national tax incidence of VAT reforms. For France, Carbonnier (2007) find pass-through rates of respectively 57% and 77% for VAT reforms of car-sales and housing repair services. There is also a smaller but burgeoning literature that has documetned the spatial and socioeconomic variations in prices and tax incidence (Harding et al., 2012; Handbury and Weinstein, 2014; Jaravel, 2017)

[7] "Bassin de vie" in French; see `https://www.insee.fr/en/metadonnees/definition/c2060`.

statistics for the original KWP household sample and the final sample used for the construction of the price indices. These are very similar, except for the type of residential area. As we drop living zones with under 10 households, the countryside and small towns are under-represented, while larger cities are over-represented.

These purchase data are then matched to the TradeDimensions panel provided by Nielsen. This panel provides exhaustive information about the presence of retailers in any given living zone in each month. Following the IO analysis in Bonnet and Réquillart (2013b,a), we define 10 homogeneous categories of retailers (or distribution channels) according to the brand name and the store format (hard discount, supermarket, hypermarket).[8] These two criteria are significant determinants of retailers' price-quality marketing mix.

Table 1: Households - Descriptive statistics

	Final sample		Full sample	
Monthly household income (SD)	1,589	(1,056)	1,521	(992)
Household income class (%)				
Rich	16.86		14.69	
Mid-rich	30.37		29.26	
Mid-poor	37.43		39.75	
Poor	15.34		16.30	
Household size (SD)	2.26	(1.35)	2.34	(1.31)
Household structure (%)				
Single	22.02		19.76	
Old	22.60		22.31	
Couple without children	22.29		22.59	
Couple with children	33.09		35.34	
Main shopper				
Age (SD)	48.79	(17.14)	48.86	(1.92)
Gender (%)	12.02		11.58	
Highest education level (%)				
Primary	5.41		5.89	
High school	21.83		23.34	
Baccalauréat	23.60		24.76	
2 years, technical/university	21.26		21.49	
3 years and more, university	27.90		24.52	
Residential area (%)				
Countryside	11.19		24.15	
Small town	4.37		11.86	
Town	9.49		10.80	
Large town	16.90		12.02	
City	58.05		41.17	
Households	30,254		43,379	
Years per household, on average (SD)	2.97	(1.90)	2.99	(1.90)
Observations (households x years)	89,930		129,911	

Notes: Kantar Worldpanel data 2008-2013. Household income is in 2011 Euros, per consumption unit (OECD scale). All statistics are weighted using the survey sample weights.

[8]The brand names are: Auchan (Atac, Maximarché); Carrefour (Stock, Shopi, Proxi); Intermarché; Leclerc; a grouping Casino (Monoprix, EcoService, PetitCasino, Spar, and Maxicoop), Cora, U and others (cheesemongers, grocery stores); subsidiary hard discount stores (Ed-Dia, Franprix, Leader Price); independent hard discount (Lidl, Aldi).

2.2 The definition of products and nomenclature

The data record weekly household purchases of non-alcoholic refreshing beverages for home consumption over the period. The Universal Product Code (UPC), quantity purchased and expenditure for each purchase are registered using a handheld scanner. KWP does not directly provide the UPC, but does include a broad set of product attributes: flavour, brand, volume, type of packaging, type of beverage (family), whether it is carbonated, whether it is light, and whether it has been sweetened using caloric or non-caloric sweeteners. We use these attributes to define a set of 526 distinct product varieties, belonging to 14 different families of beverages: colas, carbonated fruit drinks, uncarbonated fruit drinks, fruit nectars, lemonades, iced teas, tonics, energy drinks, flavored water, natural water, fruit juices without added sugar, syrups (cordials/squash), pulps and milk-based fruit juices.

Our choice of attributes is driven by business statistical sources on the dynamics of the French beverage and soft drink market. Two types of soft drinks are usually distinguished: carbonated soft drinks and sodas (colas, fruit drinks, lemonades) and uncarbonated soft drinks (fruit drinks and iced teas). They represent 78% and 22% of the soft-drink market respectively. According to the beverage business federation, the market shares were distributed as follows in 2010: cola (54%), fruit drinks (24%), lemonade (8%), iced tea (8%), flavored water (5%) and energy drinks (1%). Fruit juice and nectars are the main substitutes for soft drinks. The market has been growing by an average of over 3% per year since 2005. This is mainly driven by the development of drinks with low-sugar content or with non-caloric sweeteners (in addition to packaging innovations and marketing) that we group together in the category of Non-Calorically Sweetened Beverages in this paper. For instance, light colas represented 27% of colas in 2009, as compared to 24% in 2007; for carbonated fruit drinks, the share of light varieties rose from 18% in 2005 to 25% in 2007.[9]

We apply a three-tier nomenclature. In the upper tier, all purchases are classified into one of the four following groups: Sugar-Sweetened Beverages (SSB), Non-Calorically Sweetened Beverages (NCSB), Naturally Sweetened Beverages (NSB), and Water. In each group, we know the brand of each product purchased. The middle tier is made up of 81 brand-modules defined by interacting the four groups, the 14 beverage families and the brand names, *e.g.* standard Coca-Cola (group = SSB, family = Colas, brand = Coca-Cola), Diet Coke (group = NCSB, family = Colas, brand = Coca-Cola). The lower tier is made of "artificial" UPC, defined by the interaction of product varieties with the retailer categories defined in the previous subsection. We end up with a total of 2,770 UPC. Defining UPC as product-retailer couples captures that: (*i*) the utility obtained from purchasing a product may vary from one store to another, as stores offer different levels of amenities; and (*ii*) beverage price and promotion policies are retailer-specific, as they are a means to attract or retain customers.[10]

Last, we select the 1,891 UPC that are purchased at least 100 times over the 2008-2013 period, and retain from these the 995 UPC that are purchased at least once in each of the 72 months. Our final sample therefore consists of 995 UPC, 81 brand-modules, 4 product categories, 263 living zones, 72 periods, 12 retailers, and 30,254 distinct households over the six-year period (roughly 15,000 households are observed each year) and over four million purchases. For each UPC, household, month and retailer, we calculate the mean expenditure and mean quantity. Dividing mean expenditures by mean quantities produces the corresponding mean unit prices, which we further deflate by the general French Consumer Price Index (CPI).

[9] Sources: *Syndicat National des Boissons Rafraichissantes* and `http://www.businesscoot.com/le-march-des-boissons-rafraichissantes-49`.

[10] See Handbury and Weinstein (2014), Subsection 3.2, and Bonnet and Réquillart (2013b).

2.3 National market characteristics

Some descriptive statistics of the national market for each of the four groups appear in Tables 2 and 3. Table 2 shows the distribution of attributes in each group of beverages. There are 400 UPC in the SSB group, 127 in the NCSB group, 338 in the NSB group, and 130 in Water. There are four notable facts in this table. First, the SSB market is not dominated by carbonated drinks, while this is the case for NCSB, reflecting the innovative path taken by the market leaders (Coca and Pepsi with their light products). Second, this is also reflected in the large share of top national brands in NCSB products (68%, as against 34% for SSB). Third, the SSB and NCSB markets have lower unit values than NSB and larger unit values than Water. Last, the carbohydrate content in the SSB category is, as expected, much higher than that in NCSB, and equal to that in NSB.

Table 3 reports some market statistics broken by beverage families, for each of the four groups. The last line indicates that SSB represent 26.0% of the total volume of non-alcoholic beverages purchased for at-home consumption in France. This is much larger than the NCSB figure (only 7.9%), but smaller than that for NSB and Water (35.7% and 30.4%, respectively). Colas are dominant in the SSB and NCSB groups, but face many competitors in the SSB category. Table 3 also shows the average unit value in each segment. Interestingly, there is not a particularly large price premium for NCSB products compared to SSB products within the same beverage family. The average unit value of non-calorically sweetened colas is even lower than that of sugar-sweetened colas.

Table 2: Product varieties - Descriptive statistics

	SSB		NCSB		NSB		Water	
UPC #	400		127		338		130	
Carbonated (%)								
No	47.00		14.96		100.00		64.62	
Yes	53.00		85.04				35.38	
Carbohydrates (SD)	8.96	(1.98)	0.65	(1.25)	10.08	(3.74)	0.09	(0.41)
Light (%)								
No	100.00				97.93		90.00	
Yes			100.00		2.03		10.00	
Packaging (%)								
Plastic	63.50		77.95		23.37		100.00	
Carton	14.25		0.79		34.32			
Metal	17.25		21.26		15.68			
Glass	5.00				26.63			
Flavour (%)								
Citrus	5.94		8.40					
Plain cola	19.06		56.30					
Multifruit	9.06		0.84					
Peach	9.06		6.72					
Orange	22.81		11.76		31.07			
Plain							90.00	
Grenadine					8.88			
Mint					7.10			
Apricot-peach					1.18			
Lemon-lime	0.63		3.36		2.07		6.15	
Other	33.44		12.61		49.70		3.85	
Brand (%)								
Top national	34.00		67.72		31.95		40.00	
Other national	28.25		13.39		23.08		33.85	
Retailer	27.00		14.17		32.54		18.46	
Hard discount	10.75		4.72		12.43		7.69	

Notes: Kantar Worldpanel data 2008-2013. Carbohydrates are expressed in grams per 100 ml. The top national brand segment includes from one to six brands, depending on the product family. These are unweighted product-level statistics.

Table 3: Beverage groups - Descriptive statistics

	SSB			NCSB			NSB			Water		
	UPC #	Market share	Unit value Mean (SD)	UPC #	Market share	Unit value Mean (SD)	UPC #	Market share	Unit value Mean (SD)	UPC #	Market share	Unit value Mean (SD)
Colas	61	11.51	0.97 (0.49)	67	6.47	0.93 (0.46)						
Carbonated fruit drinks	73	3.82	1.13 (0.82)	24	0.69	1.05 (0.34)						
Uncarbonated fruit drinks	63	3.18	0.98 (0.45)									
Nectars	64	3.18	1.26 (0.60)	5	0.20	1.34 (0.65)						
Lemonades	40	1.11	0.57 (0.53)	5	0.09	0.59 (0.23)						
Iced teas	41	1.56	0.76 (0.39)	8	0.13	0.84 (0.30)						
Tonics	28	0.72	1.04 (0.57)	3	0.04	1.15 (0.07)						
Energy drinks	12	0.33	2.88 (1.66)									
Flavored water	18	0.51	0.89 (0.39)	15	0.67	0.96 (0.17)				13	0.32	0.79 (0.25)
Natural water										117	30.72	0.37 (0.26)
Juices (no added sugar)							221	29.00	1.51 (0.91)			
Syrups							94	4.57	2.86 (2.73)			
Pulps							13	0.68	3.56 (0.56)			
Milk-based fruit juices							10	0.50	1.96 (0.35)			
Total	400	25.92	1.02 (0.66)	127	8.29	0.95 (0.43)	338	34.75	1.77 (1.47)	130	31.04	0.38 (0.27)

Notes: Kantar Worldpanel data 2008-2013. Unit values are deflated by the Consumer Price Index for consumer goods (Base: 2011) and are expressed in Euros/Liter. Market shares are by volume of transactions on non-alcoholic beverages observed in the estimation sample (weighted by household sample weights).

2.4 Intra-group heterogeneity in sugar content

One important policy issue is whether the SSB group is heterogeneous in terms of sugar content. If this were the case, then a tax that is accurately linked to the sugar content of the product may favour substitution towards less-sugary SSB. In addition, a soda tax may induce a considerable amount of substitution from expensive products (top-national brands) to less expensive, but perhaps more sugary, products (retailer own brands). The left panel in Figure 1 displays the distribution of the sugar density of SSB products, both weighted by market sales (black) and unweighted (grey). The X-axis is in g/L. The grey distribution shows that most products have a sugar density of between 5 g/L and 11 g/L; the black distribution shows that households purchase products that are very homogeneous in terms of sugar content, with about 80% of purchases being concentrated at around 10-11 g/L. The right panel in Figure 1 plots the concentration curve of SSB market shares against their sugar density. There is one curve for the pre-policy year (2011) and one for the post-policy year (2012). These coincide, so that the policy did not affect the distribution of the sugar density of SSB purchases: households did not switch to more or less sugary SSB products.

This finding is in line with the ex-ante evaluation results in Bonnet and Réquillart (2013b), who use a mixed multinomial logit model explicitly taking into account all substitutions between all SSB and NCSB product varieties. Their simulation results show substantial effects of tax policies, but these are explained uniquely by substitutions from SSB to NCSB and NSB (the outside option in their model). Substitutions within SSB plays no role.[11]

One straightforward consequence is that the effectiveness of soda taxes in France depends on substitution between groups, *i.e.* from SSB to NCSB, NSB and, perhaps, Water. As such, the pass-through of the tax should be measured at the aggregate level of the group, with a price measure that accurately reflects the impact of the tax on consumer utility from purchasing SSB. In this context, the next section presents an exact price index that has desirable properties for this kind of policy evaluation.

3 An Exact Price Index for aggregate SSB consumption

This section presents a nested-CES Exact Price Index (EPI) for aggregate consumption. While the EPI has long been central in the measurement of the true cost-of-living using household budget data, a recent literature has proposed its adaptation to account for the spatial and temporal variability in product availability, which is largely related to the heterogeneity in the spatial distribution of retailers across markets. This approach is particularly tailored to the analysis of spatial heterogeneity in prices (Handbury and Weinstein, 2014). It is made possible by the availability of scanner data, which contain almost exhaustive information on markets. We first present informally our assumptions regarding the structure of consumer preferences. We then present the index formula, its interpretation and explain briefly how it was implemented. All technical details are relegated to (online) Appendices B and C.

[11] Their model predicts that a VAT increase from 5.5% to 19.6% yields an average reduction of added sugar intake of 352 g/capita/year (-21%). An excise tax of 0.09 Euro cents per 100g of sugar produces an average fall of 629 g/capita/year (-38%). However, the ex-post average sugar density of SSB varieties predicted for these two policies are respectively 92.0 g/L and 92.6 g/L, as against 92.1 g/L before the policies (see their Appendix).

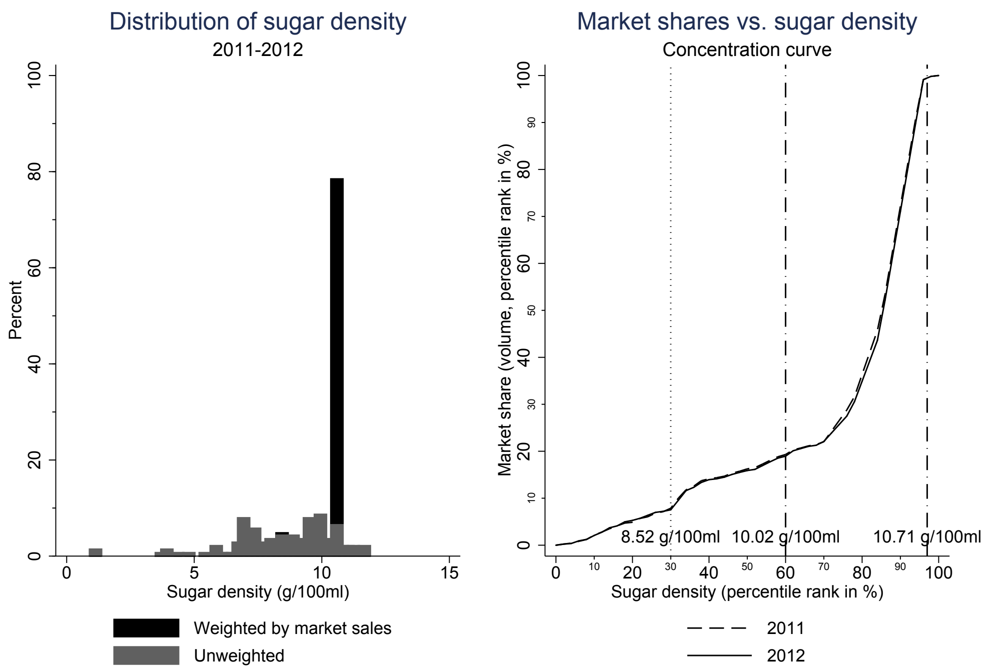


Figure 1: Distribution of the sugar density of SSB products, 2011-2012

Notes: Kantar Worldpanel data 2011-2012. The left panel shows the distribution of the sugar density of products in 2011. The histogram in grey shows the unweighted data, while that in black weights the products by market sales. The right panel shows the concentration curve of the market shares of products (Y-axis) ranked by their sugar density (X-axis). The curves are shown for 2011 and 2012.

3.1 Theoretical framework

An Exact Price Index (EPI) measures the change in expenditure required to keep utility constant as the prices of product varieties vary. It is therefore an index of consumer welfare, and can be formally defined for product group g and a representative consumer in market c as

$$\boldsymbol{P}_{gc} = \frac{C(V, \boldsymbol{p_{gc}})}{C(V, \boldsymbol{p_{g.}})}, \tag{1}$$

where $C(V, \boldsymbol{p_{gc}})$ is the cost of attaining utility V when facing prices $\boldsymbol{p_{gc}}$, and $\boldsymbol{p_{g.}}$ is a vector of reference prices.

The construction of any EPI requires explicit assumptions regarding consumer preferences (Triplett, 2001). In particular, given our focus on aggregate consumption, we assume that households take a four-stage budgeting approach to decide their beverage consumptions (Deaton and Muellbauer, 1980b). They first allocate their consumption budget between broad food groups, here alcoholic and non-alcoholic beverages. The non-alcoholic beverage budget is then allocated between the four beverage groups g: (1) SSB (sodas and fruit drinks essentially); (2) Non-Calorically Sweetened Beverages (NCSB); (3) Naturally Sweetened Beverages (NSB, mainly fruit juices with no added sugar); and (4) Water. The budget is then allocated between "brand-modules" b within each beverage group (Coca-Cola regular, Pepsi-Cola regular, Diet Coke, etc.). Last it is split up between UPC u within each brand-module: UPC are the varieties purchased from a specific retailer.

This multi-stage budgeting process thus mirrors the three-tiers nomenclature of purchases presented in Section 2.2. Purchases are classified into product groups g (the upper level), product groups are made up of brand-modules b (the intermediate level), and brand-modules include a number of distinct UPC u. For example, g = SSB; b = Coca Cola regular, and u = a 1-liter plastic bottle of Coca Cola regular sold in a Carrefour hypermarket. This classification also matches the business nomenclature used by producers and retailers.

We then assume nested-CES preferences for consumer preferences over brand-modules and UPC. This assumption yields two benefits. First, the derivation of the EPI is relatively straightforward. Second, nested-CES utility functions represent the behaviour of a household that would be representative of a population having nested-logit preferences over brand-modules (a nest) and product varieties (Anderson et al., 1988; Redding and Weinstein, 2016). Appendix B formally describes and discusses the structure of consumer preferences.

3.2 Index formula and implementation

When product varieties are not all available on every market, the EPI for g is the product of a "Conventional" Exact Price Index (CEPI) and an adjustement coefficient for Variety Availability (VA).

$$EPI_{gc} = CEPI_{gc} VA_{gc}. \tag{2}$$

$CEPI_{gc}$ is the EPI obtained under the assumption that the choice set in every market is the same as in the reference market that is chosen to calculate the reference prices. VA_{gc} is an adjustment for differences in the available choice sets between market c and the reference market.

To derive VA_{gc}, we assume that households purchase on disjoint markets that are clusters c defined by unique combinations of living zones a and time periods t. They purchase from retailers r, who may or may not be present in the cluster c. They hence have access to a market-specific set of brand-modules, B_{gc}, and a market-specific set of product varieties, U_{bgc}, depending on their residential location and the period. This set-up allows spatial and time variability in the availability of products across markets. For instance, a retailer may launch its own cola "own-brand label" in a given year, test it, and withdraw it if it does not attract a profitable market share. We denote $\mathcal{R}$ the reference market, and define it as the "national market" (*i.e.* the union of all living zones) in 2011, the pre-tax year. The reference set of brand modules is $B_g = \bigcup_{c \in \mathcal{R}} B_{gc}$, and $U_{bg} = \bigcup_{c \in \mathcal{R}} U_{bgc}$ similarly for the reference set of product varieties within a brand-module.

Then, the following explicit formula for $CEPI_{gc}$ and VA_{gc} can be derived (see the details in Appendix B)

$$CEPI_{gc} = \prod\nolimits_{u \in U_{gc}} \left(\frac{\tilde{p}_{ubgc}}{\tilde{p}_{ubg.}} \right)^{w_{ubc} W_{bc}}, \tag{3}$$

$$VA_{gc} = (\tilde{s}_{gc})^{\frac{1}{1-\sigma_g}} \prod\nolimits_{b \in B_{gc}} (\tilde{s}_{bc})^{\frac{W_{bc}}{1-\sigma_b}}, \tag{4}$$

where $\tilde{p}_{ubgc}$ and $\tilde{p}_{ubg.}$ are respectively the quality-adjusted prices of u in market c and in the reference market. W_{bc} and w_{ubc} are Sato-Vartia weights that reflect the relative importance of brand-modules b and UPC u in market c as compared to the reference market; $\tilde{s}_{gc}$ and $\tilde{s}_{bc}$ are the quality-adjusted shares of available brand-modules in market c within a product category g and available varieties in market c within a brand-module b, respectively; σ_g is the elasticity of substitution across brand-modules in product group g, and σ_b is the elasticity of substitution across product varieties within a brand-module. Appendix B provides a detailed derivation and explanation of these variables.

Using unit prices and shares adjusted for the (subjective) quality of products means that we purge within-market variations in household tastes and retailer heterogeneity. Quality-adjustment is all the more necessary that, in a given market c, the observed unit prices for a UPC are likely to vary from one household to another for three reasons. First, households choose to shop in specific stores, which may differ in terms of amenities. Stores adjust their prices as a function of the amenities they provide. Second, stores also adjust their prices as a function of customer demand and characteristics. In addition, households may differ in their shopping behaviour, sensitivity to sales promotions, etc. Third, as we define UPC from a restricted set of product characteristics, purchases in the same UPC may be heterogeneous in terms of very specific attributes (*e.g.* a particular flavour). Adjusting for household and retailer heterogeneity has therefore two desirable implications. First, the EPI will measure spatial and time welfare variations of a representative consumer shopping in homogeneous stores. These variations will primarily be caused by shocks on production, logistic and retailing costs, and variations in market structure. Second, quality-adjustment makes the UPC and brand-modules homogeneous, in terms of subjective quality. As such, it renders plausible the assumption of a constant elasticity of substitution.

The conventional price index $CEPI_{gc}$ has a straightforward interpretation. Any rise in the quality-adjusted price of a UPC increases the CEPI. However, the products that have the largest market shares have also higher Sato-Vartia weights. The latter reflect the relative importance of products for consumer welfare. Hence, the price variations of more popular products have larger impacts on the price index.

The variety-adjustment term VA_{gc} is determined by the local availability of products and their popularity at the national level. This first varies with the quality-adjusted shares of the available varieties $\tilde{s}_{bc}$ in a brand-module b, and the quality-adjusted shares of available brand-modules $\tilde{s}_{gc}$ in product category g in market c. These shares do not reflect consumer choices in market c but rather the availability of products, as $\tilde{s}_{bc}$ is defined as the ratio of total expenditure (over all markets) on product varieties u in brand-module b available in market c, to the total expenditure on all varieties u in brand-module b. This ratio is therefore below 1 whenever U_{bc} is smaller than U_b, *i.e.* when a variety in brand-module b is unavailable in market c. Now suppose that there are many varieties that are not available in market c, so that $\tilde{s}_{bc}$ falls. As $1/(1-\sigma_b)$ is negative ($\sigma_b > 1$), VA_{gc} will increase. The loss of welfare due to the absence of some varieties translates into a higher price index. For varieties within brand-modules, this is unimportant if the brand-module has a low Sato-Vartia weight W_{bc}, *i.e.* if it is not very popular among French consumers. Similarly, $\tilde{s}_{gc}$ is the ratio of the total expenditure on all brand-modules b available in market c, to the total expenditure on all brand-modules in g. This is lower than 1, and will produce a rise in VA_{gc} whenever B_{gc} is smaller than B_g.

We now briefly present the main steps of the empirical procedure applied for constructing the price indices. All of the details are relegated to Appendix C.

Household unit prices are adjusted via period specific regressions, where we control for UPC and household characteristics, retailer and store-format fixed effects, and interactions between the product and household attributes. These estimates are then used to construct market-specific prices adjusted for retailer and store period-specific fixed effects (time-varying retailer heterogeneity) and period-specific household characteristics (time-varying household heterogeneity). We use weights in all of the calculations, to ensure that prices are economically and demographically representative.

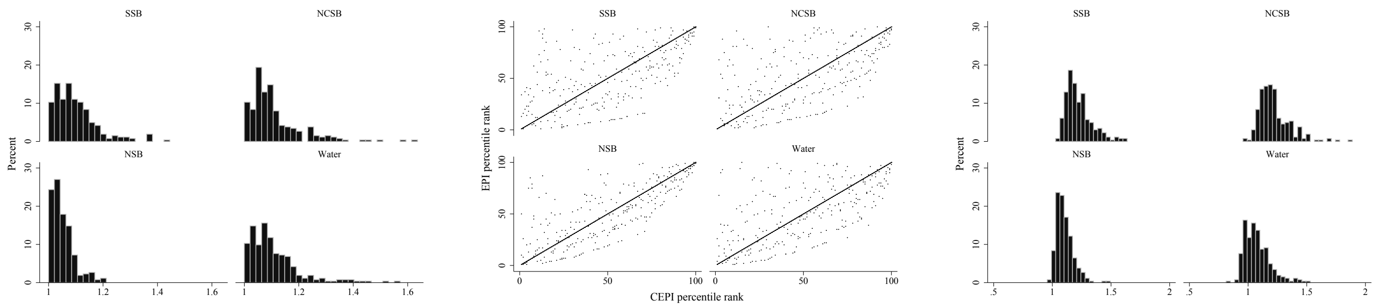
To construct the set of available products in each market, we match our data to the Nielsen TradeDimensions panel, by living zone and time period. This panel provides exhaustive information on the set of retailers operating in each living zone a at each period t. We construct the set of varieties u available in market c by assuming that each retailer proposes the same UPC in all of the living zones in which it operates at t.[12]

The computation of the variety-adjustment terms requires the computation of elasticities of substitutions within and across brand-modules. These are estimated through systems of CES demand *and* supply equations, following the method in Feenstra (1994) and extended by Broda and Weinstein (2006).[13] Intuitively, the CES model implies that, within each market, the difference between the quality-adjusted demand shares is proportional to the difference between the quality-adjusted prices. This is used to derive substitution elasticities. As suppliers also react to demand, a structural CES model is specified for the supply-side. The elasticity is obtained by solving for the equilibrium, under the identifying assumption that, within each market, within-brand-module unobserved shocks to demand are unrelated to within-brand-module unobserved shocks to supply (see Appendix C.2). A key argument in favour of this assumption is that the demand and supply functions here are estimated from the price and market share data adjusted for consumer and retailer heterogeneity. A second assumption is that the elasticities do not vary across markets, *i.e.* over time and across living zones.[14] The estimated median substitution elasticities among varieties within brand-modules are almost the same for SSB and NCSB (5.48 and 5.39, respectively). This figure is larger for NSB (9.59) and smaller for Water (4.57). The across-brand-module elasticities are fairly large for SSB and NCSB (6.04 and 6.69, respectively) and lower for NSB (3.35) and Water (3.13). For NSB, the low elasticity figure is explained by the small number of brand modules and the considerable differences between them (juices are very different from pulps). For Water, we observe strong brand loyalty in our data (see Table C.1).

[12] This procedure may overestimate the number of UPC actually available in market c. However, this is a minor issue as we focus only on the most-populated living zones, in which the local assortment of UPC proposed by a retailer likely corresponds to its national assortment. This in addition is not a concern for the evaluation of the variety of brand-modules, as all brand-modules appear on (or disappear from) all of the local markets at the same time. For example, the introduction of Coca Zero was national, and even if all package sizes were not available from every retailer, this was unlikely to have had a large effect on consumer welfare: variety/innovation biases should primarily be corrected at the brand-module level.

[13] Note that we assume that elasticities do not vary across across households, as we want to construct a local price index for a representative consumer.

[14] We have tested the robustness of our main findings to the use of separate elasticities for 2008-2011 and 2012-2013, as the soft-drink tax may also have altered consumer preferences. The elasticities are fairly similar between the two periods, and the results presented in the next sections are therefore unaffected.



Distribution of VA | EPI vs. CEPI across markets (Q-Q plot) | Distribution of EPI

Figure 2: EPI, CEPI and VA distributions in 2013

Notes: Kantar Worldpanel data 2013. This Figure shows, for the four product categories: (i) the distribution of the Variability-Adjustment term in the left panel (Equation (3)); (ii) the distribution of the Conventional Exact Price Index (CEPI) in the right panel (Equation (2)); and (iii) a Quantile-Quantile plot of the CEPI against the EPI in the middle panel, with departures from the 45-degree line indicating the effect of VA on prices.

3.3 Descriptive analysis of the resulting price indices

Figure 2 shows the spatial distributions of the VA factor (left panel), the EPI (right panel), and a Q-Q dot plot comparison of the EPI and the CEPI (middle panel) for the four groups of non-alcoholic beverages in 2013. Average yearly statistics are calculated for each living zone. The distribution of VA ranges from 1 to 1.2 for NSB (at the 99^{th} percentile), 1.4 for SSB and Water, 1.5 for NCSB, and clearly shows that it is important to adjust for product availability, as local prices can be up to 50% higher in some areas due to the absence of subsets of UPC. This result is of course mainly driven by the heterogeneity in the localisation of retailers and the existence of retailer brands. If we do not take retailer heterogeneity into account in the definition of UPC, then the maximum increase produced by a lack of variety is around 10%. The comparison of the local EPI and local CEPI, ranked by percentiles, appears in the middle panel. The VA factor largely affects the price ranking of markets, as shown by the dots far from the 45-degree line. The VA factor also explains heterogeneity in local prices. While the distribution of the CEPI for SSB has a standard deviation of 11.7% and a median of 1.10, the EPI for the same group has a standard deviation of 15.9% and a median of 1.20.

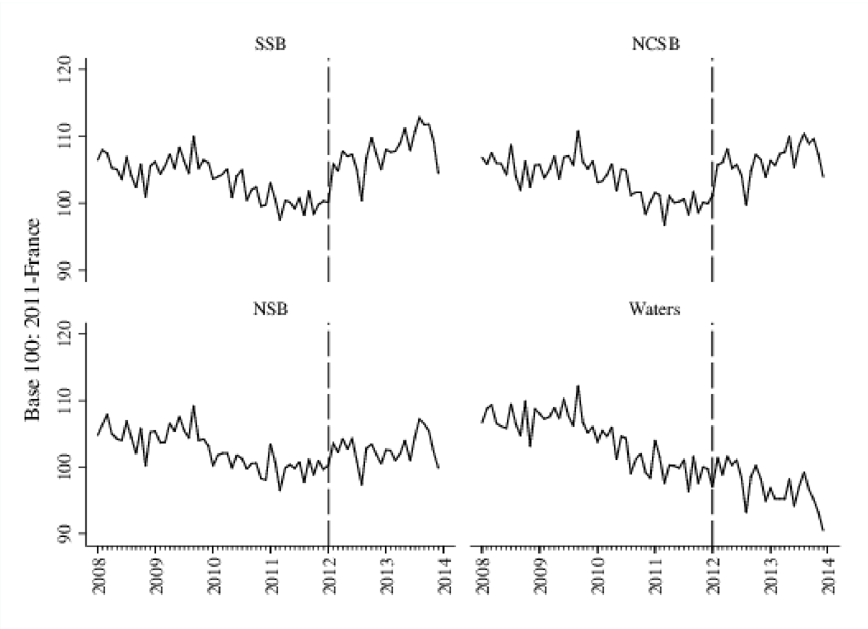


Figure 3: Exact Price Index, monthly average, 2008-2013

Notes: Kantar Worldpanel data 2008-2013. This Figure shows the changes over time in the average Exact Price Indices (EPI) of the four product categories. The average is estimated using market-sales weights. The reference market is the national market in 2011.

Figure 3 presents the evolution of a weighted-average of the EPI for the four product categories. The national average is calculated for each period by weighting each local value of the price index by its share of national sales in 2011.[15] For the four groups, the EPI shows a slight increase up to mid-2009, followed by a

[15]This share is calculated from our estimation sample, taking into account sample population weights.

fall until 2012. There is then a steep increase for SSB, NCSB and NSB (*i.e.* all soft drinks) in 2012-2013, while the price of Water fall.

Interestingly, the absence of a steep price increase before January 2012 — the month of implementation of the tax — shows that producers and retailers did not pass the tax on to consumers in advance. The soda-tax project was announced in late August. A simple event analysis shows that SSB prices in August, September, October and November were on average 1.7% higher, 1.7% lower, 0.3% lower and 0.2% higher respectively than in December.[16] This lack of anticipation can be explained by the existence of annual contracts between manufacturers and retailers (renewed in February-March) and by the uncertainty surrounding the legislative process, as the tax was eventually adopted in Parliament on the 21st of December 2011, after intense lobbying and debate (Le Bodo et al., 2017).[17]

4 Average incidence and timing of the soda tax

This section examines the impact of the tax at the national level by looking at monthly changes. We have two strategies to identify the average impact of the tax on prices and welfare. Given the absence of anticipated responses on the supply-side, we start with a before-after design. We here compare the average 2012 price to that in 2011, after controlling for changes in the cost of key inputs used in SSB production. However, it can be argued that movements in unobserved production or retailing costs also affected consumer prices. We thus take a difference-in-difference approach, where trends in SSB prices are compared to trends in the price of Water.

4.1 Before-after results

We first carry out a before-after estimation, similar to the empirical pass-through specifications that regress the annual change in prices on the annual changes in costs, and identify pass-through by comparing the change in prices to the change in costs across equilibrium situations (Hong and Li, 2017; Amiti et al., 2014). The following equation is estimated separately for each beverage group, on our sample of local EPIs, where each observation is the local aggregate price of product g observed in market c (living zone a $\times$ month t)

$$\ln(\boldsymbol{P}_{gc}) = \alpha_0 + \alpha_1 \delta_{t \geq 2012} + \delta_y + \delta_m + \gamma C_t + \delta_a + \epsilon_{gc}. \quad (5)$$

In this equation, the before-after estimate of the tax effect is given by α_1. The equation compares the average EPI in 2012 (after: $\delta_{t\geq 2012}$) to that in 2011 (before), adjusting for year effects (δ_y: 2008, 2009, 2010 and 2013), month effects (δ_m), which are restricted to be the same in all years (allowing for year-specific month effects yields the same results), and input costs C_t.[18] We add area-specific fixed-effects (δ_a) to increase the precision of the estimates.[19] Here again, observations are weighted by the share of national sales in the living area the year before the policy (2011).

[16]These differences are not significant in October and November. The numbers take into account the share of national SSB sales in each living zone over 2011.

[17]See `https://lexpansion.lexpress.fr/actualite-economique/taxe-sodas-light-comment-coca-cola-a-perdu-la-bataille_1440607.html` and `https://www.legifrance.gouv.fr/`, "LOI n°2011-1906 du 21 décembre 2011 de financement de la sécurité sociale pour 2012".

[18]We have time series on many inputs, such as oil, metal, plastic, glass, paper, electricity, gas, sugar, etc.

[19]The area fixed-effects can be dropped as they are orthogonal to the time effects. This would however entail a loss of efficiency.

We here want to control for shocks to input costs — especially sugar — as these likely played an important role in the evolution of SSB prices over the period. This is illustrated in Figure 4, which plots national statistics data on the Producer Price Index (PPI) for sugar (on the right panel), the Consumer Price Index (CPI - left panel) and the PPI for all non-alcoholic beverages and its two main components, soft drinks, juices and syrups on the one hand (SSB+NCSB+NSB) and Water on the other.

Figure 4: Consumer and Producer Price Indices (INSEE)

Notes: This Figure shows the changes over time in Consumer Price Indices (CPI: left panel) and Producer Price Indices (PPI: right panel) reported by the French National Statistics Office (*INSEE: Institut National de la Statistique et des Etudes Economiques*) and Eurostat. Producer Price Indices measure monthly changes in the trading price of products from the producers' perspective. Consumer Price Indices measure changes in the prices of consumer goods.

The CPI of both components move similarly until 2011, with a positive trend from mid-2008 to mid-2009, and then a negative trend until the end of 2011. The CPIs then diverge until mid-2012, with a much larger and longer CPI increase for soft drinks, juices and syrups than for water, before going back to a common downward-sloping trend. The steep 2012 increase in the CPI of soft drinks, juices and syrups series may reflect (at least partly) the rise in the PPI for sugar following the revision of the EU sugar quota policy in September 2011. As sugar is an important input in the production of soft drinks,[20] this shock is a major potential confounding factor in the evaluation of tax incidence.[21]

We therefore need to control for the cost of sugar in the regressions. We do not add more input prices, as this produces considerable multicollinearity in the regressions.[22] The main identifying assumption is then that the remaining variation is entirely attributable to the tax. In the next subsection, we will use Water as a control group to pick up all of the other supply-side sources of cost variation.

[20] The soft drinks produced in France do not contain high-fructose corn syrup but standard sucrose, see the analysis published by the consumer news magazine *60 millions de consommateurs* in July 2012.

[21] This precludes the use of a Regression Discontinuity Design (RDD) exploiting the discontinuity around January 2012, which in addition has a priori little internal validity due to inertia on the supply side (after-Christmas strategic inventory management and sales) and concurrent shocks to input costs.

[22] The Variance Inflation Factors for input costs are over 20 when we control for other costs as well as that of sugar. One likely explanation for multicollinearity is that most input costs are indexed on the price of oil and are driven by similar macroeconomic shocks.

Table 4 presents the before-after estimates. In column (1), we only adjust for month effects (δ_m), and add area-specific fixed-effects (δ_a) to increase the efficiency of estimates. The estimates of the tax impact on the EPI are strongly significant. The average price of SSB in 2012 was around 5.4% higher than in 2011, a much larger figure than the price changes observed throughout 2011. The increase for NCSB is about 5.2%.[23] Column (2) shows that this impact is smaller when we control for the cost of sugar, dropping to 4.1% for SSB and 4.2% for NCSB.[24] This drop is in line with available evidence regarding the pass-through of variations in sugar price onto consumer SSB prices in France.[25] However, the fall in the estimated NCSB effect is surprising at first sight, as sugar is not an input in NCSB production. Before 2015 and the introduction of Stevia-based colas in France, the artificial sweeteners were mainly aspartame and acesulfame-K, the cost of which was under 10% that of beet sugar. We do however find a significantly positive impact of the cost of sugar on NCSB. We interpret this as evidence that producers and retailers tied NCSB prices to their twin-variety SSB prices. Over 2008-2011, the elasticity of the price of a NCSB product to the price of the same-brand SSB sold in the same market by the same retailer was 0.73, after adjusting for area and retailer fixed effects. In 2012-2013, this elasticity rose slightly to 0.76.

Table 4: Tax incidence: Price-index variation (% points)

	Before-after		DiD	
	(1)	(2)	2012	2011
Groups				
SSB	5.426***	4.144***	4.261***	0.570**
	(0.171)	(0.232)	(0.402)	(0.214)
NCSB	5.217***	4.248***	3.162***	0.579
	(0.366)	(0.343)	(0.493)	(0.303)
Additional controls				
Area fixed-effects	Yes	Yes	Yes	Yes
Sugar price (in log) for SSB and NCSB	No	Yes	Yes	Yes
Group-specific month effects	No	No	Yes	Yes
Period	2008-2013	2008-2013	2010-2012	2009-2011

Notes: The dependent variable is the log of EPI. The EPI is estimated from Kantar Worldpanel data 2008-2013 using market-level observations (living zone-month) weighted by the share of the national sales in the market in 2011. These estimates represent changes in the EPI, in % points, between 2011 and 2012 (before-after columns), which is α_1 in Equation (5), and the difference in the changes between SSB/NCSB and Water (DiD: Difference-in-Difference columns), which is α_1 in Equation (6). The DiD-2011 column is a placebo test, focussing on the 2010-2011 change. Standard errors are in parentheses; ***, ** and * indicate significance at the 1%, 5% and 10% levels.

[23] In addition, the before-after estimates for NSB is positive (2.0%) and negative for Water (-1.4%). We may think that the higher NSB price is explained by substitution from NCSB to NSB, generating strategic price adjustments on the supply-side. However, the cross-price elasticity reported in Appendix A is negative (-0.035), which rules out this explanation.

[24] Introducing non-linear functions of sugar costs (higher-order polynomials or piece-wise functions) produces a considerable amount of multicollinearity, with exploding Variance Inflation Factors.

[25] Using an empirical IO model and assuming an asymmetric and full transmission of production costs, Bonnet and Requillart (2011) finds that a 36% decrease of the sugar price leads to an average decrease in SSB prices by 3.4% (see their simulations). This corresponds to an elasticity of roughly 0.1, which implies that the increase in sugar price between 2011 and 2012 (about +18%) would correspond to a +1.8% increase in consumer prices. The difference between estimates in columns (1) and (2) provides a close result ($5.426\% - 4.144\% = 1.283\%$)

4.2 Difference-in-difference results

The before-after regression results may be driven by shocks to input costs that we cannot control for due to collinearity in the cost variables. We therefore take a difference-in-difference approach, with Water as the control, and focus on the 2010-2012 period to ensure that the common-trend hypothesis holds.

We choose Water as a control group for four reasons. First, Water was obviously not targeted by the soda tax. Second, apart from sugar, the inputs used in the supply of water are similar to those for SSB, and they are also similar in terms of cost structure: plastic, glass and aluminium for packaging; natural water; and marketing, logistic and retailing costs. Third, while the companies owning SSB (and NCSB) have some important brands of NSB, they have zero or very small market shares for Water.[26] This limits any firm strategic reactions producing changes in the supply price of Water. Fourth, we have estimated an AIDS demand system for the four group of beverages to identify the price substitutions across the four markets. Our results in Appendix A show that the market for Water is largely disconnected from that for soft drinks,.

To check whether the common-trend assumption holds in the pre-policy period, Figure 5 plots the annual average of the EPI for SSB and NCSB, as compared to Water. As in all of our results, each observation is weighted by the share of national sales in each local market in 2011. Although the trends in SSB (NCSB) and Water prices differ slightly before 2010, the common-trend assumption holds for 2010-2011.

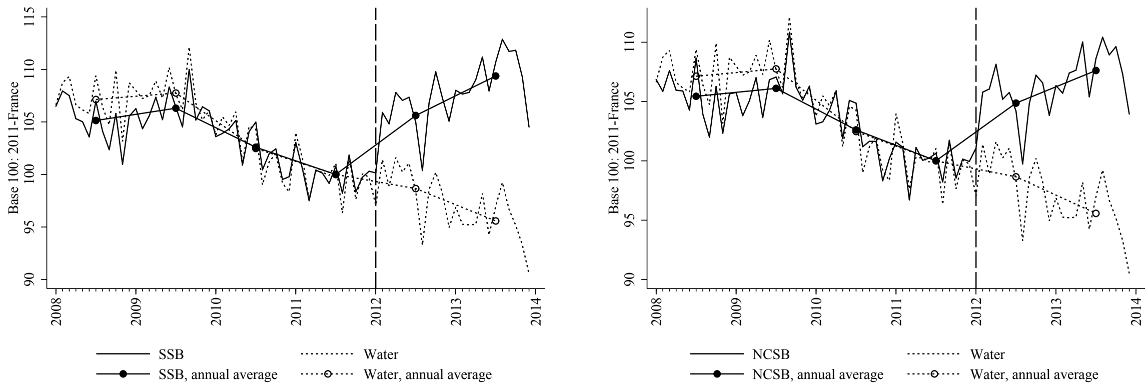


Figure 5: Common trends, difference-in-difference estimation

Notes: Kantar Worldpanel data 2008-2013. Each point represents the value of the average EPI in a given year, while the oscillating lines shows the monthly variations of the indices around their yearly trends. Each average price figure is calculated by taking the weighted mean of local values, using market sales as weights.

We estimate the following model for the comparison between SSB (or NCSB) and Water

$$\begin{aligned} \ln(\boldsymbol{P}_{gc}) = \alpha_0 + \alpha_1 \delta_{g=SSB} \times \delta_{t \geq 2012} + \delta_{g=SSB} + \delta_y \\ + \delta_m + \delta_{g=SSB,m} + \gamma \delta_{g=SSB} \times C_{t,sugar} + \delta_a + \epsilon_{gc}, \end{aligned} \tag{6}$$

[26] Coca-Cola, Pepsico and Orangina-Suntory are the main owners of the SSB national brands. Pepsico owns Tropicana, which is the leading national brand in the NSB market. Danone and Nestlé own the most popular national brands of Water.

where g identifies Water and either SSB or NCSB, $\delta_{g=SSB,m}$ are group-specific month effects for differences in seasonality between SSB and water consumption, and we control for the cost of sugar for SSB only.[27] The third column of Table 4 shows the Difference-in-Difference (DiD) estimates. The estimated impact for SSB is very similar to that from the before-after estimation: 4.2% vs. 4.1%. The NCSB effect is lower in the DiD than in the before-after estimates: 3.2% vs. 4.3%. However, these two figures are not significantly different from each other, as the 95% confidence intervals overlap.

Column (4) in Table 4 provides a very conservative test of the common-trend assumption, using a placebo policy change on the 1st of January 2011 (one year before). The estimated placebo impact for SSB, although significant, is more than seven times smaller and is insignificant for NCSB.[28] This DiD analysis thus overall confirms the before-after results, which will be used in the remainder of our analysis to calculate pass-throughs and evaluate the spatial and social heterogeneity of tax incidence.

4.3 The timing of tax shifting

The timing of the tax incidence can be analysed via an event study, by adding particular month effects for 2012 to the second specification in Table 4. The implicit concept of pass-through here is the change in price resulting from the taxation shock to costs in January 2012, the effect of which may be felt with some lags (Gopinath and Itskhoki, 2010; Nakamura and Zerom, 2010). The estimated coefficients appear in Figure 6. Each point here is the observed gap in 2012 from the usual month-of-the-year effect, with December 2011 being the absolute reference. The horizontal line represents the effect estimated in the second column of Table 4, *i.e.* the yearly average for 2012. The average prices in January are similar to those observed usually in Januaries. This is as expected, and is explained by the fall in the value of Christmas inventories owned by retailers that leads them to propose "clearance prices" (sales) to consumers (Smith and Achabal, 1998; Gupta et al., 2006). The prices of both SSB and NCSB then increase, but do not significantly vary between February and April, increase again in May, and then return to the 2012 average. The subsequent increases observed in October and November cannot be attributed to the tax.

This analysis suggests that the tax was passed on quite rapidly to consumer prices, after one quarter.[29] This is unsurprising given that, over 2008-2013, the contractual framework between manufacturers and retailers was regulated, with annual negotiations that had to be resolved by the end of March. The price levels reached in March-April 2012 are similar to our earlier results in the before-after specification. We will hence retain this latter specification in the remainder of our analysis.

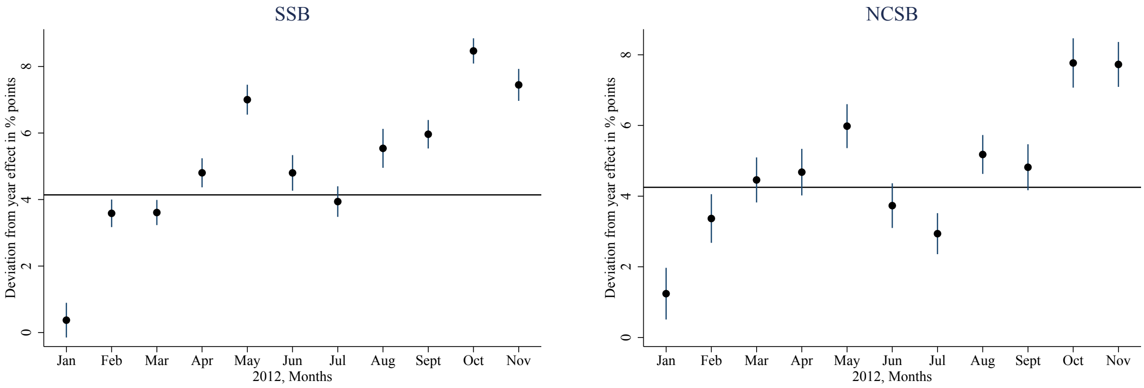
5 The behavioural responses of the demand and supply sides

Tax incidence is likely to vary across socio-economic groups, markets and products, depending on national and local consumer preferences and market structure. For instance, we can well imagine that richer households

[27] The estimates with the cost of sugar as a control variable for the price of Water are plagued by multicollinarity problems.

[28] More generally, taking any placebo date before January 2012 for the implementation of the tax produces an estimated impact that is much lower than the estimates in column (3). This can readily be seen in Figure 5. We also constructed a placebo distribution treatment by permutating SSB (treated product) and Water (control) in randomly-drawn living zones. This permutation procedure assesses the uncertainty regarding the lack of effect for Water. The DiD effect in column (3) is significantly higher than the placebo effects at any significance level.

[29] Harding et al. (2012) also find that taxes are passed through rather quickly to prices and that the pass-through remains stable thereafter



Average tax incidence: 4.14%　　　Average tax incidence: 4.25%

Figure 6: The timing of tax shifting: event study

Notes: Kantar Worldpanel data 2008-2013. Each point represents the estimated coefficient on the respective month-to-tax change indicator variable in 2012, *i.e.* EPIs relative to the EPI in December 2011. The horizontal lines represent the before-after effects estimated in Table 4, specification (2), i.e. the average effect in 2012. The bars extending from each point represent the bounds of the 95 percent confidence interval calculated from standard errors that are clustered at the area level. The control variables are as in Table 4, specification (2).

consume less SSB, but are also more attached to specific brands. They also have higher opportunity costs of time, which may prevent them from searching intensively for lower prices. The tax may thus be shifted less onto consumer prices in richer living zones. The degree of competition in the local market is also a key factor, as imperfect competition increases the incentive for greater pass-through of costs onto consumer prices. Last, varieties (brands or UPC) differ in their demand elasticities, the intensity of horizontal competition with other varieties, costs and whether they are produced by manufacturers or retailers. This section considers the heterogeneity of tax incidence to uncover the behavioural responses on the demand and supply sides. We first examine differences across consumer groups at the national level and then the reactions of retailers to local market characteristics. We last discuss the distribution of average pass-through rates calculated at the level of product varieties.

5.1 Heterogeneity across consumer segments

We first focus on tax incidence by income and consumption, which are two major segmentation variables in the soft-drinks market. For each variable, we consider an equal-split of the population using the median, and calculate local price indices for each consumer segment, *i.e.* we take into account their specific preferences. Income here is real household equivalent income, *i.e.* adjusting household income for inflation (the Consumer Price Index) and units of consumption (the OECD scale). Consumption is measured by dividing annual consumption by the number of household members. The econometric specification is the same as in Table 4, column (2).

The results appear in Table 5. The tax incidence on the SSB price index is slightly higher for low- than high-income households (4.6% vs. 3.6%), and lower for low- than high-consumers (3.6% vs. 4.2%). In each comparison, the confidence intervals overlap. The soda tax has then been only weakly regressive. One explanation is that high-income and low-consumers are only slightly more price sensitive in their product choices than low-income/high-consumers. We test this prediction by estimating AIDS models for each segment, as in Appendix A Table A.1. High-income consumers are slightly more price sensitive, with own-price elasticities of -0.91 for SSB and -0.97 for NCSB, as against -0.86 and -0.76 for low-income consumers. But we find no significant evidence of a lower price response from high-consumption households, as compared to low-consumers.

Columns (5) and (6) of Table 5 evaluate the impact of living close to a border with another European country (Belgium, Luxembourg and Germany; we exclude Spain, Italy and Switzerland, which are less accessible by road). We find small negative border effects for SSB. Although the difference from living zones further from borders are not significant, competition with stores on the other side of the border may have slightly reduced pass-through in stores closer to borders.[30]

Small differences between consumer segments can nevertheless produce large differences across markets for two reasons. First, firms' reactions depend on the responses of marginal consumers in each local market, and we here focus on average consumers rather than households who are at the margin of switching between product categories. Second, retailers will adapt their strategies to the local market structure.

Table 5: The heterogeneity of tax incidence across socio-demographic groups (% points)

	Income		Consumption		Border area	
	$\leq$ Q(50)	$>$ Q(50)	$\leq$ Q(50)	$>$ Q(50)	Yes	No
SSB	4.575***	3.597***	3.635***	4.185***	3.893***	4.170***
	(0.466)	(0.344)	(0.465)	(0.243)	(0.664)	(0.246)
NCSB	4.683***	3.801***	3.878***	4.251***	4.203***	4.253***
	(0.413)	(0.431)	(0.423)	(0.645)	(0.979)	(0.365)

Notes: The dependent variable is the log of EPI. The EPI is estimated from Kantar Worldpanel data 2008-2013. The estimated impacts in % points come from a before-after specification, similar to specification (2) in Table 4 (observations are weighted by market-specific sales). Samples: Household real equivalent income above or below the median; Household per capita yearly average SSB purchases above or below the median; Border areas are markets on a border with Belgium, Luxembourg or Germany. Standard errors are in parentheses; ***, ** and * indicate significance at the 1%, 5% and 10% levels.

5.2 Heterogeneity across markets

We here analyse the impact of local market structure to reveal strategic reactions on the supply-side. Technically, this is feasible as we retained market fixed-effects in our quality-adjusted prices, while we purged for retailer and consumer heterogeneity. The local variations in EPI do not therefore reflect national-level variations in cost or strategies across retailers and their interactions with retailer localization. Differences in tax incidence across markets will thus reflect the price-setting and assortment strategies of local retailers as a function of the local aggregate characteristics of the demand and supply sides. Price-setting is captured by the CEPI and assortment by the VA term in the EPI.

[30]Harding et al. (2012) find substantial border effects for cigarette taxes in the U.S.. However, there are also very large differences in cigarette taxes across States.

We first analyze the association between market size and tax incidence, with the former proxied by the number of consumption units and median population income. These variables come from Census data and fiscal data from the National Statistics Office (INSEE).[31] We then add indicators of the degree of local-market competition. This is first measured by the number of distinct retailers in each market, and second by the Herfindahl-Hirschman Index (HHI) of sales area per capita, dichotomized using a threshold of $2,000$ (a value of $10,000$ corresponds to a monopoly). This threshold is used by the European Commission to reflect a lack of horizontal competition. These two competition variables are strongly correlated with market size, so that we cannot simultaneously control for market size and the degree of competition.

Table 6 reports the results. Specification 1 replicates the benchmark estimates in Table 4 (the before-after results: Post = the coefficient on $\delta_{t\geq 2012}$), except that now all markets are given the same weight. The key estimates are thus slightly different, 4.94% for SSB as against 4.14% in column 2 of Table 4. Specification 2 adds the interactions between $\delta_{t\geq 2012}$ and the logarithm of median income and the number of consumption units. Median income positively affects price (8.90 percentage points). Since the price indices are adjusted for product availability, and consumer and retailer heterogeneity, one likely explanation is that retailers face higher operating and rental costs in more affluent areas. Income has a negative effect on SSB tax incidence. We have centred the log-income variable on its mean, so that the estimated coefficient (-3.08) implies that the tax incidence is about 25% lower when median income is 50% above average.[32] This partly reflects the role of local costs, which represent a higher share of consumer prices in wealthier areas.[33] The tax has thus reduced the SSB price gap between less-affluent and more-affluent living areas: it has thus been regressive. The coefficient on N_{cu} shows that doubling market size also reduces SSB tax incidence by 0.16 percentage points, *i.e.* 3% of the baseline effect. This is in line with the theoretical predictions from New Economic Geography models that competition should be more intense in larger markets (cities), reducing the possibilities of firm markup adjustments (see Handbury and Weinstein, 2014). For NCSB, the estimated effects of median income and market size in specification (2) are of the same sign and size but are not significant.

[31] Postcode-level statistics were aggregated to the level of living zones using population weights. All statistics vary year-by-year.
[32] INSEE statistics reveal that this is an extreme case. The standard deviation in median income is much lower.
[33] The role of local costs in reducing pass-through is well-documented in work on empirical trade, see Nakamura and Zerom (2010).

Table 6: The heterogeneity of tax incidence across markets (% points)

	SSB						NCSB					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Post	4.940***	4.722***	4.799***	4.849***	4.954***	5.583***	4.046***	3.980***	4.120***	4.305***	4.088***	5.294***
	(0.387)	(0.457)	(0.449)	(0.445)	(0.387)	(0.562)	(0.722)	(0.849)	(0.835)	(0.836)	(0.722)	(1.152)
$\times \ln(Income)$		-3.077*	-3.932**	-2.575				-2.162	-3.659	-2.739		
		(1.761)	(1.656)	(1.636)				(3.243)	(3.046)	(3.032)		
$\times \ln(N_{cu})$		-0.233*						-0.365				
		(0.122)						(0.226)				
$\times 1_{HHI>2000}$			0.556**		0.551**	1.130**			1.372***		1.338***	-0.116
			(0.249)		(0.244)	(0.488)			(0.458)		(0.450)	(0.979)
$\times N_{retailers}$				-0.066						-0.388***		
				(0.066)						(0.126)		
$\ln(Income)$		8.901*	8.614*	8.571*				4.910	3.456	1.001		
		(5.014)	(4.895)	(4.890)				(9.240)	(9.037)	(9.106)		
$\ln(N_{cu})$		-2.727						-0.771				
		(4.932)						(9.207)				
$1_{HHI>2000}$			1.142***		1.148***	1.237**			-0.074		-0.058	-0.497
			(0.322)		(0.321)	(0.492)			(0.598)		(0.597)	(1.009)
$N_{retailers}$				-3.696***						-2.957***		
				(0.175)						(0.331)		
Sample	Full	Full	Full	Full	Full	Inc<Q(50)	Full	Full	Full	Full	Full	Inc<Q(50)

Notes: The dependent variable is the log of EPI. The EPI is estimated from Kantar Worldpanel data 2008-2013. The estimated impacts in % points come from a before-after specification (observations are *not* weighted by market-specific sales). N_{cu}: number of Consumption Units (cu) in each market (INSEE census data). $Income$: market average of the median real equivalent income in the market's postcodes (INSEE fiscal data). $N_{retailers}$: number of distinct distribution channels operating in the market (TradeDimensions data). HHI is a Herfindahl-Hirschman index based on the sales area of retailers (TradeDimensions data). The European Commission considers that a HHI greater than 2000 reflects horizontal-competition concerns (Official Journal C 31 of 05/02/2004). All of these variables vary across markets c, *i.e.* across areas a and periods t. All estimates include area, month and year fixed effects. Full sample: $N = 18,927$ living zone-month observations. The sample Inc<Q(50) contains only markets where the median income is below the median figure ($N = 9,442$ living zone-month observations). Standard errors are clustered at the area-level in parentheses; ***, ** and * indicate significance at the 1%, 5% and 10% levels.

Specifications (3) to (6) specifically address the role of competition. In specification (3), the HHI dummy is positively correlated with SSB prices (+1.14 percentage points in concentrated markets), but not with NCSB prices. However, it does have a large, significant and positive effect on tax incidence. In concentrated markets, tax incidence is about 12% higher for SSB and 33% higher for NCSB. Specification (4) similarly shows that prices fall as the number of distinct retailing firms rises: −3.70 percentage points for SSB when one more firm operates in the living zone. The number of distinct retailers does not affect the tax incidence on SSB prices, but reduces incidence on NCSB prices (−0.39 percentage point per additional retailer).

Specifications (5) and (6) compare the impact of market competition between the full sample, and the sub-sample of living zones with median income under the national median figure. In line with our previous results in Table 5, average tax incidence is higher in low-income markets (5.58% for SSB and 5.29% for NCSB). More interestingly, we also find a stronger effect of competition in poorer areas, but only for SSB. In low-income high-HHI markets, tax incidence is 20% higher (1.13/5.58) than in low-income low-HHI market. In other words, incidence is similar in non-competitive high-income and competitive low-income markets. This illustrates that taking competition into account can significantly moderate our conclusions regarding the distributional effects of taxes.

The spatial heterogeneity in retailer aggregate price responses to taxes is driven by their price-setting and choice of assortments, *i.e.* the number of varieties they offer to consumers. We investigate these mechanisms separately in Table 7, which reports the effect of the tax on the conventional exact price index (CEPI: left panel) and the variability-adjustment factor (VA: right panel), for specifications (1), (3) and (6).

The comparison of the estimates for CEPI and VA reveals that it is the former rather than the latter that drives heterogeneity and the level of the tax incidence. The CEPI increased more in poorer areas, and competition significantly reduces the tax burden for consumers, especially in poorer areas (Table 7, upper panel). Regarding variety adjustment, we find evidence of interaction effects between the tax and affluence and market competition intensity. Specification (3) shows that the positive effect of the tax on VA was larger for NCSB only in less-competitive markets (+0.46 percentage points in high-HHI markets), but not for SSB. When we focus on low-income areas (specification (6)), the effect vanishes for NCSB, but becomes significant for SSB: the tax incidence is +0.26 percentage points higher in high-HHI areas.

One potential explanation is that, to adjust to the tax, retailers have changed their SSB assortments in order to reduce price competition (Hamilton, 2009). However, when we compare the number of varieties available in each beverage group before and after the tax, retailers do *not* seem to have changed the breadth of product variety. The moderating effect of competition on changes in variety adjustment can then only be explained by changes in the national share of varieties available in each specific market, *i.e.* changes in the popularity of product varieties and brands among French consumers. The estimated VA effects thus reflect a fall in popularity of some SSB varieties that were specifically provided by retailers in less-competitive low-income market. Likewise, there has been a fall in the popularity of some NCSB varieties that were specifically available in less-competitive high-income markets. Overall, even if the tax affected consumers more through prices than the availability of popular products, these results illustrate that the latter is an important parameter in assessing the welfare impact of public-health policies across markets that differ by their competition structure.

Table 7: The heterogeneity of tax incidence across markets - CEPI and VA (% points)

	CEPI					
	SSB			NCSB		
	(1)	(3)	(6)	(1)	(3)	(6)
Post	4.956***	4.739***	5.417***	3.938***	3.729***	5.000***
	(0.370)	(0.430)	(0.538)	(0.667)	(0.772)	(1.075)
$\times \ln(Income)$		-2.960*			-2.244	
		(1.584)			(2.815)	
$\times 1_{HHI>2000}$		0.534**	0.872*		0.916**	-0.047
		(0.238)	(0.467)		(0.423)	(0.914)
$\ln(Income)$		9.410**			8.938	
		(4.682)			(8.352)	
$1_{HHI>2000}$		0.341	0.687		-0.503	-0.830
		(0.308)	(0.471)		(0.553)	(0.941)
Sample	Full	Full	Inc<Q(50)	Full	Full	Inc<Q(50)
	VA					
	SSB			NCSB		
	(1)	(3)	(6)	(1)	(3)	(6)
Post	-0.016	0.060	0.166	0.109	0.391	0.294
	(0.108)	(0.125)	(0.141)	(0.265)	(0.307)	(0.393)
$\times \ln(Income)$		-0.973**			-1.414	
		(0.459)			(1.119)	
$\times 1_{HHI>2000}$		0.021	0.258**		0.456***	-0.070
		(0.069)	(0.122)		(0.168)	(0.334)
$\ln(Income)$		-0.796			-5.482*	
		(1.357)			(3.321)	
$1_{HHI>2000}$		0.801***	0.551***		0.429*	0.333
		(0.089)	(0.123)		(0.220)	(0.344)
Sample	Full	Full	Inc<Q(50)	Full	Full	Inc<Q(50)

Notes: The dependent variable is the log of CEPI or VA. CEPI and VA are estimated from Kantar Worldpanel data 2008-2013. The estimated impacts in % points come from a before-after specification (observations are *not* weighted by market-specific sales). N_{cu}: number of Consumption Units (cu) in each market (INSEE census data). $Income$: market average of the median real equivalent income in the market's postcodes (INSEE fiscal data). $N_{retailers}$: number of distinct distribution channels operating in the market (TradeDimensions data). HHI is a Herfindahl-Hirschman index based on the sales area of retailers (TradeDimensions data). The European Commission considers that a HHI greater than 2000 reflects horizontal-competition concerns (Official Journal C 31 of 05/02/2004). All of these variables vary across markets c, *i.e.* across areas a and periods t. All of the estimates include area, month and year fixed effects. Full sample: $N = 18,927$ living zone-month observations. The sample Inc<Q(50) contains only markets where the median income is below the median figure ($N = 9,442$ living zone-month observations). Standard errors are clustered at the area-level in parentheses; ***, ** and * indicate significance at the 1%, 5% and 10% levels.

5.3 Heterogeneity across products

The impact of the tax on the EPI for SSB and NCSB depends on product-level pass-throughs: these will differ across products, as different manufacturers and retailers face different demand elasticities and initial market conditions, and have varying degrees of market power and bargaining power with respect to the other actors in the supply chain. Products with larger market shares – in our case the national brands – will be more important in determining overall tax incidence.

To examine the heterogeneity of tax incidence across products, we estimate pass-through rates at the UPC level. To avoid the influence of outliers, the dependent variable is not the log-mean but the log of the median (unadjusted) UPC price observed in each market. We apply the before-after design controlling for sugar cost over the 2008-2013 period. Purging the tax impact (α_1) from the 2012 prices, we obtain the (counterfactual) 2012 prices had there been no tax. Adding the excise tax, we obtain the (counterfactual) 2012 prices with 100% pass-through. We then obtain a distribution for price-response and pass-through.[34]

Table 8 provides details on pass-through by product type. These are, on average, slightly higher for SSB (36.4%) than for NCSB (32.0%), and lower for top national brands (19.2% for SSB, on average) than for other national, retailer and hard-discount brands (with averages ranging from 33.5% to 66.0%).

This heterogeneity stems partly from horizontal competition on the soft-drink market. In a broad class of symmetric imperfect-competition models, theoretical pass-throughs are found to be higher when higher prices lead the industry to be less competitive (Weyl and Fabinger, 2013). We would expect this to apply to the soft-drink industry, where the major players clearly benefit from a unit tax that falls more heavily on retailer brands. However, a vertical market structure with linear pricing and double markup adjustment by producers and retailers can produce some incompleteness and heterogeneity in pass-through (Hong and Li, 2017). Under double marginalization, the leading soft-drinks manufacturer has a very large market share and is therefore likely to have higher markups and face a lower demand elasticity, so that there is less need to increase the wholesale price to offset the burden of the tax. Other manufacturers have much smaller market shares and face higher demand elasticities, so that their pass-throughs should be higher. Retailers are unlikely to increase their markups on national brands, if the latter function as “loss leaders ”used to build or maintain store traffic (Neslin et al., 1995; Pancras et al., 2013). The incentives are different for retailer brands. In France, they are produced by external manufacturers, but the marketing costs are shifted on retailers, which lowers markups. As they also have smaller market shares and cannot be considered as loss leaders, they have much higher pass-throughs than the national brands, in line with the theoretical predictions in Hong and Li (2017).

It is not clear, however, whether these arguments continue to hold if manufacturers and retailers have two-part tariff contracts, whereby manufacturers propose a contract to retailers including wholesale prices and fixed fees (Rey and Vergé, 2004, 2010; Allain and Chambolle, 2011). If retailers have little bargaining power in the French SSB market (two manufacturers have many brands and very substantial market shares), we expect these contracts to produce rather higher pass-throughs for national brands. Along these lines, Bonnet and Réquillart (2013b) find an over-shifting of the excise tax in an ex-ante evaluation study using a structural IO approach, a two-part tariff modelling of the supply chain with zero buyer power for retailers, and

[34] The excise tax of 0.0716 Euro/Liter applies to producer prices; it should be multiplied by 1.055 (5.5% being the VAT rate) to obtain the tax passed onto consumer prices with 100% pass-through. The price-response is α_1 and the pass-through rate is $\alpha_1 \exp(\alpha_0)/0.075538$.

household purchase data from the 2002-2005 French Kantar Worldpanel.[35] This discrepancy with our findings then suggests that the soda tax implied something more than a simple shock to costs for manufacturers and retailers. Other factors played a role in the incomplete adjustment of prices to the tax. Since 2009-2010, soft-drink manufacturers have taken on board public-health concerns and the risks for their brand image (Dorfman et al., 2012). In a context of market stagnation, market leaders also saw the tax as a means of reducing the price gap between their brands and national brands, in the long-term perspective of discouraging product innovation and marketing investment by retailers, and so maintaining their sales volume.[36] IO models that explore cost pass-throughs via comparative-static analyses of equilibria cannot be used to evaluate these dynamic situations and singular policy shocks, which stimulate strategic long-term considerations (anticipation of market trends, changes in public-health regulations, increasing consumer concern over health, and evolving brand images).

Table 8: Tax incidence: pass-throughs at the UPC level (% points)

	SSB		NCSB	
	#UPC	Pass-through (%)	#UPC	Pass-through (%)
All	400	36.4	127	32.0
Top national	136	19.2	86	23.9
Other national	113	48.5	17	66.0
Retailer	108	47.4	18	38.8
Hard discount	43	33.5	6	35.4
Standard Coca-Cola	31	38.5		
Diet Coke/Coke Light			28	35.3
Coca-Cola Zero			17	12.4

Notes: Kantar Worldpanel data 2008-2013. These are average pass-throughs, calculated from UPC-specific pass-throughs for the set of UPC indicated in the first column. Each UPC-specific pass-through is estimated using a before-after specification, similar to specification (2) in Table 4 (observations are weighted by market-specific sales), where the dependent variable is the median unadjusted UPC price observed in each market.

6 Tax incidence vs. public-health considerations

As a final evaluation exercise, we now calculate the pass-through of the tax on the EPI. This provides a measure of the distribution of the tax burden between consumers and suppliers. Given the regressivity of the tax, another question of central policy importance is whether consumers – especially low-income high-consumption households – reduced their SSB consumption. The behavioural impact of the tax is an important component of its impact on social welfare.

The pass-through of the tax on the EPI is calculated under the assumption that the average subjective quality on each market is constant. Hence, the ratio of adjusted to observed UPC prices does not change,

[35] Their simulated pass-throughs are higher for national brands than for retailer brands, as these latter have higher demand elasticities. This result is likely to hold even if retailers have some buyer power (retailers regularly delist Coca-Cola products in order to obtain better agreements - see for instance `https://www.lsa-conso.fr/lidl-dereference-coca-cola,106732`. Under two-part tariffs, the bargaining power of the contracting parties affects their profit but not their pass-throughs (Gaudin, 2016).

[36] This is corroborated by articles from trade publications stating that the soda tax has reduced the price gap between national and retailer brands. See the LSA article "Soft-drinks: les MDD en attente de plus de promotion ", 21/10/2013.

and we can calculate quality-adjusted prices corresponding to the counterfactual observed UPC prices (see Appendix B.4.). This allows the construction of a counterfactual EPI, showing the change in the SSB and NCSB aggregate price indices without the policy and for a 100% pass-through at the UPC level. Dividing the before-after estimates by the counterfactual variation in EPI obtained under the assumption of full pass-through yields the tax pass-through at the group level.

The estimated pass-through is 39.1% for SSB and 39.0% for NCSB. The pass-throughs for SSB and NCSB are very similar, which is another piece of evidence that retailers and producers tend to link the price changes of sister varieties across these two beverage categories. The figures are higher than the average UPC-level pass-through, which is explained by quality-adjustments in the calculation of the EPI. As the quality of national brands is higher than that of retailer and hard-discount brands, their quality-adjusted market shares are lower than their observed market shares. The EPI consequently assigns relatively less importance to the pass-through of national brands. Hence, after adjusting for differences in consumer heterogeneity and retailer heterogeneity, the tax incidence is higher. The difference reflects an aggregation bias, which arises from not being careful about the heterogeneity of the transaction prices provided by the data.

Our results are in line with the ex-post estimates in Cawley and Frisvold (2017) and Falbe et al. (2015), who take a DiD approach with geographic control groups to estimate the incidence of the Berkeley tax, and find pass-through rates of between 22% and 47%. However, different markets can yield different pass-through estimates. For instance, Colchero et al. (2015) and Grogger (2017) look at the impact of an excise tax in Mexico and find that the tax was over-shifted for carbonated varieties of SSB. Our findings appear at odds with the results in Berardi et al. (2016), who conclude that the tax was fully shifted onto SSB prices after six months, in June 2012. As noted previously, Figure 6 shows indeed little evidence that anything happened after March 2012. There are also three critical methodological differences between their study and ours. First, they exploit extracts of online shopping prices covering 12 months, from August 2011 to July 2012, which provides a set of prices that are less representative than the data we use. Second, they identify the pass-through from the month variations following December 2011, uncorrected for month-of-the-year effects and the steep increase in the price of sugar.[37] Third, they employ the tautological argument that the prices observed in June 2012 correspond to a 100% pass-through to conclude that there has been full pass-through.

Although the burden of the tax is higher on low-income consumers, the regressivity in terms of consumer welfare might be offset by progressivity in health benefits if it results in a greater drop in consumption (Etilé and Sharma, 2015; Sharma et al., 2014). To get an idea of the magnitude of these effects, we have estimated Almost Ideal Demand Systems for the four groups of non-alcoholic beverages and the four consumer segments of interest.[38] The combination of the estimated purchase elasticities and price changes provides us with an estimate of the impact of the soda tax on purchases and hence on sugar intake, as we have seen that the tax did not affect the average sugar content of products purchased within the SSB categories (see Figure 1). The tax reduced purchases by 4.5% in low-income households vs. 3.3% in high-income households, and 3.0% in low-consumption households vs. 3.9% in high-consumption households. The absolute level of consumption was also higher in 2011 for low-income households (21.2 L/cap/year vs. 16.4 L/cap/year for high-income) and high consumers (33.2 L/cap/year vs. 3.6 L/cap/year for low-consumers). Hence, the larger welfare losses for low-income households have to be weighted against the greater health benefits for this group and for society

[37] Other important differences are that they do not observe consumer purchases and work on prices observed at the level of product varieties with fixed market shares.

[38] The estimates do not differ much from the estimation results reported in Appendix A for the entire sample. The results are available upon request.

as a whole. However, given the low French consumption levels, the stakes are relatively small for consumer budgets and health.[39] Given these estimates, the intensity of the legislative battle around the tax might be interpreted as evidence that the main stakes revolved around the shift toward more stringent public-health regulations on food supply (Le Bodo et al., 2017).

7 Conclusion

This paper has analysed the incidence of the French 2012 soda excise tax using Kantar Worldpanel homescan Data on non-alcoholic beverage purchases from 2008-2013. We construct Exact Price Indices that measure the welfare that consumers receive from soft-drink consumption. In particular, our indices account for substitution between product varieties and brands, consumer and retailer heterogeneity, and changes in product variety across space and time. Using detailed information on local-market structure, we find evidence that competition limits the tax burden on consumers and that the regressivity of soft-drink taxes is partly due to the lack of retailer competition in low-income markets. On average, at the national level, the tax burden was only marginally higher in low-income households. However, at the local level, low-income households living in low-income markets with few retailers faced considerable price increases. We find incomplete pass-through, both for the Exact Prices Indices and the prices of product varieties. These results seem to be at odds with the predictions from some imperfect-competition IO models, which generally predict higher pass-throughs. One intriguing explanation would be that these models rely on misspecified demand functions, which are constrained to be very convex and "*build in the tax over-shifting property for the unit tax*" (Anderson et al., 2001, p. 189).[40] Another is that a different modelling approach might be required to understand and simulate the impact of standard cost-shocks and soft-drink taxes. The interaction of dynamic considerations, in terms of firms' expectations regarding market trends and stricter sector regulation, market structure (vertical integration and horizontal competition, and bargaining power along the supply chain) are likely to jointly determine the incidence of new taxes, as the latter represents a historical disruption of the usual market games. Our results therefore have important implications for both the analysis of the behavioural and welfare impact of nutritional taxes and theoretical research in Industrial Organization.

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A The price response of demand

The impact of taxation on equilibrium prices depends on within-group substitution, but also on substitution between SSB and NCSB and from soft drinks to other beverages. To delineate the boundaries of substitution in the market for soft drinks, we specify an Almost Ideal Demand System (AIDS) for the four groups of non-alcoholic beverages (Deaton and Muellbauer, 1980a). The dependent variables are the (market average) budget shares of SSB, NCSB, NSB and Water, and the explanatory variables are the logarithms of EPI, the logarithm of total expenditure on non-alcoholic beverages deflated by the AIDS aggregated price index, and controls for macro shocks (year and month dummies) and demographics across markets. The logarithm of real total expenditure is instrumented by the logarithm of average real household income, thus allowing for income effects. Homogeneity and symmetry constraints are imposed (Lecocq and Robin, 2015). The model is estimated using the pre-tax years only (2008-2011).

The upper panel of Table A.1 lists the estimated coefficients for budget shares, while the lower panel shows the corresponding Marshallian elasticities for quantities. The own-price elasticities of SSB and NCSB are large and significant, -0.87 and -0.85 respectively. Interestingly, the Marshallian cross-price elasticities between SSB and NCSB are negative and marginally significant. An increase in SSB price lowers NCSB consumption. A change in soft-drink prices has no impact on the consumption of Water, so that the relevant market for soft-drinks includes NSB but not Water. They also imply that the soft-drink tax had a large negative effect on soft-drink consumption, with beneficial health consequences in terms of sugar intake.

Table A.1: The response of quantity demanded to price

	SSB	NCSB	NSB	Water
Price effects				
SSB	0.040***	-0.013	-0.016**	-0.011
	(0.009)	(0.010)	(0.008)	(0.008)
NCSB	-0.013**	0.028***	-0.008	-0.008
	(0.006)	(0.007)	(0.006)	(0.005)
NSB	-0.016**	-0.008	0.061***	-0.038***
	(0.008)	(0.009)	(0.006)	(0.007)
Water	-0.011	-0.008	-0.038***	0.057***
	(0.008)	(0.009)	(0.007)	(0.007)
Budget effects	0.043***	0.069***	-0.079***	-0.033***
	(0.010)	(0.011)	(0.009)	(0.010)
Price elasticities				
SSB	-0.872***	-0.112*	-0.019	-0.027
	(0.034)	(0.051)	(0.027)	(0.031)
NCSB	-0.043*	-0.846***	-0.035*	-0.031
	(0.020)	(0.031)	(0.016)	(0.019)
NSB	-0.144***	-0.228***	-0.625***	-0.078*
	(0.037)	(0.056)	(0.030)	(0.034)
Water	-0.103***	-0.171***	-0.031	-0.742***
	(0.028)	(0.043)	(0.023)	(0.026)

Notes: These results come from the estimation of an Almost Ideal Demand System (Deaton and Muellbauer, 1980). Kantar Worldpanel data 2008-2011. The observation unit is a market (a living zone in a month); there are 11,779 observations. The dependent variables are the (market-average) budget shares on SSB, NCSB, NSB and Water in the upper panel, and the corresponding quantities in the lower panel. The independent variables are the logarithms of the Exact Price Indices, the logarithm of total expenditure on non-alcoholic beverages deflated by the AI aggregated price index, and control variables for macro shocks (year and month dummies) and market demographics (average household size, average age of the main shopper, proportion of households where the main shopper is a male, and the proportion of households in four household structures). The logarithm of real total expenditure is instrumented by the logarithm of average real household income. Homogeneity and symmetry constraints are imposed. Standard errors are in parentheses; ***, ** and * indicate significance at the 1%, 5% and 10% levels.

B Online Appendix: Derivation of the price index

B.1 Theoretical framework

An Exact Price Index (EPI) measures the change in expenditure required to keep utility constant as the prices of product varieties vary. It is therefore an index of consumer welfare, and can be formally defined for product group g and a representative consumer in market c as

$$\boldsymbol{P}_{gc} = \frac{C(V, \boldsymbol{p_{gc}})}{C(V, \boldsymbol{p_{g.}})}, \tag{B.1}$$

where $C(V, \boldsymbol{p_{gc}})$ is the cost of attaining utility V when facing prices $\boldsymbol{p_{gc}}$, and $\boldsymbol{p_{g.}}$ is a vector of reference prices.

We assume that households take a four-stage budgeting approach to decide their beverage consumptions (Deaton and Muellbauer, 1980b). They first allocate their consumption budget between broad food groups, here alcoholic and non-alcoholic beverages. The non-alcoholic beverage budget is then allocated between the four beverage groups g: (1) SSB (sodas and fruit drinks essentially); (2) Non-Calorically Sweetened Beverages (NCSB); (3) Naturally Sweetened Beverages (NSB, mainly fruit juices with no added sugar); and (4) Water. The budget is then allocated between "brand-modules" b within each beverage group (Coca-Cola regular, Pepsi-Cola regular, Diet Coke, etc.). Last it is split up between UPC u within each brand-module: UPC are the varieties purchased from a specific retailer.

This multi-stage budgeting process thus mirrors the three-tiers nomenclature of purchases presented in Section 2.2. Purchases are classified into product groups g (the upper level), product groups are made up of brand-modules b (the intermediate level), and brand-modules include a number of distinct UPC u. For example, g = SSB; b = Coca Cola regular, and u = a 1-liter plastic bottle of Coca Cola regular sold in a Carrefour hypermarket. This classification also matches the business nomenclature used by producers and retailers.

Households purchase on disjoint markets that are clusters c defined by unique combinations of living zones a and time periods t. They purchase from retailers r, who may or may not be present in the cluster c. They hence have access to a market-specific set of brand-modules, B_{gc}, and a market-specific set of product varieties, U_{bgc}, depending on their residential location and the period. This set-up allows variability in the availability of products across markets. For instance, a retailer may launch its own cola "own-brand label" in a given year, test it, and withdraw it if it does not attract a profitable market share. We denote $\mathcal{R}$ the reference market, and define it as the "national market" (*i.e.* the union of all living zones) in 2011, the pre-tax year. The reference set of brand modules is $B_g = \bigcup_{c \in \mathcal{R}} B_{gc}$, and $U_{bg} = \bigcup_{c \in \mathcal{R}} U_{bgc}$ similarly for the reference set of product varieties within a brand-module.

To be consistent with multi-stage budgeting, and given our focus on aggregate consumption, we make the following weak-separability assumption regarding household preferences.

Assumption 1 (Weak Separability):

1. *The set of products can be partitioned into G mutually-exclusive groups. Define by $\boldsymbol{q}_g$ the vector of goods in group g, with the related price vector $\boldsymbol{p}_{gc}$ in market c, and q_k an elementary product priced at p_k.*

2. *Household preferences are separable, so that each household h living in market c solves the following maximisation program*

$$Max_{\boldsymbol{q_g}, \forall g=1,\dots,G} F_h \left(U_{h1}(\boldsymbol{q_1}), ..., U_{hG}(\boldsymbol{q_G}) \right),$$
$$s.t. \sum_{g=1}^{g=G} \boldsymbol{p_{gc}}' \boldsymbol{q_g} = X_h,$$
$$\forall i, q_i \geq 0.$$

We then assume nested-CES preferences for consumer preferences over brand-modules and UPC. This assumption yields two benefits. First, the derivation of the EPI is relatively straightforward. Second, nested-

CES utility functions represent the behaviour of a household that would be representative of a population having nested-logit preferences over brand-modules (a nest) and product varieties (Anderson et al., 1988; Redding and Weinstein, 2016).

Assumption 2 (nested-CES subutility functions): *Consumer preferences over brand-modules and UPC are represented by a two-level CES utility function $U_{hg}(q_g)$:*

- *Upper-level:*

$$\boldsymbol{Q_{hg}} = U_{hg}(\boldsymbol{q_g}) = \left[\sum_{b \in B_{gc}} \boldsymbol{Q_{bg}}^{\frac{\sigma_{hg}-1}{\sigma_{hg}}} \right]^{\frac{\sigma_{hg}}{\sigma_{hg}-1}},$$

- *Lower-level:*

$$\boldsymbol{Q_{bg}} = \left[\sum_{u \in U_{bgc}} (\varphi_{hug} q_{ug})^{\frac{\sigma_{hb}-1}{\sigma_{hb}}} \right]^{\frac{\sigma_{hb}}{\sigma_{hb}-1}},$$

where φ_{hug} is the household-specific (subjective) quality of variety u.

It is important to note here that the aggregation of consumer behaviours is made possible and plausible by the introduction of a household-UPC specific quality φ_{hug}, which adjusts the quantity purchased by consumer heterogeneity in preference over quality. Adjusting for household and retailer heterogeneity makes the UPC and brand-modules homogeneous, in terms of subjective quality. As such, it renders plausible the assumption of a constant elasticity of substitution.

Quality-adjustment is all the more necessary that homescan data do not provide retailer prices, but rather unit prices (or unit values). In a given market c, the observed unit prices for a UPC are likely to vary from one household to another for three reasons. First, households choose to shop in specific stores, which may differ in terms of amenities. Stores adjust their prices as a function of the amenities they provide. Second, stores also adjust their prices as a function of customer demand and characteristics. In addition, households may differ in their shopping behaviour, sensitivity to sales promotions, etc. Third, as we define UPC from a restricted set of product characteristics, purchases in the same UPC may be heterogeneous in terms of very specific attributes (*e.g.* a particular flavour). In practice, household unit prices will be adjusted for retailer fixed effects (retailer heterogeneity) and household characteristics (household heterogeneity and within-UPC product heterogeneity) - see Appendix C.

Given our Assumption (2), the utility-maximization program at the lower level of UPC for household h purchasing in market c is

$$\begin{aligned} &Max_{q_{ug}, \forall u \in U_{bgc}} \boldsymbol{Q_{bg}}, \\ s.t. &\sum_{u \in U_{bgc}} p_{ubgc} q_{ug} = \nu_{bgc}, \\ &q_{ug} \geq 0, \end{aligned} \tag{B.2}$$

where ν_{bgc} is the budget constraint and the quantity index Q_{bg} is a direct measure of consumer utility

$$\boldsymbol{Q_{bg}} = \left[\sum_{u \in U_{bgc}} (\varphi_{hug} q_{ug})^{\frac{\sigma_{hb}-1}{\sigma_{hb}}} \right]^{\frac{\sigma_{hb}}{\sigma_{hb}-1}}. \tag{B.3}$$

Solving the dual cost-minimization problem, we obtain the following equality

$$P_{bgc} \boldsymbol{Q_{hbg}} = \nu_{bgc}, \tag{B.4}$$

where P_{bgc} is the unit cost function (*i.e.* the expenditure required to obtain one unit of utility Q_{hbg})

$$P_{bgc} = \left(\sum\nolimits_{u \in U_{bgc}} \left(\frac{p_{ubgc}}{\varphi_{hug}}\right)^{1-\sigma_b}\right)^{\frac{1}{1-\sigma_b}}. \tag{B.5}$$

We can similarly solve the household utility-maximization problem at the upper-level of brand modules in order to obtain a unit cost function P_{gc} measuring the cost of one unit of utility U_{hg} from the consumption of products in group g.

Since we have assumed that $U_{hg}(\boldsymbol{q_g}) = \left[\sum_{b \in B_{gc}} \boldsymbol{Q_{bg}}^{\frac{\sigma_{hg}-1}{\sigma_{hg}}}\right]^{\frac{\sigma_{hg}}{\sigma_{hg}-1}}$, we have

$$P_{gc} = \left(\sum\nolimits_{b \in B_{gc}} (P_{bgc})^{1-\sigma_g}\right)^{\frac{1}{1-\sigma_g}}. \tag{B.6}$$

B.2 Adjusting the EPI for product availability

Suppose that the prices are adjusted for differences in subjective quality (tastes) φ_{hug}, so that we can calculate representative prices from observed transaction prices (Appendix C explains the procedure). These representative prices are adjusted for household and retailer heterogeneity and are denoted $\tilde{p}_{ubgc}$. All quality-adjusted variables are indicated by a tilda. The reference market $\mathcal{R}$ is the "national market" (*i.e.* the union of all living zones) in 2011, and we assume that preferences do not vary between living zones. In this case, the price index for the product category g in market c can be written as

$$I_{gc} = \tilde{P}_{gc}/\tilde{P}_{g.}, \tag{B.7}$$

where

$$\tilde{P}_{gc} = \left(\sum\nolimits_{b \in B_{gc}} \left(\tilde{P}_{bgc}\right)^{1-\sigma_g}\right)^{\frac{1}{1-\sigma_g}}, \tag{B.8}$$

with $\tilde{P}_{g.}$ is the price of b in the reference market $\mathcal{R}$

$$\tilde{P}_{g.} = \left(\sum\nolimits_{b \in B_g} (\tilde{P}_{bg.})^{1-\sigma_g}\right)^{\frac{1}{1-\sigma_g}}, \tag{B.9}$$

where $\tilde{P}_{bg.}$ is the "national price" in 2011. The price indices will thus reflect deviations from the 2011 national price.

Note that we have for the (taste-adjusted) share of any specific brand module b within product group g

$$\tilde{S}_{bgc} = \left(\frac{\tilde{P}_{bgc}}{\tilde{P}_{gc}}\right)^{1-\sigma_g}, \tag{B.10}$$

and therefore

$$\ln(\tilde{P}_{gc}) = \ln(\tilde{P}_{bgc}) - \frac{\ln(\tilde{S}_{bgc})}{1-\sigma_g}, \qquad \forall b \in B_{gc}. \tag{B.11}$$

For the reference market $\mathcal{R}$, *i.e.* for all brand-modules in $B_g = \bigcup_{c \in \mathcal{R}} B_{gc}$, we have

$$\tilde{P}_{g.} = \tilde{P}_{bg.}(\tilde{S}_{bg.})^{\frac{1}{1-\sigma_g}} \Longrightarrow \ln(\tilde{P}_{g.}) = \ln(\tilde{P}_{bg.}) - \frac{\ln(\tilde{S}_{bg.})}{1-\sigma_g}, \qquad \forall b \in B_g. \tag{B.12}$$

Hence

$$I_{gc} = \tilde{P}_{gc}/\tilde{P}_{g.} = \frac{\tilde{P}_{bgc}}{\tilde{P}_{bg.}}\left(\frac{\tilde{S}_{bgc}}{\tilde{S}_{bg.}}\right)^{-\frac{1}{1-\sigma_g}}, \qquad \forall b \in B_{gc}. \tag{B.13}$$

Now, let $\tilde{\nu}_{ubgc}$ be the (taste-adjusted) expenditure on u in market c, and note that

$$\tilde{S}_{bg.} = \frac{\sum_{u \in U_b} \sum_{c'} \tilde{\nu}_{ubgc'}}{\sum_{b' \in B_g} \sum_{u \in U_{b'}} \sum_{c'} \tilde{\nu}_{ub'gc'}} = \underbrace{\frac{\sum_{u \in U_b} \sum_{c'} \tilde{\nu}_{ubgc'}}{\sum_{b' \in B_{gc}} \sum_{u \in U'_b} \sum_{c'} \tilde{\nu}_{ub'gc'}}}_{\tilde{S}^c_{bg.}} \times \underbrace{\frac{\sum_{b' \in B_{gc}} \sum_{u \in U_{b'}} \sum_{c'} \tilde{\nu}_{ub'gc'}}{\sum_{b' \in B_g} \sum_{u \in U_{b'}} \sum_{c'} \tilde{\nu}_{ub'gc'}}}_{\tilde{s}_{gc}}. \tag{B.14}$$

Define the variety-adjusted Sato-Vartia weights W_{bc} only on the set of varieties available in market c as follows

$$W_{bc} = \left(\frac{\tilde{S}_{bgc} - \tilde{S}^c_{bg.}}{\ln(\tilde{S}_{bgc}) - \ln(\tilde{S}^c_{bg.})} \right) \Big/ \sum\nolimits_{b' \in B_{gc}} \left(\frac{\tilde{S}_{b'gc} - \tilde{S}^c_{b'g.}}{\ln(\tilde{S}_{b'gc}) - \ln(\tilde{S}^c_{b'g.})} \right). \tag{B.15}$$

As these weights sum up to one, we can take the geometric mean of the log of the price index accross the varieties in B_{gc}

$$\begin{aligned} \ln(\tilde{P}_{gc}) - \ln(\tilde{P}_{g.}) &= \sum_{b \in B_{gc}} W_{bc} \Big(\ln(\tilde{P}_{gc}) - \ln(\tilde{P}_{g.}) \Big) \\ &= \sum_{b \in B_{gc}} W_{bc} \Big(\ln(\tilde{P}_{bgc}) - \ln(\tilde{P}_{bg.}) \Big) - \sum_{b \in B_{gc}} W_{bc} \frac{\Big(\ln(\tilde{S}_{bgc}) - \ln(\tilde{S}_{bg.}) \Big)}{1 - \sigma_g}, \end{aligned} \tag{B.16}$$

and

$$\begin{aligned} \sum_{b \in B_{gc}} W_{bc} \frac{\Big(\ln(\tilde{S}_{bgc}) - \ln(\tilde{S}_{bg.}) \Big)}{1 - \sigma_g} &= \sum_{b \in B_{gc}} W_{bc} \frac{\ln(\tilde{S}_{bgc}) - \ln(\tilde{S}^c_{bg.}) - \ln(\tilde{s}_{gc})}{1 - \sigma_g} \\ &= -\frac{\ln(\tilde{s}_{gc})}{1 - \sigma_g}. \end{aligned} \tag{B.17}$$

This implies that

$$I_{gc} = \left\{ \prod\nolimits_{b \in B_{gc}} \left(\frac{\tilde{P}_{bgc}}{\tilde{P}_{bg.}} \right)^{W_{bc}} \right\} (\tilde{s}_{gc})^{\frac{1}{1 - \sigma_g}} . \tag{B.18}$$

For each brand-module, we have similarly

$$I_{bgc} = \frac{\tilde{P}_{bgc}}{\tilde{P}_{bg.}} = \left\{ \prod\nolimits_{u \in U_{bc}} \left(\frac{\tilde{p}_{ubgc}}{\tilde{p}_{ubg.}} \right)^{w_{ubc}} \right\} (\tilde{s}_{bc})^{\frac{1}{1 - \sigma_b}} , \tag{B.19}$$

with $\tilde{s}_{bc}$ as

$$\tilde{s}_{bc} = \frac{\sum_{u \in U_{bc}} \sum_{c'} \tilde{\nu}_{ubgc'}}{\sum_{u \in U_b} \sum_{c'} \tilde{\nu}_{ubgc'}}, \tag{B.20}$$

and the Sato-Vartia weights

$$w_{ubc} = \left(\frac{\tilde{s}_{ubgc} - \tilde{s}^c_{ubg.}}{\ln(\tilde{s}_{bgc}) - \ln(\tilde{s}^c_{bg.})} \right) \Big/ \sum\nolimits_{u' \in U_{bc}} \left(\frac{\tilde{s}_{u'bgc} - \tilde{s}^c_{u'bg.}}{\ln(\tilde{s}_{u'bgc}) - \ln(\tilde{s}^c_{u'bg.})} \right), \tag{B.21}$$

with

$$\tilde{s}^{c}_{u'bg.} = \frac{\sum_{c'} \tilde{\nu}_{u'bgc'}}{\sum_{u' \in U_{bc}} \sum_{c'} \tilde{\nu}_{u'bgc'}}. \tag{B.22}$$

We end up with the exact price index for product group g in market c

$$EPI_{gc} = CEPI_{gc} VA_{gc}, \tag{B.23}$$

where

$$CEPI_{gc} = \prod_{u \in U_{gc}} \left(\frac{\tilde{p}_{ubgc}}{\tilde{p}_{ubg.}} \right)^{w_{ubc} W_{bc}}, \tag{B.24}$$

$$VA_{gc} = (\tilde{s}_{gc})^{\frac{1}{1-\sigma_g}} \prod_{b \in B_{gc}} (\tilde{s}_{bc})^{\frac{W_{bc}}{1-\sigma_b}}, \tag{B.25}$$

where $CEPI_{gc}$ is the EPI obtained under the assumption that the choice set in every market is the same as in the reference market that is chosen to calculate the reference prices, and VA_{gc} is an adjustment for the differences in the available choice sets. $\tilde{p}_{ubgc}$ and $\tilde{p}_{ubg.}$ are respectively the quality-adjusted prices of u in market c and in the reference market. $\tilde{p}_{ubgc} = p_{ubgc}/\varphi_{hug}$ are thus the unit prices adjusted for within-market variations in household tastes and retailer heterogeneity. W_{bc} and w_{ubc} are Sato-Vartia weights that reflect the relative importance of brand-modules b and UPC u in market c as compared to the reference market; $\tilde{s}_{gc}$ and $\tilde{s}_{bc}$ are the taste-adjusted shares of available brand-modules in market c within a product category g and available varieties in market c within a brand-module b, respectively; σ_g is the elasticity of substitution across brand-modules in product group g, and σ_b is the elasticity of substitution across product varieties within a brand-module.

Note that we assume that $\forall h, \sigma_{hg} = \sigma_g$ and $\sigma_{hb} = \sigma_b$ for both theoretical and empirical reasons. First, elasticities do not vary across markets and do not vary across households within markets, as we want to construct a local price index for a representative consumer. Second, elasticities do not vary over time, because we do not have enough observations to estimate them separately for each month.

The variety-adjustment term VA_{gc} is determined by the local availability of products and their popularity at the national level in 2011. This first varies with the quality-adjusted shares of the available varieties $\tilde{s}_{bc}$ in a brand-module b, and the quality-adjusted shares of available brand-modules $\tilde{s}_{gc}$ in product category g in market c. These shares do not reflect consumer choices in market c but rather the availability of products, as $\tilde{s}_{bc}$ is defined as the ratio of total expenditure (over all markets) on product varieties u in brand-module b available in market c, to the total expenditure on all varieties u in brand-module b available in $\mathcal{R}$. This ratio is therefore below 1 whenever U_{bc} is smaller than U_b, *i.e.* when a variety in brand-module b is unavailable in market c (which is always the case in our data). Now suppose that there are many varieties that are not available in market c, so that $\tilde{s}_{bc}$ falls. As $1/(1-\sigma_b)$ is negative ($\sigma_b > 1$), VA_{gc} will increase. The loss of welfare due to the absence of some varieties translates into a higher price index. For varieties within brand-modules, this is unimportant if the brand-module has a low Sato-Vartia weight W_{bc}, *i.e.* if it is not very popular among French consumers. Similarly, $\tilde{s}_{gc}$ is the ratio of the total expenditure on all brand-modules b available in market c, to the total expenditure on all brand-modules in g. This is lower than 1, and will produce a rise in VA_{gc} whenever B_{gc} is smaller than B_g. Entries of new products will on the contrary produce a drop in VA_{gc}, corresponding to an increase in consumer welfare.

C Online Appendix: Construction of the EPI

C.1 Adjusting unit prices, quantities and expenditures

In the EPI formula (Appendix B), prices, expenditures and quantities are adjusted for differences in subjective quality between varieties. These differences in subjective quality are related to consumer and retailer heterogeneity. We purge these by adjusting the prices via a regression approach.[41]

Let p_{ucrh} be the "unadjusted" average price that a household h paid for UPC u in retailer r in market c. We construct a quality-adjusted average price by estimating the following OLS regressions

$$\ln(p_{ucrh}) = \alpha_c + \alpha_r + X_u\beta_u + X_h\beta_h + X_{uh}\beta_{uh} + \epsilon_{ucrh}, \tag{C.1}$$

where α_c are market fixed-effects, α_r is a vector of dummy variables indicating the retailer name (seven dummies) and format (three dummies), X_u, X_h and X_{uh} are vectors of UPC characteristics, household attributes and interactions, respectively, and β_u, β_h and β_{uh} the corresponding parameters. In the empirical application (after a specification search), X_u includes carbohydrate density and dummy variables for the group (four dummies), beverage family (14 dummies), brand (26 dummies), flavor (11 dummies), packaging (4 dummies) and volume (up to five dummies per family); X_h contains the age and gender of the main shopper, household structure (four dummies), equivalent income class (four dummies), education (five dummies) and type of residential area (five dummies), and X_{uh} interacts the low-income class with carbohydrate density, and the beverage-family and volume dummies.

The adjustment regressions are performed month by month, with 263 fixed-effects for living zones. This allows to better control for variations in retailers' amenities over time and implies that there is no redundancy between the inclusion of retailer fixed effects and the definition of UPC as a given variety purchased at a given retailer. Each observation is weighted by the transaction value (household expenditures, v_{ucrh}) multiplied by the Kantar sample weight for the household (ω_{ch}). This gives more weight to varieties that attract higher national expenditure shares. The equations are estimated on data pooled over the four groups of products. Most R^2s range between 0.8 and 0.9. Note that adding UPC fixed effects instead of a large set of product characteristics only slightly increases the fit, while it greatly weakens the identification of the impact of household characteristics as it then essentially relies on households purchasing different varieties within a month. In addition, separate regressions by product category would theoretically be preferable. However, these produce lower R^2s (around 0.7-0.8) and the market fixed effects were not well-identified. As a result, the final EPI exhibited large and implausible monthly changes. The average price corrected for retailer and household heterogeneity is finally

$$\tilde{p}_{ucrh} = \exp\left[\ln(p_{ucrh}) - (\hat{\alpha}_r + X_h\hat{\beta}_h + X_{uh}\hat{\beta}_{uh})\right]. \tag{C.2}$$

We use these adjusted prices to calculate quality-adjusted market-specific expenditures

$$\tilde{v}_{ubgc} = N_c \sum_{h\in H_c} \left\{ \frac{\omega_{ch}}{\sum_{h\in H_c}\omega_{ch}} \sum_{r\in R_c} \tilde{p}_{ucrh} \frac{q_{ucrh}}{SIZE_{hc}} \right\}, \tag{C.3}$$

where H_c is the set of households observed in market c, N_c is the population in the market, $SIZE_{hc}$ is the number of members in household h, and R_c is the set of retailers operating in market c.[42] We first take a weighted average (with $\omega_{ch}/\sum_{h\in H_c}\omega_{ch}$ as the relative weights) of per capita household expenditures, and then multiply the result by the population size in c to obtain total expenditure in market c that can be compared to the total expenditure observed in other markets. In addition, we observe the following market-specific quantities

$$q_{ubgc} = N_c \sum_{h\in H_c} \left\{ \frac{\omega_{ch}}{\sum_{h\in H_c}\omega_{ch}} \sum_{r\in R_c} \frac{q_{ucrh}}{SIZE_{hc}} \right\}. \tag{C.4}$$

The prices, adjusted for consumer and retailer heterogeneity, and accounting for quantities, can then be

[41] See Handbury and Weinstein (2015, subsections 3.2. and 5.1).

[42] See Handbury and Weinstein (2015, footnote 28).

calculated as

$$\tilde{p}_{ubgc} = \tilde{v}_{ubgc}/q_{ubgc}. \tag{C.5}$$

C.2 Estimating CES elasticities for VA

We first consider the estimation of within brand-module elasticities. Given the assumption regarding the equality of within-brand elasticities in a product category,[43] for all UPC u in brand-module b in product category g we can write

$$\ln(\tilde{p}_{ubgc}) = \frac{\ln(\tilde{s}_{ubgc})}{1-\sigma_b} + \ln(\tilde{P}_{bgc}), \qquad \forall b \in B_{gc}, \forall u \in U_{bc}. \tag{C.6}$$

Let k_{bg} be one of the UPC in the set of varieties U_{bc}; we then have the following demand equation

$$\Delta^{k_{bg}}\tilde{s}_{ubgc} = (1-\sigma_b)\Delta^{k_{bg}}\tilde{p}_{ubgc}, \qquad \forall b \in B_{gc}, \forall u \in U_{bc}, \tag{C.7}$$

where $\Delta^{k_{bg}}\tilde{s}_{ubgc} = \ln(\tilde{s}_{ubgc}) - \ln(\tilde{s}_{k_{bg}bgc})$ and $\Delta^{k_{bg}}\tilde{p}_{ubgc} = \ln(\tilde{p}_{ubgc}) - \ln\left(\tilde{p}_{k_{bg}bgc}\right)$.[44] To estimate the demand equation, we jointly specify a CES supply equation, so that we have the following system describing market equilibrium

$$\begin{aligned} Demand: \Delta^{k_{bg}}\tilde{s}_{ubgc} &= (1-\sigma_b)\Delta^{k_{bg}}\tilde{p}_{ubgc} + \varepsilon^{k_{bg}}_{ubgc}, \\ Supply: \Delta^{k_{bg}}\tilde{p}_{ubgc} &= \frac{\omega_b}{1+\omega_b}\Delta^{k_{bg}}\tilde{s}_{ubgc} + \delta^{k_{bg}}_{ubgc}, \end{aligned} \tag{C.8}$$

where ω_b is the supply elasticity, and $\varepsilon^{k_{bg}}_{ubgc}$ and $\delta^{k_{bg}}_{ubgc}$ are two error terms capturing the impact of random shocks on demand and supply respectively. Note that (i) as for the demand elasticity, the supply elasticity is assumed to be the same within all brand modules, and (ii) $\delta^{k_{bg}}_{ubgc}$ captures for instance the impact of assembly-line shocks that affect some UPC within a brand module but not others (Broda and Weinstein, 2010).

The within-brand differentiation eliminates all brand-specific shocks. One credible identification restriction is then that the within-brand shocks to demand and supply are unrelated whatever the market: $\mathbb{E}(\varepsilon^{k_{bg}}_{ubgc}\delta^{k_{bg}}_{ubgc}|c) = 0$. To see this, multiply the demand and supply equations

$$\begin{aligned} \varepsilon^{k_{bg}}_{ubgc}\delta^{k_{bg}}_{ubgc} &= (\Delta^{k_{bg}}\tilde{s}_{ubgc} - (1-\sigma_b)\Delta^{k_{bg}}\tilde{p}_{ubgc})(\Delta^{k_{bg}}\tilde{p}_{ubgc} - \frac{\omega_b}{1+\omega_b}\Delta^{k_{bg}}\tilde{s}_{ubgc}) \\ &= \Delta^{k_{bg}}\tilde{s}_{ubgc}\Delta^{k_{bg}}\tilde{p}_{ubgc}\left(1 + \frac{(1-\sigma_b)\omega_b}{1+\omega_b}\right) - (1-\sigma_b)(\Delta^{k_{bg}}\tilde{p}_{ubgc})^2 \\ &- \frac{\omega_b}{1+\omega_b}(\Delta^{k_{bg}}\tilde{s}_{ubgc})^2. \end{aligned} \tag{C.9}$$

Rearranging, we have

$$\begin{aligned} \underbrace{(\Delta^{k_{bg}}\tilde{p}_{ubgc})^2}_{Y_{ubgc}} &= -\frac{\omega_b}{(1+\omega_b)(1-\sigma_b)}\underbrace{(\Delta^{k_{bg}}\tilde{s}_{ubgc})^2}_{X^1_{ubgc}} \\ &+ \frac{1+2\omega_b-\sigma_b\omega_b}{(1+\omega_b)(1-\sigma_b)}\underbrace{\Delta^{k_{bg}}\tilde{s}_{ubgc}\Delta^{k_{bg}}\tilde{p}_{ubgc}}_{X^2_{ubgc}}\underbrace{-\varepsilon^{k_{bg}}_{ubgc}\delta^{k_{bg}}_{ubgc}/(1-\sigma_b)}_{v_{ubgc}}. \end{aligned} \tag{C.10}$$

[43] We could also relax the assumption that the elasticities are the same for all brand modules in all markets. For instance, these elasticities may change over time. However, we also face a problem of empirical identification: having enough observations to estimate them.

[44] Note that Handbury and Weinstein (2015) use a double-differentiation, that is $\Delta^{k_{bg}}x_{ubgc} = [\ln(x_{ubgc}) - \ln(x_{k_{bg}bgc})] - [\ln(x_{ubg.}) - \ln(x_{k_{bg}bg.})]$ for any variable x_{ubgc}. The reason is that they consider a slightly different specification based on Broda and Weinstein (2010), where prices and shares are not "quality-adjusted".

Broda and Weinstein (2010, footnote 28) use the following reparameterization

$$\omega_b = \gamma_b/(\sigma_b(1-\gamma_b)-1), \tag{C.11}$$

so that we have

$$Y_{ubgc} = \underbrace{\frac{\gamma_b}{(\sigma_b-1)^2(1-\gamma_b)}}_{\theta_1} X^1_{ubgc} + \underbrace{\frac{(2\gamma_b-1)}{(\sigma_b-1)(1-\gamma_b)}}_{\theta_2} X^2_{ubgc} + \upsilon_{ubgc}. \tag{C.12}$$

Of course, since prices and shares are correlated with the errors $\varepsilon^{k_{bg}}_{ubgc}$ and $\delta^{k_{bg}}_{ubgc}$, X^1_{ubgc} and X^2_{ubgc} are correlated with υ_{ubgc}. Feenstra (1994) shows that a consistent estimator can be obtained by averaging (C.12) over time. Removing the variations within each living zone, we have $\mathbb{E}(\overline{X}^1_{ubga}\overline{\upsilon}_{ubga}) = 0$ and $\mathbb{E}(\overline{X}^2_{ubga}\overline{\upsilon}_{ubga}) = 0$, where the upper bar denotes the sample mean. Then, assuming that $\mathbb{E}(\overline{\upsilon}_{ubga}) = 0$ implies that the between estimator of (C.12) provides consistent estimates of θ_1 and θ_2. Let $\widehat{\theta}_1$ and $\widehat{\theta}_2$ denote these estimates, which can be obtained by applying the Weighted Least Squares (WLS) estimator to the transformed equation

$$\overline{Y}_{ubga} = \theta_1\overline{X}^1_{ubga} + \theta_2\overline{X}^2_{ubga} + \overline{\upsilon}_{ubga}, \tag{C.13}$$

where the share of expenditures on u in brand module b and living area a, $\bar{\tilde{s}}_{ubga}$, is used as the weight. If $\overline{X}^1_{ubga}$ and $\overline{X}^2_{ubga}$ are not asymptotically collinear, then θ_1 and θ_2 are separately identified from (C.13). Moreover, adding a constant term to the regression renders these estimates consistent even when the unit values are measured with errors. This estimator corresponds to Hansen's (1982) Generalized Method of Moments (GMM) estimator, where the moment condition $\mathbb{E}(\upsilon_{ubgc}) = 0$ is approximated by choosing θ_1 and θ_2 to minimize the weighted sum of squared sample moments $\overline{\upsilon}_{ubga}$. It is also equivalent to applying an Instrumental Variable (IV) estimator to equation (C.12), assuming $\mathbb{E}(\upsilon_{ubgc}|a) = 0$ and therefore using all living zone fixed effects to instrument X^1_{ubgc} and X^2_{ubgc} (see Feenstra, 1994).

It is then possible to recover σ_b and γ_b from $\widehat{\theta}_1$ and $\widehat{\theta}_2$. Feenstra (1994) shows in his Proposition 2 that as long as $\widehat{\theta}_1 > 0$ the estimates of σ_b and γ_b are as follows

$$\begin{aligned} \widehat{\sigma}_b &= 1 + \left(\frac{2\widehat{\gamma}_b - 1}{1-\widehat{\gamma}_b}\right)\frac{1}{\widehat{\theta}_2} \\ \widehat{\gamma}_b &= \frac{1}{2} \pm \left(\frac{1}{4} - \frac{1}{4+\left(\widehat{\theta}_2^2/\widehat{\theta}_1\right)}\right)^{1/2}, \end{aligned} \tag{C.14}$$

the plus and minus signs in the last expression applying for $\widehat{\theta}_2 > 0$ and $\widehat{\theta}_2 < 0$, respectively. As $\widehat{\theta}_2 \to 0$, then $\widehat{\gamma}_b \to 1/2$ and $\widehat{\sigma}_b \to 1 + \widehat{\theta}_1^{-1/2}$. For all brand-modules but three, $\widehat{\theta}_1 > 0$ so that we can use Feenstra's (1994) formulae. In the remaining brand modules, $\widehat{\theta}_1 < 0$ and we follow Broda and Weinstein (2006, 2010): we perform a grid-search over values of $\sigma_b > 1$ and $\gamma_b > 0$, and retain the values minimizing the GMM objective function, where the residuals, $\overline{\upsilon}_{ubga}$ for WLS and υ_{ubgc} for GMM, are weighted by their corresponding shares, $\bar{\tilde{s}}_{ubga}$ and $\tilde{s}_{ubgc}$ respectively.[45] The grid-search and Feenstra's original method lead to very similar results when $\widehat{\theta}_1 > 0$. The standard errors in all cases can be obtained by bootstrapping.

We can then calculate the price indices for each brand module, $\tilde{P}_{bgc}$, which are given by the formula

$$\tilde{P}_{bgc} = \left(\sum\nolimits_{u\in U_{bc}} (\tilde{p}_{ubgc})^{1-\sigma_b}\right)^{\frac{1}{1-\sigma_b}}, \tag{C.15}$$

and apply the same procedure to estimate the across brand-module elasticities, σ_g.

[45]Specifically, the objective function is evaluated for $\sigma_b \in [1.05; 131.5]$ at intervals 0.05 apart, and for $\gamma_b \in [0.01; 1]$ at intervals 0.01 apart. Only the combinations of σ_b and γ_b that imply $\sigma_b > 1$ and $\omega_b > 0$ (where ω_b is given by (C.11)) are used.

Table C.1: CES elasticity estimates

	SSB			NCSB			NSB			Water		
Within (81 brand-modules)	#UPC	σ_b	γ_b	#UPC	σ_b	γ_b	#UPC	σ_b	γ_b	#UPC	σ_b	γ_b
Percentile 1	1	0	0	1	0	0	1	0	0	12.0	3.30	0.01
Percentile 5	1	0	0	1	0	0	1	0	0	12.0	3.30	0.01
Percentile 10	2	3.07	0.27	1	0	0	20.5	5.89	0.26	12.0	3.36	0.04
Percentile 25	9.6	4.52	0.39	1.3	3.04	0.06	33.0	7.17	0.53	12.0	4.15	0.21
Percentile 50	13.4	5.48	0.59	5.9	5.39	0.30	27.7	9.59	0.57	12.0	4.57	0.41
Percentile 75	12.4	9.81	0.68	6.2	10.61	0.59	29.3	13.73	0.69	14.9	8.37	0.58
Percentile 90	11.7	14.90	0.84	5.8	34.37	0.91	26.1	16.84	0.87	13.4	14.81	0.75
Percentile 95	11.6	17.93	0.89	5.7	37.19	0.92	26.0	34.37	0.88	13.0	18.42	0.90
Percentile 99	11.4	186.55	0.98	5.8	122.35	0.96	26.0	34.37	0.88	13.0	18.42	0.90
Average	11.1	12.02	0.54	5.8	13.76	0.35	26.0	11.49	0.57	13	6.80	0.40
Across (four product groups)	#B-M	σ_g	γ_g	#B-M	σ_g	γ_g	#B-M	σ_g	γ_g	#B-M	σ_g	γ_g
	36	6.04	0.45	22	6.69	0.51	13	3.35	0.01	10	3.13	0.11

Notes: These are within brand-module elasticities (σ_b) and between brand-module elasticities for each product group (σ_g). Kantar Worldpanel data 2008-2013. #UPC is the average number of distinct UPC for brand modules at a given percentile of the distribution of within brand-module elasticities.

C.3 CES elasticities: results

Table 1 describes the distribution of the estimates for the within parameters (especially elasticities, σ_b) and the across parameters (especially elasticities, σ_g).[46] These are obtained using all available data (2008-2013). Out of the 81 brand-modules, 8 include only one UPC. For these singletons, we cannot obtain estimates of σ_b and γ_b. These are set to zero, so that the prices of the corresponding brand modules do not affect the EPI of the group. Over all four product groups, the median within-brand-module elasticity is 5.85, so that a 1% increase in the price of a UPC within a brand module reduces its sales on average by 5.85%. The larger the elasticity, the more substitutes are the UPC within a brand module. It is hence not surprising to find a positive correlation between the within-elasticity of a brand module and the number of distinct UPC in that brand module: more available alternatives yield higher elasticities of substitution. Omitting both the zeroes and the six largest values (over 20), the distribution of σ_b looks log-normal, as shown in Figure C.1. The median within brand-module elasticity is almost the same for SSB and NCSB (5.48 and 5.39, respectively); it is larger for NSB (9.59) and smaller for Water (4.57). The values that are used below for σ_b are those obtained over the whole period but it is worth noting that there is not much change in the values estimated before and after the tax: the distribution is log-normal in both cases and the quartiles are 4.41 (4.23), 6.25 (6.27) and 10.31 (11.03) in 2008-2011 (2012-2013) – see Figure C.2.

Regarding the across-brand-module elasticities, σ_g, the larger the elasticity, the closer substitutes are brand modules within a group. As can be seen at the bottom of Table 1, a distinction can be made between groups. SSB and NCSB are characterized by rather large elasticities (6.04 and 6.69, respectively), showing that they are both composed of brand modules that are highly substitutable, at least more than those composing NSB and Water (3.35 and 3.13, respectively). These low elasticities may be explained by the smaller number of brand modules in NSB and Water than in SSB and NCSB. In addition, the NSB group groups together very heterogeneous beverages (juices, syrups, pulps and milk-based drinks). The Water group is apparently more homogeneous, but there is still differentiation between sparkling and still waters and we also observe that brand loyalty is high.

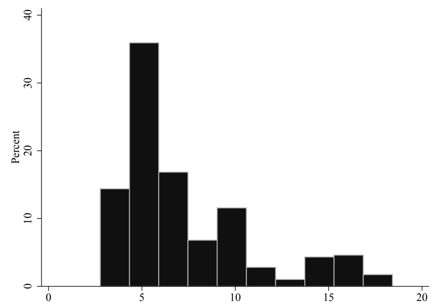

Figure C.1: **Distribution of σ_b, 2008-2013**

C.4 Pass-through formula

At the level of a UPC u, the pass-through of the tax, ρ_u, is

$$\rho_u = \frac{\Delta \overline{p_{ubgc}}^c}{T}, \tag{C.16}$$

[46]The estimates obtained for each brand module are available from the authors.

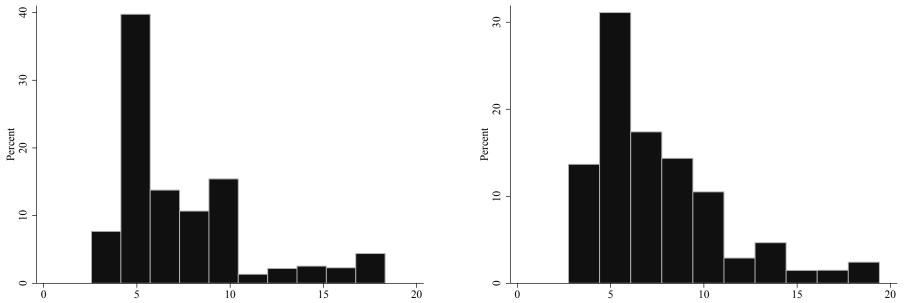

Figure C.2: **Distribution of σ_b, 2008-2011 (left) vs. 2012-2013 (right)**

where $\Delta\overline{p_{ubgc}}^c$ is the average change in local observed UPC prices and T is the unit excise tax inflated by the value-added tax. The price p_{ubgc} is itself defined by analogy with $\tilde{p}_{ubgc}$ as

$$\begin{aligned} p_{ubgc} &= v_{ubgc}/q_{ubgc} \\ &= \frac{N_c \sum_{h\in H_c} \left\{ \frac{\omega_{ch}}{\sum_{h\in H_c} \omega_{ch}} \sum_{r\in R_c} p_{ucrh} \frac{q_{ucrh}}{SIZE_{hc}} \right\}}{q_{uc}}. \end{aligned} \tag{C.17}$$

We hence use the unadjusted unit prices p_{ucrh} to calculate unadjusted local average prices, which enter as inputs in our pass-through calculations.

To calculate this pass-through, we first estimate a before-after model for each UPC in order to identify the impact of the tax T

$$\ln(p_{ubgc}) = \alpha_{0,u} + \alpha_{1,u}\delta_{t\geq 2012} + \delta_{y,u} + \delta_{m,u} + \gamma_u C_t + \delta_{a,u} + \epsilon_{u,c}, \tag{C.18}$$

where UPC-market observations are weighted by market sales. From an ex-ante perspective, the pass-through is defined relative to the expected impact of the tax on the prices observed in 2011, so that we have

$$\rho_{u,2011} = \frac{\overline{p_{ubgc}}^{y=2011}\left[exp\left(\alpha_{1,u}\right) - 1\right]}{T} \approx \frac{\overline{p_{ubgc}}^{y=2011}\alpha_{1,u}}{T}, \tag{C.19}$$

where $\overline{p_{ubgc}}^{y=2011}$ is the average UPC price observed in 2011. From an ex-post perspective, the pass-through is defined relative to the prices observed in 2011 purged of the specific impact of the tax

$$\rho_{u,2012} = \frac{\overline{p_{ubgc}}^{y=2012}\left[1 - \frac{1}{exp(\alpha_{1,u})}\right]}{T} \approx \frac{\overline{p_{ubgc}}^{y=2012}\alpha_{1,u}}{exp\left(\alpha_{1,u}\right)\times T}, \tag{C.20}$$

where $\overline{p_{ubgc}}^{y=2012}$ is the average UPC price in 2012, which takes into account all the factors that affected the change in prices between 2011 and 2012. In practice $\rho_{u,2011}$ and $\rho_{u,2012}$ are very similar. Table 4 takes the ex-ante perspective.

At the level of soft-drink groups g, we define the pass-through ϱ_g as the ratio of the estimated change in quality-adjusted unit cost $\tilde{P}_{gc}$ produced by the tax to the average change that would have been observed had the tax been fully shifted onto UPC prices. Given the relationship between the quality-adjusted unit cost and the price index, we have

$$\varrho_{gc} = \frac{EPI_{gc}^{y=2011}\left[exp\left(\alpha_1\right) - 1\right]}{EPI_{gc}^{y=2012,*} - EPI_{gc}^{y=2011}}. \tag{C.21}$$

In the numerator, α_1 is the estimated impact of the tax on a price index observed in 2011, $EPI_{gc}^{y=2011}$ (in percentage points); $EPI_{gc}^{y=2011} \times exp\left(\alpha_1\right)$ is the EPI that would have been observed in 2012 in the same living zone and same month, had nothing other than the tax policy occurred. In the denominator, $EPI_{gc}^{y=2012,*}$ is the EPI that would have been observed in 2012 had the tax been fully shifted onto UPC prices, no behavioural response had happened, and no other changes had occurred. We can rewrite the pass-through as

$$\varrho_{gc} = \frac{[exp(\alpha_1) - 1]}{\frac{EPI_{gc}^{y=2012,*}}{EPI_{gc}^{y=2011}} - 1}. \tag{C.22}$$

To construct $EPI_{gc}^{y=2012,*}$, counterfactual household specific prices p_{ucrh}^{*} are calculated under the assumption of 100% pass-through, *i.e.* $p_{ucrh}^{*} = p_{ucrh} + T$. Then, holding household subjective quality constant, we can obtain counterfactual quality-adjusted prices as $\tilde{p}_{ucrh}^{*} = (p_{ucrh}^{*}/p_{ucrh}) \times \tilde{p}_{ucrh}$. The formulae in Appendices A.2. and B.1. are then applied to construct the desired counterfactual price index (holding all quantities constant).

To understand what essentially drives the pass-through, a useful approximation can also be derived as follows. First, calculate the counterfactual market-specific prices p_{ubgc}^{*} under the assumption of 100% pass-through, *i.e.* $p_{ubgc}^{*} = p_{ubgc} + T$. Holding consumer behavior constant, suppose that the ratio of the unadjusted to quality-adjusted price $p_{ubgc}/\tilde{p}_{ubgc}$ is constant. This is a weighted average of household-specific qualities φ_{hug}, where the weights are the share of quality-adjusted household expenditures in the total quality-adjusted expenditures observed in market c. We hence ignore the small changes in shares produced by the changes in prices. We then have the counterfactual quality-adjusted UPC prices: $\tilde{p}_{ubgc}^{*} = \left(p_{ubgc}^{*}/p_{ubgc}\right) \times \tilde{p}_{ubgc}$. Using equations (B.24) and (B.25), and assuming that the VA term and the Sato-Vartia weights do not change (the quality-adjusted shares remain the same), we have

$$\begin{aligned} \varrho_{gc} &\approx \frac{[exp(\alpha_1) - 1]}{\prod_{u \in U_{gc}} \left(\frac{\tilde{p}_{ubgc}^{*}}{\tilde{p}_{ubgc}}\right)^{w_{ubc} W_{bc}} - 1} \\ &\approx \frac{\alpha_1}{\sum_{u \in U_{gc}} w_{ubc} W_{bc} \left(T/p_{ubgc}\right)}, \end{aligned} \tag{C.23}$$

where various first-order approximations have been used to derive the last expressions. The latter clearly shows that products with large Sarto-Vartia weights (and therefore market shares) are more important in the numerator. In our data, the leading national brands generally have higher prices and larger market shares than retailer brands. Ex-ante, the expected burden of the tax for consumers is therefore smaller than if the retailer brands sold at lower prices had large market shares.