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Market heterogeneity and the distributional incidence of soft-drink taxes: evidence from France

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Abstract

Market heterogeneity may affect the distributional incidence of nutritional taxes if households sort by income across markets with different characteristics. We use scanner data to analyse the distributional incidence of the 2012 French soda tax on Exact Price Indices that measure consumer welfare from the price and availability of soft-drinks at a local level. While the average pass-through was small—about 45 per cent—, tax incidence was significantly higher in low-income and less-competitive markets. Market heterogeneity ultimately has substantial distributional effects: it accounts for at least 33 per cent of the difference in welfare variation between low- and high-income consumers.

Keywords: France, soft-drink tax, tax incidence, inequality, market structure, consumer price index

JEL Classification: D12, E31, H22, I18

1. Introduction

The worldwide rise in obesity and diabetes has prompted public health researchers and officials to devote particular attention to sugar intake from sugar-sweetened beverages (SSBs). Taxing these beverages is considered a means of decreasing their consumption by increasing prices, at zero cost to public finances (Malik *et al.*, 2013; WHO, 2017). SSB taxes are often criticised on the basis of their regressivity. As the poor tend to allocate a larger budget share to SSB, they may mechanically face a higher tax burden. However, the welfare consequences of any consumer tax depend not only on initial prices and quantities consumed but also on the incidence of the tax on consumer prices. A tax is unlikely to be shifted 1:1 into market prices due to changes

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in behaviour on the demand and supply sides of markets. It is possible that low-income households face a higher tax burden partly because they are more likely to reside in markets with characteristics (e.g. fewer retailers) conducive to higher pass-through of the tax to consumer prices.

The main purpose of the present study is therefore to demonstrate how heterogeneity in market characteristics contributes to the distributional impact of soft-drink taxes. We estimate the incidence of the French soda tax on consumer welfare, with a particular focus on heterogeneity across *local* markets. The French soda tax was passed in November 2011 and introduced on the 1st of January 2012. Until 2014, it consisted of a unit excise tax of 0.0716 euro/litre on the producer price. It is levied on manufacturers or importers of SSBs (soft drinks and nectars) and non-calorically sweetened beverages (NCSBs).¹

Our empirical analysis exploits six years of nationally representative home-scan data provided by Kantar Worldpanel (KWP) (2008–2013). This dataset covers 75 per cent of soft-drink purchases in France and contains information on household purchases at the product level. Our dependent variable are theoretically rigorous nested-CES (constant elasticity of substitution) price indices constructed separately for SBB and NCSB. They exactly measure variations in the utility from one unit of consumption across local markets. These exact price indices (EPI) are constructed from local transaction prices and purchase quantities following recent methodological advances in trade and spatial economics (see, e.g. Handbury and Weinstein, 2015; Redding and Weinstein, 2016). They are tailored to provide measures of tax incidence that account for consumer substitution across products and for variations in their price and availability across locations and over time.

We have two motivations for working on price indices rather than on separate price series of product varieties. First, the welfare incidence of the tax depends essentially on household preferences for quantity and on the pass-through of the tax to the EPIs. For small taxes such as the French soda tax, the welfare loss from SSB or NCSB taxation can be measured using compensating variation, which is approximately equal to the initial quantity consumed times the variation in the price index. Hence, the distributional effects crucially depend on the tax incidence on EPIs, which varies across households as a function of their preferences for products and their place of residence. Our approach thus differs from studies that examine the impact of local market conditions on pass-through to retail prices (see, e.g. Stolper, 2016), as we explicitly account for the relative importance of each transaction for consumer welfare. Second, the EPIs can be adjusted for consumer and retailer heterogeneity to abstract from welfare changes reflecting variations in preferences for products and store formats across households within a population. To examine the tax incidence on consumer welfare, we construct for each beverage category a global EPI with full adjustment for heterogeneity in household

1 NCSB were included at the end of a political process that saw the original public-health motivation for the tax—fighting obesity—replaced by a fiscal motivation: raising revenues for Social Security. See Le Bodo *et al.* (2019) for a detailed analysis of this process.

preferences, as well as distinct EPIs for low- and high-income households. The difference in national tax incidence between the income group-specific EPIs allows us to test whether variations in preferences across income groups produce differences in the incidence on aggregate prices. The global EPIs allow us to abstract from income-related preference heterogeneity to specifically identify the impact of market characteristics on tax incidence.

We estimate the tax incidence with a difference-in-difference (DiD) design that uses changes in the EPI of water as a counterfactual. We find that the tax increased the price of SSBs and NCSBs by respectively 4.3 per cent and 5.1 per cent on average, corresponding to tax incidences of 41.0 per cent and 47.9 per cent. Section 5 discusses why these pass-throughs are lower than the estimates in Berardi *et al.* (2016) and Capacci *et al.* (2019).² The average effect of the tax was very similar for low- and high-income households. Hence, heterogeneity in preferences for products and stores across income groups did not produce significant distributional effects. We then consider tax incidence across markets and find significant spatial heterogeneity. As expected, tax incidence decreases in retailer competition. In addition, conditional on local competition, tax incidence is higher in low-income markets. Finally, using compensating variation, we find that market heterogeneity accounts for at least 33.3 per cent of the difference in welfare loss between income groups, the rest being essentially explained by heterogeneity in preference for quantity.

Overall, this ex-post evaluation study complements the literature studying the distributional effects of nutritional taxes through ex-ante evaluation methods. While a large body of literature has focused on evaluating ex ante the potential aggregate health benefits of nutritional taxes (see, for recent publications using scanner data, Finkelstein *et al.*, 2013; Wang, 2015; Tiffin *et al.*, 2015; Sharma *et al.*, 2014; Mora *et al.*, 2019), few studies have analysed the distributional impacts of these taxes (Cornelsen and Smith, 2018; Etilé, 2019). Madden (2015) and Tiffin and Salois (2014) use food expenditure surveys in Ireland and the UK to simulate the distributional effects of revenue-neutral fiscal policies combining taxes on unhealthy food and subsidies for healthier food. They conclude that such fiscal mixes tend to increase the relative burden on the poor, although they might be neutral with respect to poverty. Muller *et al.* (2017) validate these findings with incentivised framed field experiments, wherein subjects had to select an entire day's worth of food from a large set of food products, the prices of which varied substantially (± 30 per cent) across tax-subsidy treatments. Etilé and Sharma (2015), Dubois *et al.* (2019) and Allcott *et al.* (2019) use Australian, US and UK scanner data to develop ex-ante evaluations of the effectiveness and regressivity of soda taxes. They provide evidence that soda taxes are unlikely to be strongly regressive, once one accounts for future health benefits and for the internality benefits from the tax, which are higher for the poor.

2 We show that the difference with Berardi *et al.* (2016) is essentially explained by their use of online shopping data instead of a representative panel. Using a subset of our data and a different methodology, Capacci *et al.* (2019) find a pass-through of 66 per cent to average household unit values.

We also contribute to a distinct but related literature that has focused on evaluating the pass-through of soft-drink taxes onto *product-level* prices. Our results show why heterogeneity in market structure can produce heterogeneity in pass-through across markets. Existing results provide clear evidence of such heterogeneity. For instance, the Berkeley soda tax and the soft-drink tax in Catalonia resulted in low pass-through to retail prices (Cawley and Frisvold, 2017; Falbe *et al.*, 2015; Mora *et al.*, 2019). Conversely, Colchero *et al.* (2015) and Grogger (2017) for Mexico, and Schmacker and Smed (2020) for Denmark, uncover evidence of tax over-shifting.

The remainder of the paper is organised as follows. Section 2 describes the data. Section 3 presents the nested-CES EPI and sets out the identification strategies. Section 4 examines the role of income-related preference heterogeneity and analyses the heterogeneity of tax incidence across markets. Section 5 briefly discusses the results.

2. Data

We construct local monthly price indices from homescan data collected by KWP over the 2008–2013 period. KWP follows a nationally representative sample of more than 21,000 French households, which use handheld scanners to record the quantity, the expenditure and the universal product code (UPC) of every purchase they make, including online purchases.³ Each observation represents the purchase of a unique product variety in a particular store by a particular household on a given day. For each non-alcoholic beverage UPC, KWP provides a large set of product attributes, including the brand, flavour, type of packaging, beverage family and type of sweeteners. We use these attributes to define a set of 526 distinct products, belonging to 14 families: colas, carbonated fruit drinks, non-carbonated fruit drinks, fruit nectars, lemonades, iced teas, tonics, energy drinks, flavoured water, natural water, fruit juices without added sugar, syrups (cordials/squash), pulps and milk-based fruit juices (for further information, see Supplementary Appendix A.1). We also define 10 homogeneous categories of retailer stores according to the company and the store format (hard discount, supermarket, hypermarket), as these two criteria are significant determinants of retailers' price-quality marketing mix (Bonnet and Réquillart, 2013).

We apply a three-tiered nomenclature to classify household purchases. In the upper tier, all purchases are sorted into one of the four following groups: SSBs, NCSBs, unsweetened beverages (USBs) and Water. The middle tier consists of 81 brand-modules defined by interacting the four groups, the 14 beverage families and the brand names, e.g. Coca-Cola Classic (group =

3 Homescan data are collected via a barcode readers installed at home. Although these data contain much more longitudinal information on household purchases than traditional household budget data, one may worry that the participants' scanning efforts vary over time. Zhen *et al.* (2009) and Lusk and Brooks (2011) provide evidence of some under-reporting as compared to cross-sectional household budget data, especially for non-barcoded food. However, KWP provides household-purchase sampling weights that ensure the longitudinal representativeness of the sample and correct for under-reporting within a month. We use these weights in all data treatments.

SSBs, family = Colas, brand = Coca-Cola). The lower tier consists of 2,270 'artificial' UPCs, defined by the interaction of products with retailer categories (e.g. a 1-litre plastic bottle of Coca Cola Classic sold in a Carrefour hypermarket). Redefining UPCs as product-retailer pairs 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 of attracting customers (Handbury and Weinstein, 2015).

We define a local market as a 'living zone' in a given month. The French National Statistics Office (INSEE) delineates a living zone ('Bassin de vie' in French) as the smallest set of city codes where inhabitants have access to everyday facilities and services, including stores. From a retailer's perspective, these living zones represent consumer catchment areas. The purchase data are then matched by living zone to INSEE census and fiscal data and to the Nielsen TradeDimensions panel, which provide exhaustive information about the retailer stores present in each market. These information will be used to characterise market heterogeneity in terms of affluence and competition.⁴

To ensure the statistical representativeness of prices, we retain living zones where at least 10 households are observed each year over the whole period. This leaves us with 263 living zones, out of a total of 1,633. Although we lose rural living zones, this selection does not alter the distribution of other household characteristics (Supplementary Appendix A.2). We also select the 995 UPCs that are purchased at least 100 times over 2008–2013, and at least once in each month. Our final sample, therefore, consists of 30,254 distinct households (roughly 15,000 households are observed each year) and over four million purchases. We observe at least 35 households in 90 per cent of the living zones over the period, and the median number of households per local market (living zone \times month) is 100. For each UPC, household, month and retailer, we calculate the mean expenditure and mean quantity. Dividing mean expenditures by mean quantities produces mean unit prices that we further deflate by the general Consumer Price Index.

Table 1 reports selected market statistics for each of the four groups. There are 400 UPCs in the SSB group, 127 in the NCSB group, 338 in the USB group and 130 in Water. SSBs represent 25.9 per cent of the total volume of non-alcoholic beverages purchased for at-home consumption in France. This is much larger than the NCSB figure (only 8.3 per cent) but smaller than that for USBs and Water (34.7 per cent and 31.0 per cent, respectively). Colas are dominant in the SSB and NCSB groups but face many competitors in the SSB category. Table 1 also shows the average unit price in each segment. Interestingly, there is not a particularly large price premium for NCSB products compared to SSB products within the same beverage family.

4 Maps illustrating the spatial heterogeneity in market structures are presented in Supplementary Appendix A.4.

Table 1. Beverage groups—descriptive statistics

	SSB						NCSB						USB						Water					
	UPC #		Market share		Unit price Mean (SD)		UPC #		Market share		Unit price Mean (SD)		UPC #		Market share		Unit price Mean (SD)		UPC #		Market share		Unit price 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)																		
Non-carbonated 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)																					
Flavoured water	18	0.51	0.89 (0.39)	15	0.67	0.96 (0.17)																		
Natural water																								
Juices (no added sugar)																								
Syrups																								
Pulps																								
Milk-based fruit juices																								
Total	400	25.92	1.02 (0.66)	127	8.29	0.95 (0.43)	221	29.00	1.51 (0.91)	94	4.57	2.86 (2.73)	13	0.68	3.56 (0.56)	10	0.50	1.96 (0.35)	130	31.04	0.38 (0.27)	117	30.72	0.37 (0.26)

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/litre. Market shares are defined by the volume of transactions over total non-alcoholic beverage transactions observed in the estimation sample (weighted by household sample weights).

3. Methods

3.1. Exact Price Indices for consumer welfare

An Exact Price Index (EPI) measures the change in expenditure required to hold utility constant as the prices of product varieties vary. It is therefore an index of consumer welfare. It is formally defined for a representative household of population \mathcal{P} , product group g and supply available in market c as:

$$EPI_{gc}^{\mathcal{P}} = \frac{C(V, \mathbf{p}_{gc}; \mathcal{P})}{C(V, \mathbf{p}_{g\mathcal{R}}; \mathcal{P})}, \quad (1)$$

where $C(V, \mathbf{p}_{gc}; \mathcal{P})$ is the cost of attaining utility V for a household that is endowed with representative preferences of \mathcal{P} and faces prices \mathbf{p}_{gc} ; $\mathbf{p}_{g\mathcal{R}}$ are the prices on a reference market that we define as the ‘national market’ (i.e. the union of all living zones) in 2011, the pre-tax year.

The construction of any EPI relies on structural assumptions regarding household utility to adjust for preference heterogeneity in the population, substitutions across products and variations in product price and availability (Triplett, 2001). We here assume nested-CES preferences for consumer utility over brand-modules and UPCs, following recent advances on the construction of price index from scanner data (Feenstra, 1994; Broda and Weinstein, 2006; Broda and Weinstein, 2010; Handbury and Weinstein, 2015; Redding and Weinstein, 2016; Jaravel, 2018). The main advantage of the nested-CES EPI over other price indices lies in its ability to account for the spatial and time variations in product availability. Product availability is notably affected by entry and exit of retailers and products, e.g. product innovation, emergence of private labels (retailer brands), etc.

As UPCs are not all available in every market, the EPI for g is the product of a ‘conventional’ nested-CES Exact Price Index (CEPI) and an adjustment coefficient for variety availability (VA):

$$EPI_{gc}^{\mathcal{P}} = CEPI_{gc}^{\mathcal{P}} VA_{gc}^{\mathcal{P}}. \quad (2)$$

$CEPI_{gc}^{\mathcal{P}}$ is the EPI obtained under the assumption that the choice set in every market c is the same as that in the reference market \mathcal{R} chosen to calculate the reference prices. $VA_{gc}^{\mathcal{P}}$ is an adjustment for differences in the available choice sets between markets c and \mathcal{R} . We construct these quantities using techniques that have been developed by others. Hence, to save space, exhaustive details on the definition and the construction of the EPI are provided in Supplementary Appendix C.

We now explain the EPI in intuitive terms. The conventional price index $CEPI_{gc}^{\mathcal{P}}$ is a sales-weighted average of the local prices of products purchased by households of population \mathcal{P} living in c . Any rise in the price of a UPC increases the CEPI. However, since more popular products have larger market shares, they also have higher weights in the CEPI and larger impacts on consumer welfare. The CEPI is therefore adjusted for consumer preferences

over products and for conventional substitution effects. The variety-adjustment term $VA_{gc}^{\mathcal{P}}$ is determined by the local availability of products and their national market shares, i.e. their *popularity* in population \mathcal{P} at the national level. The availability of products will vary across markets as a function of the localisation of retailers, and with entries and exits of products. The loss of welfare due to locally missing varieties translates into a higher price index. The welfare loss is unimportant for varieties that have a very small share of the national market, since they are not very popular among consumers. The welfare loss from a lack of variety also decreases with an increase in the elasticities of substitution across brand-modules and across products. The welfare impact of the tax will depend on product availability, if retailers adjust to the tax by changing their SSB assortments or if the tax affects the popularity of products.

Since we wish to identify the specific role of market heterogeneity in tax incidence, we need to account for the impact of within-market preference heterogeneity on observed prices and sales. In a given market c , the observed unit prices are likely to vary across households because they choose to shop specific products in specific stores. Retailers adjust their prices as a function of customer preferences over products and store characteristics (e.g. amenities). Following Handbury and Weinstein (2015), we use an extensive list of variables to adjust unit prices and market shares for within-market variations in consumer and retailer heterogeneity: household equivalent income, age and gender of the main shopper, household structure, education, type of residential area, retailer fixed effects and some interactions between income and product characteristics. The EPI then measure the spatial and time variations in the welfare of representative consumers endowed with identical preferences and shopping in homogeneous stores. These variations are caused primarily by shocks to production, logistic and retailing costs and variations in market structure.

We construct a global EPI for the entire household population and specific EPIs for low- and high-income households (below or above the median real household equivalent income). We obtain a global EPI that measures the welfare variations of the representative French household. We leverage its variations across markets to identify the impact of market characteristics on tax incidence. We use the income group-specific EPIs to compare the average tax incidence between low- and high-income households. This will reveal the importance of income-related preference heterogeneity in the distributional effects of the tax.

Figure 1 presents the evolution of the average global EPI for the four beverage categories (plain line) with the associated 95 per cent confidence interval (dotted lines). We observe a decline between mid-2009 until 2012. There was then a steep increase for all soft drinks (SSBs, NCSBs and USBs) in 2012–2013, while the price of Water fell. Interestingly, the absence of a steep price increase before January 2012—the month that the tax was implemented—shows that producers and retailers did not pass the tax on to consumers in advance, although the soda-tax project was announced in late August. A simple event analysis reveals that SSB prices in August, September, October and November were on average 1.3 per cent higher, 0.4 per

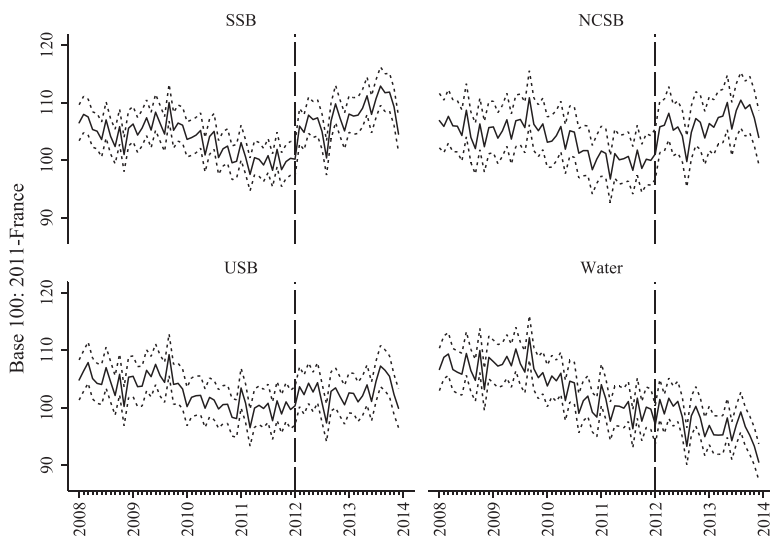


Fig. 1. EPI, monthly average, 2008–2013

cent lower, 0.1 per cent higher and -1.0 per cent lower, respectively, than in December. None of these differences is significant. 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 21 December 2011, after intense lobbying and debate (Le Bodo *et al.*, 2019).

Figure 2 illustrates the spatial heterogeneity in prices, which motivates our focus on market heterogeneity. The histogram of the EPI in 2013 for SSB (left panel) demonstrates the importance of spatial price variations, despite that the prices have been adjusted for retailer and consumer heterogeneity. In the right panel, the quantile–quantile (Q–Q) dot plot of the local EPI and CEPI, ranked by percentiles, shows that the VA factor substantially affects the price ranking of markets, as the dots spread far from the 45-degree line. The dispersion of dots is explained by the variance in the distribution of VA: local prices can be up to 50 per cent higher in some living zones due to the absence of subsets of products.

3.2. Empirical design

We identify the tax incidence at the national level by examining year-to-year changes. This follows pass-through specifications that identify the pass-through by comparing the change in prices to the change in costs across equilibrium situations (Hong and Li, 2017; Amiti *et al.*, 2014).

We have two empirical strategies. Given the absence of anticipated responses on the supply side, we first carry out a before–after estimation, which compares the average 2012 price to that in 2011. The following equation is

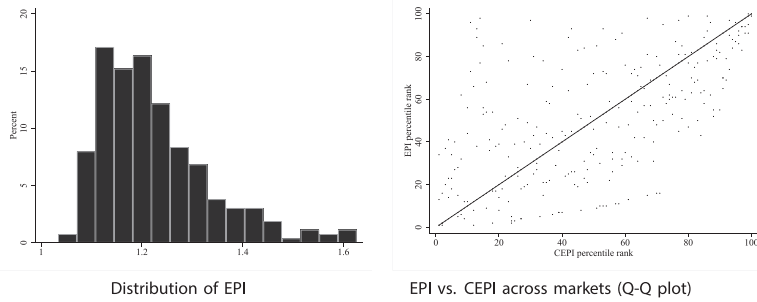


Fig. 2. Spatial distribution of SSB prices in 2013

estimated on samples of local price indices $\mathbf{P}_{g,c}$, where each observation is the local EPI of product group g observed in market c (living zone $a \times$ month t) for a given population \mathcal{P} ($EPI_{gc}^{\mathcal{P}}$):

$$\ln(\mathbf{P}_{g,c}) = \alpha_{g,T}Post_{t \geq 2012} + \gamma_g C_t + \delta_{g,y} + \delta_{g,m} + \delta_{g,a} + \epsilon_{g,c}. \tag{3}$$

In this equation, the before-after estimate of the tax effect is given by $\alpha_{g,T}$. The equation compares the average EPI in 2012 (after: $Post_{t \geq 2012}$) to that in 2011 (before), adjusting for year effects ($\delta_{g,y}$: 2008, 2009, 2010 and 2013), month-of-the-year effects ($\delta_{g,m}$), input costs C_t and living-zone fixed effects ($\delta_{g,a}$). We specifically control for the cost of sugar in C_t , as the Producer Price Index for sugar varied significantly before the policy. These variations were essentially driven by the world sugar markets.⁵ The main identifying assumption is then that the remaining variation is entirely attributable to the tax. The equation is estimated separately for SSB and NCSB.

The before-after regression results may be driven by movements in other supply-side costs. However, we cannot control for other manufacturing and retailing costs, as this produces considerable multicollinearity in the regressions (the Variance Inflation Factors are over 20). Therefore, we adopt a DiD approach, with Water as the control. We estimate the following model for the comparison between SSB and Water (group-index g):

$$\ln(\mathbf{P}_{g,c}) = \alpha_0 Post_{t \geq 2012} + \alpha_{S,T} D_{SSB} \times Post_{t \geq 2012} + \gamma_S D_{SSB} \times C_t + \delta_y + \delta_m + \delta_{S,y} + \delta_{S,m} + \delta_{g,a} + \epsilon_{g,c}, \tag{4}$$

where D_{SSB} is a dummy for SSB prices, $\delta_{S,m}$ are SSB-specific month effects for differences in seasonality between SSB and Water consumption. $\delta_{g,a}$ are product-living zone fixed effects and $\delta_{S,y}$ are SSB-specific year effects. Hence identification is achieved through the common trend assumption that

5 See Nolte *et al.* (2012) for a discussion of the World and EU sugar production and market prices in 2011. The Supplementary Appendix A.3 describes these variations and discusses our construction of the sugar price as a 6-months moving average.

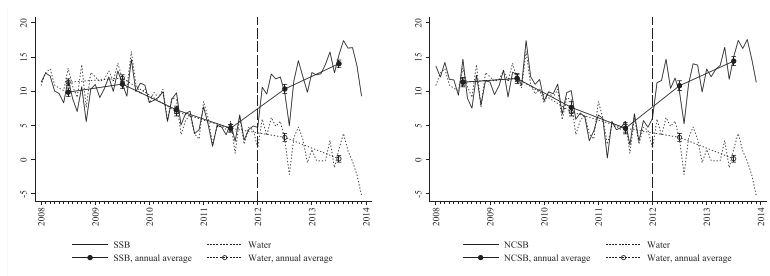


Fig. 3. Common trends, DiD estimation

$\delta_{S,2010} = 0$. The average incidence on SSB price is thus given by the coefficient α_S on the interaction term $D_{SSB} \times Post_{t \geq 2012}$. We control for the cost of sugar for SSB only, since sugar is not an input for Water, and we want to avoid multicollinearity problems. We apply a similar DiD specification for the comparison between NCSB and Water.

We choose Water as the control group for four reasons. First, Water was obviously not targeted by the soda tax. Second, apart from sugar, the inputs and cost structure for Water are similar to those for soft-drinks: glass and aluminium for packaging; natural water; and marketing, logistic and retailing costs. Third, the companies owning soft-drinks have zero or very small market shares for Water. Coca-Cola, PepsiCo and Orangina-Suntory are the main owners of the national soft-drink brands. PepsiCo owns Tropicana, which is the leading national brand in the USB market. Danone and Nestlé own the most popular national brands of Water. This limits any firm strategic reactions producing changes in the supply price of Water. Fourth, estimates of cross-price elasticities show that the market for Water is largely disconnected from that for soft drinks (Supplementary Appendix B.1). To check whether the common-trends assumption holds in the pre-policy period, Figure 3 plots the annual average of the log-EPI, compared to Water. Although the trends in soft-drink and Water prices differ slightly before 2010, the common-trends assumption holds for 2010–2011.

4. Results

4.1. Preference heterogeneity across income groups

We first estimate the average incidence of the tax at a national level. The comparison of results for the global EPI and for the income group-specific EPIs allows us to assess the importance of income-related preferences in tax incidence. The upper panel of Table 2 presents the baseline results. They are obtained from separate regressions for SSB and NCSB, with the EPI constructed from the full sample. The observations are weighted by the share of national sales in the living zone in 2011. The estimates thus represent average welfare variations for a representative French household. To get a sense of the magnitude of our estimates, the effects can be compared to the price increases

that would correspond to a full pass-through of the tax: +10.1 per cent for SSB and +10.3 per cent for NCSB.⁶

Column (1) displays the estimation of a before-after specification with month-of-the-year and living-zone fixed effects ($\delta_{g,m}$ and $\delta_{g,a}$ in Equation 3). The estimated tax impact on the EPI is significant at the 1 per cent level. The average price of SSBs in 2012 was approximately 5.4 per cent higher than in 2011. The increase for NCSB is about 5.2 per cent. Column (2) shows that these impacts are smaller when we additionally control for the cost of sugar, dropping to 2.9 per cent for SSB and 3.7 per cent for NCSB. This adjustment is in line with available evidence regarding the pass-through of variations in sugar prices onto consumer SSB prices in France (see Bonnet and Réquillart, 2011). The fall in the estimated effect might appear surprising for NCSB, as sugar is not an input in NCSB production. We indeed find a large positive impact of the cost of sugar on NCSB in the before-after specifications (see the Supplementary Appendix A.3, Table A.3). This can be interpreted as evidence that the main producers and retailers tie NCSB prices to their twin-variety SSB prices as part of product line strategic pricing.⁷

The third column of Table 2 reports the DiD estimates. The estimated impact for SSBs is higher to that from the before-after estimation: 4.3 per cent vs. 2.9 per cent. The NCSB effect is also higher in the DiD than in the before-after estimates: 5.1 per cent vs. 3.7 per cent. We conducted a test of the difference between the SSB and NCSB effects by estimating the DiD specification on pooled SSB, NCSB and Water data, with appropriate interaction terms to account for any difference in price trends or levels between these three beverage categories. The difference in tax incidence ($5.1 - 4.3 = 0.8$ percentage points) is significant at the level of 10 per cent only (see Supplementary Appendix B.2, Table B.2).

Column (4) in Table 2 provides a very conservative test of the common-trends assumption, using a placebo policy change on the 1st of January 2011 (one year before). The estimated placebo impact for SSBs, although significant, is more than seven times smaller. 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 estimate in column (3).⁸ Last, following Bertrand *et al.* (2004), we generated a placebo-treatment distribution by estimating DiD models on placebo soda tax reforms, where treated beverage categories are chosen at random within each living zone. This permutation

6 See Supplementary Appendix B.5 for methodological details on the pass-through calculation.

7 Over the pre-policy period (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 living zone and retailer fixed effects. Firms tie their pricing strategies across same-brand products in order to soften price competition across varieties, to avoid product cannibalisation and to benefit from consumers' brand loyalty. See Chen (2009) for a literature review on product line pricing, and Draganska and Jain (2006) for empirical evidence on uniform pricing within product lines.

8 Supplementary Appendix B.2, Table B.3 reports the estimates of the year fixed-effects for the DiD specification estimated on pooled SSB, NCSB and Water data. The 2010 fixed-effect does not significantly differ between SSB or NCSB, and Water.

Table 2. Tax incidence: Price-index variation (% points)—national average

Population	Before-after		DiD	
	(1)	(2)	2012	2011
All households				
SSB	5.426*** (0.171)	2.905*** (0.266)	4.269*** (0.304)	0.369* (0.207)
NCSB	5.217*** (0.366)	3.703*** (0.367)	5.067*** (0.396)	0.437 (0.307)
Low-income households				
SSB	5.965*** (0.185)	3.347*** (0.462)	4.553*** (0.521)	-0.106 (0.299)
NCSB	5.954*** (0.367)	3.472*** (0.503)	4.678*** (0.558)	-0.106 (0.412)
High-income households				
SSB	4.989*** (0.204)	2.404*** (0.438)	4.121*** (0.499)	0.518* (0.275)
NCSB	4.619*** (0.566)	2.747*** (0.717)	4.463*** (0.756)	0.850 (0.606)
Differential incidence (Low Income–High Income)				
SSB	0.920*** (0.314)	1.006 (0.748)	0.628 (0.820)	-0.632* (0.369)
NCSB	0.989 (0.505)	-0.089 (0.587)	-0.466 (0.921)	-0.154 (0.554)
Additional controls				
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	2008–2013	2008–2013

Notes: Results from separate regressions for SSB and NCSB. The dependent variable is the log of EPI or, for differential incidence, the log-difference in EPI between low- and high-income households. The EPI is estimated from Kanjar Worldpanel data 2008–2013 using market-level observations (living zone-month). These estimates represent changes in the EPI, in % points, between 2011 and 2012 (before-after columns; $\alpha_{S,T}$ in Equation (3)) and the difference in the changes between SSB or NCSB, and Water (DiD; difference-in-difference columns; $\alpha_{S,T}$ for SSB in Equation (4)). Living zone fixed effects are included. Each observation is weighted by the population-specific share of national sales in the living zone in 2011 or, for differential incidence, the share of national sales of low-income households. Standard errors are in parentheses; ***, **, * and * indicate significance at the 1%, 5% and 10% levels.

procedure assesses the uncertainty regarding the absence of policy effect for Water and the validity of the common trend assumption. The DiD effect in column (3) lies in the highest quantiles of the placebo-treatment distribution, with a p -value lower than 0.005.

Tax incidence is likely to vary across income groups, depending on consumer preferences and residential sorting of households across local markets with varying characteristics. To uncover specifically the role of income-related preferences, we examine the differences between low- and high-income households at the national level. We use local EPIs for each income group as defined in Section 3.1. As the EPIs are still corrected for within-group consumer and retailer heterogeneity, they measure the welfare variations of representative households in the low- and high-income groups. The observations are weighted by the income group-specific share of national sales in the living zone in 2011.

The results appear in the second panel of Table 2. The tax incidence is slightly higher for low-income households in the before-after estimates (SSB: 3.3 per cent vs. 2.4 per cent for high-income households in specification (2); NCSB: 3.5 per cent vs. 2.7 per cent). However, the DiD estimates in column (3) show minor differences only (4.1 per cent (SSB) and 4.5 per cent (NCSB) for the high-income vs. 4.5 per cent and 4.7 per cent for the low-income households). This indicates that income-related preference heterogeneity did not cause low-income households to be significantly more impacted by the tax than high-income households. These national-level results might still be driven by residential sorting by income across living zones, because the regression weights depend on the purchase volume of each income group in each market in 2011. Therefore, the last line of the lower panel estimates the differential in tax incidence between low- and high-income households, by replacing the log of EPI with the log-difference in EPI observed in each market between low- and high-income households. Each observation is weighted by the share of national sales observed for low-income households in the living zone in 2011. The estimated differential incidence thus reflects only the role of income-related preference heterogeneity. The DiD results confirm that there are no significant differences between the two income groups. Income-related variations in household preferences over product varieties do not produce important distributional effects.

4.2. Heterogeneity across markets

We now analyse the impact of local market characteristics to reveal their contributions to the distributional effects of the tax. We first work with the global EPI, which is constructed from the full sample of households. We can isolate the effect of local cost and market structures because we retained market fixed effects in our quality-adjusted prices, while we purged the average effects of retailer and consumer heterogeneity. The local variations in EPI therefore reflect neither preference heterogeneity nor national-level variations in costs or strategies across retailers, nor their interactions with retailer localisation.

Table 3. The heterogeneity of tax incidence across markets (% points)

	(1)	(2)	(3)	(4)	(5)
Treated × Post	5.105*** (0.523)	5.470*** (0.529)	5.442*** (0.529)	5.397*** (0.680)	6.325*** (0.696)
× NCSB	−0.001 (0.285)	−0.238 (0.288)	−0.220 (0.288)	0.873** (0.378)	−1.296*** (0.395)
× ln(<i>Income</i>)			−3.592* (2.061)	−1.186 (2.628)	−6.216** (2.661)
× ln(<i>HHI</i>)			1.613** (0.677)	2.589*** (0.870)	0.541 (0.895)
Post	−0.965*** (0.251)	−1.036*** (0.254)	−1.022*** (0.254)	−0.697** (0.320)	−1.678*** (0.322)
× ln(<i>Income</i>)			−1.162 (1.673)	−6.556*** (2.109)	−0.724 (2.117)
× ln(<i>HHI</i>)			−0.588 (0.548)	−0.557 (0.696)	0.452 (0.703)
Price index	EPI all	EPI all	EPI all	EPI poor	EPI rich
Sample		Hyper = 1	Hyper = 1	Hyper = 1	Hyper = 1

Notes: The dependent variable is the log of EPI. The EPI is estimated from Kantar Worldpanel data 2008–2013. Estimated impacts in % points from a before-after specification (observations are *not* weighted by market-specific sales). *Income*: average of the median real equivalent income in the living zone's postcodes (INSEE fiscal data) in 2011. *HHI* is a Herfindahl-Hirschman index based on the sales area of retailers (TradeDimensions data) in the living zone in 2011. All estimates include living zone, month and year fixed effects. Full sample: $N = 55,311$ price-market observations. The sample Hyper = 1 contains only markets with at least one hypermarket ($N = 52,839$). Standard errors, clustered at the living zone level, in parentheses; ***, ** and * indicate significance at the 1%, 5% and 10% levels.

Market affluence is measured by median fiscal income in 2011 (postcode-level fiscal statistics were aggregated to living-zone-level using population weights). We use as indicator for the degree of local-market competition, the logarithm of the Herfindahl-Hirschman Index (HHI) of sales area per capita in 2011.⁹ Introducing the market variables and their interactions in the DiD analysis produces multicollinearity problems when we run separate regressions for SSB and NCSB. We circumvent this difficulty by using the pooled sample of SSB and NCSB price indices (keeping Water as the control group), and we focus on average treatment heterogeneity for all treated soft-drinks (SSB and NCSB). To avoid non-conventional market structures, we also dropped living zones without hypermarket (5.6 per cent of the sample).¹⁰

9 We did not control for interactions with other market characteristics, such as market size, because they are strongly correlated with income or competition. All regressions include living zone fixed-effects that control for the direct effect of market characteristics.

10 Preliminary regressions produced noisy results with high standard errors. We realised that this was due to 12 living zones (out of 263), characterised by the absence of hypermarket. These living zones are predominately rural (11), have much less retailers (7 on average vs. 19 for the rest of the sample) and therefore higher HHI (4,508 vs. 2,404). Their population is smaller (31,819 consumption units on average vs. 170,176 for the rest of the sample) and poorer. In light of IO models, it is difficult to predict the impact of the combination of these characteristics on tax incidence. Specifically, high operating costs and expenditure elasticity may largely mitigate the impact of the lack of competition.

Table 3 reports the results. Specification (1) replicates our earlier estimates, except that now we focus on market heterogeneity, and all markets are given the same weight. The tax incidence is the same for NCSB, but it is higher for SSB (+5.1 per cent against +4.3 per cent in Table 2, column (3)). Specification (2) restricts the estimation sample to markets with a least one hypermarket ($\text{Hyper}=1$). The estimated average tax incidence slightly increases (+0.3 percentage point), but the difference with specification (1) is not significant. Specification (3) adds the interactions with the log market income and the log HHI. Market income has a negative effect on tax incidence. We have centred the income variable on its median, so that the estimated interaction coefficient (-3.59) implies that the tax incidence is approximately 27 per cent lower when market income is 50 per cent above the median ($(\ln(1.5) * -3.592)/5.442$). As baseline prices were higher in richer markets, the tax reduced the price gap between less-affluent and more-affluent markets.¹¹ The log-HHI has a positive effect on tax incidence, significant at the level of 10 per cent. Tax incidence is approximately 12 per cent higher when HHI increases by 50 per cent above the median HHI.

Considering only the interaction effect of income is not sufficient to assess the importance of market heterogeneity in the distributional effects of the tax. Market income and HHI are positively correlated in our estimation sample, with a raw correlation of 0.17. Therefore, moving from a low-income market to a high-income market implies a decrease in tax incidence as market income rises, but this negative effect may be partially offset by an increase in HHI. Figure 4 illustrates this point by showing a contour plot of the estimated tax incidence by percentile rank of market income (on the X-axis) and HHI (the Y-axis): the darker the colour, the higher the estimated tax incidence. The figure clearly reveals that tax incidence is lower in higher-income markets. However, it 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.

Specifications (4) and (5) further assess the importance of market heterogeneity separately, depending on whether one has the preferences of low-income households or those of high-income households. We just replicate the previous estimation with the income-group specific EPIs. Market-level tax incidence is on average 14 per cent lower if one has the preferences of low-income households ($5.397/6.325$). It does not significantly vary with market income, while we find a large, significant, and positive effect of market HHI. For low-income household preferences, tax incidence is 33 per cent higher when the HHI doubles. By contrast, competition does not significantly alter tax incidence when one has high-income household preferences. High-income households finally benefit from a large and negative effect of moving from a low-income market to high-income market. Residential sorting by income thus

11 In 2011, both SSB prices and NCSB prices were respectively 19.6 per cent and 18.7 per cent higher in the richer markets (those in the upper half of the median fiscal income distribution) than in the lower median ones.

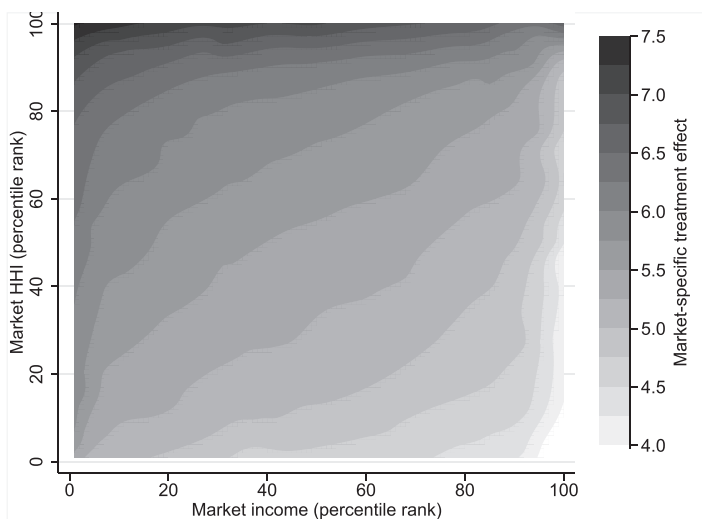


Fig. 4. Tax incidence by market income and HHI, SSB

implies that tax incidence will contribute to the distributional effects of the tax. These results illustrate that taking residential location and market structure into account can significantly enrich our conclusions regarding the distributional effects of taxes.

4.3. Price-setting vs. assortment strategies

The spatial heterogeneity in retailer aggregate price responses to taxes is driven by their price-setting and choice of assortments, i.e. the number and popularity of products they offer to consumers. We investigate these mechanisms separately in Table 4, which reports the effect of the tax on the conventional EPI (CEPI: left panel) and the variability-adjustment factor (VA: right panel), for specifications (3), (4) and (5). The comparison of the estimates for CEPI and VA reveals that it is the former rather than the latter that drives the average level of the tax incidence. The CEPI for the full sample of households increased more in much poorer markets, and competition significantly reduces the tax burden for consumers. As in Table 3, the effect of market HHI is especially large and positive for low-income consumers (Table 4, second column).

The VA component of the EPI for NCSB was positively affected by the tax, while for SSB we find a significant effect for low-income households only (see the first and second lines). The tax incidence on VA also varies with affluence and market competition, especially for high-income households (Table 4, column (6)). In specification (3), a lack of horizontal competition increases the impact of variety adjustment: VA is 0.28 percentage points higher when market HHI doubles ($\ln(2) \times 0.4$). This result seems to be essentially driven by the behaviour of high-income households, as in specification (5) market HHI has

a positive effect on VA. But for them, market income has also a large negative effect on VA. This suggests that tax incidence was lower for high-income households in part because they reside in high-income markets where variety adjustment had a distinct dynamics.

The dynamics of VA is explained by changes in the relative popularity of products and by retailers' assortment strategies. Comparing the number of UPCs available before and after the tax reveals that retailers have not changed the breadth of their product varieties on offer *at a national level*.¹² The estimated VA effects also reflect an increase in the popularity of some UPCs, specifically the top national brands. Tax incidence differs not only across markets but also across UPCs, as different retailers have different degrees of bargaining power with respect to producers. The national average pass-through rates estimated at a product level are lower for the UPCs corresponding to top national brands (19.9 per cent for SSB, 54.9 per cent for NCSB) than for other national products (56.1 per cent for SSB, 109.8 per cent for NCSB) or for retailer and hard-discount brands (67.5 per cent for SSB, 64.8 per cent for NCSB), see Supplementary Appendix B.3. As they had lower pass-through rates, top national brands gained market shares at a national level. This increase in popularity of brands that were already popular among all income groups explains our estimates of the effect of the tax on VA, especially for households residing in more affluent or more competitive markets. The heterogeneity in pass-through rates across product segments and markets eventually contributed to the spatial variations in tax incidence.

5. Discussion and conclusion

This study provides evidence on the role of market structure in the distributional incidence of the 2012 French soft-drink tax. The tax incidence was lower in high-income and more-competitive markets. To illustrate the magnitude of this market effect, we use compensating variation measures of welfare loss by income group (Supplementary Appendix B.4). Low-income households lost on average 1.28 €/year as against 0.74 €/year for high-income households. The difference (0.54 €/year) can be decomposed into a market effect that reflects both residential sorting by income across markets and differential tax incidence due to heterogeneity in market structure, and a preference effect that is produced by differences in preferences for quantity and quality between low- and high-income households living in the same market. We can compute the welfare loss of each income group under the counterfactual scenario that income does not affect residential location, and that tax incidence is everywhere equal to that observed in the most affluent most competitive market. This exercise reveals that the market effect accounts for at least 33.3 per cent of the difference in welfare loss between income groups. Residential sorting accounts for about 8 percentage points of this market effect and heterogeneity in market structure for the remaining 26 percentage points.

12 To adjust locally to the tax, retailers may have changed their SSB assortments to reduce price competition (Hamilton, 2009). Our data are not fine-grained enough to document this point.

Table 4. The heterogeneity of tax incidence across markets—CEPI and VA (% points)

	CEPI			VA	
	(3)	(4)	(5)	(4)	(5)
Treated × Post	5.646*** (0.503)	5.813*** (0.650)	6.183*** (0.662)	-0.416** (0.200)	0.142 (0.212)
× NCSB	-0.940*** (0.274)	-0.010 (0.361)	-1.717*** (0.375)	0.883*** (0.111)	0.421*** (0.120)
× ln(Income)	-4.496** (1.961)	-1.627 (2.512)	-3.077 (2.529)	0.441 (0.772)	-3.139*** (0.809)
× ln(HHI)	1.211* (0.645)	2.719*** (0.831)	-0.224 (0.851)	-0.130 (0.256)	0.765*** (0.272)
Post	-0.925*** (0.242)	-0.813*** (0.306)	-1.485*** (0.306)	0.116 (0.077)	-0.193** (0.098)
× ln(Income)	-0.093 (1.592)	-5.396*** (2.016)	-0.946 (2.012)	-1.160* (0.620)	0.222 (0.643)
× ln(HHI)	-0.134 (0.521)	-0.916 (0.665)	1.367*** (0.668)	0.360* (0.204)	-0.915*** (0.214)
Price index	EPI all	EPI poor	EPI rich	EPI poor	EPI rich
Sample	Hyper = 1	Hyper = 1	Hyper = 1	Hyper = 1	Hyper = 1

Notes: The dependent variable is the log of CEPI or VA. CEPI and VA are estimated from Kantar Worldpanel data 2008–2013. Other details are as in Table 3. Standard errors are clustered at the area level in parentheses; ***, **, * and † indicate significance at the 1%, 5% and 10% levels.

Market heterogeneity in tax incidence is essentially explained by variations in product-level pass-through rates, differences in product market shares across markets and spatial variations in pre-tax market structure. Conditional on local competition, initial prices are higher but tax incidence is lower in high-income markets. This effect does not reflect differences in household preferences across markets, since we adjusted for retailer and consumer heterogeneity: in our set-up, there is a single demand curve for the representative consumer. The likely explanation is therefore that markets were initially at different equilibrium position along the demand curve because retailers face higher operating and rental costs in high-income markets. The role of local costs in reducing pass-through has already been well-documented in empirical works in trade and environmental economics (see, e.g. Nakamura and Zerom, 2010; Stolper, 2016). From a theoretical perspective, as the supply curve is shifted by costs differential, markets differ in initial demand slope and curvature, which are two key theoretical determinants of the tax pass-through under imperfect competition and product differentiation (Weyl and Fabinger, 2013).¹³ Following a taxation shock, a profit-maximising firm has to increase its prices to maintain the equality between marginal revenue and marginal cost. The optimal price-setting strategy will eventually depend on the rate at which demand falls with the mark-up adjustment on each unit sold, i.e. the slope and curvature of demand.¹⁴ In addition, Hong and Li (2017) shows that a vertical market structure with non-integrated manufacturers and retailers leads to a mechanical reduction of the pass-throughs. As the tax is borne by producers, it pushes wholesale prices upwards. The double mark-up adjustment, by producers and retailers, then lowers the pass-through. In the end, the combination of imperfect horizontal competition and imperfect vertical integration produces incomplete and heterogeneous pass-throughs.

We have based the analysis on year-to-year comparisons, following an approach that is widely used in the literature (see, e.g. Hong and Li, 2017). An alternative approach is to track the monthly changes 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 results from this event study suggest that the tax was passed on quite rapidly to consumer prices, after one quarter (Supplementary Appendix B.6). The price levels reached in March–April–June–July 2012 are similar to our earlier results

13 Under perfect competition with no product differentiation, the pass-through rate 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). In this setting, the more elastic is the demand, the lower is ρ . This prediction does not hold anymore with imperfect competition and product differentiation.

14 Earlier models of imperfect competition produce overshifting in the excise tax (Anderson *et al.*, 2001; Delipalla and Keen, 1992; Tyagi, 1999). This comes about when demand is highly convex, so that each additional marginal price increase produces increasingly large reductions in demand. In this case, a profit-maximising 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.

in the before-after specification. This is unsurprising given that, over the period 2008–2013, the contractual framework between manufacturers and retailers was regulated by the state, with annual negotiations that had to be resolved by mid-March (a mandatory deadline).

Our results also reveal that the soda tax increased the prices of SSBs and NCSBs by respectively 4.3 per cent and 5.1 per cent on average at the national level. The corresponding national pass-through rates to the *aggregate* price are 41.1 per cent for SSBs and 47.9 per cent for NCSBs (Supplementary Appendix B.5). The national pass-through on the EPI is slightly lower than the average product-level pass-through (52.3 per cent for SSBs and 64.3 per cent for NCSBs in Supplementary Appendix B.3). While most studies have estimated the incidence of soft-drink taxes on disaggregated prices, our methodological approach shifts the focus on consumer welfare, whose variations are measured through the EPI. Adjusting the price index for household preferences over product varieties produces lower estimates of tax incidence. This partly explains why our results differ from those recently published in Capacci *et al.* (2019). Using KWP household scanner data for one French region, they find a pass-through of 66 per cent of the 2012 French soda tax to monthly average household unit values unadjusted for retailer and consumer heterogeneity, an estimate that is very similar to our product-level pass-throughs.

The estimated national pass-through is much lower than the estimates in Berardi *et al.* (2016), who conclude that the tax was over-shifted after 6 months. In Supplementary Appendix B.7, we show that this is explained by their focus on pass-through to product retail prices rather than on consumer welfare, and by important differences in data. We use similar identification designs, but they exploit retail prices collected from 1,800 drive-through outlets between August 2011 and June 2012, while our data cover all outlet formats and provide a representative sample of purchases for 2008–2013. This extended time window enables us to control for month-of-the-year effects and variations in sugar cost.

It is also worth noting that our results are robust to the use of alternative price indices, such as the Laspeyres or Fisher indices (Supplementary Appendix B.8). The EPI is the relevant price concept for evaluating the health impact of the 2012 French tax, as the distribution of the sugar density of SSB purchases is very homogeneous and did not vary between 2011 and 2012 (Supplementary Appendix B.9). This might have been different if the tax had been scaled with sugar content, although previous research has shown that the crucial behavioural margin is not SSB quality but aggregate SSB quantity (Bonnet and Réquillart, 2013).

To get an idea of the magnitude of the tax impact, we have used the pre-tax data to estimate Almost Ideal Demand Systems for the four groups of non-alcoholic beverages and by income group. The estimates do not differ much from the estimation results reported in Supplementary Appendix B.1 for the entire sample. 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, since the tax did not affect the average sugar content of purchases within the SSB categories. The tax reduced SSB purchases by 5.0 per cent in low-income households vs. 3.7 per cent in high-income households. The absolute level of consumption was also higher in 2011 for low-income households (17.3 L/cap/year vs. 13.7 L/cap/year for high-income). Hence, the larger welfare losses for low-income households have to be weighted against the greater health benefits for this group and for society as a whole. This confirms previous evidence that regressivity in terms of consumer welfare might be (at least partially) offset by progressivity in health benefits (Etilé and Sharma, 2015; Sharma *et al.*, 2014).

Finally, while this paper has demonstrated the importance of accounting for market heterogeneity in tax incidence analysis, our approach is based on a theoretical framework that sets aside concerns about consumer behavioural biases. Allcott *et al.* (2019) propose a method for estimating optimal sin taxes when direct measures of bias-proneness are available. Therefore, it would be interesting to replicate our analysis with EPIs adjusted for behavioural biases. We leave this for future research.

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Supplementary Data

[Supplementary data](#) are available at *ERAE* online.

References

- Allcott, H., Lockwood, B. B., and Taubinsky, D. (2019). Regressive sin taxes, with an application to the optimal soda tax. *Quarterly Journal of Economics*, 134:(3), 1557–1626.
- Amiti, M., Itskhoki, O., and Konings, J. (2014). Importers, exporters, and exchange rate disconnect. *American Economic Review*, 104:(7), 1942–1978.
- Anderson, S. P., De Palma, A., and Kreider, B. (2001). Tax incidence in differentiated product oligopoly. *Journal of Public Economics*, 81:(2), 173–192.
- Berardi, N., Sevestre, P., Tepaut, M., and Vigneron, A. (2016). The impact of a soda tax on prices: evidence from french micro data. *Applied Economics*, 48:(41), 3976–3994.

- Bertrand, M., Duflo, E., and Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *Quarterly Journal of Economics*, 119:(1), 249–275.
- Bonnet, C., and Réquillart, V. (2011). Does the EU sugar policy reform increase added sugar consumption? An empirical evidence on the soft drink market. *Health Economics*, 20:(9), 1012–1024.
- Bonnet, C., and Réquillart, V. (2013). Tax incidence with strategic firms in the soft drink market. *Journal of Public Economics*, 106: 77–88.
- Broda, C., and Weinstein, D. E. (2006). Globalization and the gains from variety. *Quarterly Journal of Economics*, 121:(2), 541–585.
- Broda, C., and Weinstein, D. E. (2010). Product creation and destruction: evidence and price implications. *American Economic Review*, 100:(3), 691–723.
- Capacci, S., Allais, O., Bonnet, C., and Mazzocchi, M. (2019). The impact of the french soda tax on prices and purchases: an ex-post evaluation. *PLoS one*, 14:(10), e0223196.
- Cawley, J., and Frisvold, D. E. (2017). The pass-through of taxes on sugar-sweetened beverages to retail prices: the case of Berkeley, california. *Journal of Policy Analysis and Management*, 36:(2), 303–326.
- Chen, Y. (2009). *Handbook of Pricing Research in Marketing* (Ed. Rao, V. D.), Product line pricing, Chapter 10. Cheltenham, UK: Edward Elgar, pp. 216–231.
- Colchero, M. A., Salgado, J. C., Unar-Munguía, M., Molina, M., Ng, S., and Rivera-Dommarco, J. A. (2015). Changes in prices after an excise tax to sweetened sugar beverages was implemented in Mexico: evidence from urban areas. *PLoS One*, 10:(12), e0144408.
- Cornelsen, L., and Smith, R. D. (2018). Soda taxes—four questions economists need to address. *Food Policy*, 74: 138–142.
- Delipalla, S., and Keen, M. (1992). The comparison between ad valorem and specific taxation under imperfect competition. *Journal of Public Economics*, 49:(3), 351–367.
- Draganska, M., and Jain, D. C. (2006). Consumer preferences and product-line pricing strategies: an empirical analysis. *Marketing science*, 25:(2), 164–174.
- Dubois, P., Griffith, R., O’Connell, M. (2019). How well targeted are soda taxes? *TSE Working Paper* 17 (868).
- Etilé, F. (2019). The economics of diet and obesity: public policy. <https://oxfordre.com/economics/view/10.1093/acrefore/9780190625979.001.0001/acrefore-9780190625979-e-456>.
- Etilé, F., and Sharma, A. (2015). Do high consumers of sugar-sweetened beverages respond differently to price changes? A finite mixture iv-tobit approach. *Health Economics*, 24:(9), 1147–1163.
- Falbe, J., Rojas, N., Grummon, A. H., and Madsen, K. A. (2015). Higher retail prices of sugar-sweetened beverages 3 months after implementation of an excise tax in Berkeley, California. *American Journal of Public Health*, 105:(11), 2194–2201.
- Feenstra, R. C. (1994). New product varieties and the measurement of international prices. *American Economic Review*, 84:(1), 157–177.
- Finkelstein, E. A., Zhen, C., Bilger, M., Nonnemaker, J., Farooqui, A. M., and Todd, J. E. (2013). Implications of a sugar-sweetened beverage (ssb) tax when substitutions to non-beverage items are considered. *Journal of Health Economics*, 32:(1), 219–239.
- Fullerton, D., and Metcalf, G. E. (2002). Tax incidence. *Handbook of Public Economics*, 4: 1787–1872.
- Gopinath, G., and Itskhoki, O. (2010). Frequency of price adjustment and pass-through. *Quarterly Journal of Economics*, 125:(2), 675–727.

- Grogger, J. (2017). Soda taxes and the prices of sodas and other drinks: evidence from Mexico. *American Journal of Agricultural Economics*, 99:(2), 481–498.
- Hamilton, S. F. (2009). Excise taxes with multiproduct transactions. *American Economic Review*, 99:(1), 458–471.
- Handbury, J., and Weinstein, D. E. (2015). Goods prices and availability in cities. *Review of Economic Studies*, 82:(1), 258–296.
- Hong, G. H., and Li, N. (2017). Market structure and cost pass-through in retail. *Review of Economics and Statistics*, 99:(1), 151–166.
- Jaravel, X. (2018). The unequal gains from product innovations: evidence from the US retail sector. *Quarterly Journal of Economics*, 134:(2), 715–783.
- Le Bodo, Y., Etilé, F., Gagnon, F., and De Wals, P. (2019). Conditions influencing the adoption of a soda tax for public health: analysis of the french case (2005–2012). *Food Policy*, 88: 10176–5.
- Lusk, J. L., and Brooks, K. (2011). Who participates in household scanning panels? *American Journal of Agricultural Economics*, 93:(1), 226–240.
- Madden, D. (2015). The poverty effects of a ‘fat-tax’ in Ireland. *Health economics*, 24:(1), 104–121.
- Malik, V. S., Pan, A., Willett, W. C., and Hu, F. B. (2013). Sugar-sweetened beverages and weight gain in children and adults: a systematic review and meta-analysis. *American Journal of Clinical Nutrition*, 98:(4), 1084–1102.
- Mora, T., Fichera, E., Lopez-Valvarcel, B. G., Roche, D. (2019). Do consumers respond to ‘sin taxes’ heterogeneously? New evidence from the tax on sugary drinks using longitudinal scanner data. *Unpublished manuscript*.
- Muller, L., Lacroix, A., Lusk, J. L., and Ruffieux, B. (2017). Distributional impacts of fat taxes and thin subsidies. *The Economic Journal*, 127:(604), 2066–2092.
- Nakamura, E., and Zerom, D. (2010). Accounting for incomplete pass-through. *Review of Economic Studies*, 77:(3), 1192–1230.
- Nolte, S., and Grethe, H. *et al.* (2012). Development of the EU and world sugar markets in 2011. *Sugar Industry/Zuckerindustrie*, 137:(1), 40–48.
- Redding, S. J. Weinstein, D. E. (2016). A unified approach to estimating demand and welfare. Technical report, National Bureau of Economic Research.
- Schmacker, R., and Smed, S. (2020). Do prices and consumption respond symmetrically to soft-drink tax increases and cuts? Evidence from the danish tax reforms. *Economics & Human Biology*, 37: 10086–4.
- Sharma, A., Hauck, K., Hollingsworth, B., and Siciliani, L. (2014). The effects of taxing sugar-sweetened beverages across different income groups. *Health Economics*, 23:(9), 1159–1184.
- Stolper, S. (2016). Local pass-through and the regressivity of taxes: evidence from automotive fuel markets. *Harvard Environmental Economics Program Discussion Paper 2016-70* (May).
- Tiffin, R., Kehlbacher, A., and Salois, M. (2015). The effects of a soft drink tax in the UK. *Health Economics*, 24:(5), 583–600.
- Tiffin, R., and Salois, M. (2014). The distributional consequences of a fiscal food policy: evidence from the UK. *European Review of Agricultural Economics*, 42:(3), 397–417.
- Triplett, J. E. (2001). Should the cost-of-living index provide the conceptual framework for a consumer price index?. *The Economic Journal*, 111:(472), 311–334.
- Tyagi, R. K. (1999). A characterization of retailer response to manufacturer trade deals. *Journal of Marketing Research*, 36:(4), 510–516.
- Wang, E. Y. (2015). The impact of soda taxes on consumer welfare: implications of storability and taste heterogeneity. *The RAND Journal of Economics*, 46:(2), 409–441.

- Weyl, E. G., and Fabinger, M. (2013). Pass-through as an economic tool: principles of incidence under imperfect competition. *Journal of Political Economy*, 121:(3), 528–583.
- WHO (2017). Taxes on sugary drinks: why do it? Technical report, World Health Organization.
- Zhen, C., Taylor, J. L., Muth, M. K., and Leibtag, E. (2009). Understanding differences in self-reported expenditures between household scanner data and diary survey data: a comparison of homescan and consumer expenditure survey. *Review of Agricultural Economics*, 31:(3), 470–492.