Online Appendix

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How well targeted are soda taxes?

American Economic Review

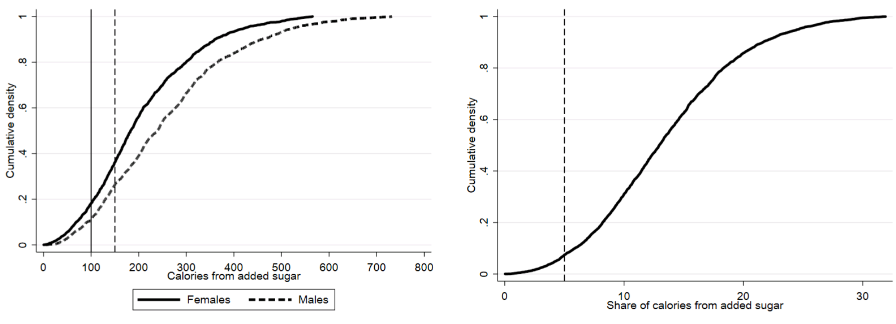
A Data appendix

A.1 Patterns of sugar consumption

In this appendix we use data from the National Diet and Nutrition Survey 2008-2011, which is an intake study of a representative sample of 3,073 UK adults and children. In Figure A.1 we document widespread excess consumption of added sugar. Panel (a) shows the cumulative distribution of calories from added sugar per day (separately for females and males) and panel (b) shows the cumulative distribution of the share of calories from added sugar. In both graphs we denote recommended medical levels with vertical lines. In the case of the level of calories from added sugar, the American Heart Association recommends no more than 100 calories per day from added sugar for females, and no more than 150 for males. In the case of the share of calories from added sugar, the World Health Organization recommends that ideally fewer than 5% of calories should be obtained from added sugar. The figure makes clear that the majority of individuals exceed these targets by a considerable amount.

Figure A.1: Cumulative density of calories from added sugar

(a) Calories from added sugar (b) % of calories from added sugar

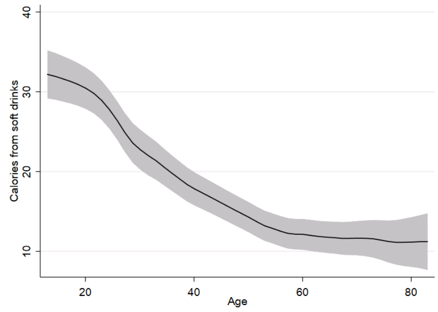


Notes: Numbers using National Diet and Nutrition Survey 2008-2011 for a representative sample of 3,073 UK adults and children. For each distribution we trim the top percentile. Vertical lines denote medical guidelines.

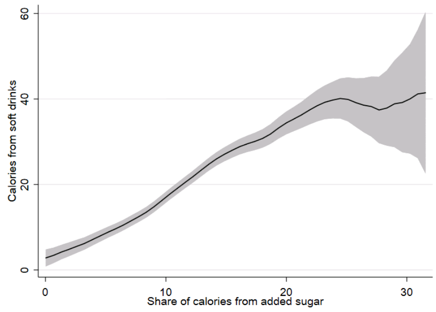
In Figure A.2 we show local polynomial regressions describing how the calories from (the sugar in) soft drinks vary with age, share of calories from added sugar and equivalized household income. The figure shows that young individuals, those with a high share of calories from added sugar, and those from relatively low income households obtain relatively large amounts of calories from soft drinks.

Figure A.2: Sugar from soft drinks

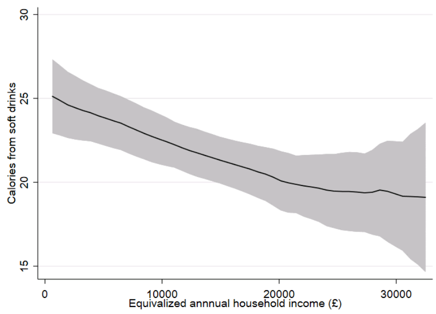
(a) by age



(b) by calories from added sugar



(c) by equivalized income

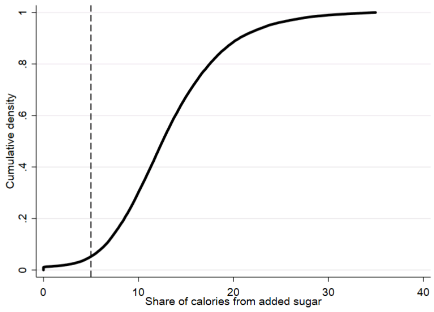


Notes: Numbers using National Diet and Nutrition Survey 2008-2011 for a representative sample of 3,073 UK adults and children. Lines are based on local polynomial regressions. Shaded area are 95% confidence bands. For each variable we trim the top percentile of the distribution.

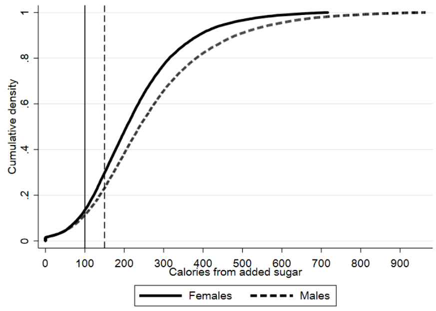
In Figures A.3 and A.4 we repeat Figures A.1 and A.2 with US data. Specifically, we use National Health and Nutrition Examination Study over 2007-2014, a sample of 39,189 adults and children. The same patterns hold in the US. Notice, the level of calories from soft drinks reported for the US in the National Health and Nutrition Examination Study is higher than those reported in the UK in the National Diet and Nutrition Survey. This may partially reflect differences in consumption levels between the two countries, but it may also reflect differences in reporting between the two surveys.

Figure A.3: Patterns in the US: Cumulative density of calories from added sugar

(a) Calories from added sugar



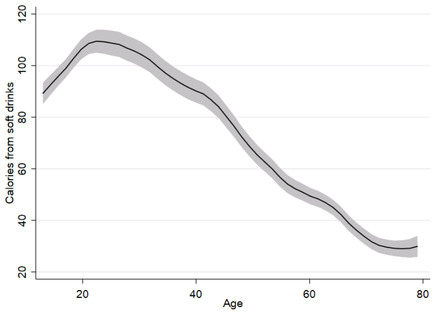
(b) % of calories from added sugar



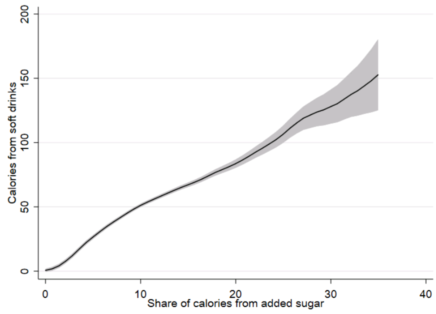
Notes: Numbers using National Health and Nutrition Examination Study 2007-2014 for a representative sample of 39,189 US adults and children. For each distribution we trim the top percentile. Vertical lines denote medical guidelines.

Figure A.4: Patterns in the US: Sugar from soft drinks

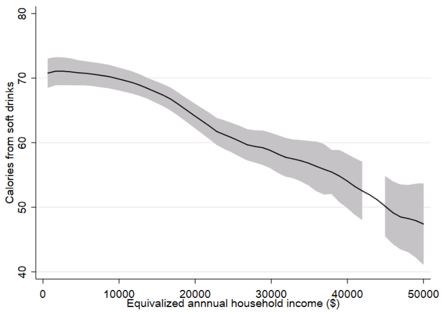
(a) by age



(b) by calories from added sugar



(c) by equivalized income



Notes: Numbers using National Health and Nutrition Examination Study 2007-2014 for a representative sample of 39,189 US adults and children. Lines are based on local polynomial regressions. Shaded area are 95% confidence bands. For each variable we trim the top percentile of the distribution.

A.2 Product definition

We consider the market for chilled non-alcoholic drinks. In the raw data there are 2,950 unique product codes (UPCs) consisting of 1,065 brands (as defined by Kantar). We use data on the 598 UPCs in 89 brands that comprise 82% of transactions. We drop niches UPCs that have very small market shares as follows:

- 975 brands that individually have a market share of less than 0.15%, accounting for 2,232 UPCs. Together these account for 15% of the market; see spreadsheet.
- 87 UPCs that are for sizes smaller than 200ml, which together account for 2% of the market; see spreadsheet.
- 33 UPCs that are for odd size-brand combinations, that individually have small market shares (the largest is 0.18%, the mean is 0.04%), which together account for 1% of the market; see spreadsheet.

This leaves us with 598 UPCs in 89 brands. We group these into 37 products as follows:

- 30 branded soft drink products, e.g. Coca Cola 330ml, Coca Cola 500ml, Coca Cola Diet 330ml, etc.; we aggregate over 104 UPCs, for example, the product Coca Cola 500ml is the aggregate of 2 UPCs that differ in the shape of bottle (COCA COLA CONTOUR PET 500ML with a market share of 7.5% and COCA COLA PET 500ML with a market share of 0.2%); together these 30 branded soft drink products account for 60% market share; see spreadsheet
- Other soda products
  - regular: we aggregate 184 UPCs that individually have market shares that range from 1.6% (Red Bull 250ml) to 0.0002% (Orangina Rouge 500ml) with a mean market share of 0.08%, and together account for 14% of the market; see spreadsheet.
  - diet: we aggregate 22 UPCs that individually have market shares that range from 0.4% (7UP Free Lemon+Limeade 600ml) to 0.001% (Lucozade Sport Lite 500ml) and together account for 1.9% of the market; see spreadsheet.
- Fruit juice: we aggregate 100 UPCs that individually all have market shares below 1% and together account for 7.9% of the market; see spreadsheet.

- Flavoured milk: we aggregate 30 UPCs that individually have market shares below 0.25% and together account for 1.8% of the market; see spreadsheet.

- Fruit water: we aggregate 11 UPCs that are different flavours of Volvic Touch of Fruit Water that together account for just under 1% of the market; see spreadsheet.

- Water: we aggregate 146 UPCs for bottled water, which together have a market share of 12%; see spreadsheet.

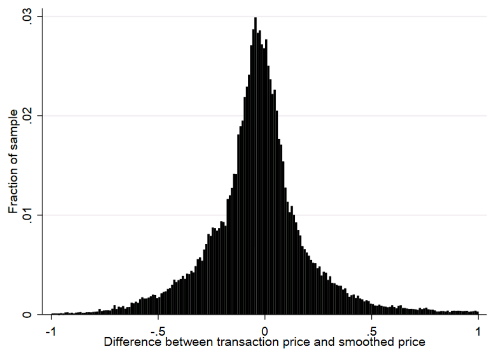
A.3 Measurement of prices

We compute the transaction level price as expenditure made for a UPC over units purchased. For products that entail some aggregation over sizes, we adjust prices so they are in terms of the most popular size. For instance, Pepsi 500ml involves aggregating over 500ml and 600ml size; for transactions involving 600ml Pepsi, we adjust the price according to $p * 5/6$. Similarly, for the composite products we express price in terms of the most common size.

For each product we compute the mean monthly price (across transactions) in each retailer type. If a product-retailer type-month involves fewer than 3 transactions, we replace the price with a missing value. For product-retailer type-months with missing prices we interpolate (across weeks). We smooth the resulting price series using a local polynomial non-parametric regression.

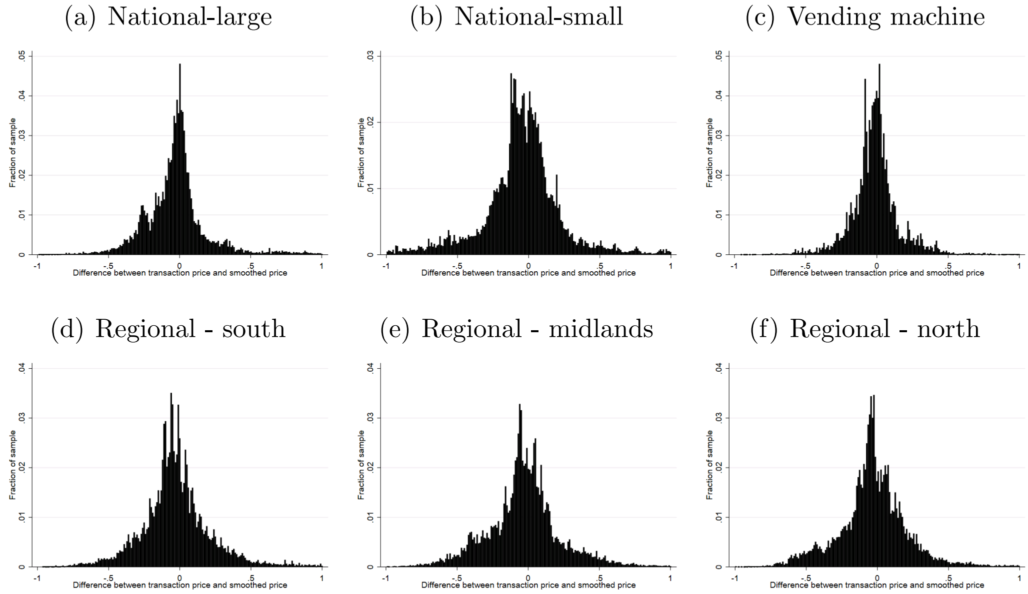
Figures A.5 and A.6 show the difference between the price the consumer actually pays for the chosen product (the transaction price) and the smoothed price used in the demand model estimation. They show that measurement error exists and exists for all stores and if anything is slightly lower for vending machines.

Figure A.5: Difference between transaction price and smoothed price



Notes: .

Figure A.6: Difference between transaction price and smoothed price, by store type



Notes: .

Measurement error in non-linear models is more problematic than in linear models, and even classical additive measurement error can bias parameter estimates, unlike in linear models. However, it is useful to consider more closely the type of measurement error we face here. The measurement errors introduced by using imputed prices instead of true prices can be thought of coming from two errors. First, there is an error when using a mean instead of the true variable. These errors are "Berkson" errors (Berkson (1950)), i.e. additive on the unobserved true price and independent of the average price used in estimation. Second, we also make an error on the true mean price in a region-store chain when using transaction prices because the sampling of transactions is not independent of prices.

Blundell, Horowtiz and Parey (2019) argue that "Berkson" errors are commonplace when we observe an average price in a group rather than the true individual price, and can lead to bias in estimates of demand. They are not classical measurement errors independent of the true unobserved variable. Schennach (2013) proposes a solution with instrumental variables in the context of non-parametric models with a continuous outcome variable. In a continuous demand estimation problem, Blundell, Horowtiz and Parey (2019) develop a consistent estimator that uses external information on the true distribution of prices in the case of demand estimation with non-separable unobserved heterogeneity. Their results do not extend to a discrete choice model for differentiated products demands.

The second source of errors is due to the imputation using transaction prices.

We leave for future research the development of a consistent estimation method in the case of discrete choices. This is a complicated problem that has not been solved.

As our imputed prices potentially suffer from both error components, we do a simple Monte Carlo simulation to see what the extent of the bias might be in our setting with respect to such measurement error in prices.

We consider a data generating process where individual prices paid by each consumer are such that the prices of good j for consumer i at different occasions τ is:

$$p_{ijrt\tau} = p_{jrt} + \Delta_{ijrt\tau}$$

where $\Delta_{ijrt\tau}$ is independent of p_{jrt} for all products j, retailers r, periods t and purchase occasions τ of each consumer denoted i. We then consider the case where all $p_{ijrt\tau}$ are not observed by the econometrician, only transaction prices.

We simulate a logit model based on the random utility of consumer i for good $j = 1, \dots, J$ on purchase occasion τ for consumer i:

$$U_{ij\tau} = \delta_j - \alpha_i p_{ijr(i)t(i)\tau} + \epsilon_{ijr(i)t(i)\tau}$$

with outside good $U_{i0\tau} = \epsilon_{i0r(i)t(i)t\tau}$ and where $r(i) \in \{1, \dots, R\}$ denotes the retailers of consumer i and $t(i) \in \{1, \dots, T\}$ the period where consumer i shops. We randomly draw purchase occasions across periods $t(i)$ (these are like markets in our application) and for simplicity we randomly assign consumers uniformly to different retailers $r(i)$.

Preferences for consumers $i = 1, \dots, I$ are heterogeneous with α_i, which is normally distributed with zero truncation (to impose that the price coefficient is negative). The price heterogeneity is calibrated to have approximately the scale of the price distribution observed for sodas in our data and the mean utilities and price coefficient are also chosen to calibrate approximately to the product market shares and the outside good market share. Consumer i chooses the highest utility alternative such that her chosen good at occasion τ is

$$y_{i\tau} = \arg \max_{j=0,1,\dots,J} \{U_{ij\tau}\}$$

Assuming all $\epsilon_{ijr(i)t(i)\tau}$ are i.i.d. type I extreme value, the choice probability of j by consumer i at choice occasion τ is

$$P_{ij\tau} = P(y_{i\tau} = j | p_{i1r(i)t(i)\tau}, \dots, p_{iJr(i)t(i)\tau}) = \frac{\exp(\delta_j - \alpha_i p_{ijr(i)t(i)\tau})}{1 + \sum_{k=1}^{J} \exp(\delta_k - \alpha_i p_{ikr(i)t(i)\tau})}$$

and the consumer i own price elasticity for good j is $e_{ij\tau} \equiv \frac{\partial \ln P_{ij\tau}}{\partial \ln p_{ijr(i)t(i)\tau}} = -\alpha_i P_{ij\tau}(1-P_{ij\tau})$.

We observe only transaction prices $p_{iy_{i\tau}r(i)t(i)\tau}$ for the chosen product $y_{i\tau} \in \{1,\ldots,J\}$. We compute average transaction prices by retailer and period as the empirical mean of observed transaction prices:

$$p_{jrt} = \frac{1}{card\{i,\tau|r(i)=r,t(i)=t,y_{i\tau}=j\}} \sum_{\{i,\tau|r(i)=r,t(i)=t,y_{i\tau}=j\}} p_{iy_{i\tau}r(i)t(i)\tau}$$

The measurement error in prices introduce a bias in the logit estimates. In order to gain intuition on how large is this bias, we compare the maximum likelihood estimation of parameters using the true prices $p_{ijr(i)t(i)\tau}$ with estimates using the average transaction prices p_{jrt}.

While theoretically there remains an asymptotic bias, our results suggest that with sufficient observations of purchases per product-retailer the bias becomes economically irrelevant. Specifically, with sample sizes similar to those in our data we obtain a bias in the elasticity estimates that is less than 5%.

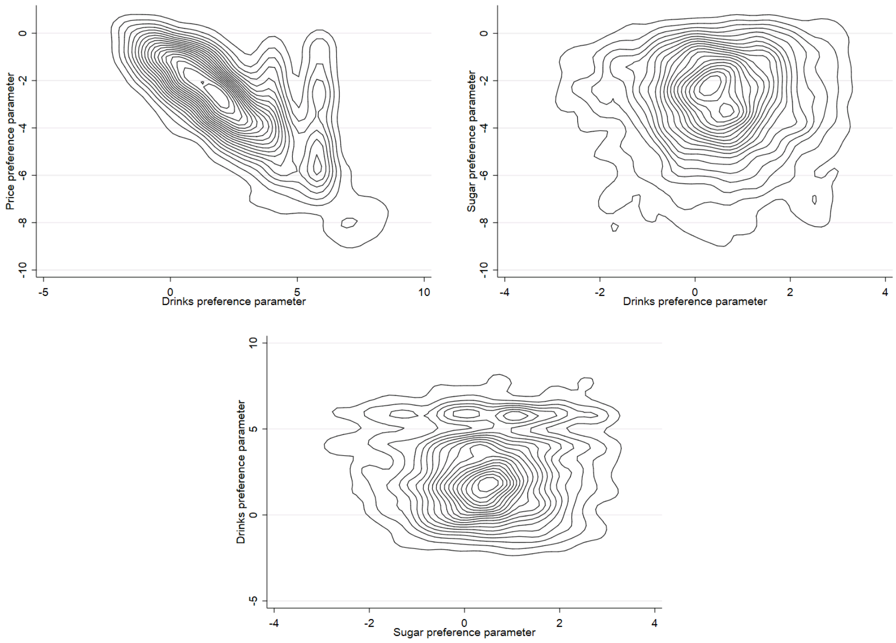
Interestingly, the bias is small and positive on the individual price coefficients while if we impose a common price coefficient (same α_i) in the true data generating process, the bias is small but negative. This shows that when the measurement error is not consumer specific, but due only to $\Delta_{ijrt\tau}$, the bias leads to an overestimation of price elasticity. Intuitively this is because the mean transaction price is underestimated (purchases occur more often when the price deviation is negative) while the outside good price normalization is constant. When the price coefficient is individual specific (as in our model), the measurement error is compounded with the price sensitivity, which introduces an additional error that is correlated with α_i, and generates a bias in the other direction. Intuitively, the fact that all prices are biased (except the outside good) makes the bias on the price elasticity of demand not too large, because choices across inside goods depend on relative prices, and it also implies that the bias is likely to be larger the larger is the outside good market share.

We think this problem is an interesting general issue that deserves more research that is out of the scope of this paper.

B Further details of on-the-go demand estimates

In Figure B.1 we plot contour plots of the bivariate preference distributions.

Figure B.1: Bivariate distributions of consumer specific preference parameters



Notes: Distribution plots use consumers with finite sugar preference parameters; those having infinite sugar preferences cannot be included in this graph. We trim the top and bottom 2.5% of the distribution.

In Tables 1 we report price elasticities for all products. 95% confidence bands are given in brackets. In column 1 we report the percent change in demand for the product when its price increases by 1%. Columns 2-5 report how demand for alternative products (sugary soft drinks, diet soft drinks, sugary alternative drinks and non-sugary alternative drinks) would change and a final column reports what would be the overall change in demand for soft drinks and alternative juices. For example, a 1% increase in the price of a 500ml bottle of Coca Cola, would result in a reduction in demand for that product of 2.36%. Demand for alternative sugary soft drinks would rise by around 0.223%, demand for diet soft drinks would rise by 0.125%, demand for alternative sugary drinks would rise by 0.201% and demand for alternative non-sugary drinks would rise by 0.129%. Demand for non-alcoholic drinks as a whole would fall by 0.114%.

Table 1: Product level price elasticities

	Own product demand	Effect of 1% price increase on: cross demand for: sugary soft drinks	diet soft drinks	sugary alternatives	non-sugary alternatives	Total drinks demand
Coca Cola 330	-2.81	0.096	0.055	0.084	0.092	-0.012
	[-2.85, -2.80]	[0.095, 0.098]	[0.054, 0.056]	[0.083, 0.086]	[0.091, 0.094]	[-0.012, -0.012]
Coca Cola 500	-2.36	0.223	0.125	0.201	0.129	-0.114
	[-2.38, -2.30]	[0.218, 0.225]	[0.122, 0.126]	[0.196, 0.203]	[0.126, 0.131]	[-0.114, -0.111]
Coca Cola Diet 330	-3.02	0.047	0.106	0.036	0.232	-0.004
	[-3.05, -3.00]	[0.046, 0.048]	[0.104, 0.107]	[0.035, 0.036]	[0.228, 0.235]	[-0.005, -0.004]
Coca Cola Diet 500	-2.51	0.100	0.235	0.098	0.224	-0.084
	[-2.53, -2.47]	[0.098, 0.102]	[0.229, 0.239]	[0.095, 0.100]	[0.221, 0.228]	[-0.085, -0.082]
Dr Pepper 330	-3.25	0.014	0.007	0.007	0.009	-0.001
	[-3.30, -3.23]	[0.014, 0.015]	[0.007, 0.008]	[0.007, 0.008]	[0.009, 0.010]	[-0.002, -0.001]
Dr Pepper 500	-2.64	0.035	0.020	0.031	0.020	-0.018
	[-2.66, -2.59]	[0.034, 0.036]	[0.019, 0.020]	[0.030, 0.031]	[0.020, 0.021]	[-0.018, -0.017]
Dr Pepper Diet 500	-2.85	0.016	0.038	0.015	0.038	-0.013
	[-2.88, -2.80]	[0.016, 0.016]	[0.037, 0.039]	[0.014, 0.015]	[0.037, 0.039]	[-0.013, -0.013]
Fanta 330	-2.99	0.020	0.010	0.015	0.018	-0.002
	[-3.04, -2.97]	[0.020, 0.020]	[0.010, 0.010]	[0.014, 0.015]	[0.018, 0.019]	[-0.003, -0.002]
Fanta 500	-2.54	0.036	0.020	0.033	0.023	-0.019
	[-2.57, -2.49]	[0.035, 0.037]	[0.020, 0.021]	[0.032, 0.034]	[0.022, 0.023]	[-0.019, -0.018]
Fanta Diet 500	-2.74	0.016	0.038	0.016	0.041	-0.014
	[-2.77, -2.70]	[0.016, 0.017]	[0.036, 0.038]	[0.016, 0.017]	[0.040, 0.042]	[-0.014, -0.014]
Cherry Coke 330	-2.99	0.014	0.006	0.009	0.011	-0.001
	[-3.03, -2.97]	[0.014, 0.015]	[0.006, 0.007]	[0.009, 0.009]	[0.010, 0.011]	[-0.001, -0.001]
Cherry Coke 500	-2.59	0.029	0.016	0.027	0.018	-0.015
	[-2.61, -2.53]	[0.029, 0.030]	[0.016, 0.016]	[0.026, 0.027]	[0.017, 0.018]	[-0.015, -0.014]
Cherry Coke Diet 500	-2.79	0.013	0.030	0.013	0.032	-0.011
	[-2.81, -2.74]	[0.013, 0.013]	[0.029, 0.031]	[0.012, 0.013]	[0.031, 0.033]	[-0.011, -0.011]
Oasis 500	-2.55	0.044	0.025	0.041	0.027	-0.023
	[-2.58, -2.49]	[0.043, 0.045]	[0.024, 0.026]	[0.040, 0.042]	[0.026, 0.027]	[-0.023, -0.022]
Oasis Diet 500	-2.72	0.020	0.047	0.020	0.047	-0.017
	[-2.74, -2.68]	[0.020, 0.020]	[0.046, 0.048]	[0.019, 0.020]	[0.046, 0.048]	[-0.017, -0.017]
Pepsi 330	-2.80	0.035	0.018	0.030	0.034	-0.004
	[-2.84, -2.79]	[0.035, 0.036]	[0.018, 0.019]	[0.029, 0.030]	[0.034, 0.036]	[-0.005, -0.004]
Pepsi 500	-2.67	0.091	0.051	0.079	0.061	-0.050
	[-2.70, -2.64]	[0.090, 0.093]	[0.049, 0.052]	[0.078, 0.081]	[0.060, 0.062]	[-0.050, -0.049]
Pepsi Diet 330	-3.06	0.016	0.043	0.012	0.089	-0.001
	[-3.09, -3.04]	[0.016, 0.016]	[0.042, 0.044]	[0.012, 0.013]	[0.087, 0.091]	[-0.002, -0.001]
Pepsi Diet 500	-2.86	0.042	0.100	0.038	0.119	-0.038
	[-2.89, -2.83]	[0.041, 0.042]	[0.098, 0.101]	[0.037, 0.039]	[0.117, 0.121]	[-0.038, -0.037]
Lucozade Energy 380	-2.72	0.053	0.029	0.052	0.040	-0.012
	[-2.76, -2.69]	[0.052, 0.055]	[0.028, 0.030]	[0.051, 0.054]	[0.039, 0.041]	[-0.012, -0.012]
Lucozade Energy 500	-2.58	0.043	0.024	0.040	0.024	-0.022
	[-2.60, -2.52]	[0.041, 0.044]	[0.023, 0.025]	[0.038, 0.041]	[0.023, 0.025]	[-0.022, -0.021]
Ribena 288	-2.87	0.015	0.008	0.012	0.016	0.000
	[-2.92, -2.85]	[0.015, 0.016]	[0.007, 0.008]	[0.012, 0.013]	[0.015, 0.016]	[0.000, 0.000]
Ribena 500	-2.64	0.026	0.014	0.024	0.017	-0.013
	[-2.66, -2.59]	[0.025, 0.026]	[0.014, 0.014]	[0.023, 0.025]	[0.016, 0.017]	[-0.014, -0.013]
Ribena Diet 500	-2.80	0.011	0.026	0.011	0.031	-0.010
	[-2.82, -2.76]	[0.011, 0.012]	[0.025, 0.026]	[0.011, 0.012]	[0.030, 0.032]	[-0.010, -0.010]
Sprite 330	-3.25	0.012	0.007	0.008	0.009	-0.001
	[-3.30, -3.23]	[0.012, 0.013]	[0.007, 0.007]	[0.008, 0.008]	[0.009, 0.010]	[-0.002, -0.001]
Sprite 500	-2.55	0.030	0.017	0.029	0.019	-0.016
	[-2.57, -2.49]	[0.029, 0.031]	[0.017, 0.018]	[0.028, 0.030]	[0.018, 0.020]	[-0.016, -0.015]
Irn Bru 330	-2.94	0.009	0.004	0.007	0.008	-0.001
	[-2.99, -2.93]	[0.009, 0.010]	[0.004, 0.005]	[0.007, 0.007]	[0.008, 0.009]	[-0.001, -0.001]
Irn Bru 500	-2.69	0.019	0.010	0.018	0.013	-0.010
	[-2.73, -2.65]	[0.019, 0.020]	[0.010, 0.011]	[0.017, 0.018]	[0.013, 0.014]	[-0.010, -0.010]
Irn Bru Diet 330	-3.24	0.004	0.012	0.003	0.024	0.000
	[-3.28, -3.22]	[0.004, 0.004]	[0.012, 0.013]	[0.003, 0.003]	[0.023, 0.025]	[0.000, 0.000]
Irn Bru Diet 500	-2.91	0.009	0.019	0.008	0.025	-0.007
	[-2.94, -2.88]	[0.008, 0.009]	[0.019, 0.020]	[0.008, 0.009]	[0.025, 0.026]	[-0.008, -0.007]

Notes: For each of the four products listed we compute the change in demand for that product, for alternative sugary and diet options and for total demand resulting from a 1% price increase. Numbers are means across time. 95% confidence intervals are shown in brackets.

Table 1 cont.

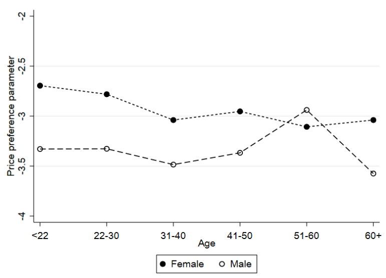
	Effect of 1% price increase on:					
	Own	cross demand for:				Total
	product demand	sugary soft drinks	diet soft drinks	sugary alternatives	non-sugary alternatives	drinks demand
Other Diet	-2.31	0.049	0.112	0.045	0.079	-0.034
	[-2.29, -2.17]	[0.047, 0.049]	[0.108, 0.114]	[0.043, 0.045]	[0.077, 0.080]	[-0.034, -0.033]
Fruit juice	-2.26	0.128	0.080	0.168	0.123	-0.012
	[-2.28, -2.22]	[0.125, 0.130]	[0.078, 0.081]	[0.164, 0.171]	[0.121, 0.125]	[-0.012, -0.011]
Flavoured milk	-2.66	0.035	0.018	0.035	0.029	-0.020
	[-2.69, -2.63]	[0.035, 0.036]	[0.018, 0.019]	[0.034, 0.036]	[0.028, 0.030]	[-0.020, -0.019]
Fruit water	-2.72	0.017	0.010	0.020	0.017	-0.011
	[-2.76, -2.69]	[0.017, 0.018]	[0.009, 0.010]	[0.019, 0.020]	[0.017, 0.018]	[-0.011, -0.010]
Water	-2.30	0.115	0.281	0.128		-0.141
	[-2.33, -2.28]	[0.114, 0.118]	[0.277, 0.284]	[0.127, 0.131]	[., .]	[-0.144, -0.141]

Notes: For each of the four products listed we compute the change in demand for that product, for alternative sugary and diet options and for total demand resulting from a 1% price increase. Numbers are means across time. 95% confidence intervals are shown in brackets.

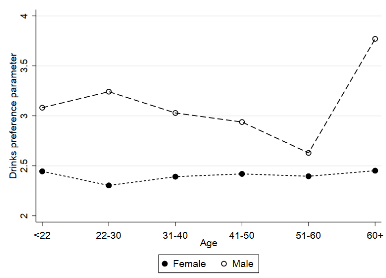
In Figures B.2 and B.3 we replicate Figures 2 and 3, splitting individuals out based on gender and in Figures B.4 and B.5 we split individuals out based on the socioeconomic status. The graphs show the patterns of how preferences vary with age and total dietary sugar broadly hold conditional on gender and socioeconomic status.

Figure B.2: Preferences variation with age and gender

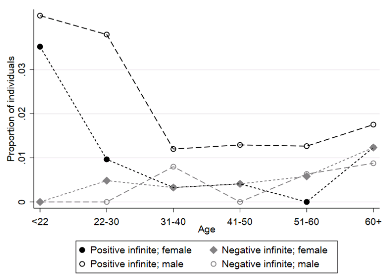
(a) price preferences



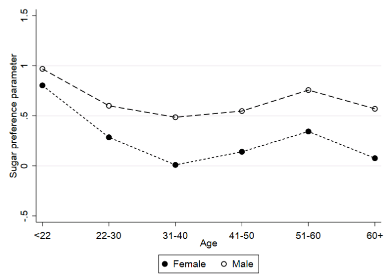
(b) drink preferences



(c) infinite sugar preferences



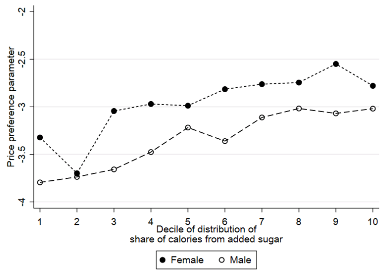
(d) finite sugar preferences



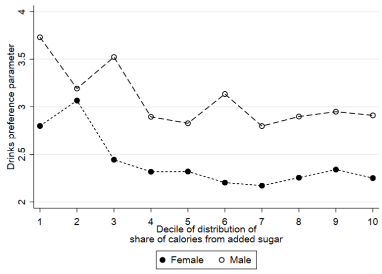
Notes: Figures show how the mean of price preferences, the mean of drinks preferences, the share of consumers with infinite sugar preferences and the mean of finite sugar preferences vary by age and gender.

Figure B.3: Preferences variation with total dietary sugar and gender

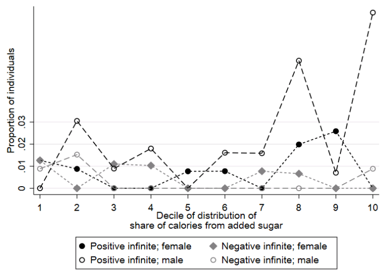
(a) price preferences



(b) drink preferences



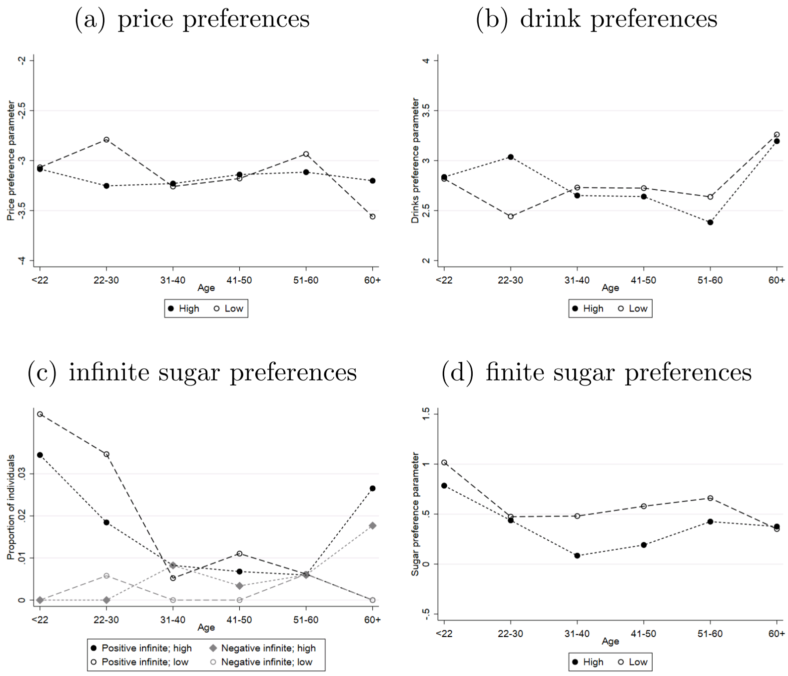
(c) infinite sugar preferences



(d) finite sugar preferences

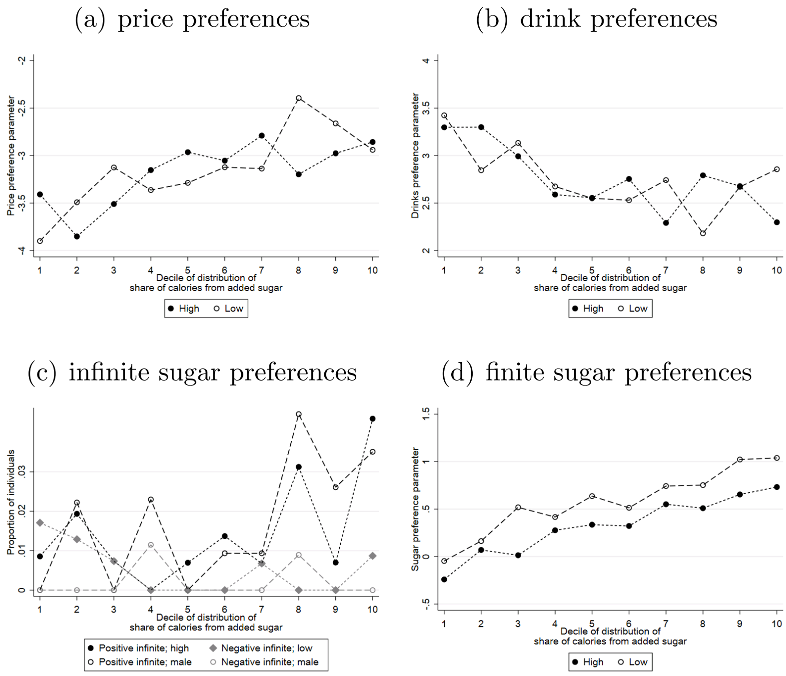
Notes: Figures show how the mean of price preferences, the mean of drinks preferences, the share of consumers with infinite sugar preferences and the mean of finite sugar preferences vary by deciles of the distribution of total annual dietary sugar and gender.

Figure B.4: Preferences variation with age and socioeconomic status



Notes: Figures show how the mean of price preferences, the mean of drinks preferences, the share of consumers with infinite sugar preferences and the mean of finite sugar preferences vary by age and socioeconomic status. “High” refers to those from a household whose head works in managerial or professional roles, “Low” refers to those from a household whose head works in manual work or relies on the state for their income.

Figure B.5: Preferences variation with total dietary sugar and socioeconomic status



Notes: Figures show how the mean of price preferences, the mean of drinks preferences, the share of consumers with infinite sugar preferences and the mean of finite sugar preferences vary by deciles of the total dietary sugar and socioeconomic status. "High" refers to those from a household whose head works in managerial or professional roles, "Low" refers to those from a household whose head works in manual work or relies on the state for their income.

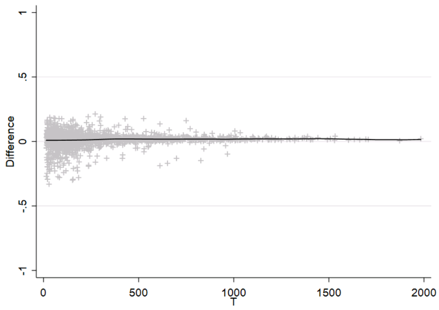
B.1 Incidental parameters problem

Figures B.6, B.7 and B.8 show, for the price, drinks and sugar preference parameters, how the jackknife ($\widetilde{\theta}_{split}$) and the maximum likelihood estimates ($\widehat{\theta}$) relate to a) the number of choice occasions of individuals that are in the sample, b) age and c) total dietary sugar. They show no systematic relationship in the mean of $(\widetilde{\theta}_{split} - \widehat{\theta})$ with any of these variables, with the dispersion of $(\widetilde{\theta}_{split} - \widehat{\theta})$ falling in T.

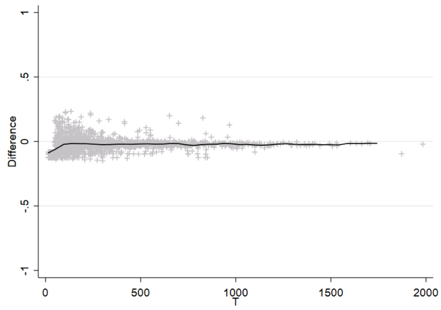
Figures B.9 plot the distributions of price, drinks and sugar preference parameter estimates for both the estimators $\widehat{\theta}$ and $\widetilde{\theta}_{split}$, showing there is little difference in the distributions.

Figure B.6: Relationship between bias and time in sample

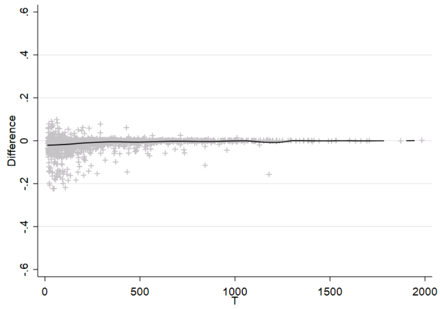
(a) Price



(b) Drinks



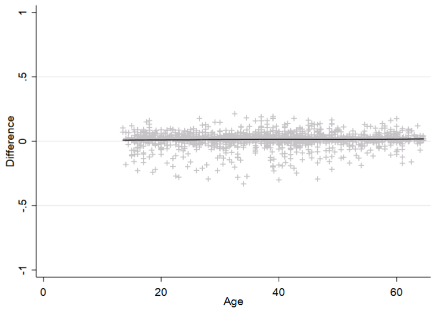
(c) Sugar



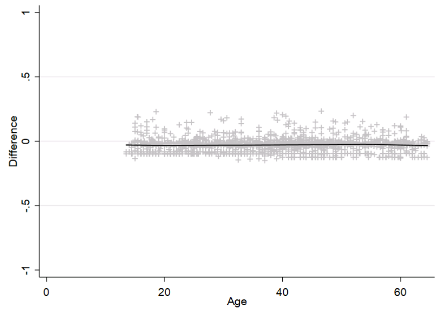
Notes: Marks represent consumer level differences. Lines are local polynomial regressions.

Figure B.7: Relationship between bias and age

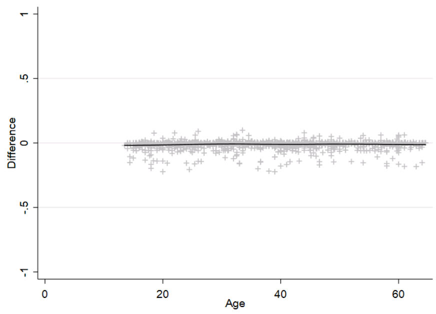
(a) Price



(b) Drinks

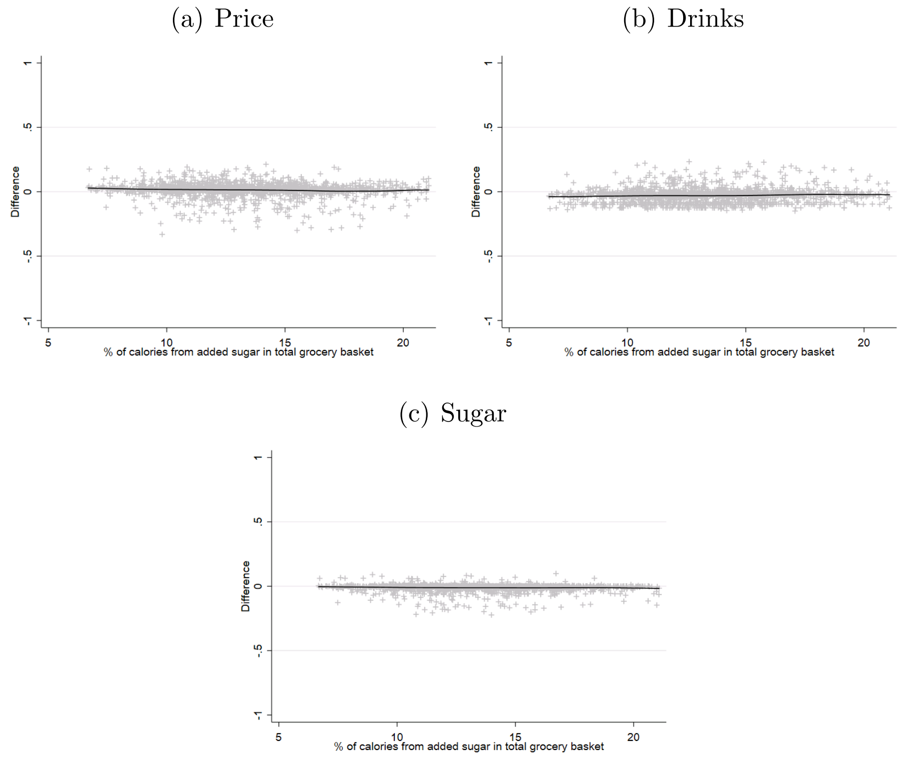


(c) Sugar



Notes: Marks represent consumer level differences. Lines are local polynomial regressions.

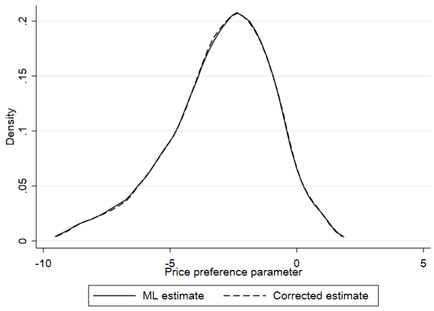
Figure B.8: Relationship between bias and dietary sugar



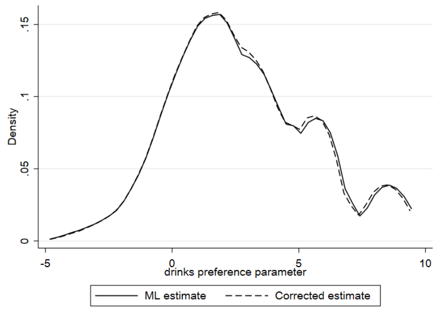
Notes: Marks represent consumer level differences. Lines are local polynomial regressions.

Figure B.9: Preference parameter distribution

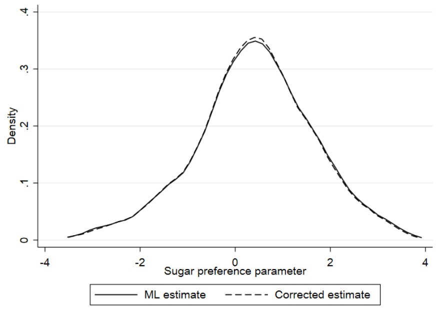
(a) Price



(b) Drinks



(c) Sugar



Notes: Lines are kernel density estimates.

C Demand estimates in at-home segment

C.1 At-home data

We use information on the at-home behavior of 4,205 households over June 2009-December 2014. Of these 3,059 households are drinks purchasers.[1] Tables 2, 3 and 4 shows the panel dimension of the data, the products we model choice over in the at-home segment and retailer types. This mirrors tables in Section I of the paper for the on-the-go segment. In the at-home demand model a choice occasion is defined as a week in which the household buys groceries and the outside option corresponds to not buying any non-alcoholic drinks (exclusive for non-flavored milk). In the estimation sample there are 653,063 choice occasions in total. Households choose the outside option on 59% of choice occasions.

[1]Defined as buying at 15 non-alcoholic drinks over the 5 and a half year period of our data.

Table 2: Time series dimension of at-home estimation sample

Number of choice occasions observed	Individuals on-the-go	
	N	%
<25	20	0.7
25-49	59	1.9
50-74	106	3.5
75-99	151	4.9
100-249	1573	51.4
250+	1150	37.6
Total	3059	100.0

Notes: The table shows the number of choice occasions on which we observe household making at-home purchase choices based on the 3,059 households in the at-home estimation sample. A choice occasion is a week in which the household visits the grocery store.

Table 3: Products in at-home sample

Firm	Brand	Product	%	price
Soft drinks				
CocaCola			22.24	
	Coke		16.70	
		Coca Cola Diet 330	0.15	0.57
		Coca Cola 330	0.21	0.57
		Coca Cola 500	0.74	1.01
		Coca Cola Diet 500	1.18	1.01
		Coca Cola multi can	2.50	3.43
		Coca Cola Diet multi can	4.05	3.37
		Coca Cola bottle	3.37	1.40
		Coca Cola Diet bottle	4.27	1.37
		Coca Cola multi bottle	0.14	5.27
		Coca Cola Diet multi bottle	0.09	5.73
	Dr Pepper		1.60	
		Dr Pepper 330	0.02	0.55
		Dr Pepper 500	0.23	1.00
		Dr Pepper multi can	0.27	2.46
		Dr Pepper Diet multi can	0.11	2.41
		Dr Pepper bottle	0.72	1.36
		Dr Pepper Diet bottle	0.26	1.31
	Fanta		1.78	
		Fanta 500	0.24	1.01
		Fanta multi can	0.23	2.33
		Fanta Diet multi can	0.25	2.53
		Fanta bottle	0.82	1.33
		Fanta Diet bottle	0.24	1.32
	Cherry Coke		0.86	
		Cherry Coke 330	0.02	0.52
		Cherry Coke Diet 500	0.10	1.03
		Cherry Coke 500	0.14	1.03
		Cherry Coke multi can	0.13	2.90
		Cherry Coke Diet multi can	0.12	2.84
		Cherry Coke bottle	0.22	1.34
		Cherry Coke Diet bottle	0.12	1.32
	Oasis		0.38	
		Oasis 500	0.38	1.01
	Sprite		0.93	
		Sprite 500	0.12	1.00
		Sprite multi can	0.11	2.37
		Sprite Diet multi can	0.16	2.38
		Sprite bottle	0.35	1.33
		Sprite Diet bottle	0.20	1.34
Pepsico			12.71	
		Pepsi Diet 330	0.16	0.40
		Pepsi 330	0.07	0.40
		Pepsi 500	0.25	0.81
		Pepsi Diet 500	0.71	0.81
		Pepsi multi can	1.04	2.14
		Pepsi Diet multi can	3.06	2.17
		Pepsi bottle	2.00	1.09
		Pepsi Diet bottle	5.43	1.10
GSK			3.62	
	Lucozade Energy		3.04	
		Lucozade Energy 380	0.21	0.76
		Lucozade Energy 500	0.32	1.03
		Lucozade Energy bottle	1.41	1.14
		Lucozade Energy multi bottle	1.11	3.05
	Ribena		0.58	
		Ribena 288	0.03	0.55
		Ribena 500	0.08	1.05
		Ribena multi	0.47	1.98
			1.09	
		Irn Bru 500	0.04	0.94
		Irn Bru Diet 500	0.04	0.94
		Irn Bru multi can	0.08	2.53
		Irn Bru Diet multi can	0.10	2.44
		Irn Bru bottle	0.44	1.19
		Irn Bru Diet bottle	0.39	1.19

Table 3 cont.

Firm	Brand	Product	%	price
Composite soft drinks				
		Other	2.23	1.23
		Other bg	2.71	1.05
		Other Diet bg	1.11	1.03
		Other multi	1.02	2.08
		Other Diet multi	0.35	1.87
Alternative drinks				
	Fruit juice		3.13	1.62
	Fruit juice		18.38	1.40
	Flavoured milk		3.32	0.79
	Flavoured milk		1.30	1.05
	Fruit water		0.04	0.76
	Fruit water		0.67	0.91
	Water		0.71	0.48
	Water		10.89	0.89

Notes: Market shares are based on transactions made by the 3,059 households in the at-home estimation sample between June 2009 and December 2014. Prices are the means across all choice occasions.

Table 4: Retailer types in at-home sample

		N	%
Retailer types			
Big four	Asda	123,576	18.9
	Morrisons	86,949	13.3
	Sainsbury's	85,486	13.1
	Tesco	215,619	33.0
Discounters		44,207	6.8
Other		97,226	14.9
Total		653,063	100.0

Notes: The table shows the number and share of purchases made by 3,059 households in the at-home estimation sample in each retailer type between June 2009 and December 2014.

C.2 At-home demand estimates

In Table 5 we summarize estimates of the household specific preference parameters governing at-home demand. In Figure C.1 we report estimates of the demographic specific preference parameters.

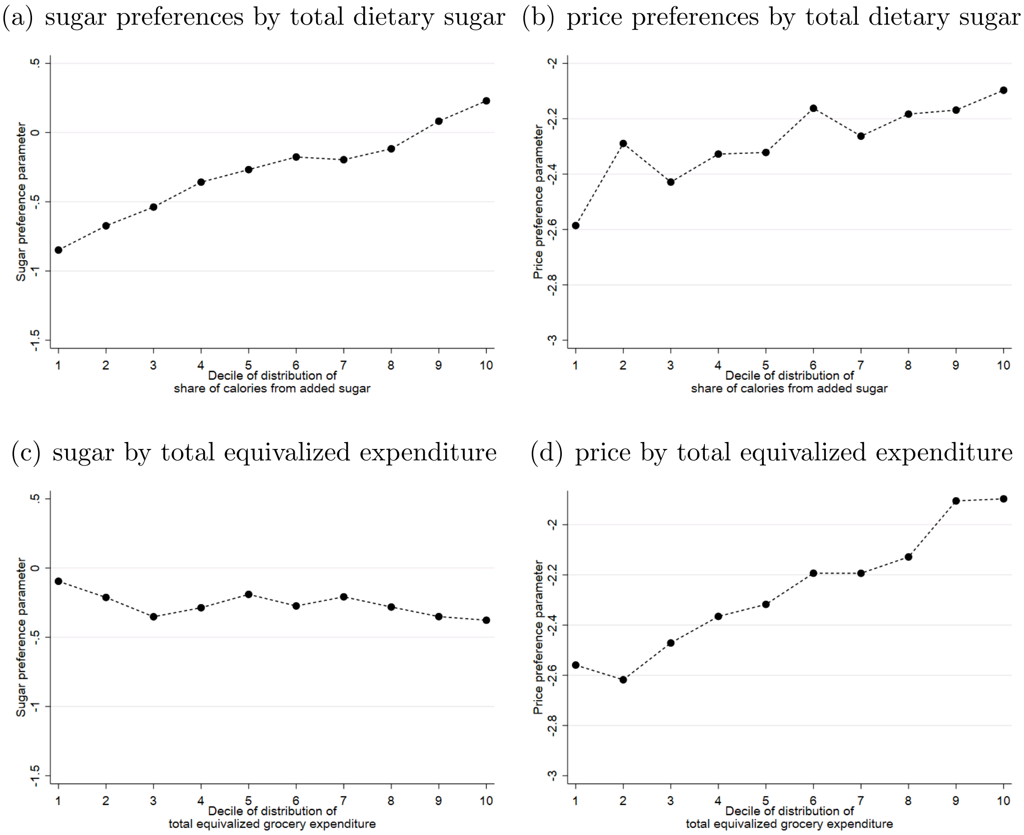
Table 5: Demand model estimates – at-home

Moments of distribution of consumer specific preferences			
Variable		Estimate	Standard error
Price (α_i)	Mean	-2.2780	0.0146
	Standard deviation	1.6388	0.0189
	Skewness	-2.2208	0.1187
	Kurtosis	11.0800	1.2050
Drinks (γ_i)	Mean	-4.4080	0.0655
	Standard deviation	2.1179	0.0167
	Skewness	0.1964	0.0362
	Kurtosis	3.7723	0.1246
Sugar (β_i)	Mean	-0.2777	0.0092
	Standard deviation	1.5127	0.0116
	Skewness	0.0154	0.0404
	Kurtosis	3.2652	0.0987
Price-Drinks	Covariance	-2.2546	0.0430
Price-Sugar	Covariance	0.0166	0.0198
Drinks-Sugar	Covariance	0.1907	0.0249
Demographic specific preferences			
At-home inventory ($\delta^{\kappa}_{d(i)}$)	No kids, high educ.	0.4017	0.0033
	No kids, low educ.	0.3899	0.0043
	Pensioners	0.3884	0.0051
	Kids, high educ.	0.6245	0.0051
	Kids, high educ.	0.6482	0.0061
Bottle	No kids, high educ.	0.9360	0.0917
	No kids, low educ.	0.6614	0.1163
	Pensioners	-0.6708	0.1908
	Kids, high educ.	0.2157	0.0873
	Kids, high educ.	1.0181	0.1022
Multi-pack	No kids, high educ.	1.5449	0.0687
	No kids, low educ.	1.8543	0.0868
	Pensioners	0.7329	0.1427
	Kids, high educ.	0.6404	0.0679
	Kids, high educ.	1.4604	0.0767
Advertising ($\delta^{\mathfrak{a}}_{d(i)}$)	No kids, high educ.	0.0033	0.0011
	No kids, low educ.	-0.0001	0.0015
	Pensioners	0.0045	0.0021
	Kids, high educ.	0.0062	0.0011
	Kids, high educ.	0.0041	0.0013
Temperature*Drinks ($\delta^{h}_{d(i)}$)	No kids, high educ.	0.0101	0.0022
	No kids, low educ.	0.0138	0.0029
	Pensioners	0.0136	0.0036
	Kids, high educ.	0.0098	0.0022
	Kids, high educ.	0.0136	0.0027
Demographic specific carton-size effects ($\delta^{z}_{d(i)}$)		Yes	
Time-demographic-brand effects ($\xi_{d(i)b(j)t}$)		Yes	
Retailer-demographic-brand effects ($\zeta_{d(i)b(j)r}$)		Yes	

Notes: We estimate demand on a sample of 3,059 households who we observe on 653,063 at-home choice occasions. Estimates of the consumer specific preferences are summarized in the table. Moments of distribution are computed using estimates of consumer specific preference parameters. These moments are based on consumers with finite parameters and omit the top and bottom percentile of each distribution. Standard errors for moments are computed using the delta method.

Figure C.1 shows variation in preferences for sugar and price in the at-home segment and how they vary by deciles of the total dietary sugar and total equivalized grocery expenditure distributions. As expected, households that have higher added sugar in their total annual grocery basket also have stronger preferences for sugar when choosing what drinks to purchase, and households in lower deciles of the equivalized total grocery expenditure (income) are more price sensitive.

Figure C.1: Preferences variation – at-home



(a) sugar preferences by total dietary sugar (b) price preferences by total dietary sugar

(c) sugar by total equivalized expenditure (d) price by total equivalized expenditure

Notes: Figure shows how, the mean of finite sugar preferences and the mean of price preferences in the at-home segment vary by deciles of the distribution of total annual dietary sugar and by deciles of the distribution of total annual equivalized grocery expenditure. 95% confidence intervals are shown by bars.

D Compensating variation

We use our demand estimates to compute compensating variation – the monetary amount an individual would require to be paid to be indifferent to the imposition of the tax based on their estimated preferences. Letting p_{jrt} and p'_{jrt} denote the retailer type r time t price of product j prior to and following the introduction of the tax, the expected compensating variation for individual i on choice occasion τ

is given by (Small and Rosen (1981)):

$$cv_{i\tau} = \frac{1}{\alpha_i}\left[\ln\left(\sum_{k\in\Omega_i\cap\Omega_{r(\tau)}} \exp(v_{ikr(\tau)t(\tau)} + \eta_{ikr(\tau)t(\tau)} - \alpha_i(p_{kr(\tau)t(\tau)} - p'_{kr(\tau)t(\tau)})) + 1_{\bar{0}\in\Omega_i}\exp(\beta_i)\right) - \right.$$
$$\left.\ln\left(\sum_{k\in\Omega_i\cap\Omega_{r(\tau)}} \exp(v_{ikr(\tau)t(\tau)} + \eta_{ikr(\tau)t(\tau)}) + 1_{\bar{0}\in\Omega_i}\exp(\beta_i)\right)\right]$$

where $v_{ijr(\tau)t(\tau)}$ and $\eta_{ijr(\tau)t(\tau)}$ are defined in Section II.A .[2] Summing $cv_{i\tau}$ over an individual's choice occasions in the year gives their annual compensating variation.

E Equilibrium tax pass-through

In Section IV.C we show that our results on the targeting of a soda tax are similar under the assumption of 100% pass-through and under estimates of equilibrium tax pass-through. Here we provide further details of our model of equilibrium tax pass-through.

We model tax pass-through by assuming that drinks manufacturers compete by simultaneously setting prices in a Nash-Bertrand game. We consider a mature market with a stable set of products, and we therefore abstract from entry and exit of firms and products from the market. We use our demand estimates for the on-the-go market, demand estimates for the at-home market (described in Appendix C) and an equilibrium pricing condition to infer firms' marginal costs (see Berry (1994) or Nevo (2001)) in order to then simulate the effect of a tax on consumer prices.

Let $f = \{1, \ldots, F\}$ index manufacturers and F_f denote the set of products owned by firm f. We assume that prices are set by manufacturers and abstract from modeling manufacturer-retailer relationships. Such an outcome can be achieved by vertical contracting (Villas-boas (2007), Bonnet and Dubois (2010)).[3] Bonnet and Dubois (2010) show that in the French grocery market price equilibria correspond to the case where manufacturers and retailers do use non-linear contracts in the form of two part tariffs. Testing for the form of vertical contracting in UK manufacturer-retailer relations is an interesting question that we leave for future research.

We index markets by m. Markets vary over time and across retailer type. In particular a market is defined as a year-retailer pair. We denote the size of the

[2] Note, that $v_{ijr(\tau)t(\tau)}$ is defined such that it includes the effect of price prior to the introduction of the tax.

[3] Non-linear contracts with side transfers between manufacturers and retailers allow them to reallocate profits and avoid the double marginalization problem.

on-the-go segment in market m by M_m^{out} and the size of the at-home segment by M_m^{in} and we denote the set of individual-choice occasions in the on-the-go and at-home segments of market m as $\mathcal{M}_m^{out}$ and $\mathcal{M}_m^{in}$. Aggregating across consumer level purchase probabilities we obtain the market level demand function for product j:

$$q_{jm}(\mathbf{p}_m) = \underbrace{M_m^{out} \sum_{(i,\tau)\in\mathcal{M}_m^{out}} P_{i\tau}(j)}_{\equiv q_{jm}^{out}(\mathbf{p}_m)} + \underbrace{M_m^{in} \sum_{(i,\tau)\in\mathcal{M}_m^{in}} P_{i\tau}(j)}_{\equiv q_{jm}^{in}(\mathbf{p}_m)}$$

for each product j and where $P_{i\tau}(j)$ follows equation (2).

If product j is available only in the at-home segment (e.g. if it is a large multi portion product), then $P_{i\tau}(j) = 0$ for all $(i,\tau) \in \mathcal{M}_m^{out}$, and if it is only available in the on-the-go segment then $P_{i\tau}(j) = 0$ for all $(i,\tau) \in \mathcal{M}_m^{in}$. However, for products available in both on-the-go and at-home segments the market demand curve depends on purchase probabilities (and hence preferences) in both segment.

Firm f's (variable) profits in market m are given by:

$$\Pi_{fm} = \sum_{j\in F_f} (p_{jm} - c_{jm}) q_{jm}(\mathbf{p}_m) \tag{1}$$

and the firm's price first order conditions are:

$$q_{jm}(\mathbf{p}_m) + \sum_{k\in F_f} (p_{km} - c_{km}) \frac{\partial q_{km}(\mathbf{p}_m)}{\partial p_{jm}} = 0 \quad \forall j \in F_f. \tag{2}$$

Under the assumption that observed market prices are an equilibrium outcome of the Nash-Bertrand game played by firms, and given our estimates of the demand function, we can invert the first order conditions to infer marginal costs c_{jm}. The introduction of a tax creates a wedge between post-tax prices, $\mathbf{p}$, and pre-tax prices, which we denote $\tilde{\mathbf{p}}$. The volumetric tax, π, on sugary soft drinks (denoted by the set Ω_{ws}) implies pre-tax and post-tax prices are related by:

$$p_{jm} = \begin{cases} \tilde{p}_{jm} + \pi l_j & \forall j \in \Omega_{ws} \\ \tilde{p}_{jm} & \forall j \notin \Omega_{ws} \end{cases}$$

where l_j is the volume of product j.

In the counterfactual equilibrium, prices satisfy the conditions:

$$q_{jm}(\mathbf{p}_m) + \sum_{k\in F_f} (\tilde{p}_{km} - c_{km}) \frac{\partial q_{km}(\mathbf{p}_m)}{\partial p_{jm}} = 0 \quad \forall j \in F_f \tag{3}$$

for all firms f. We solve for the new equilibrium prices as the vector that satisfies the set of first order conditions (equation (3)) when $\pi = 0.25$.[4] Tax pass-through describes how much of the tax is shifted through to post-tax prices, for products $j \in \Omega_{ws}$, we measure this as the difference in the post-tax and pre-tax equilibrium consumer price over the amount of tax levied, πl_j.[5]

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[4] We solve for a new equilibrium price for each of the products belonging to the main soft drinks brands; we assume there is no change in the producer price (and therefore 100% pass-through) of the composite other soft drinks brand (which aggregates together many very small soft drinks brands). We also assume no pricing response for the set of outside products.

[5] We solve for separate price equilibrium in each of the 11 retailers and for a representative month in each year, giving us 66 price equilibria.