How well targeted are soda taxes?

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Abstract

Soda taxes aim to reduce excessive sugar consumption. Their effectiveness depends on whether they target individuals for whom the harm of consumption is largest; policymakers identify these as high sugar consumers, the young and the poor. We study individual level purchases made on-the-go. We estimate demand and account for supply-side equilibrium pass-through. We exploit longitudinal data to estimate individual preferences, which allows flexible heterogeneity that we relate to key individual characteristics. We show that soda taxes are relatively effective at targeting young and poor consumers but not individuals with high total dietary sugar; they impose the highest monetary cost on poorer individuals, but are unlikely to be strongly regressive especially if we account for averted future costs from over consumption.

Keywords: preference heterogeneity, discrete choice demand, pass-through, soda tax

JEL classification: D12, H31, I18

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1 Introduction

Sugar consumption is far in excess of recommended levels in much of the developed world. Excess sugar consumption is strongly linked with a range of diet-related diseases, including diabetes, cancers and heart disease, and is particularly detrimental to children (WHO (2015)). Soft drinks are an important contributor to excess sugar consumption, particularly in the young and youth from low income households (see, for example, Han and Powell (2013), Cavadini et al. (2000), CDC (2016) and Public Health England (2015)). "Soda taxes" have been proposed as a way to reduce sugar consumption for individuals whose consumption generates costs that are borne by others (externalities) or for whom the future costs of excess consumption are large and are partially ignored at the point of consumption (internalities). A growing number of jurisdictions have adopted soda taxes.[1] Whether such measures are welfare enhancing will importantly depend on how individuals' demand responses correlate with these internalities and externalities, as well as the strategic pricing response of firms.

Our contribution in this paper is to provide evidence on how well targeted soda taxes are; in particular, are they effective at lowering the sugar consumption for those individuals that policy has targeted, and for whom the consequences of high intake are thought to be most severe. We estimate consumer choice in the non-alcoholic drinks market and simulate the introduction of a soda tax, accounting for pass-through to prices. We show that soda taxes do not do a good job at targeting individuals from households with high total dietary sugar, however they are relatively effective at targeting young consumers and those from low income households. They impose higher monetary cost on individuals from lower income households, but are unlikely to be strongly regressive, especially if we account for averted future costs from over consumption. Relative to the existing literature we make two main advances.

First, we study purchase decisions made by individuals for immediate consumption on-the-go using novel longitudinal data on British individuals (including teenagers and young adults) drawn from a representative sample of households. Studying the on-the-go segment is interesting and important for a number of reasons. We have little evidence on choice behavior on-the-go – most of the literature on choice behavior studies purchases made in supermarkets and brought into the home for future consumption – even though around half of sugar from soft drinks is obtained on-the-go. On-the-go purchases are made by individuals for immediate

[1]These include a number of US cities, including Philadelphia and San Francisco, as well as France, Mexico and the UK.

consumption, meaning that purchase decision and consumption are closely aligned. A further significant advantage of individual level on-the-go data is that they allow us to estimate individual level preferences, and individual level responses to tax, without the need to place strong restrictions on the intra-household preference structure (see, for example, Adams et al. (2014)). In addition, young adults are a particular group of interest to policymakers in this area, but they are typically not identified as a distinct group in data based on household purchases.

Second, we model consumer preferences as individual level parameters that we estimate. This approach has significant advantages for allowing us to assess whether a tax is well targeted and how regressive it is. This approach departs from the standard approach to modeling consumer preference heterogeneity in discrete choice models, where preferences are treated as random effects drawn from a known distribution. The main advantage of our approach is that we do not need to make assumptions restricting or ruling out correlation in consumer level preferences with consumer attributes (including purchase behavior for other goods). We are therefore able to directly relate individual level predictions of the impact of the tax to consumer characteristics in a flexible way. This means that we can assess precisely which individuals respond to the tax and on whom the economic burden of the tax falls most heavily.

We are interested in how well targeted soda taxes are – do they lead to the largest reductions in sugar by individuals whose consumption is associated with the highest externalities and internalities. Policymakers in the US and UK have identified individuals with a high share of sugar in their overall diet, young people and youth from low-income households or regions as groups of particular concern and policy focus (Department of Health (2016)). The propensity for people to over consume sugar, the effects that excessive intake has on health and other future outcomes, and the role soft drinks play as a significant contributor to total dietary sugar are well established (see WHO (2015)). It is also well established that young people, youth from low-income households, and people for whom sugar represents a high share of the total calories that they purchase, tend to get particularly large amounts of sugar from soft drinks.[2] These facts have motivated the implementation of soda taxes in many jurisdictions, and they suggest that soda taxes may be well targeted – sugar consumption is well above medical recommendations, products subject to soda taxes represents a substantial share of this, and their intake is especially high for the young, youth from low-income households and for individuals

[2] In Appendix A.1 we provide evidence of this based on dietary intake data from the UK and the US. See also CDC (2016) and Public Health England (2015).

with high total dietary sugar – groups for whom high soft drinks consumption is likely to be particularly costly in terms of poor social and economic outcomes (see Gortmaker et al. (2009), Currie (2009)). We provide further discussion of why we focus on these particular demographics in Section 2.3.

The effectiveness of a soda tax depends not only on the extent to which individuals consume soft drinks prior to the introduction of the tax, but also on how strongly they switch away from the sugar in these products and what alternatives they switch to. To assess the targeting of the tax we need to know how demand responses vary across demographics that are associated with likely harm from consumption (such as age, income and total dietary sugar), and to assess the redistributive consequences we need to know how they vary across the income distribution. We estimate a structural model of demand and supply that allows us to identify individual specific preference parameters and enables us to relate the effects of a soda tax in a flexible way to individual demographics.

To model consumer choice we use a discrete choice framework in which consumer preferences are defined over product attributes. Like much of the literature on choice models (Berry et al. (1995), Nevo (2001), Train (2003)), we allow for consumer specific preference parameters. We depart from the standard approach by treating these preferences as consumer level parameters to be estimated (rather than draws from a random coefficients distribution). This means that we can recover any arbitrary relationship between the individual preference parameters (including functions of them such as the predicted outcomes from a tax simulation) with any attributes of the individual consumers. In contrast, in standard random coefficient models it is necessary to specify ex ante, and with a particular functional form, how preferences depend on exogenous characteristics, and to assume independence between the preference distribution and all other individual level attributes. While much more flexible in this respect, our approach entails estimating fixed effects in a non-linear model and therefore may suffer from an incidental parameters problem (Hahn and Newey (2004), Arellano and Hahn (2007)). We show robustness to this using the split sample jackknife bias correction procedure suggested in Dhaene and Jochmans (2015).

We find that preferences vary with demographics in ways that would be difficult to capture by specifying *a priori* a random coefficient distribution. For instance, our estimates show that individuals aged 13-21 have stronger preferences for sugar than individuals aged 22-30, who in turn have stronger sugar preferences than older individuals. Among the youngest age group preferences over sugar and price are uncorrelated, but for older individuals they are positively correlated – those with strong sugar preferences tend to be the least price sensitive. This has implications for the evaluation of how well targeted is a soda tax. When we look at variation with total dietary sugar we see, unsurprisingly, that those individuals from households where sugar consumption is high have (much) stronger tastes for sugar; they are also considerably less price sensitive. In Appendix B.4 we compare our estimates to those obtained with a standard random coefficients model.

Using our estimates we analyze the effects of a soda tax on individual choice in the on-the-go segment and how they vary over the joint distribution of age, total dietary sugar and income. We are able to do this while placing only minimal restrictions on the joint distribution of preferences – we do impose that an individual's preferences are stable over choice occasions, which allows us to use the long time dimension of repeated purchases to identify individual preferences.

We model tax pass-through assuming that soft drinks manufacturers compete by simultaneously setting prices in a Nash-Bertrand game. We abstract from modeling manufacturer-retailer relations, but discuss how vertical contracting would lead to such a price equilibrium. We allow possible differences in manufacturers' responsiveness to the tax across different retailers. The market demand curves faced by firms (and relevant for the pricing equilibrium) depend both on behavior in the on-the-go segment of the market, and in the at-home segment. We use household level data to estimate at-home demand, thereby enabling us to take account of the effect of both segments on firm pricing. Our estimates suggest that an excise style tax on sugary soft drinks would be over shifted on to consumer prices and lead to marginally lower prices of diet products. Firms' pricing response would therefore amplify the price differential that the tax creates between sugary and diet varieties. In Appendix D we show that an alternative tax on all soft drinks (both sugary and diet varieties) would lead to considerably lower reductions in sugar consumption.

Our main interest in this paper is to study how well targeted soda taxes are. Soda taxes are primarily aimed at addressing externalities and internalities – internality correcting taxes have been advocated for unhealthy foods (O'Donoghue and Rabin (2006), Haavio and Kotakorpi (2011)), as the principal justification for high levels of cigarette taxation (Gruber and Koszegi (2004)), and in energy markets (Allcott et al. (2014)). While there is experimental evidence that people have behavioral biases with respect to food and drink consumption (see, for instance, Read and Van Leeuwen (1998) and Gilbert et al. (2002)), measuring the extent of these internalities is challenging, and not something we attempt to do in this paper.

Our focus on the on-the-go segment of the market enables us to provide novel evidence on how individuals' soft drinks consumption will respond to soda taxes.

Data on the at-home segment of the market is at the household level; to use these data to address how well targeted soda taxes are would require us to tackle several additional issues, such as the intra-household allocation of food, which we think is better left for future work. However, we show that our demand estimates for the at-home segment suggest that it is unlikely at-home responses would undo the individual level patterns of responses we estimate for the on-the-go segment (see Section 5.2).

Our results suggest that taxes of the form and size that have been implemented in the UK and many US locations lead to reductions in the amount of sugar that people who drink soft drinks get from these products of around 18% on average. We find that a tax on sugary soft drinks is relatively well targeted at young people, (including youth from low-income households). Reductions in sugar from the tax are highest in level terms for those aged 13-21 who reduce sugar from drinks by around 40% more than those aged over 40. This is driven by young people being much more likely to obtain large quantities of sugar from soft drinks products – in percentage terms they reduce sugar consumption by less than older people. The tax is less effective at targeting people with a consistently high level of dietary sugar in their overall diets. Individuals with high sugar diets are more likely to purchase soft drinks and to obtain relatively large amounts of sugar from them, however, their sugar intake from drinks responds less strongly in level terms (as well as percentage terms) than those with more moderate levels of sugar in their diets. This is because they tend to have a strong preferences for sugar and to be less price responsive. Compensating variation, a measure of the direct costs the tax places on the consumer, is higher for the young and those with a consistently high level of dietary sugar. The larger reductions in sugar for the former group (relative to the latter) makes it more likely that their direct consumer welfare loss will be offset with savings from averted future internalities.

A common concern about excise style taxes is that they are regressive; the poor typically spend a higher share of their income on the taxed good, and so bear a disproportionate share of the burden of the tax. However, if the tax plays the role of correcting an internality, then the distributional analysis needs to account for the fact that low income consumers might also save more from averted internalities, and this may overturn the regressivity of the traditional economic burden of taxation (Gruber and Koszegi (2004)). These redistributive concerns become more subtle when preference heterogeneity is correlated with income (Allcott et al. (2018), Allcott et al. (2019)). We show that compensating variation associated with a sugary soda tax is around 25% higher for those in the bottom half of the distribution of total annual expenditure (based on a wide set of food, drink and non-drink items) compared with those in the top half. However, some evidence suggests that low income individuals might suffer more from internalities (e.g. Haushofer and Fehr (2014) and Mani et al. (2013)), and the reduction in sugar is also larger for these individuals, leaving open the possibility that they will benefit more from averted internalities, and that therefore the full effect on their welfare is less negative than the compensating variation suggests.

The rest of this paper is structured as follows. In Section 2 we introduce the data and describe the non-alcoholic drinks market. In Section 3 we describe our model of consumer demand and oligopoly pricing and summarize estimates of the demand model. In Section 4 we present results of the sugary soda tax simulation, discussing the impact on equilibrium pricing, how well targeted the measure is, the effects on consumer welfare and its distributional implications. In Section 5 we consider three possible concerns about the robustness of our conclusions; first, we incorporate broader patterns of consumer switching, including towards food, and show that our results are robust to inclusion of these additional margins of consumer response; second, we consider the impact of at-home demand for non-alcoholic drinks on the targeting of soda taxes; third, we consider possible bias that could arise due to the incidental parameters problem. A final section concludes. Several Appendices follow on Data (Appendix A), demand estimate details (Appendix B), the simulation of an alternative soda tax on both sugary and diet soft drinks (Appendix C), and robustness of the demand model estimates to substitution to food (Appendix D).

2 The non-alcoholic drinks market

We consider the market for non-alcoholic drinks. This includes *soft drinks* (i.e. carbonated drinks – often referred to as soda – with and without sugar, energy drinks, and other sugar-sweetened non-alcoholic drinks), *alternative sugary drinks* (non-alcoholic drinks such as pure fruit juice and milk based drinks such as shakes), and *bottled water*. "Soda taxes" are typically imposed on soft drinks products that contain sugar (and sometimes also on diet varieties). Pure fruit juices that do not contain added sugar and drinks that are predominantly composed of milk are typically exempt. The existing literature on soda taxes studies their impact on purchases made in grocery stores for future consumption at home; but close to half of sugar obtained from sugar sweetened soft drinks products is purchased for immediate consumption on-the-go.[3]

Our primary interest is in behavior when purchasing on-the-go. We focus on the on-the-go segment for two reasons. First, it is an important part of the market and an important source of sugar, particularly in children (Han and Powell (2013)), yet little attention has been paid to modeling choice behavior on-the-go, largely due to the lack of high quality data.[4] Second, studying on-the-go behavior provides the opportunity to model and exploit data on *individual* level purchases, including those made by teenagers and young adults. This provides an important opportunity to study the preferences of individuals, rather than the aggregate preferences of the household. Around three-quarters of the on-the-go segment of the market is comprised of purchases made from vending machines, convenience stores, larger grocery stores when consumed immediately and kiosks; the other quarter is from restaurants and bars. We study the former, our data do not include the latter.

While our principal interest is in behavior in the on-the-go segment of the market, we also model behavior in the at-home segment, exploiting data on the at-home purchases of the households that individuals in our on-the-go sample belong to. We do this to take account of potential linkages between the at-home and on-the-go segments. When modeling supply side responses to the introduction of a tax we use information on both segments. A product that is available for purchase for on-the-go and at-home consumption has a market demand curve that depends on preferences in both segments. There is also the possibility of linkages between the segments in the demand side – for instance, recent at-home household purchases might influence on-the-go purchases. We consider this possibility describing the relationship between on-the-go and at-home purchases; this suggests little evidence for such demand linkage. Therefore it is sufficient to account for the supply linkage through the influence of on-the-go and at-home preferences on market demand curves and hence firm pricing. We also use our model of behavior in the at-home segment to assess whether our conclusions regarding the individual targeting of soda taxes could plausibly be undone by off-setting behavior of the household in the at-home segment. In Section 5.2 we show that this is unlikely to be the case.

[3] CDC (2016) and National Diet and Nutrition Survey England (2018); see Appendix A.1 for further details.

[4] This is in contrast to the at-home segment, which has been studied in Bonnet and Réquillart (2013) and Wang (2015).

2.1 Purchases

We use data from the Kantar Worldpanel and the associated food on-the-go survey. These data are collected by the market research firm Kantar. The Worldpanel data cover the at-home segment of the market. They track the grocery purchases made and brought into the home by a sample of households that are representative of the British population.[5] The food on-the-go survey covers the on-the-go segment of the market. These data track food and drink purchases people make on-the-go for immediate consumption. Individuals in the on-the-go survey are randomly drawn from households in the Worldpanel.

Households in the Worldpanel data scan the barcode of all grocery purchases made and brought into the home. These include all food, drink, alcohol, toiletries, cleaning produce and pet foods. This means that we have comprehensive information on the total grocery baskets of the households to which the individuals in our on-the-go sample belong.[6] To our knowledge the Kantar food on-the-go survey is unique. Participating individuals record all purchases of snacks and non-alcoholic drinks for consumption outside the home (with the exception of those made in bars and restaurants) using mobile phones. In both the Worldpanel and food on-the-go survey we know what products (at the barcode, or UPC, level) were purchased and the transaction price. We also observe information on the store of purchase, household and individual attributes and product attributes.

We use information on the on-the-go behavior of 5,554 individuals and the at-home behavior of 4,204 households. The on-the-go individuals are drawn from the at-home households; there are fewer households because in some cases multiple individuals from the same household are present in the on-the-go data. To estimate demand we use information only on the individuals and households that report purchasing soft drinks.[7] Our estimation sample contains 2,374 individuals and 3,314 households. The individuals who do not purchase soft drinks at current prices are unlikely to be induced to purchase soft drinks by the introduction of the tax.

We have data over the period June 2009-December 2014. We exploit the panel structure of the data to estimate consumer specific preferences. In the on-the-go estimation sample we observe consumers making non-alcoholic drinks purchases on

[5] See Appendix A.2, where we compare key demographics in these data with the Living Cost and Food Survey, the main consumer expenditure survey (similar to the CEX) in the UK.

[6] The Kantar Worldpanel (and similar data collected in the US by AC Nielsen) have been used in a number of papers studying consumer grocery demand (see, for instance, Aguiar and Hurst (2007), Dubois et al. (2014) and Kaplan and Menzio (2015)).

[7] Strictly speaking, we use individuals/households that purchase at least 15 non-alcoholic drinks and at least 10 soft drinks over the 5 and half years period. In the on-the-go segment these individuals account for around 95% of sugar from non-alcoholic drink purchases.

152 separate days on average; in the at-home estimation sample we observe households making non-alcoholic drinks purchases on 91 different weeks on average. In Table 2.1 we provide more details on the distribution of observations per consumer. In both the on-the-go and at-home samples over 85% of consumers are observed for more than 25 choice occasions, and for around half of consumers we observe 75 or more choice occasions. On 90% of choice occasions (days) in the on-the-go segment and 83% of choice occasions (weeks) in the at-home segment the consumer is observed purchasing either one soft drink product or an alternative drink. On the remaining choice occasions the consumer chooses multiple (typically two) soft drinks products. In this case we randomly select one purchase and use this in demand estimation.

Table 2.1: *Time series dimension of estimation sample*

Number of choice occasions observed	Individuals on-the-go		Households at-home	
	N	%	N	%
<25	292	12.3	475	14.3
25-49	553	23.3	761	23.0
50-74	347	14.6	541	16.3
75-99	214	9.0	406	12.3
100+	968	40.8	1131	34.1
Total	2374	100.0	3314	100.0

Notes: The table shows the number of choice occasions on which we observe individuals (on-the-go) and households (at-home) making purchase choices for the estimation sample. An on-the-go choice occasions is a day in which the individual purchases a soft drink or alternative drink; an at-home choice occasion is a week in which the household purchases a soft drink or alternative drink.

2.2 Brands, products and stores

In Tables 2.2 and 2.3 we describe the products available in the non-alcoholic drinks market, both in the on-the-go and at-home segments. Products classified as "soft drinks" are available in a number of large brands, owned by CocaCola, Pepsico and GlasoSmithKline (GSK). There are a large number of small brands (with market shares below 2%). We aggregate these small brands into a composite "Other" brand. We also aggregate generic supermarket products into a composite "Store" brand (which is only available in the at-home segment). We additionally include a composite fruit juice, flavored milk, fruit (or flavored) water and bottled water brand. These together account for about 20% of on-the-go transactions and 25% of at-home transactions. Our counterfactual involves simulating the introduction of a "soda tax". This applies to the set of sugar sweetened soft drinks.[8] Diet varieties,

[8]In Appendix D we show simulations of a broader tax that also applies to diet soft drinks.

as well as fruit juice, flavored milk and bottled water are alternative (non-taxed) goods, which consumers may choose to substitute towards. Each brand is available in a number of different sizes and container types.

Table 2.2: *Products I*

Firm	Brand	Product	On-the-go %	On-the-go price	At-home %	At-home price
Soft drinks						
CocaCola			43.34		24.10	
	Coke		28.58		18.39	
		Coca Cola 330	4.32	0.64	0.19	0.55
		Coca Cola 500	8.19	1.13	0.82	1.01
		Coca Cola Diet 330	5.30	0.64	0.14	0.56
		Coca Cola Diet 500	10.78	1.14	1.29	1.02
		Coca Cola multi can			3.12	3.37
		Coca Cola Diet multi can			4.87	3.33
		Coca Cola bottle			3.46	1.42
		Coca Cola Diet bottle			4.36	1.36
		Coca Cola multi bottle			0.15	4.39
	Dr Pepper		3.48		1.97	
		Dr Pepper 330	0.46	0.63	0.01	0.50
		Dr Pepper 500	2.83	1.10	0.25	1.00
		Dr Pepper Diet 500	0.20	1.07		
		Dr Pepper multi can			0.33	2.18
		Dr Pepper Diet multi can			0.15	2.16
		Dr Pepper bottle			0.90	1.28
		Dr Pepper Diet bottle			0.34	1.24
	Fanta		4.19		2.35	
		Fanta 330	0.62	0.61		
		Fanta 500	3.25	1.11	0.29	1.00
		Fanta Diet 500	0.32	1.08		
		Fanta multi can			0.32	2.08
		Fanta Diet multi can			0.32	2.30
		Fanta bottle			1.09	1.23
		Fanta Diet bottle			0.33	1.26
	Cherry Coke		2.99		0.95	
		Cherry Coke 330	0.46	0.63	0.01	0.43
		Cherry Coke 500	1.65	1.10	0.15	1.00
		Cherry Coke Diet 500	0.88	1.06	0.10	1.00
		Cherry Coke multi can			0.16	2.71
		Cherry Coke Diet multi can			0.15	2.71
		Cherry Coke bottle			0.25	1.32
		Cherry Coke Diet bottle			0.13	1.31
	Oasis		4.09		0.44	
		Oasis 500	3.87	1.11	0.44	0.99
		Oasis Diet 500	0.22	1.07		
Pepsico			11.03		14.47	
	Pepsi		11.03		14.47	
		Pepsi 330	1.06	0.59	0.07	0.38
		Pepsi 500	2.24	0.99	0.25	0.75
		Pepsi Diet 330	1.79	0.60	0.13	0.40
		Pepsi Diet 500	5.95	0.97	0.74	0.76
		Pepsi multi can			1.19	2.04
		Pepsi Diet multi can			3.61	2.10
		Pepsi bottle			2.35	1.05
		Pepsi Diet bottle			6.12	1.06

Notes: Market shares are based on transactions. Prices are the mean across all choice occasions. The table describes the market shares of products purchased by 2,374 individuals in the on-the-go segment and 3,314 households in the at-home segment between June 2009 and December 2014.

Table 2.3: *Products II*

Firm	Brand	Product	On-the-go %	On-the-go price	At-home %	At-home price
Soft drinks *continued*						
GSK			7.77		4.20	
	Lucozade Energy		4.76		3.51	
		Lucozade Energy 380	2.57	0.94	0.22	0.75
		Lucozade Energy 500	2.18	1.16	0.35	1.01
		Lucozade Energy bottle			1.65	1.05
		Lucozade Energy multi bottle			1.29	2.79
	Ribena		3.01		0.69	
		Ribena 288	0.75	0.66	0.03	0.48
		Ribena 500	1.72	1.11	0.09	1.03
		Ribena Diet 500	0.54	1.08		
		Ribena multi			0.58	1.98
Other			19.14		22.03	
	Other		19.14		8.32	
		Other	16.32	1.10	2.07	1.17
		Other Diet	2.82	1.35	0.01	0.88
		Other big			3.16	1.07
		Other Diet big			1.49	1.11
		Other multi			1.08	2.12
		Other Diet multi			0.52	2.06
	Store		0.00		13.71	
		Store			5.17	0.45
		Store Diet			8.54	0.50
Alternative sugary drinks			8.25		23.16	
	Fruit juice		6.08		18.42	
		Fruit juice	6.08	1.07	2.78	1.60
		Fruit juice big			15.64	1.38
	Flavoured milk		1.41		3.96	
		Flavoured milk	1.41	0.98	2.78	0.72
		Flavoured milk big			1.17	1.05
	Fruit water		0.76		0.79	
		Fruit water	0.76	0.91	0.07	0.76
		Fruit water big			0.71	1.06
Outside			10.48		12.04	
	Bottled water		10.48		12.04	
		Bottled water	10.48	0.65	1.25	0.48
		Bottled water big			10.79	0.92

Notes: Market shares are based on transactions. Prices are the mean across all choice occasions. The table describes the market shares of products purchased by 2,374 individuals in the on-the-go segment and 3,314 households in the at-home segment between June 2009 and December 2014.

Tables 2.2 and 2.3 make clear that in the on-the-go segment, individuals choose between single portion products (e.g. Coca Cola 330 refers to a 330ml, or 11oz, can and Coca Cola 500 refers to a 500ml, or 17oz bottle). These single portions are also available in the at-home segment, though they are significantly less popular than larger pack sizes. In the case of the brand Coke, large sizes available in the at-home segment alone include a multi-pack of cans, a large plastic bottle and multi-pack of bottles.[9]

[9] These multi portion products embed some aggregation. For instance, the product Coca Cola bottle comes in both a 1.25l and 2l variant, though typically only one of these two sizes is available in any given store at a given time.

For each transaction we observe in what type of store the consumer made its purchase. In demand estimation we use retailer specific prices (in Section 3.2 we discuss how we exploit cross retailer price variation). We also use retailer specific choice sets (see Manski (1977), Goeree (2008) and Crawford et al. (2017) on how failing to account for heterogeneity in choice sets can lead to inconsistent demand estimates). These choice sets are defined as all of the products we observe being purchased in a retailer type-year. Table 2.4 describes both the number and share of purchases of non-alcoholic drinks in both on-the-go and at-home samples that we observe across retailer types. In the on-the-go segment the largest share of purchases are made in branches of small national chains or independent stores (corner shops). The large national supermarket chains account together for around one-fifth of purchases, and vending machines account for around 8%. In the at-home segment most purchases are made at the large national supermarket chains (88%). These large supermarkets comprise the four large retailers that dominate the UK grocery market – Asda, Morrisons, Sainsbury's and Tesco – as well as "Discounters", which aggregates together the low price Aldi and Lidl retailers. In estimation we use national prices for the retailers that set national prices, and average regional prices for the set of small national and independent stores that are known and observed to set different prices across regions.

Table 2.4: *Retailer types in which non-alcoholic drinks purchases are observed*

	On-the-go		At-home	
Store	N	%	N	%
Small national or independent	258494	71.4	35697	11.8
Vending machines	28659	7.9		
Large national	74710	20.6	266686	88.2
Asda	10617	14.2	58475	21.9
Morrisons	7605	10.2	40678	15.3
Sainsbury's	15588	20.9	39395	14.8
Tesco	40393	54.1	110619	41.5
Discounters	507	0.7	17519	6.6
Total	361863	100.0	302383	100.0

Notes: The table describes the number and share of purchases made by 2,374 individuals in the on-the-go estimation sample and 3,314 households in the at-home estimation sample in each type of store type between June 2009 and December 2014.

Linkages between market segments

Product overlap across segments means that supply side pricing, even of products mainly purchased on-the-go, will depend on both on-the-go and at-home preferences. For instance, the market demand curve for the product Coca Cola 330 will depend on preferences over the product in the on-the-go and at-home segments. As it is the market demand curve that is relevant for firms' pricing decisions we refer to this as a supply-side link. We take account of this in counterfactual simulations.

Another possible link between segments would exist even with non overlapping products if individuals' on-the-go decisions are influenced by at-home purchases made by the households to which the individual belongs. We explore this possibility by checking for correlations in on-the-go purchases with recent at-home purchases; the results are reported in Appendix A.5. We regress individual purchases on indicators for purchases by the individual's household in the at-home segment in the recent past, controlling for individual and year-month effects.

The coefficient estimates in Table A.8 indicate little evidence of dependence between current on-the-go purchases and recent purchases at-home. Where coefficients are statistically significant their magnitude is very small. As well as being very small, the direction of these effects are opposite to what we would expect if consumers viewed on-the-go and at-home consumption as substitutes. Our conclusion from this is that, once individual heterogeneity is accounted for, there is little evidence that demand linkages are of first order importance in the current context. While it would be interesting to study more broadly the interactions between household grocery demand and individual on-the-go grocery demand, we leave this for future work.

Switching across product types

Table 2.5: *Consumer specific product sets*

	Ever purchase fruit juice, flavored milk or bottled water?		
	Yes	No	Total
Individual chooses:			
Sugary and diet varieties	76.1	8.3	84.3
Only sugary varieties	10.4	3.1	13.5
Only diet varieties	1.3	0.8	2.2
Total	87.8	12.2	100.0

Notes: For each of the 2,374 on-the-go purchasers, across all their choice occasions, we distinguish between those that only buy soft drinks or buy soft drinks and other drinks and that only buy diet, sugary or both diet and sugary varieties. Numbers are % of the on-the-go estimation sample in each cell.

An advantage of the long T dimension of our data is that we are able to distinguish between consumers that, when purchasing a non-alcoholic drink, only ever purchase soft drinks, from those that also sometimes choose alternative drinks (i.e. fruit juice, flavored milk or water). Similarly, we can distinguish between consumers who, when purchasing a non-bottled water drink, either always choose sugary products, always choose diet products, or sometimes choose sugary and sometimes diet products. This enables us to identify consumers who effectively have infinite preferences for some product attributes (e.g. a consumer who only chooses diet products, in effect, has an infinitely negative preference for sugar) – see Section 3.1. In Table 2.5 we show for the on-the-go segment what fraction of the estimation sample falls into each group. Consumers who are observed buying all three of sugar sweetened soft drinks, diet varieties, and alternative sugary drinks account for 76.1% of the sample.

2.3 Demographics

The main justification for the adoption of soda taxes is that some consumers' consumption of these products creates costs that are borne by others (externalities) or future costs they themselves will bear that they do not fully account for at the point of consumption (internalities). A large theory literature posits that not all individuals fully account for future costs of consumption (for a survey see Rabin (1998)) and there is evidence this is particularly relevant for food, both experimental (for instance Read and Van Leeuwen (1998) and Gilbert et al. (2002)) and circumstantial, through the existence of a multi-billion pound dieting industry (Cutler et al. (2003)). The more a soda tax can alter the consumption of those that create large externalities or internalities, the better targeted it will be. Our aim in this paper is to provide evidence on how well targeted soda taxes are on individuals' behavior in the on-the-go segment. We focus on three demographics that are correlated with likely harm associated with sugary soft drinks consumption – age, total annual dietary sugar and income. An important reason that we focus on these demographics is that policymakers have justified the introduction of soda taxes as a way of targeting excess consumption of sugar, in particular in these groups.

Our focus on how the effects of the tax vary by age is motivated by a number of factors. Young people are the stated target of policy (for instance, see CDC (2016), Public Health England (2015)), and on average, the young get a relatively large fraction of their calories from sugar, so excess sugar consumption is more severe among this group (see details in Appendix A.1). Cavadini et al. (2000) document an increase in soft drink consumption in the US for 11-18 years old of almost 300% for boys, and over 200% for girls between 1965 and 1996. Nielsen and Popkin (2004) document a contemporaneous fall in the share of calories children get from milk. Medical evidence suggests that exposure to sweetened beverages early in life can establish strong lifelong preferences for these products (Mennella et al. (2016)). The young are particularly susceptible to suffer from internalities from excess sugar. The consequences of poor nutrition early in life are profound:

with excess sugar associated with poor mental health and school performance in children, and poor childhood nutrition thought to be an important determinant of later life health, social and economic outcomes and of persistent inequality (see, for instance Cawley (2010), Gortmaker et al. (2009) , Han and Powell (2013), Currie (2009), Currie et al. (2010), Azaïs-Braesco et al. (2017), Baum and Ruhm (2009), and for more description of consumption patterns see Ng et al. (2012), Rugg-Gunn et al. (2007)). It is likely that young people are less inclined to take account of the long term consequences of poor dietary choices (for instance, Ameriks et al. (2007) show that the young suffer more from self-control problems than older people).

We also focus on the effects of the tax by total annual dietary sugar. Those with high sugar diets are a group that policymakers have also targeted (for instance, see CDC (2016), Public Health England (2015)). It is possible that there is some convexity in how social costs arise from sugar consumption (e.g. at lower levels of sugar consumption the probability of developing type II diabetes is trivially small, but this probability may rise non-linearly in sugar consumption). Hall et al. (2011) show that adults with greater adiposity (more fat) experience larger health gains from a given reduction in energy intake.

Our focus on how responses vary with a measure of income is motivated, in part, by concerns that soda taxes are likely to be regressive. In addition, there is some evidence that low income people are more likely to exhibit behavior that creates internalities. For example, Haushofer and Fehr (2014) and Mani et al. (2013) suggest that the stress and cognitive load of being in poverty means that people are more likely to make unwise decisions and underweight the future. Focusing on asset accumulation Bernheim et al. (2015) argue that poverty can perpetuate itself by undermining the capacity for self-control: low initial wealth precludes self-control, and hence asset accumulation, creating a poverty trap. Banerjee and Mullainathan (2010) take an alternative approach by assuming that "temptation goods" are inferior goods, which leads to a similar conclusion that self-control problems give rise to asset traps. Any propensity for self-control problems, or other sources of internality generating behavior, that are concentrated among poorer individuals is likely to result in a soda tax being less regressive. However, this does not necessarily mean that *conditional on consumption levels* the externality function differs with income. Nonetheless, it is possible that wealthier households make better compensatory investments, so that the internality associated with a marginal consumption increase is declining with income. If a soda tax achieves large reductions in consumption among poor consumers, this could improve its effectiveness, and as Allcott et al.

(2018) point out, it is important to also account for this when assessing the policy's regressivity.

We construct a measure of total annual dietary sugar as the share of total household calories that are from added sugar using data on the entire household shopping basket. We measure income using household total annual equivalized grocery expenditure[10]; we equivalize using the standard OECD modified equivalence scale. In Appendix A.4 we show that equivalized grocery expenditure is strongly correlated with current income; expenditure is often viewed as a better proxy for lifetime income than current income (e.g. Poterba (1989)) so we use that as our main measure. There are other demographics that might also be of interest, and in Appendix B.1 we show how the preference parameters that we estimate vary by gender and the household's socio-economic class (which is a good proxy for education level).

In Table 2.6 we describe the age distribution of the total on-the-go sample. We show the fraction that we ever observe purchasing soft drinks ("soft drink purchasers"). We estimate demand using the 2,374 individuals who are "soft drink purchasers". The table summarizes other aspects of purchase behavior. Young consumers (relative to older ones): (i) are more likely to be soft drink purchasers, (ii) conditional on being so, obtain more sugar from these products, and (iii) purchase soft drinks more often and are more likely to buy sugar varieties – it is this rather than any tendency to be more likely to buy the largest single portion size (the 500ml bottles) that drives the higher sugar levels.

Tables 2.7 and 2.8 show the same statistics for deciles of the distribution of total annual dietary sugar and total annual equivalized grocery expenditure. Individuals from households with more sugar in their total diet are both more likely to be soft drink purchasers and, conditional on this, to get large quantities of sugar from these products. A similar pattern holds across the total annual equivalized grocery expenditure distribution; individuals with lower total annual grocery expenditure are more likely to be soft drink purchasers and obtain a relatively high amount of sugar from these products.

[10] Grocery expenditure includes spending on food, drinks, alcohol, and a wide range of non-food items such as toiletries, pet food, and cleaning produce.

Table 2.6: *Descriptive statistics by age groups*

	Age group					
	13-21	22-30	31-40	41-50	51-60	60+
% of sample	11.1	13.8	20.3	21.5	17.2	16.1
Fraction of soft drink purchasers	.42	.49	.52	.47	.37	.25
Conditional on purchase:						
Mean sugar from soft drinks per year (g)	2076	1777	1368	1402	1293	1090
Mean number of purchases per year	48.3	44	39.7	35.3	34.7	30.5
Fraction of sugary products	.76	.71	.66	.65	.67	.67
Fraction of 500ml bottles	.76	.73	.71	.71	.71	.69

Notes: Row 1 shows the fraction of individual-year observations in each age group. Row 2 shows the fraction of each age group that is ever observed purchasing soft drinks. The remaining rows show means for the set of soft drink purchasers of; total annual sugar from these products, number of annual purchases, fraction of purchases for sugary rather than diet varieties, and fraction of purchases for the larger 500ml bottle size.

Table 2.7: *Descriptive statistics by total annual dietary sugar*

	Decile of distribution of share of calories from added sugar									
	1	2	3	4	5	6	7	8	9	10
Upper bound of decile	8.5	10	11	11.9	12.8	13.8	14.9	16.2	18.3	24.7
Fraction of soft drink purchasers	.33	.4	.4	.4	.44	.44	.45	.47	.46	.47
Conditional on purchase:										
Mean sugar from soft drinks per year (g)	1070	1338	1247	1273	1292	1372	1560	1602	2009	1820
Mean number of purchases per year	38	39.2	37.3	35.6	36.3	37.5	38.6	39.3	44	39.8
Fraction of sugary products	.59	.63	.64	.66	.68	.71	.7	.7	.7	.74
Fraction of 500ml bottles	.67	.7	.69	.72	.73	.75	.73	.72	.72	.74

Notes: Row 1 shows the upper bound of the decile of total annual dietary sugar. Row 2 shows the fraction of each decile that is ever observed purchasing soft drinks. The remaining rows show means for the set of soft drink purchasers of; total annual sugar from these products, number of annual purchases, fraction of purchases for sugary rather than diet varieties, and fraction of purchases for the larger 500ml bottle size.

Table 2.8: *Descriptive statistics by total annual equivalized grocery expenditure*

	Decile of distribution of total equivalized grocery expenditure									
	1	2	3	4	5	6	7	8	9	10
Upper bound of decile	.8	1.1	1.3	1.5	1.7	1.9	2.2	2.5	3.1	5.1
Fraction of soft drink purchasers	.47	.44	.43	.43	.46	.42	.39	.42	.42	.38
Conditional on purchase:										
Mean sugar from soft drinks per year (g)	1648	1494	1647	1447	1671	1477	1331	1326	1251	1461
Mean number of purchases per year	42.2	38.5	42.3	37.7	40	37.3	35.4	36.5	35.7	40
Fraction of sugary products	.7	.68	.66	.68	.7	.68	.71	.66	.66	.67
Fraction of 500ml bottles	.68	.7	.7	.71	.73	.72	.75	.73	.74	.73

Notes: Row 1 gives the upper bound of the decile, measured in £1000, of total annual equivalized grocery expenditure. Row 2 shows the fraction of each decile that is ever observed purchasing soft drinks. The remaining rows show means for the set of soft drink purchasers of; total annual sugar from these products, number of annual purchases, fraction of purchases for sugary rather than diet varieties, and fraction of purchases for the larger 500ml bottle size.

3 Model

In this section we develop a model of consumer demand and firm pricing in the non-alcoholic drinks markets. What distinguishes our approach from previous work is: (i) we focus on modeling the preferences of *individuals* using information on their purchases on-the-go, and (ii) we exploit the long panel nature of our data to estimate individual specific preference parameters, giving us the ability to relate individual specific preferences and counterfactual effects to a wide range of demographics and measures of individual behavior.

While our focus is on behavior in the on-the-go segment we also estimate household level demand in the at-home segment. We therefore write down our demand model in a way that is consistent with estimation in either segment. As we argued in Section 2.2, the main linkage between the segments is their common effects on market level demand and hence firm pricing. We aggregate demand estimates in the two segments into market demand curves. At the consumer level we assume demand in the two segments is independent (an assumption supported by the descriptive analysis presented in Section 2.2). In Section 5.2 we discuss the implications of our estimates in the at-home segment for the analysis of how well targeted soda taxes are; we show that accounting for what households bring into the home is unlikely to substantially alter the conclusions of our analysis.

We consider consumer behavior in the non-alcoholic drinks market; when we simulate the introduction of a soda tax we allow for the possibility of consumer switching to diet alternatives, or alternative drinks products. Ex ante, such switching to alternative drinks seems likely to be much more important than substitution towards foods, and there is some experimental evidence that calories from liquids do not displace those from solids (see, for instance, DiMeglio and Mattes (2000), DellaValle et al. (2005) and Flood et al. (2006)). However, to consider the possibility that consumers respond to the tax by switching from drinks to foods that contain sugar, we nest our model of demand for drinks within a two-stage demand model, in which, in a first stage, consumers choose between food and drinks. We present this in Section 5.1.

3.1 Demand model

We index consumers by $i \in \{1, \dots, N\}$. In the on-the-go segment consumers are individuals; in the at-home segment they are households. Notationally, we distinguish between such consumers by indicating individuals as $i \in \mathcal{M}^{out}$ and households as $i \in \mathcal{M}^{in}$ (where $\mathcal{M}^{in} \cup \mathcal{M}^{out} = \{1, \dots, N\}$). We observe each consumer on many choice occasions, indexed by $\tau = \{1, \dots, \mathcal{T}\}$. A choice occasion τ refers to a consumer visiting a retailer r_τ at time t_τ and purchasing a drink.

As outlined in Section 2.2, the choice sets facing consumers depend both on the retailer they shop at and whether they are shopping for single portion products (as in the on-the-go segment) or multi portion products (as is most commonly the case in the at-home segment). We denote the available set of products in retailer $r = \{1, \ldots, R\}$ during choice occasion τ as Ω_{r_τ}. For instance, an on-the-go individual that visits Tesco will choose between all the single portion products available in that retailer.

We index the "inside" products (i.e. soft drinks) by $j = \{1, \ldots, j'\}$ and the alternative juice options by $j = \{j' + 1, \ldots, J\}$. $j = 0$ denotes the option of selecting bottled water. These products are displayed in Tables 2.2 and 2.3. The choice set facing a consumer on choice occasion τ will contain the subset Ω_{r_τ} of the $J + 1$ products available for either on-the-go or at-home consumption from retailer r. Several soft drinks product belong to a brand – we denote the brand that product j belongs to as $b(j)$. Products within a brand differ based on whether they are a sugary or diet variety and in their pack size.

For any product j, we assume the pay-off associated with selecting the product on choice occasion τ takes the form:

$$U_{ij\tau} = \alpha_i p_{jr_\tau t_\tau} + \beta_i s_j + \gamma_i w_j + \delta^z_{d(i)} z_j + \delta^h_{d(i)} h_{c(i)t_\tau} + \xi_{d(i)b(j)t_\tau} + \zeta_{d(i)b(j)r_\tau} + \epsilon_{ij\tau}, \quad (3.1)$$

where $\epsilon_{ij\tau}$ is distributed type I extreme value independently across individuals and choices. $p_{jr_\tau t_\tau}$ denotes the price of product j, which varies over time (t) and cross-sectionally across retailers (r).[11] s_j is a dummy variable indicating whether the product is a sugary or diet variety and w_j is a dummy variable for whether the product is an inside product (i.e. a soft drink). We allow the preference parameters on these product attributes (α_i, β_i and γ_i) to be consumer specific.

We also include size-carton type effects (z_j), the effects of temperature ($h_{c(i)t}$) in the county $c(i)$ where the consumer lives at time t,[12] time-varying brand effects ($\xi_{d(i)b(j)t}$) and retailer-brand effects ($\zeta_{d(i)b(j)r}$). We allow the influence of these attributes to vary by demographic group – we denote these by $d \in \{1, \ldots, D\}$ and let $d(i)$ denote the group consumer i belongs to. For the on-the-go segment these groups are based on individual gender and age, for the at-home segment on whether the household contains children and the skill level of main shopper's occupation.[13]

[11]Specifically, prices vary across Asda, Morrisons, Sainsbury's, Tesco, Discounters, other national supermarkets, other national convenience stores, vending machines, and independent stores in the north, midlands and south.

[12]Note, this effect is for inside (i.e. soft drinks) options only and captures how temperature affects the choice of soft drinks versus alternative drinks products.

[13]Specifically, in the on-the-go segments we let these preferences vary over four groups based on individual gender and whether they are aged below 40 or not. In the at-home segment we allow them to vary over five groups based on whether the household has no children, is a pensioner household, or contains children, and for non pensioner households, whether the main shopper's occupation is classified as high or low skilled.

We denote by $\boldsymbol{\alpha} = (\alpha_1, \ldots, \alpha_N)'$, $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_N)'$ and $\boldsymbol{\gamma} = (\gamma_1, \ldots, \gamma_N)'$ the vectors of individual preference parameters. These individual level preferences enable our model to capture within individual correlation in choices across choice occasions. We do not place any *a priori* restriction on the joint distribution of these variables. We use the large $\mathcal{T}$ dimension of our data to recover estimates of individual specific parameters $(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma})$, while the large N dimension allows us to identify nonparametrically the joint probability distribution function $f(\alpha_i, \beta_i, \gamma_i)$ using the empirical probability distribution function of estimated $(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma})$. We can also construct the distribution of preferences conditional on observable consumer characteristics, X; $f(\alpha_i, \beta_i, \gamma_i|X)$. These observable characteristics can be demographic variables or measures of the overall diet or grocery purchasing behavior of the household to which the individual belongs.

A number of papers (see, for instance, Berry et al. (1995), Nevo (2001) and Berry et al. (2004)) show that incorporating consumer level preference heterogeneity is important for enabling choice models to capture switching patterns across products,[14] while a few papers have used non-parametric methods to relax parametric restrictions on random coefficients.[15] Like these papers we model consumer specific preferences, however, in contrast to them, we treat the preferences as parameters to be estimated and thereby avoid having to make independence assumptions to integrate out the density. This allows us to flexibly relate the preference parameters and individual specific effects of simulations to observable attributes of consumers. Unlike in a random coefficient approach we do not need to *a priori* specify how the preference distribution depends on exogenous attributes of consumers, and we can relate individual specific effects to any observable attributes of consumers (such as other aspects of their grocery purchasing behavior).

One potential concern is that our estimates may be subject to an incidental parameter problem that is common in non-linear panel data estimation. Even if both $N \to \infty$ and $\mathcal{T} \to \infty$, asymptotic bias may remain, although it shrinks as the sample size rises (Hahn and Newey (2004), Arellano and Hahn (2007)). The long $\mathcal{T}$ dimension of our data helps lower the chance that the incidental parameter problem leads to large biases. We implement the split sample jackknife procedure

[14] Lewbel and Pendakur (2017) show similar results apply in non-linear continuous choice models, with the incorporation of random coefficients resulting in their model much more effectively capturing the distributional impacts of taxation.

[15] Burda et al. (2008) exploit Bayesian Markov Chain Monte Carlo techniques and Train (2008) uses an expectation-maximization algorithm to estimate the random coefficient distribution. Train (2008) applies the method either with a discrete random coefficient distribution or with mixtures of normals. Bajari et al. (2007) discretize the random coefficient distribution and use linear estimation techniques to estimate the frequency of consumers at each fixed point.

suggested in Dhaene and Jochmans (2015) and in Section 5.3 show that our maximum likelihood and jackknife estimates are similar and that the bias correction does not affect our results.

Another benefit of having large $\mathcal{T}$ for each individual is that we can allow for consumers who may have sufficiently strong distaste for some product sets that they endogenously will never choose to buy them. Using the long time dimension of our data we identify consumers that never purchase products with particular characteristics (e.g. sugary soft drinks) as having zero probability of purchasing products with that characteristic. This is in contrast to standard logit discrete choice demand models where it is assumed that all consumers have non-zero purchase probabilities for all products available to them.

In particular, we identify consumers that only ever purchase inside products (i.e. soft drinks; those with $w_j = 1$), and never purchase alternative drinks (i.e. fruit juice, flavored milk or bottled water; those with $w_j = 0$). Such consumers can be thought of as having negative infinite preferences for non-inside products (which we denote by $\gamma_i = \infty$; an infinite preference for inside products). Consumers that sometimes purchase inside products and other times purchase alternative drinks have $\gamma_i \in (-\infty, \infty)$.

Similarly, we distinguish between consumers that, when buying either an inside or alternative juice product only ever select sugary options (i.e. those for which $s_j = 1$), those that only ever purchase non-sugary options (i.e. diet soft drinks; for which $s_j = 0$), and those that we observe sometimes purchasing sugary products and at other times non-sugary products. The three groups, respectively, have sugar preferences given by $\beta_i = \infty$, $\beta_i = -\infty$, and $\beta_i \in (-\infty, \infty)$.

To specify the set of products that consumers have non-zero probabilities for, it is useful to define the product sets Ω_{ws}, Ω_{wn}, Ω_{as} and Ω_{an}, which denote respectively the sets of sugar sweetened soft drinks, diet soft drinks, alternative sugar drinks and water. We can then define consumer i specific sets of products with non-zero purchase probabilities, denoted by Ω_i, as

$$\Omega_i = \begin{cases} \Omega_{ws} \cup \Omega_{wn} \cup \Omega_{as} \cup \Omega_{an} \text{ if } & \beta_i \in (-\infty, \infty) \text{ and } \gamma_i \in (-\infty, \infty) \\ \Omega_{wn} \cup \Omega_{an} \text{ if } & \beta_i = -\infty \text{ and } \gamma_i \in (-\infty, \infty) \\ \Omega_{ws} \cup \Omega_{as} \cup \Omega_{an} \text{ if } & \beta_i = +\infty \text{ and } \gamma_i \in (-\infty, \infty) \\ \Omega_{ws} \cup \Omega_{wn} \text{ if } & \beta_i \in (-\infty, \infty) \text{ and } \gamma_i = \infty \\ \Omega_{wn} \text{ if } & \beta_i = -\infty \text{ and } \gamma_i = \infty \\ \Omega_{ws} \text{ if } & \beta_i = +\infty \text{ and } \gamma_i = \infty. \end{cases}$$

The share of consumers (for the on-the-go segment) in each group is given in Table 2.5. We assume that the consumer level product sets Ω_i are measured exactly due to the large $\mathcal{T}$ dimension of observed consumer level choices. However, our sample is finite and thus a finite sample measurement error is introduced on Ω_i. We ignore this measurement error; Monte Carlo simulations show that such error is negligible in our application where $\mathcal{T}$ is relatively large.[16]

We define:

$$
\begin{aligned}
v_{ijr_\tau t_\tau} \equiv& \alpha_i p_{jrt_\tau} + \beta_i s_j 1_{\{\beta_i \in (-\infty,\infty)\}} + \gamma_i w_j 1_{\{\gamma_i \in (-\infty,\infty)\}} \\
\eta_{ijr_\tau t_\tau} \equiv& \delta^z_{d(i)} z_j + \delta^h_{d(i)} h_{c(i)t_\tau} + \xi_{d(i)b(j)t_\tau} + \zeta_{d(i)b(j)r_\tau}
\end{aligned}
$$

such that equation (3.1) can be written

$$
U_{ij\tau} = v_{ijr_\tau t_\tau} + \eta_{ijr_\tau t_\tau} + \epsilon_{ij\tau}.
$$

The assumption that $\epsilon_{ij\tau}$ is an idiosyncratic shock distributed type I extreme value means that the consumer level choice probabilities are given by the multinomial logit formula, such that the choice probability of consumer i on choice occasion τ purchasing any good $j \in \Omega_{r_\tau}$ can be written[17]

$$
P_{i\tau}(j) = \frac{1_{\{j \in \Omega_i\}} \exp(v_{ijr_\tau t_\tau} + \eta_{ijr_\tau t_\tau})}{\sum_{k \in \Omega_i \cap \Omega_{r_\tau}} \exp(v_{ikr_\tau t_\tau} + \eta_{ikr_\tau t_\tau})} \tag{3.2}
$$

If we denote consumer i's sequence of choices across all choice occasions as $\boldsymbol{y}_i = (y_{ir_1 t_1}, ..., y_{ir_\mathcal{T} t_\mathcal{T}})$, then the probability of observing $\boldsymbol{y}_i$ is given by:

$$
\mathcal{L}_i(\boldsymbol{y}_i) = \prod_{\tau=1}^{\mathcal{T}} P_{i\tau}(y_{ir_\tau t_\tau})
$$

and, denoting the demographic specific preference parameters $\boldsymbol{\eta}$, the associated log-likelihood function is:

$$
l(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\eta}) = \sum_i \ln \mathcal{L}_i(\boldsymbol{y}_i), \tag{3.3}
$$

which is globally concave with respect to all parameters.

[16]Further details available from authors on request.

[17]Of course the probability that consumer i at occasion τ purchases a good $j \notin \Omega_{r_\tau}$ is zero.

3.2 Identification

Our main identification challenge is to pin down the causal impact of price on demand. Our strategy for doing this relies on two sources of price variation. First, conditional on brand-time and retailer-drink type effects, we exploit cross-retailer variation in the *relative* prices and availability of different drinks products. This arises because we observe individuals making purchases in different retailers across time (and thereby facing different price vectors and choice sets). An important identifying assumption is that retailer choice is not driven by shocks to demand for a *specific* drinks product, but rather variation in where individuals shop is driven by other factors in daily life, in which individuals move between home, school, leisure or work. Second, we exploit variation in prices within brand across different containers and sizes. We allow for the possibility of time varying shocks to brand level demand, but we assume there is no aggregate shocks within brand for different container types. We discuss each source of variation in turn. In Appendix A.3 we provide descriptive statistics that illustrate that individuals face price variation, and that average prices across transactions reflect actual variation in underlying prices.

The price vector an individual faces at the point of purchase depends on which retailer they visited. These retailers include a set of large national retailers that price nationally, smaller retailers with regionally varying prices and vending machines (see Table 2.4). We include demographic group specific time varying brand effects $\xi_{d(i)b(j)t}$ and retailer effects, interacted with the set of soft drinks, the alternative sugary drinks and bottled water, $\xi_{d(i)b(j)r}$. The former capture aggregate (demographic specific) fluctuations in brand demand over time (e.g. driven by national advertising) and the latter capture any differential propensity of consumers to choose different drink types across retailers. Conditional on these, the cross-retailer differences in prices provide a useful source of price variation.

There are two main concerns with exploiting this type of price variation. First, an issue would arise if individual level demand shocks to specific soft drinks products drive store choice; for instance, if consumers that have a demand shock in favor of Coca Cola are driven by this to choose a retailer that temporarily has a low price for that product, and, if instead they had a demand shock in favor of Pepsi they would have selected a retailer with a relatively low Pepsi price. Such behavior would occur either if consumers could predict fluctuating relative prices across retailers or if they visited several retailers in search of a low price draw for the product they are seeking. We find either scenario unlikely in the case of soft drinks.

Second, an issue would arise if differential changes in the prices of different soft drinks across retailers are driven by retailer-time varying demand shocks for specific soft drinks products. For instance, if the consumers that shop in Tesco (a national supermarket chain) at a point in time have time varying preferences for a particular product, not controlled for in our demand model but observed by Tesco, that are systematically different from consumers visiting Sainsbury's (another national chain), or those visiting convenience stores. In the UK market the vast majority of soft drinks advertising is done nationally and by the manufacturer, so we think it is likely that the time varying brand effects we include will absorb most of the time varying shifts in preferences likely to feed into pricing decisions.[18] Conditional on these (and retailer effects), we assume the residual cross retailer price variation is driven by cost differences across retailers, by random price reduction strategies and by retailer specific decisions related to unanticipated excess stock.

The second source of price variation we exploit is non-linear pricing across container sizes. This price variation is not collinear with the size effects, and the extent of non-linear pricing varies over time and retailers. This source of identifying variation would be invalid if there were systematic shocks anticipated by firms to consumers' valuation of container sizes that were differential across brand after conditioning on time varying brand effects and container size and type effects. It seems more plausible that such tilting of brand price schedules is driven by cost variations that are not proportional to pack size, differential pass-through of cost shocks and differences in how brand advertising affects demands for different pack sizes. This identification argument is similar to that in Bajari and Benkard (2005). In an application to the computer market they assume that, conditional on observables, unobserved product characteristics are the same for products that belong to the same model. We assume that, conditional on time-varying brand characteristics, unobserved size specific attributes do not vary differentially across brands.

The main source of variation in the sugar content of products is between sugary and diet varieties (with most brands being available in each variety). We identify consumer specific preference parameters for sugary versus diet products (rather than a preference for a marginal increase in sugar quantity). We assume that the brand effects are common across sugary and diet varieties, and that the taste for sugary varieties is additively separable. This means that, for example, we do not allow the individual sugar taste to be different for Coke versus Pepsi. Table 2.5 shows that there are many individuals who purchase both sugary and diet varieties.

[18]Targeted price discounts through use of coupons – common in the US (see Nevo and Wolfram (2002)) – is not a common feature of the UK market.

3.3 Pass-through of a tax on sugary soft drinks

We consider the impact of a tax levied on sugary soft drinks. Such taxes have recently been introduced in a number of locations. These policies are often referred to as "soda taxes", though they typically apply to broader set of products than carbonates (or sodas). These taxes are typically volumetric (i.e. levied per liter or ounce) and levied either on soft drinks that contain sugar, or on all soft drinks (including diet varieties). We consider a tax levied on sugary soft drinks and in Appendix D show results for a tax on all soft drinks. A number of US cities have recently legislated for the introduction of "soda taxes",[19] the UK introduced a tax on sugary soft drinks in 2018 and France and Mexico have had taxes in place since 2012 and 2014. We model a tax of 25 pence per liter, (or 33 US cents per liter, which is 1.2 cents per ounce – similar to the US taxes of 1-1.5 cents per ounce).

The degree of pass-through of a tax to consumer prices will depend on the nature of competition in the market. 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 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)).[20] 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. We denote the size of the 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

[19] A tax of 1.5 cent per ounce on regular and diet soft drinks is effective in Philadelphia as of January 2017; Berkeley, San Francisco, Oakland, Albany California and Boulder Colorado all legislated for sugary soft drinks taxes of 1 cent per ounce (2 cents in Albany) implemented in 2017-18; a soft drinks tax of 1 cent per ounce was effective in Cook County, Illinois (which includes Chicago) as of June 2017, but was subsequently repealed.

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

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 (3.2).

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:

$$\Pi_{fm} = \sum_{j\in F_f} (p_{jm} - c_{jm}) q_{jm}(\mathbf{p}_m) \tag{3.4}$$

and the firm's price first order conditions are:

$$q_{jm}(\mathbf{p}_m) + \sum_{k\in F_f} (p_{km} - c_{km}) \frac{\partial q_{km}(\mathbf{p}_m)}{\partial p_{jm}} = 0 \quad \forall j \in F_f. \tag{3.5}$$

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 implies pre-tax and post-tax prices are related by:

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

where l_j is the volume of product j.

In the counterfactual equilibrium, prices satisfy the conditions:

$$q_{jm}(\mathbf{p}_m) + \sum_{k\in F_f} (\tilde{p}_{km} - c_{km}) \frac{\partial q_{km}(\mathbf{p}_m)}{\partial p_{jm}} = 0 \quad \forall j \in F_f \tag{3.6}$$

for all firms f. We solve for the new equilibrium prices as the vector that satisfies the set of first order conditions (equation (3.6)) when $\pi = 0.25$.[21] 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.[22]

3.4 Demand estimates

3.4.1 On-the-go

Preference distribution and elasticities In Table 3.1 we summarize the distribution of estimated consumer specific preference parameters for on-the-go behavior obtained by maximizing the likelihood function (equation 3.3); the at-home estimates are discussed in Section 3.4.2. We report the means, standard deviations, skewness and kurtosis for the price, soft drinks and sugar preference parameters, as well as the covariance between them. These numbers are based on the finite portion of the joint preference distribution. In Appendix B.1 we report coefficients estimates on brand, size and weather effects.

In Figure 3.1 we plot the marginal preference distributions for price, and the soft drinks and sugar product attributes for the on-the-go segment. These are based on individual level preference estimates, so we have a measure of statistical significance for each individual; this is represented by the shading, which indicates consumers with negative, positive and indifferent (i.e. not statistically significantly different from zero) preferences for each attribute. Table 3.1 shows that moments of each of these distributions are estimated with a high degree of statistical significance. Figure 3.1 makes clear that the univariate preference distributions depart significantly from normality (which is typically imposed in random coefficient models) – this is apparent both in the negative (for price and sugar) and positive (for soft drinks) skew in the preference distributions, and also in the infinite portions of the soft drinks and sugar preference distributions.

The estimates of the consumer specific preference parameters (on price, sugar and soft drinks) reveal a large degree of heterogeneity in preferences across individuals – the standard deviation for price preferences is 2.7 (with a coefficient of variation of 0.9), while the standard deviation for sugar and soft drinks is 1.6 and

[21] 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.

[22] 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.

1.8. Price sensitive consumers tend to have relatively strong soft drinks preferences (the correlation coefficient between price and soft drinks preferences is -0.33), while those with strong preferences for sugar tend to be less price sensitive (the correlation coefficient between price and sugar preferences is 0.15). We show contour plots of the bivariate preference distributions in Appendix B.1.

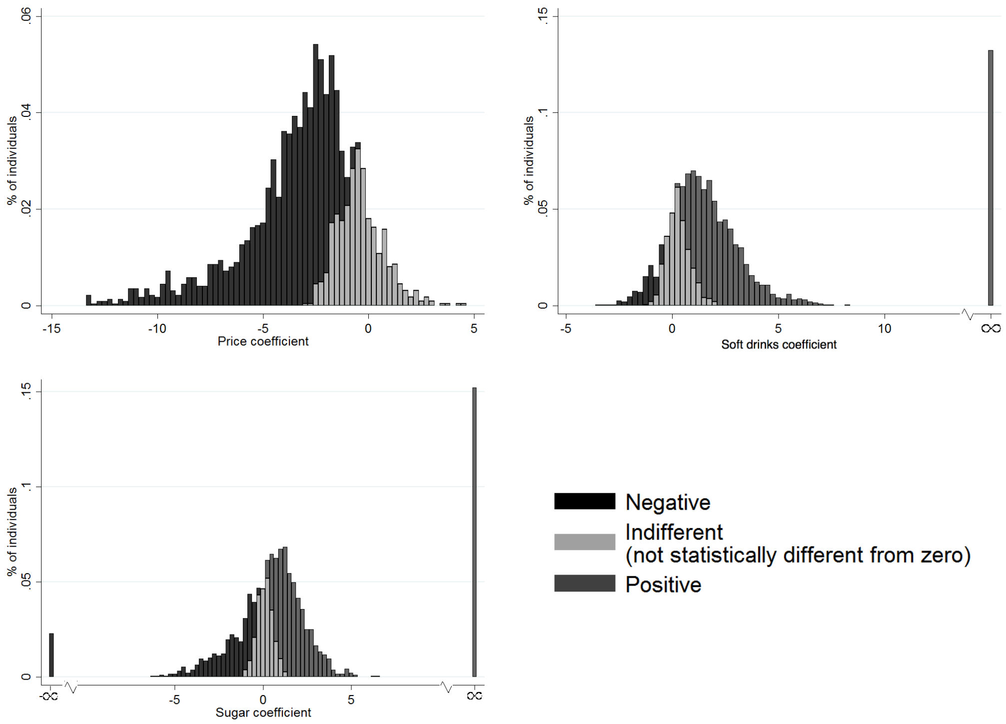
Table 3.1: *Demand model estimates – on-the-go*

Moments of distribution of consumer specific preferences			
Variable		Estimate	Standard error
Price (α_i)	Mean	-3.0737	0.0287
	Standard deviation	2.6825	0.0210
	Skewness	-0.9247	0.0462
	Kurtosis	4.3175	0.1117
Soft drinks (γ_i)	Mean	1.4297	0.0421
	Standard deviation	1.6065	0.0153
	Skewness	0.5001	0.0415
	Kurtosis	3.6833	0.1307
Sugar (β_i)	Mean	0.4244	0.0104
	Standard deviation	1.8058	0.0141
	Skewness	-0.4838	0.0407
	Kurtosis	3.5801	0.1026
Price-Soft drinks	Covariance	-1.4058	0.0463
Price-Sugar	Covariance	0.7413	0.0439
Soft drinks-Sugar	Covariance	-0.6585	0.0311
Demographic specific carton-size effects ($\delta^z_{d(i)}$)		Yes	
Demographic specific weather effects ($\delta^h_{d(i)}$)		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 2,374 individuals who we observe on 361,863 on-the-go 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.

We report price elasticities for all products in Table B.2 in Appendix B.1. A couple of interesting patterns are apparent. First, consumers are more willing to switch from sugary soft drinks products to alternative sugary soft drinks and from diet products to diet alternatives than they are between sugary and diet products. Second, the price elasticities for the 500ml products are smaller in magnitude than for the 330ml versions; consumers that choose to buy the larger bottle variants rather than smaller cans tend to be less willing to switch away from their chosen product in response to a price increase. Table B.3 reports the effect on demand of a marginal increase in the price of all sugary soft drinks and in the price of all soft drinks (i.e. both sugary and diet). The own price elasticity for soft drinks is -0.43. This is smaller than the own price elasticity of any individual soft drink product. The own price elasticity for sugary soft drinks is -0.89. This is larger than for all soft drinks, reflecting that some consumers respond to an increase in the price of sugary soft drinks by switching to diet alternatives.

Figure 3.1: *Univariate distributions of consumer specific preference parameters – on-the-go*



Notes: Distributions are based on individual level preference parameter estimates for the 2,374 individuals in the on-the-go estimation sample. We trim the top and bottom percentile of the finite portion of each distribution. The shading denote statistical significance of individual level preference estimates at the 95% level.

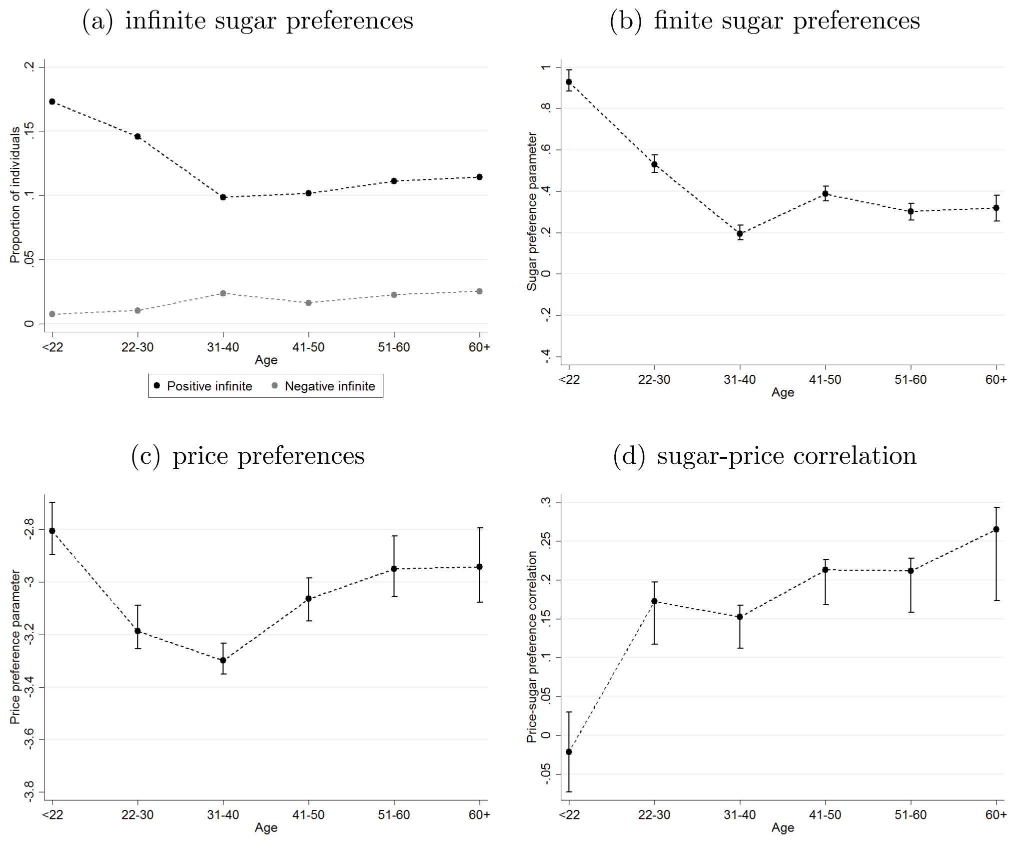
Relationship with individual attributes A key feature of our model is that it allows us to flexibly relate preference parameters to characteristics of consumers. This enables us to address the question of how well targeted soda taxes are, and to what extent they disproportionately impact the young and the poor.

In Figure 3.2 we show how features of the preference distribution vary with age.[23] Panel (a) shows how the fraction of consumers with infinitely negative and positive sugar preferences varies across groups – a higher fraction of individuals aged below 30 have infinitely positive sugars preferences (i.e. only buy sugary varieties) than older individuals. Panel (b) shows that, for those individuals with finite sugar preferences, the mean preference for sugar varies with age, with the

[23]To calculate the confidence intervals we obtain the variance-covariance matrix for the parameter vector estimates using standard asymptotic results. We then take 100 draws of the parameter vector from the joint normal asymptotic distribution of the parameters and, for each draw, compute the statistic of interest, using the resulting distribution across draws to compute Monte Carlo confidence intervals. Note these bands need not by symmetric around the estimate.

youngest group of individuals (aged 13-21) having stronger sugar preferences than older individuals. Panel (c) shows that the youngest group of consumers tend to have slightly less negative price preferences than older individuals, though the difference is small. Panel (d) shows how the *within* age group correlation in sugar and price preferences varies across age groups. Among older groups sugar and price preferences are positively correlated – those with the strongest sugar preferences are also the least price sensitive. However, among the youngest group this correlation in price and sugar preferences is close to zero. These preference patterns are important in determining the shape of demand and in driving how the responses to a soda tax vary across the age distribution.

Figure 3.2: *Preference variation with age*



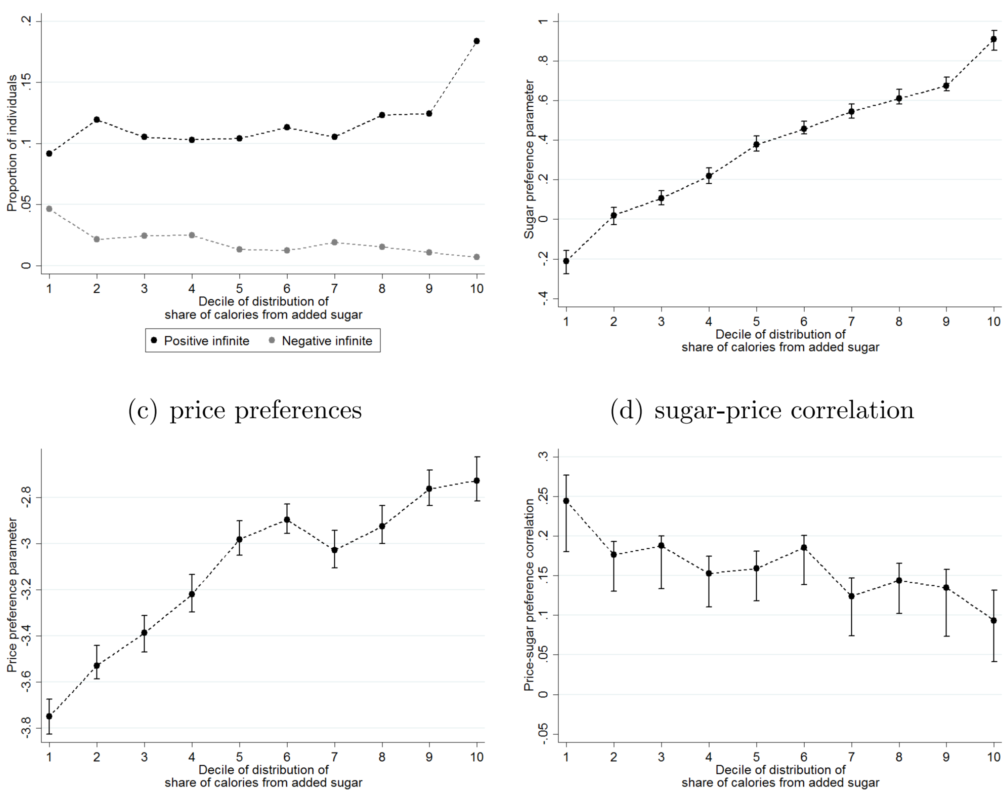
Notes: Figure shows how the share of consumers with infinite sugar preferences, the mean of finite sugar preferences, the mean of price preferences and the correlation between sugar and price preferences vary by age groups. 95% confidence intervals are shown by bars.

Figure 3.3 shows how price and sugar preferences vary across deciles of the distribution of total annual dietary sugar (measured as the share of a households' total at-home calories from added sugar). Preferences governing on-the-go drinks demand are strongly related to total annual dietary sugar. Those in the top decile of the added sugar distribution are considerably more likely than other individuals to have infinitely positive sugar preferences. For those individuals with finite sugar preferences, being in a higher decile of the added sugar distribution is strongly associated with a stronger sugar preference when buying drinks on-the-go. Price preferences vary more strongly with total annual dietary sugar than with age, with those in the top half of the added sugar distribution being considerably less price sensitive than those in the bottom half. On the other hand the within group correlation in sugar and price preferences varies less starkly across deciles than it does across age groups.

Figure 3.3: *Preference variation with total annual dietary sugar*

(a) infinite sugar preferences (b) finite sugar preferences

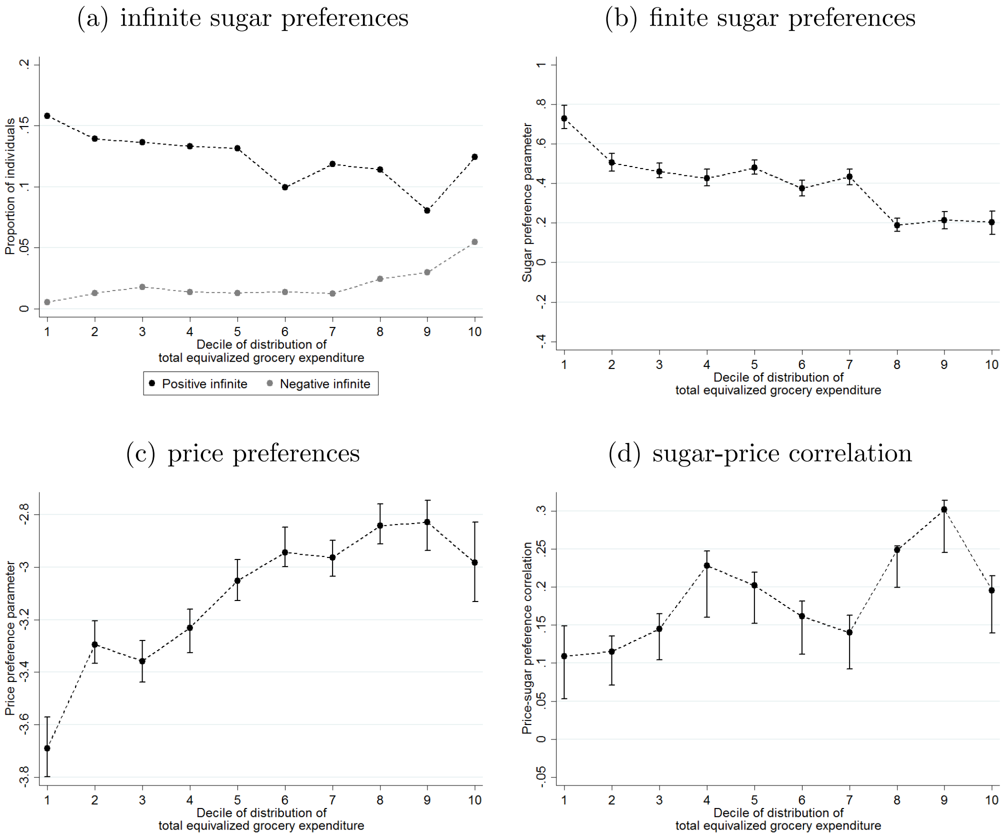
(c) price preferences (d) sugar-price correlation



Notes: Figure shows how the share of consumers with infinite sugar preferences, the mean of finite sugar preferences, the mean of price preferences and the correlation between sugar and price preferences vary by deciles of the distribution of total annual dietary sugar. 95% confidence intervals are shown by bars.

In Figure 3.4 we show how preferences vary across deciles of the distribution of total equivalized grocery expenditure (a proxy for income). There is a clear gradient for both sugar and price preference parameters; poorer individuals typically have stronger sugar preferences and more negative preferences for price than richer individuals.

Figure 3.4: *Preferences variation with equivalized expenditure*



Notes: Figure shows how the share of consumers with infinite sugar preferences, the mean of finite sugar preferences, the mean of price preferences and the correlation between sugar and price preferences vary by deciles of the distribution of total annual equivalized grocery expenditure. 95% confidence intervals are shown by bars.

3.4.2 At-home demand estimates

In Table 3.2 we summarize estimates of the household specific preference parameters governing at-home demand. In Figure 3.5 we report estimates of the demographic specific preference parameters. We need to be cautious in comparing the moments of the preference distribution reported in Table 3.2 with their on-the-go counterparts, because in the at-home segment purchases are made for future consumption by the household instead of immediate consumption by the individual. However, two noticeable differences are that in the at-home segment the difference between the mean soft drinks and mean sugar preferences is much larger – when purchasing for at-home consumption households' average preference for soft drinks relative to sugary drinks is considerably stronger than when individuals purchase for on-the-go consumption. A second noticeable difference is that in the at-home segment the correlation in preferences is less strong than in the on-the-go segment. In Section

5.2 we show that it is unlikely that differences in behavior in the at-home segment would reverse our conclusions about how well targeted soda tax is.

Table 3.2: *Demand model estimates – at-home*

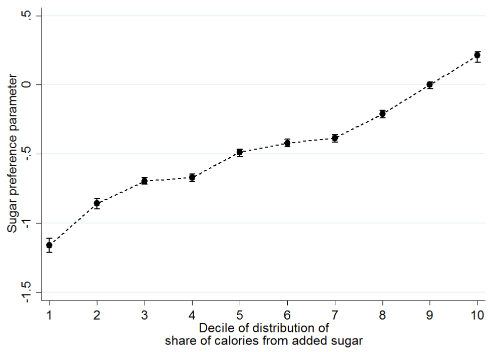
Moments of distribution of consumer specific preferences			
Variable		Estimate	Standard error
Price (α_i)	Mean	-2.1051	0.0141
	Standard deviation	1.3932	0.0115
	Skewness	-1.3236	0.0398
	Kurtosis	5.3699	0.2014
Soft drinks (γ_i)	Mean	7.6998	0.3607
	Standard deviation	1.8600	0.2609
	Skewness	0.0561	0.2646
	Kurtosis	2.9723	0.2385
Sugar (β_i)	Mean	-0.4608	0.0086
	Standard deviation	1.5219	0.0106
	Skewness	0.0084	0.0378
	Kurtosis	3.1882	0.1023
Price-Soft drinks	Covariance	-0.2336	0.0517
Price-Sugar	Covariance	-0.1076	0.0157
Soft drinks-Sugar	Covariance	-0.0844	0.0853
Demographic specific carton-size effects ($\delta^z_{d(i)}$)		Yes	
Demographic specific weather effects ($\delta^h_{d(i)}$)		Yes	
Demographic specific time-brand effects ($\xi_{d(i)b(j)t}$)		Yes	
Demographic specific retailer-brand effects ($\zeta_{d(i)b(j)r}$)		Yes	

Notes: We estimate demand on a sample of 3,314 households who we observe on 302,383 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.

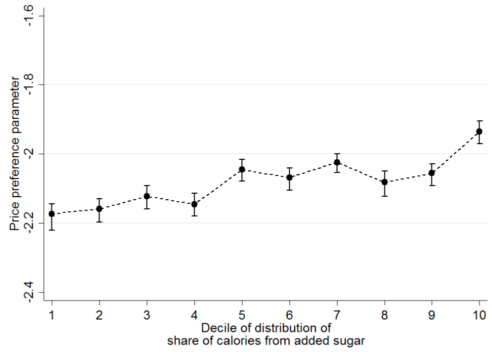
Figure 3.5 shows variation in preferences for sugar and price in the at-home segment and how they vary by deciles of the total dietary sugar and total equivalized grocery expenditure distributions. As expected, households that have higher added sugar in their total annual grocery basket also have stronger 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 3.5: *Preferences variation – at-home*

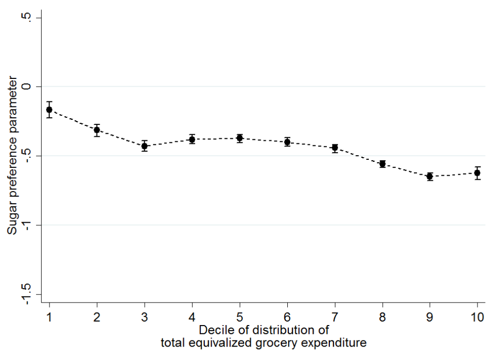
(a) sugar preferences by total dietary sugar



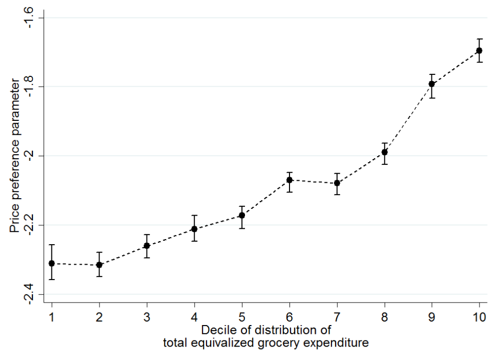
(b) price preferences by total dietary sugar



(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.

4 The effects of a soda tax on on-the-go sugar consumption

We use our demand estimates, along with the supply side model outlined in Section 3.3, to simulate the introduction of a tax levied on sugary soft drinks. In Appendix D we show results for a tax levied on all soft drinks (both sugary and diet varieties). To compute supply side responses to the tax we use both the on-the-go and at-home demand estimates. In this section we focus on how individual level on-the-go demand changes in response to a tax. In Section 5.2 we discuss how responses vary across households in the at-home segment, showing, in particular, that at-home responses are unlikely to undo the individual level effects that the on-the-go segment enables us to study.

4.1 Market equilibrium

We consider the introduction of a tax of 25 pence per liter. This is similar to what has been implemented in some locations in the US. The implied equilibrium price changes are within the range of observed price variation in our data. By construction, such a tax will be larger for larger sized products, imposing more tax on a 500ml bottle than on a 330ml can. We simulate the introduction of the tax allowing firms to re-optimize prices of the set of branded sugary and diet soft drinks products (the former are subject to the tax, the latter are not). We assume 100% pass-through for products belonging to the aggregate "other" soft drink brand, and hold fixed the pre-tax price of the alternative sugar drinks (fruit juice, flavored milk and flavored water) and bottled water.

In Table C.1 in Appendix C we report the mean tax levied per product, price change and change in share of the on-the-go segment of the drinks market due to the tax. The average tax liable on sugary soft drinks is 10.65 pence – for products with 500ml the tax liable is 12.5 pence, while for those with 330ml it is 8.25 pence. On average, the price of sugary soft drinks rises by 13.15 pence – average equilibrium pass-through of the tax is therefore around 120%.[24]

Pass-through rates vary across products; the larger 500ml bottled products typically have rates of 130-140% and smaller 330ml canned products have rates of around 100%. This means manufacturers respond to the tax by increasing margins on the 500ml products and maintaining them at around the pre-tax level for the 330ml cans. Our demand estimates imply that the bottled products have less elastic demands than the cans. By raising margins on these products, firms sacrifice some marginal consumers, who switch to alternatives, but earn more profits on the infra-marginal consumers who still buy bottles. Nevertheless, profits on the bottled products fall by more than for canned products as some consumers respond to the tax by downsizing (i.e. switching from bottles to cans).

The tax on sugary soft drinks thus increases equilibrium prices for sugary soft drinks, doing so by more for the larger sized products due to a higher tax rate and over shifting. The market share of sugary soft drinks in the on-the-go segment falls by 6.34 percentage points. Soft drink manufacturers also optimally respond to the tax by lowering the price of diet products. The average reduction in price is 1.37 pence, however, the 500ml bottle products see larger price reductions of around 2 pence, with smaller changes in the equilibrium price of the smaller 330ml canned

[24] This over shifting arises because the tax is imposed in all stores and on a broad set of products. If we impose a tax only on the products owned by the largest firm in the market, Coca Cola, the average pass-through of the tax onto its products is less than 100%.

products. The pricing response of soft drink manufacturers therefore acts to magnify the price differential that the tax creates between sugary and diet products. Relative to the case in which producers simply increase consumer prices by an amount exactly equal to the tax (so pass-through of tax is 100%), firms' equilibrium pricing response induces more switching away from sugary soft drinks and more towards diet soft drinks; the share of diet soft drinks increases by 3.96 percentage points. Alternative sugary drinks and bottled water also see increases in market share of 1.09 and 1.28 percentage points.

A number of papers use observed tax changes to estimate pass-through of taxes to prices. Results from the literature vary, but typically these papers find complete or over shifting of specific taxes, which broadly accord with our pass-through results. These include Besley and Rosen (1999), which exploits variation in state and local sales taxes in the US and looks at the impact on prices of a number of products and finds over shifting for soda products, Delipalla and O'Donnell (2001), which analyzes the incidence of cigarette taxes in several European countries and Kenkel (2005), which uses data on how the price of alcoholic beverages changed in Alaska.

Evidence from papers that study recently implemented taxes imposed on soft drinks is mixed; comparing taxed and non-tax products, Grogger (2015) finds that prices rose by more than the amount of the tax following the adoption of the Mexican soda tax in 2014, while Cawley and Frisvold (2017) find under-shifting of the Berkeley soda tax, which they rationalize as due to the ease with which consumers can avoid the tax by shopping in neighboring municipalities.[25] Cawley et al. (2018a) use a differences-in-differences approach and find evidence of average pass-through of around 100% for the Philadelphia soda tax (applied to diet drinks as well as sugary ones) that was introduced in 2017.[26] In an ex ante study of the effects of a sugary soda tax in France, Bonnet and Réquillart (2013) find pass-through that exceeds 100% and also reductions in the prices of diet products. The empirical literature on pass-through of cigarette taxes is similarly mixed; Harding et al. (2012) find taxes in the US are under-shifted and that avoidance opportunities have a sizeable effect on purchases, while Lillard and Sfekas (2013) find evidence of over shifting once the implicit tax in state lawsuits is taken account of.

There is also a related literature that looks at pass-through of cost shocks. Much of this finds under-shifting (see, for instance, Goldberg and Hellerstein (2013) and

[25]Taylor et al. (2018) show evidence that soda sales changed due to the campaign attention and election outcome in Berkeley, California, months before the tax was adopted, suggesting that the media coverage and the election may have had an important impact on purchasing behavior.

[26]Cawley et al. (2018b) also uses a difference-in-difference approach based on consumers within and outside the city, to show a reduction in consumption of taxed drinks, with larger effects for adults than for children.

Nakamura and Zerom (2010)). An important reason for incomplete pass-through of cost shocks is that often not all cost components are affected by the shock. For instance, exchange rate movements do not directly impact the cost of non-traded inputs (Goldberg and Hellerstein (2013)). In a context where firms' marginal costs are observable (in the wholesale electricity market), Fabra and Reguant (2014) find changes in marginal costs are close to fully shifted to prices.

4.2 How well targeted is the tax?

Our tax simulation suggests that consumers that purchase soft drinks will, on average, lower the total amount of sugar they purchase from soft drinks on-the-go by around 195g per annum, which represents an average reduction of 18% of sugar from soft drinks. However, some of this reduction is offset by switching to alternative (non-taxed) drinks that contain sugar. The average reduction in sugar from drinks is around 170g. However, the distribution of reductions in sugar is right skewed with the 75^{th}, 90^{th}, and 95^{th} percentiles being 201g, 451g and 706g.

Key to understanding the effectiveness of a soda tax is whether it successfully achieves reductions in sugar amongst the targeted groups of consumers – the young, youth in low-income households and those with high total annual dietary sugar. In Figure 4.1 we show how the effects of the tax vary across these dimensions. Panels (a)–(c) show how the mean reduction for soft drink purchasers in sugar from both soft drinks and all drinks varies across the distribution of individual age, total annual dietary sugar and total equivalized grocery expenditure.[27] Panels (d)–(e) show how the mean reduction in sugar from all drinks varies jointly with pairs of age, total dietary sugar, and total equivalized expenditure.

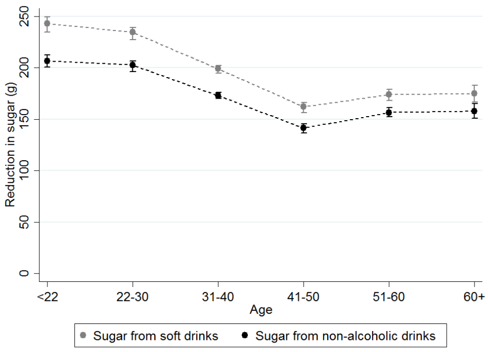
Panels (a)–(c) show that the tax on sugary soft drink products achieves relatively large reductions in sugar among the young and those from households with relatively low total equivalized expenditure, but it is unsuccessful at targeting those individuals with high total dietary sugar (those in the higher deciles of the distribution). Young consumers are both more likely to be impacted by the policy and, conditional on this, exhibit bigger level responses than older groups. While the average percent reduction in sugar from all non-alcoholic drinks is lower for those aged below 22 (11% vs 15% across all individuals), this group obtains a relatively large amount of sugar from products targeted by the tax. This means their level reductions are larger. A similar, if less stark, pattern is true across the equivalized expenditure distribution – those in low deciles are more likely to be soft drink

[27] Tables 2.6–2.8 show how the fraction of individuals who are soft drink purchasers varies across these dimensions.

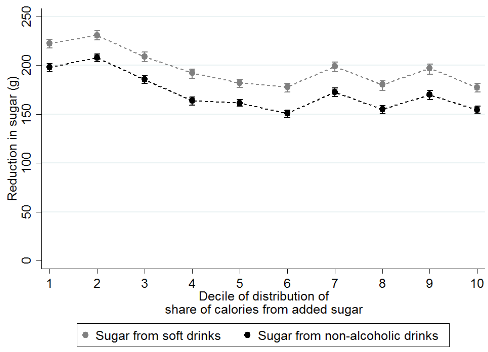
purchases (and therefore impacted by the tax), and conditional on being so exhibit larger level reductions in sugar.

Figure 4.1: *Reductions in sugar from drinks*

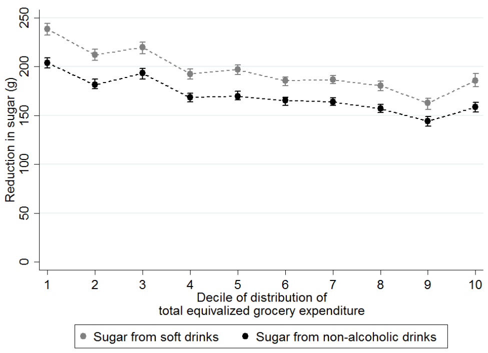
(a) by age



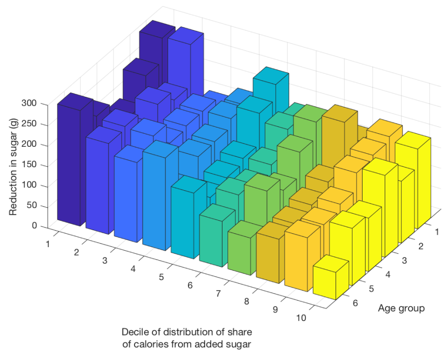
(b) by total annual dietary sugar



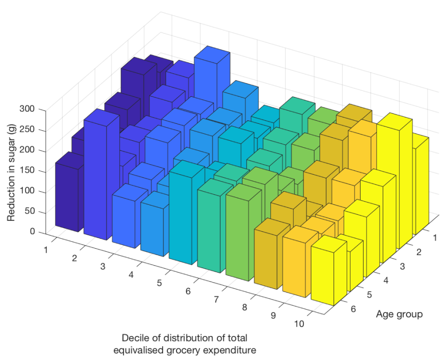
(c) by total equivalized expenditure



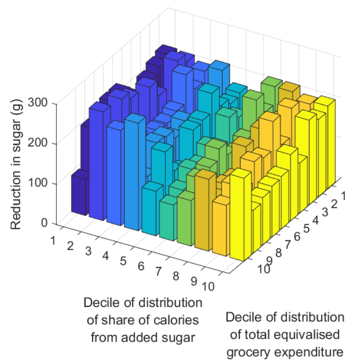
(d) by age and total annual dietary sugar



(e) by age and equivalized expenditure



(f) by total annual dietary sugar and equivalized expenditure



Notes: Figure is based on the 2,374 individuals in the on-the-go estimation sample. It shows how average reduction in annual sugar from drinks varies across the distributions of individual age, total dietary sugar and total equivalized grocery expenditure. Panels (a)–(c) shows numbers for soft drinks and all non-alcoholic drinks (95% confidence bands are shown by bars); panels (d)–(f) shows numbers for non-alcoholic drinks. In panels (d)–(f) age groups are 1=<22, 2=22-30, 3=31-40, 4=41-50, 5=51-60, 6=60+.

Individuals with high total annual dietary sugar are more likely to be soft drink purchasers (and therefore be impacted by the policy) than those lower down the dietary sugar distribution, but, conditional on being affected by the policy, their response, on average, is smaller in level terms (and much smaller in percentage terms – for instance the reduction for the top decile of the dietary sugar distribution is 9 percentage points below that for the bottom decile). This is driven by those with high levels of dietary sugar both having strong sugar preferences and being relatively price insensitive. In contrast, while the young have strong preferences for sugar, they are not particularly price insensitive.

A number of things emerge from panels (d)–(f). The pattern of relatively large responses among the young broadly holds across the deciles of both the total dietary sugar and equivalized expenditure distributions. This suggests the tax is relatively effective at achieving sugar reductions among young people in low income households. Similarly, those individuals from households in the bottom couple of deciles of the equivalized expenditure distributions exhibit relatively large reductions in sugar across all deciles of the total dietary sugar distribution. Among older people, the smallest reductions in sugar are for individuals in the top half of the total dietary sugar distribution.

4.3 Consumer welfare and redistribution

To the extent that higher taxes raise prices they impose an economic burden on consumers; after a tax is introduced consumers can obtain less for a given amount of expenditure than before. In the case of a tax on sugary soft drinks, consumers that buy sugary soft drinks will incur a welfare loss through this channel. Those consumers that never buy soft drinks will see no change in their welfare (we assume that the prices of non soft drink products are unaffected by the tax), while those individuals that drink diet soft drinks may actually benefit slightly as the optimal pricing response to the tax is to lower the price of diet soft drinks.

In Figure 4.2 we describe this effect; 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 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)):

$$cv_{i\tau} = \frac{1}{\alpha_i}\left[\ln\left(\sum_{k\in\Omega_i\cap\Omega_{r_\tau}} \exp(v_{ijr_\tau t_\tau} + \eta_{ijr_\tau t_\tau} - \alpha_i(p_{krt_\tau} - p'_{krt_\tau})\right) - \right.$$
$$\left. \ln\left(\sum_{k\in\Omega_i\cap\Omega_{r_\tau}} \exp(v_{ijr_\tau t_\tau} + \eta_{ijr_\tau t_\tau})\right)\right]$$

where $v_{ijr_\tau t_\tau}$ and $\eta_{ijr_\tau t_\tau}$ are defined in Section 3.1.[28] Summing $cv_{i\tau}$ over an individual's choice occasions in the year gives their annual compensating variation.

Panels (a)-(c) of Figure 4.2 show how compensating variation varies across soft drink purchasers by an individual's age, total annual dietary sugar, and total equivalized expenditure. Panels (d)-(f) show how it varies jointly with pairs of age, total annual dietary sugar, and total equivalized expenditure. Compensating variation is higher for younger individuals, for those with high dietary sugar, and for those from households in the bottom half of the equivalized expenditure distribution. This is mainly driven by these groups obtaining more sugar from soft drinks than other groups. The relatively large compensating variations of the young hold broadly across individuals' positions in the total annual dietary sugar or total equivalized expenditure distribution. Panel (f) shows for high dietary sugar individuals compensating variation is relatively large across the distribution of equivalized expenditure, however for low dietary sugar individuals the largest compensating variations are among those at the bottom of the equivalized expenditure distribution.

If consumers fully accounted for all costs associated with their soft drink consumption, then compensating variation would capture the total effects of the tax on consumer welfare and we could conclude that the tax makes all purchasers of sugary soft drinks worse off, with the largest effects being among the young, those with high levels of dietary sugar, and those from relatively poor households.[29] However, if sugary soft drink consumption is associated with future costs that are not taken account of by the individual at the point of consumption (internalities), or with costs imposed on others (externalities), then compensating variation measured based on revealed preference captures only part of the total consumer welfare effect of the tax.

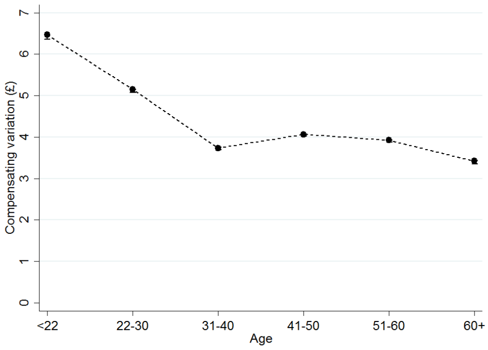
Few would argue that children and young adults fully account for all future costs when making consumption decisions. The average compensating variation for individuals aged 13-21 who are soft drink purchasers is £6.47, while the average reduction in sugar for this group is 207g. If the internality associated with drinking the amount of sugar in a can of Coca Cola is above £1.10, then for the average person aged 13-21 the soda tax will be welfare improving. If tax revenue, which is £3.56 per person, is redistributed lump-sum to soda purchasers then this threshold would be £0.49 per can of Coca Cola (or £0.04 per ounce).

[28]Note, that $v_{ijr_\tau t_\tau}$ is defined such that it includes the effect of price prior to the introduction of the tax.

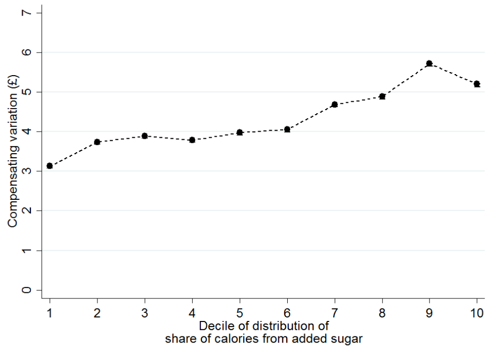
[29]Of course, if the tax revenue was redistributed back to consumers then this could be used to unwind some of these patterns.

Figure 4.2: *Revealed consumer welfare effect*

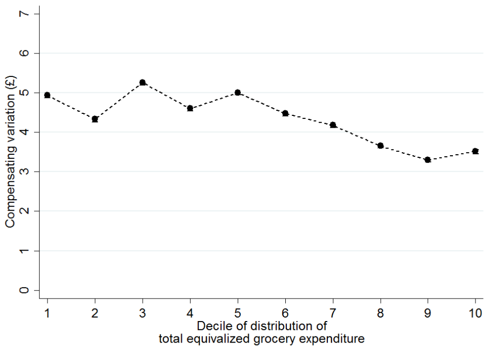
(a) by age



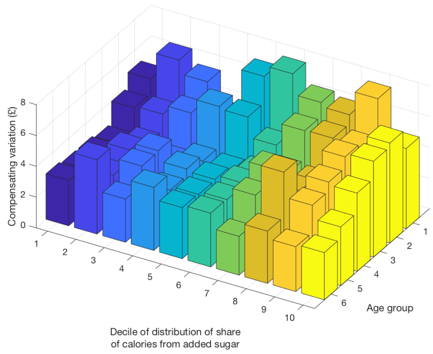
(b) by total annual dietary sugar



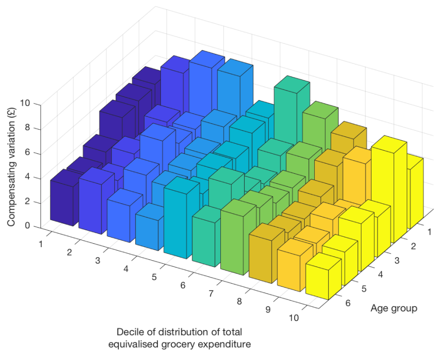
(c) by total equivalized expenditure



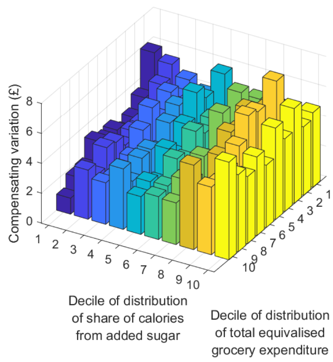
(d) by age and total annual dietary sugar



(e) by age and equivalized expenditure



(f) by total dietary sugar and equivalized expenditure



Notes: Figure is based on the 2,374 individuals in the on-the-go estimation sample. It shows how average compensating variation varies across the distributions of individual age, total dietary sugar and total equivalized grocery expenditure. In panels (a)–(c) 95% confidence bands are shown by bars. In panels (d)–(f) age groups are 1=<22, 2=22-30, 3=31-40, 4=41-50, 5=51-60, 6=60+.

A common concern about excise taxes is that they are regressive. This is typically based on the observation that those with lower incomes tend to be relatively heavy consumers of the taxed product (which, for a small change in price, is a good approximation to the revealed consumer welfare cost). Table 2.8 confirms that, in the case of sugary soft drinks, poorer individuals (those with low total annual equivalized grocery expenditure) are more likely to be soft drink purchasers and to get more sugar from these products; those in the bottom half of the distribution are around 10% more likely to be soft drink purchasers than those in the top half, and conditional on being one, on average obtain 15% more sugar from these products. Our demand and supply estimates suggest that compensating variation for a tax on sugary soft drinks is around 25% higher, on average, for soft drink purchasers in the bottom half of total equivalized grocery expenditure distribution than for those in the top half (see Figure 4.2(c)).

However, if some consumers impose internalities on themselves, then the standard revealed consumer welfare loss (compensating variation) provides an incomplete picture of the redistributive effects of the tax (a point made by Gruber and Koszegi (2004) in the case of cigarette taxation). The mean sugar reductions from the tax are somewhat higher on average among those towards the bottom of the equivalized grocery expenditure distribution compared to those further up (for instance, the average reduction in sugar for those in the bottom half of the distribution is 16% higher than those in the top half). Therefore, if the prevalence of internalities is broadly constant across the expenditure distribution, the larger reductions in sugar among low spending individuals will offset much of the compensating variation difference. If, at the margin, internalities are larger for poorer individuals, the tax may in fact overall be progressive.

5 Robustness

5.1 Substitution to sugar in food

Our analysis so far has considered the impact of a soda tax, incorporating rich patterns of consumer switching across drinks. We have thus far not modeled the possibility that consumers respond to the tax by switching from sugary soft drinks to foods that contain sugar. In this section we explore how important consumer switching from sugar in soft drinks to sugar in food is likely to be. It would be numerically difficult to estimate our model with all food on-the-go items being simultaneous choices. Instead we embed our drinks model into a two stage food on-the-go choice model. We assume that the idiosyncratic unobserved shocks that affect the choice of which drink to consume are unknown in the first stage, thereby allowing us to reduce the dimensionality of parameters generating substitution between drinks and non drinks, whilst still taking account of the heterogeneity in consumer preferences for drinks. In the first stage the consumer takes expectations over the second stage i.i.d. extreme value shocks.

Specifically, suppose the choice model of Section 3 is a second stage of a two-stage decision process, which governs which drink to select, conditional on choosing to purchase a drink. Consider a first stage in which the consumer chooses between chocolate products, a non-sugary snack and a drink. Let $k = \{\varnothing, 1, \ldots, K, \mathcal{D}\}$ denote first stage options. $k = \varnothing$ denotes the first stage outside option of a non-sugary snack, $k = 1, \ldots, K$ indexes chocolate products and $k = \mathcal{D}$ indexes choosing a drink (with the specific drinks product determined by the second stage of the decision problem). Suppose utility from these options takes the form:

$$\begin{aligned}
V_{i\varnothing\tau} &= \varepsilon_{i\varnothing\tau} \\
V_{ik\tau} &= \mu_c + W_{ik\tau} + \varepsilon_{ik\tau} \quad \text{for all } k \in \{1, \ldots, K\} \\
V_{i\mathcal{D}\tau} &= \mu_{i\mathcal{D}} + \psi_{i\mathcal{D}} W_{i\mathcal{D}\tau} + \varepsilon_{i\mathcal{D}\tau},
\end{aligned}$$

where $W_{i\mathcal{D}\tau}$ is the expected utility from choosing the preferred drink product and can be computed using estimates of the second stage choice model and where

$$W_{ik\tau} = \alpha_i p_{krt_\tau} + \beta_i s_k + \vartheta_{b(k)}$$

is the product specific utility from choosing chocolate product k. We assume that the error terms, $(\varepsilon_{i0\tau}, \varepsilon_{i1\tau}, \ldots, \varepsilon_{iK\tau}, \varepsilon_{i\mathcal{D}\tau})$ are distributed i.i.d. extreme value. This extends our choice model to capture switching between drinks, chocolates and non-sugar snacks and allows us to estimate the strength of switching between non-alcoholic drinks and chocolate (see Appendix E for further details).

We estimate the extended choice model allowing both the constant in the drinks pay-off, $\mu_{i\mathcal{D}}$, and the parameter on the expected second stage utility from drinks, $\psi_{i\mathcal{D}}$, to vary across the six age groups across which we describe results in Section 4.2. Table E.1 in Appendix E shows that for each age group the coefficient estimate is positive and statistically significant, indicating that an increase in the price of soft drinks (and thus a fall in the expected utility from choosing the preferred drink) does induce some switching away from drinks and towards foods. However, the strength of this switching to food between the baseline model (results presented in Section 4) and the extended two-stage model is relatively small. Taking account of switching to food sources of sugar dampens the mean overall reduction in sugar by between 9% (for those aged 30-39) to 13% (for those aged 21 or under) and has no bearing on the qualitative relationship that sugar reductions are considerably larger for younger individuals. More broadly, none of our conclusions about the impact of a soda tax are materially affected by accounting for the (limited) switching to sugar in food. Appendix E provides further details.

5.2 Effects in the at-home segment

Our main interest in this paper is in the on-the-go segment of the soft drinks market, which has been much less well studied than the at-home segment. Our counterfactual simulations of price equilibria after the introduction of a tax account for supply linkages across the two segments, but are focused on individual level outcomes in the on-the-go segment of the market. It is difficult to say much about individual level outcomes with household level at-home data without placing considerably more structure on how purchases are shared within the household. Our use of on-the-go data enables us to avoid this. Nonetheless, there might be concern that at-home responses could offset our conclusions about the targeting of the tax based on the on-the-go segment alone.

In order to check the robustness of our results on the targeting of a policy that aims to reduce the consumption of sugary soft drinks, we simulate the effect on drinks purchases of a 10% increase in the price of sugary soft drinks and compare percentage responses in the on-the-go and at-home segment.

Table 5.1 shows the percent changes in sugar from drinks for each of the age groups in the on-the-go and at-home segments. In the on-the-go segment the young exhibit the smaller percentage changes (though of course, they exhibit the largest level changes). For the at-home segment we report percent reductions by age based on the age of the individual from the household that is in the on-the-go sample. In the at-home segment percent changes are close to monotonic in the age groups, with the households that the youngest individuals belong to exhibiting the *largest* percent reductions. Within age group there is a positive correlation in consumer level percent changes in each of the two segments. We believe this evidence suggests it is unlikely that at-home response would undermine our conclusions on the individual targeting of soda taxes. An interesting step for future research would be to couple our demand and supply analysis with a collective model of within household consumption behavior to extent the targeting analysis to household purchase decisions.

Table 5.1: *Effects of 10% price increase on sugar from drinks*

Age group	% change in sugar	
	On-the-go	At-home
<22	-5.32	-8.52
22-30	-6.44	-7.43
31-40	-7.39	-7.29
41-50	-5.79	-7.52
51-60	-6.59	-7.67
>60	-7.53	-6.87

Notes: We simulate the effect of a 10% increase in the price of sugary soda. Columns 1 and 2 shows the percentage change in sugar from drinks in the on-the-go and at-home segments for across all soft drink purchasers.

5.3 Bias correction for incidental parameters problem

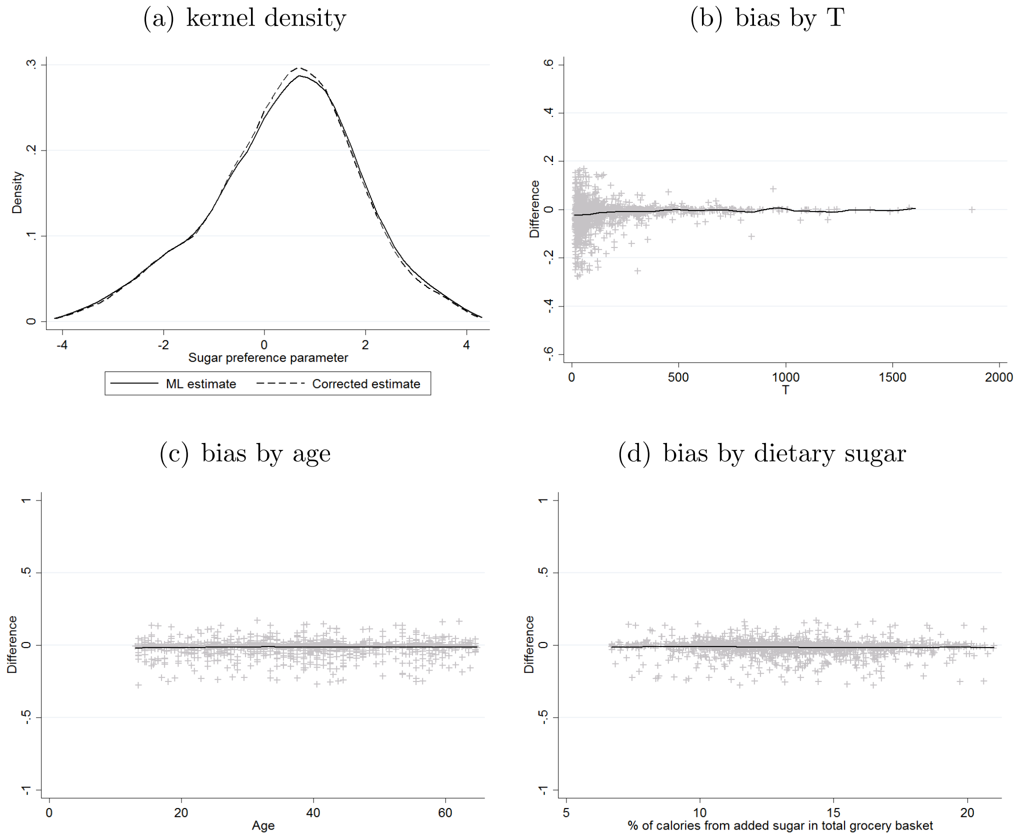
In our non-linear model with fixed effects, maximum likelihood estimates of the parameters may suffer from an incidental parameters problem, noted by Neyman and Scott (1948). Even if both $N \to \infty$ and $T \to \infty$, if N and T grow at the same rate ($\frac{N}{T} \to \rho$ where ρ is a non zero constant), our fixed effect estimator will be asymptotically biased (Arellano and Hahn (2007)). Bias correction methods exist that reduce the bias from being of order $1/T$ to $1/T^2$.

A range of bias correction methods exist (see surveys in Arellano and Hahn (2007), Arellano and Bonhomme (2011)). We use panel jackknife methods (Hahn and Newey (2004)), employing the split sample procedure suggested in Dhaene and Jochmans (2015). This entails obtaining estimates of the model parameters $\theta = (\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\eta})$ based on splitting the sample into two non-overlapping random sub-samples. Each sub-sample contains one half of the choice occasions for each individual. We denote the maximum likelihood estimate for the full sample $\widehat{\theta}$ and the estimate for the two subsamples $\widehat{\theta}_{(1,T/2)}$ and $\widehat{\theta}_{(T/2,T)}$. The jackknife (bias corrected) estimator is:

$$\widetilde{\theta}_{split} = 2\widehat{\theta} - \frac{\widehat{\theta}_{(1,T/2)} + \widehat{\theta}_{(T/2,T)}}{2}.$$

In Figure 5.1 we graph the difference between the jackknife (bias corrected) and maximum likelihood sugar preference parameters for the on-the-go segment. Panel (a) shows the distribution of estimates (for those with finite sugar preferences) for the maximum likelihood and jackknife estimates. Panel (b) shows how the difference in these estimates relates to the number of choice occasions a consumer is observed on in the sample. Panels (c) and (d) show how the difference relates to consumers' age and total dietary sugar.

Figure 5.1: *Sugar preference parameters*



Notes: Graphs are based on preferences estimates in the on-the-go segment. In panels (b)-(d) markers represent consumer level differences. Lines are local polynomial regressions.

The figure shows that the difference between the two estimates is small; the standard deviation of the sugar preference parameter estimates is 1.8, while the average absolute difference between the jackknife and maximum likelihood estimates is 0.06. The difference is decreasing in T; individuals in the sample for a relatively small number of choice occasions tend to have higher differences than those in the sample relatively many times. However, conditional on T, the average difference between the jackknife and maximum likelihood estimates is zero – a positive difference is equally likely as a negative difference. Indeed, the distribution of the maximum likelihood and jackknife estimates of the preference parameters are almost indistinguishable and the difference between the jackknife and maximum likelihood estimates is completely unrelated to individuals' age or total dietary sugar.

In Appendix B.3 we show that similar conclusions to those for sugar hold for estimated price and soft drink preferences; the maximum likelihood and jackknife procedures yield almost identical preference distributions, any individual level differences are relatively small and are equally likely to be positive or negative and there is no systematic relationship with the key variables that we relate our demand effects to. For instance, the average absolute difference between the jackknife and maximum likelihood estimates is 0.2 (relative to a mean of -3.1). For the soft drink preferences the average absolute difference is 0.1. As a consequence, our results regarding the effectiveness of soda taxes are robust to the bias correction procedure.

6 Summary and conclusion

Corrective taxes have traditionally been applied to alcohol, tobacco and gambling. Recently there has been a drive to extend them to cover some types of foods, with soda taxes being at the vanguard of this move. The principal economic rationale for such taxes is that they discourage consumption that generates costs not taken account of by individuals at the point of consumption. In the case of sugar, there is clear medical evidence that excess consumption can lead to large future costs, while almost all individuals exceed official recommendations on how much to consume. It is plausible that, at least for some consumers, these health costs are not factored in at the point of consumption. This is most obviously true for young people, but is also likely to be the case for some individuals with high total dietary sugar and who therefore are at elevated risk of suffering health problems. The efficacy of a soda tax relies on to what extent it can encourage these groups to avoid internalities and at what cost to consumers in terms of welfare loss associated with higher prices.

Our results show that young consumers would lower their sugar consumption by more than older individuals in response to a soda tax. The tax does therefore succeed in achieving relatively large reductions in sugar among one group most likely to suffer from internalities. However, the young also loose out most in terms of direct consumer surplus loss due to higher prices. The relatively large internalities some young people are likely impose on themselves raises the probability that the gain from averted internalities will outweigh this. The performance of the tax in terms of reducing the sugar intake of those with the most sugary diets is less good – those with high total dietary sugar are relatively price inelastic and therefore fail to lower their sugar consumption in response to the tax by more than more moderate sugar consumers. Nevertheless, if internalities are sufficiently convex in total sugar, this group may still benefit from the tax. The redistributive properties of the tax are more attractive than one based purely on traditional economic tax incidence. While the traditional economic burden of the tax falls, to a moderate extent, disproportionately on the poor, the poor also lower their sugar consumption to a somewhat larger extent and therefore are likely to benefit by more than better off consumers due to averted internalities. Our results are among the very first based on individual level choice behavior, while on-the-go, making the patterns of response we uncover particularly noteworthy.

In our analysis we have taken account both of consumer demand responses and the equilibrium pricing response of soft drink manufacturers. In the longer run we would expect firms to also respond to the tax by changing their product portfolios and changing the sugar content of existing products. Our results therefore provide a picture to the short-medium run impact of soda taxes. An important direction for future work will be to incorporate how firm portfolio choice will be affected by such policies.

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Appendix

How well targeted are soda taxes?

Pierre Dubois, Rachel Griffith and Martin O'Connell

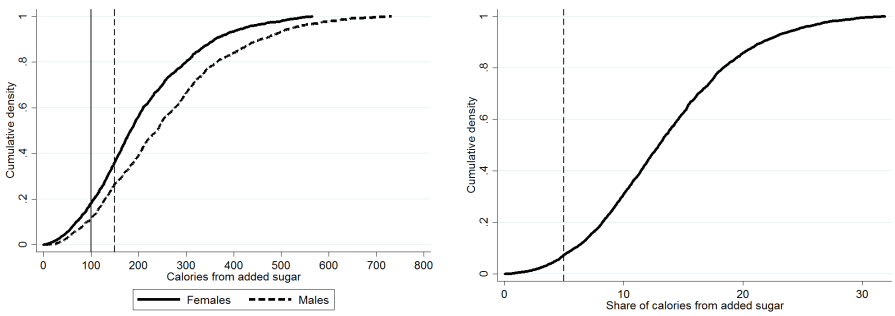
A Data appendix

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

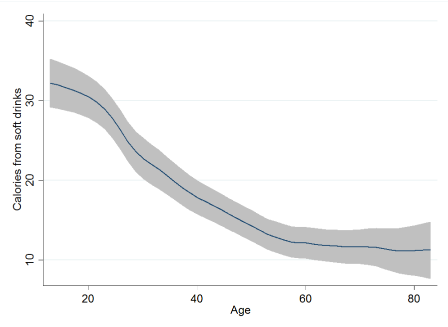


Notes: Numbers using National Diet and Nutrition Survey 2008-2011 for a representative sample of 3,073 UK adults and children. For each distribution we trim the top percentile. Vertical lines denote medical guidelines.

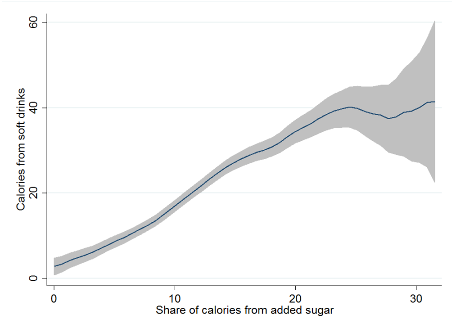
In Figure A.2 we show local polynomial regressions describing how the calories from (the sugar in) soft drinks varies with age, share of calories from added sugar and equivalized household income. The figure shows that young individuals, those with a high share of calories from added sugar, and those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

Figure A.2: *Sugar from soft drinks*

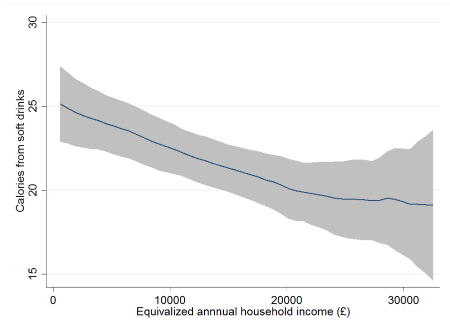
(a) by age



(b) by calories from added sugar



(c) by equivalized income

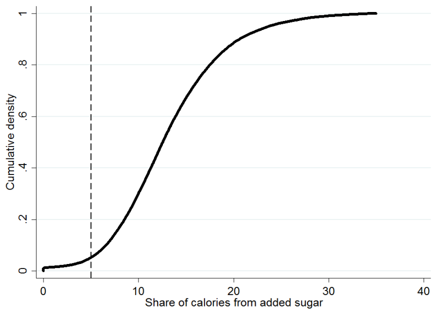


Notes: Numbers using National Diet and Nutrition Survey 2008-2011 for a representative sample of 3,073 UK adults and children. Lines are based on local polynomial regressions. Shared area are 95% confidence bands. For each variable we trim the top percentile of the distribution.

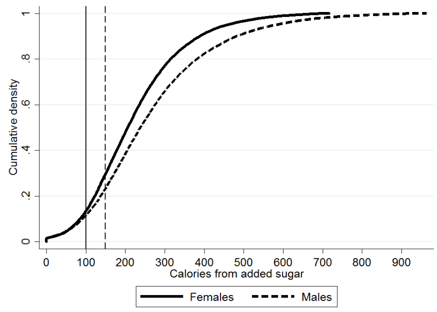
In Figures A.3 and A.4 we repeat Figures A.1 and A.2 with US data. Specifically, we use National Health and Nutrition Examination Study over 2007-2014, a sample of 39,189 adults and children. The same patterns hold in the US. Notice, the level of calories from soft drinks reported for the US in the National 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



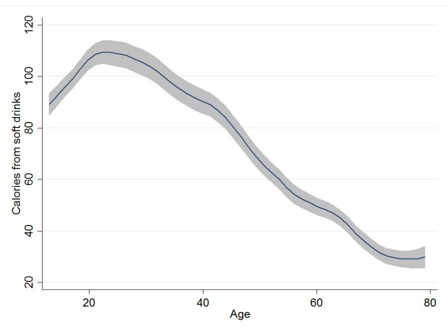
(b) % of calories from added sugar



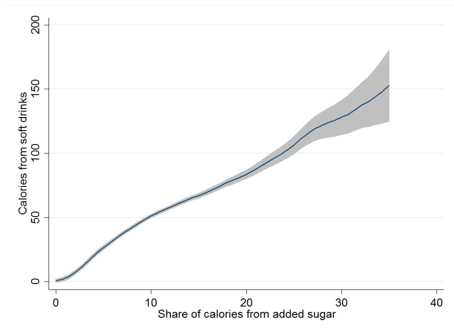
Notes: Numbers using National Health and Nutrition Examination Study 2007-2014 for a representative sample of 39,189 US adults and children. For each distribution we trim the top percentile. Vertical lines denote medical guidelines.

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

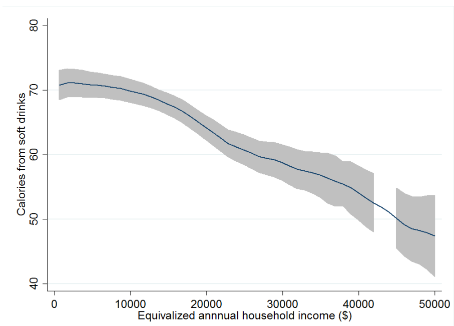
(a) by age



(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. Shared area are 95% confidence bands. For each variable we trim the top percentile of the distribution.

A.2 Comparison of Worldpanel with LCFS

In Table A.1 we compare some key demographics for the households in the Kantar Worldpanel in 2011 with those households in the Living Costs and Food Survey (LCFS), which is the standard UK consumption survey collected by the Office of National Statistics (similar to the CEX in the US).

Table A.1: *Sample descriptive statistics in LCFS and Kantar Worldpanel*

	LCFS	Kantar Worldpanel
Number of households	5,691	18,713
Mean age of household's adult members	50.79	50.90
	[50.36, 51.22]	[50.68, 51.11]
Number of household members	2.36	2.58
	[2.33, 2.39]	[2.56, 2.60]
SES: Highly skilled	0.19	0.20
	[0.18, 0.20]	[0.20, 0.21]
SES: Semi-skilled	0.53	0.57
	[0.51, 0.55]	[0.56, 0.58]
SES: Unskilled	0.28	0.23
	[0.27, 0.29]	[0.22, 0.24]
Region: North	0.34	0.35
	[0.33, 0.36]	[0.34, 0.35]
Region: Central	0.34	0.33
	[0.33, 0.35]	[0.32, 0.33]
Region: South	0.32	0.33
	[0.30, 0.33]	[0.32, 0.33]

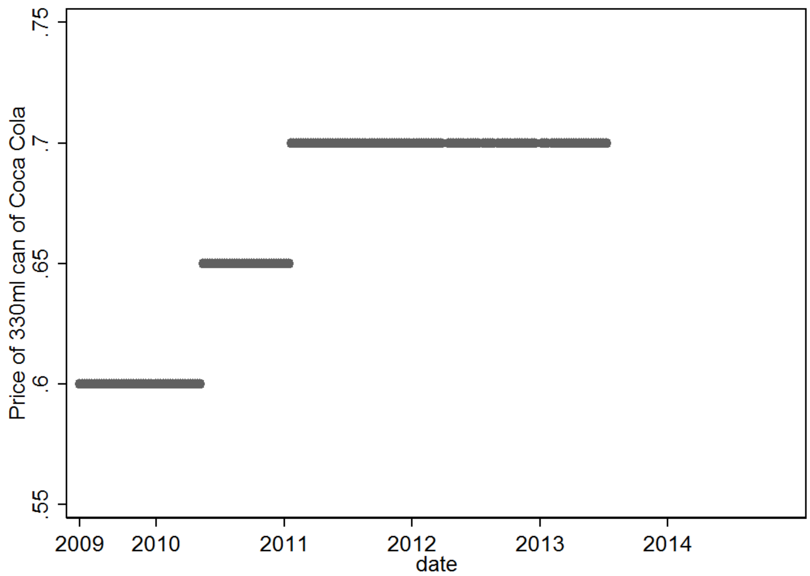
Notes: The first row shows the number of households in the Living Costs and Food Survey (LCFS) and the Kantar Worldpanel in 2011. The remaining rows show the mean of each variable listed in column (1) for each of the samples. The SES and region variables are dummy variables. 95% confidence intervals are shown below each cell.

A.3 Variation in prices

Product prices vary over time and across retail outlets. We compute the mean monthly price for each product in each retail outlet (allowing for regional variation across convenience and independent stores) and use this in demand estimation. On each choice occasion we observe where an individual shops, we assume (conditional on all the controls in the demand model) that this is independent of demand shocks for specific products, and we assume that the consumer faces the vector of prices for products in the retailer that we observe them shopping in. We exploit two sources of price variation; differential across retailer time series variation and within brand variation in the extent of non-linear pricing – see Section 3.2.

In order to illustrate that the variation originates from true variation over time within consumer and across stores in prices, in this appendix we provide some additional description of individual level variation in transaction prices in products over time and across stores. Figure A.5 shows an example of the raw data. This is a scatter plot of the 838 observed transaction prices for one individual who has purchased a 330ml can of Coca Cola from a vending machine on a regular basis. We see that the price rose on two occasions, from 60p to 65p on 12 May 2010, and from 65p to 70p on 20 January 2011.

Figure A.5: *Observed transaction prices for one individual from a vending machine*



Notes: The figure shows all observed transaction prices for a single individual for purchases of 330ml can of Coca Cola from vending machines.

This is one example. To show the full variation in our data we describe the variation in observed transaction prices for each individual over time within a store. For each individual and product we compute the coefficient of variation of transaction prices within each retailer type. This captures variation in prices within retailer (if a consumer shops at different stores within the same retailer type, for example, visits different vending machines, then we will also pick up this variation, but this is small relative to within retailer time series variation).

Table A.2 shows quantiles of the individual consumer level coefficients of variation of prices within product and retailer (in the on-the-go segment of the market) over time. A coefficient of 0.10 means that the standard deviation is 10% of the average price.

The quantiles reported by product in Table A.2 show that for each product, more than half and sometimes more than 75% of the consumer-retailer level coefficient of variation of prices is strictly positive. We find some cases of zero variation, reflecting individuals who are non-frequent purchasers of specific products in a particular retailer, and so for whom we only observe a few transaction prices. As prices will vary even when consumers do not purchase, the share of consumer-retailer observations exposed to true zero price variation is necessarily even lower. The table also shows that most individuals in our data are exposed to substantial variation in product-retailer prices series before aggregation.

Table A.2: *Variation over time: by product distribution of individual-retailer coefficient of variation of transaction prices*

Product	Mean	Q10	Q25	Q50	Q75	Q90
Coca Cola 330	.102	0	.0139	.0812	.156	.236
Coca Cola 500	.109	0	.0401	.0897	.159	.236
Dr Pepper 330	.0886	0	0	.0456	.118	.26
Dr Pepper 500	.0924	0	.00905	.0716	.137	.223
Fanta 330	.0811	0	0	.0454	.136	.231
Fanta 500	.0878	0	.00652	.0661	.131	.216
Cherry Coke 330	.0818	0	0	.0527	.121	.22
Cherry Coke 500	.078	0	.00711	.0604	.117	.195
Oasis 500	.0931	0	.019	.0787	.138	.209
Pepsi 330	.131	0	0	.0867	.202	.349
Pepsi 500	.151	0	.0444	.118	.232	.345
Lucozade Energy 380	.104	0	0	.0823	.164	.258
Lucozade Energy 500	.0966	0	.016	.0792	.145	.221
Ribena 288	.0992	0	0	.0741	.161	.241
Ribena 500	.0955	0	0	.072	.139	.228
Other	.215	0	.0773	.183	.325	.458
Other Diet	.174	0	.0345	.135	.263	.404
Fruit juice	.23	0	.0842	.212	.346	.474
Flavoured milk	.189	0	.0351	.155	.302	.42
Fruit water	.103	0	0	.0679	.169	.254
Water	.218	0	.0621	.184	.326	.481

Notes: Quantiles of the distribution across individuals of the coefficient of variation over time of individual transaction prices. The coefficient of variation is the ratio of the standard deviation over time of prices paid for that product by an individual consumer within a retailer divided by the mean price paid by that individual for that product in that retailer.

To quantify the variation that each consumer faces further, in Table A.3 we show the share of retailer-product level time series that an individual consumer faces that are zero. If prices of one product do not vary over time, so the coefficient of variation for that retailer-product is zero, the consumer could still face relative price variation if the prices of other products vary. The table shows that for the majority of individuals (59%) all of the retailer-product price vectors show variation over time, and for 95% less than 10% of the price series they face have no variation. For no individual do more than half of the price series that they face not vary over time.

Table A.3: *% of price series where an individual faces no variation*

% price series with *no* variation over time	Frequence	%	Cumulative %
0%	1,441	59.32	59.32
5%	667	27.46	86.78
10%	219	9.02	95.80
14%	62	2.55	98.35
19%	25	1.03	99.38
24%	11	0.45	99.84
29%	2	0.08	99.92
33%	1	0.04	99.96
48%	1	0.04	100.00
All	2,429	100.00	

Notes: For each individual we compute product-retailer price series based on their transaction prices. Table describes the number of the individual level price series with zero variation.

Tables A.4 and A.5 show the same statistics for the coefficient of variation using the average monthly prices that we use for estimation of the demand model. Table A.4 is based on chosen options; Table A.5 is based on all options in individual-retailer choice sets. While the means are lower than in Table A.2, it shows that there is still considerable variation over time within individual, product and retailer. In estimation we control for brand time effects and other covariates that will absorb some of this variation.

Table A.4: *Variation over time: by product distribution of individual-retailer coefficient of variation of average monthly prices of products purchased*

Product	Mean	Q10	Q25	Q50	Q75	Q90
Coca Cola 330	.0335	.00307	.0114	.0263	.0478	.0698
Coca Cola 500	.0343	.00343	.0116	.0313	.0519	.0686
Dr Pepper 330	.048	.00181	.0199	.0431	.0686	.098
Dr Pepper 500	.0372	.00294	.0103	.0294	.0528	.0836
Fanta 330	.0486	.00246	.0159	.0396	.0653	.103
Fanta 500	.03	.00152	.00826	.0247	.0446	.0653
Cherry Coke 330	.0399	.011	.0201	.036	.0541	.0757
Cherry Coke 500	.0284	.00213	.00759	.021	.0424	.0675
Oasis 500	.0304	.00226	.00931	.0237	.047	.0657
Pepsi 330	.057	.00572	.0219	.048	.0795	.117
Pepsi 500	.0313	.00365	.0141	.0301	.0426	.0599
Lucozade Energy 380	.031	.00141	.0112	.0252	.0463	.0646
Lucozade Energy 500	.0327	.00189	.0102	.0287	.0489	.0709
Ribena 288	.0426	.00485	.018	.0377	.061	.0816
Ribena 500	.0367	.00167	.01	.0266	.0492	.085
Other	.0473	.00643	.02	.0416	.0645	.0946
Other Diet	.055	.00572	.0211	.0519	.0786	.109
Fruit juice	.064	.00654	.0252	.0597	.0937	.125
Flavoured milk	.0579	.00242	.0177	.047	.0869	.129
Fruit water	.0385	.00112	.0141	.0322	.0527	.0819
Water	.0526	.00564	.0195	.0458	.077	.106

Notes: Quantiles of the distribution across individuals of the coefficient of variation over time of prices used in demand estimation. The coefficient of variation is the ratio of the standard deviation over time of price divided by the mean price for that product in that retailer.

Table A.5: *Variation over time: by product distribution of individual-retailer coefficient of variation of average monthly prices of all options*

Product	Mean	Q10	Q25	Q50	Q75	Q90
Coca Cola 330	.0442	.00453	.0211	.0429	.0651	.0822
Coca Cola 500	.0361	.00236	.0154	.037	.0551	.0658
Dr Pepper 330	.0654	.0251	.0448	.0594	.0885	.107
Dr Pepper 500	.0483	.004	.0243	.0453	.0712	.0933
Fanta 330	.0516	.0000187	.00148	.0526	.0727	.114
Fanta 500	.0346	.00225	.0177	.0339	.0499	.0645
Cherry Coke 330	.0527	.023	.0361	.0503	.0646	.0863
Cherry Coke 500	.0337	.00327	.0153	.0316	.051	.0655
Oasis 500	.0353	.00365	.0171	.0363	.0513	.0635
Pepsi 330	.089	.00582	.0374	.07	.128	.206
Pepsi 500	.0337	.00409	.0221	.0347	.0457	.0574
Lucozade Energy 380	.0449	.0162	.0306	.0453	.0596	.0695
Lucozade Energy 500	.0426	.0139	.0277	.0435	.0576	.068
Ribena 288	.0543	.0201	.0347	.0543	.0735	.0874
Ribena 500	.0436	.00387	.0256	.039	.0584	.0825
Other	.0586	.0189	.0357	.0521	.0797	.106
Other Diet	.0703	.0307	.0518	.0694	.0871	.111
Fruit juice	.0756	.0256	.0467	.0735	.102	.126
Flavoured milk	.0802	.0242	.0446	.0764	.106	.139
Fruit water	.0606	.022	.0354	.0559	.0811	.109
Water	.0632	.0206	.0392	.0617	.0831	.107

Notes: Quantiles of the distribution across individuals of the coefficient of variation over time of prices used in demand estimation. The coefficient of variation is the ratio of the standard deviation over time of price divided by the mean price for that product in that retailer.

We exploit the fact that individuals face different vectors of prices when they (exogenously) purchase from a different retailer. Table A.6 gives an example of this price variation for the same individual shown in Figure A.5. On 25 June 2009 we observe this individual purchasing a 330ml can of Coca Cola from a vending machine. On 10 October 2009 we observe this same individual purchasing a 380ml bottle of Lucozade Energy drink from a small corner store. Comparing the vectors of prices they faced the can of Coca Cola was relatively cheap on 25 June (Coke was 58% the price of Lucozade) compared with on 10 October (when Coke was 60% of the price of Lucozade). We include time-varying brand effects and retailer-drink type effects (along with other covariates) which absorb some of this variation, but there remains considerable residual variation.

Table A.6: *Price vectors for one individual on two different days*

Product	Vending machine 25 June 2009	Corner store 10 October 2009
Coca Cola 330	**0.60**	0.54
Coca Cola 500	1.09	1.03
Dr Pepper 330		0.57
Dr Pepper 500		0.95
Fanta 330	0.59	0.53
Fanta 500	1.05	1.09
Cherry Coke 500	1.00	1.01
Oasis 500	0.98	0.94
Pepsi 330	0.60	0.60
Pepsi 500	1.02	0.98
Lucozade Energy 380	1.03	**0.90**
Ribena 500		1.03
Other	1.03	1.02
Other Diet	1.30	1.35

Notes: Numbers show price vector, based on prices used in estimation, facing one example individual on two different choice occasions.

As a final exercise we regress the monthly price on all covariates included in the demand model and describe the distribution of coefficient of variation of the residual of this regression for each individual as above. This is shown in Table A.7.

Table A.7: *Variation over time: by product distribution of individual-retailer coefficient of variation of residualized average monthly prices of all options*

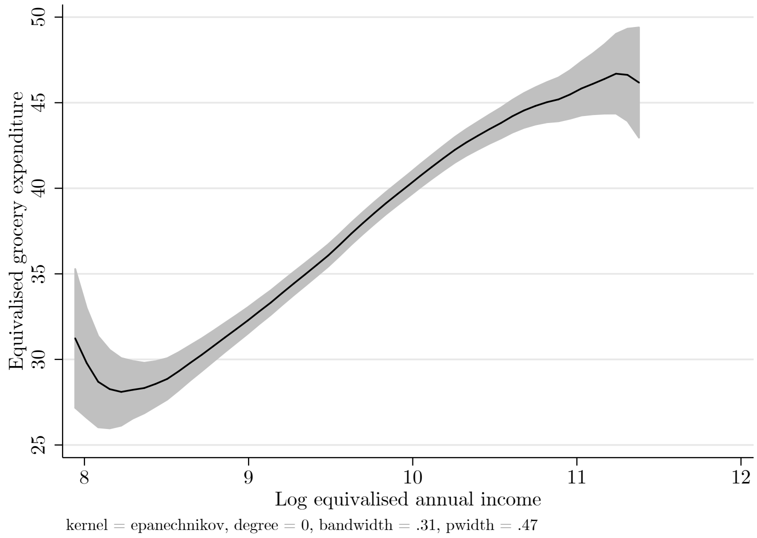
Product	Mean	Q10	Q25	Q50	Q75	Q90
Coca Cola 330	.0293	.0159	.0195	.0262	.0372	.0483
Coca Cola 500	.0234	.0157	.0189	.0225	.0278	.0326
Dr Pepper 330	.0426	.0153	.0289	.0419	.0566	.0677
Dr Pepper 500	.0413	.0195	.0243	.0376	.054	.0705
Fanta 330	.0311	.00565	.00971	.0326	.0433	.0571
Fanta 500	.0312	.0161	.0195	.0291	.04	.0504
Cherry Coke 330	.0319	.0129	.0216	.0312	.0387	.0488
Cherry Coke 500	.028	.0159	.0192	.0221	.0353	.0502
Oasis 500	.0243	.0153	.0178	.0204	.0306	.0393
Pepsi 330	.0375	.0182	.0227	.0305	.0464	.0727
Pepsi 500	.0335	.0185	.0231	.034	.0418	.0486
Lucozade Energy 380	.0389	.0165	.0266	.0391	.0497	.06
Lucozade Energy 500	.0406	.0156	.027	.041	.0537	.0652
Ribena 288	.0335	.0121	.0217	.0345	.045	.0526
Ribena 500	.0485	.0195	.0308	.0485	.0605	.0733
Other	.0637	.0227	.042	.0582	.0831	.112
Other Diet	.0933	.0385	.0659	.0934	.118	.147
Fruit juice	.0738	.0281	.0481	.0747	.0946	.113
Flavoured milk	.0686	.0279	.042	.0611	.0861	.126
Fruit water	.0454	.0158	.027	.042	.062	.0787
Water	.0327	.0105	.0166	.0288	.0406	.0599

Notes: Quantiles of the distribution across individuals of the coefficient of variation over time of the residualized prices used in demand estimation. The coefficient of variation is the ratio of the standard deviation over time of price divided by the mean price for that product in that retailer.

A.4 Relationship between equivalized expenditure and income

We use total household grocery expenditure to proxy for household income. The Living Costs and Food Survey (LCFS) is an expenditure survey that collects data on spending for a repeated cross-section of households. It also contains information on household income. Figure A.6 shows that there is a strong relationship between households' annual equivalized income and equivalized weekly grocery spending.

Figure A.6: *Relationship between household income and grocery expenditure*



Notes: Figure drawn using data on 4937 households in the Living Costs and Food Survey 2011. The horizontal axis shows logged equivalized annual income of the household, and the vertical axis shows equivalized weekly grocery expenditure. Figure trims the 5th and 95th percentiles of the logged equivalized annual income distribution. We equivalize using the standard OECD modified equivalence scale (see Hagenaars et al. (1994)).

A.5 Demand linkages between on-the-go and at-home segments

For each of the 2,374 individuals in the on-the-go estimation sample we consider one observation for every day (regardless of whether a non-alcoholic drink is purchased or not) between the individual's first and final day in the sample. We regress a dummy for whether the individual purchased a non-alcoholic drink on a particular day on dummy variables for whether the individual's household purchased non-alcoholic drinks in the at-home segment in each of the 4 preceding 7 day periods (column (1) of Table A.8) and on each of the preceding 7 days (column (3) of Table A.8). We also regress the volume of non-alcoholic drinks an individual buys on the volume bought in the at-home segment in each of the 4 preceding 7 day periods (column (2) of Table A.8) and on each of the preceding 7 days (column (4) of Table A.8). In each case we include individual and year-month effects.

The coefficient estimates in Table A.8 indicate very little evidence of dependence between current on-the-go purchases and recent purchases at-home. A number of the coefficients are statistically significant, however, this is driven by the very large sample size. The magnitude of the effects is very small. For instance, the average effect of purchases in the at-home segment in the past 4 weeks is associated with a *raised* probability of buying on-the-go of 0.005 (relative to a mean of 0.14) and *raised* volume purchased of 2ml (relative to a mean of 80ml). As well as being very small, the direction of these effects are opposite to what we would expect if consumers viewed on-the-go and at-home consumption as substitutes.

Our conclusion from this is that, once individual heterogeneity is accounted for, there is little evidence that demand linkages are of first order importance in the current context. While it would be interesting to study more broadly the interactions between household grocery demand and individual on-the-go grocery demand, we leave this for future work.

Table A.8: *Relationship between purchases on-the-go and at-home*

	(1) Purchases	(2) Volume	(3) Purchases	(4) Volume
Purchased at home in last week	0.0055	0.0002		
	(0.0006)	(0.0001)		
Purchased at home 2 weeks ago	0.0044	0.0002		
	(0.0005)	(0.0001)		
Purchased at home 3 weeks ago	0.0029	0.0002		
	(0.0005)	(0.0001)		
Purchased at home 4 weeks ago	0.0025	0.0001		
	(0.0005)	(0.0001)		
Purchased at home yesterday			-0.0018	-0.0002
			(0.0013)	(0.0002)
Purchased at home 2 days ago			-0.0007	-0.0001
			(0.0012)	(0.0002)
Purchased at home 3 days ago			0.0035	0.0001
			(0.0011)	(0.0001)
Purchased at home 4 days ago			0.0073	0.0005
			(0.0011)	(0.0002)
Purchased at home 5 days ago			0.0077	0.0005
			(0.0011)	(0.0001)
Purchased at home 6 days ago			0.0083	0.0006
			(0.0011)	(0.0002)
Purchased at home 7 days ago			0.0082	0.0005
			(0.0013)	(0.0002)
Constant	0.1402	0.0818	0.1435	0.0827
	(0.0044)	(0.0029)	(0.0044)	(0.0029)
N	3,420,627	3,420,627	3,488,632	3,488,632
Year-month effects	yes	yes	yes	yes
Individual effects	yes	yes	yes	yes

Notes: Column (1) reports coefficients of regression of a dummy for on-the-go purchase on dummies for at-home purchases in each of past 4 weeks. Column (2) reports coefficients of regression of volume of on-the-go purchase on volume of at-home purchases in each of past 4 weeks. Columns (3) and (4) repeat the analysis in (1) and (2) instead focusing on the effect of at-home purchases in each of the previous 7 days. There is an observation for every day between the first and final day in the sample for each of the 2,374 individuals in the on-the-go estimation sample.

B Further details of demand estimates

B.1 On-the-go segment

In Table 3.1 we summarize moments of the distribution of estimated consumer specific preferences. Table B.1 provides details of the estimated demographic group specific preference parameters.

Demand for soft drinks versus alternatives may fluctuate with weather conditions. To account for this in our demand model we use the mean temperature by day from the Met Office Historic station data. These data are reported monthly for 35 locations in the UK.[30] For each demographic group the effect of temperature is negative – this indicates that during warm periods individuals are more likely than normal to purchase an alternative (non soft drink) product than a soft drink.

The table also reports size effects (where the omitted group is a 500ml bottle) and brand effects. As we include a (consumer specific) soft drinks preference parameter, we omit both a Coca Cola brand effect and an outside option (bottled water) effect.[31]

[30]The data are available at https://www.metoffice.gov.uk/public/weather/climate-historic/#?tab=climateHistoric

[31]We do not report the time varying brand effects or the retailer effects. These are available upon request.

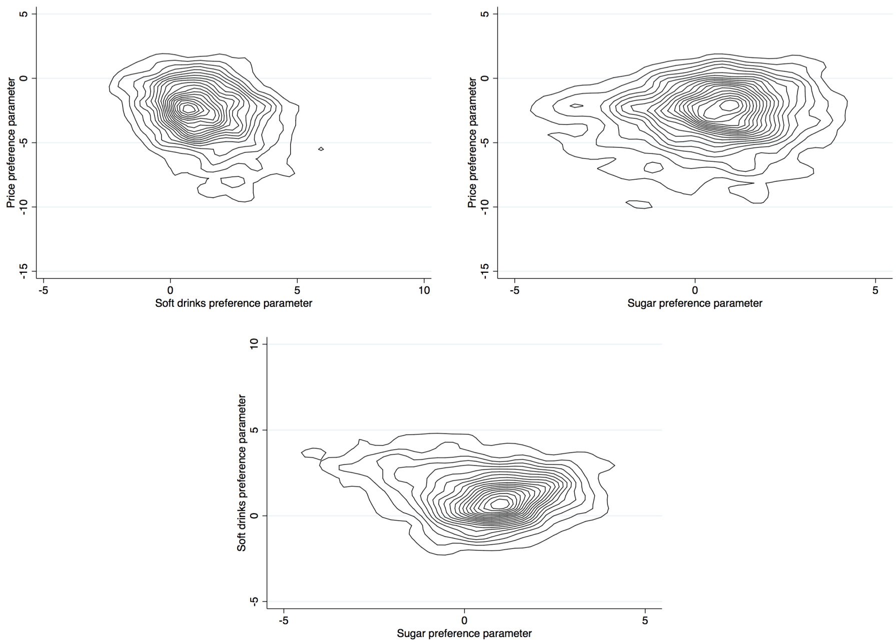
Table B.1: *Demand model estimates: demographic specific preferences – on-the-go*

Variable	*Female - <40* Estimate	Standard error	*Female - 40+* Estimate	Standard error	*Male - <40* Estimate	Standard error	*Male - 40+* Estimate	Standard error
Temperature	-0.0039	0.0042	-0.0018	0.0039	-0.0031	0.0041	-0.0102	0.0038
288ml carton	-1.0890	0.0454	-1.7468	0.0547	-2.1261	0.0493	-2.2692	0.0544
330ml can	-2.7766	0.0293	-2.7350	0.0295	-2.7673	0.0252	-2.9435	0.0275
380ml bottle	-0.2643	0.0384	-0.3738	0.0354	-0.5636	0.0294	-0.3636	0.0311
Dr Pepper	-1.5706	0.0468	-2.7651	0.0531	-1.6008	0.0445	-2.1560	0.0413
Fanta	-1.6302	0.0467	-1.9179	0.0486	-2.0054	0.0454	-1.6862	0.0396
Cherry Coke	-1.9810	0.0482	-2.5402	0.0518	-2.0021	0.0458	-1.8900	0.0405
Oasis	-1.5748	0.0469	-1.6399	0.0479	-1.5841	0.0449	-1.6256	0.0399
Pepsi	-1.3705	0.0520	-1.3766	0.0494	-1.4033	0.0482	-1.7350	0.0478
Lucozade	-1.7856	0.0672	-1.3013	0.0586	-1.2529	0.0570	-1.4363	0.0525
Ribena	-2.2299	0.0651	-2.0530	0.0574	-2.1882	0.0569	-2.1148	0.0521
Other soda	-0.7566	0.0569	-0.3382	0.0524	0.0370	0.0462	-0.3866	0.0446
Fruit juice	3.5904	0.0996	3.8352	0.0914	3.0910	0.1030	3.7545	0.0963
Flavoured milk	-0.9563	0.0914	-1.4490	0.0848	-1.1970	0.0972	-1.7485	0.0916
Flavoured water	-1.7236	0.0927	-1.7726	0.0844	-2.6850	0.1037	-2.2541	0.0929
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 2,374 individuals who we observe on 361,863 on-the-go choice occasions. The table shows estimates of the demographic specific preference parameters. Brand effects are shown for a baseline period. We allow these to vary across years and quarters.

In Figure B.1 we plot contour plots of the bivariate preference distributions (based on the finite parts of the distribution).

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



Notes: Distribution plots use consumers with finite preference parameters, those having infinite distaste for soft drinks or sugar are not included in this graph.

In Tables B.2 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 2-4 report how demand for alternative products (sugary soft drinks, diet soft drinks and alternative sugary 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 the most popular sugary product, Coca Cola 500 (a 500ml bottle of Coca Cola), would result in a reduction in demand for that product of 2.27%. Demand for alternative sugary soft drinks would rise by around 0.41%, demand for diet soft drinks would rise by 0.18% and demand for alternative sugary drinks would rise by 0.25%. Demand for soft drinks and alternative sugary drinks as a whole would fall by 0.06%. In Table B.3 we report price elasticities for all sugary soft drinks and all soft drinks.

Table B.2: *Price elasticities – on-the-go*

	Own demand	Effect of 1% price increase on: cross demand for: sugary soft drinks	diet soft drinks	sugary alternatives	Total demand
Coca Cola 330	-2.91	0.16	0.08	0.07	0.02
	[-2.96, -2.90]	[0.16, 0.17]	[0.08, 0.09]	[0.07, 0.08]	[0.02, 0.02]
Coca Cola 500	-2.27	0.41	0.18	0.25	-0.06
	[-2.30, -2.21]	[0.40, 0.41]	[0.18, 0.19]	[0.24, 0.25]	[-0.06, -0.06]
Coca Cola Diet 330	-2.90	0.06	0.29	0.02	0.02
	[-2.93, -2.88]	[0.06, 0.07]	[0.29, 0.29]	[0.02, 0.02]	[0.02, 0.02]
Coca Cola Diet 500	-2.72	0.14	0.53	0.09	-0.05
	[-2.75, -2.68]	[0.14, 0.14]	[0.52, 0.54]	[0.08, 0.09]	[-0.06, -0.05]
Dr Pepper 330	-3.64	0.02	0.01	0.01	0.00
	[-3.69, -3.61]	[0.02, 0.02]	[0.01, 0.01]	[0.01, 0.01]	[0.00, 0.00]
Dr Pepper 500	-2.73	0.07	0.03	0.04	-0.01
	[-2.78, -2.66]	[0.07, 0.07]	[0.03, 0.03]	[0.04, 0.04]	[-0.01, -0.01]
Dr Pepper Diet 500	-3.34	0.02	0.09	0.01	-0.01
	[-3.38, -3.29]	[0.02, 0.02]	[0.09, 0.09]	[0.01, 0.01]	[-0.01, -0.01]
Fanta 330	-3.58	0.03	0.01	0.01	0.00
	[-3.63, -3.55]	[0.03, 0.03]	[0.01, 0.01]	[0.01, 0.01]	[0.00, 0.00]
Fanta 500	-2.62	0.07	0.03	0.05	-0.01
	[-2.66, -2.56]	[0.07, 0.08]	[0.03, 0.03]	[0.04, 0.05]	[-0.01, -0.01]
Fanta Diet 500	-3.23	0.03	0.10	0.02	-0.01
	[-3.27, -3.18]	[0.02, 0.03]	[0.09, 0.10]	[0.01, 0.02]	[-0.01, -0.01]
Cherry Coke 330	-3.60	0.02	0.01	0.01	0.00
	[-3.65, -3.57]	[0.02, 0.02]	[0.01, 0.01]	[0.01, 0.01]	[0.00, 0.00]
Cherry Coke 500	-2.69	0.06	0.02	0.04	-0.01
	[-2.73, -2.63]	[0.05, 0.06]	[0.02, 0.03]	[0.04, 0.04]	[-0.01, -0.01]
Cherry Coke Diet 500	-3.25	0.02	0.07	0.01	-0.01
	[-3.29, -3.20]	[0.02, 0.02]	[0.07, 0.07]	[0.01, 0.01]	[-0.01, -0.01]
Oasis 500	-2.61	0.09	0.04	0.05	-0.01
	[-2.65, -2.55]	[0.08, 0.09]	[0.04, 0.04]	[0.05, 0.05]	[-0.01, -0.01]
Oasis Diet 500	-3.17	0.03	0.11	0.02	-0.01
	[-3.21, -3.12]	[0.03, 0.03]	[0.11, 0.12]	[0.02, 0.02]	[-0.01, -0.01]
Pepsi 330	-3.08	0.06	0.03	0.03	0.01
	[-3.13, -3.06]	[0.06, 0.06]	[0.03, 0.03]	[0.03, 0.03]	[0.01, 0.01]
Pepsi 500	-2.76	0.17	0.08	0.10	-0.03
	[-2.81, -2.72]	[0.17, 0.17]	[0.08, 0.08]	[0.10, 0.10]	[-0.03, -0.03]
Pepsi Diet 330	-3.41	0.02	0.13	0.01	0.01
	[-3.44, -3.38]	[0.02, 0.02]	[0.13, 0.13]	[0.01, 0.01]	[0.00, 0.01]
Pepsi Diet 500	-3.28	0.06	0.25	0.03	-0.03
	[-3.32, -3.25]	[0.06, 0.06]	[0.24, 0.25]	[0.03, 0.03]	[-0.03, -0.03]
Lucozade Energy 380	-2.84	0.10	0.05	0.06	0.01
	[-2.90, -2.82]	[0.10, 0.10]	[0.04, 0.05]	[0.06, 0.06]	[0.01, 0.01]
Lucozade Energy 500	-2.57	0.07	0.03	0.05	-0.01
	[-2.59, -2.49]	[0.07, 0.07]	[0.03, 0.03]	[0.05, 0.05]	[-0.01, -0.01]
Ribena 288	-3.23	0.03	0.01	0.01	0.01
	[-3.30, -3.21]	[0.03, 0.04]	[0.01, 0.01]	[0.01, 0.01]	[0.01, 0.01]
Ribena 500	-2.72	0.05	0.02	0.03	-0.01
	[-2.76, -2.66]	[0.05, 0.05]	[0.02, 0.02]	[0.03, 0.03]	[-0.01, -0.01]
Ribena Diet 500	-3.30	0.02	0.06	0.01	-0.01
	[-3.33, -3.25]	[0.02, 0.02]	[0.06, 0.06]	[0.01, 0.01]	[-0.01, -0.01]
Other soft drinks	-2.27	0.51	0.22	0.28	-0.07
	[-2.30, -2.22]	[0.50, 0.52]	[0.22, 0.23]	[0.27, 0.29]	[-0.08, -0.07]
Other Diet soft drinks	-2.76	0.09	0.30	0.05	-0.03
	[-2.74, -2.64]	[0.08, 0.09]	[0.30, 0.31]	[0.05, 0.05]	[-0.03, -0.03]
Fruit juice	-1.74	0.11	0.05	0.33	0.01
	[-1.76, -1.66]	[0.10, 0.11]	[0.05, 0.05]	[0.31, 0.34]	[0.01, 0.01]
Flavored milk	-2.37	0.03	0.01	0.07	-0.01
	[-2.40, -2.29]	[0.03, 0.04]	[0.01, 0.01]	[0.07, 0.08]	[-0.01, -0.01]
Fruit water	-2.42	0.02	0.01	0.04	-0.01
	[-2.48, -2.38]	[0.02, 0.02]	[0.01, 0.01]	[0.04, 0.04]	[-0.01, -0.01]

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 B.3: *Price elasticities – on-the-go*

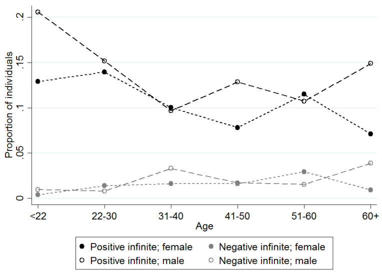
	Effect of 1% price increase on:				
	Own	cross demand for:			Total
	demand	sugary soft drinks	diet soft drinks	sugary alternatives	demand
Soft drinks	-0.43			1.36	-0.30
	[-0.44, -0.43]			[1.29, 1.37]	[-0.31, -0.30]
Sugary soft drinks	-0.89		0.86	1.09	-0.17
	[-0.90, -0.87]		[0.84, 0.87]	[1.04, 1.10]	[-0.17, -0.17]

Notes: For each of the eight 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. We also compute demand response for a 1% increase in the price of all soft drink products and all sugary soft drink products. Numbers are means across time. 95% confidence bands are shown in brackets.

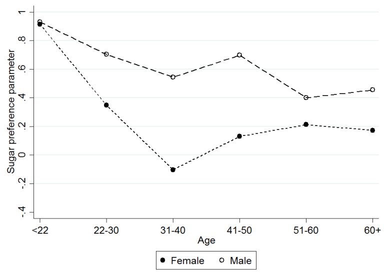
In Figures B.2 and B.3 we replicates Figures 3.2 and 3.3, splitting individuals out based on gender and in Figures B.4 and B.5 we split individuals out based on the socioeconomic status. The graphs show the patterns of how preferences vary with age and total dietary sugar broadly hold conditional on gender and socioeconomic status.

Figure B.2: *Preferences variation with age and gender*

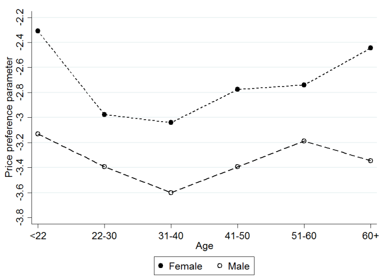
(a) infinite sugar preferences



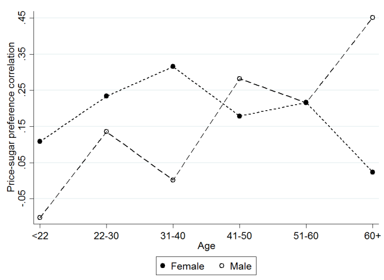
(b) finite sugar preferences



(c) price preferences



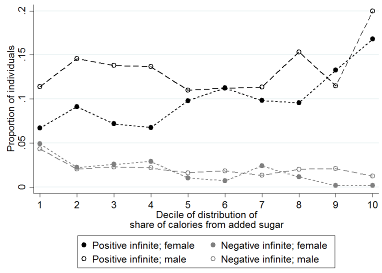
(d) sugar-price correlation



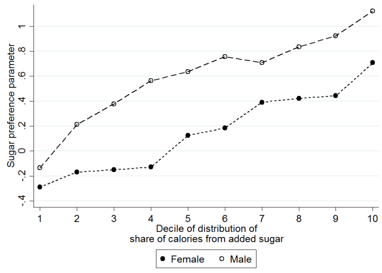
Notes: Figure shows how the share of consumers with infinite sugar preferences, the mean of finite sugar preferences, the mean of price preferences and the correlation between sugar and price preferences vary by age and gender.

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

(a) infinite sugar preferences

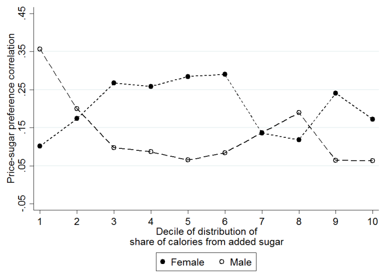


(b) finite sugar preferences



(c) price preferences

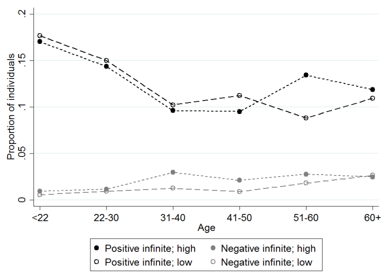
(d) sugar-price correlation



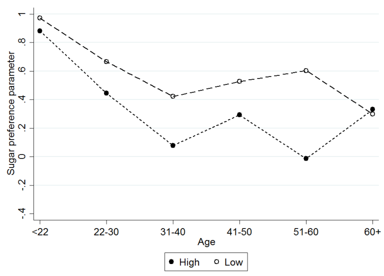
Notes: Figure shows how the share of consumers with infinite sugar preferences, the mean of finite sugar preferences, the mean of price preferences and the correlation between sugar and price preferences vary by deciles of the distribution of total annual dietary sugar and gender.

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

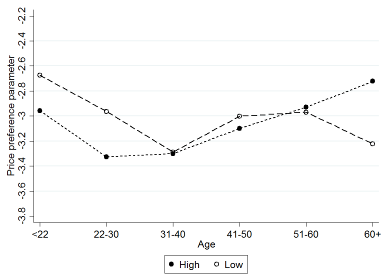
(a) infinite sugar preferences



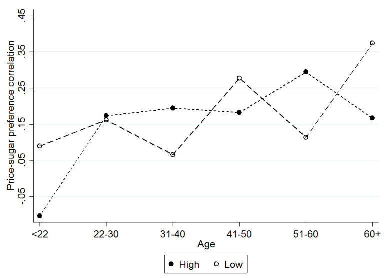
(b) finite sugar preferences



(c) price preferences



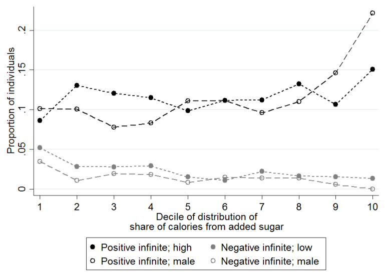
(d) sugar-price correlation



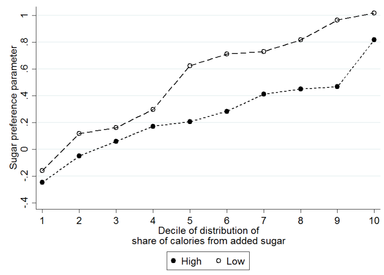
Notes: Figure shows how the share of consumers with infinite sugar preferences, the mean of finite sugar preferences, the mean of price preferences and the correlation between sugar and price preferences vary by age and socioeconomic status. "High" refers to those from a household whose head works in 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*

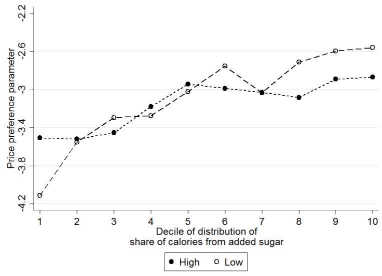
(a) infinite sugar preferences



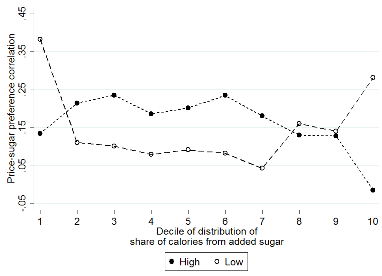
(b) finite sugar preferences



(c) price preferences



(d) sugar-price correlation



Notes: Figure shows how the share of consumers with infinite sugar preferences, the mean of finite sugar preferences, the mean of price preferences and the correlation between sugar and price 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.2 At-home segment

Table B.4 provides details of the estimated demographic group specific preference parameters in the at-home segment. It shows that, as with on-the-go purchases, higher temperature is associated with a shift from buying soft drinks towards alternative drinks. We allow for bottle vs. can and multi vs. single portions effects, as well as size fixed effects (not reported in the table) to affect utility. The table also reports brand effects, which we allow to vary across multi- and single-portion variants of the products.[32]

[32] We do not report the time varying brand effects or the retailer effects. These are available upon request.

Table B.4: *Demand model estimates: demographic specific preferences – at-home*

	No children High skill		*No children Low skill*		*Pensioner*		*Children High skill*		*Children Low skill*	
Variable	Estimate	Standard error	Estimate	Standard error	Estimate	Standard error	Estimate	Standard error	Estimate	Standard error
Temperature	-0.0154	0.0034	-0.0202	0.0046	-0.0140	0.0060	-0.0163	0.0030	-0.0124	0.0038
Bottle	-0.5381	0.0533	-0.3967	0.0649	-1.2049	0.1153	-0.1330	0.0503	-0.0262	0.0586
Multi	0.6467	0.0399	0.8504	0.0508	0.6867	0.0754	0.5146	0.0391	0.9113	0.0454
Dr Pepper	-0.8396	0.1015	-0.1632	0.1189	-1.9871	0.3203	-1.0520	0.0987	-0.3353	0.1036
Fanta	-0.8499	0.1001	-0.2847	0.1192	-0.5397	0.2388	-1.0118	0.0944	-0.6571	0.1073
Cherry Coke	-2.3434	0.1155	-0.7415	0.1035	-3.5360	0.3644	-2.1864	0.0990	-1.3569	0.1044
Oasis	-0.5637	0.0930	-0.0131	0.1105	-0.0225	0.2257	-0.4299	0.0820	-0.3762	0.0990
Pepsi	-1.0908	0.0660	-0.6783	0.0789	-1.1230	0.1494	-1.3468	0.0633	-0.8733	0.0720
Lucozade	-0.4492	0.1034	0.2759	0.1228	0.6160	0.2121	-0.9169	0.1064	-0.1951	0.1113
Ribena	-2.1418	0.1732	-0.9797	0.1787	-1.4762	0.3467	-1.5003	0.1303	-1.2729	0.1542
Other soda	-6.1458	1.0045	-3.2747	0.3028	-3.4049	0.6095	-4.1219	0.3884	-4.9368	1.0053
Store brand soda	-9.3745	1.0102	-5.4311	0.3298	-6.8853	0.6488	-6.8693	0.4012	-6.9107	1.0122
Fruit juice	4.0229	0.0878	3.1303	0.1177	4.1080	0.1581	3.3660	0.0788	2.8604	0.0980
Flavoured milk	9.0774	1.0049	5.8969	0.3068	7.3214	0.6069	7.6291	0.3886	8.6367	1.0058
Flavoured water	5.4735	1.0188	2.4549	0.3519	4.9148	0.6315	4.5249	0.4025	4.7067	1.0221
Coke*single	-7.3220	1.0042	-3.4033	0.3009	-5.4663	0.6066	-5.2858	0.3878	-5.9317	1.0054
Dr Pepper*single	-8.3424	1.0078	-4.7342	0.3161	-6.7532	0.6690	-5.8229	0.3964	-7.0296	1.0085
Fanta*single	-8.2664	1.0074	-4.5395	0.3157	-7.2744	0.6263	-5.8772	0.3949	-6.9469	1.0087
Cherry Coke*single	-7.2033	1.0086	-4.7429	0.3083	-6.0316	0.6924	-5.6750	0.3959	-7.1402	1.0086
Pepsi*single	-6.7511	1.0042	-3.2255	0.3004	-5.1496	0.6062	-4.5223	0.3884	-5.7567	1.0053
Lucozade*single	-5.3940	1.0061	-2.4803	0.3118	-4.2290	0.6159	-3.6887	0.3947	-4.7742	1.0078
Ribena*single	-7.8957	1.0208	-4.3717	0.3551	-7.6408	0.7173	-4.9072	0.4073	-6.0474	1.0168
Other soda*single	-2.6475	0.0754	-1.6828	0.0962	-2.8996	0.1460	-2.3118	0.0708	-1.8817	0.0832
Fruit juice*single	-6.7158	1.0057	-3.9924	0.3087	-5.2681	0.6189	-5.3327	0.3917	-6.4837	1.0071
Flavoured milk*single	-6.9343	1.0197	-3.1554	0.3515	-6.9946	0.6420	-4.8586	0.4028	-5.6706	1.0226
Demographic specific 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 3,314 households who we observe on 302,383 at-home choice occasions. The table shows estimates of the demographic specific preference parameters. Brand effects are shown for a baseline period. We allow these to vary across years and quarters.

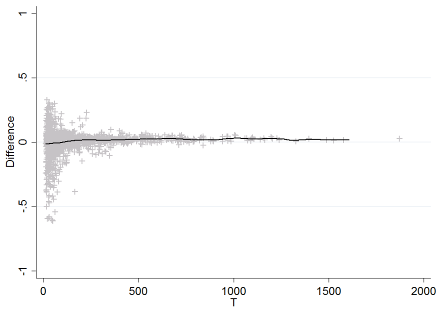
B.3 Incidental parameters problem

Figures B.6, B.7 and B.8 show, for the price, soft drinks and sugar preference parameters, how the jackknife ($\widetilde{\theta}_{split}$) and the maximum likelihood estimate ($\widehat{\theta}$) 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.

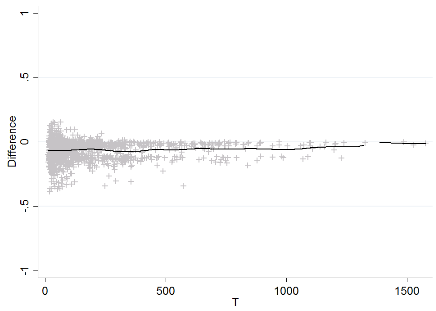
Figures B.9 plot the distributions of price, soft drinks and sugar preference parameter estimates for both the estimators $\widehat{\theta}$ and $\widetilde{\theta}_{split}$, showing there is little difference in the distributions.

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

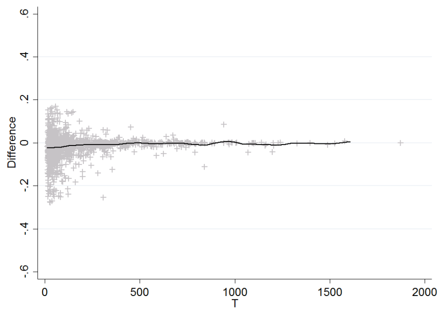
(a) Price



(b) Soft drinks



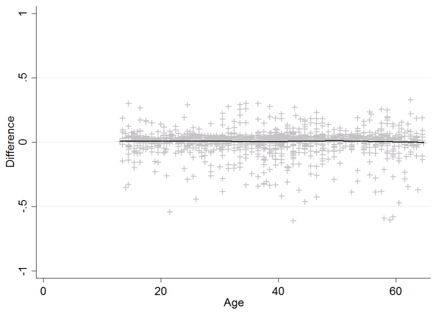
(c) Sugar



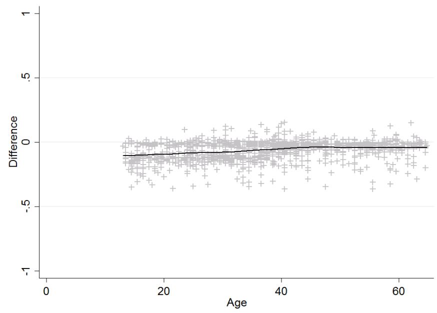
Notes: Marks represent consumer level differences. Lines are local polynomial regressions.

Figure B.7: *Relationship between bias and age*

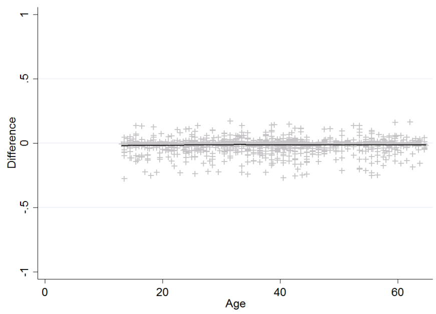
(a) Price



(b) Soft drinks



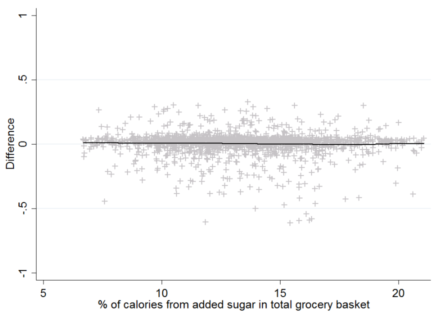
(c) Sugar



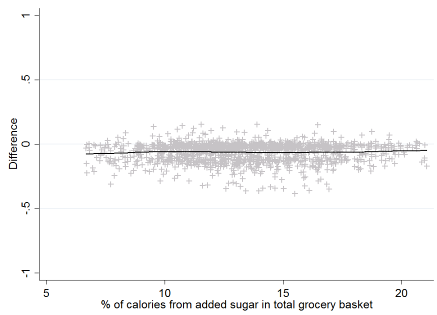
Notes: Marks represent consumer level differences. Lines are local polynomial regressions.

Figure B.8: *Relationship between bias and dietary sugar*

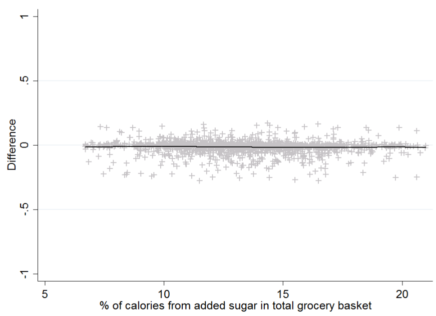
(a) Price



(b) Soft drinks



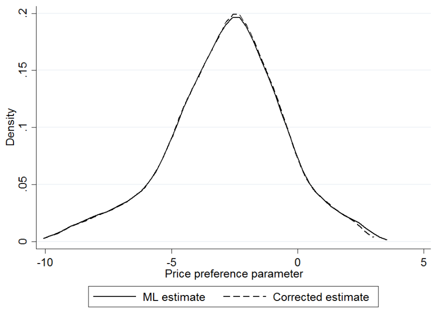
(c) Sugar



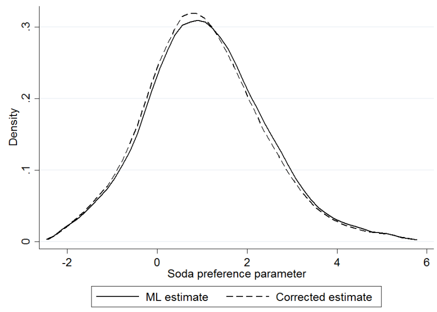
Notes: Marks represent consumer level differences. Lines are local polynomial regressions.

Figure B.9: *Preference parameter distribution*

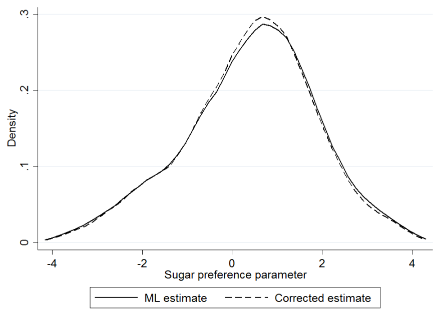
(a) Price



(b) Soft drinks



(c) Sugar



Notes: Lines are kernel density estimates.

B.4 Random coefficients model

Here we provide a comparison of our approach with the random coefficient logit model that is often used in the literature. To do this we estimate two alternative random coefficient specifications using data for the on-the-go segment. For concreteness, here we refer to our main demand model (described in Section 3.1) as the fixed coefficient logit.

The first random coefficient specification includes normally distributed random coefficients on price, a dummy indicating soft drink product, and a dummy indicating sugary product, with zero correlation between them, but with the means being allowed to vary by four demographic groups based on age (younger/older than 40) and gender. Coefficients on all other product attributes vary by the demographic groups. Restrictions this imposes, relative to the fixed coefficient logit, are (i) each of the three consumer level preference distributions are restricted to be normal (although we still allow for infinite portions of the preference space), (ii) the three consumer level preference distributions are uncorrelated, and (iii) the only variation in consumer level preferences with observables is a mean shift for each of the four demographic groups.[33] The second random coefficient specification is the same as the first with the exception that we allow for correlation between the price, soft drinks and sugar preferences.

These random coefficient specifications are two from many plausible alternatives. They are chosen to be broadly similar to what researchers do in practice. A significant advantage of the fixed coefficient logit model is that it avoids the need to pre-specify what individual level variables are related to the preference distribution and the form of this relationship.

To estimate the random coefficient models, for each individual in our sample, we randomly draw 10 choice occasions, and we weight each individual's contribution to the likelihood function by the number of choice occasions we observe them on.

In Table B.5 we compare estimates of our fixed coefficient logit model with the two alternative random coefficient models. We report the mean and standard deviation of the price, soft drinks and sugar preference distributions conditional on the four demographic groups. We also report the correlation in the preferences conditional on demographic group. The table underlines that the random coefficient specification is unable to capture how the dispersion of preferences varies across the four age-gender demographic groups. It also highlights that the random coefficient model with correlated preferences does not capture how correlations vary across the included demographic groups.

[33] In contrast, the fixed coefficient logit model places no parametric restrictions on the distribution shape or correlation in the consumer level preference parameters, and places no restrictions on the correlation in these preferences with any time invariant information about individuals.

Table B.5: *Comparison with random coefficients model: moments of preference distribution*

	Our model		Random coefficient			
			No correlation		With correlation	
	mean	std dev	mean	std dev	mean	std dev
Price						
Female, young	-2.8633	2.6387	-2.9536	2.9167	-2.9228	3.0800
Female, old	-2.7312	2.5433	-2.5218	2.9167	-2.7938	3.0800
Male, young	-3.3918	2.6947	-2.7621	2.9167	-2.7438	3.0800
Male, old	-3.2736	2.8028	-3.0286	2.9167	-2.8681	3.0800
Soft drinks						
Female, young	1.2922	1.6486	1.6130	1.6848	1.6789	1.7161
Female, old	1.1598	1.6242	1.4217	1.6848	1.4042	1.7161
Male, young	1.4256	1.3848	2.1092	1.6848	1.9942	1.7161
Male, old	1.9004	1.6855	1.7142	1.6848	1.7006	1.7161
Sugar						
Female, young	0.2666	1.8328	0.0570	2.1076	0.0659	2.1585
Female, old	0.1478	1.7385	0.0562	2.1076	0.1299	2.1585
Male, young	0.6831	1.7769	0.5863	2.1076	0.7016	2.1585
Male, old	0.5961	1.8280	0.7406	2.1076	0.6968	2.1585
Estimated correlations:						
price-soft drinks						
Female, young	-0.3976		0		-0.4316	
Female, old	-0.4259		0		-0.4316	
Male, young	-0.2017		0		-0.4316	
Male, old	-0.4044		0		-0.4316	
price-sugar						
Female, young	0.2555		0		0.3682	
Female, old	0.1988		0		0.3682	
Male, young	-0.0538		0		0.3682	
Male, old	0.2681		0		0.3682	
soft drinks-sugar						
Female, young	-0.2689		0		-0.2431	
Female, old	-0.2461		0		-0.2431	
Male, young	-0.1751		0		-0.2431	
Male, old	-0.3671		0		-0.2431	

Note: Standard errors of random coefficient estimates are not reported but show that coefficient estimates are significant. Estimated correlations in the first column (our model) report the empirical correlation between the individual level estimated coefficients, in the second column we estimate a random coefficients model without correlation, and in the third column the estimated correlations report the covariance parameter estimated from the model.

Under the fixed coefficient logit model preferences vary with any individual level variables in a flexible way. However, for the two random coefficient models, any variation in the preference distribution with a third individual variable would only be driven by the correlation in that variable across the four included demographic groups. This in practice severely limits the ability of the two random coefficient specifications that we estimate to capture the across individual variation necessary to undertake our targeting analysis. We highlight this point by discussing variation in the sugar preference parameter.

Figure B.10 shows the distribution of sugar preferences (for those individuals with finite preferences), and how the mean sugar preference varies with individual gender, age and total annual dietary sugar. In each case it does so for our fixed coefficient logit model and the two random coefficient specifications that we estimate. The figure makes clear (i) the fixed coefficient sugar preferences distribution has higher kurtosis and some negative skew not captured by the normal random coefficient, (ii) the random coefficient models successfully captures variation in sugar preferences across gender, (iii) the random coefficient models fail to capture the variation in sugar preferences across the age distribution, (iv) and they fail to capture variation across the total dietary sugar distribution. The reason for (iii) is the variation across age allowed for in the random coefficient specifications across those age below and above 40 is not flexible enough to capture the shape of preference variation across more disaggregate age groups. The reason for (iv) is the random coefficient specifications do not directly allow for preference variation with total annual dietary sugar (and the correlation of this with the four demographic groups is not strong enough to enable the model to recover the pattern).

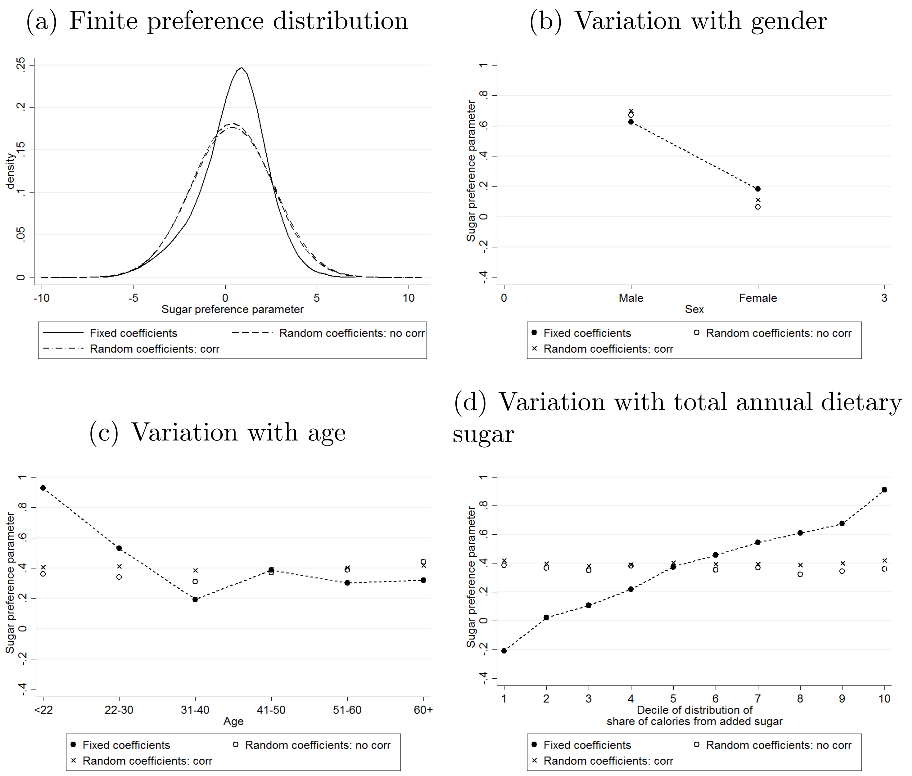
Figure B.10: *Comparison with random coefficients model: sugar preferences*

(a) Finite preference distribution

(b) Variation with gender

(c) Variation with age

(d) Variation with total annual dietary sugar



Notes: Lines are for the fixed coefficient and two random coefficient logit specifications.

It would of course be possible to enrich the random coefficient specifications we estimate. However, there would be practical limitations to the extent to which it would be possible to do this. For instance, allowing the effects of the counterfactual to vary jointly across the 10 deciles of the added sugar and total equivalized expenditure distributions, as well as across 6 age groups (as in Figure 4.1) would require allowing random coefficient means to vary across $10 \times 10 \times 6$ discrete groups (as well as potentially standard deviation and correlations). Given the question we deal with in this paper, the fixed coefficient logit model is a more suitable framework.

C Pass-through

In Table C.1 we report the mean tax levied per product, price change and change in share of the on-the-go segment of the drinks market due to the tax. We report these for the set of "inside products" – the sugary and diet soft drinks – and for the alternative (non soft drink) sugary products and bottled water.

Table C.1: *Effects of sugary soda tax at product level on products available in the on-the-go segment*

	Tax (pence)	Δ price (pence)	Δ share (p.p.)
Sugary soft drinks	10.65	13.15	-6.34
			[-6.43, -6.22]
Coca Cola 330	8.25	8.12	-0.08
Coca Cola 500	12.50	17.48	-1.94
Dr Pepper 330	8.25	8.11	-0.01
Dr Pepper 500	12.50	17.33	-0.32
Fanta 330	8.25	8.24	-0.02
Fanta 500	12.50	17.29	-0.35
Cherry Coke 330	8.25	8.09	0.00
Cherry Coke 500	12.50	17.01	-0.26
Oasis 500	12.50	17.00	-0.41
Pepsi 330	8.25	8.66	-0.08
Pepsi 500	12.50	16.19	-0.88
Lucozade Energy 380	9.50	10.83	-0.17
Lucozade Energy 500	12.50	18.33	-0.36
Ribena 288	7.20	7.11	0.03
Ribena 500	12.50	18.07	-0.23
Other soft drinks	12.50	12.50	-1.27
Diet soft drinks	0.00	-1.37	3.96
			[3.89, 4.02]
Coca Cola Diet 330	0.00	-0.77	0.63
Coca Cola Diet 500	0.00	-2.12	1.26
Dr Pepper Diet 500	0.00	-2.02	0.21
Fanta Diet 500	0.00	-1.92	0.23
Cherry Coke Diet 500	0.00	-1.84	0.17
Oasis Diet 500	0.00	-1.97	0.27
Pepsi Diet 330	0.00	-0.52	0.21
Pepsi Diet 500	0.00	-1.05	0.49
Ribena Diet 500	0.00	-1.54	0.13
Other Diet soft drinks	0.00	0.00	0.37
Sugary alternatives	0.00	0.00	1.09
			[1.07, 1.13]
Outside option	0.00	0.00	1.28
			[1.25, 1.31]

Notes: Panels 2 and 4 show the mean effect of the sugary soda tax on price and market share of products in the on-the-go segment. Panels 1, 3 and 5 show the mean effects of the tax on all sugary soft drinks, all diets soft drinks and on alternative drinks. 95% confidence intervals for the change market share are shown in brackets.

D An alternative soda tax

The paper focuses on the impact of a soda tax levied only on sugary soft drinks. We also simulate the impact of a soda tax incident on all soft drinks products (both regular and diet); this tax takes the form

$$p_{jm} = \begin{cases} \tilde{p}_{jm} + \pi l_j & \forall j \in \Omega_{ws} \bigcup \Omega_{wn} \\ \tilde{p}_{jm} & \forall j \in \Omega_{as} \bigcup \Omega_{an}. \end{cases}$$

Here we refer to this as a broad soda tax and the tax we focus on in the main paper as a sugary soda tax. We simulate the same rate for the broad soda tax as for the sugary soda tax (25 pence per liter) using the same supply side model estimates in the first step and conducting the counterfactual simulation of pass-through of this tax to consumer prices.

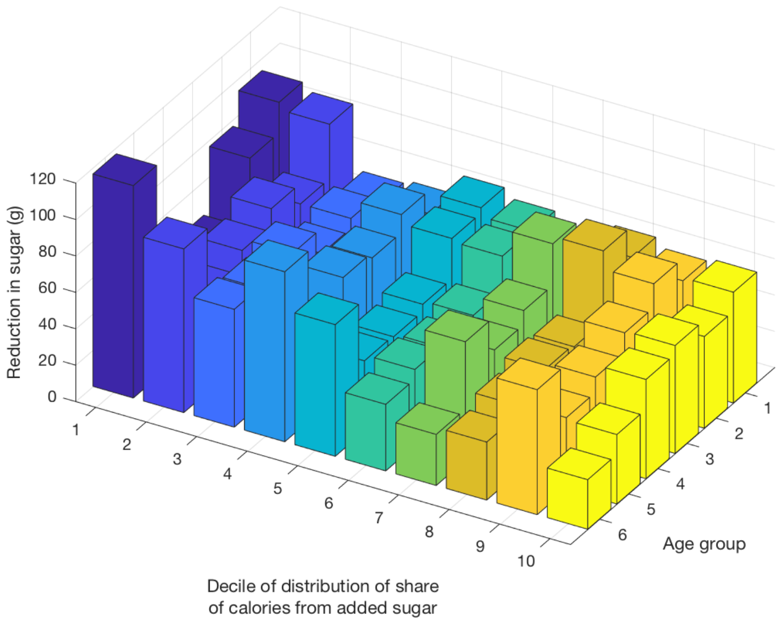
Table D.1 summarizes the impact of the broad soda tax on equilibrium prices and market shares (it contains analogous information to Table C.1). The main difference between a tax levied on only sugary soft drinks and one levied on all soft drinks is that the latter leads to prices increases for diet products (that on average are similar to those for sugary products). The result is that the broad soda tax leads to a much smaller reduction in demand for sugary soft drinks and a fall (rather than increase) in demand for diet soft drinks (relative to the sugary soda tax). Figure D.1 shows that a broad soda tax does achieve larger reductions in sugar among the young than the old, but fails to achieve relatively large reductions among those with high total dietary sugar.

Table D.1: *Effects of "broad" soda tax*

	Tax (pence)	Δ price (pence)	Δ share (p.p.)
Sugary soft drinks	10.65	11.44	-2.43
Diet soft drinks	11.65	12.40	-1.35
Sugary alternatives	0.00	0.00	1.28
Outside option	0.00	0.00	2.49

Notes: Numbers are means across products.

Figure D.1: *Reductions in sugar by age and total dietary sugar*



Notes: Numbers are for the on-the-go segment. Figure shows variation in the reduction in sugar conditional on being a soft drink purchaser. Age groups are 1=<22, 2=22-30, 3=31-40, 4=41-50, 5=51-60, 6=60+.

E Substitution to food

The choice model we outline in Section 3 captures consumer choice between drink products $j = \{0, 1, \ldots, J\} = \Omega_{\mathcal{D}}$. The drink products comprise water $j = 0$, soft drinks, $j = \{1, \ldots, j'\} = \Omega_w$ and alternative juices $j = \{j' + 1, \ldots, J\} = \Omega_n$. The expected utility to the consumer of purchasing a drink is:

$$
\begin{aligned}
E_{\epsilon_{ij\tau}}\left[\max_{j\in\Omega_{\mathcal{D}}} U_{ij\tau}\right] =& \ln\left(\exp\left(\sum_{j\in\Omega_i\cup\Omega_{r_\tau}} \exp\left(\alpha_i p_{jr_\tau t_\tau} + \beta_i s_j + \right.\right.\right. \\
& \left.\left.\left. \gamma_i w_j + \delta^z_{d(i)} z_j + \delta^h_{d(i)} h_{c(i)t_\tau} + \xi_{d(i)b(j)t_\tau} + \zeta_{d(i)b(j)r_\tau}\right)\right)\right) \\
\equiv& W_{i\mathcal{D}\tau}.
\end{aligned}
$$

Consider a first stage decision in which the consumer chooses between options $k = \{\varnothing, 1, \ldots, K, \mathcal{D}\}$, where $k = \varnothing$ denotes the outside option of a non-sugar snack, $k = \{1, \ldots, K\} = \Omega_c$ indexes chocolate products and $k = \mathcal{D}$ indexes choosing a drink. Suppose utility from these options takes the form:

$$\begin{aligned} V_{i\varnothing\mathcal{T}} &= \varepsilon_{i\varnothing\mathcal{T}} \\ V_{ik\mathcal{T}} &= \mu_c + W_{ik\mathcal{T}} + \varepsilon_{ik\mathcal{T}} \quad \text{for all } k \in \Omega_c \\ V_{i\mathcal{D}\mathcal{T}} &= \mu_{i\mathcal{D}} + \psi_{i\mathcal{D}} W_{i\mathcal{D}\mathcal{T}} + \varepsilon_{i\mathcal{D}\mathcal{T}}, \end{aligned}$$

where

$$W_{ik\mathcal{T}} = \alpha_i p_{krt_\tau} + \beta_i s_k + \vartheta_{b(k)}$$

and $(\varepsilon_{i0\mathcal{T}}, \varepsilon_{i1\mathcal{T}}, ..., \varepsilon_{iK\mathcal{T}}, \varepsilon_{i\mathcal{D}\mathcal{T}})$ are distributed i.i.d. extreme value. Note the nesting of the errors terms – consumers get a draw of first stage error terms $\boldsymbol{\varepsilon}$ and if they choose $k = \mathcal{D}$, they get a draw of second stage errors, $\boldsymbol{\epsilon}$, when selecting what drink product to choose. These idiosyncratic shocks are sequentially observed.

This first stage choice probabilities are:

$$\begin{aligned} P_{i\mathcal{T}}(k=0) &= \frac{1}{1 + \sum_{k' \in \Omega_c} \exp\left(\mu_c + W_{ik'\mathcal{T}}\right) + \exp\left(\mu_{i\mathcal{D}} + \psi_{i\mathcal{D}} W_{i\mathcal{D}\mathcal{T}}\right)} \\ P_{i\mathcal{T}}(k=\tilde{k}) &= \frac{\exp\left(\mu_c + W_{i\tilde{k}\mathcal{T}}\right)}{1 + \sum_{k' \in \Omega_c} \exp\left(\mu_c + W_{ik'\mathcal{T}}\right) + \exp\left(\mu_{i\mathcal{D}} + \psi_{i\mathcal{D}} W_{i\mathcal{D}\mathcal{T}}\right)} \quad \text{for all } \tilde{k} \in \Omega_c \\ P_{i\mathcal{T}}(k=\mathcal{D}) &= \frac{\exp\left(\mu_{i\mathcal{D}} + \psi_{i\mathcal{D}} W_{i\mathcal{D}\mathcal{T}}\right)}{1 + \sum_{k' \in \Omega_c} \exp\left(\mu_c + W_{ik'\mathcal{T}}\right) + \exp\left(\mu_{i\mathcal{D}} + \psi_{i\mathcal{D}} W_{i\mathcal{D}\mathcal{T}}\right)}. \end{aligned}$$

The second stage drinks choice model allows us to identify the drinks inclusive value, $W_{i\mathcal{D}\mathcal{T}}$, and the preference parameters (α_i, β_i) along with all the other drinks demand parameters. Let Ω_c^B denote the set of chocolate brands and ω_b be the set of chocolate products that belong to brand b. The second stage model also enables us to identify the chocolate brand indices as:

$$z_{ib\mathcal{T}} = \ln \sum_{k \in \omega_b} \exp\left[\alpha_i p_{krt_\tau} + \beta_i s_k\right].$$

Note that

$$\begin{aligned} \sum_{k \in \Omega_c} \exp\left(\mu_c + W_{ik\mathcal{T}}\right) &= \sum_{b \in \Omega_c^B} \sum_{k \in \omega_b} \exp\left(\mu_c + W_{ik\mathcal{T}}\right) \\ &= \sum_{b \in \Omega_c^B} \sum_{k \in \omega_b} \exp\left(\mu_c + \left[\alpha_i p_{krt_\tau} + \beta_i s_k + \vartheta_{b(k)}\right]\right) \\ &= \sum_{b \in \Omega_c^B} \exp\left(\tilde{\vartheta}_b + z_{ib\mathcal{T}}\right), \end{aligned}$$

where $\tilde{\vartheta}_b = \mu_c + \vartheta_b$ so that the first stage purchase probabilities can be written:

$$P_{i\tau}(k=0) = \frac{1}{1+\sum_{b'\in\Omega_c^B}\exp\left(\tilde{\vartheta}_{b'}+z_{ib'\tau}\right)+\exp\left(\mu_{i\mathcal{D}}+\psi_{i\mathcal{D}}W_{i\mathcal{D}\tau}\right)}$$

$$P_{i\tau}(k\in\omega_b) = \frac{\exp\left(\tilde{\vartheta}_{b}+z_{ib\tau}\right)}{1+\sum_{b'\in\Omega_c^B}\exp\left(\tilde{\vartheta}_{b'}+z_{ib'\tau}\right)+\exp\left(\mu_{i\mathcal{D}}+\psi_{i\mathcal{D}}W_{i\mathcal{D}\tau}\right)} \quad \text{for all } b\in\Omega_c^b$$

$$P_{i\tau}(k=\mathcal{D}) = \frac{\exp\left(\mu_{i\mathcal{D}}+\psi_{\mathcal{D}}W_{i\mathcal{D}\tau}\right)}{1+\sum_{b'\in\Omega_c^B}\exp\left(\tilde{\vartheta}_{b'}+z_{ib't\tau}\right)+\exp\left(\mu_{i\mathcal{D}}+\psi_{i\mathcal{D}}W_{i\mathcal{D}\tau}\right)}.$$

Given identified parameters from the second stage and data on decisions consumers make over purchases of chocolate products, drinks or other snacks, the first stage choice model allows us to identify the remaining parameters $\tilde{\boldsymbol{\vartheta}} = (\tilde{\vartheta}_1, ..., \tilde{\vartheta}_B)'$, $\mu_{i\mathcal{D}}$ and $\psi_{i\mathcal{D}}$.

We allow for heterogeneity in the parameters $\mu_{i\mathcal{D}}$ and $\psi_{i\mathcal{D}}$ across age groups. Table E.1 shows estimates of these parameters.

Table E.1: *Upper stage model estimates*

	$\hat{\mu}_{iD}$		$\hat{\psi}_{iD}$	
	Estimate	Standard error	Estimate	Standard error
<22	1.3132	0.0164	0.4498	0.0043
22-30	1.5677	0.0116	0.4024	0.0034
31-40	1.4522	0.0093	0.3726	0.0025
41-50	1.1361	0.0098	0.4805	0.0027
51-60	1.2328	0.0112	0.5070	0.0028
60+	1.5641	0.0182	0.4347	0.0056

Notes: Estimates based on sample of 324,818 choice occasions. Chocolate brand effects were also estimated.