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How Well Targeted Are Soda Taxes?†

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Soda taxes aim to reduce excessive sugar consumption. We assess who is most impacted by soda taxes. We estimate demand using micro longitudinal data covering on-the-go purchases, and exploit the panel dimension to estimate individual-specific preferences. We relate these preferences and counterfactual predictions to individual characteristics and show that soda taxes are relatively effective at targeting the sugar intake of the young, are less successful at targeting the intake of those with high total dietary sugar, and are unlikely to be strongly regressive especially if consumers benefit from averted internalities. (*JEL* D12, H22, H25, H71)

Sugar consumption is far in excess of medically recommended levels in much of the developed world. Excess sugar consumption is linked with a range of diet-related diseases, including diabetes, cancers, and heart disease, and is thought to be particularly detrimental to children (WHO 2015). Soft drinks products are a leading contributor to dietary sugar (see CDC 2016). Taxes on these products (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 any future costs of consumption are large and partially ignored at the point of consumption (internalities). A growing number of jurisdictions have adopted soda taxes.[1] Soft drinks are a particularly large contributor to dietary sugar among the young, those with high overall dietary sugar, and youth from low-income households, and policymakers have identified these groups as the ones whose behavior they would most like to change.[2] The impact of soda taxes, and whether ultimately they are

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[1] As of December 2019, 43 countries and 8 US cities had soda taxes in clear (GFRP 2019).

[2] See, for example, Han and Powell (2013); Cavadini, Siega-Riz and Popkin (2000); CDC (2016); Public Health England (2015), and online Appendix Section A.1 where we provide evidence of this based on dietary intake data from the United Kingdom and the United States. As an example of policymakers targeting these groups, Public Health England (2017, p. 4) says: "In August 2016, government set out its approach to reduce the prevalence of childhood obesity in Childhood obesity: a plan for action. A key commitment in the plan was to launch a broad, structured sugar reduction program to remove sugar from everyday products. … Although the program focuses

successful in improving welfare, will depend crucially on how demand responses vary across individuals from these targeted groups.

Our contribution in this paper is to assess whether soda taxes are effective at lowering the sugar consumption of individuals that policy has targeted (i.e., the young, high sugar consumers, and the poor). We focus on the important but understudied on-the-go segment of the market. We use novel data on UK individuals to estimate a model of consumer choice, uncover individual-specific preferences, and simulate the impacts of a soda tax. We show that the tax does a good job at targeting young consumers and those from low-income households, but not individuals from households with high total dietary sugar. The economic burden of the tax is moderately higher for individuals from lower-income households; however, we also find that they reduce sugar consumption by more, so this leaves open the possibility that benefits to individuals arising from this offset the economic burden. Relative to the existing literature, we make two main advances.

First, we study purchase decisions made by individuals for immediate consumption on-the-go. Studying the on-the-go segment is important for a number of reasons. Firstly, consumption on-the-go is common: close to one-half of the sugar from soft drinks is obtained outside the home. Yet there is little evidence on choice behavior on-the-go, with the bulk of the literature focusing on purchases made in supermarkets and brought into the home for future consumption. Secondly, observing individual on-the-go purchases provides an excellent opportunity for identification of individual preferences; in contrast to information on household-level at-home purchases, purchases and consumption are closely aligned and individual preference estimates can be obtained without the need to place strong restrictions on the intrahousehold preference structure (see, for example, Adams et al. 2014). Thirdly, the on-the-go data contain information on teenagers and young adults, who are explicit targets of the soda taxes, but who 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, rather than modeling them using the standard random coefficient approach (where they are treated as random effects drawn from a known distribution). This is important because it allows us to better assess how well targeted a tax is and whether it is regressive. In particular, it means we avoid placing restrictions on (or ruling out) correlation between consumer level preferences and attributes (including purchase behavior for other goods). As a result we are able to directly relate individual-level preferences and predictions of the impact of the tax to consumer attributes, and can therefore assess precisely which individuals respond to the tax and on whom the economic burden of the tax falls most heavily.

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 a non-monotonic relationship between age and sugar preferences; on average those aged 13–21 have stronger preferences than those aged 22–30, who

on foods consumed by children, the reality is that families eat the same foods. The program will therefore help all family members to reduce their sugar consumption, thereby reducing the risk of weight gain and the consequences of this to their health. It will also help to reduce health inequalities, as sugar consumption, and the rates of obesity in children, tend to be highest in the most deprived."

in turn have stronger sugar preferences than older individuals, but among older individuals sugar preferences are increasing in age. In contrast, sugar preferences exhibit a monotonically increasing relationship with deciles of the distribution of total dietary sugar. However, unlike the young, those with higher overall levels of dietary sugar also tend to be relatively price insensitive.

Our results suggest that taxes of the form and size that have been implemented in the United Kingdom and many US locations lead to reductions of around 21 percent on average in the amount of sugar consumers get from soft drinks on-the-go. Consumers switch to alternative sources of sugar (both drinks and snacks), but this effect is relatively modest. The tax is relatively well targeted at lowering the sugar consumption of young people (including those from low-income households). In particular, those aged 13–21 have the most steeply sloped demands, reducing sugar in response to the tax by over 40 percent more than those aged over 40. The tax is less effective at targeting the on-the-go sugar intake of people with a consistently high level of dietary sugar in their overall diets. Despite the individuals being more likely to purchase soft drinks and to obtain relatively large amounts of sugar from them, their sugar intake from drinks responds less strongly than those with more moderate levels of sugar in their diets. This is because they tend to have strong preferences for sugar and to be less price responsive.

Compensating variation, a measure of the direct costs the tax places on the consumer through higher prices, is relatively large for the young and those with high levels of dietary sugar. In order to understand the full welfare impact on these individuals we would also need to know the size of any saving from averted internalities achieved by the tax. We do not measure these internalities. However, the larger reductions in sugar among younger consumers (compared with that for high overall sugar consumers) makes it more likely that averted internalities will outweigh the direct consumer welfare loss from higher prices for this group.

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 end up bearing 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 Kőszegi 2004).[3] We show that compensating variation associated with a tax on sugary soft drinks is around 20 percent higher for those in the bottom half of the distribution of total annual grocery expenditure[4] (a proxy for income) compared with those in the top half. However, some evidence suggests that low-income individuals might suffer more from internalities (e.g., Allcott, Lockwood, and Taubinsky 2019a; 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

[3] Allcott, Lockwood, and Taubinsky (2019a) consider the optimal tax rate for a government with preferences for redistribution. If internalities are concentrated among the poor, all else equal, this raises the optimal rate. On the other hand, if, all else equal, rich people have relatively weak preferences for soft drinks this lowers the optimal rate as soft drinks consumption becomes a tag for (in)ability.

[4] Grocery expenditure includes expenditure on food, drink (including alcohol), pet food, toiletries, and cleaning products.

from averted internalities, and that therefore the full effect on their welfare is less negative than the compensating variation suggests.

Our work contributes to a burgeoning literature that aims at understanding the effects of soda taxes. This include a set of papers that estimate the impact of the implementation of specific soda taxes on prices and purchases (e.g., Bollinger and Sexton 2018; Rojas and Wang 2017; and Seiler, Tuchman, and Yao 2018), and a set of papers that simulate the effects of soda taxes using estimates of behavior in the market based on a period and location in which no soda tax is in place (e.g., Harding and Lovenheim 2017; Bonnet and Réquillart 2013; Wang 2015; Allcott, Lockwood, and Taubinsky 2019a; and Chernozhukov, Hausman, and Newey 2019). Our work is more closely related to this second literature. We add to this literature by using panel data to better model individual-level heterogeneity in preferences. This enables us to focus on the distribution and targeting of effects that a soda tax will have, rather than considering the average effects. We are also the first to provide evidence on responses in the on-the-go segment of the market.

In focusing on choice behavior on-the-go we face a couple of challenges. First, while a strength of our data is that it is novel, it means there are not many alternative data sources for comparison. We show that broad patterns of consumption by age in our data are consistent with other data sources. We also discuss how potential measurement error in price may impact our analysis. Second, there may be dependence of on-the-go demand on at-home purchases. Following Browning and Meghir (1991) we test for this dependence, and we also allow for it in our on-the-go demand model. We find that, once we account for individual-level preference heterogeneity, evidence of demand linkages between on-the-go and at-home soft drink consumption is weak.

We consider three main potential issues regarding the robustness of our demand estimates. First, our approach entails estimating fixed effects in a nonlinear model and therefore may suffer from an incidental parameters problem (Hahn and Newey 2004, Arellano and Hahn 2007). We show that any resulting bias is minimal using the split sample jackknife bias correction procedure suggested in Dhaene and Jochmans (2015).

Second, while a novelty of this paper is to be the first to study individual-level on-the-go behavior, it is important to consider whether our main conclusion about the targeting of the tax could be unwound by demand patterns in the at-home segment of the market. We estimate at-home demand using household-level data and show that household-level responses at-home do not undo the relatively good targeting at the young.

Third, in our main results we assume that the tax is 100 percent passed-through to prices. Using data on prices of the two major soft drinks brands after the implementation of a soda tax in the United Kingdom in 2018, we show that pass-through was very close to 100 percent. As a robustness check we show that this is similar to what is predicted using our demand model together with a supply-side model of Bertrand-Nash price competition between manufacturers. Our equilibrium pass-through estimates suggest that an excise style tax on sugary soft drinks is slightly over-shifted on to consumer prices. Firms' pricing response therefore acts to moderately amplify the price differential that the tax creates between sugary and diet varieties. We show that the patterns of demand response across individuals are very similar under 100 percent and simulated equilibrium tax pass-through.

The rest of this paper is structured as follows. In Section I we introduce the data and describe the nonalcoholic drinks market. In Section II we describe our model of consumer demand and summarize estimates of the demand model. In Section III we present results of the soda tax simulation, consider how well targeted the tax is, show the effects on consumer welfare, and show its distributional implications. In Section IV we consider possible concerns about the robustness of our results. A final section concludes. In an online Appendix we provide further details on the data and demand estimates and present estimates of demand in the at-home segment and details of our analysis of the supply-side of the market and implied equilibrium pass-through of the tax.

I. The Nonalcoholic Drinks Market

We model behavior in the market for nonalcoholic drinks, considering consumers' choice between alternative drinks and substitution toward snacks. Nonalcoholic drinks include *soft drinks* (i.e., carbonated drinks, often referred to as soda, with and without sugar, energy drinks, and other sugar-sweetened nonalcoholic drinks), *alternative sugary drinks* (nonalcoholic drinks such as pure fruit juice and milk-based drinks such as shakes), and *bottled water*. "Soda taxes" are typically imposed on soft drinks that contain sugar (and sometimes also on diet varieties). Typically exempt are pure fruit juices that do not contain added sugar and drinks that are predominantly composed of milk.

We focus on behavior when purchasing on-the-go. This is 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. The existing literature on soda taxes studies their impact on purchases made in grocery stores for future consumption at home, but close to one-half of the sugar obtained from sugar-sweetened soft drinks products is purchased for immediate consumption on-the-go.[5] 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.

A limitation of our data is that it does not include purchases in restaurants or bars; this accounts for around one-quarter of on-the-go purchases.[6] The other three-quarters of the on-the-go purchases are made from vending machines, convenience stores, kiosks, and larger grocery stores when consumed immediately, which are included in our data.

We also have data on purchases made in the at-home segment by the households to which the individuals in our on-the-go data belong. We use these data in three ways. First, they allow us to obtain a measure of the sugar intensity of the individual's entire diet (based on the total at-home calorie purchases of the household she belongs to). We show how preferences and outcomes vary along this dimension. Second,

[5] CDC (2016) and National Diet and Nutrition Survey (Public Health England 2018). See online Appendix Section A.1 for further details.

[6] Calculations based on National Diet and Nutrition Survey (Public Health England 2018).

we consider possible demand linkages between the segments: for instance, at-home household purchases might influence on-the-go purchases. We describe the within-individual correlation between on-the-go and at-home purchases. We include a measure of the inventory of at-home drinks based on household purchases in our model of demand for on-the-go purchases and find that it has little impact on choices once we control for individual heterogeneity. We also use our model of behavior in the at-home segment to assess whether our conclusions regarding the individual targeting of soda taxes on the young could plausibly be undone by offsetting behavior of the household in the at-home segment and show that this is unlikely to be the case. Third, we use the at-home data in a robustness check where we model supply-side responses to the introduction of a tax using information on both segments.

A. *Purchases*

We use data from the Kantar Worldpanel and the associated food on-the-go survey (Kantar 2014). These data are collected by the market research firm Kantar. The Worldpanel data cover the at-home segment of the market. It tracks the grocery purchases made and brought into the home by a sample of households that are representative of the British population. The food on-the-go survey tracks food and drink purchases made by individuals 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 bar code of all grocery purchases made and brought into the home. These include all food, drink (including alcohol), pet food, toiletries, and cleaning products; this gives us comprehensive information on the total grocery baskets of the households to which the individuals in our on-the-go sample belong.[7] Our main interest is behavior recorded in the on-the-go survey. To our knowledge the Kantar food on-the-go survey is unique. Participating individuals record all purchases of snacks and nonalcoholic 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 bar code, 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 5,555 individuals.[8] To estimate demand we use information only on the individuals that report purchasing soft drinks.[9] Our estimation sample contains 2,449 individuals.[10] 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.

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

[8] See online Appendix Section C.1 for further details on the at-home data.

[9] Strictly speaking, we use individuals who purchase at least 15 nonalcoholic drinks and at least 10 soft drinks over the 5.5-year period. These individuals account for around 95 percent of sugar from nonalcoholic drink purchases on-the-go.

[10] To provide a reality check, we compare this to the Living Cost and Food Survey for the years 2009–2014 and find a similar figure.

We have data over the period June 2009 to December 2014. We define a choice occasion as a day in which an individual makes an on-the-go purchase of either a nonalcoholic drink or a snack (defined as confectionery, nuts, potato chips, and fruit). We exploit the panel structure of the data to estimate consumer-specific preferences. In the estimation sample we observe individuals, on average, on 252 choice occasions. In total our sample consists of 616,544 choice occasions. In Table 1, we provide details on the distribution of observations per consumer. Over 95 percent of consumers are observed for more than 25 choice occasions, and for over 60 percent of consumers we observe 100 or more choice occasions.

These consumers purchase a drink product on 59 percent of choice occasions. When purchasing drinks, individuals choose a single product 83 percent of the time. On the remaining choice occasions the consumer chooses multiple (typically two) products. In this case we randomly select one purchase and use this in demand estimation.[11]

B. *Brands, Products, Prices, and Stores*

In Table 2, we describe the products available in the on-the-go nonalcoholic drinks market in the United Kingdom, their market shares and mean prices. Products we classify as "soft drinks" are available in brands owned by Coca-Cola Enterprises, PepsiCo, GlaxoSmithKline (GSK), and Barrs. There are a large number of small brands (each with a market share below 2 percent). We aggregate these small brands into a composite *Other* brand; in aggregate this accounts for around 16 percent of the market. We do not drop these niche brands as we are ultimately interested in the total sugar consumers get on-the-go. The implicit assumption of this aggregation is that product differentiation among these niche brands is not important to consumers. We additionally include fruit juice, flavored milk and fruit (or flavored) water, which together account for just under 10 percent of the market, and bottled water which accounts for another 11 percent. Many brands are available in two different sizes. See further details in online Appendix Section A.2 on how we define products.

For each transaction we observe the type of store in which the purchase occurred and the transaction-level price. From these transaction-level prices, and for each product, we compute the average monthly price in each type of store. We use this average monthly price in demand estimation. National chains in the United Kingdom set national prices (see Competition Commission 2000); we therefore use national prices for these, as well as for vending machines. For independent stores we compute prices that vary regionally.

In online Appendix Section A.3 we provide more details of how we use transaction-level prices to construct the price series we utilize in estimation. Effectively, this entails computing means across transaction prices. It is possible this procedure introduces some measurement error; this is a standard problem faced in many discrete choice settings in which the prices of the alternatives not chosen are not directly observed. Schennach (2013) and Blundell, Horowitz, and Parey (2019) consider how to consistently estimate continuous demand models with measurement

[11] If instead we treat multiple purchases as separate choice occasions it leads to essentially no difference in parameter estimates.

Table 1—Time Series Dimension of Estimation Sample

	Individuals on-the-go	
Number of choice occasions observed	Observations	Percent
<25	95	3.9
25–49	285	11.6
50–74	272	11.1
75–99	235	9.6
100–249	769	31.4
250+	793	32.4
Total	2,449	100.0

Notes: The table shows the number of choice occasions on which we observe individuals making purchase choices based on the 2,449 individuals in the estimation sample. A choice occasion is a day in which the individual purchases a snack.

error in prices, based on the measurement error being of the form of Berkson errors (Berkson 1950). We are not aware of solutions to this problem in the case of discrete choice demand. We have undertaken some simple Monte Carlo simulations that suggest that in our specific case the impact of measurement error on our estimates is unlikely to be large (see online Appendix Section A.3 for more details). Extending results on consistent estimation with Berkson errors to discrete choice demand settings is an interesting avenue for future work.

Table 3 describes the number and share of purchases of nonalcoholic drinks across retailer types. For convenience stores we distinguish between those in different regions of Great Britain. The largest share of purchases are made in stores belonging to small national chains or convenience stores. The large national supermarket chains account together for around one-fifth of purchases, and vending machines account for around 8 percent. In our demand model we allow for the product availability to vary across the retailer types.[12]

C. *Demand Linkages between On-the-Go and At-Home*

We study the demand behavior of individuals while on-the-go. However, it is possible that an important margin of substitution is between at-home and on-the-go consumption. In this section we present a simple test of separability of demand for soft drinks at-home and on-the-go. At-home purchases are brought into the home for future consumption, so we do not directly observe at-home consumption. We deal with this by constructing a proxy for at-home consumption based on recent purchases. We instrument for this variable using a measure of the inventory of at-home soft drinks to which a household has access, measured in a similar way as in the literature on dynamic demand (e.g., Hendel and Nevo 2006a, b).

[12] In particular, we consider a brand-size to be available in a retailer type if we observe at least 100 transactions for that product-retailer type across the 5.5 years covered by our data. There is no evidence of temporal variation in product availability over this time.

Table 2—Products

Firm	Brand	Product	Percent	Price
Soft drinks				
Coca-Cola			42.55	
	Coke		26.88	
		Coca Cola 330	4.02	0.65
		Coca Cola Diet 330	5.06	0.65
		Coca Cola 500	7.65	1.15
		Coca Cola Diet 500	10.16	1.15
	Dr Pepper		3.29	
		Dr Pepper 330	0.46	0.63
		Dr Pepper Diet 500	0.18	1.11
		Dr Pepper 500	2.64	1.11
	Fanta		3.83	
		Fanta 330	0.62	0.60
		Fanta Diet 500	0.29	1.11
		Fanta 500	2.92	1.11
	Cherry Coke		2.91	
		Cherry Coke 330	0.49	0.62
		Cherry Coke 500	1.57	1.11
		Cherry Coke Diet 500	0.85	1.11
	Oasis		3.69	
		Oasis 500	3.48	1.12
		Oasis Diet 500	0.21	1.12
	Sprite		1.96	
		Sprite 330	0.25	0.64
		Sprite 500	1.71	1.12
PepsiCo			10.32	
		Pepsi Diet 330	1.69	0.58
		Pepsi 330	0.97	0.58
		Pepsi Diet 500	5.62	1.00
		Pepsi 500	2.03	1.00
GSK			7.22	
	Lucozade energy		4.46	
		Lucozade Energy 380	2.40	0.95
		Lucozade Energy 500	2.06	1.14
	Ribena		2.76	
		Ribena 288	0.69	0.68
		Ribena 500	1.58	1.11
		Ribena Diet 500	0.50	1.11
Barrs			2.31	
		Irn Bru 330	0.71	0.58
		Irn Bru Diet 330	0.36	0.58
		Irn Bru 500	0.87	1.03
		Irn Bru Diet 500	0.37	1.03
Composite soft drinks				
		Other	14.25	1.17
		Other Diet	1.98	1.53
Alternative drinks				
Fruit juice			7.51	1.10
Flavored milk			1.64	1.01
Fruit water			0.85	0.90
Water			11.38	0.71

Notes: Market shares are based on transactions made by the 2,449 individuals in the estimation sample between June 2009 and December 2014. Prices are the means across all choice occasions.

Table 3—Retailer Types

		Observations	Percent
Retailer types			
National store	Large	128,649	20.9
	Small	88,570	14.4
Vending machines		48,435	7.9
Convenience store	North	153,727	24.9
	Midlands	83,081	13.5
	South	114,082	18.5
Total		616,544	100.0

Notes: The table shows the number and share of purchases made by 2,449 individuals in the estimation sample in each retailer type between June 2009 and December 2014. Large national stores include Aldi, Asda, Lidl, Morrisons, Sainsbury's, Tesco, and Waitrose. Small national chains include Budgens, Co-op, Costcutter, Greggs, Holland & Barrett, Iceland, Londis, M&S, Netto, Spar, and a few others.

Denote by $Q^o_{i\tau}$ individual i's date τ on-the-go soft drinks demand and $Q^h_{i\tau}$ their at-home demand. Consider demand functions of the following form:

$$Q^o_{i\tau} = D^o_i\left(\Pi^o_{r(i)\tau}, Q^h_{i\tau}\right),$$

$$Q^h_{i\tau} = D^h_i\left(\Pi^h_{r(i)\tau}, \mathcal{I}^h_{f(i)\tau}\right),$$

where $\Pi^o_{r(i)\tau}$ and, $\Pi^h_{r(i)\tau}$ capture the prices of on-the-go and at-home soft drinks in the region r where individual i resides and $\mathcal{I}^h_{f(i)\tau}$ denotes the inventory held by the individual's household $f(i)$ at-home at time τ. The at-home demand function $D^h_i(\cdot,\cdot)$ embeds the sharing rule governing how household-level demand translates into individual i at-home consumption. Under this demand structure, nonseparability between on-the-go and at-home choices arise through the (possible) dependence of on-the-go demand on at-home demand.

Following Browning and Meghir (1991) and the subsequent literature, we test weak separability in on-the-go demand with respect to at-home demand by testing the exclusion of $Q^h_{i\tau}$ in $D^o_i(\cdot,\cdot)$ conditional on prices $\Pi^o_{r(i)\tau}$. In our context we do not directly observe individual demand at home; instead we observe household purchases.

We use as a proxy for household at-home demand, $Q^h_{i\tau}$, the sum of the household's purchases in the past 7 days divided by the standard OECD modified equivalence scale. This is likely to deviate from actual consumption as some households may consume their purchases more quickly or slowly than over a week. However, we can infer a household's inventory, $\mathcal{I}_{f(i)\tau}$, using their purchase history. We use this measure of household inventory as an instrument for our proxy for at-home demand. Similarly to Hendel and Nevo (2006b), we measure the inventory as the cumulative sum of past at-home purchases minus a household-specific average consumption level.[13] This measure will be high after recent at-home purchases and will deplete to zero following a sufficiently long period of no at-home purchases.

[13] Specifically, we compute the household's average consumption as the mean at-home volume they purchase over their time in the sample: denote this by $c_{f(i)}$. We then compute the at-home inventory as $\mathcal{I}_{f(i)\tau} = \max\{0, \mathcal{I}_{f(i)\tau-1} + Q^h_{i\tau} - c_{f(i)}\}$.

We measure consumer i's on-the-go soft drinks demand on date τ, $Q^o_{i\tau}$, with an indicator variable equal to 1 if the consumer chooses to purchase.[14] We test separability between demand on-the-go and demand at-home by estimating the following regression:

$$Q^o_{i\tau} = \gamma_{r(i)\tau} + \beta Q^h_{i\tau} + \nu_i + \varepsilon_{i\tau}.$$

Testing for separability between at-home and on-the-go demands boils down to testing the hypothesis that $\beta = 0$. Rather than construct a price index, $\Pi^o_{r(i)\tau}$, we include year-month-region effects, $\gamma_{r(i)\tau}$, which flexibly control for the effect of prices; ν_i is an individual fixed effect, and $\varepsilon_{i\tau}$ is an individual-specific deviation.

For each individual in the full on-the-go sample we consider one observation for every day (regardless of whether a drink is purchased) between the individual's first and final day in the sample. We report coefficient estimates in Table 4. Column 1 shows a bivariate OLS regression between purchasing on-the-go and purchases at-home over the preceding seven days. In column 2 we report the two-stage least squares (2SLS) estimate, where we use the household inventory measure as an instrument for at-home purchases[15] and in column 3 we add in time-region fixed effects. These show that instrumenting and controlling for prices through year-month-region effects reduces somewhat the size of the coefficient on at-home purchases. In column 4 we add into the regression individual fixed effects, which control for fixed preference heterogeneity across individuals. This results in the coefficient on at-home purchases dropping further and becoming statistically insignificant. Finally, in column 5 we additionally control for time-varying demographic variables, which have little impact on the at-home purchases coefficient.

On average, in our full sample of 5,555 individuals, the probability someone purchases soft drinks on-the-go on any day is around 4 percent. The average equivalized at-home purchases over seven days is 0.8 liters, with a standard deviation of 1.7. Therefore the at-home purchase coefficient in column 3 implies a 1 standard deviation increase in at-home purchases leads to a 0.7 percentage point increase in the probability of buying on-the-go (i.e., $1.7 \times 0.0039 \times 100$). This effect is small. Once we control for individual fixed effects and demographics (column 5) the effect shrinks further (to 0.4 percentage points) and becomes statistically insignificant.

Our interpretation of this is that accounting for rich individual heterogeneity is crucial in capturing demand patterns and, conditional on this, there is little evidence that demand linkages between on-the-go and at-home soft drinks demand are of first-order importance. In our demand model we incorporate rich individual-level preference heterogeneity. Nonetheless, there remains the possibility that, while not being key in driving overall on-the-go soft drinks demand, at-home purchases could be important in driving exactly what products individuals choose. We therefore allow for the possibility that at-home inventories of different types of drinks impact consumer on-the-go product choice (see discussion in Section II and estimates in Table 9). While it would be interesting to study more broadly the

[14] Similar results hold if we use quantity purchased.

[15] Concretely, we instrument at-home purchases over the preceding 7 days with the household's inventory at the beginning of the 7-day period.

Table 4—Separability Test between Demand On-the-Go and At-Home

	(1)	(2)	(3)	(4)	(5)
At-home volume purchased	0.00485	0.00413	0.00393	0.00253	0.00241
	(0.00005)	(0.00039)	(0.00039)	(0.00530)	(0.00514)
Constant	0.03383	0.03430	0.05385	0.05156	0.05331
	(0.00007)	(0.00031)	(0.00161)	(0.00529)	(0.00922)
Instrument variable	No	Yes	Yes	Yes	Yes
Time-region effects	No	No	Yes	Yes	Yes
Individual effects	No	No	No	Yes	Yes
Time -varying demographics	No	No	No	No	Yes

Notes: Table shows the relationship between purchasing soft drinks on-the-go and weekly at-home volume purchased. There are 8,180,656 observations, one for every day between the first and final day in the sample for each of the 5,555 individuals in the full on-the-go sample. Column 1 is estimated using OLS while columns 2–5 are estimated by 2SLS with at-home inventory as an instrumental variable for the weekly at-home volume purchased. The demographic variables in column 5 are dummies for socioeconomic status, age group (<20, 20–29, 30–39, 40–49, 50–59, 60+), number of children in the household (0, 1, 2, 3+) and household size (1, 2, 3, 4, 5+).

interactions between household demand and individual on-the-go demand, we leave this for future work.

D. *Demographics*

Soda taxes are primarily justified on the grounds that they address externalities and internalities. There is evidence that added sugar consumed in liquid form raises the risk of developing a number of diseases.[16] This gives rise to externalities through increases in public health costs, and also potentially to internalities.

A number of recent papers have focused on the internality correcting rationale of taxation; including in food and drink markets (O'Donoghue and Rabin 2006; Haavio and Kotakorpi 2011; Allcott, Lockwood, and Taubinsky 2019a), cigarette markets (Gruber and Kőszegi 2004), and energy markets (Allcott, Mullainathan, and Taubinsky 2014). A large theory literature posits that not all individuals fully account for future costs of consumption (for a survey, see Rabin 1998), often offering food and drink consumption as the motivating example. There also exists both experimental evidence that people have behavioral biases with respect to food and drink consumption (see, for instance, Read and Van Leeuwen 1998 and Gilbert, Gill, and Wilson 2002), and circumstantial evidence from the existence of a multi-billion pound dieting industry (Cutler, Glaeser, and Shapiro 2003). We do not seek to measure the size of internalities. Rather, we focus on how effective soda taxes are at reducing sugar consumption among those demographics (the young, high sugar consumers, and those with low incomes) that are highlighted by policymakers as the groups whose consumption they would most like to change.

Lowering the sugar intake of young people is a stated aim of public policy (for instance, see CDC 2016, Public Health England 2015). On average the young get a relatively large fraction of their calories from sugar, so excess sugar consumption

[16] See Allcott, Lockwood, and Taubinsky (2019b) and Scientific Advisory Committee on Nutrition (2015) for summaries of the evidence.

is more severe among this group (see details in online Appendix Section A.1). This tendency has increased over time.[17] Medical evidence suggests that exposure to sweetened beverages early in life can establish strong lifelong preferences for these products (Mennella, Bobowski, and Reed 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.[18] 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).

Those with high sugar diets are a group that policymakers have also targeted (for instance, see CDC 2016, Public Health England 2015). Consuming more sugar is associated with higher instances of diet-related disease and associated medical expenditures. If the marginal social costs from sugar consumption are increasing (e.g., at lower levels of sugar consumption the probability of developing type II diabetes is trivially small, but this probability rises nonlinearly in sugar consumption) this would reinforce the rationale for focusing on this group. Supporting this hypothesis, 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. A second reason to focus on low-income individuals is that there is some evidence that they are more likely to exhibit behavior that creates internalities than those on higher incomes (see Haushofer and Fehr 2014 and Mani et al. 2013). If all consumers suffer from the same marginal internality, higher levels of soft drink consumption among low-income individuals would mean total internality costs are higher for this group. Allcott, Lockwood, and Taubinsky (2019a) provide evidence that marginal internalities may actually be higher for low-income consumers, implying any internalities may be even more concentrated among this group.[19]

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.[20] There are other demographics that might also be of interest, and in online Appendix Section B we show how the estimated preference parameters vary

[17] For instance, Cavadini, Siega-Riz, and Popkin (2000) document an increase in soft drink consumption in the United States for 11–18-year-olds of almost 300 percent for boys, and over 200 percent for girls between 1965 and 1996, and Nielsen and Popkin (2004) document a contemporaneous fall in the share of calories children get from milk.

[18] See, for instance, Cawley (2010); Gortmaker, Long, and Wang (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) and Rugg-Gunn et al. (2007).

[19] Allcott, Lockwood, and Taubinsky (2019a) use soft drinks consumption of people who state they have no self-control problems and of dietitians, conditional on demographic controls, as a measure of soft drinks consumption of non-biased consumers and measure the degree of misoptimization relative to this benchmark.

[20] Grocery expenditure includes spending on food, drink (including alcohol), pet food, toiletries, and cleaning products. In Dubois, Griffith, and O'Connell (2019), 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.

Table 5—Descriptive Statistics by Age Groups

	Age group					
	13–21	22–30	31–40	41–50	51–60	60+
Percent of sample	11.1	13.8	20.3	21.5	17.2	16.1
Fraction of soft drink purchasers	0.44	0.50	0.53	0.48	0.38	0.26
Conditional on purchase						
Mean sugar from soft drinks per year (g)	2,036	1,784	1,356	1,378	1,265	1,057
Mean number of purchases per year	46.3	43.2	38.7	34.1	33.4	28.8
Fraction of sugary products	0.73	0.67	0.60	0.61	0.62	0.62
Fraction of 500ml bottles	0.74	0.72	0.69	0.70	0.69	0.68

Notes: Row 1 shows the fraction of individual-year observations in each age group. Row 2 shows the fraction of each age that are soft drink purchasers, defined as in footnote 9. 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.

by gender and the household's socioeconomic status (which is a good proxy for education level).

In Table 5, we describe the age distribution of the total on-the-go sample. We estimate demand using the 2,449 individuals who are "soft drink purchasers." The table also 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 (500 ml bottles) that is key in driving the higher sugar levels.

Tables 6 and 7 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.

II. Model and Estimated Coefficients

In this section we develop a model of consumer choice in the nonalcoholic drinks market. 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.[21]

[21] We estimate a similar model of demand in the at-home segment; details are reported in online Appendix C.

Table 6—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	8.4	9.9	11	11.9	12.9	13.8	14.9	16.3	18.4	24.7
Fraction of soft drink purchasers	0.33	0.41	0.42	0.41	0.45	0.45	0.46	0.49	0.47	0.48
Conditional on purchase										
Mean sugar from soft drinks per year (g)	1,035	1,347	1,277	1,210	1,296	1,356	1,541	1,574	2,020	1,760
Mean number of purchases per year	35.9	39	36.2	34.1	35.4	36.3	37.7	37.7	43.3	37.9
Fraction of sugary products	0.55	0.58	0.59	0.60	0.64	0.66	0.66	0.66	0.66	0.70
Fraction of 500ml bottles	0.65	0.67	0.67	0.70	0.71	0.73	0.72	0.71	0.71	0.73

Notes: Row 1 shows the upper bound of the decile of total annual dietary sugar. Row 2 shows the fraction of each age that are soft drink purchasers, defined as in footnote 9. 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 7—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	0.8	1.1	1.3	1.5	1.7	1.9	2.1	2.5	3.1	5.1
Fraction of soft drink purchasers	0.48	0.44	0.44	0.44	0.48	0.44	0.40	0.43	0.44	0.39
Conditional on purchase										
Mean sugar from soft drinks per year (g)	1,664	1,454	1,683	1,426	1,583	1,514	1,312	1,291	1,233	1,440
Mean number of purchases per year	41.5	36.4	42.8	35.9	37.6	37.4	34.3	35	34.2	39.1
Fraction of sugary products	0.66	0.65	0.62	0.64	0.65	0.63	0.66	0.61	0.63	0.62
Fraction of 500ml bottles	0.67	0.70	0.69	0.68	0.70	0.70	0.72	0.72	0.72	0.72

Notes: Row 1 gives the upper bound of the decile, measured in £1,000, of total annual equivalized grocery expenditure. Row 2 shows the fraction of each age that are soft drink purchasers, defined as in footnote 9. 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.

A. *Demand Model*

We index consumers by $i \in \{1, \ldots, N\}$. We observe each consumer on many choice occasions, indexed by $\tau = \{1, \ldots, \mathcal{T}\}$. A choice occasion τ refers to a consumer visiting a retailer $r(\tau)$ at time $t(\tau)$ and purchasing either a nonalcoholic drink or a snack.[22] Denote the available set of drinks products in retailer $r = \{1, \ldots, R\}$ during choice occasion τ as $\Omega_{r(\tau)}$.

We index the J nonalcoholic drinks products (i.e., the "inside goods") by j with $j = \{1, \ldots, j'\}$ for the soft drinks and $j = \{j' + 1, \ldots, J\}$ for the alternative drinks. These products are reported in Table 2. We allow for the possibility that consumers instead choose either a sugary or a non-sugar snack. We refer to these

[22] We treat the decision to visit a store as exogenous.

as "outside options," and we indicate the sugary snack by $j = \bar{0}$ and the non-sugar snack by $j = \underline{0}$. The choice set facing a consumer on choice occasion τ contains the subset $\Omega_{r(\tau)}$ of the J drinks products available in retailer r plus the two outside options. Typically several soft drinks products belong to a single 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.

We assume the payoff associated with selecting a product j on choice occasion τ takes the form

$$(1) \qquad U_{ij\tau} = \alpha_i p_{jr(\tau)t(\tau)} + \beta_i s_j + \gamma_i w_j + \delta^{\kappa}_{d(i)} \kappa_{ij\tau} + \delta^{\mathfrak{a}}_{d(i)} \mathfrak{a}_{b(j)t(\tau)} + \delta^{h}_{d(i)} h_{c(i)t(\tau)} + \delta^{z}_{d(i)} z_j + \xi_{d(i)b(j)t(\tau)} + \zeta_{d(i)b(j)r(\tau)} + \epsilon_{ij\tau},$$

and the payoffs from selecting the outside options are given by

$$U_{i\bar{0}\tau} = \beta_i + \epsilon_{i\bar{0}\tau},$$

$$U_{i\underline{0}\tau} = \epsilon_{i\underline{0}\tau},$$

where $(\epsilon_{i\underline{0}\tau}, \epsilon_{i\bar{0}\tau}, \epsilon_{i1\tau}, \ldots, \epsilon_{iJ\tau})$ are distributed type I extreme value independently across individuals, options, and time.

The term $p_{jr(\tau)t(\tau)}$ denotes the price of product j, which varies through time (t) and across retailer types (r). The variable s_j is a dummy indicating whether the product contains sugar and w_j is a dummy variable for whether the product is a drink (as opposed to a snack). We include individual specific preferences over these three key product characteristics. For the remaining characteristics we restrict heterogeneity to vary across demographic groups, where we denote by $d(i)$ the group to which individual i belongs. These groups distinguish between individuals on the basis of gender and age (below 40 and 40 and above).

A convenient feature of modeling purchases made on-the-go for immediate consumption is that it minimizes concerns about dynamics in demand arising from consumer stockpiling (a situation considered in Wang 2015); by definition the consumption occasions that we are considering do not involve storage. Another form of dynamics in demand would arise if there are intertemporal nonseparabilities in preferences. An obvious form of nonseparability is that recent at-home purchases impact on-the-go demands. In Section IC we provide evidence that, once fixed unobserved individual heterogeneity is accounted for, this form of demand linkage is not of first order importance for the decision to purchase a soft drink in our setting. In our demand model we allow for the possibility that at-home inventories impact the choice of what specific (if any) drink an individual chooses. We do this by controlling for $\kappa_{ij\tau}$; a measure of the inventory of drinks the individual has access to due to recent at-home purchases: this is defined analogously to the inventory measure we use in Section IC. We include a j index on this variable to indicate that it varies across products. In practice we compute separate at-home inventory variables for sugary soft drinks, diet soft drinks, fruit juices, flavored milk, and waters and let each measure impact the on-the-go utility of products belonging to that set.

We also include a measure of weekly regional brand-level advertising expenditure, $\mathfrak{a}_{b(j)t(\tau)}$ (variation by region arises due to the geographic span of regional TV channels),[23] and the effects of temperature $(h_{c(i)t(\tau)})$ in location $c(i)$ where the consumer lives at time $t(\tau)$.[24] We include size-carton type effects (z_j), time-varying brand effects $(\xi_{d(i)b(j)t(\tau)})$ (at the year and quarter level) and retailer-brand effects $(\zeta_{d(i)b(j)r(\tau)})$.

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 enable the 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, Levinsohn, and Pakes 1995, 2004; Nevo 2001) show that incorporating consumer-level preference heterogeneity is important for enabling choice models to capture realistic switching patterns across products.[25] A few papers use nonparametric methods to relax parametric restrictions on random coefficient distributions.[26] 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 policy 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).[27]

One potential concern is that our estimates may be subject to an incidental parameter problem that is common in nonlinear panel data estimation. Even if

[23] We measure weekly advertising expenditure in the AC Nielsen Advertising Digest (AC Nielsen 2014). We compute product-specific stocks based on a monthly depreciation rate of 0.9. This is similar to the rate used in Dubois, Griffith, and O'Connell (2018) using similar data in the potato chips market.

[24] These data are from the Met Office Historic station data and are reported monthly for 35 locations in the United Kingdom (UK Met Office 2014)

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

[26] Burda, Harding, and Hausman (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, Fox, and Ryan (2007) discretize the random coefficient distribution and use linear estimation techniques to estimate the frequency of consumers at each fixed point.

[27] In Dubois, Griffith, and O'Connell (2019), an earlier version of this paper, we compare our estimates to those obtained with a standard random coefficients model, and show that the two models yield similar estimates of market-level demand curves, but the random coefficient model is not able to capture the rich correlation in preferences and consumer attributes.

both $N \rightarrow \infty$ and $\mathcal{T} \rightarrow \infty$, 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 suggested in Dhaene and Jochmans (2015) and in Section IVA show that our maximum likelihood and jackknife estimates are similar, and that the bias correction does not materially 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 will never choose to buy them. We identify consumers that never purchase products with particular characteristics (e.g., options that contain sugar) over the long time dimension of our data 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 nonzero purchase probabilities for all products available to them.

In particular, any individuals that never purchase sugary drinks or snacks reveal a strong distaste for sugar (which we denote by $\beta_i = -\infty$), and any individuals who never purchase non-sugary drinks or non-sugary snacks reveal a strong taste for sugar (which we denote by $\beta_i = \infty$). For individuals that sometimes purchase sugary options and at other times non-sugary options, their sugar preferences are such that $\beta_i \in (-\infty, \infty)$.

To specify the set of options that consumers have nonzero probabilities for, it is useful to define the product sets Ω_s and Ω_n, which denote the sets of sugary drinks and non-sugary drinks. We can then define consumer specific sets of options with nonzero purchase probabilities, denoted by Ω_i, as

$$\Omega_i = \begin{cases} \Omega_s \cup \Omega_n \cup \{\bar{0}\} \cup \{\underline{0}\} & \text{if } \beta_i \in (-\infty, \infty) \\ \Omega_n \cup \{\underline{0}\} & \text{if } \beta_i = -\infty \\ \Omega_s \cup \{\bar{0}\} & \text{if } \beta_i = +\infty. \end{cases}$$

We measure the consumer level product sets Ω_i thanks to the large $\mathcal{T}$ dimension of observed consumer level choices. We ignore the finite sample measurement error on Ω_i as Monte Carlo simulations show that such error is negligible in our application where $\mathcal{T}$ is relatively large.[28]

For drinks products $j \in \{1, \ldots, J\}$ we define

$$v_{ijr(\tau)t(\tau)} \equiv \alpha_i p_{jr(\tau)t(\tau)} + \beta_i s_j \mathbf{1}_{\{\beta_i \in (-\infty,\infty)\}} + \gamma_i w_j,$$

$$\eta_{ijr(\tau)t(\tau)} \equiv \delta^{\kappa}_{d(i)} \kappa_{ij\tau} + \delta^{\mathfrak{a}}_{d(i)} \mathfrak{a}_{b(j)t(\tau)} + \delta^{h}_{d(i)} h_{c(i)t(\tau)} + \delta^{z}_{d(i)} z_j + \xi_{d(i)b(j)t(\tau)} + \zeta_{d(i)b(j)r(\tau)},$$

such that equation (1) can be written

$$U_{ij\tau} = v_{ijr(\tau)t(\tau)} + \eta_{ijr(\tau)t(\tau)} + \epsilon_{ij\tau}.$$

[28] Further details available from authors on request.

The assumption that $(\epsilon_{i\underline{0}\tau}, \epsilon_{i\bar{0}\tau}, \epsilon_{i1\tau}, \ldots, \epsilon_{iJ\tau})$ are idiosyncratic shocks independently 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 drinks product $j \in \Omega_{r(\tau)}$ can be written[29]

$$(2)\quad P_{i\tau}(j) = \frac{\mathbf{1}_{\{j\in\Omega_i\}}\exp\left(v_{ijr(\tau)t(\tau)} + \eta_{ijr(\tau)t(\tau)}\right)}{\mathbf{1}_{\{\underline{0}\in\Omega_i\}} + \mathbf{1}_{\{\bar{0}\in\Omega_i\}}\exp(\beta_i) + \sum_{k\in\Omega_i\cap\Omega_{r(\tau)}}\exp\left(v_{ikr(\tau)t(\tau)} + \eta_{ikr(\tau)t(\tau)}\right)}.$$

Denote consumer i's sequence of choices across all choice occasions as $\mathbf{y}_i = \left(y_{ir(1)t(1)}, \ldots, y_{ir(\mathcal{T})t(\mathcal{T})}\right)$; then the probability of observing $\mathbf{y}_i$ is given by

$$\mathcal{L}_i(\mathbf{y}_i) = \prod_{\tau=1}^{\mathcal{T}} P_{i\tau}\left(y_{ir(\tau)t(\tau)}\right),$$

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

$$(3)\qquad l(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\eta}) = \sum_i \ln \mathcal{L}_i(\mathbf{y}_i),$$

which is globally concave with respect to all parameters.

B. *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 type-drink type effects, we exploit cross-retailer type variation in the *relative* prices of different drinks products. This arises because we observe individuals making purchases in different retailers across time (and thereby facing different price vectors). An important identifying assumption is that retailer choice is not driven by shocks to demand for a *specific* drinks product, but rather that 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.[30]

The price vector an individual faces at the point of purchase depends on which retailer they visit. These retailers include a set of large national retailers that price nationally, smaller retailers with regionally varying prices and vending machines (see Table 3). We include demographic group-specific time-varying brand effects $\xi_{d(i)b(j)t(\tau)}$ and retailer type effects, interacted with the drink types, $\zeta_{d(i)b(j)r(\tau)}$.[31]

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

[30] In Dubois, Griffith, and O'Connell (2019), we provide descriptive statistics that illustrate the price variation individuals face, and that the monthly prices we use in estimation reflect actual variation in underlying transaction prices.

[31] Specifically, the time varying brand effects include Coca-Cola, Coca-Cola other brands, Pepsi, Glaxo brands, Irn Bru, the composite "other" soft drinks, non-soft drinks, and each of the two outside options interacted with

The former capture aggregate (demographic-specific) fluctuations in brand demand over time 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 a number of potential concerns with exploiting this type of price variation that we need to address. First, an issue would arise if individual-level demand shocks to specific soft drinks products drive store choice; for instance, if consumers who 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 there are time-varying retailer type-specific demand shocks that are contemporaneously correlated with prices. In the UK market the vast majority of soft drinks advertising is done nationally and by the manufacturer, and we control for this in demand, including the regional variation due to regional broadcasting of some TV channels.[32] We also control for regional variation in weather conditions. Conditional on these (and retailer type effects), we assume the residual cross retailer type price variation is driven by cost differences, by random price reduction strategies and by store-specific decisions related to unanticipated excess stock.

The second source of price variation we exploit is nonlinear pricing across container sizes. This price variation is not collinear with the size effects, and the extent of nonlinear 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). Given prices and other demand controls, the proportion of a consumer's purchases that are for sugary

year and quarter effects. The retailer type–drink type effects include branded soft drinks, the composite "other" soft drinks, fruit juice, water, and each of the two outside options interacted with the store types shown in Table 3.

[32] Targeted price discounts through use of coupons, common in the United States (see Nevo and Wolfram 2002), are not a common feature of the UK market.

varieties identifies the consumer's taste for sugar. Identification here relies on the assumption that the brand effects are common across sugary and diet varieties, and that the taste for sugar is additively separable. This means that, for example, we do not allow the individual sugar taste to be different for Coke versus Pepsi. An individual consumer's preference for drink (versus snack) is identified, everything else equal, from the proportion of their on-the-go purchases that are for drinks rather than snacks.

C. *Pass-Through of a Tax on Sugary Soft Drinks*

An important issue in estimating the impact of a tax on consumption is the extent to which the tax is shifted onto prices. Here we present evidence of pass-through of the Soft Drinks Industry Levy, which was introduced in the United Kingdom in 2018, to the price of soft drinks available in the on-the-go market. This evidence suggests pass-through is around 100 percent, and accords with much of the mounting evidence of complete pass-through of soda taxes in other jurisdiction. We also simulate tax pass-through using a demand and supply model. To do this we use our on-the-go demand estimates along with estimates for the at-home segment (reported in online Appendix Section C) and couple it with a Nash-Bertrand pricing model. We report the equilibrium pass-through results in Section IVC; the results are similar to the direct evidence on tax pass-through that we present here.

There is a growing literature that estimates pass-through of soda taxes to prices using data covering the implementation of the tax.[33] The most common finding is that pass-through was full or near to full (i.e., prices rose by the full amount of the tax).[34] There are a few papers that find low pass-through, mainly studying the soda tax case of Berkeley, CA.[35] A key difference between the Berkeley setting and many of the other jurisdictions that have implemented soda taxes is that Berkeley is comparatively small, meaning that cross-border shopping is easier and there will be more competitive pressure on firms to keep prices down. The studies that look at larger jurisdictions are more relevant to the UK setting, because the taxes cover a wider geographical area, and therefore cross-border shopping is likely to be less important.

The broad finding (with the exception of Berkeley) of around full pass-through of soda taxes is consistent with studies that look at pass-through of other taxes. These include Besley and Rosen (1999), which exploits variation in state and local sales taxes in the United States and looks at the impact on prices of a number of products and finds slight overshifting for soft drinks 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 with tax reforms in Alaska.

[33] Griffith et al. (2019) provide a review.

[34] Papers that find full or near-full pass-through include Aguilar, Gutierrez, and Seira (2018); Berardi et al. (2016); Capacci et al. (2019); Castello and Lopez-Casasnovas (2018); Cawley et al. (2018a, b); Cawley, Willage, and Frisvold (2018); Colantuoni and Rojas (2015); Colchero et al. (2015); Gonçalves and dos Santos (2019); Powell, Leider, and Léger (2020); Seiler, Tuchman, and Yao (2018); Silver et al. (2017).

[35] Bollinger and Sexton (2018); Cawley and Frisvold (2017); Etilé, Lecocq, and Boizot-Szantai (2018); Falbe et al. (2015); Rojas and Wang (2017).

There is also a related literature that estimates pass-through of cost shocks. Much of this finds undershifting (see, for instance, Goldberg and Hellerstein 2013 and 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.

We provide direct evidence on pass-through of the recently introduced Soft Drinks Industry Levy in the United Kingdom using an event study design for prices (per liter) of the two main brands, Coca-Cola and Pepsi. The tax was introduced on April 1, 2018. We use data on transaction prices from the Kantar on-the-go survey for sugary Coca-Cola and Pepsi products covering the year before and after this date. Denoting transactions by ι, we estimate the regression

$$trans.price_{\iota} = a + b \times I_{\iota}[tax] + X_{\iota}c + e_{\iota}, \tag{4}$$

where $I_{\iota}[tax]$ is an indicator variable equal to 1 if the transaction took place on or after April 1, 2018, and X_{ι} includes dummy variables for brand, pack size, month, and store type. We report coefficient estimates in Table 8, both for all sugary Coca-Cola and Pepsi products together, and estimated separately by the two main on-the-go pack sizes (330 ml can and 500 ml bottles).

The Soft Drinks Industry Levy placed a tax of 24 pence per liter on the sugar variants of Coke and Pepsi. This tax rate is subject to 20 percent VAT; therefore a price increase of 28.8 pence per liter associated with the tax represents full pass-through. The estimates in Table 8 suggest that prices of these products increased by 28 pence when all considered together. The prices of smaller pack sizes increased by slightly less, 24.1 pence per liter, and prices of larger pack size increased by slightly more, 29.4 pence. In online Appendix Section E we report simulated pass-through based on our demand estimates and a classic supply-side Nash-Bertrand pricing oligopoly model. We find similar patterns; the structural model does a reasonable job of predicting the pass-through patterns that have resulted from the UK soda tax.

D. *Estimated Preference Coefficients and Elasticities*

In Table 9, we summarize the distribution of estimated consumer-specific preference parameters (upper panel) obtained by maximizing the likelihood function (equation (3)). We report means, standard deviations, skewness, and kurtosis of the estimated parameters, as well as the covariance between them. These numbers are based on the finite portion of the joint preference distribution. In the lower panel, we report the coefficients on the at-home inventory, product advertising, and air temperature. These coefficients vary across demographic groups (age and gender).

In Figure 1, we plot the marginal preference distributions for price, and the drink and sugar product attributes. 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

Table 8—Pass-Through of UK Sugar Tax

	All	330ml	500ml
After tax	0.280	0.241	0.294
	(0.012)	(0.019)	(0.016)
Constant	2.310	2.007	2.291
	(0.026)	(0.057)	(0.032)
Observations	10,179	3,920	6,259

Notes: We regress the price of Coca-Cola (including Cherry Coke) and Pepsi products that were subject to the Soft Drinks Industry Levy on a dummy variable that is equal to 1 after the implementation of the tax on April 1, 2018. The data runs from April 1, 2017 to March 31, 2019. All regressions include brand dummies, pack size dummies, month dummies, and store type dummies. Standard errors are reported in parentheses.

indifferent (i.e., not statistically significantly different from zero) preferences for each attribute. Table 9 shows that moments of each of these distributions are estimated with a high degree of precision. It is 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 skew for price preferences and the positive skew for drinks preferences, as well as the infinite portions of the sugar preference distribution.

The estimates of the consumer-specific preference parameters reveal a large degree of heterogeneity across individuals: the standard deviation for price preferences is 2.3 (with a coefficient of variation of 0.7), while the standard deviation for drinks and sugar preferences are 2.4 and 1.5. Price sensitive consumers tend to have relatively strong drinks preferences (the correlation coefficient between price and drinks preferences is -0.9).[36] We show contour plots of the bivariate preference distributions in online Appendix Section B.

The lower panel of Table 9 shows the demographic-specific preference estimates for at-home inventories, product-level advertising, and temperature. As in the descriptive analysis in Section IC, the impact of recent at-home purchases of drinks on utility on-the-go from drinks is positive and very small. For instance, allowing the at-home inventory to fully deplete to zero for sugary soft drinks results on average in a decrease in annual volume per person demanded of on-the-go sugary soft drinks of just 0.33 liters (equivalent to 1 can of Coca-Cola). Higher levels of advertising for a product has a statistically significant and positive effect on utility from that product for males (but not females). All demographic groups obtain more utility from drinks on hotter days.

We report price elasticities for all products in online Appendix Section B. 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 500 ml products are smaller in magnitude than for the 330 ml versions; consumers who choose to buy the larger bottle variants rather than

[36] The coefficient of variation of price preferences is given by the ratio of the reported standard deviation and mean $(2.33/3.15 = 0.74)$ and the correlation coefficient of price and drinks preferences is given by the reported covariance divided by the product of the reported standard deviations $(-4.97/(2.33 \times 2.42) = -0.88)$.

Table 9—Demand Model Estimates

Variable		Estimate	Standard error
Moments of distribution of consumer-specific preferences			
Price (α_i)	Mean	−3.1461	0.0228
	Standard deviation	2.3311	0.0157
	Skewness	−0.9726	0.0340
	Kurtosis	4.3029	0.1291
Drinks (γ_i)	Mean	2.0180	0.0396
	Standard deviation	2.4239	0.0171
	Skewness	0.6235	0.0361
	Kurtosis	3.9720	0.0711
Sugar (β_i)	Mean	0.4456	0.0079
	Standard deviation	1.5047	0.0111
	Skewness	−0.3126	0.0528
	Kurtosis	4.5575	0.1642
Price–drinks	Covariance	−4.9696	0.0744
Price–sugar	Covariance	0.2080	0.0277
Drinks–sugar	Covariance	−0.0482	0.0293
Demographic-specific preferences			
At-home inventory ($\delta^{\kappa}_{d(i)}$)	Female, <40	0.0860	0.0042
	Female, +40	0.0439	0.0037
	Male, <40	0.0693	0.0042
	Male, +40	0.0637	0.0038
Advertising ($\delta^{a}_{d(i)}$)	Female, <40	0.0011	0.0010
	Female, +40	0.0002	0.0010
	Male, <40	0.0040	0.0009
	Male, +40	0.0037	0.0009
Temperature × drinks ($\delta^{h}_{d(i)}$)	Female, <40	0.0214	0.0025
	Female, +40	0.0185	0.0023
	Male, <40	0.0229	0.0023
	Male, +40	0.0225	0.0022
Demographic-specific size-carton size effects ($\delta^{z}_{d(i)}$)		Yes	
Time-demographic-brand effects ($\xi_{d(i)b(j)t}$)		Yes	
Retailer-demographic-brand effects ($\zeta_{d(i)b(j)r(\tau)}$)		Yes	

Notes: We estimate demand on a sample of 2,449 individuals who we observe on 616,544 on-the-go choice occasions. Consumers choose between the products listed in Table 2 and the outside options of purchasing a sugary or non-sugary snack. 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 of these moments are computed using the delta method.

smaller cans tend to be less willing to switch away from their chosen product in response to a price increase. Table 10 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 -1.29. This is smaller than the own price elasticity of any individual soft drink product. The own price elasticity for sugary soft drinks is -1.58. 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.[37]

[37] To calculate the confidence intervals on elasticities 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 elasticity, using the resulting

FIGURE 1. UNIVARIATE DISTRIBUTIONS OF CONSUMER-SPECIFIC PREFERENCE PARAMETERS

Notes: Distributions are based on individual-level preference parameter estimates for the 2,449 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 percent level.

TABLE 10—CATEGORY-LEVEL PRICE ELASTICITY

	Effect of 1 percent price increase on:				
		Cross demand for:			
	Own demand effect	Diet soft drinks	Sugary alternatives	Non-sugary alternatives	Total drinks demand
Soft drinks	−1.29		1.271	1.719	−0.703
	[−1.30, −1.27]		[1.248, 1.287]	[1.704, 1.739]	[−0.706, −0.690]
Sugary soft drinks	−1.58	0.609	0.956	0.739	−0.468
	[−1.60, −1.56]	[0.596, 0.614]	[0.937, 0.968]	[0.731, 0.752]	[−0.471, −0.459]

Notes: We simulate the effect of a 1 percent price increase for all soft drinks (row 1) and all sugary soft drinks (row 2) and report the change in demand for those product sets in column 1. In columns 2–4 we report the effect on demand for alternative product sets and in the final column we report the change in demand for all drinks. 95 percent confidence bands are shown in brackets.

E. *Relationship with Individual Attributes*

A key feature of our model is that it allows us to flexibly relate preference parameters to the characteristics of individual consumers. This enables us to address the question of how effective soda taxes are at targeting the demographic groups whose behavior policymakers would like to change.

distribution across draws to compute Monte Carlo confidence intervals. Note these bands will not necessarily be symmetric around the estimate.

In Figure 2, we show how features of the preference distribution vary with age.[38] Panels A and B show how preferences over price and drinks vary across consumers based on six age bands. There is relatively little variation in the average of these preferences across age groups, with the exception that the oldest group has relatively strong preferences for drinks (indicating, all else equal, a relatively high likelihood that they choose a drink over a snack). However, there is considerable variation in sugar preferences across age. Panel C shows how the fraction of consumers with infinitely negative and positive sugar preferences varies with age: a higher fraction of individuals aged below 30 have infinitely positive sugar preferences (i.e., are only ever observed buying sugary varieties) than older individuals. Panel D shows that, for those individuals with finite sugar preferences (98.5 percent of the sample), the mean sugar preference for the youngest group of individuals is considerably higher than for those aged 22–30, who in turn tend to have stronger sugar preferences than those aged above 30.

Figure 3 summarizes variation in preferences across deciles of the distribution of total annual dietary sugar (measured as the share of household total at-home calories from added sugar). Preferences governing on-the-go drinks demand are strongly related to total annual dietary sugar. Individuals in higher deciles of the added sugar distribution are likely to be less price sensitive and are more likely to have strong (or infinite) preferences for sugar than those from lower deciles of the added sugar distribution. The strong association between added sugar decile and sugar preferences is not mechanical: the former is measured based on household level at-home purchases across all groceries, the latter is estimated from individual choice on-the-go among drinks products. Conversely, the drinks preference parameters are higher for those in the bottom three deciles of the added sugar distribution relative to those in higher deciles.

Figure 4 shows that there is also a relationship between preferences and deciles of the distribution of total annual equivalized grocery expenditure (a proxy for income). There is a gradient for price, drink, and sugar preference parameters; those from low-income households typically have somewhat stronger drink and sugar preferences parameters and are typically more price sensitive than richer individuals.

III. Effects of a Soda Tax on Sugar Intake On-the-Go

We use our demand estimates to simulate the introduction of a tax levied on sugary soft drinks. We consider a tax rate of 25 pence per liter. This is similar to the level of tax under the UK Soft Drinks Industry Levy, and it corresponds to around \$0.01 per ounce, similar to the soda tax rates in place in the United States. In our simulation we apply the tax rate to sugar sweetened soft drinks (treating pure fruit juices and drinks containing milk as exempt). This tax base corresponds to that in the United Kingdom and several of the US taxes.[39]

[38] The confidence bands in Figures 2–6 capture both estimation error in individual-level parameters and statistical uncertainty associated with the reported mean effects being based on a sample of individuals.

[39] Though not Philadelphia, which also taxes artificially sweetened soft drinks. In Dubois, Griffith, and O'Connell (2019), we show simulations of a broader tax that also applies to diet soft drinks.

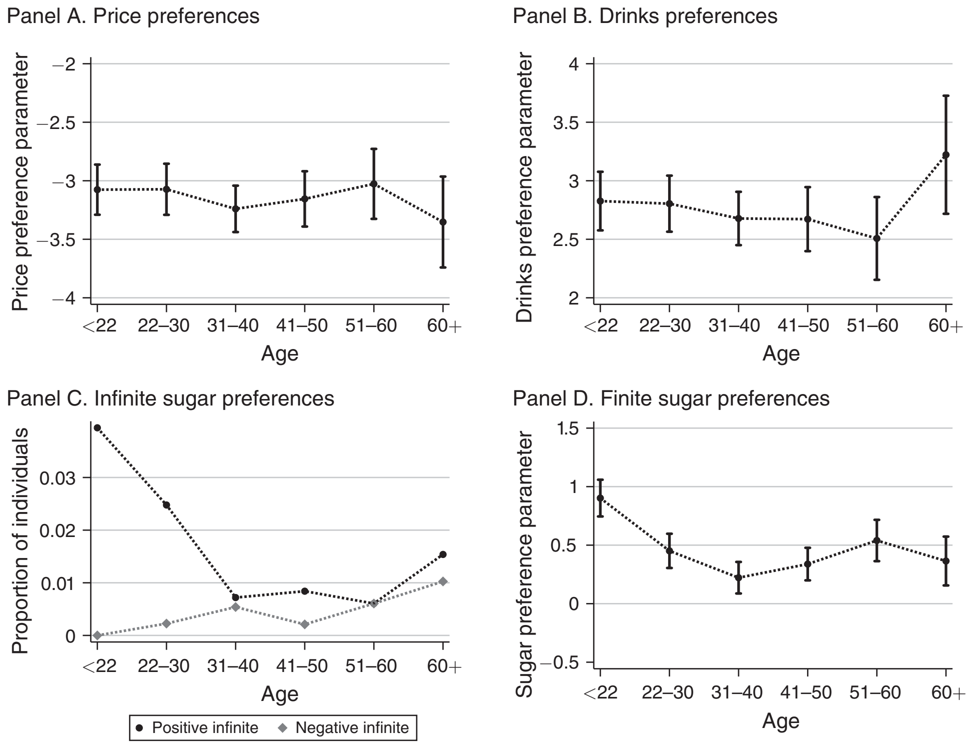

Figure 2. Preference Variation with Age

Notes: Figures show how the mean of price preferences, the mean of drinks preferences, the share of consumers with infinite sugar preferences, and the mean of finite sugar preferences vary by age groups. 95 percent confidence intervals are shown by bars.

Concretely, denote the set of sugary soft drinks (i.e., those products to which the tax applies) by Ω_{ws} and let π denote the tax rate and l_j the volume (in liters) of product j. We assume post-tax prices, $\tilde{p}_{jrt}$ are related to pre-tax prices according to

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

We study the impact of the tax on individual on-the-go sugar consumption. In Section IVB we provide evidence that variation in responses to price changes across households in the at-home segment are unlikely to undo our conclusions about the targeting of the policy on individuals based on on-the-go demand estimates. Based on the evidence of close to 100 percent tax pass-through of soda taxes (discussed in Section IIC) we present our main results assuming 100 percent pass-through. In Section IVC we show that our findings are robust to simulated pass-through based on an equilibrium oligopoly pricing model.

A. *How Well Targeted Is the Tax?*

Our tax simulation suggests that consumers who purchase soft drinks will, on average, lower the total amount of sugar they purchase from soft drinks on-the-go by

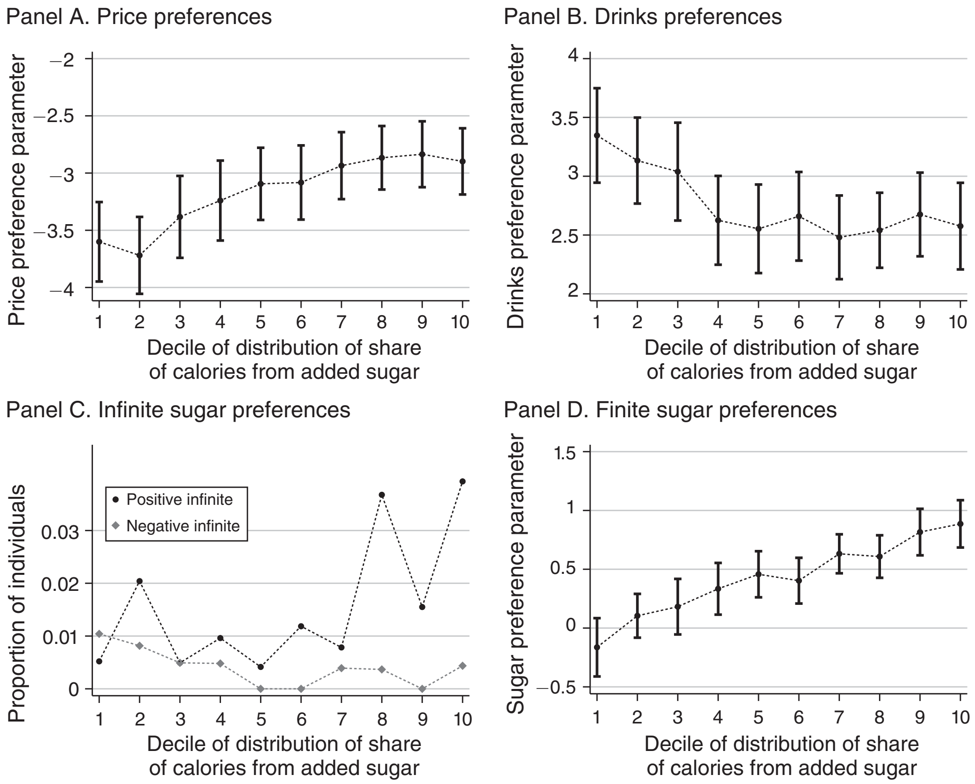

Figure 3. Preference Variation with Total Annual Dietary Sugar

Notes: Figures show how the mean of price preferences, the mean of drinks preferences, the share of consumers with infinite sugar preferences, and the mean of finite sugar preferences vary by deciles of the distribution of total annual dietary sugar. 95 percent confidence intervals are shown by bars.

around 245 g per year: the average percentage reduction is 21 percent. Some of this reduction is offset by switching to alternative (non-taxed) drinks that contain sugar: the average reduction in sugar from nonalcoholic drinks is 222 g. There is also some substitution away from drinks toward alternative snacks. Our demand model captures switching toward both non-sugary and sugary alternatives. Switching toward sugary snacks is relatively modest: the overall average reduction in sugar on-the-go resulting from the tax is 216 g. The limited degree of switching from drinks to snacks is consistent with experimental evidence that calories from liquids do not displace those from solids (see, for instance, DiMeglio and Mattes 2000; DellaValle, Roe, and Rolls 2005; and Flood, Roe, and Rolls 2006). The distribution of reductions in sugar on-the-go is right skewed with the seventy-fifth, ninetieth, and ninety-fifth percentiles being 267 g, 539 g, and 806 g.

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, those in low-income households, and those with high total annual dietary sugar. In Figure 5, we show how the effects of the tax vary across these characteristics. Panels A–C show how the mean reduction for soft drink purchasers in sugar from soft drinks, all nonalcoholic drinks and from all sugar purchased on-the-go varies

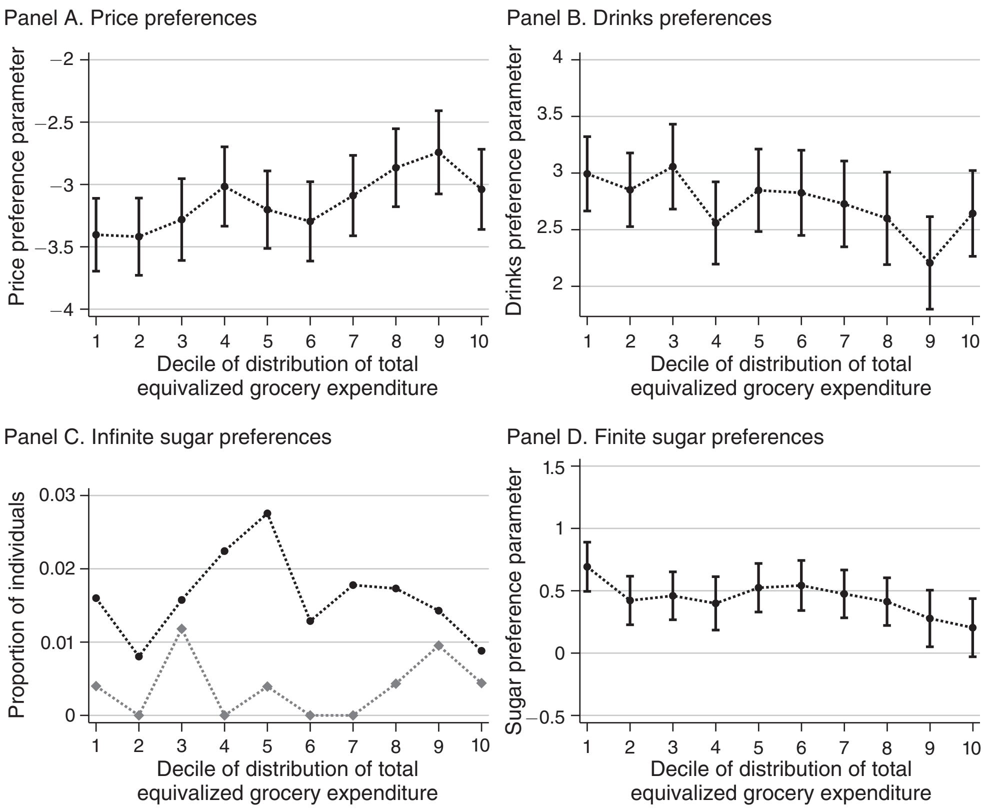

FIGURE 4. PREFERENCE VARIATION WITH TOTAL ANNUAL EQUIVALIZED GROCERY EXPENDITURE

Notes: Figures show how the mean of price preferences, the mean of drinks preferences, the share of consumers with infinite sugar preferences, and the mean of finite sugar preferences vary by deciles of the distribution of total annual equivalized grocery expenditure. 95 percent confidence intervals are shown by bars.

across the distribution of individual age, total annual dietary sugar, and total annual equivalized grocery expenditure.[40] Panels D–E show how the mean reduction in sugar on-the-go varies jointly with pairs of age, total dietary sugar, and total equivalized expenditure.

Panels A–C show that the tax on sugary soft drinks achieves relatively large reductions in sugar among the young and those from households with relatively low total equivalized expenditure (our proxy for income), but it is not successful at targeting those individuals with high total dietary sugar (in particular, 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 on-the-go is slightly lower for those aged below 22 (14 percent versus 15 percent across all individuals), this group obtains a relatively large amount of sugar from products targeted by the tax. This means their level

[40]Tables 5–7 show how the fraction of individuals who are soft drink purchasers varies across these dimensions.

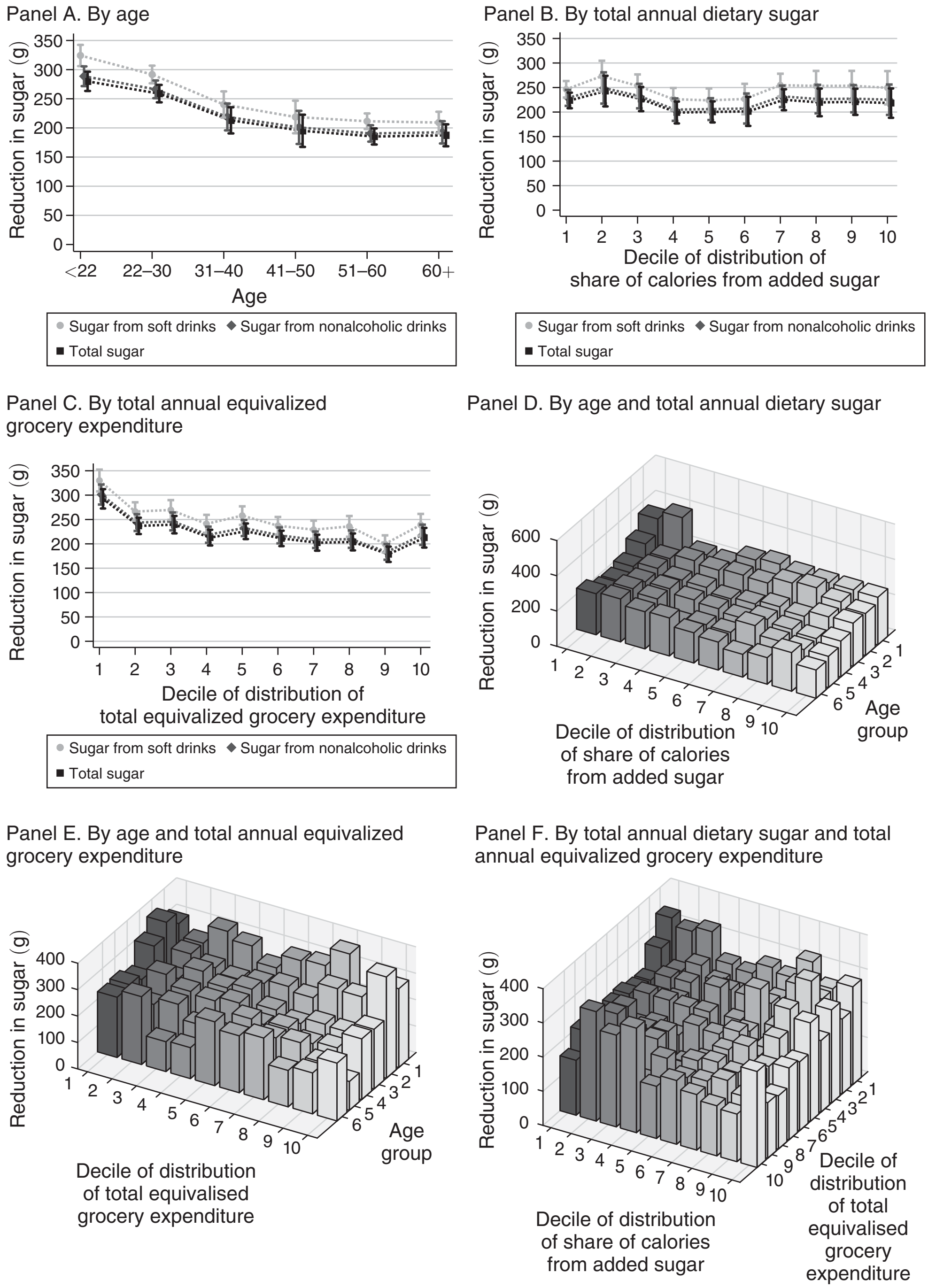

Figure 5. Reductions in Sugar from Drinks

Notes: Figure is based on the 2,449 individuals in the on-the-go estimation sample. It shows how average reduction in annual sugar on-the-go varies across the distributions of individual age, total annual dietary sugar, and total annual equivalized grocery expenditure. Panels A–C show numbers for soft drinks, all nonalcoholic drinks and all on-the-go purchases (95 percent confidence bands are shown by bars); panels D–F show numbers for all on-the-go purchases. In panels D–F age groups are 1 = <22, 2 = 22–30, 3 = 31–40, 4 = 41–50, 5 = 51–60, 6 = 60+.

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 purchasers (and therefore impacted by the tax), and conditional on being so exhibit larger level reductions in sugar.[41] Individuals with high total annual dietary sugar are more likely to be soft drinks purchasers (and therefore be impacted by the policy) than those lower down the dietary sugar distribution. However, conditional on being affected by the policy, their response is smaller on average in level terms (and much smaller in percentage terms: for instance, the reduction for the top decile of the dietary sugar distribution is over 4 percentage points below that for the bottom decile).

The difference in responses across the three targeted variables can be understood by the pattern of preference variation. While the young, those with high levels of dietary sugar, and with low equivalized expenditure all have relatively strong sugar preferences, unlike the other groups those with higher levels of dietary sugar also are relatively price insensitive.

A number of things emerge from panels D–F of Figure 5. 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, 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.

B. *Consumer Welfare and Redistribution*

To the extent that a tax raises prices it imposes an economic burden on consumers; with the tax in place consumers can obtain less for a given amount of expenditure than under zero tax. In the case of a tax on sugary soft drinks, consumers who buy sugary soft drinks will incur a welfare loss through this channel. In Figure 6 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, using the standard Small and Rosen (1981) formula (see online Appendix Section D).

Panels A–C 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. Younger consumers and those from relatively poor households (i.e., in the bottom half of the equivalized expenditure distribution) obtain more sugar from soft drinks on-the-go and therefore are more exposed to the tax. In the absence of any behavioral response they would have higher compensating

[41] Individuals in the bottom half of the equivalized expenditure distribution lower their sugar on-the-go slightly more in percentage terms than those in the top half (16 percent versus 14 percent). This finding mirrors Allcott, Lockwood, and Taubinsky (2019a) who find in the United States that low-income households are slightly more price elastic.

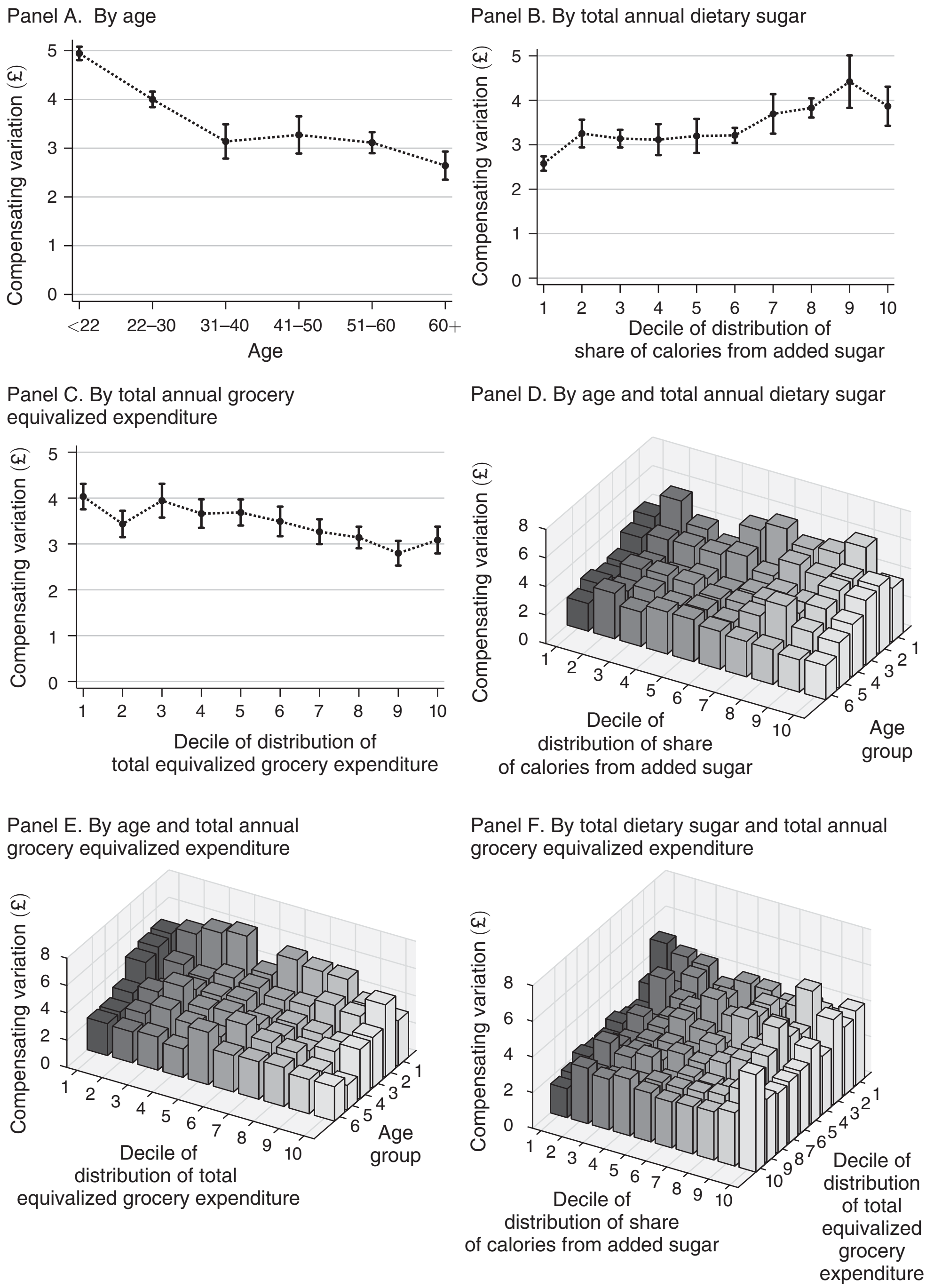

Figure 6. Revealed Consumer Welfare Effect

Notes: Figure is based on the 2,449 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 percent 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+.

variations. However, compensating variations also depend on behavioral effects, and in particular, how willing consumers are to switch away from taxed products and how much they value substitute products. Figure 6 shows that, after taking account of these behavioral effects, it remains the case that compensating variation is relatively high for young consumers and those in the bottom half of the total equivalized expenditure distribution. The pattern of relatively large compensating variation for the young holds broadly across individuals' positions in the total annual dietary sugar or total annual equivalized grocery expenditure distribution. Panel F shows that for high dietary sugar individuals compensating variations are 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 account 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. 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, then compensating variation based on revealed preference captures only part of the total consumer welfare effect of the tax.[42]

Policymakers are particularly concerned about high consumption amongst children and young adults. We find that in response to the tax soft drink consumers aged 13–21, on average, reduce sugar consumption by 280 g and have average compensating variation of £4.94. To provide intuition we use a typical sugary soft drink (a can of Coca-Cola), as our standard unit of comparison; a can of Coca-Cola in the United Kingdom is 330 ml (11.6 oz) and contains 35 g of sugar. This means that the internality from a can of Coca-Cola would need to be at least £0.62 (that is $4.94 \times (35/280)$) for this group on average to see an increase in their welfare from the tax, *assuming that they receive no benefits from the tax revenue raised*. This value is over 7 times larger than the average internality from sugar sweetened soft drinks estimated in Allcott, Lockwood, and Taubinsky (2019a).[43]

However, this does not count benefits arising from the tax revenue raised, nor any savings from any averted externalities (for instance, due to lower public costs of funding health care). The tax raises £3.14 per consumer. If this is distributed lump-sum back to soft drink purchasers then the threshold for whether the tax benefits those aged 13–21 on average is an internality in excess of £0.23 per can of Coca-Cola.[44] This is around 3 times the average internality estimated in Allcott, Lockwood, and Taubinsky (2019a). If the young have internalities above this estimate of the average value, or if they benefit disproportionately from the tax revenue

[42] Plus savings in averted public health externalities, and the use of tax revenue raised from the tax may indirectly impact on consumer welfare.

[43] They use a comparison with consumption of dietitians, as well as stated self-control preferences, to estimate an average internality of $0.09 per ounce, which corresponds to £0.08 per can of Coca-Cola.

[44] Given by $(4.94 - 3.14) \times (35/280)$.

raised or the cost savings for any averted externalities, this will make it more likely the tax is welfare improving for this group.[45]

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 products. Table 7 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 percent more likely to be soft drink purchasers than those in the top half, and conditional on being one, on average obtain 15 percent more sugar from these products. Our demand estimates suggest that compensating variation for a tax on sugary soft drinks is around 19 percent 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 6, panel C).

However, if some consumers impose internalities on themselves, then compensating variation measured on the basis of revealed preference provides an incomplete picture of the redistributive effects of the tax (a point made by Gruber and Kőszegi 2004 in the case of cigarette taxation). The mean sugar reductions from the tax are somewhat higher on average among those toward 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 20 percent higher than those in the top half). Therefore, if internalities exist and the marginal internality from sugar consumption is constant across the expenditure distribution, the larger reductions in sugar among low spending individuals will act to offset the compensating variation difference. If, at the margin, internalities are larger for poorer individuals, this will increase the likelihood that overall the tax is progressive.

We can use the internality estimates in Allcott, Lockwood, and Taubinsky (2019a) to get a sense of whether the tax is likely to be regressive. They estimate that those in the lowest income group in their sample have an internality equivalent to £0.10 per can of Coca-Cola, and those in the highest income group have an internality of £0.07.[46] With lump-sum redistribution of tax revenue (and no savings from averted externalities), individuals in the bottom decile of our permanent income measure (total equivalized grocery expenditure) would need an internality of at least £0.11 per can to benefit from the tax, while those in the top decile would marginally benefit from the tax even if they create no internality (as average compensating variation for this group is lower than tax revenue per person). Therefore, using Allcott, Lockwood, and Taubinsky (2019a) estimates of internalities (and under lump-sum redistribution) the tax is mildly regressive. However, if tax revenue is redistributed

[45] Note for the average soft drink purchaser, compensating variation is £3.45 and sugar falls by 216 g, which, under lump-sum tax redistribution, corresponds to an internality threshold of £0.05, which is below the average estimate of Allcott, Lockwood, and Taubinsky (2019a).

[46] Allcott, Lockwood, and Taubinsky (2019a) estimate that the average internality varies between \$0.011 per ounce for those with incomes below \$10,000 to \$0.008 for those with incomes above \$100,000. These are equivalent to £0.10 per can of Coca-Cola for low- and £0.07 per can of Coca-Cola for high-income households (i.e., the product of cents per ounce, number of ounces in a can of Coke, and the \$ − £ exchange rate: $1.1 \times 11.6 \times 0.8$ and $0.8 \times 11.6 \times 0.8$).

or utilized in a mildly progressive way this would be enough to ensure the tax is, at least, distribution neutral.

IV. Robustness

A. *Bias Correction for Incidental Parameters Problem*

In our nonlinear model with fixed effects, maximum likelihood estimates of the parameters may suffer from an incidental parameters problem (Neyman and Scott 1948). Even if both $N \to \infty$ and $T \to \infty$, if N and T grow at the same rate ($N/T \to \rho$ where ρ is a nonzero constant), our fixed effect estimator will be asymptotically biased (Arellano and Hahn 2007).

A range of bias correction methods exist that reduce the bias from order $1/T$ to $1/T^2$ (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 subsamples. Each subsample contains one-half of the choice occasions for each individual. We denote the maximum likelihood estimate for the full sample $\hat{\theta}$ and the estimate for the two subsamples $\hat{\theta}_{(1,T/2)}$ and $\hat{\theta}_{(T/2,T)}$. The jackknife (bias corrected) estimator is

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

In Figure 7 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.

The difference between the two estimates is small; the standard deviation of the sugar preference parameter estimates is 1.5, while the average absolute difference between the jackknife and maximum likelihood estimates is 0.02. 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 annual dietary sugar.

In online Appendix Section B.1 we show that similar conclusions to those for sugar hold for estimated price and 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

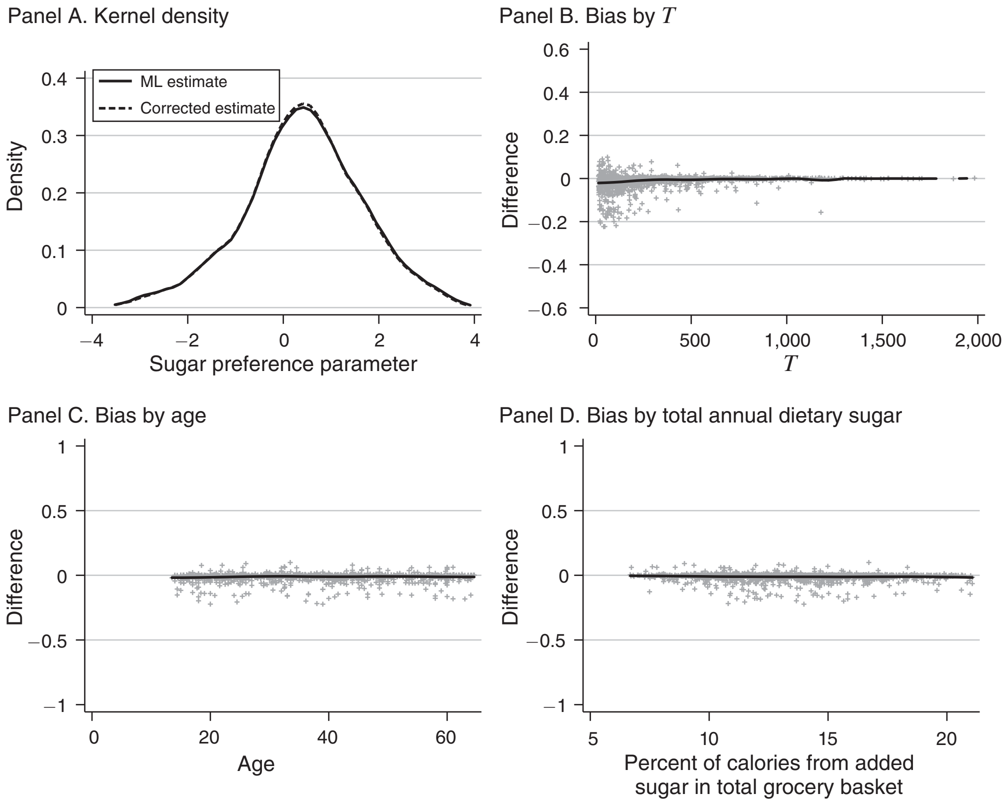

Figure 7. Sugar Preference Parameters

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.

negative and there is no systematic relationship with the key demographic variables of interest. For instance, the average absolute difference between the jackknife and maximum likelihood price estimates is 0.05 (relative to a mean price preferences of -3.15). As a consequence, our results regarding the effectiveness of soda taxes are robust to the bias correction procedure.

B. *Effects in the At-Home Segment*

Our main interest in this paper is the on-the-go segment of the soft drinks market, which has been much less well studied than the at-home segment. To say anything about individual-level outcomes with household level at-home data would require placing structure on how purchases are shared within the household. Our use of on-the-go data enables us to avoid this.

A possible issue is that our conclusion that soda taxes are well targeted at young people could be unwound by at-home demand responses. To assess this possibility we estimate a model of demand in the at-home segment, which we specify similarly to our on-the-go demand model. We provide details in online Appendix Section C.2. We assume consumers solve a static problem, controlling for at-home inventories, which allow for nonseparabilities over time in purchasing that arise through the storable nature of drinks (allowing, for instance, for the possibility that a household that has recently bought drinks is, as a consequence of the recent purchase, less likely to buy them on the next choice occasion). Hendel and Nevo (2006b) and Wang (2015) provide evidence that in the United States soft drinks market consumers behave in a forward-looking way, intertemporally switching the timing of purchases when buying on sale. Hendel and Nevo (2006a) show that this behavior can bias static demand estimates. This is a threat to our at-home demand estimates (and underlines an advantage of studying on-the-go demand).[47] In our at-home demand model we also treat retailer choice as exogenous, assuming it is not driven by demand shocks for drinks.

We use these estimates to simulate the impact of the soda tax on individual-level demands in the at-home segment assuming a naïve within-household sharing rule based on the OECD equivalence scale. In Figure 8 we report the reduction in sugar from drinks achieved by the tax for each age group relative to those aged younger than 22. Numbers reported in this graph are for the full sample of on-the-go individuals (i.e., including soft drink purchasers and non-soft drink purchasers). The black line shows the on-the-go relationship. It is strongly decreasing across age groups reflecting that (i) older individuals are less likely to be on-the-go soft drinks purchasers (see Table 5) and (ii) conditional on being soft drink purchasers, the tax lowers their sugar from on-the-go drinks by less that it does for younger individuals (see Figure 5, panel A). The gray line shows the relationship based on at-home demands. There is no obvious pattern with age: the households that the young individuals in our on-the-go sample belong to, on average, respond approximately as strongly as those older individuals belong to. This suggests at-home demand responses are not likely to unwind (nor reinforce) our conclusion about the effective targeting of soda taxes at young individuals.

C. *Supply*

The results in Section III are based on the assumption that the prices of taxed products increase one-for-one with the tax (100 percent pass-through) and the prices of substitute goods remain unchanged. We provide evidence in Section IIC that this is the central estimate in the literature and is what has happened after the recent introduction of a soda tax in the United Kingdom. In this section we report results based on an equilibrium model of tax pass-through. We model the supply-side of the market in the standard way (see Berry, Levinsohn, and Pakes 1995; Nevo 2001), assuming drinks firms compete in each market in a Nash-Bertrand pricing game.[48]

[47] Note that O'Connell, and Smith (2020) present evidence that in the UK households tend to respond to sales by switching across brands, pack types and sizes, and, on average, there is little evidence in changes in the timing of purchases. This suggests any biases from ignoring forward-looking dynamics are likely to be much smaller in the UK drinks market compared to the US context.

[48] We define markets by retailer-year. The retailers include the main supermarkets, Asda, Morrisons, Sainsbury's and Tesco, as well as discounters, other national stores and convenience stores, in the North, Midlands, and South. We assume drinks firms set final consumer prices. This is consistent with efficient contracting between drinks firms and retailers and can be sustained by side payments between retailers and drinks firms (see Villas-Boas 2007, Bonnet and Dubois 2010).

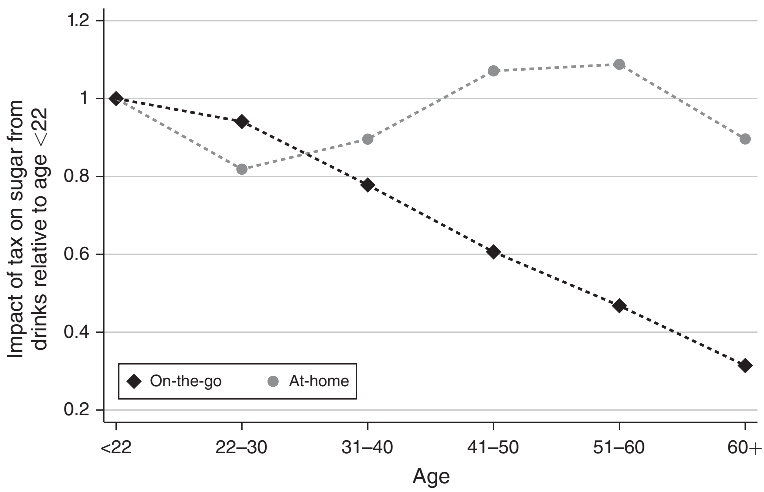

Figure 8. Reductions in Sugar from Drinks in On-the-Go and At-Home Segments

Notes: Figure is based on the 5,550 individuals in the full on-the-go sample, and data on the households to which they belong in the at-home data. It shows the reduction in sugar from drinks achieved by the tax by age groups in both on-the-go and at-home segments. Numbers are expressed relative to the average reduction for those aged younger than 22.

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. Therefore in computing equilibrium tax pass-through it may be important 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 use our on-the-go and at-home demand estimates to derive market-level demand curves. We can estimate product-level marginal costs using these demand estimates and assuming prices are the equilibrium outcome of the Nash-Bertrand game. Using the demand and supply model we can simulate the impact of the soda tax on equilibrium prices. We provide details in online Appendix Section E.

In the top panel of Table 11, we report simulated price increases across all products subject to the tax and across small variants (288–330ml) and large variants (500ml) separately. This is the structural model analogue to the direct evidence in Table 8. The demand and supply model predicts average pass-through of 116 percent (given by 0.29/0.25). It also predicts pass-through that is higher for 500ml bottles (124 percent) than for smaller sizes (104 percent). For large sizes demand is less elastic, and in response to the tax, it is optimal for firms to pass-through more of the price increase to these products, with the resulting increase in profits from intra-marginal consumers offsetting the profit reduction associated with consumers switching away from these products. This pattern of differential pass-through accords with the descriptive evidence in Table 8. In the bottom panel of Table 11 we report the average price changes for drinks not subject to the tax; in equilibrium firms marginally lower the price of substitute drinks.

In Figure 9, we show how the total reduction in sugar on-the-go due to the tax varies with age, total dietary sugar, and equivalized grocery expenditure under 100

Table 11—Price Changes under Equilibrium Pass-Through

	All	330ml	500ml
Sugar sweetened drinks			
Number of products	20	9	11
Pre-tax price	2.07	1.96	2.16
Price rise	0.29	0.26	0.31
Tax	0.25	0.25	0.25
Alternative drinks			
Number of products	16	4	12
Pre-tax price	2.11	2.13	2.10
Price rise	−0.02	−0.02	−0.02
Tax	0.00	0.00	0.00

Notes: We simulate the equilibrium pricing response to the soda tax based on a Nash-Bertrand pricing game. The top panel reports the impact for products subject to the tax. The bottom panel reports the impact for drinks products exempt from the tax.

percent tax pass-through (repeating information in Figure 5) and under equilibrium tax pass-through based on our demand and supply model. The figure makes clear that the patterns of price changes across these key targeted demographics are the same under the alternative pass-through assumptions. The only difference is a constant level shift; the fact that the equilibrium model predicts that firms' optimal response amplifies the price differential between sugary and alternative drinks created by the tax results in somewhat higher reductions in sugar relative to under 100 percent pass-through.

V. Summary and Conclusion

Excise taxes have traditionally been applied to alcohol, tobacco, and gambling, in part to tackle socially costly consumption. Recently there has been a drive to extend them to cover some foods and drinks, with soda taxes being at the vanguard of this move. In the case of sugar, there is clear evidence that most individuals exceed official recommendations on how much to consume (Griffith et al. 2020). Policymakers have targeted young people, individuals with high total dietary sugar, and low-income people. We evaluate how well targeted a soda tax is on those groups whose behavior policymakers wish to change.

We provide an analysis based on individual-level choice behavior while on-the-go; to our knowledge we are the first to study this segment of the market. 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 targeted group. However, the young also lose out most in terms of direct consumer surplus loss due to higher prices. If young people's soft drinks consumption gives rise to future costs that they partially ignore at the point on intake, then gains from averted internalities may outweigh this loss in consumer surplus. The performance of the tax in terms of reducing the on-the-go sugar intake of those with the most sugary diets is not as good. Those with high total dietary sugar are relatively price inelastic and so respond less to the tax, so their sugar consumption falls by less than more moderate sugar consumers. If internalities are important, the redistributive properties of the tax are likely to be

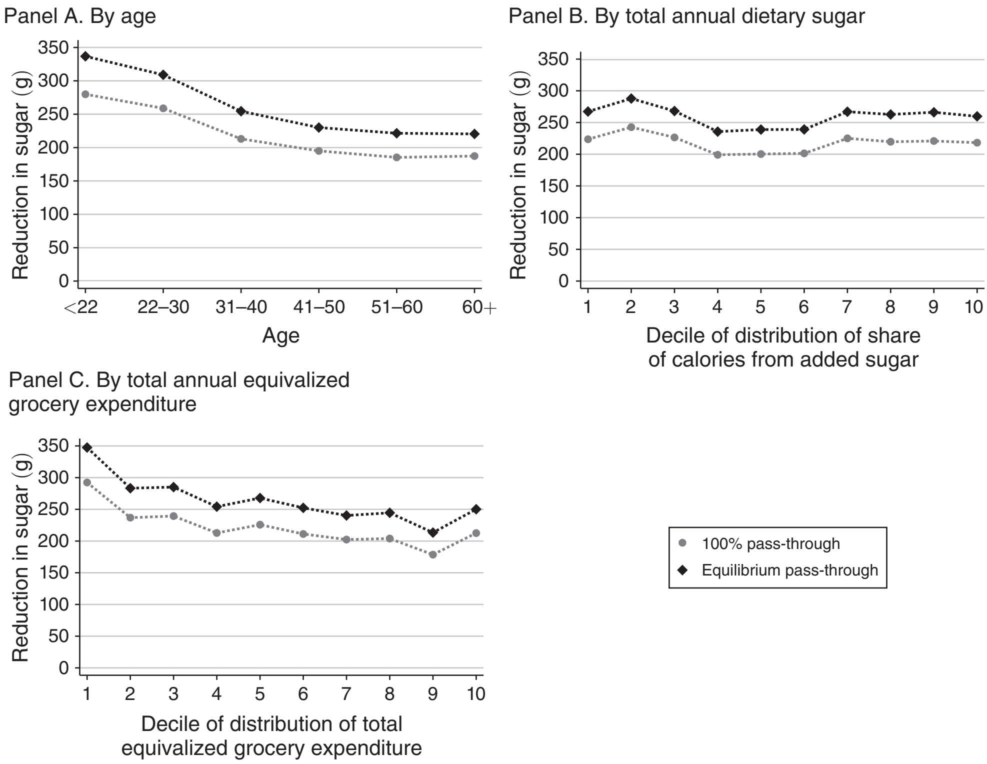

Figure 9. Reductions in Sugar from Drinks under 100 Percent and Equilibrium Pass-Through

Note: Figure shows how the average reduction in annual sugar on-the-go varies across the distributions of individual age, total dietary sugar and total equivalized grocery expenditure under 100 percent and equilibrium tax pass-through.

more attractive than suggested by an analysis based purely on traditional economic tax incidence. The traditional economic burden of the tax falls, to a moderate extent, disproportionately on low-income households, but the poor also lower their sugar consumption to a larger extent and therefore if they benefit from averted internalities this could outweigh the loss of consumer surplus. We provide evidence of the pricing responses of soft drinks manufacturers to the tax. However, firms may respond by adjusting other elements of their strategies. For instance, they may change the extent and focus of their advertising and they may introduce new products that are outside the scope of the tax. Our results therefore provide a picture of the short- to medium-run impact of soda taxes. An important direction for future work will be to incorporate these elements of firm response into analysis of these forms of tax.

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