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The Effects of Sin Taxes and Advertising Restrictions in a Dynamic Equilibrium†

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We develop a dynamic equilibrium model of firm competition to analyze the effects of counterfactual policies, such as taxes and advertising restrictions, on pricing, advertising, consumption, and welfare. Using micro-level data, we estimate how consumer exposure to television commercials influences product choice and model firms' strategic competition over advertising budgets and pricing. We exploit firms' practice of delegating advertising slot decisions to agencies to link consumer-level advertising variation to firms' strategic choices. Our results show that a sugar-sweetened beverage tax reduces advertising, while the additional impact of advertising restrictions is significantly weaker when a tax is already in place. (*JEL* D12, D22, H25, L13, L66, L82, M37)

Many governments seek to reduce consumption of sin goods, such as tobacco, alcohol, and sugar-sweetened beverages, by imposing taxes to raise their price and by restricting advertising to reduce their appeal.[1] However, there is little research on how firms jointly re-optimize prices and advertising expenditures in response to such policies, adjustments that may amplify or weaken their effects, or on the interaction between taxes and advertising restrictions in shaping their effectiveness.

In this paper, we make two contributions to the existing literature. First, we develop and empirically implement a framework that integrates a rich model of consumer choice, including the influence of individual-level exposure to television advertising, with firms' dynamic supply-side decisions regarding television advertising budgets.

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[1] See World Health Organization (WHO) (2025) for a list of countries with alcohol advertising restrictions, DeCicca, Kenkel and Lovenheim (2022) for a discussion of the tobacco policies, and GFRP (2021) for jurisdictions that have taxes on soft drinks.

The dynamics arise because advertising influences product demand both contemporaneously and over time. Firms face the choice of advertising on a vast number of possible TV times and channel slots, meaning they face a high-dimensional decision. To address the challenge of solving a dynamic game with such a large action space, we developed a tractable framework that reflects the organization of the advertising market. Specifically, we model firms as choosing overall television advertising expenditures, while delegating slot selection to advertising agencies. Delegation, which we show can arise as an equilibrium decision, reduces the action space of firms to a decision over advertising expenditures, while preserving the link between these choices and the rich patterns of consumer exposure to aired advertisements.

Our second contribution is to provide, to the best of our knowledge, the first estimates of the effects of a tax and advertising restriction within a dynamic equilibrium model that incorporates firms' strategic advertising and pricing decisions. We focus on the cola market—the largest and most heavily advertised segment of the non-alcoholic drinks market—and leverage unique household-level measures of advertising exposure to identify the effects of advertising on consumer choice.

Our results suggest that a ban on advertising sugary colas, if implemented alone, would have a relatively modest impact on total sugar consumption from drinks, reducing it by 2.7 percent. This evidence is timely, as the role of advertising in driving excess consumption is an active area of policy interest.[2] In comparison, taxes of a scale similar to those implemented globally have a much larger effect, reducing sugar consumption by approximately 16.5 percent. If an advertising restriction is implemented alongside a tax, its additional impact is minimal (0.4 percent), partly because tax-induced price increases lead the most advertising-sensitive consumers to substitute to alternatives.

To tractably capture strategic advertising competition, we explicitly account for the intermediary role played by advertising agencies. This institutional feature of the UK television advertising market (see Crawford, Deer, Smith, and Sturgeon 2017) is also common in other countries, including in the United States (see Hristakeva and Mortimer 2023). This approach mirrors recent work by Hortaçsu, Natan, Parsley, Schwieg, et al. (2024), who exploit within-firm delegation in decision-making to simplify the complex dynamic optimization problem faced by airline companies. We study the UK cola market, where two dominant firms (Coca-Cola and PepsiCo) compete. There are also a few cheaper store-branded alternatives. Both Coca-Cola and PepsiCo advertise, while store brands do not.[3] We model the decisions Coca-Cola and PepsiCo make over their monthly advertising budgets and rationalize the decision to delegate the buying of advertising slots to an agency. The model links

[2] Many governments already restrict advertising of other sin goods, such as tobacco and alcohol, and the WHO recommends extending these restrictions to advertising of unhealthy foods (see, WHO 2025). The UK government has announced plans to introduce regulations that will restrict the advertising of unhealthy foods, aiming to reduce consumption (Department of Health and Social Care (DHSC) (2024)).

[3] We focus on television advertising, the form of advertising that accounts for the highest share of advertising spending in the cola (and broader food and drinks) market. During the period covered by our data, the next most significant forms of cola advertising, after television, were billboards and press (magazines and newspapers). Internet advertising is a relatively small share of the total food and drink expenditure, estimated at 5 percent of all drinks advertising in the United Kingdom in 2019 (Department for Digital, Culture, Media and Sport (DCMS) and Department (2021)).

the rich variation in consumer advertising exposure resulting from the choice of advertising slots to the firms' strategic decisions over advertising investment. The agencies simplify the dynamic advertising game by reducing firms' action space from a highly multidimensional set (entailing choices over the timing and channels of each advertising slot) to a decision over total monthly expenditure. This reduction in dimensionality makes solving Coca-Cola and PepsiCo intertemporal profit-maximization problems feasible.

Our model incorporates firms' monthly decisions over prices and brand advertising expenditures. Advertising expenditures increase consumer exposure, which in turn influences future demand and profits. As a result, firms' pricing decisions depend on the distribution of consumers' stock of exposure to brand-level advertising, meaning optimal prices are a function of past advertising choices. Firms' advertising budget decisions depend on how current advertising affects future prices and demand for their products. Therefore, competition over advertising budgets is dynamic, and we solve the game using a Markov Perfect Equilibrium (Maskin and Tirole 1988). We apply this model to study the counterfactual effects of taxes and advertising restrictions.

A key component of our framework is a consumer model of product choice, which we specify to capture flexibly the impact of firms' strategic pricing and advertising decisions on product-level demand. We combine household-level longitudinal data on purchases and TV viewing behavior with the universe of TV advertisements for drinks. To estimate advertising effects, we exploit variation in advertising exposure across households with the same demographic characteristics and television viewing habits (genres, viewing times, and channels), conditioning on a rich set of time, retailer, product, and brand effects. Our strategy, which extends and improves on the one we used in our earlier work on potato chip demand (Dubois, Griffith, and O'Connell 2018), controls for variables reflecting predictable demand components advertisers may target, while isolating quasi-random variation in exposure. This residual variation arises from the considerable discretion television stations have in fulfilling advertising agency orders, leading to differences in advertising exposure across otherwise similar households. We complement our demand model with an analysis that isolates within-household variation in exposure and shows that the two approaches yield similar advertising elasticities. Our work contributes new evidence on the impact of TV advertising in the drink market, recently studied in the US context in Shapiro, Hitsch, and Tuchman (2021).

Our empirical specification allows for rich patterns of correlation in consumer preference parameters and spillovers from one brand's advertising to the demand for other brands. We find quantitatively significant correlations in consumer preferences for price and advertising: On average, consumers who are particularly sensitive to price changes also tend to be relatively sensitive to advertising. We also provide evidence of positive spillovers in brand advertising. For instance, the own-advertising demand elasticity for regular Coke is 0.12, while the cross-advertising elasticity of demand is 0.05 for Diet Coke and 0.02 for regular Pepsi. In other words, regular Coke advertising not only increases demand for regular Coke but also stimulates demand for Diet Coke and, to a lesser extent, regular Pepsi. These features of consumer demand play a crucial role in shaping advertising responses to policy changes.

We solve the model without taxes or advertising restrictions and re-solve it under several counterfactual policies, including a specific tax on sugar-sweetened products, an ad valorem tax on sugar-sweetened products, a prohibition on advertising for sugar-sweetened (regular) cola products, and a combination of both a tax and an advertising restriction. We find that under either form of tax, firms reduce advertising for taxed products. A key driver of this effect is the correlation between consumer prices and advertising sensitivities: Higher prices from a tax lead the most advertising-sensitive consumers to switch away from taxed brands, reducing firms' incentives to invest in advertising. The reduction in advertising is more pronounced under an ad valorem tax because it lowers optimal price-cost margins, while a specific tax has the opposite effect, slightly increasing them. These lower margins reduce the profitability of marginal consumers, weakening firms' incentives to advertise taxed brands. Both the tax and the advertising restriction also reduce advertising for diet brands. This effect stems from a within-firm complementarity in advertising strategies that is driven by advertising demand spillovers—advertising diet products becomes less valuable when advertising for taxed sugary products declines.

We also quantify the impact of policy changes on the distribution of economic surplus and total sugar consumption. Taxes of the scale implemented in practice lead to larger declines in firm profits than advertising restrictions but result in greater reductions in sugar intake and generate tax revenue. An ad valorem tax, compared to a specific tax of a similar level, reduces market power, leading to a larger decline in profits and higher tax revenue. The impact of these policies on consumer welfare depends on whether consumers are subject to behavioral biases. There is a long tradition of treating advertising as persuasive (Bagwell 2007), and direct evidence suggests that consumers impose internalities on themselves through sugar consumption (Allcott, Lockwood, and Taubinsky 2019). Our equilibrium model is agnostic about the existence of such biases. We report consumer welfare outcomes under a range of alternative assumptions, showing that internalities of the scale estimated by Allcott, Lockwood, and Taubinsky (2019) are sufficient to overturn the otherwise regressive nature of these taxes.

Our work contributes to a strand of literature that builds on the model of dynamic games developed by Ericson and Pakes (1995) and applies it to dynamic investment games (e.g., Ryan 2012; Sweeting 2013) and, specifically, to firm advertising choices (e.g., Dubé, Hitsch, and Manchanda 2005; Doraszelski and Markovich 2007). We are the first to apply a dynamic game framework in a rich empirical setting to study policies aimed at reducing sin-good consumption. Additionally, our framework introduces a novel way of linking consumer-level advertising exposure, a key driver of consumer demand, to firms' advertising investments. Our approach exploits a common feature of advertising markets, providing a method for solving an otherwise intractable dynamic oligopoly game, with implications for other markets and policy contexts.

Our paper advances the literature on the ex ante evaluation of the effects of sin taxes. This literature, which studies the incidence and optimal design of sin taxes, focuses on the impact that a tax has on consumption through higher prices (e.g., Bonnet and Réquillart 2013; Harding and Lovenheim 2017; Griffith, O'Connell, and Smith 2019; Dubois, Griffith, and O'Connell 2020; O'Connell and Smith 2024).

Wang (2015) estimates a demand model that incorporates dynamics through consumer stockpiling, while Kim and Ishihara (2021) estimate a model of rational addiction, both simulating consumer responses to a tax on sugar-sweetened beverages. In contrast, we focus on dynamics that arise through the persistent effects of advertising. We contribute to this literature by showing how firms' dynamic advertising decisions shape the impact of sin taxes and highlighting an important interaction between margin adjustment and the returns on advertising investment.[4]

The rest of the paper is structured as follows. Section I introduces our main data sources, summarizes key features of the cola market, and provides evidence on the relationship between advertising exposure and consumption. Section II describes our dynamic equilibrium model. Sections III and IV describe our empirical specification, present estimates, and characterize market equilibrium in the absence of taxes or advertising restrictions. Section V presents our results on the impact of tax and advertising restrictions.[5]

I. The Market for Colas

As of April 2021, sugar-sweetened beverage (SSB) taxes were in place in over 50 jurisdictions (GFRP 2021). These taxes are typically implemented to mitigate the negative health effects associated with SSB consumption, which may create internalities if individuals underestimate the private health costs or externalities if some of the costs are borne by others, for instance, through higher public healthcare expenditures or increased health insurance premiums.

We focus on the cola market, which accounts for the majority (over 70 percent) of sugar- and artificially-sweetened beverage advertising. We use UK data covering the period 2010–2016. The United Kingdom introduced an SSB tax in April 2018, structured to incentivize firms to reduce sugar content and thereby avoid the tax. As a result, only the two leading cola brands, along with a few niche energy drinks, were subject to the tax (Dickson, Gehrsitz, and Kemp 2025). Therefore, our focus on the UK cola market captures the majority of products directly affected by the country's SSB tax.

A. *Market Structure*

We use microdata on drink purchases from a sample of consumers in Great Britain, collected by the market research firm Kantar as part of their Take Home Purchase panel (Kantar 2010–2016). Our dataset covers over 21,000 households

[4] A small public health literature examines changes in local promotion of soft drink products following the introduction of soda taxes in several US cities. Asa, Knox, Oddo, Walkinshaw et al. (2023) find no effect in Seattle, as do Zenk, Leider, Pugach, Pipito et al. (2020) and Zenk, Li, Leider, Pipito et al. (2021) in Oakland. In Philadelphia, Lee, Gibson, Hua, Lowery et al., (2023) find weak evidence of an increase in local advertising. Forde, Penney, White, Levy et al. (2022) conduct a small number of interviews to provide qualitative evidence following the introduction of the UK Soft Drinks Industry Levy (SDIL) and report that "marketing responses following the SDIL were coordinated and context-dependent."

[5] A number of supplemental appendices provide additional information: A (Purchase Data), B (Advertising Market and Data), C (Equilibrium Delegation), D (Monopoly Advertising Response to Tax), E (Solution to Advertising Agency Problem), F (Additional Estimation Results), G (Transition Function), H (Solution Algorithm), I (Consumer Surplus Decomposition) and J (Additional Counterfactual Results).

Table 1—Firms and Brands

Firm	Brand	Expenditure share	No. of products	Average price (£ per liter)
Coca-Cola Enterprises	Regular Coke	25.9%	15	0.82
	Diet Coke	34.8%	15	0.81
PepsiCo	Regular Pepsi	7.6%	3	0.72
	Diet Pepsi	25.8%	5	0.73
Store brands	Regular store	2.4%	2	0.21
	Diet store	3.5%	2	0.21
All		100.0%	42	0.74

Notes: Authors' calculations using data from Kantar Take Home Purchase panel for 2010–2016. Diet Coke includes Coke Zero and Diet Pepsi includes Pepsi Max.

that record all grocery purchases they bring into the home using a handheld scanner or mobile phone app. We observe detailed product information, including transaction prices, along with demographic variables and detailed measures of household television viewing behavior. The data have a panel structure covering from 2010 to 2016, with the average household present in the data for over 100 weeks.

The cola market is dominated by two firms: Coca-Cola Enterprises, with a market share of 60.7 percent and PepsiCo, with 33.4 percent (see Table 1). Each firm sells regular and diet versions of its cola. Coca-Cola Enterprises' market share is split approximately equally between regular Coke and Diet Coke, with the latter accounting for just under 60 percent of its market share. In contrast, around three-fourths of PepsiCo's market share is accounted for by Diet Pepsi. The remaining products in the market are store brands (also referred to as own-brand and private-label products). Each brand is sold in various container types and sizes (e.g., 4 $\times$ 330ml cans or 2l bottle). In total there are 42 products in the UK cola market.[6]

B. *Television Advertising*

We use data on television advertising of nonalcoholic beverages from the market research firm AC Nielsen, covering the period 2009–2016 (AC Nielsen 2009–2016).[7] Our dataset contains detailed information on over 1 million cola advertisements, including the advertised brand, airtime details (date, time, channel and during/between which program(s)), and the expenditure required to advertise during the slot. For the period 2015–2016, we have additional data on TV advertising for all food and alcohol products, and for 2015, we observe industry-standard measures of advertisement viewership.

[6] We exclude a small number of minor products, including niche Coca-Cola and Pepsi sub-brands (e.g., Diet Coke with vitamins), each with market share below 0.5 percent, and products with fewer than 10,000 (0.67 percent) transactions in our data. In our product definition, we aggregate Diet Coke and Coke Zero, and Diet Pepsi and Pepsi Max. The 42 cola products in our analysis cover over 80 percent of total cola sales. See Supplemental Appendix A for details of the cola products.

[7] Although digital advertising is growing, it remains a relatively small share of total *food and drink* advertising, accounting for an estimated 5 percent of all drinks advertising spending (DCMS 2021).

In an average month, Coca-Cola Enterprises spends £1.1 million, purchasing 9,300 slots, amounting to 3,515 minutes of total advertising time. The price of these slots varies widely based on the expected audience number; for instance, prime-time advertisements on popular channels can cost several times more than those on niche channels. PepsiCo advertises less than Coca-Cola Enterprises, spending £0.2 million per month, on average. Store brand colas do not advertise. Figure B.1 in the Supplemental Appendix shows advertising spending over time for regular Coke and Diet Coke, and for Diet Pepsi. PepsiCo almost exclusively advertises its diet brand.[8] Our analysis focuses on Coca-Cola's advertising decisions for its regular and diet brands and Pepsi's decision for its diet brand.

A key institutional feature of television advertising is that advertisers (i.e., Coca-Cola Enterprises and PepsiCo) contract with advertising agencies that purchase slots on their behalf. In 2016, there were 40 different agencies handling TV advertising for food and drink products. Each year, we observe that Coca-Cola and PepsiCo contract with only one agency, using different agencies. In 2016, Coca-Cola Enterprises accounted for 29 percent of the food and drinks advertising handled by its agency, while PepsiCo accounted for 3 percent. Another important feature of UK TV advertising is its predominantly national nature. For 2016, 73 percent of Coca-Cola and PepsiCo's advertisements aired nationally, while the remaining advertisements were shown in 1 of 11 broad regional markets, typically airing concurrently across multiple regions.

In our analysis, we model how advertising influences consumer choice, and remain agnostic—except in Sections VB and VC, where we discuss welfare effects—about whether these choices reveal underlying preferences or are influenced by behavioral bias. Since both Coca-Cola and Pepsi are universally recognized brands, and their advertisements primarily emphasize the pleasure of consuming them, we do not consider the case where advertising for Coca-Cola and Pepsi is informative, either about product existence or characteristics.

C. *Household Exposure to TV Advertising*

Firms invest in advertising to influence current and future demand for their products, in order to increase their profits. The effectiveness of this investment depends on the exposure of consumers to the advertising, which varies based on when advertisements are shown and the television viewing of households.

We observe when advertisements are aired through the advertising data. In the purchase data, we observe measures of household television viewing behavior, as provided by the Kantar media questionnaire. Specifically, households complete a detailed survey each year, indicating which shows and stations they watch, during which time slots, and how regularly they do so. By combining the timing of advertising with household viewing behavior patterns, we build a measure of a household's exposure to brand-level advertising. We exploit variation in exposure across consumers to identify the impact of advertising on consumer choice.

[8] PepsiCo maintains a stated marketing strategy not to advertise regular Pepsi as part of its "Responsible Marketing" commitment, which it frames as a reflection of concern for consumers' health. See PepsiCo (2025).

Let i index consumer (in our application a household), b brand (e.g., regular Coke, Diet Pepsi), and k advertising slots. A slot refers to a specific time, date, station, and broad region in which an advertisement is shown. Within an interval of time, such as a week, the number of potential slots is large—over 70,000 slots per week, given approximately 100 channels and 4 advertising breaks per hour. Let $w_{ik} \in [0,1]$ denote the probability that household i watches television during slot k, $T_{bk} \geq 0$ represent the length of an advertisement for brand b during slot k, and $\omega(\cdot)$ be a concave function capturing any diminishing returns to advertising length (for instance, see Dubé, Hitsch, and Manchanda 2005, Bagwell 2007, and Gentzkow, Shapiro, Yang, and Yurukoglu 2024). The advertising exposure of consumer i during time period t (we consider a week) is given by

$$a_{ibt} = \sum_{\{k|t(k)=t\}} w_{ik}\omega(T_{bk}), \tag{1}$$

where $t(k)$ is the week of slot k.

We directly observe T_{bk} in the advertising data. To measure each consumer's exposure to specific advertisements, we use two pieces of information. First, we have data on the total number of impacts (i.e., pairs of eyes viewing each advertisement) for all advertisements in 2015. Second, households in our purchase data provide ordinal survey responses about their TV viewing habits, indicating whether they regularly, sometimes, rarely, or never watch specific TV shows, channels, and at what times of day. By combining these survey responses with viewership data from 2015, we estimate the probabilities w_{ik}, which reflect each consumer's likelihood of watching a given advertisement based on their qualitative viewing survey response for slot k. We use these estimates to construct household-specific advertising exposure measures, which we incorporate into our demand model. We allow all preference parameters to vary by demographic group, avoiding the need to estimate the probabilities jointly in the demand model, which would entail expanding further our multidimensional set of exposure measures (see Supplemental Appendix B.3).

D. *Evidence of Advertising Effects*

Key strengths of our data are that they track individual households over time and provide a *household-level* measure of advertising exposure. In this section, we provide evidence on the relationship between household brand-level advertising exposure and consumption choices.

We estimate the following equation separately for each of the three advertising cola brands (regular Coke, Diet Coke, and Diet Pepsi):

$$vol_{ibt} = \alpha \log A_{ibt} + \tau_t + \iota_{d,q(t)} + \kappa_{r,q(t)} + \eta_i + \epsilon_{it}. \tag{2}$$

vol_{ibt} is the volume of brand b purchased by household i in week t. If the household purchases any other drink (e.g., another cola brand, noncola soft drink, or fruit juice), then $vol_{ibt} = 0$. A_{ibt} represents the household's stock of advertising exposure for brand b, τ_t are year-week fixed effects, and $\iota_{d,q(t)}$ and $\kappa_{r,q(t)}$ capture demographic-year-quarter and region-year-quarter effects, respectively. We define

Table 2—Estimate of Effect of Advertising on Volume

	Volume of:		
	Regular Coke	Diet Coke	Diet Pepsi
Log of adv. stock ($\hat{\alpha}$)	22.26	28.90	13.26
	(1.45)	(2.06)	(1.46)
Mean dep. var.	214.16	277.27	272.31
Elasticity	0.104	0.104	0.049
Week effects	Yes	Yes	Yes
Demographic-quarter effects	Yes	Yes	Yes
Region-quarter effects	Yes	Yes	Yes
Household effects	Yes	Yes	Yes
Observations	2,579,691	2,579,691	2,579,691

Notes: We estimate equation (2) separately for regular Coke, Diet Coke, and Diet Pepsi and report the coefficient estimate on the log of the advertising stock. The elasticity is defined as the ratio of the coefficient estimate and dependent variable mean.

A_{ibt} as $A_{ibt} = \delta A_{ibt-1} + a_{ibt-1}$, where δ is the weekly "carry-over" parameter, which we set to 0.9. In Supplemental Appendix B.4, we provide empirical support for this value.[9]

A challenge in estimating the impact of advertising on consumer choices is that high-demand households may be exposed to more advertising, or advertising may be higher during periods when demand is elevated for other reasons. Equation (2) controls for these confounding factors by including household fixed effects, year-week effects, and time-varying demographic and region effects. The residual variation is within-household. In the TV advertising market, advertisers delegate to agencies, who purchase slots from stations, often weeks in advance. This, combined with the predominately national nature of UK TV advertising, makes precise targeting of individual households, beyond predicted demand across relatively broad demographic groups, challenging. Equation (2) controls for the small amount of regional variation in advertising through time-varying region effects. The remaining variation in exposure arises because, while agencies negotiate with stations to secure advertising impressions, they do not determine the exact timing of advertisements, with stations having some flexibility in ad placement when fulfilling agencies' orders (see Crawford, Deer, Smith, and Sturgeon 2017; Hristakeva and Mortimer 2023). The task of fulfilling orders across all markets (not just cola advertisements) and constraints on slot availability results in substantial variation in advertising exposure across similar households.

In Table 2, we report estimates of the advertising coefficient from equation (2), along with the mean of the dependent variable and implied elasticities. The coefficients indicate positive and statistically significant advertising effects, with elasticities of approximately 0.1 for regular Coke and Diet Coke, and 0.05 for Diet

[9] Specifically, we conduct non-nested tests of $\delta = 0.9$ against alternatives, which provide empirical support in favor of $\delta = 0.9$. Note, this is the same value used in Shapiro, Hitsch, and Tuchman (2021). To construct A_{ibt}, we also need the form of $\omega(\cdot)$ in equation (1). As discussed in Section IIIA, we specify this is as a power function, estimating an exponent value that implies a 60 second advertisement generates 1.56 times the exposure of one 30 second advertisement, rather than twice as effective, which would be the case without diminishing returns in consumer attention. We use this estimated value here.

Pepsi. Recent work by Shapiro, Hitsch, and Tuchman (2021) has provided evidence that TV advertising elasticities are lower than previously thought. Our elasticity estimates fall within the upper third of the brand-level elasticities they report for 288 brands, based on quasi-random cross-region variation in gross rating points. Our estimates are somewhat larger in magnitude than their elasticity estimates for cola brands (in their baseline specification, their regular Coke and Diet Pepsi own-brand advertising elasticities are 0.03, p-value under 0.01, and 0.02, p-value of 0.07, and they do not find a statistically significant positive elasticity for Diet Coke). However, it is important to note that their estimates are for the US market, while our estimates are for the United Kingdom. There are many possible reasons why the precise magnitude of effects may vary between the two countries. For example, the lower level of advertising on UK TV, due to tighter restrictions on commercial break lengths, coupled with diminishing returns to advertising, may be one factor that contributes to larger effects in the United Kingdom.

Advertising enters equation (2) via a concave (log) transformation. In Figure B.5 in the Supplemental Appendix, we show the relationship between regular Coke volumes and advertising stocks (conditional on the same controls) nonparametrically. The graph confirms the positive relationship between advertising exposure and volume, with diminishing marginal effects at higher levels of exposure.

In the structural model that follows, we account for heterogeneous responses to advertising, correlation between advertising and price sensitivity, and potential advertising spillover effects. We use controls for household TV viewing behavior, along with time-varying demographic effects, to capture advertisers targeting based on predictable aspects of demand. As we show in Section IIID, our structural advertising elasticity estimates align with the evidence we present in this section.

II. Structural Model

To analyze the impacts of policies such as taxes and advertising restrictions, we specify a dynamic oligopoly model. While we apply this model to the market for cola, it is applicable to other oligopoly markets where firms compete in both prices and television advertising budgets. In each period, firms select product prices and brand advertising budgets, delegating the decision of which slots to run advertisements on to an agency tasked with maximizing consumer exposure to brand-level advertising.

These advertising agencies serve as intermediaries, reducing the firms' action space from choosing whether to advertise in thousands of specific slots, to choosing overall advertising budgets. This is an institutional feature of the television advertising market, which makes the dynamic oligopoly game tractable, transforming it from one with many potential actions to one involving advertising expenditures by brand as the dynamic controls of firms (see Supplemental Appendix C for further details).

Consumers choose which products to purchase based on their preferences, the prices they face, and their history of exposure to advertising. Advertising exposure in one period can influence future choices, meaning that a firm's advertising budget not only impacts current demand but also has lasting effects on future profits.

We describe the structure of the dynamic oligopoly game, the role of advertising agencies in mapping advertising budgets to slots, and hence to consumer advertising exposure, and we outline our consumer demand model. In this section we describe the structure of the model; we provide details of the empirical specification in Sections III and IV.

A. *The Firm's Decision*

We index (cola) firms by $f = 1, \ldots, F$, brands by $b = 1, \ldots, B$, and products by $j = 1, \ldots, J$. The set of products and brands owned by firm f is denoted by $\mathcal{J}_f$ and $\mathcal{B}_f$, respectively. We assume the set of firms, brands, and products in the market remain fixed. Let p_{jt} and c_{jt} denote the price and marginal cost of product j in period t. Advertising expenditures for brand b in period t are given by e_{bt}. The agency managing these expenditures may charge a markup, denoted by $\psi_b \geq 0$, to cover fixed costs and due to any market power it exercises. Therefore, the total cost of brand advertising is $\left(1 + \psi_b\right) e_{bt}$.

Each period, firm f selects advertising budgets for its brands and sets product prices. The advertising expenditures are used by an agency to purchase advertising slots on the firm's behalf, which in turn determine consumer advertising exposure, a_{ibt} (defined in equation (1)), of all consumers $i \in I$ for brand b in period t. We denote the advertising exposure stock for consumer i to brand b at time t by $\mathcal{A}_{ibt} = g\left(a_{ib0}, a_{ib1}, \ldots, a_{ibt-1}\right)$, the vector of consumer exposure stocks across brands $\mathcal{A}_{it} = \left(\mathcal{A}_{i1t}, \ldots, \mathcal{A}_{iBt}\right)$, and the set of exposure stocks across consumers $\mathcal{A}_t = \left\{\mathcal{A}_{it}\right\}_{i \in I}$.

The market demand function for product j is given by its share $s_{jt}\left(\mathbf{p}_t, \mathcal{A}_t\right)$ of the potential market, M_t, where $\mathbf{p}_t = \left(p_{1t}, \ldots, p_{Jt}\right)$. Since demand depends on exposure stocks, $\mathcal{A}_t$, it captures potential persistence in advertising effects, meaning that a firm's current advertising expenditure, e_{bt}, influences future demand and makes firm competition inherently dynamic.

Firm f's flow profits take the form:

$$\pi_f\left(\mathcal{A}_t, \mathbf{p}_t, \mathbf{e}_t\right) = \sum_{j \in \mathcal{J}_f} \left(p_{jt} - c_{jt}\right) s_{jt}\left(\mathbf{p}_t, \mathcal{A}_t\right) M_t - \sum_{b \in \mathcal{B}_f} \left(1 + \psi_b\right) e_{bt}. \tag{3}$$

The firm's problem at period $t = 0$ is to choose prices and advertising budgets to maximize the present discounted value of its profits:

$$\max_{\left\{p_{jt}\right\}_{\forall t, j \in \mathcal{J}_f}, \left\{e_{bt}\right\}_{\forall t, b \in \mathcal{B}_f}} \sum_{t=0}^{\infty} \beta^t \pi_f\left(\mathcal{A}_t, \mathbf{p}_t, \mathbf{e}_t\right), \tag{4}$$

subject to the law of motion for advertising exposure stocks, $\mathcal{A}_t\left(e_{t-1}, \mathcal{A}_{t-1}\right)$.

Firms simultaneously set prices to maximize profits, given the distribution of advertising exposure stocks. Since prices directly impact current but not future flow profits, firm f's first-order condition for period t prices is

$$s_{jt}\left(\mathbf{p}_t, \mathcal{A}_t\right) + \sum_{j' \in \mathcal{J}_f} \left(p_{j't} - c_{j't}\right) \frac{\partial s_{j't}\left(\mathbf{p}_t, \mathcal{A}_t\right)}{\partial p_{jt}} = 0, \tag{5}$$

for all $j \in \mathcal{J}_f$. Let $\mathbf{p}_t^*(\mathcal{A}_t)$ denote the optimal price vector as a function of the advertising exposure stock distribution. We define the optimized flow profit, $\tilde{\pi}_f(\mathcal{A}_t, \mathbf{e}_t) \equiv \pi_f(\mathcal{A}_t, \mathbf{p}_t^*(\mathcal{A}_t), \mathbf{e}_t)$. Thus, the firm's intertemporal profits simplify to $\sum_{t=0}^{\infty} \beta^t \tilde{\pi}_f(\mathcal{A}_t, \mathbf{e}_t)$.

To determine firms' optimal advertising strategies, we focus on Markov Perfect Equilibrium (MPE), where strategies are a function of payoff-relevant state variables (Maskin and Tirole 1988). For firm f, a strategy σ_f maps state variables $\mathcal{A}_t$ to brand-level advertising expenditures: $\sigma_f(\mathcal{A}_t) \equiv (\{e_{bt}\}_{b \in \mathcal{B}_f})$. Given competing firms' strategy profiles, $\sigma_{-f}(\mathcal{A}_t)$, firm f solves the Bellman equation:

$$\pi_f^*(\mathcal{A}_t) = \max_{\{e_{bt}\}_{b \in \mathcal{B}_f}} \tilde{\pi}_f(\mathcal{A}_t, \mathbf{e}_t) + \beta \pi_f^*(\mathcal{A}_{t+1}). \tag{6}$$

An MPE consists of strategies, σ_f^* for $f = 1, \ldots, F$ such that no firm has an incentive to deviate at any $\mathcal{A}_t$.

We solve for an equilibrium in pure strategies using an approach similar to Pakes and McGuire (1994). While a pure-strategy MPE may not exist or be unique, the prior literature (e.g., Aguirregabiria and Mira 2007; Doraszelski and Satterthwaite 2010) provides conditions for existence in games with similar structures. However, these conditions do not directly apply to our setting. We assume the existence of an MPE and use necessary conditions to characterize equilibrium behavior (Maskin and Tirole 1988), while empirically checking for equilibrium multiplicity.

B. *The Advertising Agency's Problem*

Firms delegate the selection of advertising slots to agencies. There are a couple of reasons that rationalize this delegation choice. First, selecting among thousands of TV slots requires specialized expertise—for instance, human capital in marketing and media relations—making agencies more cost-effective. Second, delegation may serve as a strategic tool to soften advertising competition. We illustrate this with two examples in Supplemental Appendix C: (i) a static equilibrium where delegation is optimal due to a fixed cost of not delegating, and (ii) a dynamic equilibrium of a repeated game where delegation emerges for similar reasons as tacit collusion in prices.

As in Section IC, we use T_{bk} to denote the length of advertising for brand b during slot (i.e., station-date-time) k, w_{ik} to denote the probability that consumer i watches it during slot k, and we denote the expected flow of advertising exposure for consumer i for brand b in period t, as in equation (1), by $a_{ibt} = \sum_{\{k|t(k)=t\}} w_{ik}\omega(T_{bk})$, where $\omega(\cdot)$ is an increasing concave function, capturing any diminishing returns to advertisement length.

Letting ρ_k denote the price of advertising during slot k, total expenditure for purchasing advertising slots for brand b during period t is given by $e_{bt} = \sum_{\{k|t(k)=t\}} \rho_k T_{bk}$. Advertising prices are determined by the overall demand for advertising, across all markets, and the supply of expected advertising views, which depends on the expected audience size of a show or TV station (see empirical evidence in Bel and Laia Domènech (2009) and this prediction from an equilibrium model in Gentzkow, Shapiro, Yang, and Yurukoglu 2024 and Zubanov 2021). As cola firms account for only a small share of total advertising (3 percent of food and drink and less than 1 percent of overall TV advertising), their influence on advertising pricing is likely negligible. We therefore assume that advertising prices do not vary across cola brands and are invariant to the—cola market specific—counterfactuals we consider.

Each period, the firm that owns brand b contracts an advertising agency to maximize the flow of advertising exposure given a budget e_{bt}. The agency's problem is

$$\max_{\{T_{bk}\}_k} \sum\nolimits_{i \in \Omega_b} a_{ibt} \tag{7}$$

subject to

$$\sum\nolimits_{\{k | t(k)=t\}} \rho_k T_{bk} \leq e_{bt},$$

where Ω_b denotes the targeted population.

The first-order condition of the agency's problem implies that the ratio of total marginal impacts during two advertising slots, k and k', is set equal to the ratio of the prices of advertising during these slots:

$$\frac{\sum_{i \in \Omega_b} w_{ik} \omega'(T_{bk})}{\sum_{i \in \Omega_b} w_{ik'} \omega'(T_{bk'})} = \frac{\rho_k}{\rho_{k'}}.$$

The optimal choice during slot k satisfies

$$T_{bk}^* = \omega'^{-1}\left(\frac{\rho_k}{\sum_{i \in \Omega_b} w_{ik}} \frac{1}{\lambda_{bt}^*}\right), \tag{8}$$

where λ_{bt}^* is the Lagrange multiplier on the constraint in the agency's problem. The concavity of $\omega(\cdot)$ implies that T_{bk}^* is a decreasing function of the price per viewer during slot k, $\rho_k / \sum_{i \in \Omega_b} w_{ik}$.

While equation (7) frames the agency's problem as if it directly selects advertising slots, in practice, agencies purchase advertising views at a somewhat more aggregated level, leaving TV stations some discretion over the exact timing of ads, as long as they generate the same total impact within the same budget.

C. *The Consumer's Problem*

We model consumer choice as a discrete decision over which, if any, cola product to purchase each period. At this stage, we do not take a normative stance on the relationship between advertising and consumer welfare, nor do we rule out the possibility that consumers experience internalities. Therefore, we use the term "decision utility," following Bernheim (2009). We return to this point when making consumer welfare statements in Sections VB and VC.

We specify the decision utility that consumer i obtains from choosing product j in period t as

$$U_{ijt} = V(\mathcal{A}_{it}, p_{jt}, \mathbf{x}_{jt}; \theta_i) + \epsilon_{ijt}. \tag{9}$$

Consumer i's decision utility for product j depends on their stock of exposure to advertising for all brands, $\mathcal{A}_{it}$, the product's price, p_{jt}, its observable and unobservable product characteristics, $\mathbf{x}_{jt}$, and a vector of preferences parameters, θ_i. ϵ_{ijt} is an idiosyncratic shock that we assume is distributed type I extreme value. The decision utility from choosing the noncola outside option $(j = 0)$ is $U_{i0t} = V(\theta_i) + \epsilon_{i0t}$.

The probability consumer i chooses product $j \in \{1,..,J\}$ is given by

$$s_{ijt} = \frac{\exp\big(V(\mathcal{A}_{it}, p_{jt}, \mathbf{x}_{jt}; \theta_i)\big)}{\exp\big(V(\theta_i)\big) + \sum_{j'=1}^{J} \exp\big(V(\mathcal{A}_{it}, p_{j't}, \mathbf{x}_{j't}; \theta_i)\big)}.$$

The market share function for product $j \in \{1,..,J\}$ is obtained by integrating over the distribution of consumer-specific preferences and advertising exposure:

$$s_{jt}(\mathbf{p}_t, \mathcal{A}_t) = \iint \frac{\exp\big(V(\mathcal{A}_{it}, p_{jt}, \mathbf{x}_{jt}; \theta_i)\big)}{\exp\big(V(\theta_i)\big) + \sum_{j'=1}^{J} \exp\big(V(\mathcal{A}_{it}, p_{j't}, \mathbf{x}_{j't}; \theta_i)\big)} dF(\theta_i, \mathcal{A}_{it}).$$

D. *Counterfactual Policy Simulations*

We use our equilibrium model to simulate the effects of two forms of sugar-sweetened beverage tax, an advertising restriction on sugar-sweetened colas, and a combination of these policies. Specifically, we consider taxes that apply to products containing more than 5 grams of sugar per 100 ml, similar to the structure of the UK tax. Let $j \in \Omega_{\mathcal{S}}$ denote the set of sugar-sweetened cola products exceeding this threshold and $j \in \Omega_{\mathcal{N}}$ denote the set of other colas. We simulate taxes implying the following relationship between the tax-inclusive price $\mathbb{p}_{jt}$ and the tax-exclusive price p_{jt}:

$$\mathbb{p}_{jt} = \begin{cases} p_{jt} + tax_{jt} & \forall j \in \Omega_{\mathcal{S}} \\ p_{jt} & \forall j \in \Omega_{\mathcal{N}} \end{cases}$$

where tax_{jt} is the tax levied on product j. We consider two common forms of tax: a specific (or volumetric) tax, $\text{tax}_{jt} = \mathbb{t}^s$, and an ad valorem tax, $\text{tax}_{jt} = \mathbb{t}^{ad} p_{jt}$.

With a tax in place a firm's flow profit function is

$$\pi_f^{\mathbb{t}}(\mathcal{A}_t, \mathbf{p}_t, \mathbf{e}_t) = \sum_{j \in \mathcal{J}_f} (p_{jt} - c_{jt})\, s_{jt}(\mathbb{p}_t, \mathcal{A}_t)\, M_t - \sum_{b \in \mathcal{B}_f} (1 + \psi_b)\, e_{bt}.$$

Solving the system of first-order conditions for prices yields each counterfactual optimal price vector, conditional on the distribution of advertising exposure stocks, $\mathbf{p}_t^{\mathbb{t}}(\mathcal{A}_t)$. We use the corresponding flow profit function for each firm, $\tilde{\pi}_f^{\mathbb{t}}(\mathcal{A}_t, \mathbf{e}_t) \equiv \pi_f^{\mathbb{t}}(\mathcal{A}_t, \mathbf{p}_t^{\mathbb{t}}(\mathcal{A}_t), \mathbf{e}_t)$, to solve for the counterfactual MPE.

Both specific and ad valorem taxes are commonly employed as corrective measures aimed at changing the relative prices of alcohol, cigarettes, fuels, cars, and sugar-sweetened beverages. Pass-through rates tend to be lower for ad valorem taxes than for specific taxes since, under an ad valorem, unlike a specific, tax, a firm that raises its margin by implementing a marginal (tax-exclusive) price rise of dp will raise the tax-inclusive (consumer) price by $dp(1 + \mathbb{t}) > dp$ (e.g., see Anderson, De Palma, and Kreider 2001). The extent of pass-through will directly influence consumption responses to a tax and interact with firms' advertising responses. For example, if a tax is under-shifted, it means the price-cost margins of taxed products are lower than in the absence of the tax. This reduces the profitability associated with attracting the marginal consumer, diminishing firms' incentives to invest in advertising (see Supplemental Appendix D for an illustrative example).

Under an advertising restriction prohibiting adverts for sugary products (those in $\Omega_{\mathcal{S}}$), the firm's problem described in equation (4) becomes

$$\max_{\{p_{jt}\}_{\forall t, j \in \mathcal{J}_f}, \{e_{bt}\}_{\forall t, b \in \mathcal{B}_f \cap \Omega_{\mathcal{N}}}} \sum_{t=0}^{\infty} \beta^t \pi_f(\mathcal{A}_t, \mathbf{p}_t, \mathbf{e}_t), \tag{10}$$

where $\mathcal{B}_f \cap \Omega_{\mathcal{N}}$ is the set of firm f's brands not subject to the advertising restriction.

III. Empirical Demand Model

A key input to our dynamic model is product-level demand functions, which we estimate using a consumer-level, discrete choice model for cola products. We define a choice occasion as any week in which a household purchases a drink and model the household's decision over which, if any, cola product to choose. To capture the purchase of a noncola drink, we include two outside options: one for sugary noncola drinks and another for sugar-free noncola drinks.[10] A key feature of our demand model is that it incorporates the effect of consumer-level advertising exposure on purchase decisions.

A. *Advertising Exposure*

As discussed in Section IC, we measure household i's exposure to brand advertising in week t as $a_{ibt} = \sum_{\{k|t(k)=t\}} w_{ik}\omega(T_{bk})$, where $\omega(\cdot)$ captures diminishing returns to advert length. We assume ω is a power function, $\omega(T) = T^{\gamma}$, which results in a log-linear relationship between slot price per viewer and advert length (conditional on brand-time fixed effects) in the solution to the advertising agency's problem (equation (7)).

Using 2015 advertising data—where we observe slot prices, viewership, and the length of all food and drink TV advertisements—we estimate $\hat{\gamma} = 0.64$ (p-value < 0.0001). This implies a 60-second advertisement is 1.56 ($= 2^{0.64}$) times as effective as a 30-second advertisement in increasing consumer exposure, indicating

[10] These are selected on 37 percent and 39 percent of choice occasions, respectively

diminishing returns to advertisement length. See Supplemental Appendix E for further details.

We model consumer demand for cola products as a function of their stock of exposure to brand advertising. We specify the consumer's exposure stock to brand b advertising at the beginning of week t as the discounted sum of past advertising exposure:

$$A_{ibt} = \sum_{s=0}^{t-1} \delta^{t-1-s} a_{ibs} = \delta A_{ibt-1} + a_{ibt-1}.$$

This formulation implies that exposure from two weeks ago contributes δ times as much to the current stock of exposure as the same amount of exposure from one week ago. Based on the evidence we discuss in Section ID, we set $\delta = 0.9$. To initialize exposure stocks, we use data on advertising and household TV viewing behavior from the pre-sample year 2009, as advertising exposure older than 52 weeks has a negligible impact on stocks. We provide descriptive evidence on variation in flow and stock of advertising exposure in Supplemental Appendix B.4.

B. *Utility Specification*

In this section, we specify the empirical form of decision utility (equation (9)), paying particular attention to allow for heterogeneity in consumer sensitivity to price and advertising, as well as spillovers in the effect of advertising for one brand on demand for another.

We allow all preference parameters to vary across 12 demographic groups, denoted $d(i)$, based on household type (household with children, working-age household without children, and pensioner household) and income quartiles (see Supplemental Appendix A). This controls for demographic attributes advertisers may target.

Let $j = 1, \ldots, J_1$ denote the advertised products (i.e., those owned by Coca-Cola and PepsiCo), $j = J_1 + 1, \ldots, J$ denote the non-advertised store brands, $j = \underline{0}$ denote sugary noncola drinks, and $j = \bar{0}$ denote non-sugary cola alternatives. Define $b(j)$ as the brand to which product j belongs, $-b(j)$ as other brands owned by the firm, $f(j)$ as the firm that produces product j, and $-f(j)$ as its rival firm. For example, if j is a 2 liter bottle of regular Coke, $b(j)$, $-b(j)$, $f(j)$ and $-f(j)$ correspond to the regular Coke brand, the Diet Coke brand, Coca-Cola Enterprises, and PepsiCo, respectively.

We specify the decision utility function for product $j \in \{1, \ldots, J_1\}$ as

$$\begin{aligned} U_{ijt} = {} & \alpha_i p_{jr(i,t)t} + \beta_i^O \sinh^{-1}\left(A_{ib(j)t}\right) + \beta_{d(i)}^W \sinh^{-1}\left(A_{i-b(j)t}\right) \\ & + \beta_{d(i)}^X \sinh^{-1}\left(A_{i-f(j)t}\right) + \gamma_i Sug_{b(j)} + \phi_{d(i)} \mathbf{Z}_{if(j)} + \eta_{if(j)} + \chi_{d(i)j} \\ & + \xi_{d(i)b(j)\tau(t)} + \zeta_{d(i)b(j)r(i,t)} + \epsilon_{ijt}, \end{aligned} \tag{11}$$

where $p_{jr(i,t)t}$ is the price (per unit) of product j, in the retailer consumer i shops with, $r(i,t)$, in week t. We incorporate three distinct effects of advertising on decision utility: (i) an own-brand advertising effect, β_i^O, which captures the impact of a consumer's exposure to advertising for the brand of product j, (ii) a within-firm spillover effect, $\beta_{d(i)}^W$, which captures spillovers from advertising of other brands within the same firm, and (iii) a cross-firm spillover effect, $\beta_{d(i)}^X$, which captures spillovers from advertising of rival firms. Each advertising stock enters the decision utility function through the inverse-hyperbolic sine function, which accounts for diminishing returns to advertising exposure.[11]

Decision utility also depends on consumer-specific preferences as to whether the brand is sugar-sweetened $(Sug_{b(j)})$ and firm—i.e., Coca-Cola versus PepsiCo $(\eta_{if(j)})$. Additionally, it incorporates a vector of household TV viewing behavior measures interacted with firm $(\mathbf{Z}_{if(j)})$ and product $(\chi_{d(i)j})$ year-quarter-brand $(\xi_{d(i)b(j)\tau(t)})$ and retailer-brand $(\zeta_{d(i)b(j)r(i,t)})$ effects, all of which vary by demographic group.

The inclusion of the three exposure stocks, $\left(A_{ib(j)t}, A_{i-b(j)t}, A_{i-f(j)t}\right)$, in the decision utility function is crucial for flexibly capturing the impact of advertising on consumer choice. A specification with only the own-brand effect would imply negative cross-advertising effects—meaning an increase in demand for one brand from higher advertising exposure would necessarily reduce demand for all other brands. However, by incorporating advertising for other brands, we relax this restriction, allowing for the possibility that an increase in advertising for one brand may also raise demand for another. Moreover, spillover effects may be stronger within a firm than across firms. To account for this, our specification distinguishes between within-firm and cross-firm spillover effects.

We model preferences for price, own-brand advertising, sugar, and firm effects as random coefficients. The sugar and firm coefficients, $\left(\gamma_i, \eta_{i,b(j)}\right)$, follow independent normal distributions specific to each demographic group. For the price and own-brand advertising coefficients, we specify that $\left(\ln\left(-\alpha_i\right), \ln\left(\beta_i^O\right)\right)$ follows a joint normal distribution with demographic-group-specific parameters and nonzero covariance.[12]

Allowing for correlation between price and advertising sensitivity is crucial for modeling the effects of tax policy on advertising. A tax increases the price consumers face for taxed products, leading the most price-sensitive consumers to switch away. Whether the posttax marginal consumer is more or less sensitive to advertising than the pretax marginal consumer will influence whether firms respond to the tax by increasing or decreasing advertising.[13]

Since we specify random coefficient distributions conditional on 12 demographic groups, the overall preference distribution is a mixture of these conditional

[11] This is similar to a log transformation but has the advantage of being defined at zero advertising, which is relevant in our counterfactual analysis.

[12] The log-normal specification ensures that price increases cannot raise demand and that advertising increases cannot lower it. For comparison, we also estimate a model using normal distributions, which yields similar average price and advertising elasticities but implies that some consumers exhibit upward-sloping demand. In an additional specification, we allow for correlation between price and advertising sensitivities and consumers' preferences for sugar. This modification does not materially affect the correlation between price and advertising sensitivities, and we find that the correlation between these sensitivities and sugar preferences is low.

[13] We estimate the impact of advertising exposure and permanent preference heterogeneity on consumer choice using panel microdata and variation in advertising exposure over a seven-year period. In the long run—e.g., through childhood exposure—advertising may also shape preference formation.

distributions. This rich preference specification allows our model to capture realistic patterns of substitution across products. Additionally, it substantially relaxes restrictions otherwise placed on the curvature of product-level market demands, allowing the model to flexibly predict tax pass-through (see Griffith, Nesheim, and O'Connell 2018; Miravete, Seim, and Thurk 2023).

For store brands (which never advertise), $j \in \{J_1 + 1, .., J\}$, we specify decision utility as

$$U_{ijt} = \alpha_i p_{jr(i,t)t} + \gamma_i Sug_{b(j)} + \chi_{d(i)j} + \xi_{d(i)b(j)\tau(t)} + \zeta_{d(i)b(j)r(i,t)} + \epsilon_{ijt}.$$

The decision utility from each of the two outside options is $U_{i\underline{0}t} = \gamma_i + \chi_{d(i)\underline{0}} + \xi_{d(i)\underline{0}\tau(t)}, + \epsilon_{i\underline{0}t}$ and $U_{i\bar{0}t} = \epsilon_{i\bar{0}t}$.

C. *Identification*

We face two main identification challenges: determining the causal impact of changes in advertising and price on product-level demands.

Advertising.—Firms invest in advertising to increase demand for their brands and, consequently, their profits. They hire advertising agencies to purchase television airtime, with advertisements typically airing nationally several months later. Firms determine their advertising investment based on predictable components of demand and the price of advertising, which is driven by the interaction of advertising demand conditions across all advertising markets, not just colas, and the supply of airtime. Advertisers may target specific consumer groups. However, their ability to target consumers via mass media is limited, and as many households from different demographic groups watch the same shows, there are cross-group spillovers (see Thomas 2020; Li, Hartmann, and Amano 2024). We exploit the fact that, after advertising agencies purchase airtime to maximize exposure within the budget set by cola firms, TV stations retain discretion in fulfilling these orders due to the availability of multiple slots with similar viewership. This discretion generates variation in advertising exposure across otherwise similar households. Our data captures this variation by combining comprehensive records of individual cola TV advertisements with household-level TV viewing behavior, enabling us to measure household-specific advertising exposure.

Manufacturers may target households of a particular demographic type by purchasing airtime during shows typically watched by that group. To account for this, we allow all preference parameters in our demand model to vary by demographic group, including time-varying brand effects (the $\xi_{d(i)b(j)\tau(t)}$'s in equation (11)).

A potential concern is that manufacturers may target viewers of specific TV programs. In practice, their ability to do so is constrained by the nature of the ad-buying process. Nonetheless, our demand model includes a detailed vector of household TV-watching behavior measures interacting with Coca-Cola and PepsiCo effects ($\mathbf{Z}_{if(j)}$ in equation (11)). Specifically, we include controls for how regularly a household watches: (i) TV in a typical week, (ii) shows within six genres (e.g., sport, documentaries, entertainment), (iii) shows on different stations (including the three

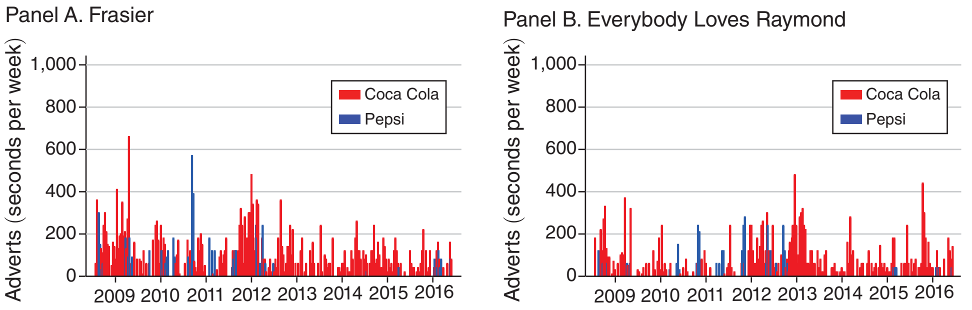

FIGURE 1. WITHIN GENRE ADVERTISING VARIATION

Notes: Authors' calculations using data from AC Nielsen Advertising data for 2010–2016. Panels show number of seconds of adverts shown during the indicated show per week. See Supplemental Appendix Figure B.2 for another example.

main terrestrial channels and the group of cable/satellite channels),[14] and (iv) shows shown during different time slots (e.g., prime-time weekday, non-prime time weekend). This means that the variation we use to estimate advertising effects arises across households of the same demographic group and TV viewing profile.[15]

Figure 1 illustrates this source of variation. It shows weekly advertising (in seconds) for Coca-Cola and PepsiCo brands during two US sitcoms, *Frasier* and *Everybody Loves Raymond*. These shows aired across most months during the period 2009–2016, with Coca-Cola and PepsiCo advertisements varying in quantity and timing. Households are differentially exposed to Coca-Cola and Pepsi advertising depending on whether they watch neither show, watch one of the shows, or watch both shows.

Prices.—An important feature of the UK grocery market is that the major supermarkets operate national store networks and adhere to national pricing policies (see Competition Commission 2000). As a result, our analysis does not rely on cross-sectional regional price variation, a common approach in studies of US markets that often use Hausman instruments (Hausman, Leonard, and Zona 1994).[16] Instead, we exploit the fact that drinks firms (i.e., Coca-Cola Enterprises and PepsiCo) negotiate annually with major retailers to set a recommended (national) retail price and agree on the number, type, and timing of temporary price reductions for the upcoming year (e.g., Competition Commission 2013). While the recommended prices for a given product are generally similar across retailers, the timing

[14] In the United Kingdom, five terrestrial channels are available to all households that pay for a TV license. Three of these—ITV, Channel 4, and Channel 5—air advertisements. Other stations are available via Freeview, cable, and satellite. See Supplemental Appendix B.1 for details.

[15] The descriptive evidence in Section ID additionally conditions on household fixed effects. We compare these results with the advertising effects we estimate in our model below.

[16] Additionally, the cola market during our study period consists of a stable set of brands and products, preventing us from using variation in product characteristics as price instruments (e.g., Berry 1994; Berry, Levinsohn, and Pakes 1995; Gandhi and Houde 2020).

of temporary price reductions varies, leading to differences in the prices shoppers face depending on when and where they shop.

This strategy relies on two assumptions. First, we must adequately control for aggregate demand shocks that could be correlated with nationally set prices. To this end, we include a rich set of demographic-varying brand effects, including time- and retailer-varying effects, $\xi_{d(i)b(j)\tau(t)}$ and $\zeta_{d(i)b(j)r(i,t)}$). Second, it requires that retailer choice is exogenous with respect to cola choice—meaning consumers do not systematically visit multiple retailers to find the lowest price for a specific cola product. This assumption is reasonable for two reasons. First, cola represents a small share of consumer expenditure, making the potential savings from shopping around relatively small. Second, temporary price reductions in the UK grocery market are numerous, meaning that if a specific product is not discounted at the time of purchase, a close substitute (e.g., the same brand in a different package size) is likely to be on sale.

A third assumption underlying our strategy is that our estimates capture intra-temporal consumer responses rather than intertemporal responses, such as stockpiling in response to sales. If consumers primarily stock up during sales, this could lead us to overestimate own-price elasticities and underestimate cross-price elasticities (Hendel and Nevo 2006). While we cannot rule out that some consumers stockpile a priori, empirical evidence suggests that this effect is not quantitatively important in our UK context. Using the same dataset as in this paper (the Kantar Take Home Purchase panel), O'Connell and Smith (2024) show that when consumers purchase a drink on sale, they are more likely to switch brands, container type (i.e., can versus bottle), and size relative to their previous purchase; however, they do not systematically alter the timing of their purchases. This evidence indicates that consumers respond to sales by intra-temporally substituting across products rather than stockpiling.[17]

D. *Demand Estimates*

We estimate the demand model by simulated maximum likelihood. In Table 3, panel A, we report brand-level price and advertising elasticities.[18] The price elasticities measure the percent change in demand for the brand listed in the first column in response to a 1 percent increase in the price of all products belonging to the brand detailed in the first row. The own-price elasticity for regular and Diet Coke is -2.2, which is somewhat larger in magnitude than the own-price elasticities for regular and Diet Pepsi. The cross-price elasticities indicate consumers are more willing to switch within Coca-Cola and Pepsi brands than across them, and that they are more willing to substitute within regular and diet brands than across them—for example, the cross-price elasticity of demand for regular Pepsi with respect to a rise in the price of regular Coke products is nearly twice as large as that for Diet Pepsi.

The advertising elasticities describe the impact of a 1 percent increase in the stock of all consumers' exposure to advertising for the brand in the first row on

[17] O'Connell and Smith (2024) also show that purchasing on sale does not meaningfully affect the likelihood of shopping at a different retailer compared to the previous purchase, supporting our assumption of exogenous retailer choice.

[18] For estimation details, parameter estimates and product-level price elasticities, see Supplemental Appendix F.

Table 3—Brand Price and Advertising Elasticities

	Price elasticities			
	Coke		Pepsi	
	Regular	Diet	Regular	Diet
(1)	(2)	(3)	(4)	(5)
Regular Coke	**−2.210**	0.511	0.050	0.092
	[−2.285, −2.143]	[0.492, 0.539]	[0.048, 0.054]	[0.087, 0.095]
Diet Coke	0.378	**−2.192**	0.023	0.142
	[0.366, 0.407]	[−2.249, −2.126]	[0.022, 0.025]	[0.135, 0.147]
Regular Pepsi	0.210	0.128	**−1.842**	0.552
	[0.169, 0.219]	[0.102, 0.134]	[−1.906, −1.485]	[0.442, 0.585]
Diet Pepsi	0.110	0.232	0.157	**−1.679**
	[0.107, 0.117]	[0.223, 0.243]	[0.150, 0.168]	[−1.723, −1.621]
Regular store	0.243	0.155	0.063	0.106
	[0.233, 0.262]	[0.149, 0.163]	[0.060, 0.068]	[0.101, 0.111]
Diet store	0.130	0.276	0.031	0.170
	[0.125, 0.140]	[0.268, 0.289]	[0.030, 0.034]	[0.165, 0.178]
Regular outside	0.185	0.138	0.050	0.095
	[0.180, 0.196]	[0.133, 0.144]	[0.048, 0.054]	[0.091, 0.099]
Diet outside	0.104	0.236	0.027	0.152
	[0.101, 0.111]	[0.228, 0.246]	[0.025, 0.029]	[0.147, 0.158]
	Advertising elasticities			
	Coke		Pepsi	
	Regular	Diet	Diet	
	(6)	(7)	(8)	
Regular Coke	**0.115**	0.043	0.020	
	[0.099, 0.162]	[−0.006, 0.086]	[0.008, 0.031]	
Diet Coke	0.054	**0.110**	0.016	
	[0.009, 0.090]	[0.095, 0.147]	[0.003, 0.027]	
Regular Pepsi	0.021	0.020	0.015	
	[0.002, 0.037]	[0.003, 0.035]	[−0.013, 0.039]	
Diet Pepsi	0.015	0.011	**0.057**	
	[−0.002, 0.031]	[−0.005, 0.024]	[0.050, 0.074]	
Regular store	−0.021	−0.017	−0.011	
	[−0.030, −0.017]	[−0.024, −0.012]	[−0.015, −0.007]	
Diet store	−0.020	−0.021	−0.012	
	[−0.027, −0.016]	[−0.027, −0.017]	[−0.016, −0.009]	
Regular outside	−0.020	−0.017	−0.009	
	[−0.025, −0.018]	[−0.021, −0.015]	[−0.012, −0.007]	
Diet outside	−0.019	−0.021	−0.011	
	[−0.024, −0.015]	[−0.025, −0.018]	[−0.014, −0.009]	

Notes: Numbers show the elasticity of demand for the brand shown in column 1 with respect to the price (columns 2–5) or advertising stocks (columns 6–8) of the brands shown in the first row. The price elasticities are with respect to a 1 percent price rise of all products comprising the brand. The advertising elasticities are with respect to a 1 percent rise in all consumer exposure stocks. Ninety-five percent confidence bands are shown in square brackets.

demand for the brand in the first column, and should be interpreted as long-run elasticities.[19] The own-brand elasticities for regular and Diet Coke advertising are approximately 0.11, while the Diet Pepsi own-brand elasticity is around half this

[19] Suppose flow exposure is constant over time, so that $A_{ibt} = \frac{1}{1-\delta} a_{ib}$, then a 1 percent increase in the stock is equivalent to a 1 percent permanent increase in the flow.

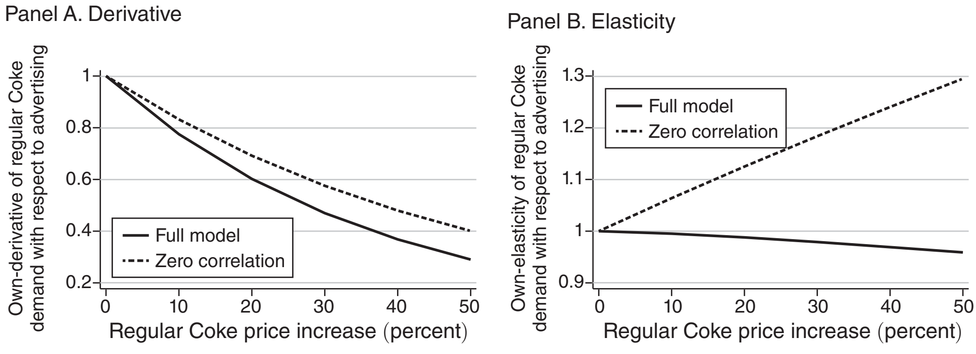

Figure 2. Impact of Regular Coke Price Level on Advertising Sensitivity of Demand

Notes: Figure shows how the derivative (panel A) and elasticity (panel B) for demand for regular Coke with respect to regular Coke advertising varies with the price of regular Coke products. The solid lines correspond to our full demand model, the dashed lines correspond to when we switch off the within-demographic group correlation in price and advertising preferences. In all cases, we express numbers relative to zero price increase.

magnitude. These estimates, derived from the structural model, align with those we present in Section ID, which are based on brand-level regressions using only within-household variation in exposure. The cross-elasticities indicate substantial within-firm advertising spillovers. For instance, a 1 percent increase in regular Coke advertising raises demand for Diet Coke products by 0.05 percent—about half the increase in regular Coke demand. There is also evidence for cross-firm advertising spillovers (i.e., regular and Diet Coke advertising raising Pepsi demand and Diet Pepsi advertising raising Coke demand), though these effects are substantially smaller in magnitude than the within-firm spillovers.

Figure 2 illustrates how the sensitivity of brand demand to advertising varies with the brand's price level. Panel A shows how the derivative of demand for regular Coke with respect to regular Coke advertising changes as the price of all regular Coke products increases. Panel B shows how the regular Coke's own advertising elasticity varies with price. In both cases, we plot the relationship based on our full model estimates (solid line) and on a restricted version where the within-demographic group covariance between advertising and price sensitivity is set to zero (dashed line).

The figure highlights the role of covariance parameters in determining the shape of demand functions. When set to zero, the advertising derivative declines gradually as the price rises, leading to an increase in the advertising elasticity (since the derivative falls more slowly than the quantity demanded of regular Coke). However, using our estimates of within-demographic group correlation in price and advertising sensitivity, we find that the advertising derivative declines rapidly enough with price that the advertising elasticity also falls. In other words, as the price rises, the consumers who substitute away from the brand tend to be more advertising-sensitive. This feature of demand influences how firms adjust their advertising in response to a tax. With a tax in place, demand for the taxed products will consist of a consumer base that is relatively insensitive to advertising compared with the absence of a tax. Assuming zero correlation between price and advertising sensitivity would imply that the advertising elasticity increases along the demand curve, whereas our estimates suggest the opposite.

IV. Supply-Side Estimation

In the supply model, Coca-Cola and PepsiCo are the strategic players, competing over product prices and brand advertising budgets. Store brands are not advertised, and during the time period we consider, PepsiCo did not advertise regular Pepsi. Therefore, we model advertising choices for regular Coke, Diet Coke, and Diet Pepsi. We assume that PepsiCo would not begin advertising its regular brand in a counterfactual scenario where a sugar-sweetened soft drinks tax is introduced. In Section V, we show that Coca-Cola reduces advertising for its regular brand in response to a tax. Given PepsiCo faces similar incentives to advertise, relaxing this assumption would have little impact on our results.[20] Store brand prices are significantly lower than those of Coca-Cola and PepsiCo. In our policy simulations, we hold these prices fixed, treating store-brand products as if they are priced at cost.

In demand estimation, we exploit week-to-week variation in advertising exposure. However, firms set advertising expenditures at a lower frequency, with week-to-week exposure varying based on advertising slots arranged by agencies. We assume that firms set both prices and advertising expenditures monthly. While prices vary across retailers at a given time, this variation primarily reflects the staggered timing of temporary price reductions. Instead of incorporating a formal model of vertical relations, we make the simplifying assumption that drinks firms set a uniform price for each product across retailers.[21] To solve for the model equilibrium, we must specify how firms form expectations of how advertising expenditures affect the distribution of consumer advertising exposure stocks. We first outline this process before presenting the static and dynamic equilibrium conditions in the observed (zero-tax) case.

A. *The State Transition Function*

Advertising agencies simplify firms' decision-making by reducing their action space to setting product prices and brand advertising expenditures. However, the state space in the firm's decision problem, outlined in Section IIA, remains large, as it consists of the joint distribution of consumer-level exposure stocks for each brand ($\mathcal{A}_t = \{(A_{i1t}, \ldots, A_{iBt})\}_{i \in I}$). While the behavior of advertising agencies implies

[20] We also compute the derivative of PepsiCo's gross profit function with respect to the stock of regular Pepsi advertising in the observed zero-tax equilibrium, and in the counterfactual equilibria with a specific or ad valorem tax in place. We find that this derivative falls by around 15 percent and 20 percent, respectively, under the two tax regimes, indicating weaker incentives to advertise. These declines are similar in magnitude to those for regular Coke, which our model predicts reduces its advertising.

[21] In practice, for a given product-year, a drinks firm and retailer agree on a base price $\bar{p}$ and a sale price p_S, with the base price applying ρ proportion of weeks. Instead of modeling the firm's choice over $(\bar{p}, p_S, \rho)$, we model choice over $p = (1-\rho)\bar{p} + \rho p_S$, which exhibits minimal variation across retailers. Cross-retailer price differences at a given point in time stem primarily from asynchronized sales. We thus specify the relationship between prices in the supply model, p_{jm}, and the prices consumers face in retailer r in week $t \in m$ as $p_{jrt} = p_{jm} + e_{jrt}$, where $\mathbb{E}[e_{jrt} | (j,m)] = 0$.

that advertising exposure evolves predictably based on firms' expenditures, viewership behavior, and realized television slot choices, the information burdens on firms from tracking this entire distribution, and from forming optimal expenditure strategies that depend on it, are formidable and render the dynamic oligopoly game computationally intractable. To address this, we assume that firms track a summary statistic of the brand-specific exposure distribution—specifically, the mean exposure in the population. We estimate the transition function that maps advertising expenditures to this summary statistic and, to solve the MPE, discretize the state space using a fine grid for the three advertising states (regular Coke, Diet Coke, and Diet Pepsi). Supplemental Appendix G provides further details, including evidence that tracking the mean of the distribution results in negligible prediction error in product level demands (because overprediction and underprediction of individual demands, when using the mean exposure, offset each other in aggregate demand).

B. *State-Specific Optimal Prices*

We use the advertising state-specific optimal pricing conditions from equation (5), evaluated at observed prices and advertising state variables, to infer product-level marginal costs. Among Coca-Cola products, the average (quantity-weighted) marginal cost and price-cost margin per liter are 0.45 and 0.38, respectively, while the average (expenditure-weighted) Lerner index is 0.46. For PepsiCo products, the corresponding figures are 0.25, 0.41 and 0.62, indicating that PepsiCo products, on average, have lower costs but similar price-cost margins (and thus higher Lerner indexes) to Coca-Cola products.[22]

Using our estimates of product-level demand and marginal costs, along with the price first-order conditions (equation (5)), we solve for the vector of optimal prices at each point of the advertising state space. Figure 3, panel A, shows how the average price-cost margins of regular Coke products vary across the advertising state space. The state space is three-dimensional; the figure holds the Diet Pepsi state fixed and shows how the average margins of regular Coke products vary with the Diet Coke and regular Coke advertising states. It shows that, conditional on the Pepsi and Diet Coke states, the average margin of regular Coke products decreases as the regular Coke advertising state increases. This pattern arises due to the correlation between consumers' price and advertising sensitivities. As the regular Coke advertising state increases, its consumer base becomes more price sensitive, leading to lower optimal prices. In contrast, there is a weaker positive relationship between the Diet Coke advertising state and regular Coke margins. This occurs because higher Diet Coke advertising shifts relatively advertising-sensitive consumers from regular to Diet Coke, making the remaining regular Coke consumer base less sensitive to both advertising and price.

Figure 3, panel B, shows how demand for regular Coke products varies across the Coca-Cola advertising states. This variation reflects both the direct effect of advertising on demand and the indirect effect through optimal pricing adjustments.

[22] We report product-level costs, margins, and Lerner indexes in Supplemental Appendix F.

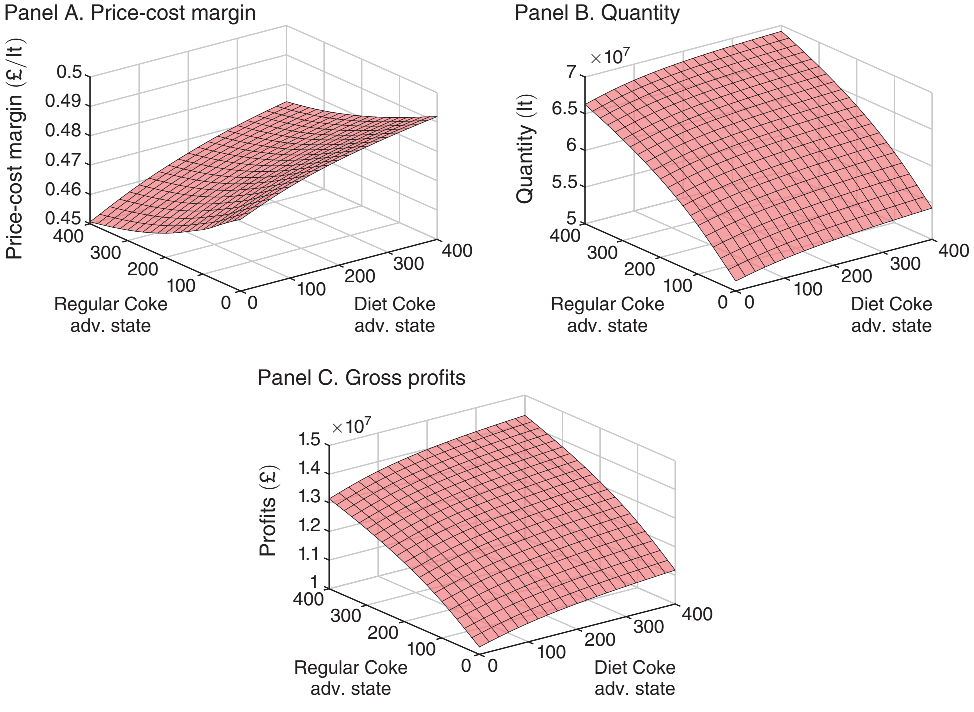

Figure 3. Variation in Regular Coke Outcomes with Coca-Cola Advertising States

Notes: Panel A shows variation in the average price-cost margin for regular Coke products. Panels B and C show variation in total quantity and gross profits for regular Coke. In each panel, we hold fixed the Diet Pepsi advertising state at the highest probability state in the dynamic equilibrium distribution.

Demand for regular Coke increases with the regular Coke advertising state due to both channels—the direct advertising impact and lower prices at higher advertising states. Regular Coke demand also rises with the Diet Coke advertising state, though less strongly. This is driven by a within-firm advertising spillover effect, where Diet Coke advertising stimulates demand for both Diet Coke and regular Coke. This spillover is strong enough to outweigh an opposing indirect effect—regular Coke prices increase as Diet Coke advertising rises.

Figure 3, panel C, shows how gross profits (excluding advertising expenses) for regular Coke products vary with the Coca-Cola advertising states. As the regular Coke advertising state increases, there are two opposing forces: demand rises but margins decline. The demand effect dominates, leading to higher profits. Regular Coke profits are also increasing in Diet Coke advertising, but the effect is weaker compared to changes in the regular Coke advertising state.

In Figure 4, we plot how Coca-Cola's and PepsiCo's gross profits (which sum across all products they own) vary with Coca-Cola's two advertising states, holding PepsiCo's state fixed. Coca-Cola's gross profits increase in its advertising states. PepsiCo's profits also rise with Coca-Cola's advertising, though less strongly. This reflects a cross-firm spillover, where Coca-Cola's advertising increases decision

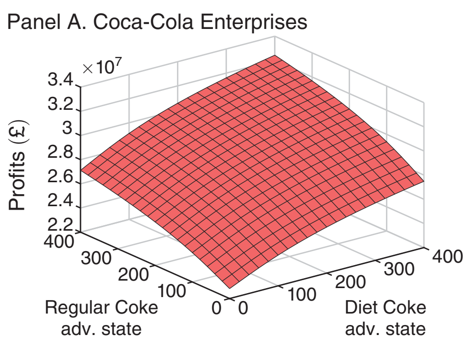

Figure 4. Variation in Firm-Level Gross Profits with Coca-Cola Advertising States

Notes: Panel A shows variation in Coca-Cola Enterprises gross profits, and panel B shows variation in PepsiCo gross profits. In each panel, we hold fixed the Diet Pepsi advertising state at the highest probability state in the dynamic equilibrium distribution.

utility for PepsiCo products, boosting their demand. At higher levels of Coca-Cola advertising, PepsiCo's profits become less sensitive to further increases. These firm-level profit functions, which incorporate strategic pricing competition, serve as an input into the dynamic advertising game.

C. *Markov Perfect Equilibrium*

We use the Bellman equations for Coca-Cola and PepsiCo (equation (6)) to solve for the Markov Perfect Equilibrium (see Supplemental Appendix H for details of the solution algorithm). We calibrate the brand-level agency mark-up, ψ_b, over television expenses so that the model's equilibrium predictions for average advertising expenditures match their observed levels.[23] This implies PespsiCo, which advertises less, faces a mark-up that is 1.5 times higher than the average paid by Coca-Cola, which is consistent with the mark-up partly reflecting fixed cost recovery by advertising agencies. We set firms' monthly discount factor to $\beta = 0.992$.

We obtain MPE strategies (policy functions) for each advertised brand, prescribing the optimal advertising expenditure at each point in the advertising state space. Figure 5, panel A, illustrates how the policy functions for regular Coke (red) and Diet Coke (grey) vary across the Coca-Cola advertising states, holding the Diet Pepsi advertising state fixed. The policy functions show that for both regular and Diet Coke, when the average of consumers' stock of advertising exposure is low, the returns on additional advertising are relatively high, leading to higher optimal expenditures. Conversely, as exposure stocks increase, diminishing returns reduce the incentive to invest further, resulting in lower optimal expenditures. The

[23] We set the agency markup so that the model's predicted ergodic average of advertising expenditure matches the observed average. In practice, matching these moments requires some trial and error. An alternative approach would be to estimate these parameters. Doing so would not materially affect our analysis but would impose a substantial additional computational burden, as it entails solving for the dynamic model for each trial parameter value. Further, note that the average agency markup is isomorphic with the potential market size.

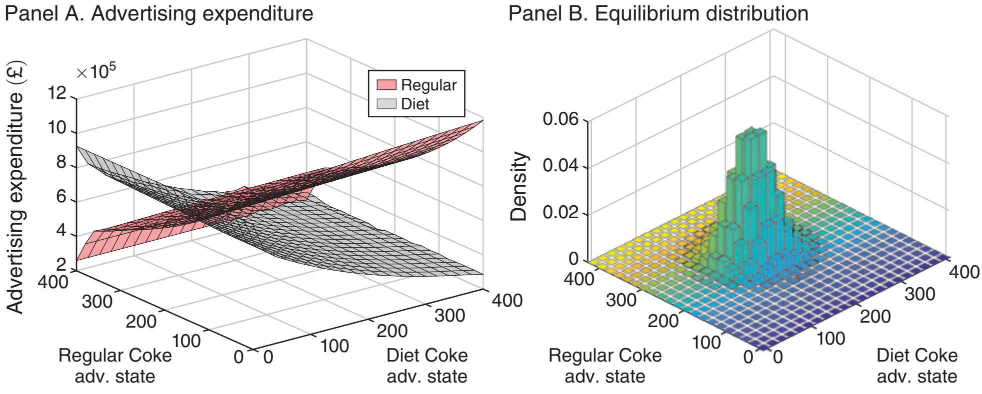

Figure 5. Optimal Policy Function for Coca-Cola Enterprises

Notes: In panel A, the red surface shows regular Coke advertising expenditure, and the grey surface shows Diet Coke expenditure, where we hold fixed the Diet Pepsi advertising state at the highest probability state in the dynamic equilibrium distribution. In panel B, we integrate over the Diet Pepsi advertising state space.

cross-brand relationship between states and optimal expenditures is much weaker, with regular Coke's optimal advertising expenditure being relatively insensitive to the Diet Coke state, and vice versa.

Firms' optimal policy functions, combined with the state-to-state transition function, generate an MPE (ergodic) distribution over the state space. In Figure 5, panel B, we plot the ergodic distribution of the equilibrium across Coca-Cola advertising states, integrating over the PepsiCo state.

V. Counterfactual Policy Analysis

We use our model to simulate a series of counterfactual policies, characterizing their impact on equilibrium prices, advertising expenditures, quantities and aggregate profits. We also consider their distributional effects across consumers. Specifically, we consider a regulation prohibiting sugar-sweetened cola advertising, as well as both a specific and an ad valorem tax on sugar-sweetened beverages tax. The tax applies to regular Coke and Pepsi, with the specific tax set at £0.22 per liter and the ad valorem tax calibrated to achieve the same reduction in equilibrium quantity as the specific tax, holding advertising fixed. We also analyze the combined effect of the advertising restriction and the tax.[24]

Our model generates a set of functions describing how static outcomes (e.g., state-specific optimal prices, quantities, profits, consumer surplus) vary across the

[24] We model the tax as being levied on cola advertisers, since one of our objectives is characterizing advertising responses to tax policy. The specific tax closely resembles the UK Soft Drinks Industry Levy introduced in April 2018, which imposed a rate of £0.24 per liter (approximately £0.22 per liter in real terms for our earlier period) on beverages containing more than 8g of sugar per 100ml and £0.18 per liter on those with 5–8g of sugar per 100ml. Many store-brand colas and noncola soft drinks reformulated their products to avoid the tax by reducing sugar content below 5g per 100ml. In our counterfactual analysis, we assume that store-brand cola and the sugary outside option contain 5g of sugar per 100ml and are untaxed, whereas Coca-Cola and Pepsi, which contained approximately 10.5g of sugar when the tax was introduced, are subject to the higher tax rate.

TABLE 4—AGGREGATE IMPACT OF COUNTERFACTUAL POLICIES

	No tax	Specific tax			Ad valorem tax		
	Adv. restrict. (1)	Fixed adv. (2)	+ Eq. adv. response (3)	+ Adv. restrict. (4)	Fixed adv. (5)	+ Eq. adv. response (6)	+ Adv. restrict. (7)
Δ *Price*							
Regular Coke/Pepsi	0.7%	28.8%	0.1%	0.5%	37.0%	0.1%	0.4%
Diet Coke/Pepsi	−1.0%	−1.4%	−0.1%	−0.7%	−1.4%	−0.2%	−0.6%
Δ *Margin*							
Regular Coke/Pepsi	1.6%	5.1%	0.2%	1.1%	−34.8%	0.2%	0.5%
Diet Coke/Pepsi	−2.1%	−2.8%	−0.2%	−1.4%	−2.8%	−0.4%	−1.2%
Δ *Advertising exp.*							
Regular Coke/Pepsi	−100.0%	–	−33.1%	−100.0%	–	−47.3%	−100.0%
Diet Coke/Pepsi	−7.7%	–	−3.3%	−10.8%	–	−8.5%	−15.1%
Δ *Quantity*							
Regular Coke/Pepsi	−13.0%	−55.1%	−1.0%	−4.5%	−55.2%	−1.5%	−3.9%
Diet Coke/Pepsi	−3.8%	11.2%	−0.9%	−4.7%	10.8%	−1.7%	−4.2%
Δ *Sugar*							
All drinks	−2.7%	−16.2%	−0.1%	−0.4%	−16.5%	−0.1%	−0.3%

Notes: Numbers are expressed as a percentage of the pre-policy level (i.e., before the tax and advertising restriction). Columns 1, 2, and 5 show changes relative to the pre-policy level. Column 3 (column 6) presents the incremental change relative to column 2 (column 5), while column 4 (column 7) shows the incremental change relative to column 3 (column 6).

advertising state space ($\mathbb{A} = \{\mathbb{A}\}_b$), denoted by $y_\chi(\mathbb{A})$. It also produces an equilibrium (ergodic) distribution over the state space, denoted $g_\chi(\mathbb{A})$ for different scenarios $\chi \in \{\varnothing, \mathbb{r}, \mathbb{s}, \mathbb{sr}, \mathbb{a}, \mathbb{ar}\}$. $\varnothing$ represents the—no policy intervention—status quo, while $\mathbb{s}$ and $\mathbb{a}$ denote the counterfactual imposition of a specific and ad valorem tax, respectively. $\mathbb{r}$ represents the counterfactual imposition of an advertising restriction, which we consider both as a standalone policy and in combination with each tax type. The average equilibrium outcome is given by $\bar{Y}_\chi = \int_{\mathbb{A}} y_\chi(\mathbb{A})\, g_\chi(\mathbb{A})$.

A. *Impact on Market Equilibrium*

Table 4 summarizes the impact of each counterfactual policy on equilibrium (tax-inclusive) prices, price-cost margins, advertising expenditures, quantities and sugar consumption. The values represent percentage changes relative to the no policy intervention equilibrium. Column 1 reports the effects of an advertising restriction prohibiting sugar-sweetened cola advertising. Column 2 presents the impact of a specific tax, holding the equilibrium distribution across advertising states fixed (thus keeping firms' advertising expenditures unchanged). Columns 3 and 4 show the *incremental* effects of incorporating equilibrium advertising responses and combining the tax with the advertising restriction, respectively. Columns 5–7 mirror columns 2–4 for an ad valorem tax. We discuss each policy in turn.

Advertising Restriction.—Column 1 shows that banning sugar-sweetened cola advertising (which directly affects regular Coke advertising) reduces regular Coke and Pepsi consumption by 13.0 percent, leading to a 2.7 percent decline in overall sugar consumption from drinks.[25] The ban also reduces Diet Coke and Pepsi consumption by 3.8 percent. While prices and margins of diet products remain relatively unchanged, Diet advertising declines by 7.7 percent, driven almost entirely by a reduction in Diet Coke advertising. The restriction on regular advertising, combined with the decline in Diet Coke advertising, shifts the equilibrium distribution (see panels B and C of Figure 6, which compare pre- and post-ban equilibrium distributions).

The decline in the equilibrium quantity of Diet Coke and Pepsi products reflects two channels. First, since advertising for regular products has positive spillover effects on diet product demand, banning it—holding all else equal—reduces demand for Diet Coke and Pepsi. Second, Coca-Cola's equilibrium response to the policy is to reduce Diet Coke advertising, which directly lowers Diet Coke demand.

In Figure 7, we illustrate why, in response to the advertising restriction, Coca-Cola lowers advertising of its diet brand. Panel A shows how equilibrium gross profits for regular (red lines) and Diet (grey lines) Coke vary with the Diet Coke advertising state. We present this relationship under two conditions: where the regular Coke advertising state is at its modal "no policy intervention" equilibrium value (solid lines) and when it is at 0 (dashed lines), corresponding to the advertising restriction. The graph indicates that, after the ban, the returns to advertising Diet Coke—both in terms of regular and Diet Coke profits—are lower, leading Coca-Cola to reduce its diet advertising expenditure.

Panel B highlights the primary reason for this decline in the returns. It shows how the average price-cost margins for regular and Diet Coke products change with the Diet Coke advertising state. As the Diet Coke advertising state increases, the average equilibrium margin for Diet Coke falls while the margin for regular Coke rises, reflecting a shift of the most advertising-sensitive—and due to correlation in preferences, the most price-sensitive—consumers towards Diet Coke. When the restriction is in place, higher Diet Coke advertising leads to a sharper decline in Diet Coke margins and a weaker increase in regular Coke margins. This occurs because, in the absence of regular Coke advertising, Diet Coke advertising attracts advertising—and hence price—sensitive consumers who might otherwise remain regular Coke buyers.

Specific Tax.—Column 2 of Table 4 summarizes the impact of a £0.22 per liter specific tax, holding firms' advertising policy functions (and hence the equilibrium distribution over states) at their pretax level. The tax leads to a 28.8 percent increase in the average price of regular Coke and Pepsi (i.e., the taxed products), reflecting both the mechanical impact of the tax on prices and firms' equilibrium margin adjustments. On average the pass-through of the tax is approximately 110 percent, corresponding to a 5 percent increase in equilibrium price-cost margins for taxed products (see panel A of Figure 6, where we show how the average regular Coke

[25] This accounts for changes in sugar intake from regular Coke and Pepsi (each containing 106g of sugar per liter), as well as regular store brand colas and the sugary outside option drink (each containing 50g of sugar per liter). We assume the size (in liters) of the sugary outside option equals the average size of products.

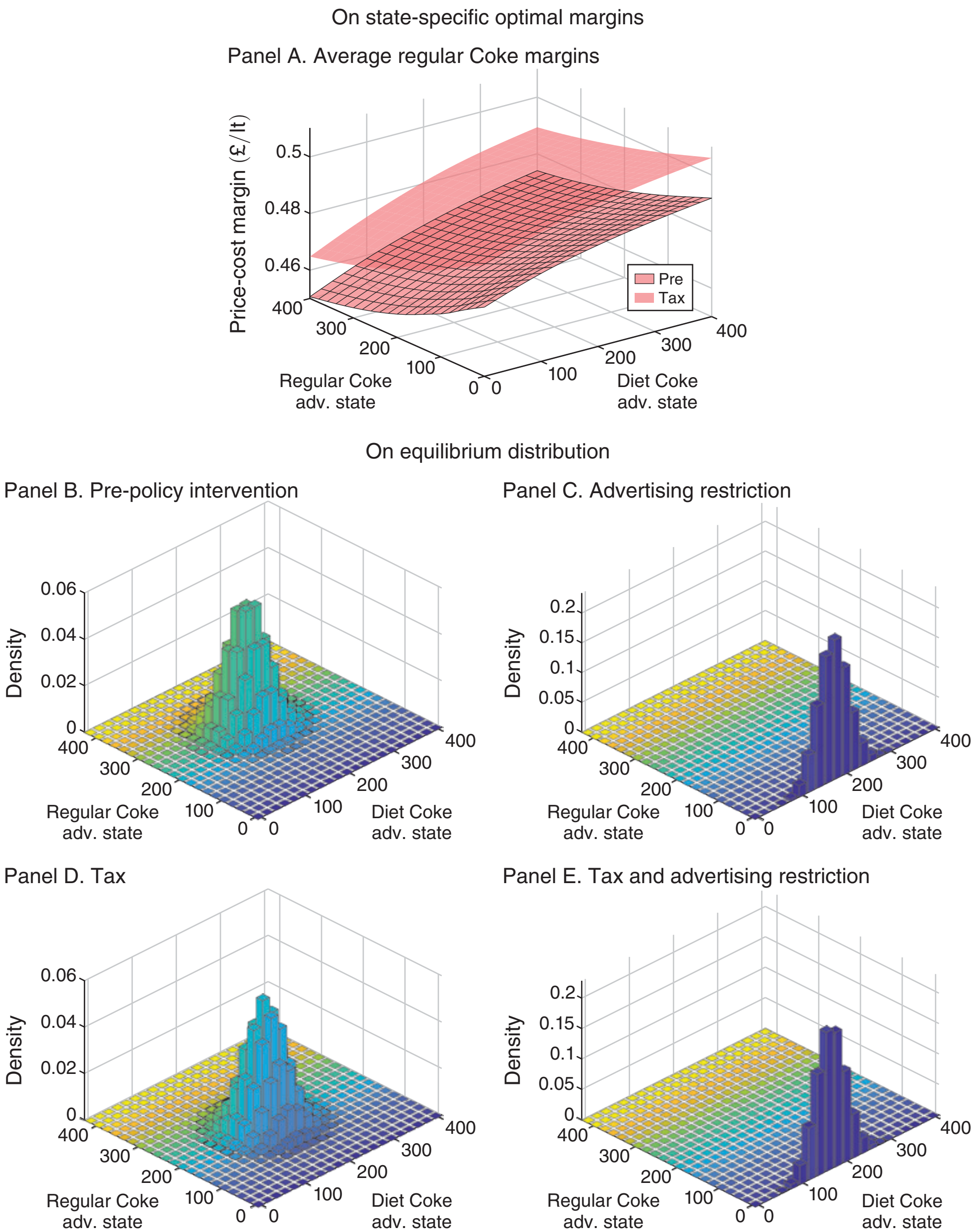

Figure 6. Impact of Specific Tax and Advertising Restriction

Notes: Panel A shows variation in the average price-cost margin for regular Coke products. The hatched surface is pre-policy intervention (and repeats Figure 3, panel A), and the smooth surface corresponds to when a specific tax is in place. In each case, we hold fixed the Diet Pepsi advertising state at the highest probability state in the pre-policy intervention equilibrium distribution. Panels B–E show the ergodic distribution, integrating over the Diet Pepsi advertising state space. Panel B repeats Figure 5, panel B. In Supplemental Appendix J, we show the equivalent figure for the ad valorem tax.

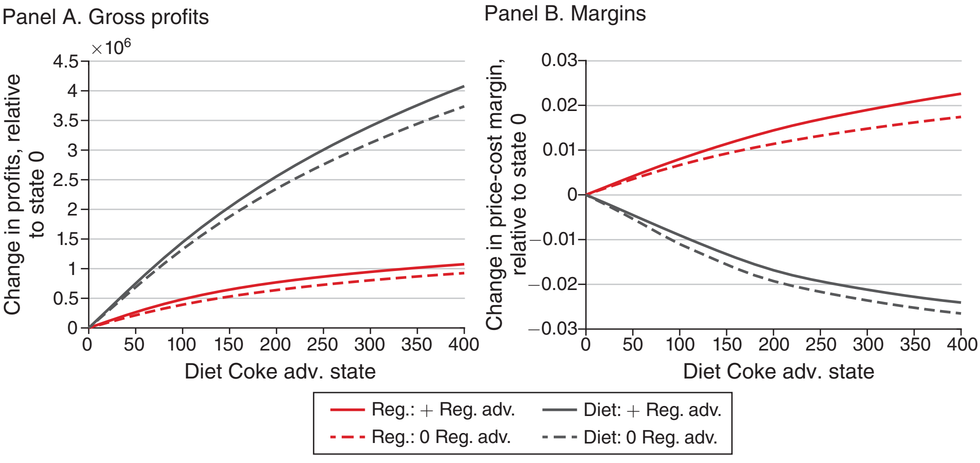

Figure 7. Return to Diet Coke Advertising

Notes: The figure shows how the equilibrium profits (panel A) and average price-cost margin (panel B) of regular Coke (red lines) and Diet Coke (grey lines) vary with the Diet Coke advertising state. The solid line holds the regular Coke advertising state fixed at the highest probability state in the pre-policy intervention equilibrium distribution. The dashed lines hold fixed the regular Coke advertising state at zero. In all cases, the Diet Pepsi advertising state is held fixed at the highest probability state in the pre-policy intervention equilibrium distribution.

price-cost margins vary across the advertising state space with no tax in place (hatched surface) and with the tax in place (smooth surface)). The corresponding change in regular Coke and Pepsi equilibrium quantity is a 55.1 percent decrease, with overall sugar intake from drinks falling by 16.2 percent.[26]

Column 3 shows the incremental impact of accounting for Coca-Cola and Pepsi's optimal advertising responses to the specific tax, by re-solving for the MPE. The tax results in a 33.1 percent reduction in regular Coke advertising expenditure. A key mechanism driving this effect is the correlation in consumers' price and advertising sensitivities. The tax induces a large increase in regular products' prices, which drives away price and advertising sensitive consumers and lowers the returns to further advertising. The tax also results in a modest reduction in advertising for diet products (panels B and D of Figure 6 show the implications for the equilibrium distribution over states). This reduction in advertising expenditure further contributes to a modest decline in demand for regular products of around 1 percent.

Column 4 shows the impact of coupling the specific tax with the advertising restriction that prohibits advertising of regular brands. Without the tax, the advertising restriction reduced regular Coke and Pepsi consumption by 13 percent and total sugar intake by 2.7 percent. When the tax is in place, the effect of the restriction is

[26] Seiler, Tuchman, and Yao (2021) study the introduction of a beverage tax (levied on both sugar and artificially sweetened drinks) in Philadelphia, a setting where a natural control group (nearby counties) exists. They find the tax raised average prices by 34 percent, led to a 46 percent reduction in consumption of taxed products, and a 22 percent fall once cross-border shopping is accounted for. The tax we consider has a narrower base, resulting in larger quantity fall for taxed goods.

attenuated; it leads to a reduction in regular Coke and Pepsi consumption of 4.5 percent, and a small fall of 0.4 percent in total sugar intake.

Ad Valorem Tax.—We calibrate the ad valorem tax so that it results in approximately the same reduction in equilibrium quantity for regular Coke and Pepsi as the specific tax, holding advertising strategies fixed. By construction, column 5 shows a 55.1 percent reduction in regular Coke and Pepsi quantity, closely matching the reduction reported in column 2. The tax rate required to achieve this reduction is 64 percent. The average pass-through of the tax is approximately 55 percent, which is reflected in a 34.8 percent fall in equilibrium price-cost margins of the taxed products.

Column 6 presents the incremental impact of accounting for firms' advertising responses to the tax. Equilibrium advertising expenditure on regular products falls by 47.3 percent, a significantly larger decline than the 33.1 percent reduction under the specific tax. This stronger advertising response is linked to the under-shifting of the tax. Unlike a specific tax, an ad valorem tax introduces a multiplicative wedge between the tax-inclusive consumer price and the tax-exclusive firm price; to increase the latter by 1 percent, requires a 1.64 percent increase in the former. This wedge puts downward pressure on prices, inducing firms to lower their margins. Lower margins, in turn, reduce the profitability of attracting additional consumers, thereby lowering the return on advertising. Since advertising for diet products has a positive spillover effect on demand for regular products, this same mechanism lowers (albeit to a lesser extent) the incentives for advertising diet products. As a result, the ad valorem tax leads to a fall in diet advertising. Due to these stronger advertising responses (relative to the specific tax), their incremental impact on equilibrium quantities is larger. As with the specific tax, the additional impact of adding the advertising restriction on top of the ad valorem tax is smaller than the advertising restriction's impact in the absence of a tax.

B. *Impact on Economic Surplus*

In Table 5, we summarize the impact of each policy on economic surplus. We express numbers as percent changes relative to total consumer spending (or equivalently, firm revenue) in the no policy intervention equilibrium. We report tax revenue, changes in Coca-Cola and PepsiCo profits, and consumer surplus, and the sum of three, which we refer to as gross surplus.

For consumer surplus, we report two numbers: the static and total (i.e., static plus dynamic) effects. The static effect reflects changes in optimal prices, conditional on advertising state, while the total effect incorporates both this and the change in the equilibrium distribution over states due to firms reoptimizing their advertising expenditures (see Supplemental Appendix I for details). Since the main channel through which policy affects prices is via changes to state-specific optimal prices,[27] this provides an approximate decomposition of consumer surplus changes

[27] For instance, the specific tax results in a 28.9 percent increase in the average price of a regular Coke and Pepsi product. 28.8 percent is due to changes in state-specific price equilibrium, and 0.1 percent is due to shifts in the equilibrium distribution over states (see columns 2 and 3 of Table 4).

Table 5—Aggregate Surplus Impact of Counterfactual Policies

	No tax	Specific tax		Ad valorem tax	
	Adv. restrict. (1)	(2)	Adv. restrict. (3)	(4)	Adv. restrict. (5)
Tax revenue	–	4.3%	3.8%	7.1%	6.4%
Δ Profits	−2.1%	−5.6%	−7.0%	−9.0%	−10.1%
Consumer surplus					
Static effect	0.0%	−6.5%	−6.2%	−6.5%	−6.2%
Total effect	−4.5%	−7.2%	−10.3%	−7.7%	−10.6%
Gross surplus					
Static effect	−2.1%	−7.9%	−9.4%	−8.5%	−9.9%
Total effect	−6.5%	−8.6%	−13.6%	−9.7%	−14.2%
Δ Sugar	−2.7%	−16.3%	−16.7%	−16.6%	−16.8%

Notes: Numbers (with the exception of the final row) are expressed as a percentage of pre-policy total consumer expenditure and show changes relative to the pre-policy intervention level. We report consumer surplus changes that result from a "static effect," which strips out advertising responses, and a "total effect," which does not. We also report gross surplus (the sum of tax revenue, profits changes, and consumer surplus changes) under these two versions of consumer surplus. The final row shows the percent change in sugar from all drinks relative to pre-policy, repeating information in Table 4.

into price and advertising effects. A policymaker who wishes to discount the apparent impact of reduced advertising on utility—on the basis that advertising does not directly contribute to underlying consumer welfare—can rely on the static effect numbers.

The primary motivation behind policies aimed at reducing sugar-sweetened beverage consumption is to lower the social costs of sugar consumption. These costs may arise through externalities, such as higher healthcare expenditures, or internalities, where consumers underweight the future health consequences of their consumption choices. The reduction in gross surplus (which we report both based on the total and static consumer surplus numbers) must be weighed against the reduction in social costs achieved by the policies. In Table 4, we do not take a stance on these costs, but simply report changes in total sugar intake.

The advertising restriction leads to a reduction in firm profits of 2.1 percent. Its impact on consumer and gross surplus depends on whether advertising is viewed as directly contributing to consumer welfare. If it does contribute, the consumer surplus falls by 4.5 percent and gross surplus falls by 6.5 percent. However, if we exclude consumer surplus changes stemming from shifts in the advertising state distribution, the fall in gross surplus is limited to 2.1 percent. The advertising restriction reduces sugar intake from drinks by 2.7 percent.

Both the specific and ad valorem taxes result in larger reductions in firm profits (5.6 percent and 9.0 percent, respectively) and consumer surplus (which declines by approximately 6.5 percent due to the static pricing effect alone). These larger losses are partially offset by tax revenue generation and the fact that these taxes achieve much greater reductions in sugar consumption from drinks (approximately 16.5 percent). Adding the advertising restriction on top of either tax leads to only a small additional reduction in sugar consumption. However, if advertising is not assumed

Table 6—Distributional Impact of Counterfactual Policies

	No tax	Specific tax		Ad valorem tax	
Income quartile	Adv. restrict. (1)	(2)	Adv. restrict. (3)	(4)	Adv. restrict. (5)
Change in sugar					
Bottom	−2.88%	−17.64%	−18.12%	−17.88%	−18.25%
Second	−2.78%	−17.07%	−17.45%	−17.23%	−17.45%
Third	−2.32%	−17.29%	−17.63%	−17.70%	−17.96%
Top	−2.83%	−12.22%	−12.73%	−12.56%	−12.83%
Change in consumer surplus					
Bottom	0.00%	−8.13%	−7.69%	−8.07%	−7.68%
Second	0.00%	−6.52%	−6.19%	−6.47%	−6.18%
Third	0.00%	−7.14%	−6.87%	−7.23%	−6.99%
Top	0.00%	−4.00%	−3.74%	−4.10%	−3.86%
Change in consumer surplus net of internalities					
Bottom	1.22%	−0.68%	−0.03%	−0.52%	0.03%
Second	1.01%	−0.36%	0.11%	−0.25%	0.12%
Third	0.71%	−1.87%	−1.50%	−1.84%	−1.52%
Top	0.69%	−1.02%	−0.64%	−1.04%	−0.73%

Notes: Change in sugar is expressed as a percent of the income quartile specific pre-policy total drink sugar consumption. Change in consumer surplus (including net of internalities) is expressed as a percent of income quartile, specific pre-policy total expenditure. The consumer surplus measure strips out advertising responses.

to directly contribute to consumer welfare, the additional decline in gross surplus is also minimal.

The main lessons from Table 5 are that the specific and ad valorem taxes perform similarly in reducing sugar consumption. The ad valorem tax leads to a somewhat larger reduction in gross surplus compared to the specific tax. However, it also generates higher tax revenue (7.1 percent versus 4.3 percent), albeit at the cost of larger reductions in firm profits, as it reduces firms' market power. The advertising restriction, on its own, results in a much more modest reduction in sugar consumption than either of the taxes. However, if advertising does not directly contribute to consumer welfare, the gross surplus loss from the restriction is relatively small. The case for adding an advertising restriction on top of a tax is weak, as it results in only a small additional reduction in sugar.

C. *Distributional Impact*

The aggregate consumer surplus numbers in Table 5 mask heterogeneity across households. In Table 6, we present how each policy affects sugar consumption and consumer surplus in each household income quartile. The numbers reflect the heterogeneity we incorporate in our demand model, where preferences parameters vary by household income quartiles (interacted with household type). In this table, we focus on the static consumer surplus effect, excluding the effects of advertising.[28]

[28] We reproduce the table based on the total effect in Supplemental Appendix J.

A distributional analysis of the impact of advertising restrictions and taxes for sin goods is influenced by any internality savings the policies generate, and how such savings vary across income groups. To illustrate the potential importance of this channel, we also report changes in consumer surplus net of internality savings in Table 5. We do not directly estimate these savings; rather, we base our measure on the estimates in Allcott, Lockwood, and Taubinsky (2019), who find that the internality per fluid ounce of sugar-sweetened beverage consumption decreases linearly from US$1.10 for the lowest income group to $0.83 for the highest income group. This translates to £0.0029, £0.0027, £0.0025 and £0.0022 per gram of sugar for our income quartiles 1 to 4.[29]

Under all policies, the reduction in consumer surplus (both as a fraction of total spending and in monetary terms) is largest for households in the bottom income quartile. However, both the specific and ad valorem taxes result in the largest sugar reductions for this group. Given this, and the fact that their internality per sugar gram is higher, the taxes (whether or not they are coupled with advertising restrictions) are no longer regressive once internality savings are accounted for.

VI. Conclusion

In this paper, we develop a model of firm competition in advertising and pricing, which we use to quantify the impact of sin taxes and advertising restrictions, accounting for the dynamic equilibrium response of firms' advertising strategies. Our model explicitly incorporates the role of advertising agencies, linking rich consumer-level variation in advertising exposure to the strategic advertising expenditures that comprise firms' action space. We apply the model to the cola segment of the UK nonalcoholic drink market, the most heavily advertised segment. To estimate the impact of advertising on demand, we exploit variation in advertising exposure across households with similar demographics and TV viewing behaviors. We solve for the Markov Perfect Equilibrium of the dynamic advertising game played by firms. We use our model to simulate the effects of various forms of sin tax and advertising restrictions.

We show that both specific and ad valorem taxes lead firms to reduce advertising for taxed products. This effect is driven by our finding that price-sensitive consumers also tend to be more advertising-sensitive, meaning taxes induce the most advertising-responsive consumers to switch away from taxed brands, thereby reducing the incentive to advertise. The reduction in advertising is larger under an ad valorem tax because, unlike a specific tax, it lowers price-cost margins, reducing the profitability of the marginal consumer and further diminishing the incentive to advertise. We also find that both taxes and an advertising restriction on sugary brands lead to a decline in advertising for diet brands. This occurs due to within-firm complementarities in advertising—advertising diet products becomes less profitable when advertising for sugary products declines. Overall, we show that the specific and ad valorem taxes we consider lead to similar reductions in sugar consumption

[29] A fluid ounce equals 0.03 liters. Regular Coke and Pepsi have around 100g of sugar per 1l, so 1.10 cents per fl. oz., using an exchange-rate of 1.25 £-$, corresponds to 0.29 pence per gram of sugar.

and gross consumer surplus. However, the ad valorem tax generates more revenue and reduces firm profits more. Once internalities are accounted for, neither tax is regressive. An advertising restriction results in a smaller reduction in sugar consumption, and its incremental impact is diminished if a tax is already in place.

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