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

Rossi Abi-Rafeh, Pierre Dubois, Rachel Griffith, Martin O'Connell*

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**Abstract**

We develop a dynamic equilibrium model of firm competition to study the impact of counterfactual policies, such as taxes and advertising restrictions, on pricing, advertising, consumption and welfare, and estimate it using micro level data on the market for colas. We use consumer level exposure to television commercials to estimate the impact of advertising on product choice, model firms dynamic competition through their choice of advertising budgets and product prices, and exploit firms' practice of delegating decisions over advertising slots to agencies to link the rich consumer-level advertising variation with firms' strategic choices. We show that a sugar-sweetened beverage tax leads to a reduction in advertising and that the incremental effects of implementing advertising restrictions are substantially reduced with a tax in place.

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*Abi-Rafeh: Institute for Fiscal Studies and Toulouse School of Economics, rossi.abi-rafeh@tse-fr.eu; Dubois: Toulouse School of Economics, pierre.dubois@tse-fr.eu; Griffith: Institute for Fiscal Studies and University of Manchester, rgriffith@ifs.org.uk; O'Connell: University of Wisconsin-Madison and Institute for Fiscal Studies, moconnell9@wisc.edu. The authors would like to gratefully acknowledge financial support from the Economic and Social Research Council (ESRC) under the Centre for the Microeconomic Analysis of Public Policy (CPP), grant number ES/T014334/1 and under the Open Research Area (ORA) grant number ES/VO13513/1 and the Agence Nationale de la Recherche (ANR) under grant ANR-20-ORAR-0008 PPFM (EST010223 1 EST010924 1) and ANR-17-EURE-0010 (Investissements d'Avenir program). The contents of this publication are the authors' own analysis and findings. The analysis and findings have been undertaken by authors' on the basis of their own work using data supplied by Kantar FMCG At-Home Purchase Panel (all use is subject to Kantar UK Limited's terms and conditions) and Kantar does not represent any endorsement of the efficacy or accuracy of the analysis and findings. The use of Kantar FMCG At-Home Purchase Panel data in this work does not imply the endorsement of Kantar FMCG Purchase Panel from the interpretation or analysis of the data. All errors and omissions remain the responsibility of the authors.

# 1 Introduction

Governments often seek to reduce consumption of sin goods, such as tobacco, alcohol, and sugar-sweetened beverages, by levying taxes on them. In response firms are likely to adjust their strategic choices, including their prices and potentially their advertising expenditures. As advertising can affect product demands both contemporaneously, and into the future, the introduction of sin taxes can have dynamic effects on the market equilibrium. With many sin goods, such as tobacco and alcohol, governments have implemented restrictions to advertising in addition to taxes (DeCicca et al. (2022)). However, there is little work that studies the interactions of these taxes and advertising restrictions, or that accounts for the possibility that firms re-optimize advertising expenditures in response. The market for sugar-sweetened beverages is an example of where these considerations are relevant. Taxes that aim to reduce consumption (due to the association with obesity and diet-related disease) have been implemented in many jurisdictions,[1] and restrictions to advertising are being introduced.[2]

In this paper we study the equilibrium impacts of sin taxes and advertising restrictions in the cola market, accounting for firms' dynamic supply-side responses over advertising expenditures. The existing literature has largely studied these policies in isolation, and has not accounted for potential supply-side dynamics. In order to overcome the challenge of solving a dynamic game in which players have a large action space - firms' advertising strategies are complicated high-dimensional objects - we exploit the organization of the advertising market to develop a tractable framework. We estimate a model of consumer demand and use it, along with a dynamic supply-side model and simulate the impact of policy changes on firms' choices over their optimal pricing decisions and advertising budgets.

The UK cola market has two dominant manufacturers – Coca Cola and Pepsico – and a few lower quality, cheaper store brands alternatives. Both Coca Cola and Pepsico advertise, while store brands do not. Coca Cola and Pepsico decide their monthly advertising budgets and delegate to an advertising agency the task of choosing specific slots to maximize the exposure of consumers to their advertising. The intermediary role played by advertising agencies is an institutional feature of advertising markets that is common across the US and UK (see Crawford et al. (2017)). It simplifies the dynamic game by reducing their action space from being highly multidimensional (entailing choices over the timing and channels of each advertising slot, given advertising prices and their expectations over viewing behav-

[1] Widely known as soda taxes, as of April 2021 over 50 different jurisdictions had introduced taxes on soft drinks (GFRP (2021)).

[2] For example in the US and UK advertising of junk foods to children is restricted. In the UK wider restrictions were going through the legislative process but were put on hold during the pandemic.

ior of consumers) to a decision over total monthly expenditure, which makes solving Coca Cola and Pepsico's intertemporal profit maximization problems feasible. Solving the full dynamic game with such a large action space without intermediary advertising agencies would otherwise be intractable.

We estimate the demand model using rich longitudinal micro data consumption choices by UK households over the period 2010-2016. We observe the disaggregate barcode-level products they purchase, as well as detailed information on the individual household TV viewing habits. We couple this with data on the universe of UK TV advertisements, which includes details of when, on what stations, and during which programs specific brands were advertised; these data enable us to construct household-specific measures of exposure to brand-level advertising. To identify the impact of advertising on demand we exploit variation in advertising exposure that arises due to idiosyncratic differences in individual household's viewing habits paired with idiosyncratic differences in the timing of adverts across very similar shows (see section 4.3 for details). We allow for demographic effects and measure of households' TV watching behavior, which control for key variables targeted by advertisers.

We use these demand estimates, along with a Nash-Bertrand equilibrium pricing condition, to recover marginal costs. In our simulations we model firms as competing in prices and advertising budgets in a Markov Perfect Equilibrium. We simulate the counterfactual equilibria with taxes and restrictions on advertising on sugar-sweetened colas. We compare a specific tax and an ad valorem tax. Both lead to a reduction in advertising of the taxed products. A key driver of this result is our finding that consumers who are price sensitive also tend to be more advertising sensitive (we allow for a flexible covariance structure between these preference parameters in demand, which turns out to be important), meaning the tax induces the most advertising sensitive consumers to switch away from taxed brands, lowering the incentive to advertise. Advertising reductions are larger under the ad valorem than the specific tax. This is because firms optimally reduce their margins under the ad valorem tax (tax pass-through is below 100%), which lowers the profitability of the marginal consumer and hence the incentive to advertise. In contrast, the specific tax is marginally over-shifted to equilibrium prices. Under both taxes advertising of diet products is also reduced. This is driven by a within-firm complementarity in advertising strategies – the returns to advertising diet products is lower the lower is advertising of taxed, sugary products. Overall, the specific tax reduces the sum of consumer surplus and profits (net of tax revenue) by a smaller amount than the ad valorem tax for a fixed reduction in sugar consumption.

The literature on ex ante evaluations of the effects of taxes on sin goods has mostly focused on their impacts on prices and, through this, consumption, either assuming complete tax pass-through (e.g. Harding and Lovenheim (2017), Allcott et al. (2019)) or modeling the pricing responses of firms in a static environment (e.g. Bonnet and Réquillart (2013), Dubois et al. (2020)). Wang (2015) estimates a dynamic model of consumer stockpiling and uses it to simulate consumer responses to a soda tax. Our work also relates to the literature that seeks to estimate the impact of advertising on demand.[3] Dubois et al. (2018) use estimates of the impact of television advertising in the potato chips market to simulate the impact of an advertising ban. In their policy simulation, the counterfactual equilibrium they consider entails banning firms' dynamic instruments (advertising) and thus is static.

Our empirical approach draws on the literature on dynamic games in empirical IO, using the solution concept of Markov Perfect Equilibrium (Maskin and Tirole, 1988), and the algorithms proposed to solve them in Ericson and Pakes (1995) and Pakes and McGuire (1994). Like us Dubé et al. (2005) and Doraszelski and Satterthwaite (2003) use this approach to solve for a dynamic equilibrium in models in which firms choose advertising strategies. Advertising can be interpreted as a form of investment firms make to raise future profits. There therefore is an analogy with dynamic investments games such as in Ryan (2012), or the dynamic product re-positioning model of Sweeting (2013).

A number of papers consider other mechanisms through which advertising can impact market equilibria. This includes Murry (2017) who focuses on how advertising decisions can impact the contracting between car manufacturers and their dealers, and some recent papers, drawing on the two-sided market theory of Rochet and Tirole (2003) of advertising, that model the determination of prices in the advertising market (Gentzkow et al. (2021), Zubanov (2021)). As we focus on policy intervention in a specific consumer goods market in which advertising is dominated by manufacturers, we abstract from manufacturers-retailers vertical relations and equilibrium in the advertising market itself.

This approach exploits a common feature of advertising markets, so it provides a way of solving an otherwise intractable dynamic oligopoly game that will be useful in other markets and contexts. Our setting could for example be used to evaluate the impact of taxes on other consumer goods markets where television advertising is important.

Section 2 introduces our main data sources and summarizes the key features of the cola market. Section 3 describes our dynamic equilibrium model. Sections 4 and 5 describe our empirical model, present estimates and characterize market equilibrium in the absence of tax. Section 6 presents the impact of tax policy on market equilibrium and a final section summarizes the results and discusses robustness/external validity etc.

[3]This includes Dubé et al. (2005), Erdem et al.(2008a, 2008b), Goeree (2008) Shapiro (2018) and Shapiro et al. (2021)

# 2 The market for colas

As of April 2021 sugar-sweetened beverage taxes were in place in over 50 jurisdictions (GFRP (2021)). These taxes are typically motivated as a means to tackle the negative health effects associated with consumption of these products (which may give rise to internalities if people partially ignore privately borne health costs, or externalities if some of the costs are borne by others, for instance, due to higher public health care, or health insurance premium, costs). Sugar- and artificially-sweetened beverages are highly advertised; despite comprising 4% of consumer grocery spending in 2016, they accounted for over 7% of all television advertising on food and drinks products. Almost two-thirds of this advertising was for cola products. For this reason we focus our analysis on the cola market. We use data from the UK covering the period 2010-2016.

In the UK a sugar-sweetened beverage tax was introduced in April 2018. The structure of the tax provides firms with the opportunity to avoid it through lowering the sugar content of their products. As a result only the two main cola brands, in addition to a few niche energy drinks, pay the tax (Dickson et al. (2023)). Therefore, our focus on the UK cola market captures the majority of products subject to UK sugar-sweetened beverage taxation.[4]

## 2.1 Market structure

We use micro data on the drinks purchases made by a sample of consumers living in Great Britain that is collected by the market research firm Kantar, as part of their FMCG At-Home Purchase Panel. We have a sample of over 21,000 households that record over 2010-2016, using a hand held scanner or mobile phone app, all grocery purchases they make and bring into the home. We observe details of all products households purchase, including the transaction price, as well as demographic variables and detailed measures of household television viewing behavior. The data has a panel structure, with the average household being present in the data for over 100 weeks.

The cola market is dominated by two firms, Coca Cola Enterprises, which has a market share of 60.7% and Pepsico, which has a market share of 33.4% (see Table 2.1). Each firm sells a Regular and Diet version of its cola. Coca Cola Enterprises' market share is split approximately equally between Regular and Diet Coke (the latter comprises just under 60% of its market share), while around three-fourths of Pepsico's market share is accounted for

[4]We estimate our model using data prior to the introduction of the tax. We do this to avoid the complication of having to model product reformulation; while interesting in its own right (see, for instance, Barahona et al. (2023)), reformulation is not the focus of this paper and would unnecessarily complicate modeling the dynamic advertising game.

by Diet Pepsi. The remaining products in the market are store (also referred to as own and private label) brands. Each brand is available in numerous different container types and sizes (for instance 4×330ml cans or 2l bottle). In total there are 42 products in the UK cola market.[5]

Table 2.1: *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 FMCG At-Home Purchase Panel.*

## 2.2 Television advertising

We use data on television advertising of non-alcoholic beverages from the market research firm AC Nielsen for the period 2009-2016.[6] Our data contain details on individual adverts (we observe over 1 million adverts for cola), including the brand that was advertised, when the advert was shown (date, time, channel and during/between which program(s)), and the expenditure required to advertise during the slot. For 2015-2016 we have additional data on TV advertising on all other food and drink products, and for 2015 we also observe the industry standard measures of how many people viewed each advert.

In an average month Coca Cola Enterprises spends £1.1m purchasing 9,300 slots and total advertising time of 3,515 minutes. The price of these slots varies widely depending on the expected audience number (for instance, the price of advertising on a popular channel during prime-time can be several times the price of advertising on a more niche channel). Pepsico advertises less than Coca Cola Enterprises, spending £0.2m purchasing slots in a typical month. There is no advertising for the store brand colas.

[5]We drop a small number of minor products. These include niche Coca Cola and Pepsi sub-brands (e.g., Diet Coke with Vitamins) that each have market shares below 0.5% and a large number of minor products that each account for fewer than 10,000 (0.67%) transactions in our data. In our product definition we aggregate together Diet Coke and Coke Zero, and Diet Pepsi and Pepsi Max. In total the 42 cola products in our analysis cover over 80% of total cola sales. See Appendix A for details of the cola products.

[6]Digital advertising is growing, however, it remains a relatively small share of total *food and drink* advertising, with it being estimated to account for only 5% of all drinks advertising spend (DCMS (2021))

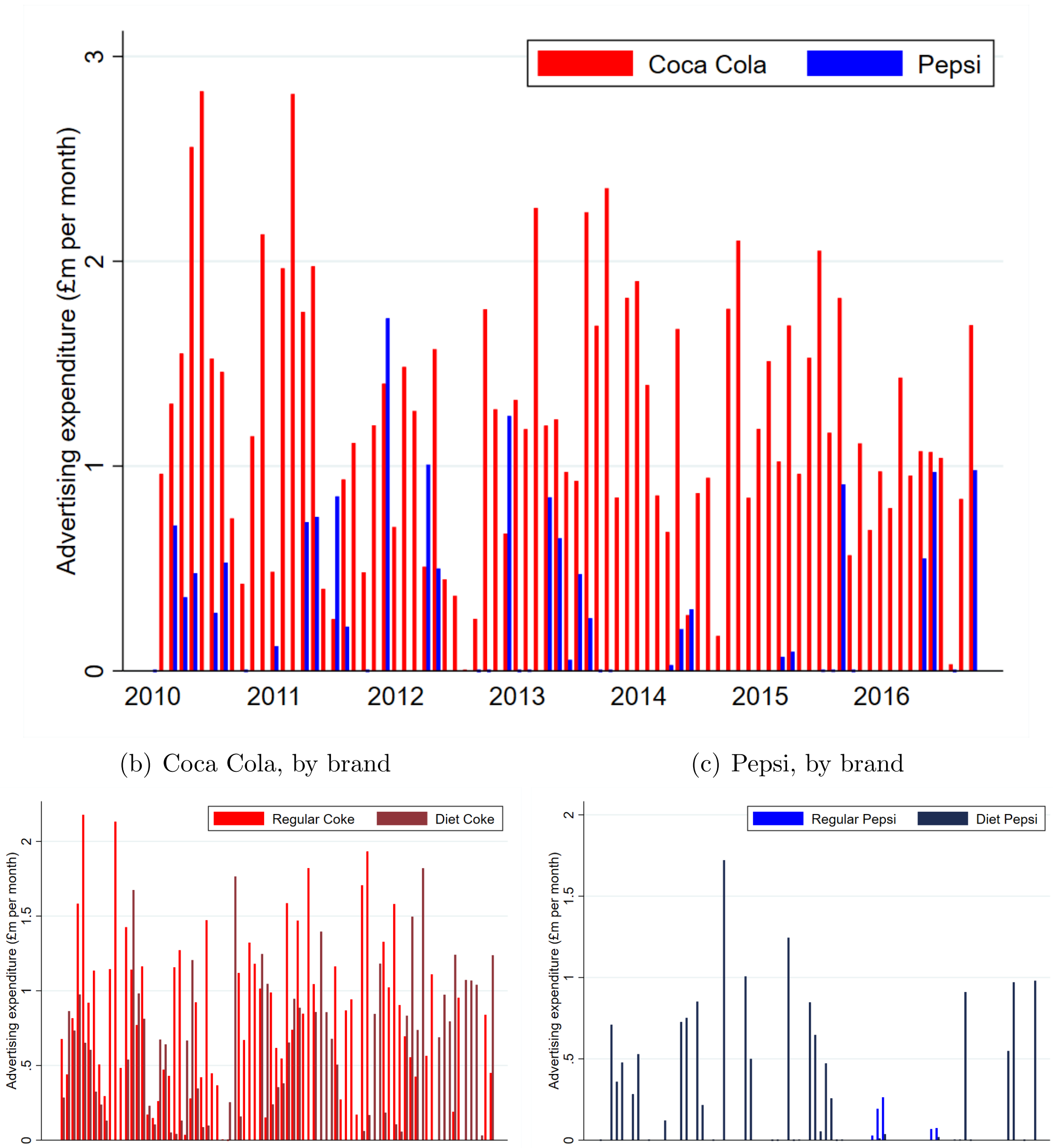
Figure 2.1 shows the evolution of advertising spending over time, separately for Coca Cola Enterprises (Coca Cola) and Pepsico (Pepsi), and within firm separately by Regular and Diet brands. It illustrates that spending fluctuates over time, and that while Coca Cola Enterprises tends to invest more in advertising its Regular than Diet brand (the former accounts for 57% of their total spend), Pepsico advertises almost exclusively its Diet brand.

An important institutional feature of television advertising is that advertisers (i.e., Coca Cola Enterprises and Pepsico) contract with advertising agencies that purchase advertising slots from channels on their behalf. In each year each firm contracts with one agency (Coca Cola and Pepsico use different agencies). In 2016 we observe 40 different agencies; Coca Cola Enterprises accounts for 29% of the food and drinks advertising of the agency it contracts with, Pepsico accounts for 3% (see Appendix B.2 for further details). A second important feature of UK TV advertising is that it is primarily national in nature. For 2016, across all Coca Cola and Pepsico advertising, 73% of slots aired nationally. The remaining slots were aired on one of 11 broad regions, with the majority of regional slots running concurrently across several regions.

In our analysis we allow for the possibility that either advertising enhances the experience of consuming a good, or that it is persuasive and distorts consumer choice behavior. As both Coca Cola and Pepsi are universally known, and television advertising for them mainly focuses on emphasizing the pleasure associated with consuming them, we do not consider the case of where advertising for Coca Cola and Pepsi is informative, either about product existence or characteristics.

Figure 2.1: *Advertising Expenditure*

(a) by firm




(b) Coca Cola, by brand

(c) Pepsi, by brand

*Notes: Authors' calculations using data from AC Nielsen Advertising Digest for 2010-2016. Coca Cola Diet include Coca Cola Zero.*

## 2.3 Household exposure to TV advertising

Firms invest in advertising to influence current and future demand for their products, in order to raise their profits. The extent to which a given financial investment in advertising will influence profitability will depend in part on which consumers are exposed to the advertising.

Exposure depends on when adverts are shown, and on the television viewing behavior of households.

We observe when adverts air in the advertising data. In the purchase data, we observe measures of household television viewing behavior. Specifically, each year households fill in a detailed survey of which (of over 250) shows and stations they watch and during which time slots in a typical week they watch TV, and how regularly they do so. We use the combination of advertising slot information and TV viewing behavior to build a measure of a household's expected exposure to brand level advertising. We exploit variation in exposure across consumers to identify the impact of advertising on consumer choice (see Section 4.3 for details of our strategy for isolating exogenous variation in advertising exposure).

Let $i$ index consumer (in our application a household), $b$ brand (Regular Coke, Diet Pepsi, etc.) and $k$ advertising slot. A slot refers to a specific time, date, station and region when an advert is shown. Within an interval of time, such as a week, the number of potential slots is very large; for instance with arround 100 channels and 4 advertising breaks per hour there are over 70,000 slots each week. Let $w_{ik} \in [0, 1]$ denote the probability a household watches television during slot $k$, $T_{bk} \geq 0$ be the length of an advert for brand $b$ that ran during slot $k$, and $f(.)$ be some concave function that captures any diminishing returns to advertising length. The expected advertising exposure of consumer $i$ during time period $t$ (we consider a week) is given by:

$$a_{ibt} = \sum\nolimits_{\{k|t(k)=t\}} w_{ik} f(T_{bk}), \tag{2.1}$$

where $t(k)$ is the week of slot $k$. We directly observe $T_{bk}$ in the advertising data. We use the TV watching survey in the purchase data to measure $w_{ik}$. In order to estimate how the ordinal survey responses (households state whether they regularly/sometimes/rarely/never watch) map into probabilities we combine the information we have on total viewership of each individual advert in 2015 with the survey answers given by households in 2016 (see Appendix B.3).

# 3 Equilibrium model

In order to analyze the impacts of policies such as taxes and restrictions to advertising, we specify a dynamic equilibrium model. We apply this model to the market for cola, but it could be applied in other oligopoly markets in which firms compete in prices and television advertising. Each period firms choose product prices and brand advertising budgets, delegating the choice of advertising slots to an advertising agency with the objective to maximize impact. Consumers choose which products to purchase based on their preferences, the prices they face, and their exposure to television advertising. If a consumer is exposed to advertising in one period, it may impact their future choices; hence firms' choice of advertising budgets affects both their current and future profits. Our equilibrium model is therefore one of dynamic competition. We take as given that firms delegate the choice over advertising slots to agencies. However, we detail in Appendix C why the resulting problem is intractable if firms themselves choose all advertising slots optimally (which provides a rationale for why firms in practice use advertising agencies). We also show that delegation to advertising agencies can result in equilibrium profits that are higher than if firms did not delegate, and that it can be an equilibrium choice for firms to delegate, even if they were able to solve the advertising optimization over slots of the dynamic game.

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 then we outline our consumer demand model. In this section we describe the structure of the model and we provide details of the empirical specification in the following two sections.

## 3.1 The firm's decision

We index (cola) firms by $f = 1, \ldots, F$, brands by $b = 1, \ldots, B$ and products by $j = 1, \ldots, J$; we denote the set of products and brands owned by firm $f$ respectively by $\mathcal{J}_f$ and $\mathcal{B}_f$. Throughout we assume the sets of firms, brands and products that comprise the market are fixed. $p_{jt}$ and $c_{jt}$ denote the period $t$ price and marginal cost of product $j$. We denote advertising expenses used to purchase television advertising slots for brand $b$ during period $t$ by $e_{bt}$. We allow for the possibility that agencies charge a markup over these expenses to cover fixed costs, and due to any market power they exercise, which we denote by $\psi_b \geq 0$, meaning a firm's total brand advertising cost is $(1 + \psi_b)e_{bt}$.

Each period firm $f$ chooses advertising expenditures for its brands (along with prices for its products). These expenditures are used by an advertising agency to purchase advertising slots on the firm's behalf, which determines the flow of advertising exposure, $a_{ibt}$, of all consumers $i \in I$ for brand $b$ in period $t$. We denote the period $t$ stock of consumer brand advertising exposure by $\mathcal{A}_{ibt} = g(a_{ib0}, a_{ib1}, \ldots, a_{ibt-1})$, the vector of consumer exposure stocks across brands $\mathcal{A}_{it} = (\mathcal{A}_{i1t}, \ldots, \mathcal{A}_{iBt})$, and the set of exposure stocks across consumers $\mathcal{A}_t = \{\mathcal{A}_{it}\}_{i \in I}$. The market demand function for each product depends on $\mathcal{A}_t$, capturing the potentially persistent effects of advertising. Specifically, the share of the potential market $M_t$ accounted for by product $j$, is $s_{jt}(\mathbf{p}_t, \mathcal{A}_t)$, where $\mathbf{p}_t = (p_{1t}, \ldots, p_{Jt})$. Note that the dependence of demand on $\mathcal{A}_t$ means a firm's current choice of $e_{bt}$ will impact the advertising exposure stock in future periods (making competition between firms dynamic).

Firm $f$'s flow profits take the form:

$$\pi_f\left(\mathcal{A}_t, \mathbf{p_t}, \mathbf{e_t}\right) = \sum\nolimits_{j \in \mathcal{J}_f} \left(p_{jt} - c_{jt}\right) s_{jt}\left(\mathbf{p}_t, \mathcal{A}_t\right) M_t - \sum\nolimits_{b \in \mathcal{B}_f} (1+\psi_b) e_{bt}. \tag{3.1}$$

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

$$\max_{\{p_{jt}\}\forall t, j \in \mathcal{J}_f, \{e_{bt}\}\forall t, b \in \mathcal{B}_f} \sum\nolimits_{t=0}^{\infty} \beta^t \pi_f\left(\mathcal{A}_t, \mathbf{p_t}, \mathbf{e_t}\right), \tag{3.2}$$

given the relationship between advertising budgets and exposure stocks, $\mathcal{A}_t(e_{t-1}, \mathcal{A}_{t-1})$. Firms simultaneously set prices to maximize profit (conditional on 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:

$$s_{jt}\left(\mathbf{p}_t, \mathcal{A}_t\right) + \sum\nolimits_{j' \in \mathcal{J}_f} \left(p_{j't} - c_{j't}\right) \frac{\partial s_{j't}\left(\mathbf{p}_t, \mathcal{A}_t\right)}{\partial p_{jt}} = 0, \tag{3.3}$$

for all $j \in \mathcal{J}_f$. These price first order conditions hold for all $f$ and will allow identifying marginal costs as in a static Bertrand-Nash equilibrium in prices.

Let $p^*_{jt}\left(\mathcal{A}_t\right)$ denote the optimal price given the advertising exposure stock distribution. We can re-write the flow profit, $\tilde{\pi}_f\left(\mathcal{A}_t, \mathbf{e}_t\right)$, as $\tilde{\pi}_f\left(\mathcal{A}_t, \mathbf{e}_t\right) \equiv \pi_f\left(\mathcal{A}_t, p^*_{jt}\left(\mathcal{A}_t\right), \mathbf{e_t}\right)$, and the firm's intertemporal profits as $\sum_{t=0}^{\infty} \beta^t \tilde{\pi}_f\left(\mathcal{A}_t, \mathbf{e}_t\right)$.

In solving for firms' optimal advertising strategies, we focus on Markov perfect equilibrium, where strategies are a function of payoff-relevant state variables (Maskin and Tirole (1988)). For firm $f$, a strategy $\sigma_f$ is a mapping between state variables $\mathcal{A}_t$ (i.e., the current advertising exposure stock distribution) and advertising expenditure for the brands it owns, $\sigma_f\left(\mathcal{A}_t\right) \equiv \left(\{e_{bt}\}_{b \in \mathcal{B}_f}\right)$. Given a strategy profile of competing firms, $\sigma_{-f}\left(\mathcal{A}_t\right)$, we can write the firm's intertemporal profit maximization using a recursive formulation. Given other firms' strategies $\sigma_{-f}\left(\mathcal{A}_t\right)$, firm $f$ solves the Bellman equation:

$$\pi^*_f\left(\mathcal{A}_t\right) = \max_{\{e_{bt}\}_{b \in \mathcal{B}_f}} \tilde{\pi}_f\left(\mathcal{A}_t, \mathbf{e}_t\right) + \beta \pi^*_f\left(\mathcal{A}_{t+1}\right). \tag{3.4}$$

A Markov perfect equilibrium is a list of strategies, $\sigma^*_f$ for $f = 1, \ldots, F$, such that no firm has an incentive to deviate from the action prescribed by $\sigma^*_f$ in any subgame that starts at some state $\mathcal{A}_t$.

We use the Markov perfect equilibrium algorithm solution, restricted to pure strategies, of Pakes and McGuire (1994) (we describe in more details our empirical implementation in

Section 4). A Markov perfect equilibrium in pure strategies of this dynamic game may not exist, and if it exists, it need not be unique.[7] We assume that conditions for the existence of a subgame perfect Markov equilibrium of this game are satisfied, we use necessary conditions to characterize an equilibrium (as suggested by Maskin and Tirole (1988)) and we check empirically for multiplicity of equilibria.

## 3.2 The advertising agency's problem

Firms delegate their choice of advertising slots to an advertising agency. In exchange for a payment, the agency chooses slots to maximize the flow of brand level consumer advertising exposure subject to a budget constraint. The agencies play an important role in simplifying dynamic competition between the firms. Without them firms would be tasked with directly choosing advertising slots (rather than making decisions over total brand advertising expenditures), meaning their action space would consist of potentially many thousands of slot decisions. By incorporating the intermediary role of advertising agencies in our model we capture an important feature of the advertising market, that, conveniently, drastically reduces firms' action space and ensures the dynamic oligopoly game is tractable.

As in Section 2.3, we use $T_{bk}$ to denote the length of advert for brand $b$ during slot (i.e., station-date-time) $k$, $w_{ik}$ to denote the probability that consumer $i$ watches during slot $k$, and we measure expected flow advertising exposure of consumer $i$ for brand $b$ in period $t$ as in equation (2.1), $a_{ibt} = \sum_{\{k|t(k)=t\}} w_{ik} f(T_{bk})$, for some increasing concave function, $f(.)$.[8]

Letting $\rho_k$ denote the price of advertising during slot $k$; total expenditure for buying advertising slots for brand $b$ during period $t$ is given by $e_{bt} = \sum_{\{k|t(k)=t\}} \rho_k T_{bk}$. Each period the firm that owns brand $b$ contracts with an advertising agency to maximize a flow of advertising exposure for a budget $e_{bt}$. The agency chooses the set of slots, $T_{bk}$, to solve:

$$\begin{aligned} &\max_{\{T_{bk}\}_k} \sum\nolimits_i a_{ibt} \\ &\text{s.t.} \quad \sum\nolimits_{\{k|t(k)=t\}} \rho_k T_{bk} \leq e_{bt}. \end{aligned} \tag{3.5}$$

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 price of

[7]Ericson and Pakes (1995) and Doraszelski and Satterthwaite (2003) provide conditions for existence in games with similar structures. However, the structure of our game differs meaning these conditions do not directly apply.

[8]This captures the possibility of advertising effectiveness diminishing in advert length, see Dubé et al. (2005), Bagwell (2007), Gentzkow et al. (2021).

advertising during these slots:

$$\frac{\sum_i w_{ik} f'(T_{bk})}{\sum_i w_{ik'} f'(T_{bk'})} = \frac{\rho_k}{\rho_{k'}}.$$

The optimal choice during slot $k$ satisfies

$$T^*_{bk} = f'^{-1}\left(\frac{\rho_k}{\sum_i w_{ik}} \frac{1}{\lambda^*_{bt}}\right) \tag{3.6}$$

where $\lambda^*_{bt}$ is the Lagrange multiplier on the constraint in the agency's problem. Concavity of $f(.)$ means $T^*_{bk}$ is a decreasing function of the price per viewer during slot $k, \frac{\rho_k}{\sum_i w_{ik}}$.

The optimization problem (3.5) assumes that the agencies are price-takers in the advertising slot market when purchasing slots for the cola firms. Given the small share of total advertising accounted for by cola firms,[9] this assumption is a natural one. Variation in advertising slots prices will be driven by the expected audience of a show or TV station (see empirical evidence in Bel and Laia Domènech (2009) and prediction from an equilibrium model by Gentzkow et al. (2021) and Zubanov (2021)). In Appendix B.2 we show that the average price paid by Coca Cola Enterprises and Pepsico are similar.

## 3.3 The consumer's problem

We model consumers as making a discrete decision over which (if any) cola product to purchase each period. At this point we take no normative stance on the relationship between advertising and consumer welfare, nor do we rule out the possibility that consumers are subject to internalities. Therefore, we refer to "decision utility" as in Bernheim (2009). We return to this point when making consumer welfare statements in Section 6.

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

$$U_{ijt} = V\left(\mathcal{A}_{it}, p_{jt}, \mathbf{x}_{jt}; \theta_i\right) + \epsilon_{ijt}. \tag{3.7}$$

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

[9] Cola advertising accounts for 3% of total food and drink TV advertising expenditure and slots.

The consumer level choice probability for product $j \in \{1, .., J\}$ is:

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

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

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

## 3.4 Counterfactual policy simulations

We use our equilibrium model to simulate the introduction of two different forms of tax on sugar-sweetened beverages, an advertising restriction on sugar-sweetened colas, and a combination of these policies. Let $j \in \Omega_{\mathcal{S}}$ denote the set of sugar-sweetened cola products and $j \in \Omega_{\mathcal{N}}$ denote the set of artificially-sweetened (i.e., diet or non-sugary) colas. We simulate taxes implying the following relationship between the tax-inclusive price $\mathbb{p}_{jt}$ and the tax-exclusive price $p_{jt}$:

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

where $\text{tax}_{jt}$ 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 the firm's flow profit function is:

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

Solving the associated system of price first order conditions yields each product's counterfactual optimal price, conditional on the distribution of advertising exposure stocks, $p_{jt}^{\mathbb{t}}(\mathcal{A}_t)$. The associated flow profit function for each firm, $\tilde{\pi}_f^{\mathbb{t}}(\mathcal{A}_t, \mathbf{e_t}) \equiv \pi_f^{\mathbb{t}}\left(\mathcal{A}_t, p_{jt}^{\mathbb{t}}(\mathcal{A}_t), \mathbf{e_t}\right)$ can then be used to solve for the counterfactual Markov perfect equilibrium.

Both specific and ad valorem taxes are commonly used as corrective policies aimed at changing the relative prices of alcohol, cigarettes, fuels, cars, and sugar-sweetened beverages. The fact that under an ad valorem tax (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 $dp(1+\mathbb{t}) > dp$ tends to mean there is lower pass-through of ad valorem than specific taxes (e.g., see Anderson et al. (2001)). The extent of pass-through will directly influence the sizes of consumption responses to a tax. Additionally, it will interact with firms' advertising responses. For instance, if in equilibrium the tax is under-shifted, this means the price-cost margins of taxed products are lower (than under no tax) and the profitability associated with a marginal consumer is lower, all else equal, acting to reduce the incentive a firm has to invest in advertising (see Appendix E for an illustrative example).

Under a restriction that allows only advertising of diet (but not sugar-sweetened) colas, the firm's problem described in equation (3.2) becomes:

$$\max_{\{p_{jt}\}_{\forall t, j \in \mathcal{J}_f}, \{e_{bt}\}_{\forall t, b \in \mathcal{B}_f \bigcup \Omega_{\mathcal{N}}}} \sum_{t=0}^{\infty} \beta^t \pi_f \left( \mathcal{A}_t, \mathbf{p_t}, \mathbf{e_t} \right), \tag{3.8}$$

where $\mathcal{B}_f \bigcup \Omega_{\mathcal{N}}$ is the set of firm $f$'s brands that are not sugar sweetened and therefore not subject to the advertising restriction.

# 4 Empirical demand model

A key input to our dynamic model are product-level demand functions. We estimate these using a consumer-level discrete choice model for cola products. We define a choice occasion as a week in which a household purchases any drink product, and model the decision of which (if any) cola product the household chooses. We capture the purchase of a non-cola through two "outside options" – one that comprises non-cola drinks with sugar and one that consists of non-cola drinks that contain no sugar. An important feature of our demand model is that it incorporates the impact of consumer-level advertising exposure on choice.

## 4.1 Advertising exposure

As discussed in Section 2.3, we measure the flow of exposure to brand advertising in week $t$ for household $i$, according to $a_{ibt} = \sum_{\{k|t(k)=t\}} w_{ik} f(T_{bk})$, where $f(.)$ captures diminishing returns to advert length. We assume $f$ is a power function, $f(T) = T^{\gamma}$, in which case the solution to the advertising agency's problem (equation (3.5)) takes a log-linear form, between the price per viewer of a slot and advert length (conditional on brand-time fixed effects). We use the advertising data for 2015 (where we observe the slot price, viewership and length of all food and drink TV advertising) to estimate $\hat{\gamma} = 0.64$ (the estimated p-value is smaller than 0.0001). This implies a 60 second advert is 1.56 ($= 2^{.64}$) times as productive as a 30 second advertising in raising consumer exposure, indicating a degree of diminishing returns to advert length. See Appendix D for more details.

We model a consumer's demand for cola products as a function of their stock of exposure to brand advertising. We specify the consumer's expected 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 specification implies exposure to brand advertising two weeks ago contributes $\delta$ as much to the current stock of exposure as the same amount of exposure one week ago. We set $\delta = 0.9$, which is the value estimated in Shapiro et al. (2021) at the week level for consumer good markets. We use advertising data (as well as data on household TV viewing) in a pre-sample year (2009) to construct initial exposure stocks (advertising exposure older than 52 weeks will be negligible).

## 4.2 Utility specification

We now specify the form of the decision utility that consumer $i$ obtains from choosing product $j$ in week $t$ (i.e., the form of equation (3.7)). In doing this we use a specification designed to capture any heterogeneity in consumer responses to variation in price and advertising, and any spillovers in the effects of advertising of one brand on demand for another.

We estimate the demand model separately by 12 demographic groups, denoted $d(i)$, based on household type (household with children, working age household with no children, pensioner household) and within household type income quartiles (see Appendix A). This controls for demographic attributes advertisers may target.

Let $j = 1, \ldots, J_1$ denote the advertised (Coca Cola and Pepsico) products, $j = J_1 + 1, \ldots, J$ denote the non-advertised store brands, $j = \underline{0}$ denote choosing a sugary non-cola and $j = \bar{0}$ denote choosing a non-sugary alternative to cola. Let $b(j)$ denote the brand to which product $j$ belongs, $-b(j)$ the other brands owned by the firm that sells product $j$, $f(j)$ the firm that makes product $j$, and $-f(j)$ the rival firm. So, for instance, if $j$ is a 2 liter bottle of Regular Coke, $b(j)$, $-b(j)$, $f(j)$ and $-f(j)$ denote, respectively, Regular Coke brand, Diet Coke brand, Coca Cola Enterprises and Pepsico.

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

$$\begin{aligned} U_{ijt} = {} & \alpha_i p_{jr(i,t)t} + \beta_i^O \sinh^{-1}(A_{ib(j)t}) + \beta_{d(i)}^W \sinh^{-1}(A_{i-b(j)t}) + \beta_{d(i)}^X \sinh^{-1}(A_{i-f(j)t}) \\ & + \gamma_i \mathrm{Sug}_{b(j)} + \phi_{d(i)} \mathbf{Z}_{if(j)} + \eta_{if(j)} + \chi_{d(i)j} + \xi_{d(i)b(j)\tau(t)} + \zeta_{d(i)b(j)r(i,t)} + \epsilon_{ijt}. \end{aligned} \tag{4.1}$$

where $p_{jr(i,t)t}$ is the price (measured per-unit) of product $j$ in the retailer consumer $i$ shops with, $r(i,t)$, in week $t$. We allow for three distinct effects of advertising on decision utility: an own-brand advertising effect, $\beta_i^O$, a within-firm spillover effect, $\beta_{d(i)}^W$, and a cross-firm spillover effect, $\beta_{d(i)}^X$. In each case we enter the relevant advertising stock into decision utility through the inverse-hyperbolic sine function, to capture diminishing returns of advertising exposure on consumers' decision utility. Decision utility also depends on whether the brand is sugar-sweetened or not ($\text{Sug}_{b(j)}$), a vector of detailed measures of household TV viewing behavior interacted with firm, $\mathbf{Z}_{if(j)}$, consumer specific firm (i.e., Coca Cola vs. Pepsi) valuations, $\eta_{if(j)}$, and product, $\chi_{d(i)j}$, time (year-quarter) varying brand, $\xi_{d(i)b(j)\tau(t)}$ and retailer varying brand effects, $\zeta_{d(i)b(j)r(i,t)}$ (all of which are demographic group specific).

The inclusion of the three exposure stocks, $(A_{ib(j)t}, A_{i-b(j)t}, A_{i-f(j)t})$ in the decision utility function is important in enabling our model to flexibly capture the impact of advertising on consumer choice. Suppose instead we included only the own-brand effect; then, if (as is expected) the own-brand effect is positive (i.e., an increase in advertising exposure for a brand raises demand for products belonging to that brand), this specification would impose that cross-advertising effects are negative (the advertising exposure lowers demand for all other brands). By including advertising of other brands in the decision utility function, we break this restriction, allowing, for instance, that an increase in advertising for one brand raises demand for a second one. It is possible this type of spillover effect is stronger within-firm than across them, which we allow for in our specification by including separate within- and cross-firm spillover effects. In the case of this Cola market, advertising of a brand may indeed raise the preference for soda versus any other drinks irrespective of the brand or more strongly for brands of the same firm (for example across the diet and non diet brands from the same company).

We model preferences over price, own-brand advertising, sugar and the firm effects as random coefficients. We specify that the sugar and firm coefficients $(\gamma_i, \eta_{i,b(j)})$ follow demographic-group specific independent normal distributions and that the price and own-brand coefficient distribution are such that $(\ln(-\alpha_i)), \ln(\beta_i^O))$ follows a demographic-group specific joint normal distribution (with non-zero covariance).[10] Allowing for correlation in price and advertising preference is potentially important for modeling the impact of tax policy on advertising. Any tax will raise the price the consumer faces for the taxed product. This will act to lead the most price sensitive consumers to switch away from the good. Whether sensitivity of the post-tax marginal consumer's demand to advertising is higher or lower than the marginal consumer prior to the introduction of the tax will influence whether the firm responds to the tax by raising or lowering its advertising.

[10] The log-normality imposes a sign restriction that means a price increase for a product cannot raise demand for a product and an advertising increase cannot lower it. We have experimented with using normal distribution that do not impose the sign restriction. They result in similar price and advertising elasticities but have the undesirable property of implying some consumers have upward sloping demands.

Our rich specification for consumer preferences also helps our model capture realistic patterns of substitution across products. In addition, it allows for flexibility in the curvature of product-level market demands, which are an important determinant of tax pass-through (see Weyl and Fabinger (2013)).[11]

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

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

The decision utility associated with 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 $U_{i\bar{0}t} = \epsilon_{i\bar{0}t}$.

## 4.3 Identification

We face two main identification challenges; pinning down the causal impact of advertising changes and price changes on product-level demands.

### 4.3.1 Advertising

We observe in our data rich variation in consumer-level exposure to brand advertising. Some of this variation likely reflects targeting of advertising to groups of consumers and/or time periods where demand is particularly susceptible to advertising. We include rich controls for demographics and television viewing behavior in our demand model that are designed to control for this targeting, and use the residual variation in exposure, among households belonging to the same demographic group and with similar TV viewing habits, to identify the impact of brand advertising on product-level demands.

The consumer level variation in our advertising exposure measure is driven by our consumer specific measures of TV watching behavior (the $w_{ik}$s in equation (2.1)) coupled with the (overwhelmingly national) brand slots chosen by advertisers ($T_{bk}$s in equation (2.1)). A threat to identification of advertising effects from using this form of variation is that cola advertisers can target their advertising at consumers on the basis of their anticipated demand for cola products.

One possibility is that advertisers systematically target households of a particular demographic type. To control for this we estimate our demand model separately by demographic

[11] A feature of logit demand models with no heterogeneity in preference parameters is that they heavily restrict demand curvature. However, the addition of preference heterogeneity breaks the link between the curvature of individual and market-level demand curves, allowing for more flexibility in the latter, as curvature now also depends on how the composition of individuals along the market demand curve changes (Griffith et al. (2018)).

groups (based on household income and structure), thereby allowing all preference parameters to vary by demographic group. Included in these preferences are time varying brand effects that are demographic specific (the $\xi_{d(i)b(j)\tau(t)}$'s in equation (4.1)). These control for the possibility that placement of advertising slots is driven by time-varying (and demographic specific) shocks to brand-level demands.

A related concern is that advertisers are able target viewers of particular TV programs. In the UK television advertising market, advertisers typically purchase exposure on the basis of achieving a certain number of impacts by demographic group within an interval of time (see Crawford et al. (2017)). Therefore, systematic variation in brand advertising across programs with similar total viewership is most likely when the composition of that viewership is correlated with demographics. We include in our demand model a detailed vector of measures of household TV watching behavior, interacted with Coca Cola and Pepsico ($\mathbf{Z}_{if(j)}$ in equation (4.1)). This includes how regularly the household watches TV in a typical week, shows within each of six genres (e.g., sport, documentaries, entertainment), shows on different stations (the three main terrestrial channels, and the group of cable/satellite channels)[12] and during different time slots (e.g., prime-time weekday, non-prime time weekend).

Our strategy, therefore, is to exploit variation in exposure to TV advertising across consumers within the same demographic group and with comparable average TV viewing habits. There is substantial variation in advertising exposure of this sort. For instance, a regression of individual brand exposure stocks on demographic-time-brand effect and the TV viewing behavior controls (with demographic group specific coefficients) has an $R^2$ of 0.54, indicating that, conditional on our controls for targeting there is substantial residual variation in advertising exposure.

In Figure 4.1 we illustrate graphically two examples that highlight the kind of variation that we use. In the top two panels we show variation in advertising in seconds per week separately for Coca Cola and Pepsico brands during two shows, The X Factor and Britain's Got Talent. These are popular prime-time talent contest shows, both shown on the station ITV, but at different times of the year (one in Spring, one in Autumn). According to the TV viewing data 46% of households regularly watch Britain's Got Talent (25% of which do not regularly watch The X Factor) and 39% regularly watch The X Factor (12% of which do not regularly watch Britain's Got Talent). Both Coca Cola and Pepsico adverts are aired during each show, but while Pepsico advertising makes up just 11% of the cola advertising time during The X Factor over 2009-2016, it makes up 27% of the Britain's Got Talent cola

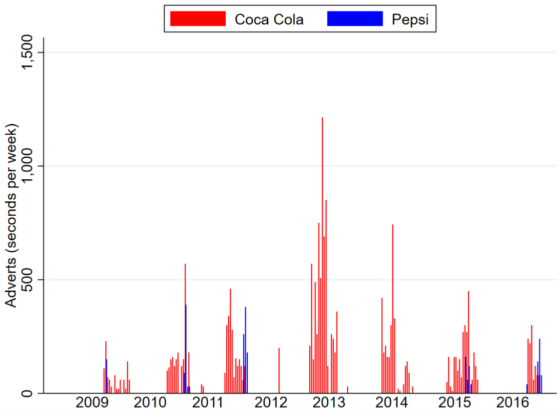
[12] In the UK there are five terrestrial channels available to all households that pay for a TV license. Three of these – ITV, Channel 4 and Channel 5 show adverts. Other stations are available via freeview, cable and satellite. See B.1 for more details.

advertising time. Households will therefore be differentially exposed to advertising by the two firms depending on whether they watch neither, one, or both shows. The bottom two panels show a similar comparison between two US sitcoms, Frasier and Everybody Loves Ramond. These shows are aired across most months of 2009-2016 and entail different amounts and timing of Coca Cola and Pepsico advertising.

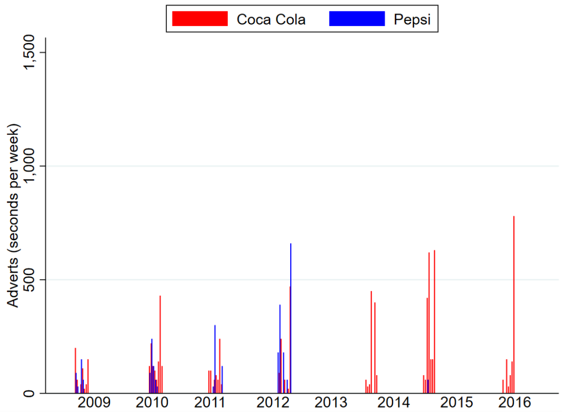
Figure 4.1: *Within genre advertising variation*

Talent contests

(a) The X Factor

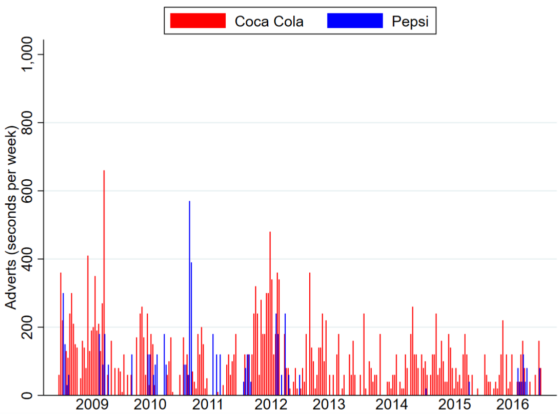



(b) Britain's Got Talent

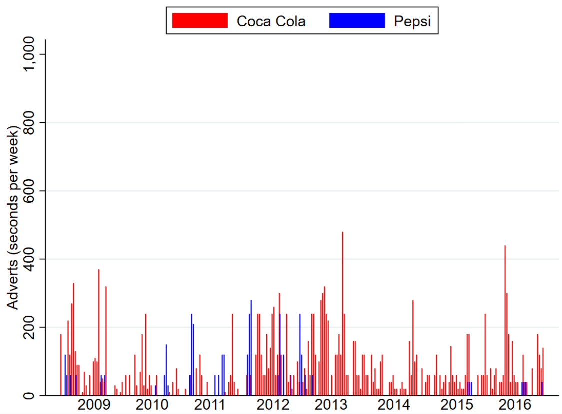



US sitcoms

(c) Frasier




(d) Everybody Loves Raymond




*Notes: Authors' calculations using data from AC Nielsen Advertising Digest for 2010-2016. Figures show number of seconds of adverts shown during the indicated show per week week.*

### 4.3.2 Prices

Our strategy for identifying the effect of prices on demand is to control for the primary potential sources of endogeneity bias and to thereby isolate variation in prices faced by individual consumers that is plausibly exogenous. This strategy relies on the combination of UK market setting and our rich micro level data.

An important feature of the UK grocery market is that the main supermarkets have both national store networks and pricing policies (see UK Competition Commission (2000)). This means we do not rely on cross-sectional regional price variation, common in studies of US markets (which typically entail use of Hausman instruments (Hausman et al. (1994)).[13] Rather we exploit the fact the drinks firms (i.e., Coca Cola Enterprises and Pepsico) engage in annual negotiation with each of the main retailers to agree a recommended (national) retail price and agreements on the number, type and timings of promotions for the forthcoming year (see Competition Commission (2013)). While the recommended price for a given product tends to be similar across retailers, the timing of promotions vary. This results in shoppers facing different prices depending on when and at which retailer they shop with.

This strategy relies on the following assumptions. First, it requires that we are able to control for aggregate demand shocks that potentially are correlated with nationally set prices. To do this 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 from the point of view of cola choice (ruling out, for instance, a consumer visiting several retailers to find the lowest price for a particular product). We think this assumption is reasonable for a number of reasons. First, cola is a small share of consumer expenditure, so the gains from shopping around are small. Second, promotions in the UK market tend to be numerous, so it is likely that if a specific product is not on sale when a shopper visits a retailer, a close substitute will be (i.e., the same brand in a different size).

The third assumption underpinning our strategy is that our estimates capture intra-temporal consumer response, rather than intertemporal responses (e.g., whereby consumers stock-up in response to sales). Such intertemporal responses would likely lead us to over-estimate own price elasticities and underestimate cross price elasticities (Hendel and Nevo (2006)). We cannot rule out a priori that some consumers stockpile in responses to sales, but we can offer empirical evidence that this effect is not quantitatively important in our UK context). Using the same dataset as in this paper (i.e., the Kantar FMCG Purchase Panel) O'Connell and Smith (2023) show that when a consumer purchases a drink product on sale, they are more likely to choose a different brand, container type (i.e., can/bottle) and size relative to their previous purchase, but they do not systematically change the timing

[13] In addition, as the cola market over the period of our study is one with a stable set of brands and products, the use of variation in the set of characteristics of all products across markets as price instruments (e.g., Berry et al. (1995), Gandhi and Houde (2020)) is unavailable.

of their purchases. This is evidence that consumers respond to sales by intra-temporally substituting across products rather than stockpiling.[14]

## 4.4 Demand estimates

We estimate the demand model by simulated maximum likelihood; we present parameter estimates and product-level price elasticities in Appendix H. In Table 4.1 we report brand-level price and advertising elasticities. The price elasticities give the percent change in demand for the brand listed in the first column in response to a 1% increase in the price of all products belonging to the brand detailed in the first row. The brand own-price elasticity for Regular and Diet Coke is around -2.2 and 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 between them, and that they are more willing to substitute within Regular and Diet brand than between them (for instance, the cross-price elasticity of demand for Regular Pepsi, with respect to a rise in the price of Regular Coke products, is almost twice as large than for demand of Diet Pepsi).

The advertising elasticities describe the impact of a 1% increase in the stock of all consumers' exposure to advertising of the brand in the first row on demand for the brand in the first column, and therefore should be interpreted as long-run elasticities.[15] The own-brand elasticities for Regular and Diet Coke advertising are around 0.11, while the Diet Pepsi own-brand elasticity is around half this. The cross-elasticities indicate substantial within firm advertising spillovers. For instance, a 1% increase in Regular Coke advertising raises demand for Diet Coke products by 0.05% (around half the increase in Regular Coke demand). There is also evidence for cross-firm advertising spillovers (Regular and Diet Coke advertising raising Pepsi demand and Diet Pepsi advertising raising Coke demand), however these are substantially smaller in magnitude than the within-firm spillovers.

[14] O'Connell and Smith (2023) also show that there is no economic meaningful change in the probability that, when buying on sale, a consumer shops at a difference retailer compared with their previous purchase, which support our assumption of exogenous retailer choice.

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

Table 4.1: *Brand price and advertising elasticities*

| | Price elasticities | | | | Advertising elasticities | | |
|---|---|---|---|---|---|---|---|
| | Coke | | Pepsi | | Coke | | Pepsi |
| | Regular | Diet | Regular | Diet | Regular | Diet | Diet |
| (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Regular Coke | **-2.210** | 0.511 | 0.050 | 0.092 | **0.115** | 0.043 | 0.020 |
| | [-2.259, -2.171] | [0.503, 0.519] | [0.049, 0.052] | [0.091, 0.094] | [0.111, 0.152] | [0.027, 0.051] | [0.009, 0.026] |
| Diet Coke | 0.378 | **-2.192** | 0.023 | 0.142 | 0.054 | **0.110** | 0.016 |
| | [0.369, 0.400] | [-2.233, -2.166] | [0.022, 0.024] | [0.143, 0.145] | [0.036, 0.065] | [0.109, 0.140] | [0.005, 0.019] |
| Regular Pepsi | 0.210 | 0.128 | **-1.842** | 0.552 | 0.021 | 0.020 | 0.015 |
| | [0.188, 0.212] | [0.110, 0.126] | [-1.840, -1.610] | [0.487, 0.567] | [0.003, 0.029] | [0.005, 0.027] | [0.006, 0.018] |
| Diet Pepsi | 0.110 | 0.232 | 0.157 | **-1.679** | 0.015 | 0.011 | **0.057** |
| | [0.107, 0.117] | [0.227, 0.237] | [0.156, 0.164] | [-1.723, -1.662] | [-0.000, 0.020] | [-0.003, 0.015] | [0.057, 0.071] |

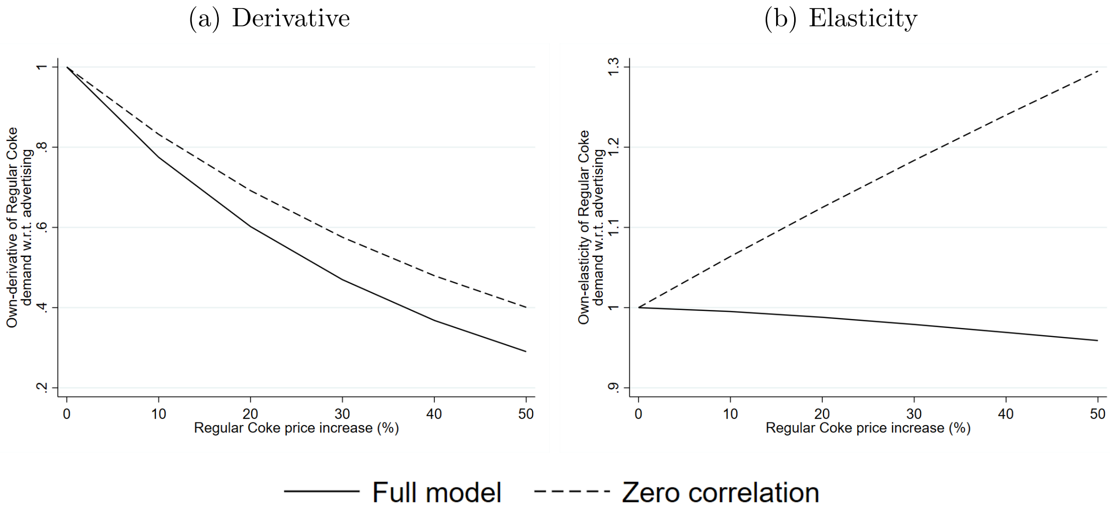
*Notes: Numbers show the elasticity of demand for the brand shown in column (1) with respect to the price (columns (2)-(5)) or advertising stocks (columns (6)-(8)) of the brands shown in the first row. The price elasticities are with respect to a 1% price rise of all products comprising the brand. The advertising elasticities are with respect to a 1% rise in all consumer exposure stocks. 95% confidence bands are shown in square brackets.*

The positive cross-advertising elasticities indicate the importance of including spillover advertising effects in consumer's decision utilities. When we exclude these effects, and re-estimate the model, we find similar own advertising elasticities, but negative cross-elasticities between Coca Cola and Pepsi products (see Appendix H). Hence, with this specification we would conclude that brand advertising steals market share from all rival brands, even within firm. However, Table 4.1 shows that in fact brand advertising leads to substantial within firm (positive) spillovers, and modest cross-firm ones.

Figure 4.2 shows how the sensitivity of brand demand to advertising varies with the brand price level. Panel (a) shows how the derivative of demand for Regular Coke with respect to Regular Coke advertising varies with a (simulated) increase in the price of all Regular Coke products. Panel (b) shows how the own-advertising elasticity for Regular Coke varies with price. In each case we plot the relationship with our full model estimates (the solid line) and when we set the within demographic group advertising and price sensitivity covariance parameters to zero (the dashed line).

The figure highlights the role the correlation parameters play in determining the shape of demands. When they are set to zero the advertising derivative declines gradually enough as price rise, that the advertising elasticity rises (as the derivative falls less quickly with price than the quantity demand of Coke Regular). However, using our estimates of the within demographic group correlation in price and advertising sensitivities, we find the advertising derivative declines sufficiently quickly as price rises, that the advertising elasticity also falls. In other words, as price rises, the consumers that substitute away from the brand are relatively advertising sensitive. This feature of demand influences how firms adjust their advertising in response to the introduction of the tax, as with a tax in place demand for the taxed products will comprise a less advertising sensitive consumer base (relative to there being no tax). Had we assumed zero correlation in price and advertising sensitivity we would have imposed that the advertising elasticity rises as we move upwards along the demand curve, whereas in fact our estimates suggest the opposite is true.

Figure 4.2: *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 corresponds 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 are relative to 0% price increase.*

# 5 Supply-side estimation

In the supply model we treat Coca Cola and Pepsico as the strategic players. They compete over the prices of their products and their brand advertising budgets. Store brands are not advertised, and during the time period we consider Pepsico almost never chooses to advertise Regular Pepsi; therefore we model advertising choices for Regular Coke, Diet Coke and Pepsi Diet. Prices for the store brands are much lower than for Coca Cola and Pepsico products. In policy simulations we hold fixed their prices, treating these products as if they are priced at cost.

We exploit week-to-week variation in advertising exposure in our demand model. However, firms make decisions over their advertising expenditures at lower frequency (with these decisions generating week-to-week variation in exposure as the advertising slots arranged by agencies are aired). We assume firms make decisions over prices and advertising expenditures each month. While there is variation in prices across retailers (at a given point in time), this is primarily driven by the differential timing of price promotions. Rather than complicate our framework with a formal model of vertical relations, we make the simplifying assumption that drinks firms set a single price for each product across retailers.[16] To solve for the equilibrium of our model we need to specify how firms form expectations about how the distribution of consumer stocks of advertising exposure is impacted by investments in advertising expenditure. We first outline how we do this before presenting the static and dynamic equilibrium conditions in the (observed) zero-tax case.

## 5.1 The state transition function

Advertising agencies play the role of shrinking firms' action space to a tractable decision over product prices and brand advertising expenditures. However the state space in the firm's decision problem, outlined in Section 3.1, is still large as it consists of the joint distribution of consumer level exposure stocks for each brand (which we denote $\mathcal{A}_t = \{(A_{i1t}, \dots, A_{iBt})\}_{i \in I}$). While the behavior of advertising agencies implies that the advertising exposure distribution in the population depends on these advertising expenditures in a known way, via viewership behavior and realized television slots choices, the information burden on firms in tracking, and forming optimal expenditure strategies that depend on, this entire distribution is formidable and renders the dynamic oligopoly game computationally intractable.

We therefore posit that firms track a summary statistic for the brand-specific consumer exposure distribution and present evidence that doing so results in negligible prediction error. In particular, we assume that the state space consists of the expected value of the exposure stock distribution for each brand $(\mathbb{A}_{1t}, \dots, \mathbb{A}_{Bt})$, where $\mathbb{A}_{bt} = \frac{1}{I}\sum_i \mathcal{A}_{ibt} = \delta \mathbb{A}_{bt-1} + \mathbb{a}_{bt-1}$, and where $\mathbb{a}_{bt} = \frac{1}{I}\sum_i a_{ibt}$ is the average flow exposure. By tracking the mean of the distribution, firms make a prediction error in their demands, equal to $s_{jt}(\mathbf{p}_t, \mathbb{A}_{1t}, \dots, \mathbb{A}_{Bt}) - E_{\mathcal{A}_t}[s_{jt}(\mathbf{p}_t, \mathcal{A}_{i1t}, \dots, \mathcal{A}_{iBt})]$. In practice this error is very small, with the average absolute error being 2% of each product demand. This is because errors are upward for consumers who are more exposed than the mean and downward for those less exposed than the mean and thus those errors tend to compensate each other on average.

Using the optimal determination of advertising slots from equation (3.2) together with the estimates of the $\gamma$ parameter of function $f(.)$ in the exposure determination of each consumer (equation (2.1)), the evolution of the brand $b$ state variable can be re-written

[16] 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 former applying $\rho$ proportion of weeks. Instead of modeling choice over $(\bar{p}, p_S, \rho)$, we model choice over $p = (1-\rho)\bar{p} + \rho p_S$. This average price exhibits little variation across retailers. Cross-retailer variation in the price of a given product at a point in time is driven by non-synchronization of sales. Hence, we specify the relationship between prices in the supply game, $p_{jm}$, and those faced by consumers in retailer $r$, week $t \in m$ as $p_{jrt} = p_{jm} + e_{jrt}$, where $\mathbb{E}[e_{jrt}|(j,m)] = 0$.

$\mathbb{A}_{bt} = \delta\mathbb{A}_{bt-1} + \lambda_{t-1}e_{bt-1}^{\gamma}$, where $\lambda_{t-1}$ is a period specific rate of transformation of advertising expenses into additional brand level advertising exposure, and depends on advertising slot prices (see Appendix F). However, firms do not observe the realization of $\lambda_{t-1}$ when making decisions over their advertising budgets $e_{bt-1}$ (as slot advertising prices are not yet known), and therefore at this point in time $\lambda_{t-1}$ is a random variable. We assume that firms form expectations of the changes in the advertising state conditional on expenditure which implies the stock satisfies:

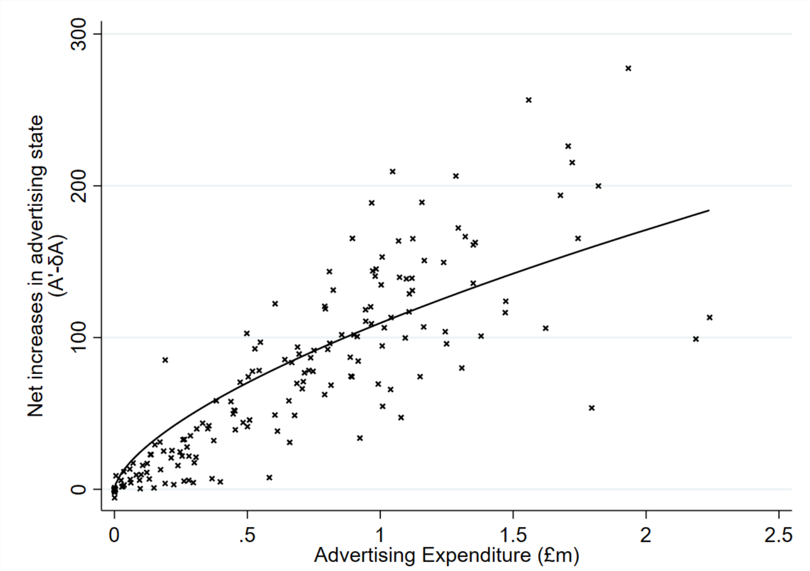
$$\mathbb{A}_{bt} - \delta\mathbb{A}_{bt-1} = \lambda e_{bt-1}^{\gamma} + v_{bt-1} \tag{5.1}$$

where $v_{bt-1} = (\lambda_{t-1} - \lambda)e_{bt-1}^{\gamma}$ and $E(v_{bt-1}|e_{bt-1}) = 0$. We estimate equation (5.1) using a Tobit model with $\gamma$ known, which yields an estimate $\hat{\lambda} = 0.015$ (with standard error 0.0004) and $\text{var}(v_{bt}) = 784$. We plot the estimates in Figure 5.1. To solve for a Markov perfect equilibrium we discretize the state space. Specifically, for a set of evenly spaced discrete values $\{A_1, \dots, A_K\}$, where $A_1 = 0$, we use the state transition function:

$$\begin{aligned} P(\mathbb{A}_{bt} = \mathbb{A}_{k'}|\mathbb{A}_{bt-1} = \mathbb{A}_k, e_{bt-1}) = & \int_{\mathbb{A}_{k'-1}}^{\mathbb{A}_{k'}} f_v(\mathbb{A}_{bt} - \delta\mathbb{A}_k - \lambda e_{bt-1}^{\gamma}) \frac{\mathbb{A}_{bt} - \mathbb{A}_{k-1}}{\mathbb{A}_{k'} - \mathbb{A}_{k'-1}} d\mathbb{A}_{bt} \\ & + \int_{\mathbb{A}_{k'}}^{\mathbb{A}_{k'+1}} f_v(\mathbb{A}_{bt} - \delta\mathbb{A}_k - \lambda e_{bt-1}^{\gamma}) \frac{\mathbb{A}_{k'+1} - \mathbb{A}_{bt}}{\mathbb{A}_{k'+1} - \mathbb{A}_{k'}} d\mathbb{A}_{bt}. \end{aligned} \tag{5.2}$$

As there are three advertising states, one for Regular Coke, Diet Coke and Diet Pepsi, the state grid $\{A_1, ..., A_K\}^3$ is of dimension $K^3$. We set $K = 21$, meaning there are 9,261 points in the discretized state space.

Figure 5.1: *Advertising state law of motion*




*Notes: Figure shows a scatter plot of monthly advertising expenditure and net changes in the advertising state,* $\mathbb{A}_{bt} - \delta\mathbb{A}_{bt-1}$ *(across brands and year-months). The solid line is the estimate of equation (5.1) with* $\gamma = 0.64$.

## 5.2 State-specific price equilibrium

We use the Bertrand-Nash equilibrium conditions of equation (3.3), evaluated at the observed prices and advertising state variables, to infer product-level marginal costs. The average (quantity-weighted) marginal cost and price-cost margin per liter among Coca Cola products is 0.45 and 0.38, and the average (expenditure-weighted) Lerner index is 0.46. For Pepsico products the average cost, margin and Lerner index is 0.25, 0.41 and 0.62. Hence, on average Pepsico products have lower costs and similar price-cost margins (meaning higher Lerner indexes) than Coca Cola products.[17]

We use estimates of product-level demands and marginal costs, along with the Bertrand-Nash conditions (equation (3.3)) to solve for the vector of equilibrium prices at each point of the advertising state space. Figure 5.2(a) shows how the average price-cost margins of Regular Coke products varies across the advertising state space. The state space is three dimensional; the figure holds fixed the Diet Pepsi state 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 is decreasing in the Regular Coke advertising state. The mechanism underlying this is the negative correlation in consumer's price and advertising sensitivities (reflecting in the covariance parameters in the demand model random coefficient distribution); as the

[17]We report product-level costs, margins and Lerner indexes in Appendix H.

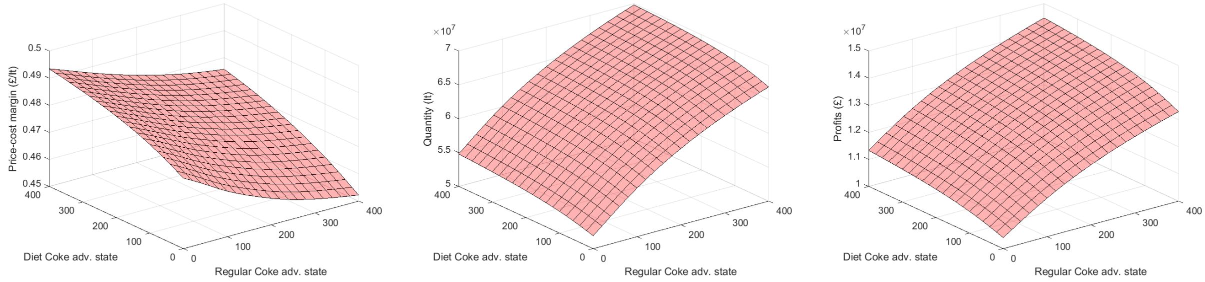
Regular Coke advertising state increases, the composition of demand for Regular Coke is increasingly made up of more price sensitive consumers, which lowers the (conditional on state) optimal Regular Coke prices. In contrast there is a (weaker) positive relationship between the Diet Coke advertising state and Regular Coke margins. This reflects the fact that, as Diet Coke is advertised more, relatively advertising sensitive consumers shift from Regular Coke toward Diet Coke, which lowers the advertising and price sensitivity of the Regular Coke consumer base.

Figure 5.2(b) shows how demand for Regular Coke products varies across the Coca Cola advertising states. Variation in the demand function across the state space reflects both the direct effect of different advertising levels on demand and the indirect effect of the impact of different advertising states on demand via the price equilibrium. Intuitively, demand for Regular Coke products increases in the Regular Coke advertising state, both due to the direct channel and the indirect channel (Regular Coke prices are lower at higher states). Regular Coke demand is also increasing in the Diet Coke advertising state, though less strongly. This reflects a demand spillover (Diet Coke advertising stimulates Regular Coke demand in addition to Diet Coke demand – an effect that comes through the within firm advertising spillover effects in our utility specification), which is strong enough to overcome an offsetting indirect effects (Regular Coke prices are rising in Diet Coke advertising).

Figure 5.2(c) shows how gross profits (i.e., excluding advertising expenses) for Regular Coke products vary with the two Coca Cola advertising states. As the Regular Coke advertising state rises there are two off-setting forces, demand rises but margins fall – the former dominates and hence profits rise. Regular Coke profits are also increasing in Diet Coke advertising (due to the within firm demand spillover), but comparatively less strongly with the Regular Coke state.

Figure 5.2: *Variation in Regular Coke Nash equilibrium with Coca Cola advertising states*

(a) Price-cost margin | (b) Quantity | (c) Gross profits

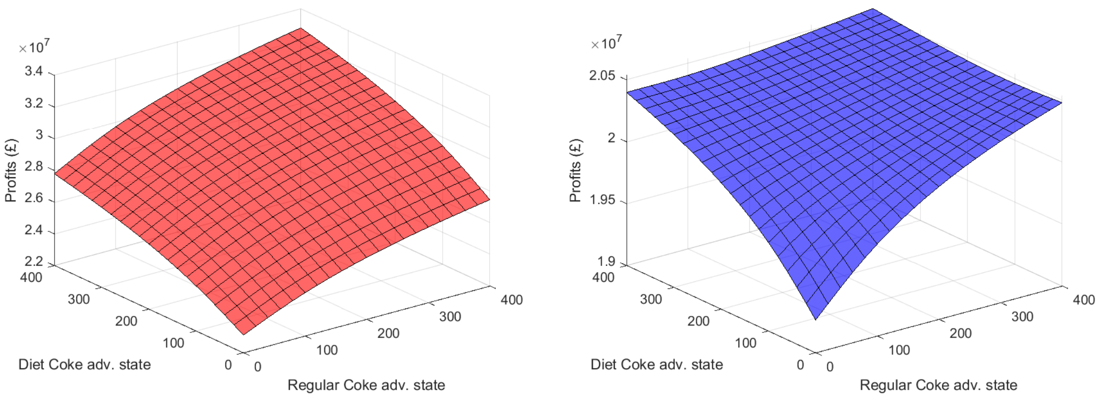



*Notes: Panel (a) shows variation in the average price-cost margin for Regular Coke products. Panels (b) and (c) show variation in total quantity and gross profits for Regular Coke. In each panel we hold fixed the Diet Pepsi advertising state at the highest probability state in the (dynamic) equilibrium distribution.*

In Figure 5.3 we plot how the Coca Cola and Pepsico gross profit functions (which sum across all products they own) vary with the two Coca Cola advertising states, holding the Pepsico state fixed. Coca Cola gross profits are increasing in both Coca Cola advertising states. Pepsico profits are increasing in each dimension of Coca Cola advertising (although much less strongly than Coca Cola profit). This largely reflects a cross-firm spillover effect of advertising in demand – Coca Cola advertising raises decision utility from Pepsico products which act to raise demand for them. At higher levels of Coca Cola advertising Pepsico profits are less sensitive to further increases in Coca Cola advertising. These firm-level profit functions, which incorporate strategic pricing competition, serve as an input into the dynamic advertising game.

Figure 5.3: *Variation in firm-level gross profits with Coca Cola advertising states*

(a) Coca Cola Enterprises (b) Pepsico




*Notes: Panel (a) shows variation in total 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.*

## 5.3 Markov perfect equilibrium

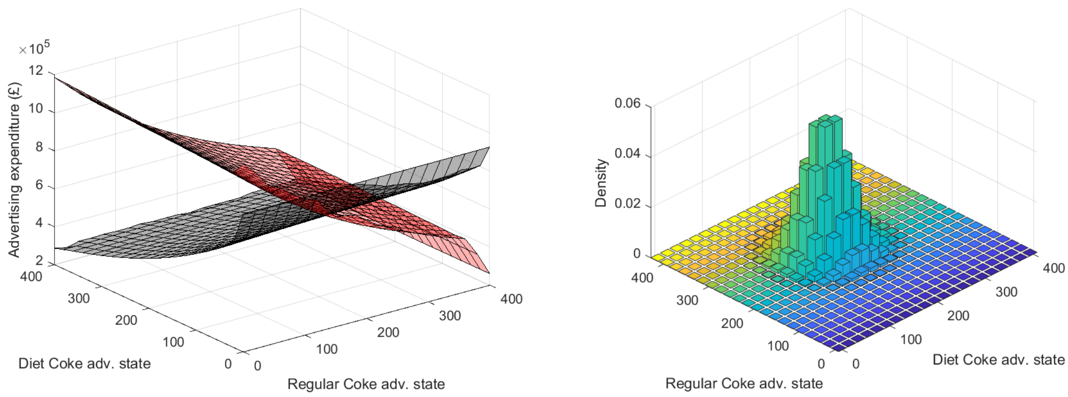
We use the Bellman equations for Coca Cola and Pepsico (equation (3.4)) to solve for the Markov perfect equilibrium (see Appendix G for details of the solution algorithm). We fix the brand level agency mark-up over expenses so that our model's equilibrium predictions about average advertising expenditures matches their levels in the data. This implies Pespsico, who advertise less, pay a mark-up that is 1.5 times higher than the average paid by Coca Cola, which is consistent with the mark-up partly being driven by fixed cost recovery for the advertising agency.

We obtain Markov perfect equilibrium strategies (policy functions) for each advertised brand, which prescribes the optimal choice of advertising expenditure at each point in the advertising state space. In Figure 5.4(a) we plot how the policy functions for Regular Coke (red) and Diet Coke (grey) vary across the Coca Cola advertising states. As in the previous figures, we hold 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 depleted, the returns from investing in more advertising are relatively high and therefore optimal expenditures are higher, whereas as stocks become large the returns decline so optimal expenditure is lower. The cross-brand relationship between states and optimal expenditures is much weaker, with optimal advertising expenditure for Regular Coke being relatively insensitive to the Diet Coke state (and the converse).

Firms' optimal policy functions, coupled with the state-to-state transition function (equation (5.2)) generate a Markov perfect equilibrium (ergodic) distribution over the state space. In Figure 5.4(b) we plot the ergodic distribution of the equilibrium over the Coca Cola advertising states (integrating across the Pepsico state).

Figure 5.4: *Optimal policy function for Coca Cola Enterprises*

(a) Advertising expenditure (b) Equilibrium distribution




*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 the panel (b) we integrate over the Diet Pepsi advertising state space.*

# 6 Counterfactual policy analysis

We use our model to simulate a series of counterfactual policies. We characterize their impact on equilibrium prices, advertising expenditure and quantities, and on aggregate profits and consumer surplus, and we show their distributional consequences. We consider a regulation that prohibits advertising of sugar-sweetened cola, a specific tax levied on sugar-sweetened beverages of £0.25 per liter (similar to the tax levied in the UK and other jurisdictions), an ad valorem tax levied on sugar-sweetened beverages (calibrated to achieve the same fall in equilibrium quantity as the specific tax), and the combination of an advertising restriction and tax.

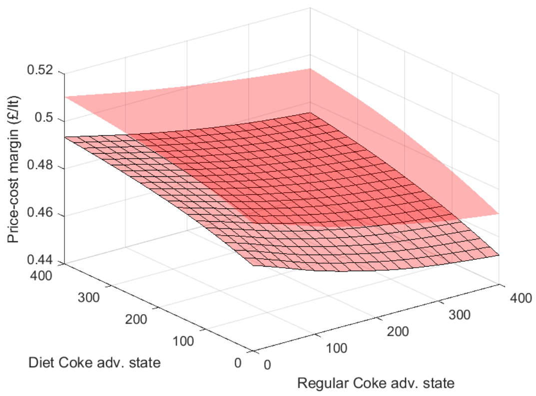
Our model generates a set of functions that describe how static equilibrium objects (e.g., price, quantity, profits, consumer surplus) vary across the advertising state space, which we denote by $y_\chi(\{\mathbb{A}\}_b)$, and an equilibrium (ergodic) distribution over the state space, which we denote by $p_\chi(\{\mathbb{A}\}_b)$. $\chi \in \{0, \mathbb{r}, \mathbb{s}, \mathbb{sr}, \mathbb{a}, \mathbb{ar}\}$ denotes no policy in place, 0, or the (counterfactual) imposition of an advertising regulation, $\mathbb{r}$, specific tax, $\mathbb{s}$, ad valorem tax, $\mathbb{a}$, or a combination of regulation and tax $\mathbb{ar}$. The average equilibrium outcome is given by $\bar{Y}_\chi = \int_{\{\mathbb{A}\}_b} y_\chi(\{\mathbb{A}\}_b) p_\chi(\{\mathbb{A}\}_b)$. In Figure 6.1 we show how the specific tax impacts how the price equilibrium varies across advertising states, and how advertising restrictions and the specific tax impact the equilibrium distribution.[18] In Table 6.1 we report how various average equilibrium outcomes change under each counterfactual policy regime.

[18]Note, the advertising restriction impacts the ergodic distribution, but not the conditional on state, static equilibrium. Hence, $y_{\mathbb{r}}(\{\mathbb{A}\}_b) = y_0(\{\mathbb{A}\}_b)$, $y_{\mathbb{sr}}(\{\mathbb{A}\}_b) = y_{\mathbb{s}}(\{\mathbb{A}\}_b)$, and $y_{\mathbb{ar}}(\{\mathbb{A}\}_b) = y_{\mathbb{a}}(\{\mathbb{A}\}_b)$. In Appendix H we show the equivalent of Figure 6.1 for the ad valorem tax.

Figure 6.1: *Impact of specific tax and advertising restriction*

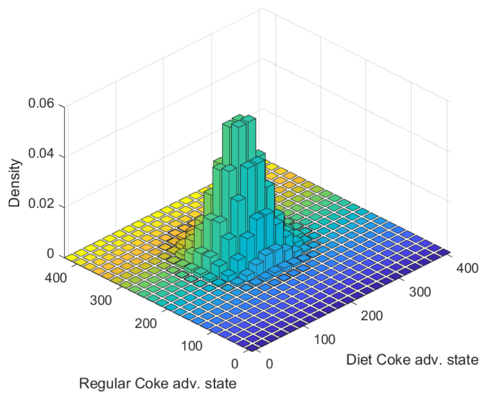
*On static equilibrium*

(a) Regular Coke margins

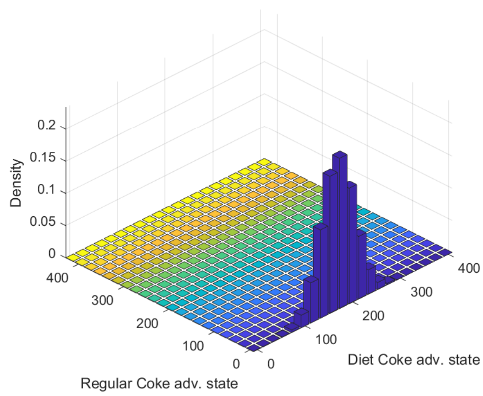



*On equilibrium distribution*

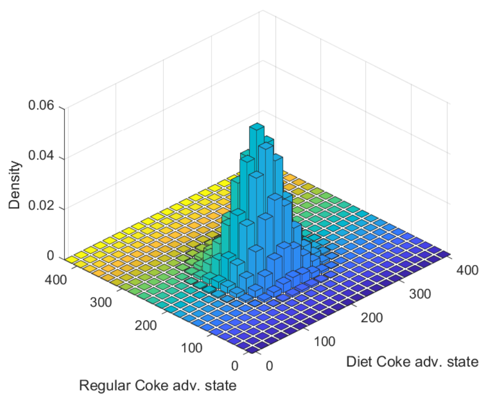
(b) Pre-policy



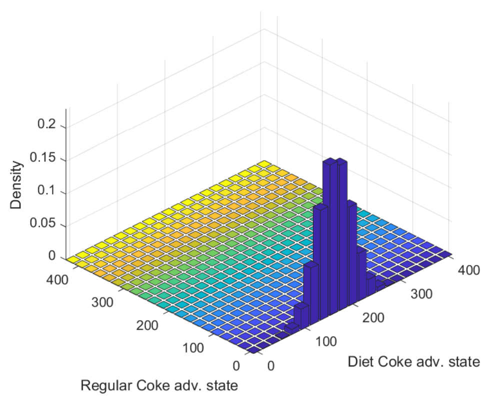

(c) Advertising restriction




(d) Tax




(e) 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 (and repeats Figure 5.2(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 equilibrium distribution. Panels (b)-(e) show the ergodic distribution, integrating over the Diet Pepsi advertising state space. Panel (b) repeats Figure 5.4(b).*

## 6.1 Impact on market equilibrium

In Table 6.1 we summarize the impact of each counterfactual policy on equilibrium (tax-inclusive) prices, price-cost margins, advertising expenditures, quantities and sugar consumption. Column (1) reports the impact of an advertising restriction that prohibits advertising of sugar-sweetened cola – numbers are percent changes relative to the no policy (observed) equilibrium. Column (2) reports the impact of the introduction of a specific tax, holding fixed the equilibrium distribution across advertising states (and hence holding fixed firms' advertising expenditures). Columns (3) and (4) show the *incremental* impact of accounting for equilibrium advertising responses (column (3)) and adding to the tax the advertising restriction. Columns (5)-(7) repeat columns (2)-(4) for an ad valorem tax. We discuss each policy in turn.

Table 6.1: *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% | 32.9% | 0.1% | 0.5% | 42.9% | 0.1% | 0.4% |
| Diet Coke/Pepsi | -1.0% | -1.5% | -0.1% | -0.6% | -1.5% | -0.2% | -0.6% |
| **Δ margin** | | | | | | | |
| Regular Coke/Pepsi | 1.6% | 6.0% | 0.2% | 1.0% | -37.8% | 0.1% | 0.5% |
| Diet Coke/Pepsi | -2.1% | -3.0% | -0.2% | -1.3% | -3.0% | -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% | -59.6% | -0.9% | -4.0% | -59.7% | -1.4% | -3.4% |
| Diet Coke/Pepsi | -3.8% | 12.2% | -1.0% | -4.8% | 11.8% | -1.8% | -4.3% |
| **Δ sugar** | | | | | | | |
| *All drinks* | -2.7% | -17.5% | -0.1% | -0.3% | -17.8% | -0.0% | -0.2% |

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

**Advertising restriction.** Column (1) shows that a ban on advertising sugar-sweetened cola (which directly impacts Regular Coke advertising) leads to a reduction in consumption of Regular Coke and Pepsi products of 13.0% and a fall in sugar consumption (from all drinks) of 2.7%.[19] It also leads to a reduction in consumption of Diet Coke and Pepsi of 3.8%. While

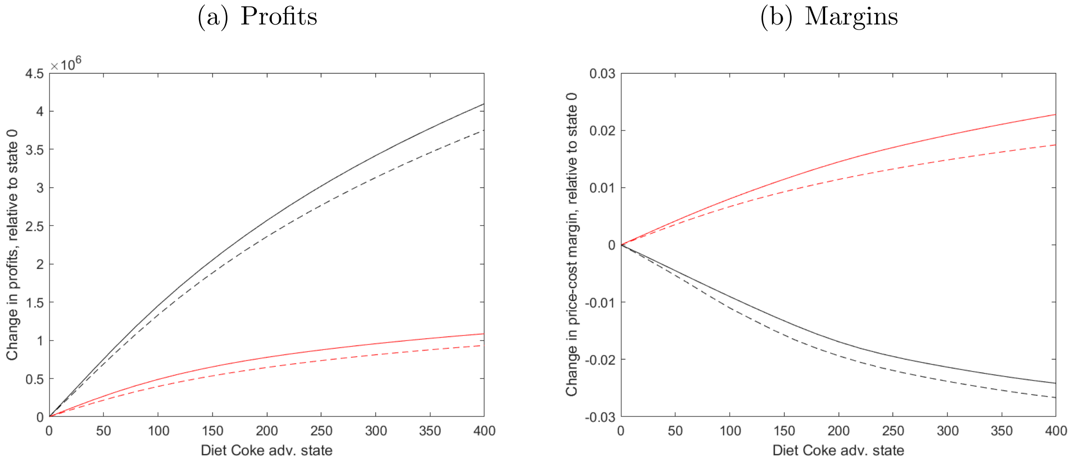
[19] This accounts for changes in sugar from Regular Coke and Pepsi – which each have 106g of sugar per liter, and regular store brands and the sugary outside drink – which have 50g of sugar per liter. We assume the size (in liters) of the sugary outside option is equal to the mean size of the inside (cola) products.

price and margins change relatively little, the advertising restriction leads to 7.7% reduction in Diet advertising (almost entirely driven by a reduction in Diet Coke advertising). The ban on Regular advertising and the decline in investment in Diet Coke advertising leads to a change in the equilibrium distribution (see panels (b) and (c) of Figure 6.1).

The decline in the equilibrium quantity of Diet Coke and Pepsi products reflects two channels. First, as advertising on Regular products has positive spillovers to demand for Diet products, banning it, all else equal, acts to reduce demand for Diet Coke and Pepsi. Second, the equilibrium response of Coca Cola to the policy is to reduce advertising of Diet Coke which directly acts to lower Diet Coke demand.

In Figure 6.2 we illustrate why, in equilibrium, Coca Cola lowers advertising of its Diet brand. Panel (a) shows how equilibrium profits for Regular (red lines) and Diet (grey lines) Coke vary with the Diet Coke advertising state. We show this relationship holding the Regular Coke advertising state at its modal "no policy" equilibrium value (solid lines) and at 0 (dashed lines), corresponding to the advertising restriction. The graph shows that after the ban is in place the returns to advertising Diet Coke, both in terms of Regular and Diet Coke profits are lower. This is what leads Coca Cola to lower its equilibrium expenditure on Diet advertising. Panel (b) shows the main reason why the restriction leads to a fall in the returns to Diet advertising. In particular, it shows how the average price-cost margin for Regular and Diet Coke products change with the Diet Coke advertising state. Moving to higher Diet Coke advertising states results in the equilibrium margin for Diet Coke falling and for Regular Coke rising (reflecting a sorting of the most advertising, and due to correlation in preference, the most price sensitive consumers towards Diet Coke). However, when the restriction is in place the extent to which higher Diet Coke advertising lowers the average equilibrium margins for Diet Coke products rises and the extent to which it raises margins for Regular Coke products falls. This happens as, with zero Regular Coke advertising, raising Diet Coke advertising attracts particularly advertising (and hence price) sensitive consumers who (had Regular Coke advertising been positive) may have remained Regular Coke consumers.

Figure 6.2: *Return to Diet Coke advertising*




*Notes: 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 dashed 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 0. In all cases the Pepsi Diet advertising state is held fixed at the highest probability state in the pre-policy intervention equilibrium distribution.*

**Specific tax.** Column (2) of Table 6.1 shows the impact of a £0.25 per liter specific tax on sugar-sweetened beverages, holding firms' advertising policy functions (and hence the equilibrium distribution over states) at its pre-tax level. The tax results in a 32.9% rise in the average price of Regular Coke and Pepsi (i.e., the taxed products') prices. This reflects both the mechanical impact of the tax on prices and firms' equilibrium margin adjustment; on average the pass-through of the tax is around 110%, which corresponds to an increase in equilibrium price-cost margins for taxed products of 6% (see panel (a) of Figure 6.1 where we show how the average Regular Coke price-cost margins vary across the advertising state space with no tax in place (hatched surface) and the tax in place (smooth surface)). The corresponding change in Regular Coke and Pepsi equilibrium quantity is 59.6%, with overall sugar intake from drinks falling by 17.5%.

Column (3) shows the incremental impact of accounting for Coca Cola and Pepsi's change in optimal advertising resulting from the introduction of the specific tax (by re-solving for the Markov perfect equilibrium). The tax results in a 33.1% reduction in spending on Regular Coke advertising. 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 of Diet products (panels (b) and (d) of Figure 6.1 show the implication for the equilibrium distribution over states).

This lower level of advertising expenditure induces a further modest reduction in demand for Regular products of around 1%.

Column (4) shows the impact of coupling the specific tax with the advertising restriction that prohibits advertising of Regular brands. With no tax in place the advertising restriction lowers Regular Coke and Pepsi consumption by 13% and total sugar intake by 2.7%. With a tax in place, the effect of the restriction is attenuated; it leads to a reduction in Regular Coke and Pepsi consumption of 4% and a small fall of 0.3% in total sugar intake.

**Ad valorem tax.** We calibrate the ad valorem tax such that it results in approximately the same reduction in equilibrium quantity for Regular Coke and Pepsi as the specific tax, holding fixed advertising strategies. Hence, by construction, in column (5), we see the same reduction in Regular Coke and Pepsi quantity of 59.7% as in column (2). The tax rate required to achieve this reduction is 74%. Average pass through of tax is around 65%, which is reflected in the 37.8% fall in equilibrium price-cost margins of the taxed products.

Column (6) shows the incremental impact of accounting for firms' advertising responses to the tax. Equilibrium advertising expenditure on Regular products falls by 47.3%, which is significantly larger than the 33.1% fall under the specific tax. This larger advertising response is linked to the under-shifting of the tax. An ad valorem (unlike a specific) tax puts a multiplicative wedge between the tax-inclusive consumer price and the tax-exclusive firm price; to increase the latter by 1% requires a 1.74% increase in the former. This puts downwards pressure on prices, inducing firms to lower their margins. Lower margins, in turn, reduce the profitability of attracting additional consumers, which acts to lower the return on advertising. As advertising of Diet products has a positive spillover to demand for Regular products, this same mechanism lowers (though to a lesser extent) the desirability of advertising Diet products – hence the ad valorem tax also results in a sizeable fall in Diet advertising. As a consequence of these larger advertising responses (relative to under a specific tax), the impact on equilibrium quantities is larger. Similarly, to the specific tax, the incremental impact of adding the advertising restriction on top of the ad valorem tax is smaller than the advertising restrictions' impact in the absence of tax.

## 6.2 Impact on economic surplus

In Table 6.2 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 (observed) equilibrium. We report tax revenue, change in Coca Cola and Pepsico profits, change in consumer surplus, and their sum, which we refer to as gross surplus. The primary motivation behind policies that aim to reduce sugar-sweetened beverage consumption is to lower the social costs of sugar consumption (which may arise through an externality due to higher health care costs, or people imposing internalities on themselves by under weighting private costs arising from future health problems). The reduction in gross surplus must be weighed against the reduction in social costs achieved by the policies.

The advertising restriction leads to a fall in gross surplus of 6.4%, with around 0.35 of this being due to a reduction in firm profits and the rest due to a reduction in consumer surplus, and achieves a reduction in sugar from drinks of 2.7%. Both specific and ad valorem taxes result in larger reductions in gross surplus (of 9.5% and 10.6%). The total consumer surplus burden of the two taxes is similar, but the ad valorem tax results in a reduction in firm profits that is over 40% higher than the specific tax and it results in tax revenue that is 64% higher. This reflects the undershifting of the tax, which lowers' firms equilibrium margins, meaning firm's share of total surplus falls at the expense of government tax revenue. Both taxes achieve similar reduction in sugar, of around 17.6-17.8%. The addition of the advertising restriction on top of either tax leads to only a small additional fall in sugar, at the expense of substantially higher fall in consumer surplus.

The main lessons from Table 6.2 are that the specific and ad valorem taxes do a similar job at reducing sugar consumption for a given gross surplus burden, though as the latter acts to lower firms' market power and raises more tax revenue, it is preferable. The comparison of the relative merits of an advertising restriction and taxes (at the level we consider) is less clear, as the former represents a smaller intervention in the market (in terms of the impact on total sugar and gross surplus), but it is noteworthy that the ratio of gross total surplus loss per unit of sugar reduction is considerably higher for the advertising brand. However, the case for an advertising restriction applied on top of a tax is weak as it results in only small additional reduction in sugar.

Table 6.2: *Aggregate surplus impact of counterfactual policies*

| | No tax | Specific tax | | Ad valorem tax | |
|---|---|---|---|---|---|
| | Adv. restrict. | | Adv. restrict. | | Adv. restrict. |
| | (1) | (2) | (3) | (4) | (5) |
| Tax revenue | - | 4.4% | 3.9% | 7.1% | 6.4% |
| Δ profits | -1.9% | -6.1% | -7.3% | -9.4% | -10.3% |
| Consumer surplus | -4.5% | -7.8% | -10.8% | -8.3% | -11.1% |
| Δ gross surplus | -6.4% | -9.5% | -14.2% | -10.6% | -15.0% |
| Δ sugar | -2.7% | -17.6% | -17.9% | -17.8% | -18.0% |

*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 level. Numbers for compensating variation and gross surplus (the sum of tax revenue profits changes and compensating variation) are shown under the characteristic view of advertising. The final row shows the percent change in sugar from all drinks relative to pre-policy, repeating information in Table 6.1.*

## 6.3 Distributional impact

The aggregate consumer surplus numbers in Table 6.2 mask heterogeneity across households. In Table 6.3 we show how each policy changes the sugar consumption and consumer surplus in each household income quartile. The numbers reflect the heterogeneity we incorporate in our demand model, by allowing all preferences parameters to vary by household income quartiles (interacted with household type).

A distributional analysis of the impact of advertising restrictions and taxes for sin goods, will be affected by any internalities savings the policies generate, and how these savings vary across the income distribution. To illustrate the potential importance of this channel, in Table 6.2, we also report changes in consumer surplus net of internality savings. We base our measure of internalities on the estimates in Allcott et al. (2019); they find that the internality per fl oz of sugar-sweetened beverage consumption ranges, linearly, from 1.10 cents for the lowest income group to 0.83 cents for the highest income groups. The translates to £0.0029, £0.0027, £0.0025 and £0.0022 per gram of sugar for our income quartiles 1 to 4.[20]

Under all policies, the reduction in consumer surplus (both as a fraction of total spending, and in monetary terms) is largest for households that belong to the bottom income quartile. However, under both the specific and ad valorem taxes sugar reductions are also largest for this group. Given this, and the fact that their internality per sugar gram is higher, the taxes (in the absence of advertising restrictions) are no longer regressive once these internality

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

savings are accounted for. In contrast, accounting for internality savings makes relatively little difference to the consumer surplus income gradient of the advertising restriction.

Table 6.3: *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% | -19.03% | -19.36% | -19.27% | -19.49% |
| 2nd | -2.78% | -18.36% | -18.59% | -18.47% | -18.56% |
| 3rd | -2.32% | -18.70% | -18.91% | -19.10% | -19.25% |
| Top | -2.83% | -13.19% | -13.57% | -13.54% | -13.68% |
| **Change in consumer surplus** | | | | | |
| Bottom | -6.22% | -9.84% | -14.16% | -10.50% | -14.38% |
| 2nd | -3.88% | -7.68% | -10.24% | -8.05% | -10.35% |
| 3rd | -4.12% | -8.46% | -11.35% | -9.05% | -11.67% |
| Top | -3.61% | -4.97% | -7.44% | -5.52% | -7.67% |
| **Change in consumer surplus net of internalities** | | | | | |
| Bottom | -5.00% | -1.77% | -5.96% | -2.33% | -6.12% |
| 2nd | -2.87% | -1.03% | -3.51% | -1.37% | -3.63% |
| 3rd | -3.41% | -2.75% | -5.57% | -3.21% | -5.79% |
| Top | -2.92% | -1.75% | -4.12% | -2.21% | -4.33% |

*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. Numbers for compensating variation are shown under the characteristic view of advertising.*

# 7 Conclusion

In this paper, we develop a model of competition in advertising and pricing to allow firms responses in advertising after a sin tax implementation or an advertising restriction. We show how we can model the organization of advertising decisions through agencies and study how a policy would affect equilibrium prices and the advertising dynamic equilibrium. We develop a dynamic structural model applied to the UK cola soft drinks market with an explicit behavior of advertising agencies choosing advertising slots on behalf of soda manufacturers, and compute the dynamic equilibrium impact of taxes or advertising restrictions. We use rich consumer level purchases over time as well as television viewing behavior and the universes of television advertising spots to identify the demand model. We show how to estimate the full dynamic equilibrium thanks to the agency delegation and an assumption on the state space summary statistic that firms use when deciding how much to advertise. We compare a specific tax and an ad valorem tax. Both lead to a reduction in advertising of the taxed products. A key driver of this result is our finding that consumers who are price sensitive also tend to be more advertising sensitive, meaning the tax induces the most advertising sensitive consumers to switch away from taxed brands, lowering the incentive to advertise. Advertising reductions are larger under the ad valorem than the specific tax. Under both taxes advertising of diet products is also reduced. This is driven by a within-firm complementarity in advertising strategies – the returns to advertising diet products is lower the lower is advertising of taxed, sugary products. Overall, the specific tax reduces the sum of consumer surplus and profits (net of tax revenue) by a smaller amount than the ad valorem tax for a fixed reduction in sugar consumption.

TBC..

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# Appendix:
# For online publication

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

Rossi Abi-Rafeh, Pierre Dubois, Rachel Griffith, Martin O'Connell
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## A Purchase data

In Table A.1 we report the set of cola products over which we model demand and supply. A product is defined as a firm-brand-pack combination. For each product we report its share of total cola expenditure and its average price per liter. We model consumer demand over this set of products and two outside options that are other (non-cola) drinks (either with or without sugar).

In Table A.2 we report 12 demographic groups over which we allow all consumer preference parameters to vary. These are based on the interaction of household type and income. The household types are: whether the household is working age with no child present, a pensioner households with no child present, or a household with a child present. We define working age household as one with at least one member aged 18-65 and a household with a child as one with any member aged 18 or less. For each household type we group households based on the (within type) income distribution. In particular we define equivalized income as household income divided by the OECD equivalence scale. The table reports the number of households and transactions (cola and outside option purchases) for each household type.

Table A.1: *Firms and brands*

| Firm | Brand | Pack | Expenditure share | Average price (£ per liter) |
|---|---|---|---|---|
| Coca Cola Enterprises | Regular Coke | Bottle(s): 1.25l: Single | 0.6% | 0.83 |
| | | Bottle(s): 1.5l: Single | 0.3% | 0.72 |
| | | Bottle(s): 1.75l: Single | 0.5% | 0.83 |
| | | Bottle(s): 1.75l: Multiple | 2.7% | 0.63 |
| | | Cans: 10x330ml: Single | 0.9% | 0.99 |
| | | Cans: 12x330ml: Single | 2.5% | 0.96 |
| | | Cans: 15x330ml: Single | 0.6% | 0.88 |
| | | Cans: 24x330ml: Single | 2.1% | 0.84 |
| | | Bottle(s): 2l: Single | 0.9% | 0.83 |
| | | Bottle(s): 2l: Multiple | 4.7% | 0.61 |
| | | Cans: 30x330ml: Single | 1.1% | 0.76 |
| | | Bottle(s): 3l: Single | 1.0% | 0.61 |
| | | Bottle(s): 4x1.5l: Single | 0.4% | 0.65 |
| | | Cans: 6x330ml: Single | 1.4% | 1.10 |
| | | Cans: 8x330ml: Single | 6.1% | 0.99 |
| | Diet Coke | Bottle(s): 1.25l: Single | 0.5% | 0.84 |
| | | Bottle(s): 1.5l: Single | 0.3% | 0.73 |
| | | Bottle(s): 1.75l: Single | 0.4% | 0.85 |
| | | Bottle(s): 1.75l: Multiple | 3.1% | 0.62 |
| | | Cans: 10x330ml: Single | 1.5% | 1.02 |
| | | Cans: 12x330ml: Single | 4.6% | 0.97 |
| | | Cans: 15x330ml: Single | 1.0% | 0.88 |
| | | Cans: 24x330ml: Single | 2.8% | 0.83 |
| | | Bottle(s): 2l: Single | 0.9% | 0.80 |
| | | Bottle(s): 2l: Multiple | 5.4% | 0.62 |
| | | Cans: 30x330ml: Single | 1.3% | 0.76 |
| | | Bottle(s): 3l: Single | 0.6% | 0.61 |
| | | Bottle(s): 4x1.5l: Single | 0.4% | 0.65 |
| | | Cans: 6x330ml: Single | 1.8% | 1.00 |
| | | Cans: 8x330ml: Single | 10.3% | 0.99 |
| Pepsico | Regular Pepsi | Bottle(s): 2l: Single | 5.1% | 0.52 |
| | | Cans: 6x330ml: Single | 0.4% | 0.82 |
| | | Cans: 8x330ml: Single | 2.1% | 0.82 |
| | Diet Pepsi | Bottle(s): 1.5l: Single | 0.2% | 0.63 |
| | | Cans: 12x330ml: Single | 0.6% | 0.82 |
| | | Bottle(s): 2l: Single | 15.0% | 0.52 |
| | | Cans: 6x330ml: Single | 0.9% | 0.84 |
| | | Cans: 8x330ml: Single | 9.2% | 0.83 |
| Store brands | Regular store | Bottle(s): 2l: Single | 2.1% | 0.18 |
| | | Bottle(s): 4x2l: Single | 0.2% | 0.24 |
| | Diet store | Bottle(s): 2l: Single | 3.0% | 0.19 |
| | | Bottle(s): 4x2l: Single | 0.5% | 0.24 |
| All | | | 100.0% | 0.74 |

*Notes: Authors' calculations using data from Kantar FMCG At-Home Purchase Panel.*

Table A.2: *Households' demographic groups*

| | | Number of: | |
|---|---|---|---|
| | | households | transactions |
| Working age | Bottom income quartile | 1660 | 184536 |
| | 2nd income quartile | 1718 | 192576 |
| | 3rd income quartile | 1398 | 163288 |
| | Top income quartile | 2550 | 257582 |
| Pensioner | Bottom income quartile | 1455 | 177450 |
| | 2nd income quartile | 1154 | 134867 |
| | 3rd income quartile | 568 | 71455 |
| | Top income quartile | 411 | 46172 |
| Household with children | Bottom income quartile | 3015 | 385244 |
| | 2nd income quartile | 3447 | 448110 |
| | 3rd income quartile | 1950 | 242701 |
| | Top income quartile | 2384 | 281669 |

*Notes: Numbers are for our analysis sample from the Kantar FMCG At-Home Purchase Panel.*

# B Advertising market and data

## B.1 The UK TV market

The UK TV market is heavily regulated. Four large public service broadcasters – the BBC, ITV1, Channel 4 (C4) and Channel 5 (C5) – face restrictions on how much they advertise. The BBC is funded by an annual license fee and is not allowed to show any adverts. ITV1, C4 and C5 can show adverts and do not receive license fee income, but face some restrictions regarding programming, including the total amount of adverts shown. These public broadcasters have relatively large audience shares – BBC1 has a viewing share of around 20%, ITV around 16%, BBC2 and C4 around 7% and C5 around 5%. These channels compete for consumers by offering programs designed for broad audience appeal (see Crawford et al. (2017) for a detailed discussion of the UK advertising market).

There are also a large number of commercial channels that do not face any specific restrictions to their programming.[21] Access to these additional channels is through TV subscriptions. Households can view TV in four ways: free to air, freeview, satellite or cable. All households with a TV have to pay the license fee that funds the BBC. Free to air does not require any additional payment, but gives access to only the public service broadcasters. Freeview requires purchasing a box to decode the digital signal, but does not require any additional payment, and gives access to a small number of additional channels. Satellite and cable require subscriptions and provide access to a broader range of mainly commercial

[21] There are additional BBC channels (e.g., BBC3, BBC4, BBC News, BBC Parliament) which have low viewing figures and prohibited from advertising.

channels. Any household subscribing to satellite or cable will have access to all of the free to air and freeview channels.

## B.2 Advertising agencies

Table B.1: *Advertising of Coca Cola and Pepsi, 2009-2016*

| | Coca Cola | | | Pepsi | | |
|---|---|---|---|---|---|---|
| Station | Number of ads (per month) | Average length (seconds) | Average price for 30sec (£) | Number of ads (per month) | Average length (seconds) | Average price for 30sec (£) |
| C4 (Scotland) | 178 | 23.8 | 151.04 | 43 | 25.6 | 110.50 |
| C4 (North West) | 173 | 23.8 | 226.11 | 43 | 25.6 | 183.42 |
| Itv1 (West) | 176 | 23.5 | 508.16 | 27 | 25.8 | 384.89 |
| Sky Sports (National) | 154 | 23.9 | 139.30 | 43 | 29.1 | 338.68 |
| Comedy Central (National) | 162 | 22.8 | 83.42 | 31 | 27.0 | 70.79 |
| E4 (National) | 142 | 23.8 | 349.16 | 28 | 26.6 | 336.49 |
| The Box (National) | 135 | 25.0 | 11.44 | 23 | 25.9 | 35.26 |
| Itv1 (South East) | 134 | 24.1 | 998.71 | 21 | 25.4 | 878.18 |
| Itv1 (Scotland) | 136 | 23.4 | 326.83 | 19 | 24.9 | 272.76 |
| Itv1 (North West) | 133 | 23.5 | 934.27 | 19 | 25.2 | 1096.20 |
| Top 10 | 1524 | 23.8 | 372.84 | 296 | 26.1 | 370.72 |
| All Regional | 2561 | 23.9 | 382.48 | 507 | 25.3 | 383.62 |
| All National | 6549 | 21.4 | 67.52 | 1270 | 23.3 | 62.72 |
| All Stations | 9110 | 21.7 | 104.17 | 1777 | 23.5 | 101.38 |

## B.3 Estimating advertising impact probability

For one year, 2015, we have data on advertising impactS. Table B.2 shows the specific match quality of the adverts between the Kantar media data and AC Nielsen advert data. It shows that the adverts that we managed to match on shows are those where adverts have the largest reach, and are the most expensive.

Table B.2: *Match in 2015 between Kantar media data and AC Nielsen advert data*

| Match | No. ads | Mean TVR | Mean expend | Sum expend |
|---|---|---|---|---|
| Show 1 or 2 | 35,481 | .053371 | 214 | 7,584,502 |
| Station+Slot | 77,083 | .017002 | 105 | 8,104,405 |
| Slot only | 62,270 | .000678 | 13 | 833,836 |

Table B.3: *Match between Kantar media data and AC Nielsen advert data*

| | | |
|---|---|---|
| Show | 209,733 | 20 |
| Station+Slot | 483,180 | 46 |
| Slot only | 352,267 | 34 |
| Total | 1,045,180 | 100 |

In order to estimate each individual consumer's impact to advertising, as specified in equation (2.1) we need an estimate of $w_{ik}$, the probability that consumer $i$ viewed advert $k$.

We use data on viewing for each advert in 2015 from the Broadcasters Audience Research Board (BARB) on "Ratecard Weighted TVR" for adults.[22]. The Television Rating (TVR) values, also called Gross Rating Points (GRP), are the impacts divided by the total target audience.[23] The impacts are the number of pairs of eyes, e.g. 1 person watching an ad 5 times or 5 people seeing an ad once.[24] Ratecard weighted impacts is the metric used by broadcasters to sell advertising slots. They apply different weights to the unweighted impacts to account for differences in cost by slot length contained within that minute. Ordinarily, 1 impact refers to 1 viewer watching one 30-second advertising slot, but as a pair of 15-second slots may be of higher value to an advertiser than a single 30-second slot, unweighted impacts would be insufficient to accurately account for the value of an advertising break. Ratecard weighted impacts account for these differences and allow comparisons to be made in terms of advertising revenue – e.g. one slot generating 50 ratecard weighted impacts can be said to generate half as much revenue as another slot generating 100 ratecard weighted impacts.

Using these data we estimate the relationship between Rate Card Weighted TVRs and whether households report watching a show or station. The households' answers denoted $v_{ik}$ are qualitative and range from "regularly", "sometimes", "hardly ever", "never" watch the show, and the same for the station or slot. We use these to come up with empirical estimates of $w_{ik}$, thanks to the relationship that the viewing answers should have with impacts. We denote $w_q$ the value of the probability of viewing an ad when the answer is $q$ for household $i$ and channel slot $k$.

[22]BARB collects these data as follows: Households are given a remote control with a button on it for each member of the household (and a button to register the presence of guests); each individual must press their button each time they enter or leave the room while the television is on. https://www.barb.co.uk/about-us/how-we-do-what-we-do/. Each household's TV is fitted with a meter, which records 15 seconds of audio from the TV advert and matches this to a reference library.

[23]See https://www.thinkbox.tv/research/barb-data/barb-glossary/; https://www.marketingiq.co.uk/tv-media-planning-terms-calculating-media-reach-and-frequency-using-tvrs/.

[24]See https://www.ofcom.org.uk/__data/assets/pdf_file/0021/63291/costa-statement.pdf

Table B.4 shows the empirical estimates of the following constrained linear regression

$$TVR_k = \sum_q w_q(\frac{1}{N}\sum_i 1_{\{v_{ik}=q\}}) + \omega_k$$

subject to

$$0 \leq w_1 \leq w_2 \leq w_3$$

estimated over all the shows $k$ or stations $k$ or slots $k$ for which we match the BARB rating data and the Kantar media data.

Table B.4: *Estimates of w*

| dep var: Rate Card Weighted TVR | | |
|---|---|---|
| | show | station slot |
| $w_1$ | .0352 | .0274 |
| | (.0223) | (.0040) |
| $w_2$ | .0352 | .0274 |
| | (.0223) | (.0040) |
| $w_3$ | .4975 | .4454 |
| | (.1153) | (.0159) |
| N | 88 | 1208 |

*Notes:* .

# C Equilibrium delegation decision of advertising

To simplify notations and without loss of generality, we assume firms are single product.

The problem of the manufacturing firm willing to use advertising in addition to setting price in its competition game without delegating choices to ad agencies amounts to the following maximization:

$$\max_{p_{jt},T_{jkt},\forall k,t} \sum_{t=0}^{\infty} \beta^t \pi_{jt}(p_{1t},..,p_{Jt},(T_{11\tau},...,T_{JK\tau})_{\tau\leq t}) \tag{C.1}$$

which depends on other firms' decisions, leading to use the concept of Markov Perfect Equilibrium.

In the case of delegation of advertising decisions to an ad agency, the manufacturer however will solve the following problem:

$$\max_{p_{jt},e_{jt},\forall k,t} \sum_{t=0}^{\infty} \beta^t \pi_{jt}(p_{1t},..,p_{Jt},(T^*_{11t}(e_{1t}),...,T^*_{JKt}(e_{jt}))_{\tau\leq t}), \tag{C.2}$$

where $T^*_{jk}(e_{jt})$ represents the optimal choice of ad agencies given the objective to maximize impact and the budget $e_{bt}$.

A manufacturer can choose either to fix prices and advertising to maximize its discounted sum of profit or choose to delegate advertising choices to maximize an impact function subject to a budget. We will consider first a static game and then its dynamic version.

## C.1 Static endogenous choice of delegation of advertising

**Price and advertising competition without delegation** Let's denote the profit of firm $j$ whose single product is sold at price $p_j$ and advertised with $T_{jk}$ on channel $k$ as:

$$\pi_j(p_j, T_j, p_{-j}, T_{-j}) = (p_j - c_j)q_j(p_j, T_j, p_{-j}, T_{-j}) - \sum\nolimits_k \rho_k T_{jk}$$

where $T_j$ is the vector of $(T_{jk})_{k=1,..,K}$ and $\rho_k$ is the price of ads on channel $k$ ($k$ denotes channels and time slots but use the term channel for simplicity).

Denoting with $^*$ the Nash equilibrium when firms don't delegate advertising, a Nash equilibrium $(p^*_j, T^*_{jk}, p^*_{-j}, T^*_{-jk})$ will be solution of:

$$\max_{p_j, T_{jk}} \pi_j(p_j, T_j, p^*_{-j}, T^*_{-j}) \equiv \pi^*_j$$

and symmetrically for $-j$.

**Price and advertising competition with advertising delegation** When the manufacturer delegates to an advertising agency, providing an impact function $f(T_{j1}, .., T_{jK})$ to maximize (independent of prices and of the competing firm's choices), the problem of the manufacturer consists in choosing prices and an advertising budget as solution of:

$$\max_{p_j, e_j} \pi_j(p_j, \tilde{T}_j(e_j), p^{**}_{-j}, \tilde{T}_{-j}(e^{**}_{-j}))) \equiv \pi^{**}_j$$

$$\begin{aligned} \text{where } \tilde{T}_j(e_j) &= \arg\max f(T_{j1}, .., T_{jK}) \\ st &\sum\nolimits_k \rho_k T_{jk} \leq e_j \end{aligned}$$

given the optimal choices of competing firms $p^{**}_{-j}$ and $e^{**}_{-j}$.

The Nash equilibrium $(p^{**}_j, T^{**}_{jk}, p^{**}_{-j}, T^{**}_{-jk})$ are solutions of the above problem with $T^{**}_{jk} \equiv \tilde{T}_j(e^{**}_{-j})$.

Remark first that depending on the own and cross demand effects of advertising, it can be that

$$\pi^*_j \leq \pi^{**}_j \text{ or that } \pi^*_j \geq \pi^{**}_j$$

**Choice of delegation of advertising** Now imagine each manufacturer can choose to delegate or not its advertising decisions.

We assume that each manufacturer has a relative additional fixed cost $\kappa_j$ to solve the price and advertising game in house compared to choosing only prices and advertising budgets, while delegating to ad agencies the slot choices maximizing impact. [25]

In case $\kappa_j$ are both zero, there is only one equilibrium which is not to delegate the advertising decisions to an ad agency because it's always a best response to choose both price and advertising to maximize profit, given the competitors' choices. Note that this is the case even if $\pi_j^{**} \geq \pi_j^*$ because if the manufacturer can choose to delegate or not, the equilibrium decision will be not to delegate but compete more fiercely on both prices and advertising. The reason is that if the competing firm delegates to an advertising agency, the best response should be not to delegate as the manufacturer can then do better by not delegating. Thus in this simultaneous game, all manufacturers will not delegate to an advertising agency.

However, when $\kappa_j > 0$, both firms delegating to an ad agency [26] can be a Nash equilibrium and manufacturers can then get higher profits than if delegating to an ad agency. The reason is that the demand shape can be such that delegation possibly lowers the competition in advertising that can be strong and harmful in a business stealing market environment.

To see this in more details, let's denote :

- $p_j^*(p_{-j}, T_{-j})$ and $T_j^*(p_{-j}, T_{-j})$ the price and advertising best responses of $j$ to the competing price and competing advertising if not delegating to an agency.

- $p_j^{**}(p_{-j}, T_{-j})$ and $T_j^{**}(p_{-j}, T_{-j})$ the price and advertising best responses of $j$ through delegating to an agency, in which case $T_j^{**}(p_{-j}, T_{-j}) \equiv \tilde{T}_j(e_j^{**}(p_{-j}, T_{-j}))$ and $e_j^{**}(p_{-j}, T_{-j})$ is part of the best response of firm $j$ to firm $-j$ as follows: $\max_{p_j, e_j}(p_j - c_j)q_j(p_j, \tilde{T}_j(e_j), p_{-j}, T_{-j}) - \sum_k \rho_k \tilde{T}_{jk}(e_j)$

We then denote $\pi_j^*(p_{-j}, T_{-j})$ the profit of $j$ in case of best response to $(p_{-j}, T_{-j})$ without delegating and $\pi_j^{**}(p_{-j}, T_{-j})$ in case of delegation, that is:

$$\pi_j^*(p_{-j}, T_{-j}) \equiv (p_j^*(p_{-j}, T_{-j}) - c_j)q_j(p_j^*(p_{-j}, T_{-j}), T_j^*(p_{-j}, T_{-j})), p_{-j}, T_{-j}) - \sum_k \rho_k T_{jk}^*(p_{-j}, T_{-j})$$

[25] We do not add here the additional cost that the manufacturer may also have to solve the ad agency problem directly (choosing ad slots to maximize impact) that can justify why ad agencies can ask a markup. Indeed advertising firms may have efficiency gains in solving advertising choices, specialized marketing human capital, knowledge of television advertising markets.

[26] Only one firm delegating can also be an equilibrium, but we do not investigate this particular case.

and

$$\pi_j^{**}(p_{-j},T_{-j}) \equiv (p_j^{**}(p_{-j},T_{-j})-c_j)q_j(p_j^{**}(p_{-j},T_{-j}),T_j^{**}(p_{-j},T_{-j})),p_{-j},T_{-j})-\sum\nolimits_k \rho_k T_{jk}^{**}(p_{-j},T_{-j})$$

By construction $\pi_j^{**}(p_{-j},T_{-j}) \leq \pi_j^{*}(p_{-j},T_{-j})$ for any vector $(p_{-j},T_{-j})$, thus delegating to an agency cannot be a Nash equilibrium of this static game if $\kappa_j = 0$, but can be if $\kappa_j$ and $\kappa_{-j}$ satisfy:

$$\pi_j^{**}(p_{-j}^{**},T_{-j}^{**}) \geq \pi_j^{*}(p_{-j}^{**},T_{-j}^{**}) - \kappa_j \quad \text{and} \quad \pi_{-j}^{**}(p_j^{**},T_j^{**}) \geq \pi_{-j}^{*}(p_j^{**},T_j^{**}) - \kappa_{-j}$$

delegating can also be an equilibrium if

$$\pi_j^{*}(p_{-j}^{*},T_{-j}^{*}) - \kappa_j \geq \pi_j^{**}(p_{-j}^{*},T_{-j}^{*}) \quad \text{and} \quad \pi_{-j}^{*}(p_j^{*},T_j^{*}) - \kappa_{-j} \geq \pi_{-j}^{**}(p_j^{*},T_j^{*})$$

We thus have shown that firms can choose endogenously to delegate to an advertising agency and obtain higher profits than without delegation as soon as there are some fixed cost to solve the full dynamic intractable model of competition in prices and advertising slots. Without fixed cost, it cannot be an equilibrium of the static game but we firms compete dynamically.

## C.2 Endogenous choice of delegation of advertising in the repeated game

For simplicity, we consider the simpler case where advertising has no dynamic effect on demand (because consumers are memory less).

Considering the repeated game of firms wishing to maximize their intertemporal sum of profits with discount factor $\beta \in (0,1)$, delegating to an agency can be a subgame perfect Nash equilibrium even if $\kappa_j = \kappa_{-j} = 0$ provided firms are patient enough ($\beta$ large enough). Indeed, the standard trigger strategy to delegate to an advertising agency as long as the competitor delegates and deviate to the no delegation choice forever as soon as the competing firm does not delegate can support tacitly the delegation equilibrium. For this, we need $\beta$ large enough such that (assuming for simplicity that everything is stationary so that all demand and profit function are time independent)

$$\frac{1}{1-\beta} \underbrace{\pi_j^{**}(p_{-j}^{**},T_{-j}^{**})}_{\substack{\text{Profit of } j \text{ with delegation} \\ given(p_{-j}^{**},T_{-j}^{**})}} \geq \underbrace{\pi_j^{*}(p_{-j}^{**},T_{-j}^{**})}_{\substack{\text{Profit of } j \text{ without delegation} \\ given(p_{-j}^{**},T_{-j}^{**})}} + \frac{\beta}{1-\beta} \underbrace{\pi_j^{*}(p_{-j}^{*},T_{-j}^{*})}_{\substack{\text{profit of } j \\ \text{under no delegation equilibrium}}}$$

and symmetrically for firm $-j$:

$$\frac{1}{1-\beta}\pi^{**}_{-j}(p^{**}_j, T^{**}_j) \geq \pi^{*}_{-j}(p^{**}_j, T^{**}_j) + \frac{\beta}{1-\beta}\pi^{*}_{-j}(p^{*}_j, T^{*}_j)$$

We know that it must be that $\pi^{*}_j(p^{**}_{-j}, T^{**}_{-j}) \geq \pi^{**}_j(p^{**}_{-j}, T^{**}_{-j})$ but as $\frac{1}{1-\beta} > 1$ and $\frac{\beta}{1-\beta} < \frac{1}{1-\beta}$ the inequality above will be satisfied whenever

$$\beta \geq \frac{\pi^{*}_j(p^{**}_{-j}, T^{**}_{-j}) - \pi^{**}_j(p^{**}_{-j}, T^{**}_{-j})}{\pi^{*}_j(p^{**}_{-j}, T^{**}_{-j}) - \pi^{*}_j(p^{*}_{-j}, T^{*}_{-j})}$$

which is always true if $\pi^{*}_j(p^{**}_{-j}, T^{**}_{-j}) - \pi^{*}_j(p^{*}_{-j}, T^{*}_{-j}) < 0$, but could be impossible if

$$\pi^{*}_j(p^{**}_{-j}, T^{**}_{-j}) - \pi^{**}_j(p^{**}_{-j}, T^{**}_{-j}) \geq \pi^{*}_j(p^{**}_{-j}, T^{**}_{-j}) - \pi^{*}_j(p^{*}_{-j}, T^{*}_{-j})$$

that is $\pi^{**}_j(p^{**}_{-j}, T^{**}_{-j}) \leq \pi^{*}_j(p^{*}_{-j}, T^{*}_{-j})$ meaning that the delegation can be an equilibrium of the dynamic game only if the per period profit under joint delegation of all manufacturers are larger than the per period profit under joint no delegation. If that is the case, then there exists a discount factor $\beta^* < 1$ above which the delegation is a subgame perfect Nash equilibrium of the dynamic game.

In conclusion, this simple model shows that the observed delegation of advertising to advertising agency can be rationalized as an equilibrium strategy and can be a more profitable equilibrium than the no delegation strategy.

# D Solution to advertising agency problem

The optimal advertising length during slot $k$ satisfies equation (3.2), which we repeat here

$$T^*_{bk} = f'^{-1}\left(\frac{\rho_k}{\sum_i w_{ik}}\frac{1}{\lambda^*_{bt}}\right).$$

We specify that $f$ is a power function, $f(T) = T^\gamma$, hence $(f')^{-1}(x) = (\frac{x}{\gamma})^{\frac{1}{\gamma-1}}$, and therefore:

$$T^*_{bk} = \left(\frac{1}{\gamma}\frac{\rho_k}{\sum_i w_{ik}}\frac{1}{\lambda^*_{bt}}\right)^{\frac{1}{\gamma-1}}.$$

Note total brand advertising expenditure is

$$e_{bt} = \sum_{\{k|t(k)=t\}} \rho_k T^*_{bk} = \sum_{\{k|t(k)=t\}} \rho_k \left( \frac{\rho_k}{\gamma \sum_i w_{ik}} \right)^{\frac{1}{\gamma-1}} \left( \frac{1}{\lambda^*_{bt}} \right)^{\frac{1}{\gamma-1}}$$

Hence, combining the last two equations, we obtain:

$$T^*_{bk} = \left( \frac{\rho_k}{\sum_i w_{ik}} \right)^{\frac{1}{\gamma-1}} \left( \sum_{\{k|t(k)=t\}} \rho_k \left( \frac{\rho_k}{\sum_i w_{ik}} \right)^{\frac{1}{\gamma-1}} \right)^{-1} e_{bt} \tag{D.1}$$

Allowing for a multiplicative error in the measurement of $\rho_k$, this implies

$$\begin{aligned} \ln \left( \frac{\rho_k}{\sum_i w_{ik}} \right) &= \tau_{t(k)} - (1-\gamma) \log(T^*_{bk}/e_{bt(k)}) + \omega_k \\ &= \tau_{t(kb)} - (1-\gamma) \log(T^*_{bk}) + \omega_k \end{aligned} \tag{D.2}$$

where $\tau_t(kb)$ is a slot-brand fixed effect.

We estimate equation (D.2) using 2015 television advertising data for all food and drink brands. We aggregate the data slightly to the level of brand-station-week-slot type, where slot type is the interaction of weekday/Saturday/Sunday with 1am-6am/6am-9.30am/9.30am-12pm/12pm-2pm/2pm-4pm/4pm-6pm/6pm-10pm/10pm-10.30pm/10.30pm-1.00am. We measure price per views, $\frac{\rho_k}{\sum_i w_{ik}}$, as advertising spend for brand-station-week-slot type divided by rate card weighted television rating among adult viewers. We measure advertising length, $T^*_{bk}$, as advertising duration in seconds. We report estimates in Table D.1. These correspond to the $\hat{\gamma} = 0.64$ (with p-value is smaller than 0.0001) reported in the paper.

Table D.1: *Estimation of* $\gamma$

| | $\ln\left(\frac{\rho_k}{\sum_i w_{ik}}\right)$ |
|---|---|
| $-(1-\gamma)$ | -0.358 |
| | 0.001 |
| Constant | 10.268 |
| | 0.005 |
| Brand-week fixed effects | Yes |
| R-Square | 0.08 |
| N | 2,503,591 |

# E A simple example

In the case of a static single-product monopolist, we illustrate how tax policy impacts the profit-maximizing advertising choice. This serves to highlight two important mechanisms that determine the incentives a firm faces to alter advertising in response to the introduction (or change in the level of) a tax, which in turn can impact of equilibrium outcomes including consumption.

The static single-product monopolist chooses its price, $p$, and its level of advertising, $A$, to maximize its profits. It faces the demand function $Q(p, A)$ (where $Q_p < 0$ and $Q_A > 0$), a constant marginal cost of production, $c$, a specific tax, $\tau$, and a constant marginal cost of advertising, $k$. The monopolist's problem is therefore to choose: $(p^*, A^*) = \arg\max_{p,A}(p-c-\tau)Q(p, A) - kA$.[27] Denote optimal output by $Q^* \equiv Q(p^*, A^*)$, the optimal price-cost margin by $\mu^* \equiv p^* - \tau - c$ and pass-through of a marginal tax increase (holding advertising fixed) on the tax exclusive price $(p^* - \tau)$, relative to the tax inclusive price, by $\rho^* \equiv \left(\frac{dp^*}{d\tau}\big|_{A^*} - 1\right) / \frac{dp}{d\tau}\big|_{A^*}$. Note $\rho^* > / < 0$ if a marginal tax rise is over/under-shifted to prices – i.e., if the monopolist increases/decreases its margin in response (holding advertising fixed). The impact of a marginal increase in the tax rate on optimal advertising depends on the following condition:[28]

$$\text{sign}\left\{\frac{dA^*}{d\tau}\right\} = \text{sign}\left\{\mu^* Q^*_{Ap} + \rho^* Q^*_A\right\}.$$

To interpret this condition, first assume the monopolist sets an exogenous fixed margin (meaning $\frac{dp^*}{d\tau} = 1$ and $\rho^* = 0$). In this case whether the tax raises advertising depends on the cross derivative of demand, $Q^*_{Ap}$. A tax rise increases the (tax-inclusive) price, meaning the firm is forced to produce further up its demand curve. If, at this new higher point of the demand curve, consumers are more/less responsive to advertising then the firm is incentivized to raise/lower its level of advertising. When the firm can adjust its margin (meaning price is also a choice variable), there is a second force at play. If the firm responds to the tax by raising its margin (so $\rho^* > 0$) this will increase the profitability of the marginal consumer and, all else equal, incentivize the firm to raise advertising (with the converse being the case if $\rho^* < 0$). Hence, in the monopoly case, how the composition of demand responsiveness to advertising varies along the demand curve, and whether, in equilibrium, taxes are under- or over-shifted (which depends, inter alia, on the structure of the tax and the curvature

[27] We assume that the profit function in concave in $(p, A)$.

[28] The condition stated in terms of demand primitives is: $\text{sign}\left\{\frac{dA^*}{d\tau}\right\} = \text{sign}\left\{-\frac{Q^*}{Q^*_p}Q^*_{Ap} + \left(-1 + \frac{Q^* Q^*_{pp}}{(Q^*_p)^2}\right) Q^*_A\right\}$.

of demand) will determine advertising responses to taxes. In addition, the fact that the monopolist can vary advertising, leads to a feedback effect on price-setting, and therefore will have direct and indirect effects on the impact of tax on equilibrium consumption.[29]

In reality in most markets firms sell multiple products, tax liability varies across products, firms engage in competition, and advertising has persistent impacts on consumer choice meaning that competition is dynamic in nature. Our model captures these additional determinants of advertising choice, as well as the two forces highlighted in this simple example.

# F Transition function

The mean exposure flow for brand $b$ advertising is

$$\mathbb{a}_{bt} = \frac{1}{I}\sum_i \sum_{\{k|t(k)=t\}} w_{ik} f(T^*_{bk}),$$

and the mean exposure stock is

$$\mathbb{A}_{bt} = \sum_{s=0}^{t-1} \delta^{t-1-s}\mathbb{a}_{bs} = \delta\mathbb{A}_{bt-1} + \mathbb{a}_{bt-1}.$$

Given our power function specification for $f(.)$, $f(T^*_{bk}) = T^{*\gamma}_{bk}$, and the optimality condition for $T^*_{bk}$ (equation (D.1)), this implies that

$$\begin{aligned}
\mathbb{A}_{bt} - \delta\mathbb{A}_{bt-1} =& \frac{1}{I}\sum_i \sum_{\{k|t(k)=t-1\}} w_{ik} T^{*\gamma}_{bk} \\
=& \frac{1}{I}\sum_i \sum_{\{k|t(k)=t-1\}} w_{ik} \left( \left(\frac{\rho_k}{\sum_i w_{ik}}\right)^{\frac{1}{\gamma-1}} \left( \sum_{\{k|t(k)=t\}} \rho_k \left(\frac{\rho_k}{\sum_i w_{ik}}\right)^{\frac{1}{\gamma-1}} \right)^{-1} \right)^{\gamma} e^{\gamma}_{bt-1} \\
\equiv& \lambda_{t-1} e^{\gamma}_{bt-1}
\end{aligned}$$

Defining $\lambda$ as $\mathbb{E}[\mathbb{A}_{bt} - \delta\mathbb{A}_{t-1}] = \lambda e^{\gamma}_{bt-1}$, we get

$$\mathbb{A}_{bt} - \delta\mathbb{A}_{bt-1} = \lambda e^{\gamma}_{bt-1} + \nu_{bt-1}$$

with $\nu_{bt-1} = (\lambda_{t-1} - \lambda)e^{\gamma}_{bt-1}$.

[29] In particular, tax pass-through depends on advertising adjustment, with $\frac{d(p-\tau)^*}{d\tau} > 0$ if and only if $\left(-1 + \frac{Q^* Q^*_{pp}}{(Q^*_p)^2}\right) > \frac{1}{(-Q_p)(-Q_A)}\left(-Q^2_{Ap}\frac{Q}{-Q_P} - Q_A Q_{Ap}\right)$. In contrast, with fixed advertising, $\frac{d(p-\tau)^*}{d\tau} > 0$ if and only if $\left(-1 + \frac{Q^* Q^*_{pp}}{(Q^*_p)^2}\right) > 0$.

# G Solution algorithm

We use the Bellman equations for Coca Cola and Pepsico (equation (3.4)) to solve for the Markov perfect equilibrium. The solution algorithm of the Markov Perfect Equilibrium (Maskin and Tirole, 1988) follows Ericson and Pakes (1995) and Pakes and McGuire (1994) using a discretization after our discretization of the state space as shown in equation (5.2). We have three advertising states for Regular Coke, Diet Coke and Diet Pepsi, and the state grid is of dimension $21^3 = 9,261$, meaning there are points in the discretized state space. We chose a maximum grid point that is way above the observed maximum advertising state exposure in the data and check that the probability to reach this maximum is close to zero for our equilibrium. The value functions for Coke and Pepsi in each state of the grid points are computed by forward simulation. ...

# H Additional estimation and simulation results

Table H.1: *Coefficient estimates*

| | No kids | | | | Pensioner | | | |
|---|---|---|---|---|---|---|---|---|
| Inc. qrt | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 |
| Price | 0.173 | 0.174 | 0.050 | -0.087 | 0.017 | 0.086 | -0.130 | 0.012 |
| | (0.040) | (0.033) | (0.034) | (0.037) | (0.039) | (0.040) | (0.054) | (0.058) |
| Adv | -1.074 | -1.591 | -2.217 | -1.415 | -1.637 | -1.215 | -0.981 | -0.981 |
| | (0.147) | (0.215) | (0.279) | (0.191) | (0.304) | (0.200) | (0.188) | (0.272) |
| Price ($\sigma^2$) | 0.180 | 0.129 | 0.164 | 0.151 | 0.147 | 0.172 | 0.340 | 0.198 |
| | (0.017) | (0.012) | (0.016) | (0.016) | (0.014) | (0.019) | (0.045) | (0.029) |
| Adv ($\sigma^2$) | 0.475 | 0.597 | 1.766 | 0.642 | 0.559 | 0.517 | 0.426 | 0.383 |
| | (0.088) | (0.104) | (0.281) | (0.151) | (0.186) | (0.137) | (0.091) | (0.185) |
| Price-Adv (COV) | 0.283 | 0.276 | 0.463 | 0.311 | 0.079 | 0.293 | 0.348 | 0.207 |
| | (0.031) | (0.027) | (0.040) | (0.041) | (0.021) | (0.044) | (0.049) | (0.057) |
| Coke ($\sigma^2$) | 2.390 | 2.062 | 1.921 | 2.385 | 2.640 | 1.563 | 2.354 | 1.834 |
| | (0.192) | (0.148) | (0.139) | (0.171) | (0.215) | (0.134) | (0.209) | (0.221) |
| Pepsi ($\sigma^2$) | 3.834 | 3.943 | 3.556 | 5.882 | 5.451 | 3.831 | 4.448 | 2.941 |
| | (0.240) | (0.260) | (0.248) | (0.358) | (0.385) | (0.302) | (0.359) | (0.390) |
| Sugary ($\sigma^2$) | 1.731 | 2.029 | 1.898 | 2.702 | 2.150 | 2.079 | 2.358 | 2.254 |
| | (0.088) | (0.099) | (0.098) | (0.130) | (0.104) | (0.105) | (0.153) | (0.161) |
| Adv within firm | 0.126 | 0.076 | 0.142 | 0.066 | 0.234 | 0.299 | 0.118 | 0.364 |
| | (0.062) | (0.057) | (0.053) | (0.056) | (0.065) | (0.065) | (0.081) | (0.097) |
| Adv across firm | 0.190 | -0.028 | 0.096 | 0.107 | 0.440 | 0.303 | 0.093 | -0.292 |
| | (0.061) | (0.060) | (0.057) | (0.062) | (0.070) | (0.071) | (0.089) | (0.108) |
| Entertainment× Coke | 1.156 | -0.858 | 0.234 | -1.477 | 0.393 | 1.418 | -0.997 | 1.765 |
| | (0.454) | (0.440) | (0.353) | (0.500) | (0.515) | (0.544) | (0.564) | (0.720) |
| Shows× Coke | -0.101 | -0.130 | -0.505 | 0.023 | 0.479 | -1.428 | 1.306 | 0.680 |
| | (0.335) | (0.299) | (0.225) | (0.271) | (0.297) | (0.371) | (0.354) | (0.570) |
| Factual× Coke | 0.797 | 0.699 | -0.498 | 0.705 | 0.114 | -0.106 | -0.298 | -0.484 |
| | (0.314) | (0.289) | (0.279) | (0.297) | (0.271) | (0.320) | (0.451) | (0.492) |
| Drama× Coke | -1.260 | -0.031 | 0.326 | -0.936 | -0.272 | -0.088 | 1.318 | -1.430 |
| | (0.361) | (0.315) | (0.374) | (0.323) | (0.324) | (0.308) | (0.378) | (0.504) |
| Reality× Coke | -1.157 | 1.698 | 0.810 | -0.862 | 0.533 | -1.309 | 1.034 | 2.575 |
| | (0.434) | (0.456) | (0.437) | (0.461) | (0.536) | (0.604) | (0.716) | (0.946) |
| Sports× Coke | 1.057 | 0.602 | -0.031 | -0.197 | -1.221 | -0.273 | -0.513 | 0.025 |
| | (0.175) | (0.186) | (0.169) | (0.167) | (0.182) | (0.159) | (0.193) | (0.270) |
| Entertainment× Pepsi | -0.909 | 0.380 | 0.056 | 0.558 | -2.768 | 1.830 | -2.161 | -2.044 |
| | (0.463) | (0.517) | (0.447) | (0.521) | (0.624) | (0.585) | (0.731) | (0.924) |
| Shows× Pepsi | 0.865 | -0.880 | -1.200 | -1.648 | -0.199 | -2.538 | 0.806 | 3.575 |
| | (0.297) | (0.362) | (0.420) | (0.394) | (0.399) | (0.403) | (0.445) | (0.448) |
| Factual× Pepsi | -1.052 | -1.120 | 1.006 | 1.785 | 0.679 | 0.612 | -0.597 | -2.840 |
| | (0.340) | (0.347) | (0.405) | (0.514) | (0.442) | (0.397) | (0.501) | (0.703) |
| Drama× Pepsi | -0.498 | 0.791 | -0.057 | 0.642 | -0.365 | -0.293 | 1.336 | 2.083 |
| | (0.387) | (0.369) | (0.476) | (0.476) | (0.368) | (0.365) | (0.489) | (0.604) |
| Reality× Pepsi | 1.210 | 3.152 | 2.082 | 0.588 | 1.341 | 3.091 | 2.704 | 0.546 |
| | (0.450) | (0.662) | (0.727) | (0.602) | (0.604) | (0.590) | (0.787) | (1.267) |
| Sports× Pepsi | 0.628 | 0.728 | -0.042 | -0.226 | -1.301 | 0.754 | 0.356 | -0.262 |
| | (0.177) | (0.217) | (0.235) | (0.197) | (0.226) | (0.204) | (0.253) | (0.326) |
| ITV× Coke | 0.480 | -0.237 | 0.126 | 0.188 | -0.180 | 0.216 | -0.376 | -0.600 |
| | (0.169) | (0.118) | (0.097) | (0.114) | (0.110) | (0.128) | (0.129) | (0.183) |
| C4× Coke | -0.105 | 0.007 | 0.192 | -0.222 | -0.388 | -0.428 | 0.015 | -0.515 |
| | (0.123) | (0.126) | (0.102) | (0.105) | (0.124) | (0.109) | (0.178) | (0.196) |
| C5× Coke | -0.166 | -0.635 | -0.219 | -0.191 | -0.239 | -0.024 | -0.239 | 0.132 |
| | (0.123) | (0.130) | (0.110) | (0.108) | (0.120) | (0.106) | (0.160) | (0.180) |
| Cable× Coke | 0.984 | 0.380 | 0.331 | 0.633 | -0.141 | 0.273 | 0.202 | -0.082 |
| | (0.138) | (0.119) | (0.112) | (0.111) | (0.121) | (0.116) | (0.130) | (0.181) |
| ITV× Pepsi | -0.257 | -0.681 | -0.335 | 0.327 | 0.097 | -0.087 | -0.200 | -0.262 |
| | (0.153) | (0.141) | (0.118) | (0.176) | (0.143) | (0.161) | (0.201) | (0.266) |
| C4× Pepsi | 0.035 | 0.020 | 0.233 | 0.516 | -0.348 | -0.571 | 0.144 | 0.441 |
| | (0.118) | (0.138) | (0.134) | (0.152) | (0.143) | (0.154) | (0.227) | (0.327) |
| C5× Pepsi | 0.089 | 0.243 | -0.312 | -0.926 | 0.044 | 0.120 | -1.001 | -0.031 |
| | (0.124) | (0.132) | (0.202) | (0.169) | (0.138) | (0.148) | (0.186) | (0.314) |
| Cable× Pepsi | -0.102 | 0.157 | 0.097 | 1.079 | 0.806 | 0.073 | -0.097 | 0.694 |
| | (0.134) | (0.133) | (0.144) | (0.151) | (0.144) | (0.158) | (0.149) | (0.220) |
| Wkend-prime× Coke | 0.289 | -0.152 | -0.054 | -0.369 | -0.781 | -1.306 | 0.818 | -0.244 |
| | (0.222) | (0.170) | (0.140) | (0.168) | (0.229) | (0.238) | (0.311) | (0.307) |
| Wkend-non prime× Coke | -0.337 | -0.394 | -0.513 | 0.505 | -0.155 | 0.777 | 0.490 | -0.298 |
| | (0.168) | (0.127) | (0.113) | (0.134) | (0.170) | (0.162) | (0.211) | (0.252) |
| Wkday-prime× Coke | -0.368 | 0.380 | 0.403 | -0.169 | 0.140 | 0.326 | 0.007 | -0.479 |
| | (0.277) | (0.203) | (0.183) | (0.168) | (0.281) | (0.300) | (0.267) | (0.313) |
| Wkday-non prime× Coke | -0.500 | 0.145 | 0.278 | -0.106 | -0.066 | -0.390 | 0.379 | -0.198 |
| | (0.168) | (0.144) | (0.105) | (0.117) | (0.181) | (0.187) | (0.194) | (0.183) |
| Wkend-prime× Pepsi | -0.092 | -0.496 | -0.173 | -0.607 | 0.290 | -0.239 | 0.595 | 0.604 |
| | (0.206) | (0.209) | (0.216) | (0.207) | (0.357) | (0.293) | (0.352) | (0.504) |
| Wkend-non prime× Pepsi | 0.065 | 0.383 | 0.533 | -0.226 | -0.372 | 0.821 | -0.569 | 0.544 |
| | (0.162) | (0.175) | (0.152) | (0.187) | (0.241) | (0.219) | (0.220) | (0.284) |
| Wkday-prime× Pepsi | 0.517 | 0.570 | -0.208 | -1.041 | 1.133 | 0.511 | 0.428 | -0.548 |
| | (0.220) | (0.281) | (0.231) | (0.281) | (0.422) | (0.383) | (0.341) | (0.406) |
| Wkday-non prime× Pepsi | 0.233 | 0.062 | -0.236 | -0.183 | -0.844 | -0.360 | 0.295 | -0.031 |
| | (0.150) | (0.161) | (0.152) | (0.155) | (0.241) | (0.215) | (0.211) | (0.277) |
| Viewing hours× Coke | -0.125 | 0.007 | -0.060 | -0.043 | -0.389 | -0.048 | -0.105 | 0.072 |
| | (0.087) | (0.077) | (0.072) | (0.063) | (0.087) | (0.087) | (0.112) | (0.079) |
| Viewing hours× Pepsi | -0.262 | -0.188 | -0.141 | 0.238 | -0.600 | -0.170 | -0.219 | -0.039 |
| | (0.064) | (0.075) | (0.074) | (0.103) | (0.107) | (0.117) | (0.148) | (0.158) |

Table H.2: *Coefficient estimates*

| | Family | | | |
|---|---|---|---|---|
| Inc. qrt | Q1 | Q2 | Q3 | Q4 |
| Price | 0.154 (0.031) | 0.149 (0.032) | 0.092 (0.033) | -0.036 (0.033) |
| Adv | -2.754 (0.652) | -1.658 (0.232) | -2.210 (0.332) | -1.372 (0.166) |
| Price ($\sigma^2$) | 0.145 (0.012) | 0.118 (0.011) | 0.159 (0.014) | 0.118 (0.013) |
| Adv ($\sigma^2$) | 0.777 (0.424) | 0.659 (0.194) | 0.889 (0.257) | 0.451 (0.082) |
| Price-Adv (COV) | -0.015 (0.013) | 0.229 (0.040) | 0.339 (0.053) | 0.230 (0.027) |
| Coke ($\sigma^2$) | 2.448 (0.172) | 2.401 (0.174) | 2.059 (0.156) | 1.983 (0.136) |
| Pepsi ($\sigma^2$) | 3.169 (0.229) | 3.999 (0.251) | 4.178 (0.338) | 3.677 (0.238) |
| Sugary ($\sigma^2$) | 1.773 (0.088) | 1.904 (0.096) | 1.909 (0.096) | 1.720 (0.088) |
| Adv within firm | 0.063 (0.053) | 0.065 (0.055) | 0.046 (0.054) | 0.123 (0.054) |
| Adv across firm | 0.134 (0.057) | 0.034 (0.058) | 0.080 (0.057) | -0.124 (0.058) |
| Entertainment× Coke | -0.283 (0.331) | 0.325 (0.375) | -1.250 (0.392) | -0.065 (0.402) |
| Shows× Coke | 0.346 (0.259) | -0.789 (0.295) | 0.825 (0.248) | -0.050 (0.250) |
| Factual× Coke | 0.391 (0.279) | 0.297 (0.261) | -0.422 (0.256) | -0.842 (0.252) |
| Drama× Coke | -1.472 (0.389) | 0.862 (0.349) | -0.222 (0.422) | 0.330 (0.444) |
| Reality× Coke | 1.619 (0.357) | -0.915 (0.367) | 1.702 (0.452) | 1.238 (0.441) |
| Sports× Coke | -0.610 (0.154) | 0.016 (0.177) | -0.819 (0.210) | 0.434 (0.153) |
| Entertainment× Pepsi | 0.598 (0.372) | 0.219 (0.489) | -0.825 (0.403) | 0.230 (0.500) |
| Shows× Pepsi | 0.402 (0.254) | 0.518 (0.353) | 0.338 (0.303) | -1.426 (0.309) |
| Factual× Pepsi | -0.759 (0.308) | -1.878 (0.309) | 0.383 (0.311) | 0.998 (0.390) |
| Drama× Pepsi | -1.698 (0.370) | 0.193 (0.486) | -0.452 (0.401) | 0.691 (0.852) |
| Reality× Pepsi | 3.237 (0.414) | -0.486 (0.418) | -0.024 (0.669) | 1.898 (0.528) |
| Sports× Pepsi | -0.086 (0.196) | 0.017 (0.210) | -0.173 (0.212) | 0.152 (0.192) |
| ITV× Coke | 0.109 (0.113) | 0.083 (0.112) | -0.105 (0.161) | -0.308 (0.107) |
| C4× Coke | -0.493 (0.119) | 0.452 (0.108) | 0.001 (0.119) | -0.559 (0.105) |
| C5× Coke | -0.358 (0.113) | -0.390 (0.108) | -0.090 (0.125) | -0.273 (0.146) |
| Cable× Coke | 0.188 (0.117) | 0.134 (0.129) | 0.339 (0.146) | -0.051 (0.102) |
| ITV× Pepsi | 0.103 (0.123) | 0.002 (0.131) | -0.766 (0.167) | 0.400 (0.140) |
| C4× Pepsi | -0.635 (0.144) | 0.472 (0.127) | 0.393 (0.119) | -1.129 (0.134) |
| C5× Pepsi | -0.160 (0.137) | 0.223 (0.122) | 0.427 (0.153) | 0.135 (0.145) |
| Cable× Pepsi | 0.174 (0.131) | 0.616 (0.125) | -0.031 (0.141) | 0.568 (0.150) |
| Wkend-prime× Coke | -0.167 (0.157) | 0.234 (0.163) | -0.518 (0.198) | -0.038 (0.141) |
| Wkend-non prime× Coke | 0.069 (0.122) | -0.115 (0.128) | 0.477 (0.146) | -0.023 (0.123) |
| Wkday-prime× Coke | 0.293 (0.171) | -0.073 (0.213) | 0.327 (0.193) | 0.082 (0.149) |
| Wkday-non prime× Coke | -0.241 (0.113) | -0.059 (0.113) | 0.190 (0.130) | 0.402 (0.104) |
| Wkend-prime× Pepsi | 0.338 (0.183) | -0.182 (0.218) | 0.608 (0.236) | -0.515 (0.184) |
| Wkend-non prime× Pepsi | -0.280 (0.128) | 0.216 (0.135) | -0.221 (0.216) | -0.076 (0.188) |
| Wkday-prime× Pepsi | 0.352 (0.192) | 0.543 (0.226) | -0.080 (0.203) | 0.478 (0.203) |
| Wkday-non prime× Pepsi | 0.213 (0.122) | -0.400 (0.130) | 0.852 (0.190) | 0.069 (0.170) |
| Viewing hours× Coke | 0.014 (0.087) | 0.118 (0.087) | -0.103 (0.079) | 0.059 (0.056) |
| Viewing hours× Pepsi | -0.074 (0.104) | 0.158 (0.078) | 0.001 (0.074) | -0.031 (0.080) |

Table H.3: *Product level markups*

| Firm | Brand | Pack | Marginal cost (£/l) | Price-cost margin (£/l) | Lerner index |
|---|---|---|---|---|---|
| Coca Cola Enterprises | Regular Coke | Bottle(s): 1.25l: Single | 0.07 | 0.77 | 0.92 |
| | | Bottle(s): 1.5l: Single | 0.21 | 0.71 | 0.77 |
| | | Bottle(s): 1.75l: Single | 0.12 | 0.78 | 0.87 |
| | | Bottle(s): 1.75l: Multiple | 0.33 | 0.41 | 0.56 |
| | | Cans: 10x330ml: Single | 0.60 | 0.42 | 0.41 |
| | | Cans: 12x330ml: Single | 0.57 | 0.38 | 0.40 |
| | | Cans: 15x330ml: Single | 0.58 | 0.39 | 0.40 |
| | | Cans: 24x330ml: Single | 0.58 | 0.24 | 0.29 |
| | | Bottle(s): 2l: Single | 0.17 | 0.70 | 0.80 |
| | | Bottle(s): 2l: Multiple | 0.30 | 0.34 | 0.53 |
| | | Cans: 30x330ml: Single | 0.56 | 0.24 | 0.30 |
| | | Bottle(s): 3l: Single | 0.29 | 0.30 | 0.50 |
| | | Bottle(s): 4x1.5l: Single | 0.41 | 0.31 | 0.43 |
| | | Cans: 6x330ml: Single | 0.73 | 0.64 | 0.47 |
| | | Cans: 8x330ml: Single | 0.57 | 0.42 | 0.42 |
| | Diet Coke | Bottle(s): 1.25l: Single | 0.03 | 0.82 | 0.96 |
| | | Bottle(s): 1.5l: Single | 0.10 | 0.70 | 0.88 |
| | | Bottle(s): 1.75l: Single | 0.09 | 0.79 | 0.90 |
| | | Bottle(s): 1.75l: Multiple | 0.31 | 0.41 | 0.56 |
| | | Cans: 10x330ml: Single | 0.59 | 0.42 | 0.42 |
| | | Cans: 12x330ml: Single | 0.56 | 0.37 | 0.40 |
| | | Cans: 15x330ml: Single | 0.50 | 0.39 | 0.44 |
| | | Cans: 24x330ml: Single | 0.58 | 0.25 | 0.30 |
| | | Bottle(s): 2l: Single | 0.03 | 0.67 | 0.96 |
| | | Bottle(s): 2l: Multiple | 0.26 | 0.33 | 0.56 |
| | | Cans: 30x330ml: Single | 0.56 | 0.24 | 0.30 |
| | | Bottle(s): 3l: Single | 0.30 | 0.28 | 0.48 |
| | | Bottle(s): 4x1.5l: Single | 0.44 | 0.32 | 0.42 |
| | | Cans: 6x330ml: Single | 0.69 | 0.55 | 0.44 |
| | | Cans: 8x330ml: Single | 0.58 | 0.41 | 0.42 |
| Pepsico | Regular Pepsi | Bottle(s): 2l: Single | 0.14 | 0.38 | 0.74 |
| | | Cans: 6x330ml: Single | 0.27 | 0.59 | 0.68 |
| | | Cans: 8x330ml: Single | 0.36 | 0.47 | 0.56 |
| | Diet Pepsi | Bottle(s): 1.5l: Single | -0.03 | 0.66 | 1.04 |
| | | Cans: 12x330ml: Single | 0.49 | 0.48 | 0.49 |
| | | Bottle(s): 2l: Single | 0.16 | 0.37 | 0.70 |
| | | Cans: 6x330ml: Single | 0.28 | 0.59 | 0.68 |
| | | Cans: 8x330ml: Single | 0.44 | 0.41 | 0.48 |

*Notes:* .

Table H.4: *Price-level price elasticities*

| | Reg Coke | | Diet Coke | | Reg Pepsi | | Diet Pepsi | |
|---|---|---|---|---|---|---|---|---|
| | 2l | 10×330ml | 2l | 10×330ml | 2l | 8×330ml | 2l | 10×330ml |
| Regular Coke: 1.5l | 0.047 | 0.041 | 0.024 | 0.034 | 0.037 | 0.012 | 0.062 | 0.024 |
| Regular Coke: 2l | -1.915 | 0.044 | 0.024 | 0.040 | 0.039 | 0.013 | 0.061 | 0.024 |
| Regular Coke: 10x330ml | 0.023 | -3.829 | 0.013 | 0.044 | 0.035 | 0.014 | 0.058 | 0.033 |
| Regular Coke: 24x330ml | 0.012 | 0.051 | 0.006 | 0.044 | 0.029 | 0.015 | 0.046 | 0.037 |
| Diet Coke: 1.5l | 0.024 | 0.021 | 0.049 | 0.059 | 0.018 | 0.006 | 0.099 | 0.038 |
| Diet Coke: 2l | 0.023 | 0.024 | -1.793 | 0.069 | 0.020 | 0.006 | 0.097 | 0.038 |
| Diet Coke: 10x330ml | 0.012 | 0.026 | 0.021 | -3.844 | 0.016 | 0.007 | 0.085 | 0.051 |
| Diet Coke: 24x330ml | 0.007 | 0.026 | 0.011 | 0.078 | 0.014 | 0.007 | 0.072 | 0.056 |
| Reg Pepsi: 2l | 0.008 | 0.013 | 0.004 | 0.011 | -2.019 | 0.091 | 0.361 | 0.156 |
| Regular Pepsi: 8x330ml | 0.007 | 0.015 | 0.004 | 0.012 | 0.242 | -2.890 | 0.332 | 0.171 |
| Diet Pepsi: 1.5l | 0.005 | 0.006 | 0.008 | 0.014 | 0.117 | 0.037 | 0.565 | 0.214 |
| Diet Pepsi: 2l | 0.005 | 0.007 | 0.008 | 0.019 | 0.119 | 0.041 | -1.951 | 0.240 |
| Diet Pepsi: 8x330ml | 0.004 | 0.008 | 0.006 | 0.022 | 0.101 | 0.042 | 0.473 | -3.302 |
| Regular store: 2l | 0.011 | 0.015 | 0.006 | 0.012 | 0.047 | 0.016 | 0.073 | 0.030 |
| Diet store: 2l | 0.006 | 0.008 | 0.011 | 0.022 | 0.024 | 0.008 | 0.116 | 0.048 |
| Regular outside | 0.011 | 0.012 | 0.007 | 0.011 | 0.039 | 0.012 | 0.068 | 0.026 |
| Diet outside | 0.007 | 0.007 | 0.012 | 0.019 | 0.021 | 0.007 | 0.108 | 0.040 |

Table H.5: *Brand price and advertising elasticities, with no advertising spillovers*

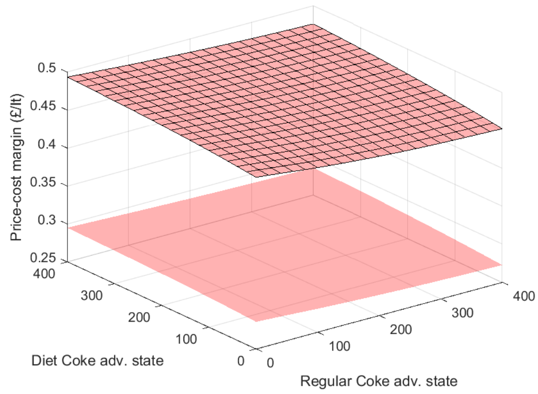
| | Price elasticities | | | | Advertising elasticities | | |
|---|---|---|---|---|---|---|---|
| | Coke | | Pepsi | | Coke | | Pepsi |
| | Regular | Diet | Regular | Diet | Regular | Diet | Diet |
| (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Regular Coke | **-2.218** | 0.507 | 0.050 | 0.091 | **0.143** | -0.024 | -0.003 |
| Diet Coke | 0.378 | **-2.210** | 0.023 | 0.142 | -0.021 | **0.134** | -0.005 |
| Regular Pepsi | 0.212 | 0.129 | **-1.853** | 0.541 | -0.010 | -0.006 | -0.018 |
| Diet Pepsi | 0.111 | 0.234 | 0.155 | **-1.702** | -0.006 | -0.012 | **0.070** |
| Regular Store | 0.244 | 0.154 | 0.063 | 0.105 | -0.013 | -0.008 | -0.004 |
| Diet Store | 0.130 | 0.276 | 0.031 | 0.169 | -0.007 | -0.015 | -0.006 |
| Regular outside | 0.184 | 0.136 | 0.050 | 0.093 | -0.013 | -0.009 | -0.004 |
| Diet outside | 0.104 | 0.234 | 0.026 | 0.150 | -0.007 | -0.015 | -0.006 |

*Notes: Numbers repeat those in Table 4.1, but based on demand estimates with no spillover effects (i.e., where we re-estimate the model constraining $\beta_d^W = \beta_d^X = 0$ for all d.)*

Figure H.1: *Impact of ad valorem tax and advertising restriction*

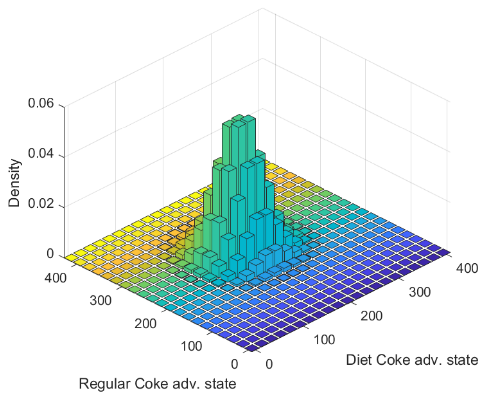
*On static equilibrium*

(a) Regular Coke margins

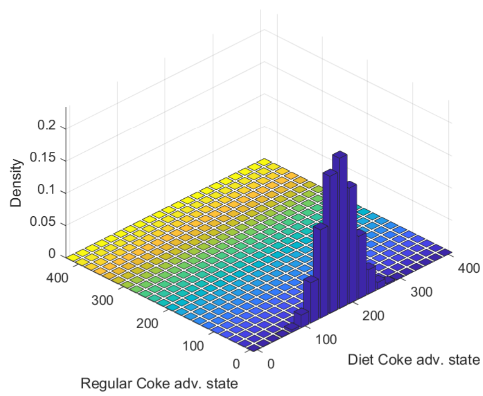



*On equilibrium distribution*

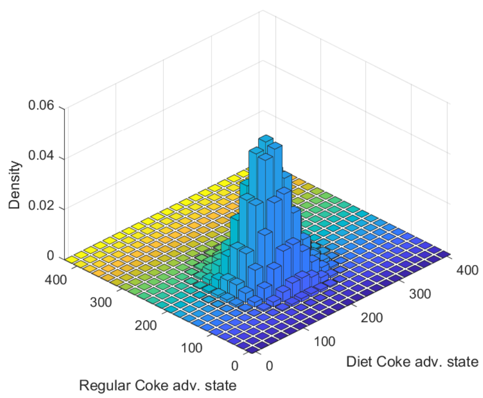
(b) Pre-policy



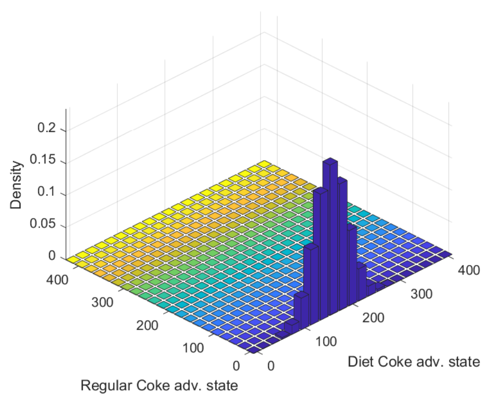

(c) Advertising restriction




(d) Tax




(e) 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 (and repeats Figure 5.2(a)) and the smooth surface corresponds to when an ad valorem tax is in place. In each case we hold fixed the Diet Pepsi advertising state at the highest probability state in the pre-policy equilibrium distribution. Panels (b)-(e) show the ergodic distribution, integrating over the Diet Pepsi advertising state space. Panel (b) repeats Figure 5.4(b).*

Table H.6: *Aggregate impact of counterfactual policies, by brand*

| | No tax | Specific tax | | | Ad valorem tax | | |
|---|---|---|---|---|---|---|---|
| | Adv. restrict. | Fixed adv. | + Eq. adv. response | + Adv. restrict. | Fixed adv. | + Eq. adv. response | + Adv. restrict. |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **Δ price** | | | | | | | |
| Reg Coke | 0.9% | 32.1% | 0.1% | 0.6% | 44.6% | 0.1% | 0.5% |
| Diet Coke | -1.3% | -1.7% | -0.1% | -0.8% | -1.8% | -0.2% | -0.7% |
| Reg Pepsi | -0.1% | 38.9% | -0.0% | -0.1% | 29.6% | -0.1% | -0.1% |
| Diet Pepsi | -0.0% | -0.6% | -0.0% | -0.0% | -0.2% | -0.0% | -0.0% |
| Reg Store | - | - | - | - | - | - | - |
| Diet Store | - | - | - | - | - | - | - |
| Reg Outside | - | - | - | - | - | - | - |
| Diet Outside | - | - | - | - | - | - | - |
| **Δ margin** | | | | | | | |
| Reg Coke | 1.9% | 5.9% | 0.3% | 1.3% | -37.5% | 0.2% | 0.6% |
| Diet Coke | -2.8% | -3.7% | -0.3% | -1.7% | -3.9% | -0.5% | -1.6% |
| Reg Pepsi | -0.1% | 6.5% | -0.0% | -0.2% | -39.2% | -0.1% | -0.1% |
| Diet Pepsi | -0.0% | -1.0% | -0.0% | -0.0% | -0.3% | -0.1% | -0.0% |
| Reg Store | - | - | - | - | - | - | - |
| Diet Store | - | - | - | - | - | - | - |
| Reg Outside | - | - | - | - | - | - | - |
| Diet Outside | - | - | - | - | - | - | - |
| **Δ advertising exp.** | | | | | | | |
| Reg Coke | -100.0% | - | -33.1% | -100.0% | - | -47.3% | -100.0% |
| Diet Coke | -12.0% | - | -6.4% | -17.5% | - | -13.7% | -23.5% |
| Reg Pepsi | - | - | - | - | - | - | - |
| Diet Pepsi | 0.1% | - | 2.3% | 1.6% | - | 1.0% | 0.3% |
| Reg Store | - | - | - | - | - | - | - |
| Diet Store | - | - | - | - | - | - | - |
| Reg Outside | - | - | - | - | - | - | - |
| Diet Outside | - | - | - | - | - | - | - |
| **Δ quantity** | | | | | | | |
| Reg Coke | -16.4% | -60.1% | -1.1% | -5.0% | -66.6% | -1.7% | -4.1% |
| Diet Coke | -6.0% | 15.6% | -1.6% | -7.5% | 16.9% | -3.0% | -6.9% |
| Reg Pepsi | -1.8% | -58.2% | -0.2% | -0.8% | -37.0% | -0.5% | -1.2% |
| Diet Pepsi | -1.6% | 8.7% | -0.2% | -1.9% | 6.4% | -0.5% | -1.7% |
| Reg Store | 3.2% | 8.6% | 0.4% | 2.0% | 8.3% | 0.7% | 1.8% |
| Diet Store | 2.8% | 3.8% | 0.4% | 2.0% | 3.7% | 0.7% | 1.8% |
| Reg Outside | 3.1% | 6.3% | 0.4% | 1.8% | 5.9% | 0.7% | 1.7% |
| Diet Outside | 2.6% | 2.9% | 0.4% | 1.8% | 2.7% | 0.7% | 1.7% |

Table H.7: *Aggregate impact of counterfactual policies, by brand*

| | 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 profits** | | | | | | | |
| Reg Coke | -4.7% | -25.2% | 0.4% | -0.8% | -35.8% | 0.8% | 0.2% |
| Diet Coke | -3.7% | 5.2% | -0.8% | -4.0% | 5.6% | -1.3% | -3.6% |
| Reg Pepsi | -1.3% | -36.7% | -0.1% | -0.7% | -42.4% | -0.2% | -0.5% |
| Diet Pepsi | -1.0% | 4.5% | -0.2% | -1.1% | 3.6% | -0.4% | -1.0% |
| Reg Store | - | - | - | - | - | - | - |
| Diet Store | - | - | - | - | - | - | - |
| Reg Outside | - | - | - | - | - | - | - |
| Diet Outside | - | - | - | - | - | - | - |

*Notes: Numbers for price, margins, advertising expenditure and quantities are expressed as a percentage of the pre-policy (i.e., pre tax and advertising restriction) level; numbers for profits are expressed as a percentage of pre-policy total consumer expenditure. Columns (1), (2) and (5) show changes relative to the pre-policy level. Column (3) (column (6)) shows the incremental change relative to column (2) (column (5)) and column (4) (column (7)) shows the incremental change.*