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

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*Abi-Rafeh: Institute for Fiscal Studies and Amazon, rossi.abi-rafeh@ifs.org.uk; Dubois: Toulouse School of Economics, pierre.dubois@tse-fr.eu; Griffith: University of Manchester and Institute for Fiscal Studies, 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 the authors on the basis of their own work using data supplied by the Kantar Take 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 authors' analysis and findings. All errors and omissions remain the responsibility of the authors of this publication.

# 1 Introduction

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

In this paper, we make two contributions to the existing literature. First, we develop and empirically implement a framework that integrates a rich model of consumer choice, including the influence of individual-level exposure to television advertising, with firms' dynamic supply-side decisions regarding television advertising budgets. The dynamics arise because advertising influences product demand both contemporaneously and over time. Firms face the choice of advertising on a vast number of possible TV time and channel slots, meaning they face a high-dimensional decision. To address the challenge of solving a dynamic game with such a large action space, we develop a tractable framework that reflects the organization of the advertising market. Specifically, we model firms as choosing overall television advertising expenditures, while delegating slot selection to advertising agencies. Delegation, which we show can arise as an equilibrium decision, reduces the action space of firms to a decision over advertising expenditures, while preserving the link between these choices and the rich patterns of consumer exposure to aired advertisements.

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

Our results suggest that a ban on advertising sugary colas, if implemented alone, would have a relatively modest impact on total sugar consumption from drinks, reducing it by 2.7%. This evidence is timely, as the role of advertising in driving excess consumption is an active area of policy interest.[2] In comparison, taxes of the scale similar to those implemented

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

[2] Many governments already restrict advertising of other sin goods, such as tobacco and alcohol, and the World WHO recommends extending these restrictions to advertising of unhealthy foods (see, WHO

globally have a much larger effect, reducing sugar consumption by approximately 16.5%. If an advertising restriction is implemented alongside a tax, its additional impact is minimal (0.4%), partly because tax-induced price increases lead the most advertising-sensitive consumers to substitute to alternatives.

To tractably capture strategic advertising competition, we explicitly account for the intermediary role played by advertising agencies. This institutional feature of the UK television advertising market (see Crawford et al., 2017) is also common in other countries, including in the US (see Hristakeva and Mortimer, 2023). This approach mirrors recent work by Hortaçsu et al. (2024), who exploit within-firm delegation in decision-making to simplify the complex dynamic optimization problem faced by airline companies. We study the UK cola market, where two dominant firms (Coca Cola and Pepsico) compete. There are also a few cheaper store brand alternatives. Both Coca Cola and Pepsico advertise, while store brands do not.[3] We model the decisions Coca Cola and Pepsico make over their monthly advertising budgets and rationalize the decision to delegate the buying of advertising slots to an agency. The model links the rich variation in consumer advertising exposure resulting from the choice of advertising slots to the firms' strategic decisions over advertising investment. The agencies simplify the dynamic advertising game by reducing firms' action space from a highly multi-dimensional set (entailing choices over the timing and channels of each advertising slot) to a decision over total monthly expenditure. This reduction in dimensionality makes solving Coca Cola and Pepsico intertemporal profit-maximization problems feasible.

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

(2025). The UK government has announced plans to introduce regulations that will restrict the advertising of unhealthy foods, aiming to reduce consumption (DHSC, 2024).

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

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

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

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

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

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

Our paper advances the literature on the ex ante evaluation of the effects of sin taxes. This literature, which studies the incidence and optimal design of sin taxes, focuses on the impact that tax has on consumption through higher prices (e.g., Bonnet and Réquillart, 2013; Harding and Lovenheim, 2017; Griffith et al., 2019; Dubois et al., 2020; O'Connell and Smith, 2024). Wang (2015) estimate a demand model that incorporates dynamics through consumer stockpiling, while Kim and Ishihara (2021) estimate a model of rational addiction, both simulating consumer responses to a tax on sugar-sweetened beverages. In contrast, we focus on dynamics that arise through the persistent effects of advertising. We contribute to this literature by showing how firms' dynamic advertising decisions shape the impact of sin taxes and highlighting an important interaction between margin adjustment and the returns to advertising investment.[4]

The rest of the paper is structured as follows. Section 2 introduces our main data sources, summarizes key features of the cola market, and provide evidence on the relationship between advertising exposure and consumption. Section 3 describes our dynamic equilibrium model. Sections 4 and 5 describe our empirical specification, present estimates, and characterize market equilibrium in the absence of taxes or advertising restrictions. Section 6 presents our results on the impacts of tax and advertising restrictions.[5]

# 2 The Market for Colas

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

We focus on the cola market, which accounts for the majority (over 70%) of sugar- and artificially-sweetened beverages advertising. We use UK data covering the period 2010–2016. The UK introduced an SSB tax in April 2018, structured to incentivize firms to reduce sugar content and thereby avoid the tax. As a result, only the two leading cola brands, along with a few niche energy drinks, are subject to the tax (Dickson et al., 2023). Therefore, our focus on the UK cola market captures the majority of products affected by the country's SSB tax.

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

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

## 2.1 Market Structure

We use microdata on drinks purchases from a sample of consumers in Great Britain, collected by the market research firm Kantar as part of their Take Home Purchase Panel. Our dataset covers over 21,000 households that record all grocery purchases they bring into the home using a handheld scanner or mobile phone app. We observe detailed product information, including transaction prices, along with demographic variables and detailed measures of household television viewing behavior. The data have a panel structure covering from 2010 and 2016, with the average household present in the data for over 100 weeks.

The cola market is dominated by two firms: Coca Cola Enterprises, with a market share of 60.7% and Pepsico, with 33.4% (see Table 2.1). Each firm sells Regular and Diet versions of its cola. Coca Cola Enterprises' market share is split approximately equally between Regular and Diet Coke, with the latter accounting for just under 60% of its market share. In contrast, around three-fourths of Pepsico's market share is accounted for by Diet Pepsi. The remaining products in the market are store brands (also referred to as own brand and private-label products). Each brand is sold in various container types and sizes (e.g., 4×330ml cans or 2l bottle). In total there are 42 products in the UK cola market.[6]

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 Take Home Purchase Panel for 2010-2016. Diet Coke includes Coke Zero and Diet Pepsi includes Pepsi Max.*

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

## 2.2 Television Advertising

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

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

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

In our analysis, we model how advertising influences consumer choice and remain agnostic—except in Sections 6.2 and 6.3, where we discuss welfare effects—about whether these choice reveal underlying preferences or are influenced by behavioral bias. Since both Coca Cola and Pepsi are universally recognized brands, and their advertisements primarily emphasize the pleasure of consuming them, we do not consider the case where advertising for Coca Cola and Pepsi is informative, either about product existence or characteristics.

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

## 2.3 Household Exposure to TV Advertising

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

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

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

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

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

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

## 2.4 Evidence of Advertising Effects

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

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

$$vol_{ibt} = \alpha \log A_{ibt} + \tau_t + \iota_{d,q(t)} + \kappa_{r,q(t)} + \eta_i + \epsilon_{it}. \tag{2.2}$$

$vol_{ibt}$ is the volume of brand $b$ purchased by household $i$ in week $t$. If the household purchases any other drink (e.g., another cola brand, non-cola soft drink, or fruit juice), then $vol_{ibt} = 0$. $A_{ibt}$ represents the household's stock of advertising exposure for brand $b$, $\tau_t$ are year-week fixed effects, and $\iota_{d,q(t)}$ and $\kappa_{r,q(t)}$ capture demographic-year-quarter and region-year-quarter effects, respectively. We define $A_{ibt}$ as $A_{ibt} = \delta A_{ibt-1} + a_{ibt-1}$, where $\delta$ is the weekly "carry-over" parameter, which we set to 0.9. In Appendix B.4 we provide empirical support for this value.[8]

A challenge in estimating the impact of advertising on consumer choices is that high-demand households may be exposed to more advertising, or advertising may be higher during periods when demand is elevated for other reasons. Equation (2.2) controls for these confounding factors by including household fixed effects, year-week effects and time-varying demographic and region effects. The residual variation is within-household. In the TV advertising market, advertisers delegate to agencies, who purchase slots from stations, often weeks in advance. This, combined with the predominately national nature of UK TV advertising, makes precise targeting of individual households, beyond predicted demand across relatively broad demographic group, challenging. Equation (2.2) controls for the small amount of regional variation in advertising through time-varying region effects. The remaining variation in expo-

[8]Specifically, we conduct non-nested tests of $\delta = 0.9$ against alternatives, which provide empirical support in favor of $\delta = 0.9$. Note, this is same value used in Shapiro et al. (2021). To construct $A_{ibt}$ we also need the form of $\omega(\cdot)$ in equation (2.1). As discussed in Section 4.1, we specify this is as a power function, estimating an exponent value that implies a 60 second advertisement generates 1.56 times the exposure of one 30 second advert, rather than twice as effective, which would be the case without diminishing returns in consumer attention. We use this estimated value here.

sure arises because, while agencies negotiate with stations to secure advertising impressions, they do not determine the exact timing of adverts, with stations having some flexibility in ad placement when fulfilling agencies' orders (see Crawford et al., 2017; Hristakeva and Mortimer, 2023). The task of fulfilling orders across all markets (not just cola advertisements) and constraints on slot availability results in substantial variation in advertising exposure across similar households.

In Table 2.2, we report estimates of the advertising coefficient from equation (2.2), along with the mean of the dependent variable and implied elasticities. The coefficients indicate positive and statistically significant advertising effects, with elasticities of approximately 0.1 for Regular Coke and Diet Coke, and 0.05 for Diet Pepsi. Recent work by Shapiro et al. (2021) has provided evidence that TV advertising elasticities are lower than previously thought. Our elasticity estimates fall within the upper third of the brand-level elasticities they report for 288 brands, based on quasi-random cross-region variation in gross rating points. Our estimates are somewhat larger in magnitude than their elasticity estimates for cola brands (in their baseline specification, their Regular Coke and Diet Pepsi own brand advertising elasticities are 0.03, p-value under 0.01, and 0.02, p-value of 0.07, and they do not find a statistically significant positive elasticity for Diet Coke). However, it is important to note that their estimates are for the US market, while our estimates are for the UK. There are many possible reasons why the precise magnitude of effects may vary between the two countries; for example, the lower level of advertising on UK TV, due to tighter restrictions in commercial break lengths, coupled with diminishing returns to advertising may be one factor that contribute to larger effects in the UK.

Advertising enters equation (2.2) via a concave (log) transformation. In Figure B.5 in the Appendix, we show the relationship between Regular Coke volumes and advertising stocks (conditional on the same controls) non-parametrically. The graph confirms the positive relationship between advertising exposure and volume, with diminishing marginal effects at higher levels of exposure.

In the structural model that follows, we account for heterogeneous responses to advertising, correlation between advertising and price sensitivity, and potential advertising spillover effects. We use controls for household TV viewing behavior, along with time-varying demographic effects, to capture advertisers targeting based on predictable aspects of demand. As we show in Section 4.4, our structural advertising elasticities estimates align with the evidence we present in this section.

Table 2.2: *Estimate of effect of advertising on volume*

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

*Notes: We estimate equation (2.2) separately for Regular Coke, Diet Coke and Diet Pepsi and report the coefficient estimate on the log of the advertising stock. The elasticity is defined as the ratio of the coefficient estimate and dependent variable mean.*

# 3 Structural Model

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

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

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

We describe the structure of the dynamic oligopoly game, the role of advertising agencies in mapping advertising budgets to slots, and hence to consumer advertising exposure, and we outline our consumer demand model. In this section we describe the structure of the model; we provide details of the empirical specification in Section 4 and 5.

### 3.1 The Firm's Decision

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

Each period, firm $f$ selects advertising budgets for its brands and sets product prices. The advertising expenditures are used by an agency to purchase advertising slots on the firm's behalf, which in turn determine consumer advertising exposure, $a_{ibt}$ (defined in equation (2.1)), of all consumers $i \in I$ for brand $b$ in period $t$. We denote the advertising exposure stock for consumer $i$ to brand $b$ at time $t$ by $\mathcal{A}_{ibt} = g(a_{ib0}, a_{ib1}, \ldots, a_{ibt-1})$, 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 product $j$ is given by its share $s_{jt}(\mathbf{p}_t, \mathcal{A}_t)$ of the potential market, $M_t$, where $\mathbf{p}_t = (p_{1t}, \ldots, p_{Jt})$. Since demand depends on exposure stocks, $\mathcal{A}_t$, it captures potential persistence in advertising effects, meaning that a firm's current advertising expenditure, $e_{bt}$, influences future demand and makes firm competition inherently dynamic.

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

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

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

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

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

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

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

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

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

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

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

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

## 3.2 The Advertising Agency's Problem

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

As in Section 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 it during slot $k$ and we denote the expected flow of advertising exposure for consumer $i$ for brand $b$ in period $t$, as in equation (2.1), by $a_{ibt} = \sum_{\{k|t(k)=t\}} w_{ik}\omega(T_{bk})$, where $\omega(\cdot)$ is an increasing concave function, capturing any diminishing returns to advert length.

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

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

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

where $\Omega_b$ denotes the targeted population.

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

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

The optimal choice during slot $k$ satisfies

$$T^*_{bk} = \omega'^{-1}\left(\frac{\rho_k}{\sum_{i\in\Omega_b} w_{ik}}\frac{1}{\lambda^*_{bt}}\right), \tag{3.6}$$

where $\lambda^*_{bt}$ is the Lagrange multiplier on the constraint in the agency's problem. The concavity of $\omega(\cdot)$ implies that $T^*_{bk}$ is a decreasing function of the price per viewer during slot $k$, $\frac{\rho_k}{\sum_{i\in\Omega_b} w_{ik}}$.

While equation (3.5) frames the agency's problem as if it directly selects advertising slots, in practice, agencies purchase advertising views at a somewhat more aggregated level, leaving TV stations some discretion over the exact timing of ads, as long as they generate the same total impact within the same budget.

## 3.3 The Consumer's Problem

We model consumer choice as a discrete decision over which, if any, cola product to purchase each period. At this stage, we do not take a normative stance on the relationship between advertising and consumer welfare, nor do we rule out the possibility that consumers experience internalities. Therefore, we use the term "decision utility," following Bernheim (2009). We return to this point when making consumer welfare statements in Sections 6.2 and 6.3..

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

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

Consumer $i$'s decision utility for product $j$ depends on their stock of exposure to advertising for all brands, $\mathcal{A}_{it}$, the product's price, $p_{jt}$, its observable and unobservable product characteristics, $\mathbf{x}_{jt}$, and a vector of preferences parameters, $\theta_i$. $\epsilon_{ijt}$ 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 $U_{i0t} = V(\theta_i) + \epsilon_{i0t}$.

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

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

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

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

## 3.4 Counterfactual Policy Simulations

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

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

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 a firm's flow profit function is:

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

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

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

Under an advertising restriction prohibiting adverts for sugary products (those in $\Omega_{\mathcal{S}}$), the firm's problem described in equation (3.2) becomes:

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

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

# 4 Empirical Demand Model

A key input to our dynamic model are product-level demand functions, which we estimate using a consumer-level discrete choice model for cola products. We define a choice occasion as any week in which a household purchases a drink and model the household's decision over which, if any, cola product to choose. To capture the purchase of a non-cola drinks, we include two outside options: one for sugary non-cola drinks and another for sugar-free non-cola drinks.[9] A key feature of our demand model is that it incorporates the effect of consumer-level advertising exposure on purchase decisions.

## 4.1 Advertising Exposure

As discussed in Section 2.3, we measure household $i$'s exposure to band advertising in week $t$ as $a_{ibt} = \sum_{\{k|t(k)=t\}} w_{ik}\omega(T_{bk})$, where $\omega(\cdot)$ captures diminishing returns to advert length. We assume $\omega$ is a power function, $\omega(T) = T^{\gamma}$, which results in a log-linear relationship between slot price per viewer and advert length (conditional on brand-time fixed effects) in the solution to the advertising agency's problem (equation (3.5)).

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

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

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

This formulation implies that exposure from two weeks ago contributes $\delta$ times as much to the current stock of exposure as the same amount of exposure from one week ago. Based on the evidence we discuss in Section 2.4, we set $\delta = 0.9$. To initialize exposure stocks, we use data on advertising and household TV viewing behavior from a pre-sample year (2009), as advertising exposure older than 52 weeks has a negligible impact on stocks. We provide descriptive evidence on variation in flow and stock of advertising exposure in Appendix B.4.

[9]These are selected on 37% and 39% of choice occasions, respectively

## 4.2 Utility Specification

In this section we specify the empirical form of decision utility (equation (3.7)), paying particular attention to allow for heterogeneity in consumer sensitivity to price and advertising, as well as spillovers in the effect of advertising for one brand on demand for another.

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

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

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

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

where $p_{jr(i,t)t}$ is the price (per unit) of product $j$, in the retailer consumer $i$ shops with, $r(i,t)$, in week $t$. We incorporate three distinct effects of advertising on decision utility: 1) an own-brand advertising effect, $\beta_i^O$, which captures the impact of a consumer's exposure to advertising for the brand of product $j$, 2) a within-firm spillover effect, $\beta_{d(i)}^W$, which captures spillovers from advertising of other brands within the same firm, and 3) a cross-firm spillover effect, $\beta_{d(i)}^X$, which captures spillovers from advertising of rival firms. Each advertising stock enters the decision utility function through the inverse-hyperbolic sine function, which accounts for diminishing returns to advertising exposure.[10]

Decision utility also depends on consumer-specific preferences over whether the brand is sugar-sweetened ($\mathrm{Sug}_{b(j)}$) and firm—i.e., Coca Cola vs. Pepsico ($\eta_{if(j)}$). Additionally, it incorporates: a vector of household TV viewing behavior measures interacted with firm

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

($\mathbf{Z}_{if(j)}$) and product ($\chi_{d(i)j}$) year-quarter-brand ($\xi_{d(i)b(j)\tau(t)}$) and retailer-brand ($\zeta_{d(i)b(j)r(i,t)}$) effects, all of which vary by demographic group.

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

We model preferences for price, own-brand advertising, sugar, and firm effects as random coefficients. The sugar and firm coefficients, $(\gamma_i, \eta_{i,b(j)})$, follow independent normal distributions specific to each demographic group. For the price and own-brand advertising coefficients, we specify that $(\ln(-\alpha_i), \ln(\beta_i^O))$ follows a joint normal distribution with demographic-group-specific parameters and nonzero covariance.[11]

Allowing flexibly for correlation between price and advertising sensitivity is crucial for modeling the effects of tax policy on advertising. A tax increases the price consumers face for taxed products, leading the most price-sensitive consumers to switch away. Whether the post-tax marginal consumer is more or less sensitive to advertising than the pre-tax marginal consumer will influence whether firms respond to the tax by increasing or decreasing advertising.[12]

Since we specify random coefficient distributions conditional on 12 demographic groups, the overall preference distribution is a mixture of these conditional distributions. This rich preference specification allows our model capture realistic patterns of substitution across products. Additionally, it substantially relaxes restrictions otherwise placed on the curvature of product-level market demands, allowing the model to flexibly predict tax pass-through (see Griffith et al., 2018; Miravete et al., 2023).

[11] The log-normal specification ensures that price increases cannot raise demand and that advertising increases cannot lower it. Using normal distributions yield similar price and advertising elasticities, but imply some consumers have upward-sloping demand.

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

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

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

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

## 4.3 Identification

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

### 4.3.1 Advertising

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

Manufacturers may target households of a particular demographic type by purchasing airtime during shows typically watched by that group. To account for this, we allow all preference parameters in our demand model to vary by demographic group, including time-varying brand effects (the $\xi_{d(i)b(j)\tau(t)}$'s in equation (4.1)).

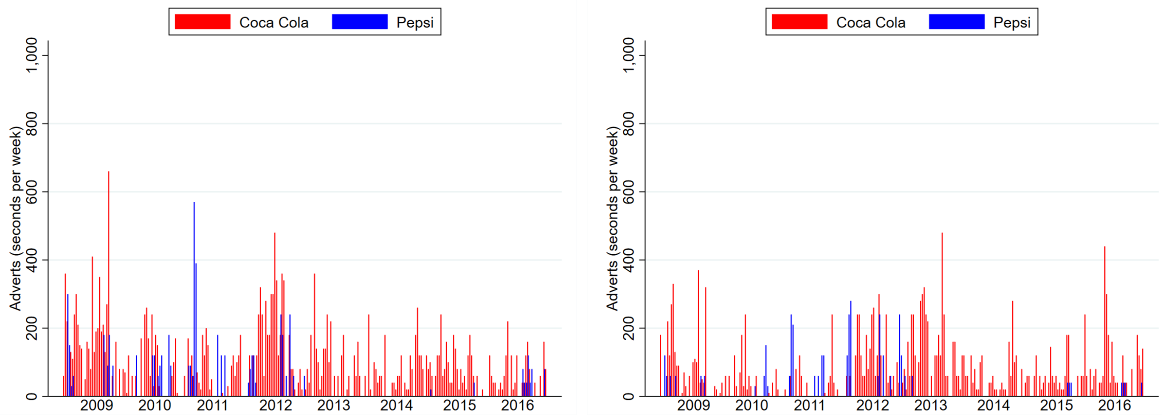
A potential concern is that manufacturers may target viewers of specific TV programs. In practice, their ability to do so is constrained by the nature of the ad-buying process. Nonetheless, our demand model includes a detailed vector of household TV watching behavior measures, interacted with Coca Cola and Pepsico effects ($\mathbf{Z}_{if(j)}$ in equation (4.1)).

Specifically, we include controls for how regularly a household watches: (i) TV in a typical week, (ii) shows within six genres (e.g., sport, documentaries, entertainment), (iii) shows on different stations (including the three main terrestrial channels and the group of cable/satellite channels),[13] and (iv) shows shown during different time slots (e.g., prime-time weekday, non-prime time weekend). The means that the variation we use to estimate advertising effects arises across households of the same demographic group and TV viewing profile.[14]

Figure 4.1 illustrates this source of variation. It shows weekly advertising (in seconds) for Coca Cola and Pepsico brands during two US sitcoms, *Frasier* and *Everybody Loves Raymond*. These shows aired across most months during 2009-2016, with Coca Cola and Pepsico advertisements varying in quantity and timing. Households are differentially exposed to Coca Cola and Pepsi advertising depending on whether they watch neither, one or both shows.

Figure 4.1: *Within genre advertising variation*

(a) Frasier (b) Everybody Loves Raymond




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

### 4.3.2 Prices

An important feature of the UK grocery market is that the major supermarkets operate national store networks and adhere to national pricing policies (see Competition Commission,

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

[14]The descriptive evidence in Section 2.4 additionally conditions on household fixed effects. We compare these results with the advertising effects we estimate in our model below.

2000). As a results, our analysis does not rely on cross-sectional regional price variation, a common approach in studies of US markets that often use Hausman instruments (Hausman et al., 1994).[15] Instead, we exploit the fact that drinks firms (i.e., Coca Cola Enterprises and Pepsico) negotiate annually with major retailers to set a recommended (national) retail price and agree on the number, type, and timings of temporary price reductions for the upcoming year (e.g., Competition Commission, 2013). While the recommended prices for a given product are generally similar across retailers, the timing of temporary price reductions varies, leading to differences in the prices shoppers face depending on when and where they shop.

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

A third assumption underlying our strategy is that our estimates capture intra-temporal consumer responses rather than intertemporal responses—such as stockpiling in response to sales. If consumers primarily stock up during sales, this could lead us to overestimate own-price elasticities and underestimate cross-price elasticities (Hendel and Nevo, 2006). While we cannot rule out that some consumers stockpile a priori, empirical evidence suggests that this effect is not quantitatively important in our UK context. Using the same dataset as in this paper (the Kantar Take Home Purchase Panel), O'Connell and Smith (2024) show that when consumers purchase a drink on sale, they are more likely to switch brands, container type (i.e., can vs. bottle), and size relative to their previous purchase, however, they do not systematically alter the timing of their purchases. This evidence indicates that consumers respond to sales by intra-temporally substituting across products rather than stockpiling.[16]

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

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

## 4.4 Demand Estimates

We estimate the demand model by simulated maximum likelihood. In Table 4.1 we report brand-level price and advertising elasticities.[17] The price elasticities measure 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 own-price elasticity for Regular and Diet Coke is -2.2, which is somewhat larger in magnitude than the own-price elasticities for Regular and Diet Pepsi. The cross-price elasticities indicate consumers are more willing to switch within Coca Cola and Pepsi brands than across them, and that they are more willing to substitute within Regular and Diet brands than across them—for example, the cross-price elasticity of demand for Regular Pepsi with respect to a rise in the price of Regular Coke products is nearly twice as large as that for Diet Pepsi.

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

*Notes: Numbers show the elasticity of demand for the brand shown in column (1) with respect to the price (columns (2)-(5)) or advertising stocks (columns (6)-(8)) of the brands shown in the first row. The price elasticities are with respect to a 1% 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 advertising elasticities describe the impact of a 1% increase in the stock of all consumers' exposure to advertising for the brand in the first row on demand for the brand in the first

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

column, and should be interpreted as long-run elasticities.[18] The own-brand elasticities for Regular and Diet Coke advertising are approximately 0.11, while the Diet Pepsi own-brand elasticity is around half this magnitude. These estimates, derived from the structural model, align with those we present in Section 2.4, which are based on brand-level regressions using only within-household variation in exposure. The cross-elasticities indicate substantial within-firm advertising spillovers. For instance, a 1% increase in Regular Coke advertising raises demand for Diet Coke products by 0.05%—about half the increase in Regular Coke demand. There is also evidence for cross-firm advertising spillovers (i.e., Regular and Diet Coke advertising raising Pepsi demand and Diet Pepsi advertising raising Coke demand), though these effects are substantially smaller in magnitude than the within-firm spillovers.

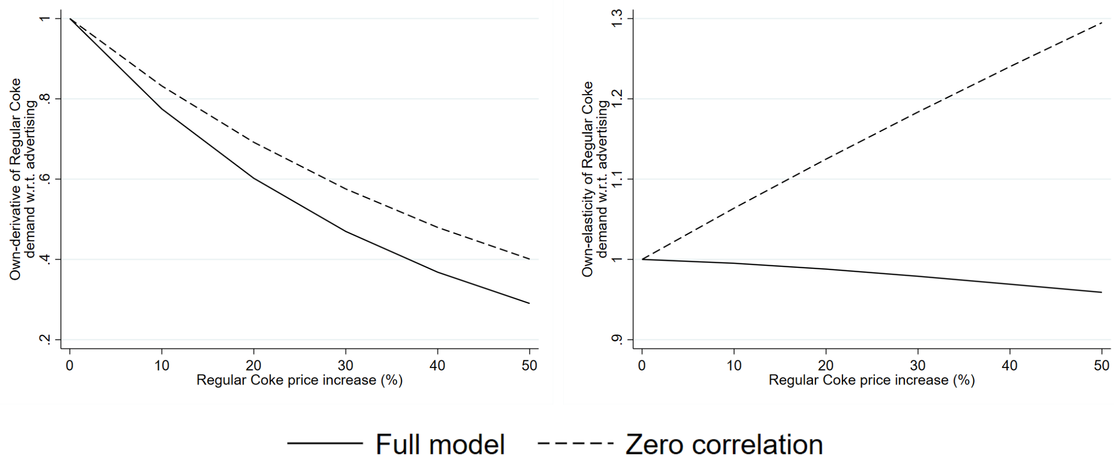
Figure 4.2 illustrates how the sensitivity of brand demand to advertising varies with the brand's price level. Panel (a) shows how the derivative of demand for Regular Coke with respect to Regular Coke advertising changes as the price of all Regular Coke products increase. Panel (b) shows how the Regular Coke's own-advertising elasticity varies with price. In both cases, we plot the relationship based on our full model estimates (solid line) and on a restricted version where the within-demographic group covariance between advertising and price sensitivity is set to zero (dashed line).

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

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

Figure 4.2: *Impact of Regular Coke price level on advertising sensitivity of demand*

(a) Derivative (b) Elasticity




*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 relative to zero price increase.*

# 5 Supply-Side Estimation

In the supply model, Coca Cola and Pepsico are the strategic players, competing over product prices and brand advertising budgets. Store brands are not advertised, and during the time period we consider, Pepsico does not advertise Regular Pepsi. Therefore, we model advertising choices for Regular Coke, Diet Coke and Diet Pepsi. We assume that Pepsico would not begin advertising its Regular brand in a counterfactual scenario where a sugar-sweetened soft drinks tax is introduced. In Section 6, we show that Coca Cola reduces advertising for its Regular brand in response to a tax. Given Pepsico faces similar incentives to advertise, relaxing this assumption would have little impact on our results. Store brand prices are significantly lower than those of Coca Cola and Pepsico. In our policy simulations, we hold these prices fixed, treating store brand products as if they are priced at cost.

In demand estimation, we exploit week-to-week variation in advertising exposure. However, firms set advertising expenditures at lower frequency, with week-to-week exposure varying based on advertising slots arranged by agencies. We assume that firms set both prices and advertising expenditures monthly. While prices vary across retailers at a given time, this variation primarily reflects the staggered timing of temporary price reductions. Instead of incorporating a formal model of vertical relations, we make the simplifying assumption that drinks firms set a uniform price for each product across retailers.[19] To solve for the model equilibrium, we must specify how firms form expectations over how advertising expenditures affect the distribution of consumer advertising exposure stocks. We first outline this process before presenting the static and dynamic equilibrium conditions in the observed (zero-tax) case.

## 5.1 The State Transition Function

Advertising agencies simplify firms' decision-making by reducing their action space to choices over product prices and brand advertising expenditures. However, the state space in the firm's decision problem, outlined in Section 3.1, remains large, as it consists of the joint distribution of consumer-level exposure stocks for each brand ($\mathcal{A}_t = \{(A_{i1t}, \ldots, A_{iBt})\}_{i \in I}$). While the behavior of advertising agencies implies that advertising exposure evolves predictably based firms' expenditures, 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. To address this, we assume that firms track a summary statistic of the brand-specific exposure distribution—specifically, the mean exposure in the population. We estimate the transition function that maps advertising expenditures to this summary statistic and, to solve the MPE, discretize the state space using a fine grid for the three advertising states (Regular Coke, Diet Coke, and Diet Pepsi). Appendix G provides further details, including evidence that tracking the mean of the distribution results in negligible prediction error in product level demands (because over-prediction and under-prediction of individual demands, when using the mean exposure, offset each other in aggregate demand).".

## 5.2 State-Specific Optimal Prices

We use the advertising state-specific optimal pricing conditions from equation (3.3), evaluated at observed prices and advertising state variables, to infer product-level marginal costs. Among Coca Cola products, the average (quantity-weighted) marginal cost and price-cost margin per liter are 0.45 and 0.38, respectively, while the average (expenditure-weighted)

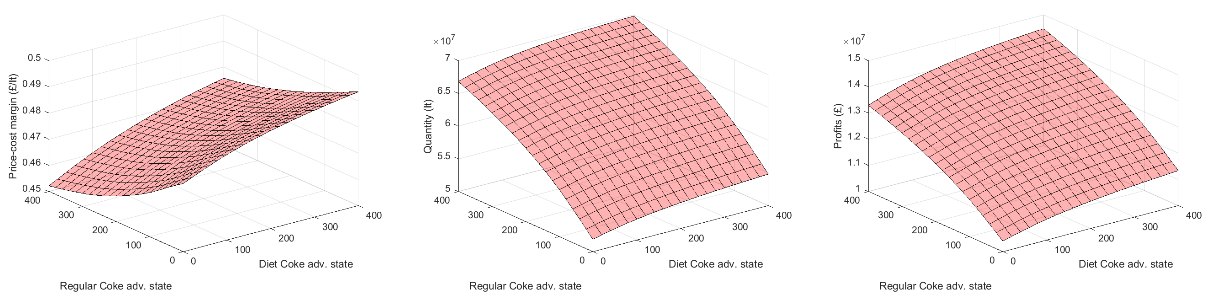
[19] In practice, for a given product-year, a drinks firm and retailer agree on a base price $\bar{p}$ and a sale price $p_S$, with the base price applying $\rho$ proportion of weeks. Instead of modeling the firm's choice over $(\bar{p}, p_S, \rho)$, we model choice over $p = (1-\rho)\bar{p} + \rho p_S$,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

Lerner index is 0.46. For Pepsico products, the corresponding figures are 0.25, 0.41 and 0.62, indicating that Pepsico products, on average, have lower costs but similar price-cost margins (and thus higher Lerner indexes) than Coca Cola products.[20]

Using our estimates of product-level demand and marginal costs, along with the price first-order conditions (equation (3.3)), we solve for the vector of optimal prices at each point of the advertising state space. Figure 5.1(a) shows how the average price-cost margins of Regular Coke products vary across the advertising state space. The state space is three dimensional; the figure holds the Diet Pepsi state fixed and shows how the average margins of Regular Coke products vary with the Diet Coke and Regular Coke advertising states. It shows that, conditional on the Pepsi and Diet Coke states, the average margin of Regular Coke products decrease as the Regular Coke advertising state increases. This pattern arises due to the correlation in consumers' price and advertising sensitivities. As the Regular Coke advertising state increases, its consumer base becomes more price sensitive, leading to lower optimal prices. In contrast, there is a weaker positive relationship between the Diet Coke advertising state and Regular Coke margins. This occurs because higher Diet Coke advertising shifts relatively advertising-sensitive consumers from Regular to Diet Coke, making the remaining Regular Coke consumer base less sensitive to both advertising and price.

Figure 5.1: *Variation in Regular Coke outcomes 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.*

Figure 5.1(b) shows how demand for Regular Coke products varies across the Coca Cola advertising states. This variation reflects both the direct effect of advertising on demand and the indirect effect through optimal pricing adjustments. Demand for Regular Coke increases with the Regular Coke advertising state due to both channels—direct advertising impact and

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

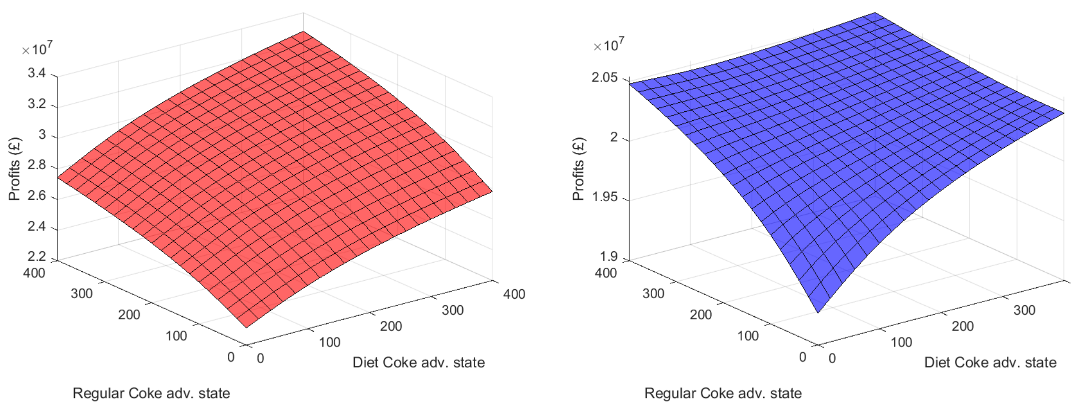
lower prices at higher advertising states. Regular Coke demand also rises with the Diet Coke advertising state, though less strongly. This is driven by a within-firm advertising spillover effect, where Diet Coke advertising stimulates demand for both Diet Coke and Regular Coke. This spillover is strong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

Figure 5.1(c) shows how gross profits (excluding advertising expenses) for Regular Coke products vary with the Coca Cola advertising states. As the Regular Coke advertising state increases, there are two opposing forces: demand rises but margins decline. The demand effect dominates, leading to higher profits. Regular Coke profits are also increasing in Diet Coke advertising, but the effect is weaker compared to changes in the Regular Coke advertising state.

In Figure 5.2 we plot how Coca Cola's and Pepsico's gross profits (which sum across all products they own) vary with Coca Cola's two advertising states, holding Pepsico's state fixed. Coca Cola's gross profits increase in its advertising states. Pepsico's profits also rise with Coca Cola advertising's, though less strongly. This reflects a cross-firm spillover, where Coca Cola's advertising increases decision utility from Pepsico products, boosting their demand. At higher levels of Coca Cola advertising, Pepsico's profits become less sensitive to further increases. These firm-level profit functions, which incorporate strategic pricing competition, serve as an input into the dynamic advertising game.

Figure 5.2: *Variation in firm-level gross profits with Coca Cola advertising states*

(a) Coca Cola Enterprises (b) Pepsico




*Notes: Panel (a) shows variation in Coca Cola Enterprises gross profits and panel (b) shows variation in Pepsico gross profits. In each panel we hold fixed the Diet Pepsi advertising state at the highest probability state in the dynamic equilibrium distribution.*

## 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 H for details of the solution algorithm). We calibrate the brand-level agency mark-up, $\psi_b$, over television expenses so that the model's equilibrium predictions for average advertising expenditures match their observed levels.[21] This implies Pespsico, who advertises less, face a mark-up that is 1.5 times higher than the average paid by Coca Cola, which is consistent with the mark-up partly reflecting fixed cost recovery by advertising agencies. We set firms' monthly discount factor to $\beta = 0.992$.

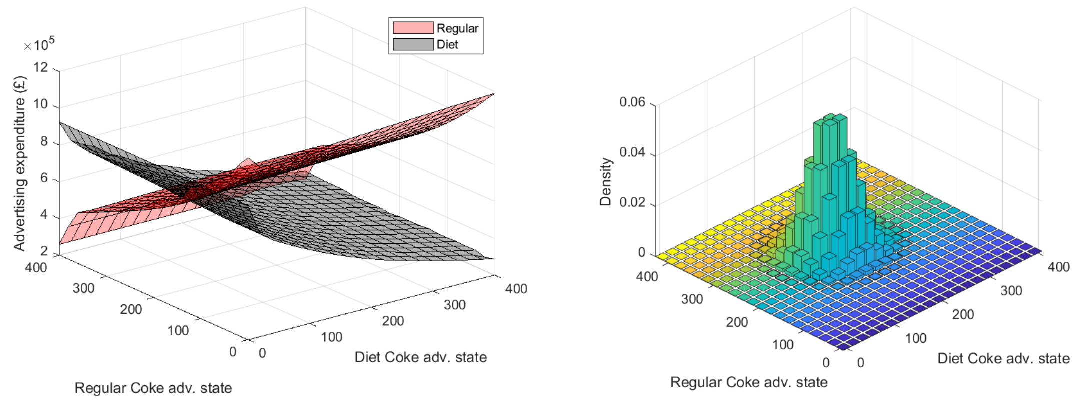
We obtain MPE strategies (policy functions) for each advertised brand, prescribing the optimal advertising expenditure at each point in the advertising state space. Figure 5.3(a) illustrates how the policy functions for Regular Coke (red) and Diet Coke (grey) vary across the Coca Cola advertising states, holding the Diet Pepsi advertising state fixed. The policy functions show that for both Regular and Diet Coke, when the average of consumers' stock of advertising exposure is low, the returns on additional advertising are relatively high, leading to higher optimal expenditures. Conversely, as exposure stocks increase, diminishing returns reduce the incentive to invest further, resulting in lower optimal expenditures. The cross-brand relationship between states and optimal expenditures is much weaker, with Regular Cokes' optimal advertising expenditure being relatively insensitive to the Diet Coke state, and vice versa.

Firms' optimal policy functions, combined with the state-to-state transition function (equation (G.2)), generate an MPE (ergodic) distribution over the state space. In Figure 5.3(b) we plot the ergodic distribution of the equilibrium across Coca Cola advertising states, integrating over the Pepsico state.

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

Figure 5.3: *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, characterizing their impact on equilibrium prices, advertising expenditure, quantities and aggregate profits. We also consider their distributional effects across consumers. Specifically, we consider a regulation prohibiting sugar-sweetened cola advertising, as well as both a specific and an ad valorem tax on sugar-sweetened beverage tax. The tax applies to Regular Coke and Pepsi, with the specific tax set at £0.22 per liter and the ad valorem tax calibrated to achieve the same reduction in equilibrium quantity as the specific tax, holding advertising fixed. We also analyze the combined effect of the advertising restriction and the tax.[22]

Our model generates a set of functions describing how static outcomes (e.g., state-specific optimal prices, quantities, profits, consumer surplus) vary across the advertising state space ($\mathbb{A} = \{\mathbb{A}\}_b$), denoted by $y_\chi(\mathbb{A})$. It also produces an equilibrium (ergodic) distribution over

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

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

## 6.1 Impact on Market Equilibrium

Table 6.1 summarizes the impact of each counterfactual policy on equilibrium (tax-inclusive) prices, price-cost margins, advertising expenditures, quantities and sugar consumption. The values represent percentage changes relative to the no policy intervention equilibrium. Column (1) reports the effects of an advertising restriction prohibiting sugar-sweetened cola advertising. Column (2) presents the impact of a specific tax, holding the equilibrium distribution across advertising states fixed (thus keeping firms' advertising expenditures unchanged). Columns (3) and (4) show the *incremental* effects of incorporating equilibrium advertising responses and combining the tax with the advertising restriction, respectively. Columns (5)-(7) mirror columns (2)-(4) for an ad valorem tax. We discuss each policy in turn.

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% | 28.8% | 0.1% | 0.5% | 37.0% | 0.1% | 0.4% |
| Diet Coke/Pepsi | -1.0% | -1.4% | -0.1% | -0.7% | -1.4% | -0.2% | -0.6% |
| **Δ margin** | | | | | | | |
| Regular Coke/Pepsi | 1.6% | 5.1% | 0.2% | 1.1% | -34.8% | 0.2% | 0.5% |
| Diet Coke/Pepsi | -2.1% | -2.8% | -0.2% | -1.4% | -2.8% | -0.4% | -1.2% |
| **Δ advertising exp.** | | | | | | | |
| Regular Coke/Pepsi | -100.0% | - | -33.1% | -100.0% | - | -47.3% | -100.0% |
| Diet Coke/Pepsi | -7.7% | - | -3.3% | -10.8% | - | -8.5% | -15.1% |
| **Δ quantity** | | | | | | | |
| Regular Coke/Pepsi | -13.0% | -55.1% | -1.0% | -4.5% | -55.2% | -1.5% | -3.9% |
| Diet Coke/Pepsi | -3.8% | 11.2% | -0.9% | -4.7% | 10.8% | -1.7% | -4.2% |
| **Δ sugar** | | | | | | | |
| *All drinks* | -2.7% | -16.2% | -0.1% | -0.4% | -16.5% | -0.1% | -0.3% |

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

**Advertising restriction.** Column (1) shows that banning sugar-sweetened cola advertising (which directly affects Regular Coke advertising) reduces Regular Coke and Pepsi consumption by 13.0%, leading to a 2.7% decline in overall sugar consumption from drinks.[23] The ban also reduces Diet Coke and Pepsi consumption by 3.8%. While prices and margins of diet products remain relatively unchanged, Diet advertising declines by 7.7%, driven almost entirely by a reduction in Diet Coke advertising. The restriction on Regular advertising, combined with the decline in Diet Coke advertising, shifts the equilibrium distribution (see panels (b) and (c) of Figure 6.1, which compare pre- and post-ban equilibrium distributions).

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

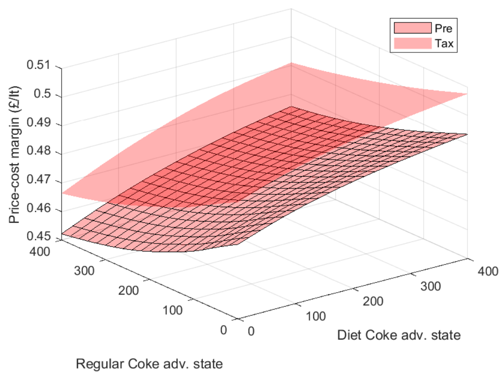
In Figure 6.2, we illustrate why, in response to the advertising restriction, Coca Cola lowers advertising of its Diet brand. Panel (a) shows how equilibrium gross profits for Regular (red lines) and Diet (grey lines) Coke vary with the Diet Coke advertising state. We present this relationship under two conditions: where the Regular Coke advertising state is at its modal "no policy intervention" equilibrium value (solid lines) and when it is at 0 (dashed lines), corresponding to the advertising restriction. The graph indicates that, after the ban, the return to advertising Diet Coke—both in terms of Regular and Diet Coke profits—are lower, leading Coca Cola to reduce its Diet advertising expenditure.

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

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

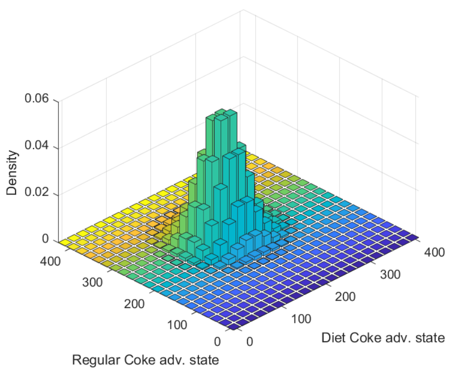
Figure 6.1: *Impact of specific tax and advertising restriction: On state-specific optimal margins*

(a) Average Regular Coke margins

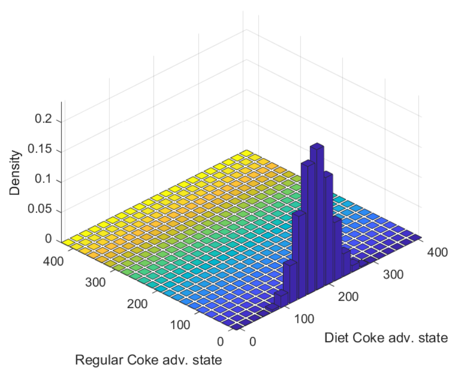



*On equilibrium distribution*

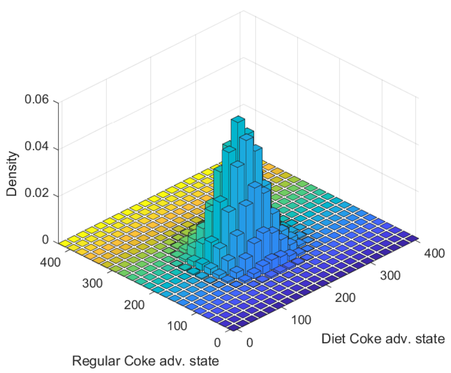
(b) Pre-policy intervention



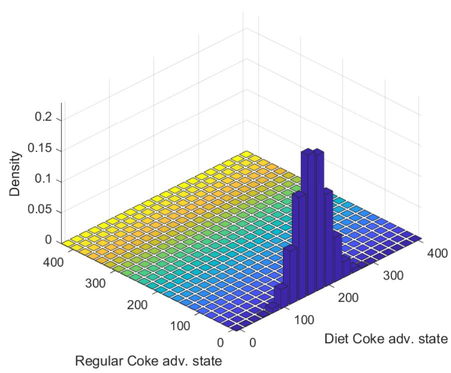

(c) Advertising restriction




(d) Tax



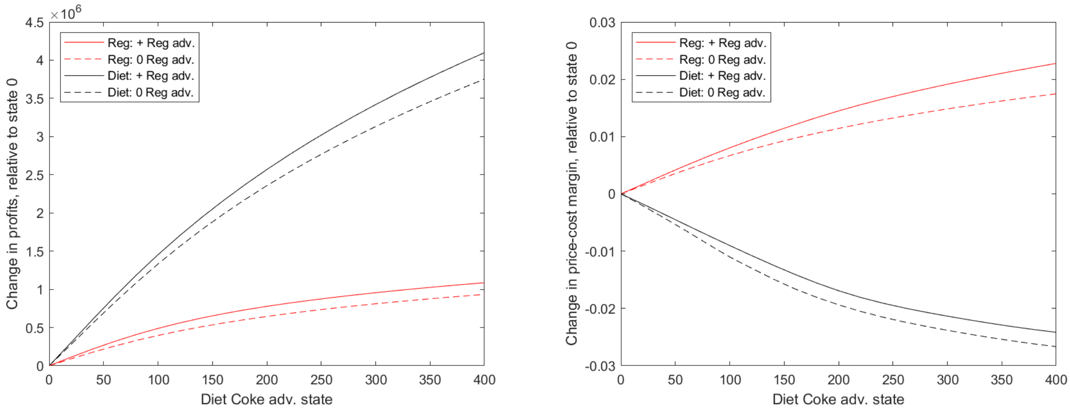

(e) Tax and advertising restriction




*Notes: Panel (a) shows variation in the average price-cost margin for Regular Coke products. The hatched surface is pre-policy intervention (and repeats Figure 5.1(a)) and the smooth surface corresponds to when a specific tax is in place. In each case we hold fixed the Diet Pepsi advertising state at the highest probability state in the pre-policy intervention equilibrium distribution. Panels (b)-(e) show the ergodic distribution, integrating over the Diet Pepsi advertising state space. Panel (b) repeats Figure 5.3(b). In Appendix J we show the equivalent figure for the ad valorem tax.*

Figure 6.2: *Return to Diet Coke advertising*

(a) Gross profits (b) Margins




*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 summarizes the impact of a £0.22 per liter specific tax, holding firms' advertising policy functions (and hence the equilibrium distribution over states) at their pre-tax level. The tax leads to a 28.8% increase in the average price of Regular Coke and Pepsi (i.e., the taxed products), reflecting both the mechanical impact of the tax on prices and firms' equilibrium margin adjustments. On average the pass-through of the tax is approximately 110%, corresponding to a 5% increase in equilibrium price-cost margins for taxed products (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 with the tax in place (smooth surface)). The corresponding change in Regular Coke and Pepsi equilibrium quantity is a 55.1% decrease, with overall sugar intake from drinks falling by 16.2%.[24]

Column (3) shows the incremental impact of accounting for Coca Cola and Pepsi's optimal advertising responses to the specific tax, by re-solving for the MPE. The tax results in a 33.1% reduction in Regular Coke advertising expenditure. A key mechanism driving this effect is the correlation in consumers' price and advertising sensitivities. The tax induces a large increase

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

in Regular products' prices, which drives away price and advertising sensitive consumers and lowers the returns to further advertising. The tax also results in a modest reduction in advertising for Diet products (panels (b) and (d) of Figure 6.1 show the implications for the equilibrium distribution over states). This reduction in advertising expenditure further contributes to a modest decline in demand for Regular products of around 1%.

Column (4) shows the impact of coupling the specific tax with the advertising restriction that prohibits advertising of Regular brands. Without the tax, the advertising restriction reduced Regular Coke and Pepsi consumption by 13% and total sugar intake by 2.7%. When the tax is in place, the effect of the restriction is attenuated; it leads to a reduction in Regular Coke and Pepsi consumption of 4.5%, and a small fall of 0.4% in total sugar intake.

**Ad valorem tax.** We calibrate the ad valorem tax so that it results in approximately the same reduction in equilibrium quantity for Regular Coke and Pepsi as the specific tax, holding advertising strategies fixed. By construction, column (5) shows the same 55.2% reduction in Regular Coke and Pepsi quantity as in column (2). The tax rate required to achieve this reduction is 64%. The average pass-through of the tax is approximately 55%, which is reflected in a 34.8% fall in equilibrium price-cost margins of the taxed products.

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

For consumer surplus we report two numbers: the static and total (i.e., static plus dynamic) effects. The static effect reflects changes in optimal prices, conditional on advertising state, while the total effect incorporates both this and the change in the equilibrium distribution over states due to firms reoptimizing their advertising expenditures (see Appendix I for details). Since the main channel through which policy affects prices is via changes state-specific optimal prices,[25] this provides an approximate decomposition of consumer surplus changes into price and advertising effects. A policymaker who wishes to discount the apparent impact of reduced advertising on utility—on basis that advertising does not directly contribute to underlying consumer welfare—can rely on the static effect numbers.

The primary motivation behind policies aimed at reducing sugar-sweetened beverage consumption is to lower the social costs of sugar consumption. These costs may arise through externalities—such as higher healthcare expenditures—or internalities, where consumers underweight the future health consequences of their consumption choices. The reduction in gross surplus (which we report both based on the total and static consumer surplus numbers) must be weighed against the reduction in social costs achieved by the policies. In Table 6.1 we do not take a stance of these costs, but simply report changes in total sugar intake.

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

Both the specific and ad valorem taxes result in larger reductions in firm profits (5.6% and 9.0%, respectively) and consumer surplus (which declines by approximately 6.5% due to the static pricing effect alone). These larger losses are partially offset by tax revenue generation and the fact that these taxes achieve much greater reductions in sugar consumption from

[25] For instance, the specific tax results in a 28.9% increase in the average price of Regular Coke and Pepsi product. 28.8% is due to changes in state-specific price equilibrium and 0.1% due to shifts in the equilibrium distribution over states (see columns (2) and (3) of Table 6.1).

drinks (approximately 16.5%). Adding the advertising restriction on top of either tax leads to only a small additional reduction in sugar consumption. However, if advertising is not assumed to directly contribute to consumer welfare, the additional decline in gross surplus is also minimal.

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 | - | 4.3% | 3.8% | 7.1% | 6.4% |
| Δ profits | -2.1% | -5.6% | -7.0% | -9.0% | -10.1% |
| Consumer surplus | | | | | |
| Static effect | 0.0% | -6.5% | -6.2% | -6.5% | -6.2% |
| Total effect | -4.5% | -7.2% | -10.3% | -7.7% | -10.6% |
| Gross surplus | | | | | |
| Static effect | -2.1% | -7.9% | -9.4% | -8.5% | -9.9% |
| Total effect | -6.5% | -8.6% | -13.6% | -9.7% | -14.2% |
| Δ sugar | -2.7% | -16.3% | -16.7% | -16.6% | -16.8% |

*Notes: Numbers (with the exception of the final row) are expressed as a percentage of pre-policy total consumer expenditure and show changes relative to the pre-policy intervention level. We report consumer surplus changes that result from a "static effect", which strips out advertising responses, and a "total effect" which does not. We also report gross surplus (the sum of tax revenue, profits changes and consumer surplus changes) under these two versions of consumer surplus. The final row shows the percent change in sugar from all drinks relative to pre-policy, repeating information in Table 6.1.*

The main lessons from Table 6.2 are that the specific and ad valorem taxes perform similarly in reducing sugar consumption. The ad valorem tax leads to a somewhat larger reduction in gross surplus compared to the specific tax. However, it also generates higher tax revenue (7.1% vs. 4.3%), albeit at the cost of larger reductions in firm profits, as it reduces firms' market power. The advertising restriction, on its own, results in a much more modest reduction in sugar consumption than either of the taxes. However, if advertising does not directly contribute to consumer welfare, the gross surplus loss from the restriction is relatively small. The case for adding an advertising restriction on top of a tax is weak, as it results in only a small additional reduction in sugar.

## 6.3 Distributional Impact

The aggregate consumer surplus numbers in Table 6.2 mask heterogeneity across households. In Table 6.3, we present how each policy affects sugar consumption and consumer surplus in each household income quartile. The numbers reflect the heterogeneity we incorporate in our demand model, where preferences parameters vary by household income quartiles (interacted with household type). In this table we focus on the static consumer surplus effect, excluding the effects of advertising.[26]

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% | -17.64% | -18.12% | -17.88% | -18.25% |
| 2nd | -2.78% | -17.07% | -17.45% | -17.23% | -17.45% |
| 3rd | -2.32% | -17.29% | -17.63% | -17.70% | -17.96% |
| Top | -2.83% | -12.22% | -12.73% | -12.56% | -12.83% |
| **Change in consumer surplus** | | | | | |
| Bottom | 0.00% | -8.13% | -7.69% | -8.07% | -7.68% |
| 2nd | 0.00% | -6.52% | -6.19% | -6.47% | -6.18% |
| 3rd | 0.00% | -7.14% | -6.87% | -7.23% | -6.99% |
| Top | 0.00% | -4.00% | -3.74% | -4.10% | -3.86% |
| **Change in consumer surplus net of internalities** | | | | | |
| Bottom | 1.22% | -0.68% | -0.03% | -0.52% | 0.03% |
| 2nd | 1.01% | -0.36% | 0.11% | -0.25% | 0.12% |
| 3rd | 0.71% | -1.87% | -1.50% | -1.84% | -1.52% |
| Top | 0.69% | -1.02% | -0.64% | -1.04% | -0.73% |

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

A distributional analysis of the impact of advertising restrictions and taxes for sin goods is influenced by any internality savings the policies generate, and how such savings vary across income groups. To illustrate the potential importance of this channel, we also report changes in consumer surplus net of internality savings in Table 6.2. We do not directly estimate these savings; rather, we base our measure on the estimates in Allcott et al. (2019), who find that

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

the internality per fluid ounce of sugar-sweetened beverage consumption decreases linearly from 1.10 cents for the lowest income group to 0.83 cents for the highest income groups. This translates to £0.0029, £0.0027, £0.0025 and £0.0022 per gram of sugar for our income quartiles 1 to 4.[27]

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

# 7 Conclusion

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

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

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

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

# References


Aguirregabiria, V. and P. Mira (2007). Sequential Estimation of Dynamic Discrete Games. *Econometrica 75*(1), 1–53.

Allcott, H., B. B. Lockwood, and D. Taubinsky (2019). Regressive Sin Taxes, with an Application to the Optimal Soda Tax. *Quarterly Journal of Economics 134*(3), 1557–1626.

Anderson, S. P., A. De Palma, and B. Kreider (2001). Tax incidence in differentiated product oligopoly. *Journal of Public Economics 81*(2), 173–192.

Asa, N., M. A. Knox, V. M. Oddo, L. P. Walkinshaw, B. E. Saelens, N. Chan, and J. C. Jones-Smith (2023). Seattle's sweetened beverage tax implementation and changes in interior marketing displays. *Journal of Public Health Policy 44*(4), 588–601.

Bagwell, K. (2007). The Economic Analysis of Advertising. In *Handbook of Industrial Organization*, Volume 3, pp. 1701–1844. North-Holland.

Bel, G. and Laia Domènech (2009). What influences advertising price in television channels?: An empirical analysis on the spanish market. *Journal of Media Economics 22*(3), 164–183.

Bernheim, B. D. (2009). Behavioral Welfare Economics. *Journal of the European Economic Association 7*(2-3), 267–319.

Berry, S., J. Levinsohn, and A. Pakes (1995). Automobile Prices in Market Equilibrium. *Econometrica 63*(4), 841–890.

Berry, S. T. (1994). Estimating Discrete-Choice Models of Product Differentiation. *RAND Journal of Economics 25*, 242–262.

Bonnet, C. and V. Réquillart (2013). Tax incidence with strategic firms in the soft drink market. *Journal of Public Economics 106*, 77–88.

Competition Commission (2000). *Supermarkets: A Report on the Supply of Groceries from Multiple Stores in the United Kingdom.* London: The Stationary Office.

Competition Commission (2013). *AG Barr / Britvic Merger Inquiry.* London: The Stationary Office.

Crawford, G., L. Deer, J. Smith, and P. Sturgeon (2017). The Regulation of Public Service Broadcasters: Should There be More Advertising on Television? *CEPR Discussion Paper 12428*.

DCMS (2021). Impact assessment. *Government Report https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/f assessment-hfss-advertising.pdf*, 163.

DeCicca, P., D. Kenkel, and M. F. Lovenheim (2022). The Economics of Tobacco Regulation: A Comprehensive Review. *Journal of Economic Literature 60*(3), 883–970.

DHSC (2024). Introducing further advertising restrictions on TV and online for products high in fat, salt or sugar: Government response to consultation on secondary legislation. Technical report.

Dickson, A., M. Gehrsitz, and J. Kemp (2023). Does a Spoonful of Sugar Levy Help the Calories Go Down? An Analysis of the UK Soft Drinks Industry Levy. *Review of Economics and Statistics forthcoming*.

Doraszelski, U. and S. Markovich (2007). Advertising dynamics and competitive advantage. *RAND Journal of Economics 38*(3), 557–592.

Doraszelski, U. and M. Satterthwaite (2010). Computable Markov-perfect industry dynamics. *RAND Journal of Economics 41*(2), 215–243.

Dubé, J.-P., G. J. Hitsch, and P. Manchanda (2005). An empirical model of advertising dynamics. *Quantitative Marketing and Economics 3*, 107–144.

Dubois, P., R. Griffith, and M. O'Connell (2018). The Effects of Banning Advertising in Junk Food Markets. *Review of Economic Studies 1*(1), 396–436.

Dubois, P., R. Griffith, and M. O'Connell (2020). How well targeted are soda taxes? *American Economic Review 110*(11), 3661–3704.

Ericson, R. and A. Pakes (1995). Markov-perfect industry dynamics: A framework for empirical work. *Review of Economic Studies 62*, 53–82.

Forde, H., T. L. Penney, M. White, L. Levy, F. Greaves, and J. Adams (2022). Understanding Marketing Responses to a Tax on Sugary Drinks: A Qualitative Interview Study in the United Kingdom, 2019. *International Journal of Health Policy and Management 11*(11), 2618–2629.

Gandhi, A. and J.-F. Houde (2020). Measuring Substitution Patterns in Differentiated-Products Industries. Technical Report w26375, National Bureau of Economic Research, Cambridge, MA.

Gentzkow, M., J. M. Shapiro, F. Yang, and A. Yurukoglu (2024). Pricing Power in Advertising Markets: Theory and Evidence. *American Economic Review 114*(2), 500–533.

GFRP (2021, April). Sugary drink taxes around the world. *Global Food Reserach Programe, University of North Carolina Available at https://globalfoodresearchprogram.org/wp-content/uploads/2021/04/SSB_sugary_drink_taxes_maps.pdf.*

Griffith, R., L. Nesheim, and M. O'Connell (2018). Income effects and the welfare consequences of tax in differentiated product oligopoly. *Quantitative Economics 9*(1).

Griffith, R., M. O'Connell, and K. Smith (2019). Tax design in the alcohol market. *Journal of Public Economics 172*, 20–35.

Harding, M. and M. Lovenheim (2017). The effect of prices on nutrition: Comparing the impact of product- and nutrient-specific taxes. *Journal of Health Economics 53*, 53–71.

Hausman, J., G. Leonard, and J. D. Zona (1994). Competitive Analysis with Differenciated Products. *Annales D'Économie et de Statistique* (34).

Hendel, I. and A. Nevo (2006). Sales and Consumer Inventory. *RAND Journal of Economics 37*(3), 543–561.

Hortaçsu, A., O. R. Natan, H. Parsley, T. Schwieg, and K. R. Williams (2024, May). Organizational Structure and Pricing: Evidence from a Large U.S. Airline. *The Quarterly Journal of Economics 139*(2), 1149–1199.

Hristakeva, S. and J. H. Mortimer (2023). Price Dispersion and Legacy Discounts in the National Television Advertising Market. *Marketing Science*.

Kim, J. Y. and M. Ishihara (2021). Evaluating the Effect of Soda Taxes Using a Dynamic Model of Rational Addiction. *SSRN Electronic Journal 3892506*.

Lee, M. M., L. A. Gibson, S. V. Hua, C. M. Lowery, M. Paul, C. A. Roberto, H. G. Lawman, S. N. Bleich, N. Mitra, and E. L. Kenney (2023). Advertising and Stocking at Small Retailers: A Sweetened Beverage Excise Tax in Philadelphia. *American Journal of Preventive Medicine*.

Li, X., W. Hartmann, and T. Amano (2024). Preference Externality Estimators: A Comparison of Border Approaches and IVs. *Management Science 70*(11).

Maskin, E. and J. Tirole (1988). A theory of dynamic oligopoly, I: Overview and quantity competition with large fixed costs. *Econometrica 56*, 549–569.

Miravete, E. J., K. Seim, and J. Thurk (2023). Pass-through and tax incidence in differentiated product markets. *International Journal of Industrial Organization 90*.

O'Connell, M. and K. Smith (2024). Optimal sin taxation and market power. *American Economic Journal: Applied 16*(4).

Pakes, A. and McGuire (1994). Computing markov-perfect nash equilibria: Numerical implications of a dynamic differentiated product model. *RAND Journal of Economics 25*, 555–589.

Ryan, S. (2012). The costs of environmental regulation in a concentrated industry. *Econometrica 80*, 1019–1062.

Seiler, S., A. Tuchman, and S. Yao (2021). The Impact of Soda Taxes: Pass-through, Tax Avoidance, and Nutritional Effects. *Journal of Marketing Research 58*(1), 24–49.

Shapiro, B., G. J. Hitsch, and A. Tuchman (2021). TV Advertising Effectiveness and Profitability: Generalizable Results from 288 Brands. *Econometrica 89*(4), 1855–1879.

Sweeting, A. (2013). Dynamic product positioning in differentiated product markets: The effect of fees for musical performance rights on the commercial radio industry. *Econometrica 81*(5), 1763–1803.

Thomas, M. (2020). Spillovers from Mass Advertising: An Identification Strategy. *Marketing Science 39*(4), 807–826.

Wang, E. Y. (2015). The impact of soda taxes on consumer welfare: Implications of storability and taste heterogeneity. *The RAND Journal of Economics 46*(2), 409–441.

WHO (2025). Advertising restrictions on national television. https://www.who.int/data/gho/data/indicators/indicator-details/GHO/advertising-restrictions-on-national-television.

Zenk, S. N., J. Leider, O. Pugach, A. A. Pipito, and L. M. Powell (2020). Changes in Beverage Marketing at Stores Following the Oakland Sugar-Sweetened Beverage Tax. *American Journal of Preventive Medicine 58*(5), 648–656.

Zenk, S. N., Y. Li, J. Leider, A. A. Pipito, and L. M. Powell (2021). No long-term store marketing changes following sugar-sweetened beverage tax implementation: Oakland, California. *Health & Place 68*, 102512.

Zubanov, A. (2021). The TV Advertising Industry: Demographic Segmentation and the Impact of Viewership Decline. *Zubanov, Andrey, The TV Advertising Industry: Demographic Segmentation and the Impact of Viewership Decline (November 16, 2021). Available at SSRN: https://ssrn.com/abstract=3853300 or http://dx.doi.org/10.2139/ssrn.3853300*.

# 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 present 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: other (non-cola) drinks, categorized as either sugar-sweetened or non-sugar-sweetened.

Table A.2 details the 12 demographic groups over which we allow all consumer preference parameters to vary. These groups are based on the interaction of household type and income quantile. Household types include: (i) working-age households without children, (ii) pensioner households without children, and (iii) households with children. A working-age household is one with at least one member aged 18–65, while a household with children has at least one member aged 18 or younger. Income quartiles are based on equivalized income, calculated as household income divided by the OECD equivalence scale. The table reports the number of households and transactions (including 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 Take Home Purchase Panel for 2010-2016. Diet Coke includes Coke Zero and Diet Pepsi includes Pepsi Max.*

Table A.2: *Households' demographic groups*

| | | Number of: households | Number of: 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 for 2010-2016.*

# B Advertising Market and Data

## B.1 The UK TV Market

The UK TV market is heavily regulated. Four large public service broadcasters—BBC, ITV1, Channel 4 (C4), and Channel 5 (C5)—face constraints on advertising. The BBC, funded by an annual license fee, is not permitted to air adverts. ITV1, C4 and C5, which do not receive license fee income, are allowed to show adverts but face some restrictions regarding programming, and total time dedicated advertising. These public broadcasters have relatively large audience shares: BBC1 accounts for approximately 20%, ITV for 16%, BBC2 and C4 for 7% each and C5 for 5%. They compete for viewers by offering programs designed for broad audience appeal (see Crawford et al. (2017) for a detailed discussion of the UK television advertising market).

In addition to these public service broadcasters, there are numerous commercial channels that do not face specific programming restrictions.[1] Access to these channels depends on the household's TV subscription type. Households can watch TV in four ways: free-to-air, Freeview, satellite, or cable. All households with a TV must pay the BBC license fee. Free-to-air provides access only to public service broadcasters without additional cost. Freeview

[1]The BBC also operates additional channels (e.g., BBC3, BBC4, BBC News, BBC Parliament) with low viewership, which are legally prohibited from advertising.

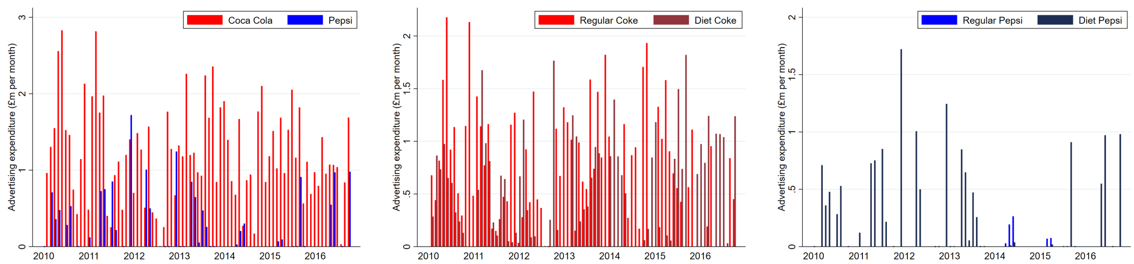
requires purchasing a compatible TV or set-top box but involves no further fees and offers a limited selection of additional channels. Satellite and cable subscriptions provide access to a broader range of mainly commercial channels while also including all free-to-air and Freeview channels.

## B.2 Advertising Expenditure

Figure B.1 presents advertising spending over time, separately for Coca Cola Enterprises (Coca Cola) and Pepsico (Pepsi), and further disaggregated by Regular and Diet brands within each firm. The figure highlights fluctuations in spending and reveals distinct advertising strategies: Coca Cola Enterprises allocates more to advertising its Regular brand than its Diet brand, with the former accounting for 57% of its total spend. In contrast, Pepsico advertises almost exclusively its Diet brand. Our analysis focuses on Coca Cola's advertising decisions for its Regular and Diet brands and Pepsico's decision for its Diet brand.

Figure B.1: *Advertising Expenditure*

(a) by firm (b) Coca Cola, by brand (c) Pepsi, by brand

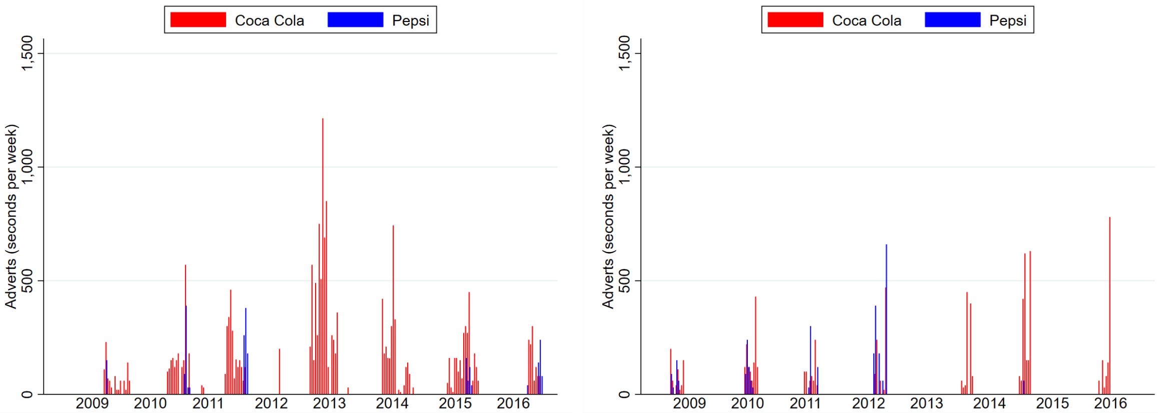



*Notes: Authors' calculations using data from AC Nielsen Advertising data for 2010-2016.*

Figure B.2 illustrates weekly variation in advertising (measured in seconds) for Coca Cola and Pepsico brands during two prime-time talent shows, The X Factor and Britain's Got Talent. Both shows air on ITV but at different times of the year—one in spring and the other in autumn. According to TV viewing data, 46% of households regularly watch Britain's Got Talent (25% of whom do not regularly watch The X Factor), while 39% regularly watch The X Factor (12% of whom do not regularly watch Britain's Got Talent). Advertisements from both Coca Cola and Pepsico appear during each show, but the distribution differs: Pepsico accounts for only 11% of cola advertising time during The X Factor (2009–2016), whereas its share rises to 27% during Britain's Got Talent. As a result, households' exposure to advertising from each firm varies depending on whether they watch neither, one, or both shows.

Figure B.2: *Within genre advertising variation*

(a) The X Factor (b) Britain's Got Talent




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

Table B.1 lists the advertising agencies in our dataset for 2016, covering all food and drink advertising. It shows that Coca Cola works with Mediacom, representing 29% of the agency's total food and drinks advertising, while Pepsico works with OMD, accounting for 3% OMD's food and drinks advertising.

Table B.1: *Advertising agencies in 2016*

| | Total agency advertising spend (£m) on | | |
|---|---|---|---|
| | All food & drink | Coca Cola | Pepsi |
| Omd | 94.75 | - | 2.52 |
| Zenith | 77.35 | - | - |
| Carat | 57.04 | - | - |
| Mediacom | 37.93 | 10.87 | - |
| Um | 27.49 | - | - |
| Blue 449 | 24.68 | - | - |
| Mec | 20.42 | - | - |
| Mindshare Media Uk Ltd | 16.80 | - | - |
| Rocket | 15.86 | - | - |
| Initiative Media London | 8.79 | - | - |
| Arena Media | 7.59 | - | - |
| M/six | 7.51 | - | - |
| Phd | 5.65 | - | - |
| Maxus | 4.13 | - | - |
| The7stars | 4.07 | - | - |
| Starcom | 3.85 | - | - |
| Mnc | 3.69 | - | - |
| Spirit Media Scotland Ltd | 1.17 | - | - |
| Spark Foundry | 0.92 | - | - |
| Goodstuff Communications | 0.77 | - | - |
| Direct (In House) Advertising | 0.64 | - | - |
| Specialist Works Ltd | 0.62 | - | - |
| Ams Media Group Ltd | 0.43 | - | - |
| The Lane Agency | 0.36 | - | - |
| Nick Stewart Media Consultancy | 0.22 | - | - |
| Overseas Agency - Ireland | 0.21 | - | - |
| Bray Leino | 0.19 | - | - |
| Anderson Spratt Group | 0.14 | - | - |
| Not Allocated | 0.11 | - | - |
| We Are Boutique | 0.10 | 0.01 | - |
| Republic Of Media | 0.09 | - | - |
| Genesis Advertising Ltd | 0.05 | - | - |
| Rla Group | 0.02 | - | - |
| Morvah | 0.02 | - | - |
| John Ayling & Associates Ltd | 0.01 | - | - |
| Juice Media Uk Ltd | 0.01 | - | - |
| Hello Starling | 0.01 | - | - |
| Di5 Ltd | 0.01 | - | - |
| Walker Communications | 0.01 | - | - |
| Tcs Media Ltd | 0.00 | - | - |

*Notes: Authors' calculations using data from AC Nielsen Advertising data for 2016.*

## B.3 Estimating Advertising Impact Probability

For one year, 2015, we have data on advertising impacts—the industry-standard measure of viewership—collected by the Broadcasters Audience Research Board (BARB).[2]

Impacts are measured based on Ratecard Weighted TV Ratings (TVRs), also known as Gross Rating Points (GRPs). TVRs are calculated as the number of impacts divided by the total target audience. Broadcasters use ratecard-weighted TVRs to sell advertising slots, applying weights to adjust for differences in slot length. While one impact typically represents a single viewer watching a 30 second ad, a pair of 15 second slots may hold greater value for advertisers than a single 30 second slot. Ratecard weighting accounts for these differences, enabling revenue comparisons—e.g., a slot generating 50 ratecard-weighted impacts produces half as much advertising revenue as a slot generating 100 ratecard-weighted impacts.

Table B.2 presents descriptive statistics on the match between our purchase data (which includes information on households' TV viewing habits by show, station, and time slot) and our advertising data. While we undertake this matching for all years in our dataset, we focus on 2015 in Table B.2 since it is the only year where we observe impacts.

In 2015, there were 35,481 Coca Cola and Pepsico adverts for which we could match at the show level, meaning we observe whether households watched the show during which the advert aired. Since the purchase data only record the most popular shows watched by households, some adverts in the advertising data could not be matched at the show level. In these cases, we matched based on station and time slot, covering an additional 77,083 adverts. A small number of adverts aired on minor stations for which household viewing behavior is not recorded in the purchase data; in these cases, we could only match on time slot. However, as shown in Table B.2, these adverts account for a small fraction of advertising spending and have very low measured impacts.

[2] BARB collects these data as follows: A sample of households is provided with a remote control featuring a button for each household member (and an additional button for guests). Each individual must press their button whenever they enter or leave the room while the television is on. Each household's TV is fitted with a meter that records 15 seconds of audio from TV adverts and matches this to a reference library. (See https://www.barb.co.uk/about-us/how-we-do-what-we-do/)

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

| | Total agency advertising spend (£m) on | | |
|---|---|---|---|
| Matched on | No. adverts | Mean impacts (TVR) | Total expenditure (£m) |
| Show | 35481 | 0.0534 | 7.58 |
| Station & Time slot | 77083 | 0.0170 | 8.10 |
| Time slot only | 62270 | 0.0007 | 0.83 |

Consumer advertising exposure (equation (2.1)) depends on whether a household has seen an advert during slot $k$, denoted as $w_{ik}$. These weights correspond to the $Q$ possible values of ordinal survey responses:

$$w_{ik} = \sum\nolimits_{q=1,..,Q} w_r 1_{\{v_{ik}=q\}}$$

where $v_{ik} = q$ if household $i$ reported response $q$ to the survey question related to slot $k$ (e.g., "how regularly do you watch show X?" if they show aired during that slot).

Households' answers to these questions are qualitative and categorized as: "never", "hardly ever", "sometimes", and "regularly". Since these responses are not directly quantitative, we leverage data from 2015—when we observe advertising impacts—to estimate the probabilities associated with each response category.

Let $q = \{1, 2, 3\}$ correspond to the three nonzero responses {"hardly ever", "sometimes", and "regularly"}, with $v_{ik}$ denoting household $i$'s response for slot $k$ and $w_q$ representing the probability of watching corresponding to answer $q$.

We estimate $w_q$ using constrained nonlinear least squares:

$$TVR_k = \sum\nolimits_q w_q \left( \frac{1}{N} \sum\nolimits_i 1_{\{v_{ik}=q\}} \right) + e_k$$

subject to

$$0 \leq w_1 \leq w_2 \leq w_3 \leq 1$$

We estimate this separately for slots matched based on the show and for slots matched based on station and time slot. Table B.3 presents the estimates, where we find that the constraint that $w_1 \leq w_2$ binds.

Table B.3: *Estimates of $w_q$ ($q = 1, 2, 3$)*

| | *TVR* | |
|---|---|---|
| | show | station slot |
| $w_1$ | 0.0352 | 0.0274 |
| | (0.0223) | (0.0040) |
| $w_2$ | 0.0352 | 0.0274 |
| | (0.0223) | (0.0040) |
| $w_3$ | 0.4975 | 0.4454 |
| | (0.1153) | (0.0159) |
| N | 88 | 1208 |

Note that if total viewership were unavailable, we could estimate $w_q$ directly within the demand model. To see this, we we can rewrite individual advertising exposure as

$$\begin{aligned} a_{ibt} &= \sum\nolimits_{q=1}^{Q} w_q \sum\nolimits_{\{k|t(k)=t\}} 1_{\{v_{ik}=q\}} \omega(T_{bk}) \\ &= \sum\nolimits_{q=1}^{Q} w_q a_{ibt}^q \end{aligned}$$

where $a_{ibt}^q = \sum_{\{k|t(k)=t\}} 1_{\{v_{ik}=q\}} \omega(T_{bk})$. This formulation implies that we could estimate $w_q$ as part of the demand model instead of relying on estimates derived from the TV survey and viewership data.

The main advantage of estimating $w_q$ within the demand model is that it would allow for additional heterogeneity, for example, through demographic-specific $w_q$. However, given that we already allow for substantial heterogeneity in how advertising exposure affects random utility—including demographic-specific effects—this approach would add little benefit while significantly increasing the number of advertising controls in the demand model.

## B.4 Advertising Exposure and Stock

We specify the consumer's exposure stock to brand $b$ advertising at the beginning of week $t$ as the discounted sum of past advertising exposure:

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

To initialize exposure stocks, we use data on advertising and household TV viewing behavior from a pre-sample year (2009), as advertising exposure older than 52 weeks has a negligible impact on stocks.

We set $\delta = 0.9$. To support this choice we use the regression (equation (2.2)) in Section 2.4 as the basis for conducting non-nested hypothesis test. We evaluate this equation with $\delta = 0.9$ against alternative values $\delta = 0.1, 0.15, 0.2, ..., 0.95$. We use the test proposed by MacKinnon (1983).

The idea behind this test is to obtain the fitted values of equation (2.2) for two competing models and then to re-estimate one model additionally including the fitted values from the alternative model as an extra regressor. The test itself is a t-test on the significance of the fitted value, if they are significant, it suggests that the alternative model has additional explanatory power. We conduct two sets of tests. First, we examine whether models with $\delta \neq 0.9$ provide additional expanatory power compared to the baseline model with $\delta = 0.9$ (reported in the Table B.4). Second, we test whether including advertising with $\delta = 0.9$ improves explanatory power in models where $\delta \neq 0.9$ (reported in the Table B.5). The results from the first table indicate we almost always reject the additional explanatory power of models with $\delta \neq 0.9$, compared to the $\delta = 0.9$ model. Conversely, the results in the second table show that for models with $\delta \neq 0.9$, we almost always cannot reject the additional explanatory power of including advertising with $\delta = 0.9$.

Table B.4: *MacKinnon tests*

| | Coke Reg | | | Coke Diet | | | Pepsi Diet | | |
|---|---|---|---|---|---|---|---|---|---|
| x | $\alpha$ | s.e. | P-value | $\alpha$ | s.e. | P-value | $\alpha$ | s.e. | P-value |
| 10 | 0.072 | 0.066 | 0.279 | 0.032 | 0.072 | 0.660 | 0.039 | 0.087 | 0.650 |
| 15 | 0.084 | 0.068 | 0.212 | 0.019 | 0.074 | 0.792 | 0.047 | 0.086 | 0.587 |
| 20 | 0.096 | 0.069 | 0.168 | 0.012 | 0.075 | 0.876 | 0.041 | 0.088 | 0.641 |
| 25 | 0.104 | 0.071 | 0.141 | 0.007 | 0.077 | 0.932 | 0.035 | 0.090 | 0.699 |
| 30 | 0.111 | 0.073 | 0.127 | 0.003 | 0.078 | 0.974 | 0.027 | 0.092 | 0.768 |
| 35 | 0.116 | 0.075 | 0.121 | -0.001 | 0.080 | 0.987 | 0.018 | 0.095 | 0.850 |
| 40 | 0.120 | 0.077 | 0.118 | -0.006 | 0.082 | 0.944 | 0.008 | 0.100 | 0.938 |
| 45 | 0.124 | 0.080 | 0.118 | -0.012 | 0.084 | 0.887 | -0.001 | 0.105 | 0.995 |
| 50 | 0.129 | 0.083 | 0.119 | -0.021 | 0.086 | 0.811 | -0.003 | 0.112 | 0.978 |
| 55 | 0.132 | 0.086 | 0.125 | -0.033 | 0.090 | 0.714 | 0.002 | 0.121 | 0.987 |
| 60 | 0.135 | 0.091 | 0.138 | -0.049 | 0.094 | 0.602 | 0.011 | 0.132 | 0.931 |
| 65 | 0.139 | 0.098 | 0.155 | -0.072 | 0.103 | 0.482 | 0.013 | 0.147 | 0.931 |
| 70 | 0.151 | 0.108 | 0.163 | -0.106 | 0.116 | 0.364 | -0.019 | 0.174 | 0.915 |
| 75 | 0.183 | 0.128 | 0.150 | -0.159 | 0.140 | 0.259 | -0.141 | 0.227 | 0.533 |
| 80 | 0.252 | 0.167 | 0.133 | -0.257 | 0.186 | 0.168 | -0.405 | 0.311 | 0.193 |
| 85 | 0.416 | 0.287 | 0.147 | -0.524 | 0.324 | 0.106 | -0.963 | 0.497 | 0.053 |
| 90 | 0.000 | 0.000 | | 0.000 | 0.000 | | 0.000 | 0.000 | |
| 95 | -0.151 | 0.179 | 0.399 | 0.315 | 0.213 | 0.138 | 0.653 | 0.220 | 0.003 |

*Notes: $t > 2$ says we reject the null, $\delta = x$ matters (in addition to $\delta = 0.9$)*

Table B.5: *MacKinnon, Inverse*

| | Coke Reg | | | Coke Diet | | | Pepsi Diet | | |
|---|---|---|---|---|---|---|---|---|---|
| x | $\alpha$ | s.e. | P-value | $\alpha$ | s.e. | P-value | $\alpha$ | s.e. | P-value |
| 10 | 0.928 | 0.066 | 0.000 | 0.968 | 0.072 | 0.000 | 0.961 | 0.087 | 0.000 |
| 15 | 0.916 | 0.068 | 0.000 | 0.981 | 0.074 | 0.000 | 0.953 | 0.086 | 0.000 |
| 20 | 0.904 | 0.069 | 0.000 | 0.988 | 0.075 | 0.000 | 0.959 | 0.088 | 0.000 |
| 25 | 0.896 | 0.071 | 0.000 | 0.993 | 0.077 | 0.000 | 0.965 | 0.090 | 0.000 |
| 30 | 0.889 | 0.073 | 0.000 | 0.997 | 0.078 | 0.000 | 0.973 | 0.092 | 0.000 |
| 35 | 0.884 | 0.075 | 0.000 | 1.001 | 0.080 | 0.000 | 0.982 | 0.095 | 0.000 |
| 40 | 0.880 | 0.077 | 0.000 | 1.006 | 0.082 | 0.000 | 0.992 | 0.100 | 0.000 |
| 45 | 0.876 | 0.080 | 0.000 | 1.012 | 0.084 | 0.000 | 1.001 | 0.105 | 0.000 |
| 50 | 0.871 | 0.083 | 0.000 | 1.021 | 0.086 | 0.000 | 1.003 | 0.112 | 0.000 |
| 55 | 0.868 | 0.086 | 0.000 | 1.033 | 0.090 | 0.000 | 0.998 | 0.121 | 0.000 |
| 60 | 0.865 | 0.091 | 0.000 | 1.049 | 0.094 | 0.000 | 0.989 | 0.132 | 0.000 |
| 65 | 0.861 | 0.098 | 0.000 | 1.072 | 0.103 | 0.000 | 0.987 | 0.147 | 0.000 |
| 70 | 0.849 | 0.108 | 0.000 | 1.106 | 0.116 | 0.000 | 1.019 | 0.174 | 0.000 |
| 75 | 0.817 | 0.128 | 0.000 | 1.159 | 0.140 | 0.000 | 1.141 | 0.227 | 0.000 |
| 80 | 0.748 | 0.167 | 0.000 | 1.257 | 0.186 | 0.000 | 1.405 | 0.311 | 0.000 |
| 85 | 0.584 | 0.287 | 0.042 | 1.524 | 0.324 | 0.000 | 1.963 | 0.497 | 0.000 |
| 90 | 0.000 | 0.000 | | 0.000 | 0.000 | | 0.000 | 0.000 | |
| 95 | 1.151 | 0.179 | 0.000 | 0.685 | 0.213 | 0.001 | 0.347 | 0.220 | 0.114 |

*Notes: $t > 2$ says we reject the null, $\delta = 0.9$ matters (in addition to $\delta = x$)*

Table B.6 summarizes the variation in brand advertising flows and stocks using the within-group standard deviation (measured over time and individuals). Figures B.3 and B.4 present heatmaps illustrating the weekly variation in the distribution of advertising flow and stock for each brand, pooled across demographic groups.

Table B.6: *Advertising exposure*

| Demographic | Income quartile | Flow s.d. Coke Reg | Flow s.d. Coke Diet | Flow s.d. Pepsi Diet | Stock s.d. Coke Reg | Stock s.d. Coke Diet | Stock s.d. Pepsi Diet |
|---|---|---|---|---|---|---|---|
| Working age | 1 | 32.8 | 29.2 | 24.0 | 168.6 | 138.6 | 67.3 |
| | 2 | 32.6 | 28.7 | 23.7 | 165.3 | 135.1 | 66.5 |
| | 3 | 32.2 | 28.3 | 23.2 | 162.3 | 132.6 | 65.3 |
| | 4 | 31.3 | 27.5 | 22.8 | 157.9 | 128.6 | 63.9 |
| Pensioner | 1 | 30.6 | 26.4 | 22.5 | 152.3 | 123.9 | 62.8 |
| | 2 | 29.5 | 24.9 | 21.3 | 147.4 | 116.9 | 59.7 |
| | 3 | 31.9 | 26.3 | 22.7 | 157.9 | 123.7 | 63.5 |
| | 4 | 28.6 | 24.2 | 20.4 | 141.4 | 114.1 | 57.3 |
| Household with children | 1 | 31.4 | 28.2 | 23.2 | 161.9 | 132.6 | 65.7 |
| | 2 | 32.0 | 28.6 | 23.7 | 164.1 | 133.6 | 67.1 |
| | 3 | 30.9 | 27.4 | 22.5 | 158.2 | 127.4 | 63.7 |
| | 4 | 30.0 | 26.4 | 21.7 | 152.6 | 122.6 | 61.5 |

Figure B.3: *Ad flow*

(a) Regular Coke (b) Diet Coke (c) Diet Pepsi

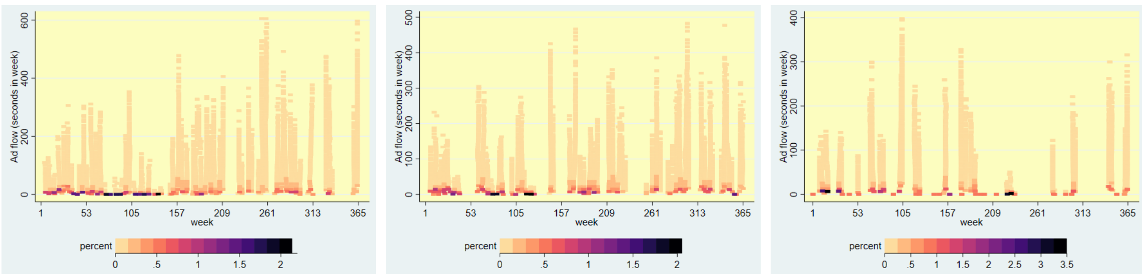
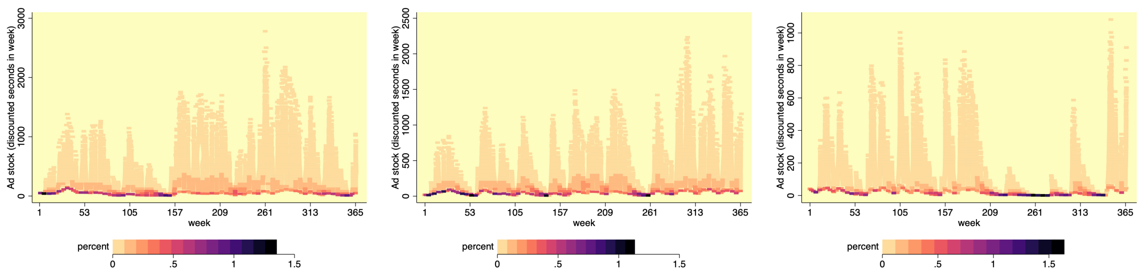



Figure B.4: *Ad stock*

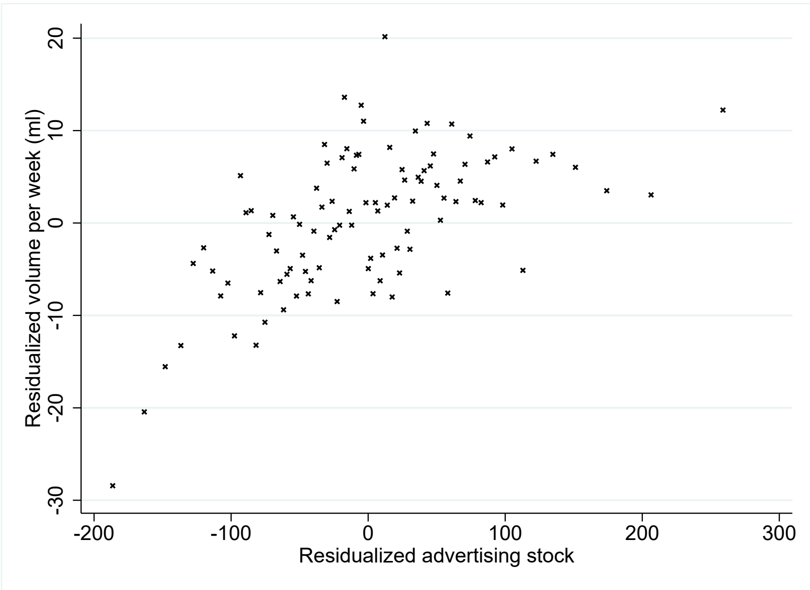
(a) Regular Coke (b) Diet Coke (c) Diet Pepsi



## B.5 Non-parametric Evidence of Advertising Effects

In Section 2.4 we provide evidence based on within-household variation on the relationship between purchase volume and advertising exposure stocks. Here, we estimate a more flexible version of equation (2.2) by first residualizing $vol_{ibt}$, and $A_{ibt}$ using regression on $\tau_t$, $\iota_{d,q(t)}$, $\kappa_{r,q(t)}$ and $\eta_i$. In Figure B.5 we plot the non-parametric conditional expectation of $vol_{ibt}$ given $A_{ibt}$ for Regular Coke, the most heavily advertised brand. It provides data-driven support for a concave relationship between purchases and advertising stocks.

Figure B.5: *Non-parametric relationship between residualized Regular Coke volume and advertising*




*Notes: For both Regular Coke volumes and advertising stocks, we regress the variable on week, demographic-quarter, region-quarter and household fixed effects, and obtain the residuals. The graphs plots the relationship between residualized Regular Coke volume and percentiles of the distribution of residualized Regular Coke volume.*

# C Equilibrium Delegation

To simplify notation and without loss of generality, we assume each firm sells a single product. A firm that directly chooses its advertising slots (rather than delegating decisions to an advertising agency) and its price solves the following problem:

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

where

$$\pi_{jt}(p_{1t},..,p_{Jt},(T_{11\tau},...,T_{JK\tau})_{\tau\leq t}) \equiv (p_{jt}-c_{jt})q_{jt}(p_{1t},..,p_{Jt},(T_{11\tau},...,T_{JK\tau})_{\tau\leq t}) - \sum\nolimits_k \rho_{kt}T_{jkt}$$

and $\rho_{kt}$ represents the price of advertising on channel $k$ (Here, $k$ indexes both channels and time slots, but for simplicity, we refer to it as a channel.) The firm's profits depend on the decisions of other firms. We seek a Markov Perfect Equilibrium.

If the firm delegates advertising decisions to an advertising agency, its problem becomes:

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

where

$$T^*_{jk}(e_{jt}) = \arg\max \omega(T_{j1t},..,T_{jKt})$$
$$\text{s.t. } \sum\nolimits_k \rho_k T_{jkt} \leq e_{jt}$$

This represents the optimal choice of an advertising agency, which aims to maximize aggregate impact $\omega(T_{j1t},..,T_{jKt})$ subject to the budget $e_{jt}$:

A firm can either:

1. Directly set prices and advertising to maximize its discounted sum of profits, or
2. Delegate advertising choices to an agency, which maximizes impacts subject to a budget.

We first analyze a game where the delegation decision is made in a static equilibrium, and then extend the analysis to a dynamic equilibrium.

## C.1 Endogenous Delegation in Static Equilibrium

**Price and advertising competition without delegation** Denote the profit of firm $j$, whose product is sold at price $p_j$ and advertised for duration $T_{jk}$ on slot $k$ 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 advertising on channel $k$ (where $k$ indexes both channels and time slots, but for simplicity, we refer to it as a channe).

Let $^*$ denote the Nash equilibrium when firms do not delegate advertising. A Nash equilibrium $(p_j^*, T_j^*, p_{-j}^*, T_{-j}^*)$ will be solution of:

$$\max_{p_j, T_j} \pi_j(p_j, T_j, p_{-j}^*, T_{-j}^*) \equiv \pi_j^*$$

with a symmetric condition holding for firm $-j$.

**Price and advertising competition with delegation** When the firm delegates advertising decisions to an agency, it provides an impact function $\omega(T_{j1}, .., T_{jK})$ to be maximized This function is independent of prices and the competing firm's choices. The firm's problem then reduced to choosing prices and an advertising budget to solve:

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

subject to the advertising agency's optimal allocation of advertising across slots:

$$\begin{array}{rcl} \tilde{T}_j(e_j) & = & \arg\max \omega(T_{j1}, .., T_{jK}) \\ & & \text{s.t.} \quad \sum_k \rho_k T_{jk} \leq e_j \end{array}$$

and given the optimal choices of competing firms, $p_{-j}^{**}$ and $e_{-j}^{**}$. The Nash Equilibrium $(p_j^{**}, T_j^{**}, p_{-j}^{**}, T_{-j}^{**})$ consists of solutions of the above problem, where the equilibrium advertising allocation satisfies $T_j^{**} \equiv \tilde{T}_j(e_{-j}^{**})$.

Depending on the own and cross-demand effects of advertising, the firm's profit under delegation may be higher or lower than when it controls advertising directly:

$$\pi_j^* \leq \pi_j^{**} \text{ or that } \pi_j^* \geq \pi_j^{**}$$

**Choice of delegation of advertising** Now, suppose each firm can choose whether or not to delegate its advertising decisions. Each firm incurs an additional fixed cost $\kappa_j$ if it chooses to manage both price and advertising decisions in-house. However, this cost is not incurred if the firm delegates slot selection to an advertising agency while retaining control over prices and the overall advertising budget.[3]

[3]We do not explicitly model the cost that firms may incur when engaging advertising agencies, such as markups charged by agencies. The fixed cost $\kappa_j$ represents the additional burden of in-house management, which may arise due to efficiency gains from delegation, specialized marketing expertise, or agencies' superior knowledge of television advertising markets.

If $\kappa_j = 0$ for both firms, the unique equilibrium outcome is that neither firm delegates its advertising decisions. This is because, in the absence of delegation costs, each firm finds it optimal to control both price and advertising in order to maximize profit, given the competitor's choices. This remains true even if delegation would lead to higher profits $\pi_j^{**} \geq \pi_j^*$. If firms are free to choose delegation, the equilibrium outcome will always be non-delegation, as each firm has an incentive to compete more aggressively on both price and advertising when its rival delegates. In equilibrium, this leads all firms to retain direct control over advertising.

However, when $\kappa_j > 0$, delegation can emerge as a Nash equilibrium. If both firms delegate their advertising decisions,[4] they may achieve higher profits than under direct competition. This is because the structure of demand can be such that delegation softens competition in advertising, mitigating the intense rivalry that would otherwise arise in a business-stealing environment.

To see this in more detail, define the following:

- $p_j^*(p_{-j}, T_{-j})$ and $T_j^*(p_{-j}, T_{-j})$ as firm $j$'s price and advertising best responses to the competing price and advertising choice when the firm does not delegate to an agency.
- $p_j^{**}(p_{-j}, T_{-j})$ and $T_j^{**}(p_{-j}, T_{-j})$ as firm $j$'s price and advertising best responses when it does delegate, where $T_j^{**}(p_{-j}, T_{-j}) \equiv \tilde{T}_j(e_j^{**}(p_{-j}, T_{-j}))$ and $e_j^{**}(p_{-j}, T_{-j})$ is firm $j$'s advertising choice, solving: $\max_{p_j, e_j}(p_j - c_j)q_j(p_j, \tilde{T}_j(e_j), p_{-j}, T_{-j}) - \sum_k \rho_k \tilde{T}_{jk}(e_j)$

Next, we denote firm $j$'s profit under its best response without delegation as $\pi_j^*(p_{-j}, T_{-j})$ and with delegation as $\pi_j^{**}(p_{-j}, T_{-j})$, given by:

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

and

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

By construction, we always have $\pi_j^{**}(p_{-j}, T_{-j}) \leq \pi_j^*(p_{-j}, T_{-j})$ for any given $(p_{-j}, T_{-j})$, meaning that delegating cannot be a Nash Equilibrium if there is no delegation cost ($\kappa_j = 0$). However, delegation can be an equilibrium if the delegation costs $\kappa_j$ and $\kappa_{-j}$ satisfy:

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

[4] A mixed strategy where only one firm delegates can also be an equilibrium, but we do not explore this case here.

That is, delegation becomes an equilibrium when firms find it optimal to avoid the fixed cost of managing advertising in-house.

Delegation can also arise as an equilibrium if:

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

Thus, firms may endogenously choose to delegate advertising to an agency and obtain higher profits if there is some fixed cost associated with directly managing advertising slot choices.

In the absence of this cost ($\kappa_j = 0$), delegation cannot be an equilibrium in this one-period static game. However, in a dynamic setting, where firms decide on delegation for the long term, the outcome can differ.

## C.2 Endogenous Delegation in Dynamic Equilibrium

For simplicity, we consider the case where advertising has no dynamic effect on demand (i.e., consumers are memoryless).

Consider the repeated game where firms maximize their intertemporal sum of profits with discount factor $\beta \in (0, 1)$. In this setting, delegating to an agency can be a Subgame perfect Nash Equilibrium even if $\kappa_j = \kappa_{-j} = 0$, provided firms are sufficiently patient (i.e., $\beta$ large enough). The standard trigger strategy can sustain delegation as an equilibrium: firms delegate as long as their competitor does, but if one firm deviates by not delegating, both switch permanently to the no-delegation equilibrium. For this strategy to work, we need $\beta$ to be large enough to satisfy (assuming stationary, where demand and profit function are time invariant)

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

and symmetrically for firm $-j$:

$$\frac{1}{1-\beta}\pi_{-j}^{**}(p_j^{**}, T_j^{**}) \geq \pi_{-j}^*(p_j^{**}, T_j^{**}) + \frac{\beta}{1-\beta}\pi_{-j}^*(p_j^*, T_j^*)$$

Since we know that $\pi_j^*(p_{-j}^{**}, T_{-j}^{**}) \geq \pi_j^{**}(p_{-j}^{**}, T_{-j}^{**})$ and given that $\frac{1}{1-\beta} > 1$ while $\frac{\beta}{1-\beta} < \frac{1}{1-\beta}$, the condition holds whenever

$$\beta \geq \frac{\pi_j^*(p_{-j}^{**}, T_{-j}^{**}) - \pi_j^{**}(p_{-j}^{**}, T_{-j}^{**})}{\pi_j^*(p_{-j}^{**}, T_{-j}^{**}) - \pi_j^*(p_{-j}^{*}, T_{-j}^{*})}.$$

This condition is always satisfied if: $\pi_j^*(p_{-j}^{**}, T_{-j}^{**}) - \pi_j^*(p_{-j}^{*}, T_{-j}^{*}) < 0$. However, delegation cannot be sustained as an equilibrium 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 delegation is only an equilibrium of the dynamic game if the per-period profit under mutual delegation is higher than under mutual non-delegation. If this condition holds, there exists a discount factor $\beta^* < 1$ such that for all $\beta \geq \beta^*$, delegation is a Subgame Perfect Nash Equilibrium.

This model provides a rationale for why firms delegate advertising to agencies in equilibrium. It shows that delegation can be a more profitable strategy than direct competition in advertising, particularly in a dynamic setting where firms use strategies that sustain tacit coordination on delegation.

# D Monopoly Advertising Response to Tax

In the case of a static single-product monopolist, we illustrate how tax policy affects the profit-maximizing advertising choice. This highlights two key mechanisms that shape a firm's incentives to adjust advertising in response to the introduction or modification of a tax.

The monopolist chooses its price $p$ and its level of advertising $A$ to maximize profits, facing 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 firm's problem is: $(p^*, A^*) = \arg\max_{p,A}(p - c - \tau)Q(p, A) - kA$. We assume that the profit function in concave in $(p, A)$. Denote optimal output by $Q^* \equiv Q(p^*, A^*)$, 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 $\rho^* > 0$ ($\rho^* < 0$) implies that a marginal tax increase is over-shifted (under-shifted) to prices—i.e., the monopolist increases (decreases) its margin in response, holding advertising fixed. The impact of a marginal tax increase on optimal advertising is determined by:[5]

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

To interpret this condition, first consider the case where the monopolist sets an exogenous fixed margin, meaning $\frac{dp^*}{d\tau} = 1$ and $\rho^* = 0$. In this case, whether the tax increases advertising depends on the cross-derivative of demand, $Q^*_{Ap}$. A tax rise increases the (tax-inclusive) price, pushing the firm further up its demand curve. If, at this new higher price level, consumers are more (less) responsive to advertising, the firm has an incentivize to increase (decrease) its advertising.

When the firm can adjust its margin—so price is also a choice variable—an additional effect comes into play. If the firm raises its margin in response to the tax (so $\rho^* > 0$), this increases the profitability of acquiring the marginal consumer, incentivizing greater advertising. Conversely, if the firm lowers its margin $\rho^* < 0$, advertising incentives weaken.

Thus, in the monopoly case, advertising responses to taxes depend on two factors:

1. Variation in demand responsiveness to advertising along the demand curve: If consumer sensitivity to advertising changes with price, this shapes the firm's advertising incentives.
2. Pass-through of the tax: Whether the tax is under- or over-shifted depends on the tax structure and demand curvature, influencing the firm's optimal margin and, consequently, its advertising decisions.

Moreover, the ability to adjust advertising introduces a feedback effect on price-setting. This creates both direct and indirect effects on consumption.[6]

In reality, most firms sell multiple products, tax liabilities varies across products, firms engage in competition, and advertising has persistent effects on consumer choice meaning that competition is dynamic in nature. Our model incorporates the additional factors influencing advertising decisions, while also capturing the two forces highlighted in this simplified example.

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

[6]In particular, tax pass-through depends on advertising adjustments. Specifically, $\frac{d(p-\tau)^*}{d\tau} > 0$ 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 $\left(-1 + \frac{Q^* Q^*_{pp}}{(Q^*_p)^2}\right) > 0$.

# E Solution to Advertising Agency Problem

The optimal advertising length during slot $k$ satisfies equation (3.6), which we repeat here

$$T^*_{bk} = \omega'^{-1}\left(\frac{\rho_k}{\sum_{i\in\Omega_b} w_{ik}}\frac{1}{\lambda^*_{bt}}\right).$$

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

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

Note, total brand advertising expenditure is

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

Hence, combining the last two equations, we obtain:

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

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

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

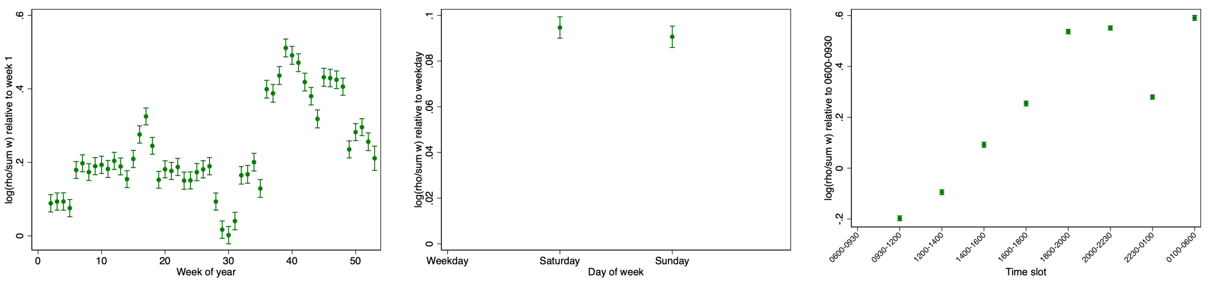
where $\tau_{t(kb)}$ is a slot-brand fixed effect.

We estimate equation (E.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 level, where slot type is defined by the interaction of weekday/Saturday/Sunday with thwo following time intervals: 1am-6am, 6am-9.30am, 9.30am-12pm, 12pm-2pm, 2pm-4pm, 4pm-6pm, 6pm-10pm, 10pm-10.30pm and 10.30pm-1.00am. We measure price per view, $\frac{\rho_k}{\sum_i w_{ik}}$, as the advertising spend for brand-station-week-slot type divided by rate card-weighted television rating among adult viewers.

Figure E.1 illustrates variation in these prices, plotting mean differences across weeks, days of the week, and time slots. These patterns align with intuition—for instance, advertising tends to be more expensive (and impactful) during Easter and Christmas, on weekends, and in the evening.

Figure E.1: *Variation in* $\log(\frac{\rho_k}{\sum_i w_{ik}})$

(a) by week (b) by day of week (c) by time slot




We measure advertising length, $T^*_{bk}$, as advertising duration in seconds. We report estimates in Table E.1. These correspond to the $\hat{\gamma} = 0.64$ (with p-value is smaller than 0.0001) reported in the paper.

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

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

# F Additional Estimation Results

Our purchase data covers 21,710 households and 2,585,650 choice occasions (i.e., weeks in which a drink is purchased). To estimate our demand model, we randomly select up to 1,000 households from each of the 12 demographic groups and up to 25 choice occasions per household. This results in 267,677 choice occasions, which we use for estimation. We estimate the model separately for each demographic group, allowing all parameters to vary across groups. We use simulated maximum likelihood, approximating each random coefficient integral using 50 Modified Latin Hypercube draws per observation (see Hess et al. (2006)) and allowing for correlated draws for the price and advertising coefficients. Table F.1 reports the parameter estimates, omitting product and time-effects for brevity.

In Table F.2 we report selected mean product-level price elasticities. In Table F.3 we report product-level mean marginal cost and markups.

Table F.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) |

*Coefficient estimates cont.*

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

Table F.2: *Product 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 F.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 |

# G Transition Function

We posit that firms track a summary statistic of the brand-specific consumer exposure distribution and present evidence that doing so results in negligible prediction error. Specifically, we assume that the state space consists of the expected value of the exposure stock distribution for each brand, denoted as $(\mathbb{A}_{1t}, \ldots, \mathbb{A}_{Bt})$, 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. This sum is taken over the set of soft drinks consumers, consistent with them being the targeted population in the agency problem (equation (3.5)). Alternatively, firms could track exposure stocks among a subset of this population. We experimented with the possibility that firms track exposure stocks for specific demographic groups. However, since average stocks across groups tend to co-move, this results in qualitatively similar outcomes in the dynamic game.

By tracking the mean of the distribution, firms make a prediction error in their demands, equal to $s_{jt}(\mathbf{p}_t, \mathbb{A}_{1t}, \ldots, \mathbb{A}_{Bt}) - E_{\mathcal{A}_t}[s_{jt}(\mathbf{p}_t, \mathcal{A}_{i1t}, \ldots, \mathcal{A}_{iBt})]$. In practice, this error is small, with the average absolute error (across products) being 2% of product level demands. This occurs 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.

Combining the consumer-level advertising exposure (equation (2.1)) with our estimate of the optimal condition for the choice of advertising slots (captured by our estimate of the curvature parameter for $\omega(\cdot)$ in equation (3.6), $\gamma$), the evolution of the brand $b$ state variable can be rewritten as $\mathbb{A}_{bt} = \delta\mathbb{A}_{bt-1} + \lambda_{t-1}e^{\gamma}_{bt-1}$, 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 below).

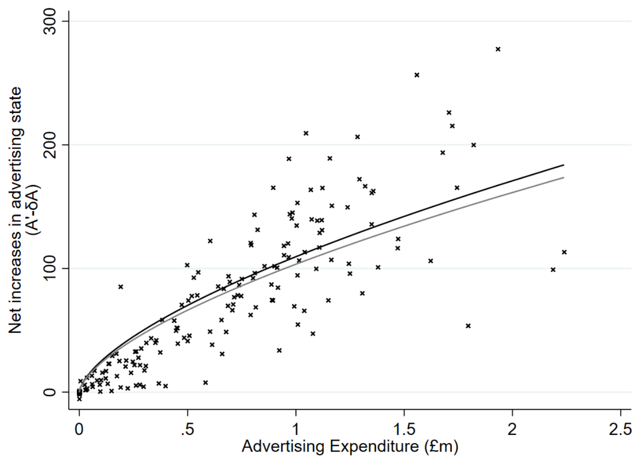
Firms do not observe the realization of $\lambda_{t-1}$ when making decisions about their advertising budgets $e_{bt-1}$ (since slot advertising prices are not yet known). Therefore, at this point in time, $\lambda_{t-1}$ is a random variable. We assume that firms form expectations about changes in the advertising state conditional on expenditure, which implies the stock satisfies:

$$\mathbb{A}_{bt} - \delta\mathbb{A}_{bt-1} = \lambda e^{\gamma}_{bt-1} + v_{bt-1}, \tag{G.1}$$

where $v_{bt-1} = (\lambda_{t-1} - \lambda)e^{\gamma}_{bt-1}$. We estimate this equation with linear methods (as $\gamma$ is already known).

Table G.1: *Advertising state law of motion*

| | $\mathbb{A}_{bt} - \delta\mathbb{A}_{bt-1}$ (1) | $\mathbb{A}_{bt} - \delta\mathbb{A}_{bt-1}$ (2) |
|---|---|---|
| $e_{bt-1}$ $(\hat{\lambda})$ | 0.0153 | 0.0145 |
| | (0.0004) | (0.0006) |
| var$(v_{bt-1})$ | 776 | 800 |
| $r^2$ | 0.8751 | 0.8728 |
| $N$ | 249 | 246 |
| Instrument | No | Yes |




*Notes: Table shows estimates of equation (G.1). Column (1) are OLS estimates, column (2) are IV estimates instrumenting $e^{\lambda}_{bt-1}$ with $\mathbb{A}_{bt-2}$. The figure shows a scatter plot of monthly advertising expenditure, $e_{bt-1}$, and net changes in the advertising state, $\mathbb{A}_{bt} - \delta\mathbb{A}_{bt-1}$ (across brands and year-months). The black line is based on the OLS estimate and the grey line on the IV estimate (in both cases with $\gamma = 0.64$).*

Column (1) in Table G.1 shows estimates of $\lambda$ and the variance of the error term under the assumption that $\mathbb{E}[v_{bt-1}|e_{bt-1}] = 0$ (which holds if $\mathbb{E}[\lambda_{t-1}|e_{bt-1}] = \lambda$). In column (2), we allow for this possibility that $\mathbb{E}[v_{bt-1}|e_{bt-1}] \neq 0$ by instrumenting $e^{\gamma}_{bt-1}$ with the two period lagged mean advertising stock $\mathbb{A}_{bt-2}$. Since this variable is observed, it is included in firms' information sets when they choose advertising expenditure $e_{bt-1}$. Moreover, given the likely diminishing returns to investment in a brand's advertising stock, $\mathbb{A}_{bt-2}$ is likely to influence the firm's flow investment decision. We find that instrumenting with $\mathbb{A}_{bt-2}$ leads to a modest decline in $\hat{\lambda}$ relative to column (1). Additionally, we include a scatter plot of the underlying data and plot the relationship implied between the change in net stock and advertising investment, which shows that the implied relationship is very similar across both sets of estimates.

To solve for a Markov Perfect Equilibrium we discretize the state space. Specifically, for a set of evenly spaced discrete values $\{A_1, \ldots, A_K\}$, where $A_1 = 0$, we use the state transition function:

$$P(\mathbb{A}_{bt} = \mathbb{A}_{k'}|\mathbb{A}_{bt-1} = \mathbb{A}_k, e_{bt-1}) = \int_{\mathbb{A}_{k'-1}}^{\mathbb{A}_{k'}} f_v(\mathbb{A}_{bt} - \delta\mathbb{A}_k - \lambda e^{\gamma}_{bt-1}) \frac{\mathbb{A}_{bt} - \mathbb{A}_{k-1}}{\mathbb{A}_{k'} - \mathbb{A}_{k'-1}} d\mathbb{A}_{bt} \quad \text{(G.2)}$$
$$+ \int_{\mathbb{A}_{k'}}^{\mathbb{A}_{k'+1}} f_v(\mathbb{A}_{bt} - \delta\mathbb{A}_k - \lambda e^{\gamma}_{bt-1}) \frac{\mathbb{A}_{k'+1} - \mathbb{A}_{bt}}{\mathbb{A}_{k'+1} - \mathbb{A}_{k'}} d\mathbb{A}_{bt}.$$

Since there are three advertising states—one for Regular Coke, Diet Coke and Diet Pepsi—the state grid $\{A_1, ..., A_K\}^3$ has dimension $K^3$. We set a value for $A_K$ above the $99^{th}$ percentile of observed mean stocks in the data and check ex post that the maximum state has zero probability mass in the equilibrium ergodic distribution. We use an evenly spaced grid and set $K = 21$, meaning there are 9,261 points in the discretized state space.

## G.1 State Transition Function

The mean exposure flow for brand $b$ advertising is

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

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 $\omega(.)$, $\omega(T^*_{bk}) = T^{*\gamma}_{bk}$, and the optimality condition for $T^*_{bk}$ (equation (E.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 $\nu_{bt-1} = (\lambda_{t-1} - \lambda) e^{\gamma}_{bt-1}$.

# H Solution Algorithm

Our solution algorithm is similar in spirit to that of Pakes and McGuire (1994).

**State space discritization.** The state space consists of the expected value of the exposure stock for each of brand, $(\mathbb{A}_{1t}, \ldots, \mathbb{A}_{Bt})$ (see Section 5.1). In our application $B = 3$, (corresponding to Regular Coke ($RC$), Diet Coke ($DC$) and Diet Pepsi ($DP$)). For each $b$, we discretize the state spaced into $K = 21$ evenly spaced values, $A_1, \ldots, A_K$. We set a value for $A_K$ above the $99^{th}$ percentile of observed mean stocks in the data and check ex post that the maximum state has zero probability mass in the equilibrium ergodic distribution. The state space is of dimension $21^3 = 9,261$. Denote by $a_{\Bbbk}$ a single point in the state space grid, which corresponds to discrete advertising levels for each brand, i.e., $(A_{RC,k}, A_{DC,k'}, A_{DP,k''})$ where $k, k', k'' \in \{1, \ldots, 21\}$.

**Profit function.** In our application there are two firms, $f = \{C, P\}$, which correspond to Coca Cola Enterprises and Pepsico. Denote the state-specific gross profit function (i.e., prior to deducting any advertising expenditure) of firm $f$ by $\pi_f(a_{\Bbbk})$. Note, $\pi_f(a_{\Bbbk})$ is evaluated at the state-specific equilibrium price vector $\mathbf{p}(a_{\Bbbk})$. We compute $\pi_f(a_{\Bbbk})$ for $f \in \{C, P\}$ in each of the 9,261 states. This entails, at each point in the state space grid, solving the price vector that satisfies the set of first-order conditions (equation (3.3)). In matrix notation, these conditions are:

$$\mathbf{p}(a_{\Bbbk}) = \mathbf{c} - \left[\mathbf{\Gamma} \circ \left(\frac{\partial \mathbf{q}(a_{\Bbbk}, \mathbf{p}(a_{\Bbbk}))}{\partial \mathbf{p}}\right)\right]^{-1} \mathbf{q}(a_{\Bbbk}, \mathbf{p}(a_{\Bbbk}))$$

where $\mathbf{\Gamma}$ is the product ownership matrix. Re-write this as $\mathbf{p}_{\Bbbk} = f_{\Bbbk}(\mathbf{p}_{\Bbbk})$. We start with an initial guess of $\mathbf{p}_{\Bbbk}^r$, compute $\mathbf{p}_{\Bbbk}^{r+1} = f_{\Bbbk}(\mathbf{p}_{\Bbbk}^r)$ and continue updating until $||\mathbf{p}_{\Bbbk}^{r+1} - \mathbf{p}_{\Bbbk}^r|| = \max|\mathbf{p}_{\Bbbk}^{r+1} - \mathbf{p}_{\Bbbk}^r| < 10^{-4}$. Once we have obtained state-specific equilibrium prices we also compute the state-specific equilibrium quantity vector, $\mathbf{q}(a_{\Bbbk})$, and consumer surplus, $\mathrm{CS}(a_{\Bbbk})$.

Our counterfactual simulations entail the imposition of a specific and (separately) an ad valorem tax. In order to implement these counterfactuals we must repeat the computation of the state-specific profit functions with each tax in place.

**Bellman equations.** Let $a = (a_{RC}, a_{DC}, a_{DP})$ denote the current levels of the Regular Coke, Diet Coke and Diet Pepsi advertising states. The two firms value functions are joint solutions of:

$$V_C(a, e_{RC}, e_{DC}) = \pi_C(a) + \max_{e_{RC}, e_{DC} \in R^+} \Bigg\{ -(\psi_{RC} e_{RC} + \psi_{DC} e_{DC}) + \beta \sum_{a'_{RC}, a'_{DC}} \tag{H.1}$$

$$\bar{V}_C(a'_{RC}, a'_{DC}, e_{RC}, e_{DC}) p(a'_{RC}|a_{RC}, e_{RC}) p(a'_{DC}|a_{DC}, e_{DC}) \Bigg\}$$

$$V_P(a, e_{DP}) = \pi_P(a) + \max_{e_{DP} \in R^+} \Bigg\{ -\psi_{DP} e_{DP} + \beta \sum_{a'_{DP}} \bar{V}_P(a'_{DP}, e_{DP}) p(a'_{DP}|a_{DP}, e_{DP}) \Bigg\}, \tag{H.2}$$

where

$$\bar{V}_C(a'_{RC}, a'_{DC}, e_{RC}, e_{DC}) = \sum_{a'_{DP}} V_C(a', e_{RC}, e_{DC}) p(a'_{DP}|a_{DP}, e_{DP})$$

$$\bar{V}_P(a'_{DP}, e_{DP}) = \sum_{a'_{RC}, a'_{DC}} V_P(a', e_{RC}, e_{DC}) p(a'_{RC}|a_{RC}, e_{RC}) p(a'_{DC}|a_{DC}, e_{DC}),$$

and the transition function, $p(a'_b|a_b, e_b)$, is given by equation (G.2).

**Solving for the MPE.** The solution algorithm is as follows:

1. Start with an initial guess of optimal advertising expenditures and value functions in each advertising state. When solving for the no tax equilibrium we use as starting values, for all $\mathbb{k}$:

   $$e^l_{RC}(a_{\mathbb{k}}) = e^l_{DC}(a_{\mathbb{k}}) = 0.3e^6, \quad e^l_{DP}(a_{\mathbb{k}}) = 0.2e^6 \quad V^l_C(a_{\mathbb{k}}) = \frac{\pi_C}{1-\beta} \quad V^l_P(a_{\mathbb{k}}) = \frac{\pi_P}{1-\beta}$$

   When solving for the specific or ad valorem tax equilibrium we use the optimal values from the no tax equilibrium as starting values.

2. For each point in the state space, $\mathbb{k}$, use equations (H.1) and (H.2), evaluated at the initial guess of $(V^l_C(a_{\mathbb{k}}), V^l_R(a_{\mathbb{k}}), e^l_{CR}(a_{\mathbb{k}}), e^l_{CD}(a_{\mathbb{k}}), e^l_{PD}(a_{\mathbb{k}}))$ to solve for the optimal advertising expenditures $\tilde{e}^{l+1}_{CR}(a_{\mathbb{k}}), \tilde{e}^{l+1}_{CD}(a_{\mathbb{k}}), \tilde{e}^{l+1}_{PD}(a_{\mathbb{k}})$.

3. Use as the iteration $l+1$ advertising expenditures $e^{l+1}_b(a_{\mathbb{k}}) = (1-\lambda)e^l_b(a_{\mathbb{k}}) + \lambda \tilde{e}^{l+1}_b(a_{\mathbb{k}})$ with dampening parameter $\lambda = 0.5$.

4. Use these expenditures to evaluate the right hand side equations (H.1) and (H.2) and thereby update the value functions $(V^{l+1}_C(a_{\mathbb{k}}), V^{l+1}_P(a_{\mathbb{k}}))$.

5. Repeat steps 2-4 until the stopping criteria, for $f = \{C, P\}$:

$$\left|\left|\frac{V_f^{l+1} - V_f^l}{1 + |V_f^l|}\right|\right| = \max_{\mathbb{k}} \left|\frac{V_f^{l+1} - V_f^l}{1 + |V_f^l|}\right| < 10^{-6}$$

is satisfied.

# I Consumer Surplus Decomposition

Denote the advertising state-specific consumer surplus under regime $\chi \in \{\emptyset, \mathbb{s}, \mathbb{a}\}$ (corresponding to no-tax, specific tax and ad valorem tax), by $\text{cs}_\chi(\mathbb{A}, \mathbf{p}_\chi(\mathbb{A}))$, where $\mathbb{A} = \{\mathbb{A}\}_b$ denotes the value of the brand advertising state and $\mathbf{p}_\chi(\mathbb{A})$ the optimal price vector. Denote the equilibrium distribution over states in regime $\chi \in \{\emptyset, \mathbb{r}, \mathbb{s}, \mathbb{sr}, \mathbb{a}, \mathbb{ar}\}$ (where $\mathbb{r}$ corresponds to advertising restriction) by $g_\chi(\mathbb{A})$. Consider the change in equilibrium consumer surplus that results from the introduction of a specific tax (relative to when no tax is in place, and where advertising is unrestricted). This is given by:

$$\Delta\text{CS}_s = \int_{\mathbb{A}} \text{cs}_s(\mathbb{A}, \mathbf{p}_s(\mathbb{A}))g_s(\mathbb{A}) - \int_{\mathbb{A}} \text{cs}_0(\mathbb{A}, \mathbf{p}_0(\mathbb{A}))g_0(\mathbb{A}).$$

We decompose this into a static component, which reflects the change in the state-specific consumer surplus function, and a dynamic component, which reflects the change in the equilibrium distribution over states. In particular:

$$\begin{aligned}\Delta\text{CS}_s = & \underbrace{\int_{\mathbb{A}} \left(\frac{1}{2}g_0(\mathbb{A}) + \frac{1}{2}g_s(\mathbb{A})\right)\left(\text{cs}_s(\mathbb{A}, \mathbf{p}_s(\mathbb{A})) - \text{cs}_0(\mathbb{A}, \mathbf{p}_0(\mathbb{A}))\right)}_{\text{static effect}} + \\ & \underbrace{\int_{\mathbb{A}} \left(\frac{1}{2}\text{cs}_s(\mathbb{A}, \mathbf{p}_s(\mathbb{A})) + \frac{1}{2}\text{cs}_0(\mathbb{A}, \mathbf{p}_0(\mathbb{A}))\right)\left(g_s(\mathbb{A}) - g_0(\mathbb{A})\right)}_{\text{dynamic effect}}.\end{aligned}$$

We decompose the consumer surplus effects of the other policy interventions analogously. Notice that the advertising restriction only impacts the equilibrium distribution, so the impact of an advertising restriction (in the absence of any tax) engenders zero static effect.

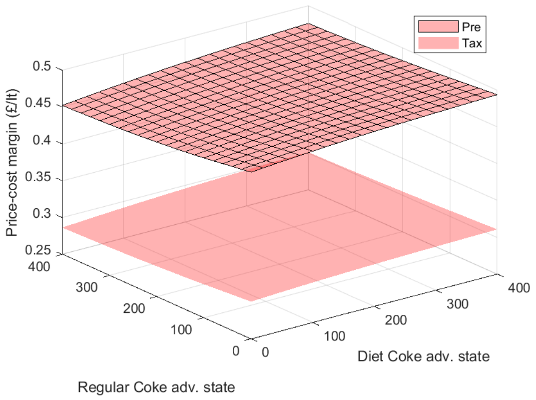
# J Additional Counterfactual Results

In Figure J.1 we show the impact of the ad valorem tax on price-cost margins and the equilibrium distribution. The corresponding figure for a specific tax is reported in the main paper (Figure 6.1). Tables J.1 and J.2 shows aggregate effects by brand (providing a by-brand breakdown on Table 6.1). Table J.3 reports distributional effects, including the dynamic consumer surplus effect (Table 6.3 reports these results excluding the dynamic effect).

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

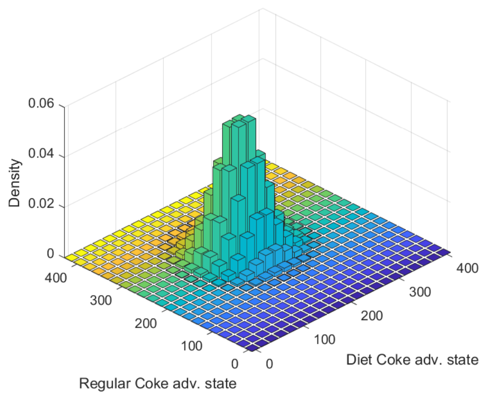
*On static-specific optimal margins*

(a) Average Regular Coke margins

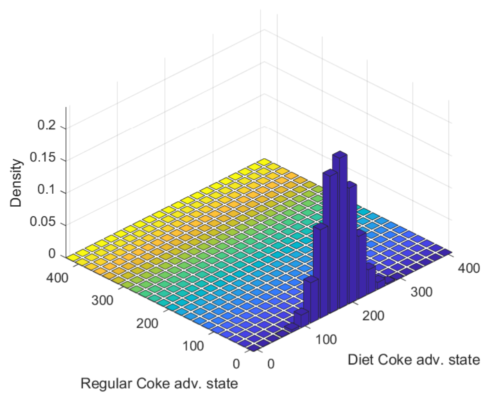



*On equilibrium distribution*

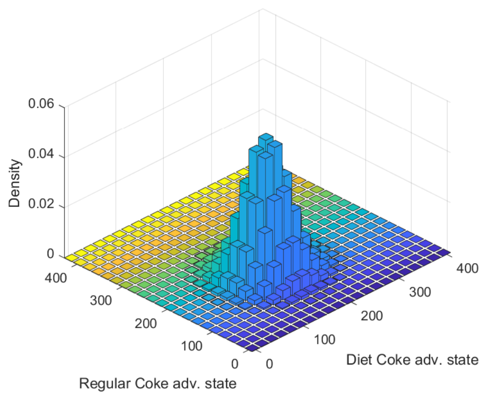
(b) Pre-policy



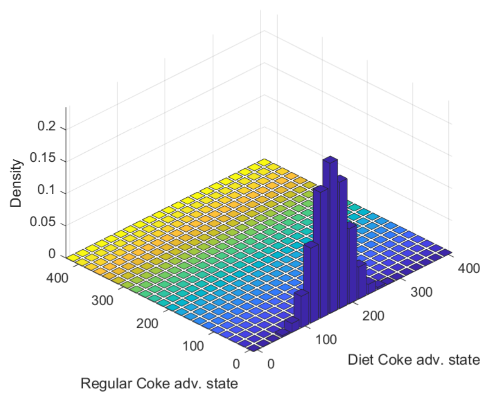

(c) Advertising restriction




(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 5.1(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 5.3(b).*

Table J.1: *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 price** | | | | | | | |
| Reg Coke | 0.9% | 28.2% | 0.1% | 0.6% | 38.4% | 0.1% | 0.5% |
| Diet Coke | -1.3% | -1.6% | -0.1% | -0.8% | -1.6% | -0.2% | -0.7% |
| Reg Pepsi | -0.1% | 34.2% | -0.0% | -0.1% | 25.6% | -0.1% | -0.1% |
| Diet Pepsi | -0.0% | -0.6% | -0.0% | -0.0% | -0.2% | -0.0% | -0.0% |
| **Δ margin** | | | | | | | |
| Reg Coke | 1.9% | 5.0% | 0.3% | 1.3% | -34.6% | 0.2% | 0.7% |
| Diet Coke | -2.8% | -3.4% | -0.3% | -1.8% | -3.6% | -0.5% | -1.6% |
| Reg Pepsi | -0.1% | 5.7% | -0.0% | -0.2% | -35.9% | -0.1% | -0.1% |
| **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% |
| **Δ quantity** | | | | | | | |
| Reg Coke | -16.4% | -55.6% | -1.2% | -5.6% | -62.0% | -1.9% | -4.7% |
| Diet Coke | -6.0% | 14.2% | -1.6% | -7.3% | 15.5% | -2.9% | -6.7% |
| Reg Pepsi | -1.8% | -53.6% | -0.2% | -0.9% | -33.0% | -0.5% | -1.2% |
| Diet Pepsi | -1.6% | 8.0% | -0.2% | -1.9% | 5.7% | -0.5% | -1.7% |
| Reg Store | 3.2% | 7.9% | 0.4% | 2.0% | 7.6% | 0.7% | 1.9% |
| Diet Store | 2.8% | 3.5% | 0.4% | 2.1% | 3.4% | 0.8% | 1.9% |
| Reg Outside | 3.1% | 5.8% | 0.4% | 1.9% | 5.4% | 0.7% | 1.7% |
| Diet Outside | 2.6% | 2.7% | 0.4% | 1.9% | 2.5% | 0.7% | 1.7% |

*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)). As stores brands prices, margins and advertising expenditures are held fixed we omit them from the table.*

Table J.2: *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. |
| **Δ profits** | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Reg Coke | -2.2% | -23.1% | 1.1% | 0.6% | -33.9% | 1.9% | 1.3% |
| Diet Coke | -3.4% | 4.7% | -0.6% | -3.7% | 5.1% | -1.0% | -3.3% |
| Reg Pepsi | -1.3% | -33.7% | -0.2% | -0.7% | -39.2% | -0.2% | -0.6% |
| Diet Pepsi | -1.0% | 4.2% | -0.3% | -1.1% | 3.3% | -0.4% | -1.0% |

*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.*

Table J.3: *Distributional impact of counterfactual policies (under "Total effect"' consumer surplus)*

| | No tax | Specific tax | | Ad valorem tax | |
|---|---|---|---|---|---|
| Income quartile | Adv. restrict. | | Adv. restrict. | | Adv. restrict. |
| | (1) | (2) | (3) | (4) | (5) |
| **Change in sugar** | | | | | |
| Bottom | -2.88% | -17.64% | -18.12% | -17.88% | -18.25% |
| 2nd | -2.78% | -17.07% | -17.45% | -17.23% | -17.45% |
| 3rd | -2.32% | -17.29% | -17.63% | -17.70% | -17.96% |
| Top | -2.83% | -12.22% | -12.73% | -12.56% | -12.83% |
| **Change in consumer surplus** | | | | | |
| Bottom | -6.20% | -9.11% | -13.50% | -9.78% | -13.72% |
| 2nd | -3.87% | -7.13% | -9.73% | -7.52% | -9.85% |
| 3rd | -4.10% | -7.81% | -10.73% | -8.38% | -11.03% |
| Top | -3.60% | -4.60% | -7.11% | -5.15% | -7.33% |
| **Change in consumer surplus net of internalities** | | | | | |
| Bottom | -4.98% | -1.66% | -5.84% | -2.22% | -6.01% |
| 2nd | -2.86% | -0.96% | -3.43% | -1.29% | -3.55% |
| 3rd | -3.40% | -2.54% | -5.36% | -2.99% | -5.56% |
| Top | -2.91% | -1.63% | -4.00% | -2.08% | -4.20% |

*Notes: Change in sugar is expressed as a percent of the income quartile specific pre-policy total drink sugar consumption. Change in consumer surplus (including net of internalities) is expressed as a percent of income quartile specific pre-policy total expenditure. The consumer surplus measure includes both the static impact of policy on the state-specific optimal prices and the impact of the changes in the equilibrium distribution over advertising state due to changes in optimal advertising expenditure.*

# References

Crawford, G., L. Deer, J. Smith, and P. Sturgeon (2017). The Regulation of Public Service Broadcasters: Should There be More Advertising on Television? *CEPR Discussion Paper 12428*.

Hess, S., K. E. Train, and J. W. Polak (2006). On the use of a Modified Latin Hypercube Sampling (MLHS) method in the estimation of a Mixed Logit Model for vehicle choice. *Transportation Research Part B 40*.

MacKinnon, J. G. (1983). Model specification tests against non-nested alternatives. *Econometric Reviews 2*(1), 85–110.

Pakes, A. and McGuire (1994). Computing markov-perfect nash equilibria: Numerical implications of a dynamic differentiated product model. *RAND Journal of Economics 25*, 555–589.