# The effects of banning advertising in junk food markets

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**Abstract**

There are growing calls to restrict advertising of junk foods. Whether such a move will improve diet quality will depend on how advertising shifts consumer demands and how firms respond. We study an important and typical junk food market – the potato chips market. We exploit consumer level exposure to adverts to estimate demand, allowing advertising to potentially shift the weight consumers place on product healthiness, tilt demand curves, have dynamic effects and spillover effects across brands. We simulate the impact of a ban and show that the potential health benefits are partially offset by firms lowering prices and by consumer switching to other junk foods.

**Keywords:** advertising, demand estimation, dynamic oligopoly, welfare

**JEL classification: L13, M37**

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# 1 Introduction

Governments around the world are grappling with how to tackle the obesity epidemic. Central to this are attempts to reduce consumption of junk foods – foods high in calories, salt, sugar and fat and low in fiber, proteins and vitamins. Junk food markets, such as those for confectionery, soda and potato chips, share a number of common features; they tend to be dominated by a small number of firms that sell multiple brands and that heavily advertise their products. A number of organisations have called for restrictions to advertising of junk foods as a means to reduce consumption. The effects of such an intervention are complex and will depend on whether advertising predominantly acts to expand the market size, or steal rival market share, what products consumers who substitute out of the market switch to instead and how the firms in the market adapt their behaviour in response to a ban.

Our contribution in this paper is to study the impacts of banning advertising in the UK market for potato chips – a typical junk food market and an important source of junk food calories. We show that the effects of advertising on product level demands are various and heterogeneous across consumers. Advertising of one brand may steal market share from some rival brands, while boosting demand of others; advertising also acts to tilt demand curves and change consumer willingness to pay for a more healthy product. We simulate the effects of banning advertising on market equilibria, taking account of the consumer demand response and the strategic pricing response of firms in the market. We show that banning advertising, holding prices fixed, leads to a reduction in the quantity of potato chips sold of around 15%. However, one effect of advertising on demand is to lower consumer sensitivity to price, reducing the slope of market demands. Therefore, the ban acts to make the market more competitive and firms respond to the ban by, on average, lowering their prices. Lower prices lead to an offsetting increase in demand, meaning, in equilibrium, that the advertising ban lowers the quantity of potato chips sold by around 10%.

Similar to advertising regulations in markets such as tobacco and alcohol, the aim of restricting junk food advertising is to lower consumption.[1] The World Health Organization (WHO (2010)) published the recommendation that the "overall policy objective [of an advertising ban] should be to reduce both the exposure of children to, and the power of, marketing of foods high in saturated fats, *trans*-fatty acids, free sugars, or salt." The medical literature has called for restrictions on advertising; for example, in a well cited paper, Gortmaker et al. (2011) state that "marketing of food and beverages is associated with increasing obesity rates", citing work by Goris et al. (2010), and say that advertising is especially effective amongst children, citing National Academies (2006) and Cairns et al. (2009).[2]

[1] In other markets, such as pharmaceuticals and some professional services, the aim is more focused on consumer protection and information provision.

[2] In the UK, regulations ban the advertising of foods high in fat, salt or sugar during children's programming (see http://www.bbc.co.uk/news/health-17041347) and there have been recent calls to extend this ban (see

Understanding the impact of an advertising ban relies not only on estimating the equilibrium reduction in potato chip consumption, but also in understanding how the ban affects consumer choice within the market (do consumers switch to healthier varieties?) and to what other products consumers who switch outside the market switch towards. We measure nutritional quality using the nutritional profiling score, (Arambepola et al. (2008)), which is the official measure of the nutritional quality of products used by the UK Government to classify which products should be subject to regulation and other policy restrictions. We allow advertising to shift the weight a consumer places on the nutritional characteristics of a product and show that advertising acts to lower willingness to pay for more healthy products. Therefore, the advertising ban induces some switching from relatively unhealthy towards relatively healthy potato chips – a pattern that is reinforced by the equilibrium pricing response of firms. We also include in our model two outside options – non-potato chips junk foods and healthier non junk foods. This allows us to capture whether consumers respond to the ban simply by switching to alternative (and often less healthy) junk foods. We show that following the ban consumers are more likely to switch to another junk food market than to a non-junk food, which (in addition to the pricing response of firms) acts to partially offset any health gains from the policy.

Identifying the causal impact of advertising on demand is challenging (see, for example, the recent discussion in Lewis and Rao (2015)). Our strategy for identifying the effect of advertising on demand is to exploit variation in consumers' exposure to TV brand advertising. We exploit information on the precise time and station of potato chip advertising and link this to information on the TV viewing behaviour of individual consumers, for whom we also have panel data on purchases. This allows us to control for demographic-time specific shocks to brand demand and exploit differential exposure across consumers, within demographic groups, to TV advertising that is driven by (idiosyncratic) variation in viewing behaviour to pin down the effects of advertising on demands.

While it is typically not controversial to impose that cross-price elasticities in differentiated product markets are positive, it is important to not impose sign restrictions on cross-advertising elasticities. Brand advertising may be predatory, in which case its effect is to steal market share of rival products, or it might be cooperative, so that an increase in the advertising of one product increases demand for other products (Friedman (1983)). By including both own brand and competitor advertising in consumer payoff functions, our demand specification allows for the possibility of advertising that is either predatory, cooperative or some combination of both.

Our work relates to a strand of the literature that models advertising spillovers in the pharmaceutical market (see, for instance, Bernt et al. (1997), Ching (2010) and Ching and Ishihara (2012)). Most relevant is

http://www.guardian.co.uk/society/2012/sep/04/obesity-tv-junk-food-ads). In the US the Disney Channel has plans to ban junk food advertising (http://www.bbc.co.uk/news/world-us-canada-18336478).

Shapiro (2015), which studies whether TV advertising of specific antidepressant products increases demand only for that product, or for all products with similar molecular structures, or for all products in the market. He uses a multi-level demand and exploits variation in consumers' advertising exposure across TV boundaries to show that in the antidepressant market advertising has a strong market expansion effect. Conversely, Anderson et al. (2012) show that comparative advertising of pharmaceuticals has strong business stealing effects and reduces aggregate demand. Also related to our work is Liu et al. (2015), which studies whether there is evidence of advertising spillovers in the market for statin drugs or the market for yoghurt, finding that TV advertising induces market expansion in the latter market but not the former. A number of other papers find evidence of spillovers from advertising in the markets for alcohol and tobacco. For example, Rojas and Peterson (2008) find that advertising increases aggregate demand for beer; while other papers show that regulating or banning advertising has led to more concentration (for example Eckard (1991), for cigarettes and Sass and Saurman (1995), for beer; Motta (2007) surveys numerous other studies) and in the case of partial ban in the cigarette industry, more advertising (Qi (2013)).

There is a large literature on the mechanism through which advertising affects consumer choice; Bagwell (2007) provides a comprehensive survey. Much of this literature distinguishes between the persuasive, characteristic and informative advertising traditions. The early literature on advertising focused on its persuasive nature (Marshall (1921), Braithwaite (1928), Robinson (1933), Kaldor (1950) and Dixit and Norman (1978)), where the purpose of advertising is to change consumer tastes. More recently, the behavioural economics and neuroeconomics literatures have explored the mechanisms by which advertising affects consumer decision making. Gabaix and Laibson (2006) consider models in which firms might try to shroud negative attributes of their products, while McClure et al. (2004) and Bernheim and Rangel (2004, 2005) consider the ways that advertising might affect the mental processes that consumers use when taking decisions (for example, causing a shift from the use of deliberative systems to the affective systems that respond more to emotional cues). An alternative view of advertising is that it enters utility directly (see Becker and Murphy (1993) and Stigler and Becker (1977)). Consumers may like or dislike advertising, and advertising might act as a complement to other goods or characteristics that enter the utility function. Another branch of the literature focuses on the role that advertising plays in providing information to consumers (as distinct from being persuasive). For instance, advertising might inform consumers about the quality or characteristics of a product (Stigler (1961) and Nelson (1995)), product price (for instance, see Milyo and Waldfogel (1999) who study the alcohol market), or about the existence and availability of products (see, inter alia, Sovinsky-Goeree (2008) on personal computers and Ackerberg (2001) and Ackerberg (2003) in the yoghurt market). Although, as Anderson and Renault (2006) point out, firms may actually have an incentive to limit the informative content of adverts even when consumers are imperfectly informed (see also Spiegler (2006)).

Rao and Wang (2015) show that in a market in which consumers are not perfectly informed and informative advertising plays a role, false advertising claims can have a positive effect on demand.

For our purpose, evaluating the impact of banning advertising on demand for differentiated products, the important thing is to specify a demand model that accommodates the various ways that advertising can alter the shape of demand, both at the consumer and market level and for individual products and the product category as a whole. Our flexible demand model captures the major ways in which advertising might affect demand. It does not, however, encompass all forms of informative advertising (for example, if the main impact of advertising was to inform consumers about the existence of a product so that without advertising the consumer would be unaware of the product's existence). While we can learn about the impact of an advertising ban on market equilibria and consumer health while remaining agnostic about how exactly advertising affects consumer utility, to make statements about the impact on consumer welfare we need to take a view. We derive expressions for consumer welfare under the two most plausible views of potato chip advertising – that it is a product characteristic and that it is persuasive.

The advertising choice of a firm affects both current and future payoffs of all firms in the market, so that when firms choose their advertising strategies they play a dynamic game. Solving such a game entails specifying precisely the details of firms' dynamic problem and of the equilibrium concept that prevails in the market (as in, for instance, Dubé et al. (2005)). We shows that we can identify marginal costs of all products without estimating the full dynamic game; we require only price optimality conditions which are static, along with observed values of the relevant advertising state variables. We are interested in the effects of an advertising ban on market equilibrium, so to implement our counterfactual we only have to solve the new price first order conditions. As a consequence we can remain agnostic about many of the details of the dynamic game played by firms and therefore our results are robust to these details. We are able to implement our counterfactual in a realistic market setting in which multi-product firms compete in price and advertising, and in which firms' strategies in prices and advertising are multidimensional and continuous with a very large set of state variables.

The rest of the paper is structured as follows. In Section 2 we outline our model of consumer demand: we describe the flexible way in which we include advertising, how and why we include rich preference heterogeneity and we discuss identification. Section 3 discusses firm competition in the market and outlines how we identify the unobserved marginal cost parameters of the model and how we simulate a counterfactual advertising ban. Section 4 describes our application to the UK potato chips market. We begin with describing our disaggregate advertising and consumer purchase data – a unique feature of which is that we observe purchase decisions for consumption outside the home as well as in the home. We then present our empirical estimates and highlight the importance of allowing advertising to flexibly affect consumer level demand. We describe market equilibria with advertising and in the counterfacual with a ban on advertising potato chips, emphasising the effect the ban has on what nutrients consumers purchase, and we discuss how to approach the measurement of consumer welfare. We also consider a number of potential concerns about our empirical application and show our main conclusions are robust to a set of modeling modifications. A final section summarizes and concludes.

# 2 Consumer demand

We specify and estimate a random utility discrete choice model in the vein of Berry et al. (1995), Nevo (2001) and Berry et al. (2004). We allow a consumer specific measure of exposure to current and past advertising to effect the shape of demand in a flexible way; capturing the possibility that advertising might be cooperative or predatory and it might shift the weight consumers place on different product characteristics in their payoff function. This may occur either because advertising itself is a characteristic that consumers inherently value, or it could be that advertising either changes the information consumers have, or persuades consumers to place more or less weight on other characteristics. This flexibility in consumer level demand translates into flexible market demand. We first present the demand model, then discuss the reasons that both a flexible functional form and rich consumer heterogeneity are important to understand the impacts that advertising has on demand and hence to our counterfactual of banning advertising, and then we discuss the challenges to identification.

## 2.1 Consumer choice model

Consumers, indexed by $i$, choose between products (in our empirical application, potato chip products), indexed by $j = 1, ..., J$, and two possible outside goods with $j = \underline{0}$ denoting a junk food 'unhealthy outside option' and $j = \overline{0}$ indexing a non-junk food 'healthy outside option'. Each product belongs to one brand. Brands are indexed $b = 1, ..., B$; we denote the brand product $j$ belongs to as $b(j)$. $B < J$; products belonging to the same brand differ in terms of their pack size.

The consumer purchases the product that provides her with the highest payoff, trading off characteristics that increase her valuation of the product with those that decrease her valuation. A product's characteristics include its price, nutrient characteristics, pack size, brand and unobserved characteristics. The nutrient characteristics might capture both tastiness, if consumers like the taste of salt and saturated fat, and the health consequences of consuming the product, which might reduce the payoff of selecting the product for some consumers. We allow for a product characteristic that is unobserved by the econometrician, which captures the consumer's baseline valuation of the product's brand and other unobserved characteristics.[3]

Advertising in the market is for brands, several products might share a brand, which we denote $b(j)$. Consumer $i$'s exposure to the advertising of brand $b(j)$ at time $t$ is denoted $\mathfrak{a}_{ib(j)t}$; this is a function of the consumer's exposure to current and past advertising. The set of advertising state variables of all $B$ brands for consumer $i$ at time $t$ is denoted by the vector $\mathfrak{a}_{it} = (\mathfrak{a}_{i1t}, ..., \mathfrak{a}_{iBt})$. $\mathfrak{a}_{it}$ will depend on the past and current decisions that firms in the market make over which TV stations, the date and time of day to advertise their brands, and on the TV viewing behaviour of consumers. We discuss the precise nature of these variables in more detail in Sections 2.4 and 4.1.

Let $\bar{v}_{ijt} = \bar{v}_i(p_{jt}, \mathfrak{a}_{it}, \mathbf{x}_j, \xi_{ib(j)}, \tau^d_{b(j)t}, \epsilon_{ijt})$ denote the consumer's payoff from selecting product $j$. $p_{jt}$ is product price and $\mathbf{x}_j = (z_j, z_j^2, n_{b(j)})'$ are other observed product characteristics, $z_j$ denotes pack size and $n_{b(j)}$ is a measure of the nutrient content of brand $b(j)$. $\xi_{ib(j)}$ is an unobserved brand effect that might vary across individuals, $\tau^d_{b(j)t}$ is an unobserved brand effect that potentially varies across time and observed demographics $d$,[4] and $\epsilon_{ijt}$ is an i.i.d. shock to the payoff.

One of our main aims in specifying the form of the payoff function is to allow changes in prices and advertising to affect demand in a flexible way. We incorporate both observable and unobservable heterogeneity in consumer preferences; the $i$ subscript on the payoff function indicates that we allow coefficients to vary with observed and unobserved consumer characteristics (through random coefficients); the $d$ subscript on the brand-time effects indicates that we will allow them to vary with observed consumer characteristics. In differentiated product markets it is typically reasonable to impose that goods are substitutes (lowering the price of one good increases demand for a second). However, there is no reason a priori to impose that cross advertising effects are of a particular sign; advertising of one brand might increase or decrease demand for another brand. We specify the payoff function to allow for both positive and negative cross advertising effects and for the possibility that advertising expands or contracts the size of the market.

We assume that consumer $i$'s payoff from selecting product $j$ is given by:

$$\begin{aligned}\bar{v}_{ijt} =& v_{ijt} + \epsilon_{ijt} \\ =& \alpha_{1i} p_{jt} + \psi_{1i} \mathbf{x}_j + \left[ \lambda_i \mathfrak{a}_{ib(j)t} + \alpha_{2i} \mathfrak{a}_{ib(j)t} p_{jt} + \psi_{2i} \mathfrak{a}_{ib(j)t} n_{b(j)} + \rho_i \left( \sum\nolimits_{l \neq b(j)} \mathfrak{a}_{ilt} \right) \right] + \xi_{ib(j)} + \tau^d_{b(j)t} + \epsilon_{ijt}\end{aligned} \tag{2.1}$$

[3] In our framework dynamics in demand arise only due to the long lasting effect of exposure to advertising. In Appendix A.1 we show reduced form evidence that once we account for consumer specific heterogeneity there is little evidence of state dependence in the sense of a relationship between current and recent past purchases.

[4] In the empirical application we investigate the appropriate level of time and brand aggregation for this variable, trading off parsimony with the need to control for shocks to demand; we include month-demographic level controls for the major brands.

Our main focus is on the terms in the square brackets, which capture the impact of advertising on the payoff function. Own advertising enters directly in levels; the coefficient $\lambda_i$ captures the extent to which differential time series exposure to own advertising affects the valuation or weight the consumer places on the unobserved brand effect. Own advertising also potentially interacts with price and the brand nutrient characteristic. The coefficient $\alpha_{2i}$ allows the marginal effect of price on the payoff function to shift with own advertising (as in Erdem et al. (2008)). The coefficient $\psi_{2i}$ allows the marginal effect of the nutrient characteristic on the payoff function to also shift with own advertising.

Importantly, we allow competitor advertising to enter the payoff function. The coefficient $\rho_i$ captures the extent to which time variation in competitor advertising affects the valuation or weight the consumer places on the unobserved brand effect. We show in the next section that all of these effects are potentially important for understanding the effects of banning advertising, and in particular including competitor advertising in the payoff function is crucial both for allowing for the possibility of advertising that is cooperative, and for the possibility that advertising is so strongly predatory that it leads the market size to shrink.

We assume that the payoff from selecting the unhealthy outside option takes the form:

$$\begin{aligned}\bar{v}_{i\underline{0}t} =& v_{i\underline{0}t} + \epsilon_{i\underline{0}t} \\ =& \xi_{i\underline{0}j} + \psi_{1i} x_{\underline{0}} + \tau^{d}_{\underline{0}t} + \epsilon_{i\underline{0}t},\end{aligned}$$

where $x_{\underline{0}}$ denotes the nutrient characteristics of the unhealthy outside option and where we allow the mean utility to vary over time. As in all discrete choice models only differences in payoff between options matter; we normalise the mean utility from the healthy outside option to be zero in all time periods, $\bar{v}_{i\bar{0}t} = \epsilon_{i\bar{0}t}$.

Consumer $i$ will choose product $j$ at time $t$ if:

$$\bar{v}_{ijt} > \bar{v}_{ij't} \quad \forall\ j' \neq j.$$

Assuming $\epsilon_{ijt}$ is i.i.d. and drawn from a type I extreme value distribution, and denoting by $\boldsymbol{\tau^d_t} = (\tau^d_{\underline{0}t}, \tau^d_{1t}, ...., \tau^d_{Bt})$ the vector of time effects affecting demand, the probability that consumer $i$ buys product $j$ at time $t$ is:

$$s_{ij}(\mathfrak{a}_{it}, \mathbf{p_t}, \boldsymbol{\tau^d_t}) = \frac{\exp\left(v_{ijt}\right)}{1 + \exp(v_{i\underline{0}t}) + \sum\limits_{j'=1}^{J} \exp\left(v_{ij't}\right)}. \tag{2.2}$$

## 2.2 The effects of advertising on consumer level demands

We are careful to incorporate enough flexibility in the model to allow for the possibility that advertising is predatory (stealing market share from competitors) or cooperative (increasing market share of competitors);

that advertising leads to market expansion or contraction; and that advertising may tilt the demand curve or change the marginal rate of substitution between product characteristics (Johnson and Myatt (2006)).

Let $\mathcal{J}_{b(j)}$ denote the set of products belonging to brand $b(j)$. The marginal impact of a change in the brand advertising state variable of one product ($j \neq (\underline{0}, \overline{0})$) on the individual level choice probabilities is given by:

$$
\begin{aligned}
\frac{\partial s_{ijt}}{\partial \mathfrak{a}_{ib(j)t}} &= \sum_{l \in \mathcal{J}_{b(j)}} s_{ijt} \left[ \tilde{\lambda}_{ijt} - \rho_i (1 - s_{i0t}) - (\tilde{\lambda}_{ilt} - \rho_i) s_{ilt} \right] \\
\frac{\partial s_{ij't}}{\partial \mathfrak{a}_{ib(j)t}} &= \sum_{l \in \mathcal{J}_{b(j)}} s_{ij't} \left[ \rho_i s_{i0t} - (\tilde{\lambda}_{ilt} - \rho_i) s_{ilt} \right] \qquad \text{for } j' \neq (\underline{0}, \overline{0}) \quad \text{and} \quad b(j) \neq b(j') \\
\frac{\partial s_{i0t}}{\partial \mathfrak{a}_{ib(j)t}} &= \sum_{l \in \mathcal{J}_{b(j)}} -s_{i0t} \left[ \rho_i (1 - s_{i0t}) + (\tilde{\lambda}_{ilt} - \rho_i) s_{ilt} \right],
\end{aligned}
$$

where $\tilde{\lambda}_{ijt} = \lambda_i + \alpha_{2i} p_{jt} + \psi_{2i} n_{b(j)}$ and $s_{i0t} = s_{i\overline{0}t} + s_{i\underline{0}t}$. The interaction of the advertising state variable with price and the nutrient characteristic, and the possibility that competitor advertising directly enters the payoff function are important in allowing for advertising to flexibly impact demands.

If we did not allow for advertising of one product to directly enter the payoff of other products (imposing $\rho_i = 0$), then we require $\tilde{\lambda}_{ijt} > 0$ for advertising to have a positive own effect (so $\partial s_{ijt} / \partial \mathfrak{a}_{ib(j)t} > 0$). In this case advertising would necessarily be predatory, stealing market share from competitor products ($\partial s_{ij't} / \partial \mathfrak{a}_{ib(j)t} < 0$) and it would necessarily lead to market expansion ($\partial s_{i0t} / \partial \mathfrak{a}_{ib(j)t} < 0$). By including competitor advertising in the payoff function we allow for the possibility that, regardless of the sign of own demand advertising effects, advertising may be predatory or cooperative and it may lead to market expansion or contraction (i.e we do not constrain the signs of $\partial s_{ij't} / \partial \mathfrak{a}_{ib(j)t}$ or $\partial s_{i0t} / \partial \mathfrak{a}_{ib(j)t}$).

Allowing advertising to interact with the consumer's responsiveness to price and the nutrient characteristic allows advertising to have a direct effect on consumer level price elasticities and willingness to pay for the nutrient characteristic. The consumer level price elasticities are, for any $j \neq (\underline{0}, \overline{0})$:

$$
\begin{aligned}
\frac{\partial \ln s_{ijt}}{\partial \ln p_{jt}} &= \left( \alpha_{1i} + \alpha_{2i} \mathfrak{a}_{ib(j)t} \right) (1 - s_{ijt}) p_{jt} \\
\frac{\partial \ln s_{ij't}}{\partial \ln p_{jt}} &= - \left( \alpha_{1i} + \alpha_{2i} \mathfrak{a}_{ib(j)t} \right) s_{ijt} p_{jt} \qquad \text{for } j' \neq j.
\end{aligned}
$$

This allows advertising to impact consumer level price elasticities in a flexible way, through its impact on choice probabilities and through its impact on the marginal effect on the payoff function of price, captured by $\alpha_{2i}$.

The empirical measure of the nutrient characteristic is such that an increase corresponds to a less healthy brand (see Section 4.2.3). Therefore the willingness to pay for a marginally more healthy brand (equal to the marginal rate of substitution between price and the characteristic) is given by

$$WTP_{ijt}(\mathfrak{a}_{ib(j)t}) = \frac{\partial \bar{v}_{ijt}/\partial n_{b(j)}}{\partial \bar{v}_{ijt}/\partial p_{jt}} = \frac{\psi_{1i}^{n} + \psi_{2i}\mathfrak{a}_{ib(j)t}}{\alpha_{1i} + \alpha_{2i}\mathfrak{a}_{ib(j)t}}, \tag{2.3}$$

where $\psi_{1i}^{n}$ denotes the element in $\psi_{1i}$ that is the coefficient on $n_{b(j)}$.[5] The interaction of advertising with price and the nutrient characteristic allows the willingness to pay to vary in a flexible way with advertising. We expect the consumer to positively value more money ($\alpha_{1i}+\alpha_{2i}\mathfrak{a}_{ib(j)t} < 0$), so that if the consumer prefers a more nutritious product ($\psi_{1i}+\psi_{2i}\mathfrak{a}_{ib(j)t} < 0$), the willingness to pay for a decrease in $n_{b(j)}$ will be positive. Whether the willingness to pay for a decreases in $n_{b(j)}$ will increase or decrease with advertising will depend on the relative signs and magnitudes of the coefficients of the interactions between advertising with price and the nutrient characteristic;

$$\frac{\partial}{\partial \mathfrak{a}_{ib(j)t}} WTP_{ijt}(\mathfrak{a}_{ib(j)t}) = -\frac{\alpha_{2i}\psi_{1i}^{n} - \alpha_{1i}\psi_{2i}}{(\alpha_{1i} + \alpha_{2i}\mathfrak{a}_{ib(j)t})^2},$$

can be positive or negative for different consumers depending on the sign of $\alpha_{2i}\psi_{1i}^{n} - \alpha_{1i}\psi_{2i}$.

Direct interpretation of the advertising coefficients is difficult. For example, it may be that $\lambda_i < 0$, but nonetheless advertising has a positive own demand effect, either because advertising also affects the payoff for other brands negatively ($\rho_i < 0$), or because advertising lowers the consumer's price sensitivity for the advertised good ($\alpha_{2i} > 0$) or shifts the weight the consumer places on the nutrient characteristic of the advertised good. However, it is straightforward to describe the implications of the estimated coefficients by, for example, shutting off advertising of one brand and determining the overall effect it has on demands for that and other brands; we do this in Section 4.3.1.

## 2.3 Consumer level heterogeneity

In the payoff function (equation 2.1) we write all the preference parameters with consumer subscripts, indicating that we allow for heterogeneity in all preference parameters. Here we discuss the exact form of this heterogeneity and why it is important for understanding the effects of banning advertising.

We model the coefficients on price, own advertising, competitor advertising, the nutrient characteristic and the major brand effects as random coefficients. This allows preferences over these characteristics to vary across individual consumers. We model the distribution of the random coefficients, conditional on demographic groups, and we allow all other preference parameters to vary across demographic groups.

[5] We model $\psi_{1i}^{n}$ as a random coefficient – see Section 2.3. The means (conditional on demographic group) of the $\psi_{1i}^{n}$ are absorbed into the brand effects. We recover them using an auxiliary regression of brand effects on product characteristics.

Specifically, let $d = \{1, ..., D\}$ index demographic groups. Table 4.4 shows the groups, which are based on income, education, household composition and which separate consumers into those that are observed purchasing food at home and those purchasing food on-the-go. For the non-random coefficients we can replace the $i$ subscript with a $d$ subscript: the non-random coefficients on observed attributes are therefore $(\psi^z_{1d}, \psi^{z^2}_{1d}, \phi_d, \alpha_{2d}, \psi_{2d})'$ and the non-random coefficients on unobserved effects are $\xi_{db}$ and $(\tau^d_{\underline{0}t}, \tau^d_{1t}, ..., \tau^d_{Bt})'$.

In addition to price, own and competitor advertising and the nutrient characteristic, we include a random coefficient on the unobserved brand effects for Walkers products on food at home purchase occasions; denote this by $\xi_{iW}$. Denote the set of consumers in group $d$ by $\mathcal{D}_d$. We assume random coefficients follow the distribution

$$(-\ln \alpha_{1i}, \psi^n_{1i}, \lambda_i, \rho_i, \xi_{iW})' \Big| i \in \mathcal{D}_d \sim \mathcal{N}\left(\bar{\boldsymbol{\mu}}_{\boldsymbol{d}}, \boldsymbol{\Sigma}_{\boldsymbol{d}}\right).$$

We model the distribution of minus the log of the price coefficient, thereby assuming the price coefficient is log-normally distributed and all demands slope downwards. We assume that the conditional covariance matrix is diagonal and the variance components associated with the different food at home Walkers brands are the same.[6] We estimate the parameters of the random coefficient distributions conditional on demographic group, so we estimate separate $\bar{\boldsymbol{\mu}}_{\boldsymbol{d}}$ vectors and $\boldsymbol{\Sigma}_{\boldsymbol{d}}$ matrices for all $D$ demographic groups.

We allow for preference heterogeneity across the observable demographic groups because it seems likely that junk food purchase decisions will vary along these dimensions. For instance, households with children might be more likely to purchase junk foods and be more responsive to advertising, while low income households are likely to be more price sensitive. Similarly, consumers making purchases on-the-go for immediate consumption might place different weight on some product characteristics than consumers making decisions for future consumption. This observable preference heterogeneity turns out to be empirically important – for instance, the advertising ban leads to quite different price responses on products for home consumption than products for on-the-go consumption.

A number of papers have shown that including random coefficients in discrete choice demand models is crucial to capture realistic substitution patterns (see, for instance, Train (2003) and references therein). We are interested in the optimal pricing response of firms following an advertising ban, so there is a clear rationale for including random coefficients on price, own and competitor advertising. We are also particularly interested in the consequence of the ban on the nutritional content of the products consumers purchase. We therefore include a random coefficient on the nutritional characteristic of products, which allows for flexible substitution across this dimension, importantly capturing differential substitution from the set of inside options towards the unhealthy and healthy outside options.

[6] The common random coefficient on the set of Walkers products captures the possibility that consumers are more willing to substitute between these products than to alternative brands.

## 2.4 Identification

We face three principal challenges to identification; identifying the causal impact of advertising and prices on demand and identifying the distribution of consumer preference heterogeneity. We discuss the assumptions we require and what variation in the data we exploit for each of these in turn.

We identify the effect of advertising on demand from variation in the timing and channels that adverts of different brands were aired and variation in individual consumers' TV viewing behaviour. Together these lead to considerable variation in the timing and intensity of individuals' exposures to the advertising of different brands. We control for aggregate shocks to brand demand through including brand-time-demographic group effects. The variation in advertising we use to estimate the model is the differential time series variation in exposure of individual consumers to advertising of a specific brand, relative to the mean consumer within the relevant demographic group. Allowing the time effects to vary across demographic groups is important, since in the UK TV market advertisers purchase expected "impacts" by time and demographic group – indicating advertising is targeted at specific demographic groups (Crawford et al. (2012)). In addition to this rich individual variation we exploit the institutional set up of the UK TV market, which has a number of features that are useful for our identification strategy.

Specifically we use data on all potato chip adverts (around 150,000) that aired on TV over a two year period. These data include details on what brand was advertised, the time the advert aired and what channel it was shown on. We combine this with information on the TV shows, channels and times of day that individual consumers report watching TV to construct an individual specific, time varying measure of exposure to the advertising of each brand. This provides us with a large amount of variation in exposure to advertising across consumers, brands and time. We describe these data and this variation in detail in Section 4.1.

The UK institutional set up means that there is variation in advertising regulations across UK TV channels. There are four large public service broadcasters – the BBC, ITV1, Channel 4 (C4) and Channel 5 (C5) – which face some requirements over the programs that they air. The BBC is funded by an annual television license fee and is not allowed to air adverts. ITV1, C4 and C5 do not receive license fee income and can air adverts, but have some requirements regarding the programs they air. These public broadcasters have relatively large audience shares – BBC1 has viewing figures of around 20%, ITV around 16%, BBC2 and C4 around 7% and C5 around 5%. These channels compete for consumers by offering programs designed for broad audience appeal (see Crawford et al. (2012) for a detailed discussion of the UK advertising market).

There are also a large number of other smaller channels. These are mostly commercial channels that do not face any specific restrictions to their programming.[7] Access to these additional channels varies across

[7] The exception is five other BBC channels which have very low viewing figures (BBC3, BBC4, BBC News, BBC Parliament).

consumers depending on what TV subscription they have. Specifically, households can view TV in four ways: free to air, freeview, satellite or cable. All households with a TV have to pay the license fee that funds the BBC. Free to air does not require any additional payment, but gives access to only the public service broadcasters. Freeview requires purchasing a box to decode the digital signal, but does not require any additional payment, and gives access to a small number of additional channels. Satellite and cable both require subscriptions (of the order of £15-£50 per month depending on what channels the household subscribes to) and provide access to a much broader range of mainly commercial channels. Any household subscribing to satellite or cable will have access to all of the free to air and freeview channels.

Both the variation in access to channels and the channels consumers choose to watch (as well as when they choose to watch) lead to rich variation in advertising exposures across consumers. To illustrate the type of variation we rely on consider an example. Soap operas are amongst the shows with the highest viewing figures in the UK, as in other countries. Consider household viewing behaviour with regard to three popular soap operas. Coronation Street (aired on ITV1) and Eastenders (aired on BBC1) compete for first place in the TV ratings with average audience shares of around 30%. Hollyoaks (aired on C4) gets lower viewing figures and is targeted at, and very popular with, teenagers and young adults. Potato chips are heavily advertised during Coronation Street and Hollyoaks, while the BBC does not air adverts. There is considerable variation in the viewing behaviour of households in our sample across these shows. Around 40% do not watch any of them, around 10% just watch Eastenders, with the remaining 50% watching some combination of the shows (12% watch only Coronation Street, 22% watch both Eastenders and Coronation Street). The exposure of individuals to the adverts aired during these shows will vary due to these long run average viewing preferences in ways that are unlikely to be related to their idiosyncratic demand shocks for specific potato chips products. To show that we do get some bite from the within household time series variation in the timing of household exposure to adverts we correlate the probability of purchasing a specific brand in a linear probability model with the household's exposure to adverts for that brand, conditional on household, brand and time effects. The coefficient is positive and statistically significant.

A potential threat to identification would be if the individual advertising exposure was related to unobserved aspects of purchase decisions captured in $\epsilon_{ijt}$. We allow for time-varying effects that vary across brand and demographic group. These will absorb aggregate shocks to brand demands. Therefore endogeneity of the advertising variable will arise if firms are able to target specific consumers with advertising based on knowledge of their idiosyncratic demand shocks. While firms target demographic groups with TV advertising, they do not (yet) target individual consumers in this market, and therefore, conditional on the time varying demographic specific shocks we control for, we think advertising exposure is unlikely to be correlated with idiosyncratic demand shocks for specific potato chips products.

One additional specific issue for us, because the counterfactual we study is banning advertising, is whether we are able to identifying the shape of demand at zero advertising. We observe some brands that never advertise and there are some periods of time when the advertising of some brands is zero, meaning that we can identify the demand shape at zero and we are not doing out of sample predictions in the counterfactual. In addition, the TV viewing behaviour of some consumers means that they are not exposed to adverts for some periods of time (see Section 4.1).

Turning to how we identify the effect of price on demand, we exploit differences in the nonlinear within brand price schedules across brands over time (an identification strategy suggested by Bajari and Benkard (2005)). The large retail chains in the UK food market operate close to national pricing, meaning that there is very little geographical variation in prices.[8] The most common concern regarding the endogeneity of price is that it is correlated with an unobserved product characteristic or a market specific demand shock, of which advertising is the most commonly cited source. To control for other possible unobservable characteristics we include brand-time effects in the model, so our key identifying assumption is that there are no unobserved taste shocks for specific pack sizes that are differential across brands (and are correlated with price). We describe the variation in prices that we use for identification in Section 4.2.2.

While we believe that the combination of rich data and institutional features of the UK advertising and grocery markets allow us to isolate exogenous variation in advertising and prices, there might nonetheless remain concerns about endogeneity of advertising and price effects. As robustness we therefore also estimate the model including control functions for advertising and for prices.

In the case of advertising, correlation with the $\epsilon_{ijt}$ demand shocks could arise if firms choose to advertise on specific channels and times that they expect specific groups of consumers to have temporary demand shocks. As we control for brand-time-demographic effects, to cause a problem this kind of targeting would have to happen within demographic groups. This would require the firm both to have viewer information beyond the demographic information collected and published (and on which advertising pricing is based) by the advertising industry and it would require the firm to be able to predict idiosyncratic demand shocks. This seems unlikely. Nevertheless, to allow for such a possibility we construct a control function for the flow component of the advertising variable based on advertising prices. We observe the price paid for each advert. We construct, for each consumer, an average advertising price per second for the stations and times they watch TV, and use this as an instrument. Prices are correlated with advertising flows and the identifying assumption is that advertising prices are independent of consumers' idiosyncratic demand shocks for potato chips.

[8] In the UK most supermarkets implement a national pricing policy following the Competition Commission's investigation into supermarket behaviour (Competition Commission (2000)).

In the case of price, correlation with the $\epsilon_{ijt}$ demand shocks could arise if there were systematic and forecasted shocks to demand for different pack sizes that vary by brand. To allow for this possibility we construct a control function for price using lagged prices. The control function controls for any contemporaneous differential demand shocks to pack sizes across brands. In Section 4.6 we show that including control functions induces no qualitative changes in our main results.

A third identification issue is how we identify the distribution of unobserved heterogeneity (which we model as random coefficients). We use data that are at the micro level and that are longitudinal so that we observe each individual making repeated choices. Micro data has been shown to be particularly useful in identifying and estimating substitution patterns (see Berry and Haile (2010), Berry et al. (2004)). We specify the distribution of random coefficients conditional on demographic group, assuming a parametric form, and we estimate the parameters that characterize the distribution. There is cross-sectional variation in choice situations (e.g. two consumers will face different advertising states and, if they are observed in different markets, different price vectors). There is also within consumer variation in choice situations across time. This variation allows us to include rich interactions between observable and unobservable preference heterogeneity. Studies using market level data typically involve allowing only the mean of some random coefficients to shift with one or two demographic variables. Because we observe many consumers from different demographic groups making repeated choices, we are able to model the distribution of random coefficients conditional on each of the demographic groups.

Formally, Berry and Haile (2010) and Fox and Gandhi (2016) establish conditions for nonparametric identification of random coefficients in random utility discrete choice models by placing restrictions on the covariate supports. Fox et al. (2012) show that the identification conditions are weaker in the case where $\epsilon_{ijt}$ shocks are distributed type I extreme value, and that even with cross sectional data the model is always identified if utilities are a function of linear indices with continuously distributed covariates.

# 3 Supply model and counterfactual advertising ban equilibrium

## 3.1 Market demand

Market level demand is obtained by aggregating consumer level demands. Denote the set of random coefficients by $\pi_i$. To aggregate individual choice probabilities into market shares we assume that, conditional on demographic groups (indexed $d$), random coefficients are i.i.d. across consumers. We integrate over the distribution of unobserved preferences and demographics to obtain the market share of product $j$ in market $t$ (i.e. at time $t$):

$$s_j(\mathfrak{a}_t, \mathbf{p_t}, \boldsymbol{\tau_t}) = \int s_{ij}(\mathfrak{a}_{it}, \mathbf{p_t}, \boldsymbol{\tau_t^d}) f(\pi|d) f(d) \mathrm{d}\pi \mathrm{d}d, \tag{3.1}$$

where $\mathfrak{a}_t$ collects the vectors of all consumer specific brands' advertising state variables, $\mathfrak{a}_{it}$, across all consumers.

## 3.2 Supply

If firms are forward looking, they will account for the fact that advertising decisions taken in one period affect demand contemporaneously and in the future. In addition, these decisions will affect current and future demand of other firms in the market. Therefore, when setting their price and advertising budgets, firms will play a dynamic oligopoly game. In any equilibria to this game profit maximising firms will form dynamic strategies that may be very complex. The applied literature has typically dealt with such complicated dynamic games by considering Markov Perfect Equilibrium and by focusing on relatively stylized settings (see, for instance, Maskin and Tirole (1988) and Ericson and Pakes (1995)). In Appendix A we outline how such modeling can be applied to our market setting in which multi-product firms make dynamic advertising decisions.

For our purposes though, it is not necessary to specify fully the dynamic oligopoly game. We can use the fact that, in our demand model, product prices are an argument of current demand and profits, but not future demand and profits. In addition, only advertising expenditures and not product prices influence the evolution of the advertising state variables. Therefore, conditional on the state variables, equilibrium prices are chosen by firms to maximize current static profits. Given that we observe the advertising states (which are simply functions of current and past advertising), we can use the static price conditions to identify firms' marginal costs.

In particular, let firms in the market be indexed by $f = 1, ..., F$ denote the set of products offered by firm $f$, $\mathcal{J}_f$ and the set of brands offered by firm $f$, $\mathcal{B}_f$. Conditional on the advertising state variables $\mathfrak{a}_t$ firm $f$, at time $t$, chooses the prices of its products to maximize flow variable profits:

$$\sum\nolimits_{j \in \mathcal{J}_f} (p_{jt} - c_{jt})\, s_j\left(\mathfrak{a}_t, \mathbf{p_t}, \boldsymbol{\tau_t}\right) M_t - \sum\nolimits_{b \in \mathcal{B}_f} e_{bt}, \tag{3.2}$$

where $M_t$ denotes the total potential size of the market, $c_{jt}$ is the marginal cost of product $j$ at time $t$ and $\sum_{b \in \mathcal{B}_f} e_{bt}$ is the total advertising expenditure by firm $f$ during period $t$. The set of price first order conditions for firm $f$ are then:

$$s_j\left(\mathfrak{a}_t, \mathbf{p_t}, \boldsymbol{\tau_t}\right) + \sum_{j' \in \mathcal{J}_f} (p_{j't} - c_{j't}) \frac{\partial s_{j'}\left(\mathfrak{a}_t, \mathbf{p_t}, \boldsymbol{\tau_t}\right)}{\partial p_{jt}} = 0 \qquad \forall j \in \mathcal{J}_f. \tag{3.3}$$

With knowledge of the shape of demand, and observations on the advertising states and prices, we can use the set of price first order conditions (3.3) for all firms to identify marginal costs, provided the system of equations is invertible, which will be the case if goods are "connected substitutes" as in Berry and Haile (2014). The first order conditions, equation (3.3), assume that firms set prices according to a per period Nash-Bertrand game. In Section 4.6 we test this assumption against the alternative that firms set prices collusively and find the evidence supports the Nash-Bertrand assumption.

A second set of conditions characterising the optimal choice of advertising flows as a function of past state variables may exist. However, we do not need to appeal to these conditions to identify marginal costs; the price first order conditions are sufficient for this purpose.

Following the introduction of an advertising ban, equilibria will satisfy the per period Nash-Bertrand conditions of profit maximization, whatever the beliefs of firms about whether the regulatory change is permanent or not. We assume that technical conditions on the demand shape are satisfied to guarantee uniqueness of a Nash equilibrium. In the absence of advertising, the new price equilibrium $\mathbf{p_t^0}$ must be such that, for all $j$ and $f$,

$$s_j\left(\mathbf{0}, \mathbf{p_t^0}, \boldsymbol{\tau_t}\right) + \sum_{j' \in \mathcal{J}_f} \left(p^0_{j't} - c_{j't}\right) \frac{\partial s_{j'}\left(\mathbf{0}, \mathbf{p_t^0}, \boldsymbol{\tau_t}\right)}{\partial p_{jt}} = 0, \tag{3.4}$$

where

$$s_j(\mathbf{0}, \mathbf{p_t^0}, \boldsymbol{\tau_t}) = \int s_{ij}(\mathbf{0}, \mathbf{p_t^0}, \boldsymbol{\tau_t^d}) f(\pi|d) f(d) \mathrm{d}\pi \mathrm{d}d. \tag{3.5}$$

is the market level demand for product $j$ when advertising exposures are all zero and at prices $\mathbf{p_t^0}$. Additional second order conditions must also be satisfied and we check these for any candidate equilibrium prices.

To evaluate the impact of an advertising ban we solve for the counterfactual pricing equilibrium, defined by the equations (3.4) and (3.5), in each market and compare the quantities, prices and profits relative to the equilibrium prior to the ban (the outcome of which we observe).

The price equilibrium under an advertising ban will be different from the observed one because of the change in the demand shape. In particular, advertising state variables affect the price first order conditions in two ways. They affect the demanded quantities through the way $s_j\left(\mathfrak{a}_t, \mathbf{p_t}, \boldsymbol{\tau_t}\right)$ depends on $\mathfrak{a}_t$ and they affect the price derivatives of market shares through the way $\frac{\partial s_{j'}(\mathfrak{a}_t, \mathbf{p_t}, \boldsymbol{\tau_t})}{\partial p_{jt}}$ depends on $\mathfrak{a}_t$. In Section 2.2 we highlighted that our demand model allows advertising to have flexible effects on consumer demand levels and slopes. The inclusion of rich consumer heterogeneity in the model translates into an even more flexible relationship between advertising and the shape of market demand.

# 4 Application to potato chips market

We apply our model to the UK market for potato chips. This market shares several important characteristics with other junk food markets. It is dominated by a small number of multi-product firms that have large advertising budgets and that sell several well establish brands. Advertising is dominated by TV campaigns. Consumers purchase both for future consumption (as part of the main household grocery shop) and for immediate consumption while on-the-go. Therefore, as well as telling us the likely impact of an advertising ban in the potato chips market, we believe our results are more generally informative about the likely impact of restricting advertising in junk food markets more broadly.

Potato chips are an important source of junk food calories. In the US the potato chips market was worth \$9 billion in 2013, and 86% of people consumed some potato chips. The UK potato chips market had an annual revenue of more than £1.2 billion in 2010 with 84% of consumers buying some potato chips.[9]

We estimate the model using two main data sources. The Kantar Worldpanel contains transaction level data on the grocery purchases of a panel of households and individuals, along with details of their media viewing behaviour. We use detailed advertising data collected by AC Nielsen.

## 4.1 Advertising exposure

### 4.1.1 Advertising data

We use advertising data collected by AC Nielsen. The data contain aggregate advertising expenditure across all platforms (cinema, internet, billboards, press, radio and TV) and detailed disaggregate information for TV advertising. In the potato chip market, in common with other junk food markets, TV advertising is by far the most important form of advertising. Over 2009-2010 the annual expenditure on TV advertising on the products that we consider was £19.1m, while annual expenditure on advertising in magazines and newspapers was £2.3m, on outdoor billboards £1.9m, in cinema £0.6m, on radio £0.5m and on the internet £0.2m. Given the dominance of TV advertising, and the rich TV advertising data we have access to, we focus on its effect on demand. The common effects of non-TV advertising will be absorbed in the brand-time effects that we include in the model.

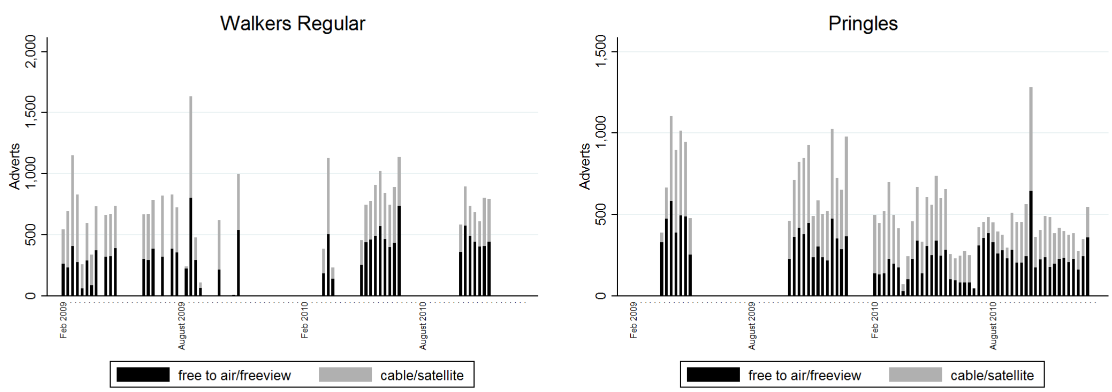
We use information on the 144,898 TV advertisements for potato chip brands that were aired over the period February 2009 to October 2010. For each advert we have information on the time the advert was aired, the brand that was advertised, the TV station, the duration of the advert, the cost of the advert and the TV shows that immediately preceded and followed the advert. For example, one observation in these data is that Walkers Regular crisps were advertised nationally on 15 April 2009 at 9:11:24 on ITV1 for 30 seconds, during the show GMTV (Good Morning TV).

Figure 4.1 shows the total number of adverts screened each week by the two largest brands (Walkers Regular and Pringles), split by whether they were aired on a channel that was free to air or on freeview and

[9] For the size of the US market see http://www.marketresearch.com/MarketLine-v3883/Potato-Chips-United-States-7823721/ ; the size of the UK market see http://www.marketingmagazine.co.uk/article/1125674/sector-insight-crisps-salty-snacks ; and for the number of people who consume potato chips in each country see http://us.kantar.com/business/health/potato-chip-consumption-in-the-us-and-globally-2012/.

channels that were available only via cable or satellite subscription (see discussion in Section 2.4); there is similar variation across other brands. The time path of advertising varies across brands, and all brands have some periods of zero advertising expenditure. These non-smooth strategies are rationalised in the model of Dubé et al. (2005) when the effectiveness of advertising can vary over time. This variation in the timing of adverts, coupled with variation in TV viewing behaviour (described below), will generate considerable household level variation in exposure to brand level advertising.

Figure 4.1: *Number of TV adverts aired by the two largest brands per week across all channels*




*Notes: free to air/freeview (cable/satellite) refer to stations that do not (that do) have a monthly subscription charge.*

Table 4.1 describes the average advertising per week by brand, showing the average number of adverts, average expenditure and the average total seconds of advertising aired over the week. Pringles airs the most adverts on average per week, though Walker's adverts are on average more expensive. Some brands rarely advertise, meaning that for these brands the stock of advertising is close to zero at most points in time.

Table 4.1: *Average TV advertising per week by brand across all TV channels*

| Brand | Number of weeks with zero adverts (out of 90) | Mean number of adverts per week | Standard deviation of number of adverts per week | Mean expenditure (£) per week | Mean length (seconds) per week |
|---|---|---|---|---|---|
| Walkers Regular | 46 | 322 | 406 | 77270 | 8928 |
| Walkers Sensation | 78 | 63 | 223 | 12554 | 1665 |
| Walkers Doritos | 65 | 161 | 379 | 24373 | 3671 |
| Walkers Other | 61 | 257 | 439 | 47185 | 7722 |
| Pringles | 31 | 359 | 333 | 56795 | 10256 |
| KP | 70 | 162 | 374 | 28024 | 4873 |
| GW | 87 | 9 | 62 | 837 | 89 |
| Asda | 88 | 8 | 78 | 1216 | 83 |
| Other | 53 | 286 | 409 | 54220 | 6992 |

*Notes: Average across weeks in February 2009 to October 2010 for all TV channels, including zeros.*

### 4.1.2 Media viewing

We combine the information on when adverts were aired with information on households' TV viewing behaviour in order to get a household level measure of exposure to each advert. We use data from the Kantar media survey, an annual survey asking Kantar Worldpanel participants about their TV subscriptions and TV viewing behaviour.

Households are asked "How often do you watch ...?" for 206 different TV shows, and can choose to answer Never, Hardly Ever, Sometimes or Regularly. At least one advert for potato chips is shown before, during or after 112 of these shows (many of the shows with no potato chip advertising are on BBC channels, which are prohibited from showing adverts). From this information we define the variable:

$$w_{is} = \begin{cases} 1 & i \text{ reports they "regularly" or "sometimes" watch show } s \\ 0 & \text{otherwise} \end{cases} \tag{4.1}$$

Households are also asked "How often do you watch ...?" 65 different TV channels and when they usually watch TV. In particular, for weekdays, Saturday and Sunday and for 9 different time periods[10] households are asked questions like "Do you watch live TV on Saturdays at breakfast time (6.00-9.30am)?" In each case the household can answer Never, Hardly Ever, Sometimes or Regularly. We use this information, along with information on where the household lives (some TV channels are regional), to construct the variable:

$$w_{ikc} = \begin{cases} 1 & i \text{ says they "regularly" or "sometimes" watch on the day and time slot } k \\ & \qquad \text{and "regularly" or "sometimes" watch channel } c \\ & \qquad \text{and they live in the region in which } c \text{ is aired (or the channel is national)} \\ 0 & \text{otherwise} \end{cases} \tag{4.2}$$

### 4.1.3 Household level advertising exposure

We combine the data on household viewing behaviour with the detailed data on individual adverts to create a household specific measure of exposure to advertising. Variation in TV viewing behaviour creates considerable variation in the timing and extent of exposure an individual household has to adverts of a specific brand. As argued in Section 2.4, this leads to cross household variation in advertising exposure that is plausibly unrelated to idiosyncratic shocks to potato chip products, conditional on all the controls in our demand model.

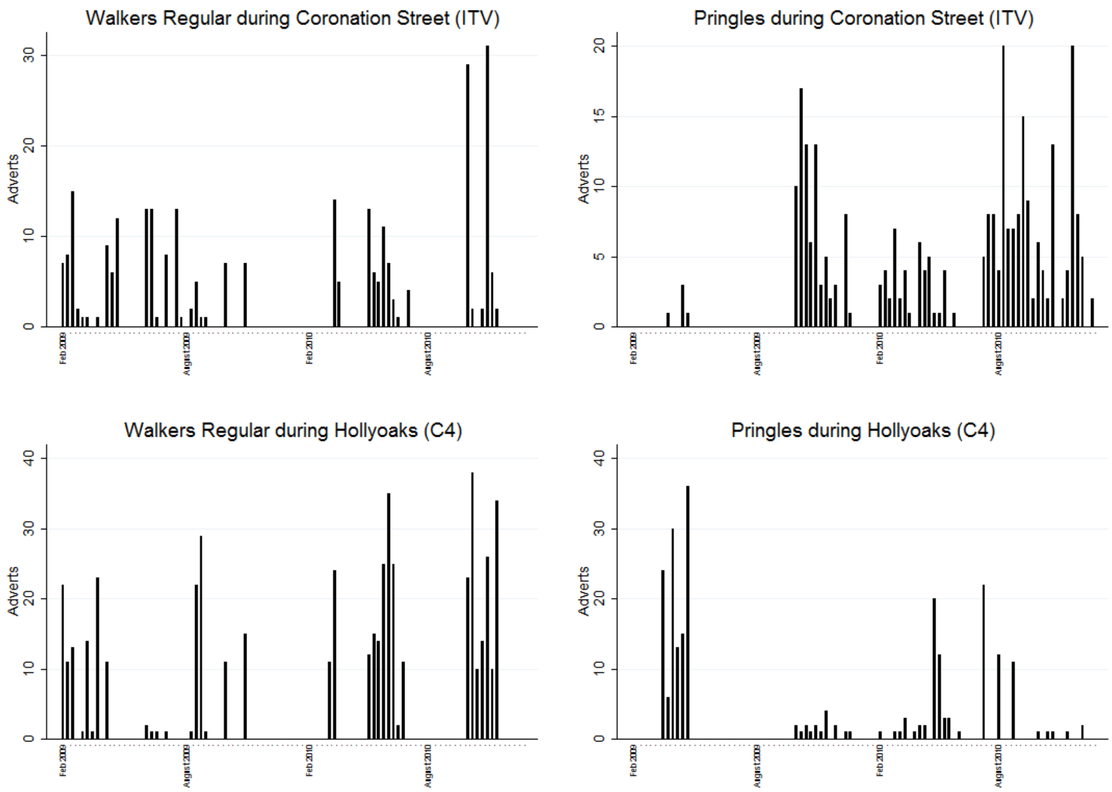
[10] Breakfast time 6.00am-9.30am, Morning 9.30am-12.00 noon, Lunchtime 12.00 noon-2.00pm, Early afternoon 2.00pm-4.00pm, Late afternoon 4.00pm-6.00pm, Early evening 6.00pm-8.00pm, Mid evening 8.00pm-10.30pm, Late evening 10.30-1.00am and Night time 1.00am-6.00am.

Denote by $T_{bskct}$ the duration of time that an advert for brand $b$ is shown during show $s$ on day and time slot $k$ on channel $c$ during week $t$. From the viewing data we construct an indicator variable of whether household $i$ was likely to be watching channel $c$ on day and time slot $k$ during show $s$, $w_{iskc}$. If show $s$ is among the 206 specific shows households were asked for viewing information we set $w_{iskc} = w_{is}$, otherwise we set $w_{iskc} = w_{ikc}$. From this we define the household's total exposure to advertising of brand $b$ during week $t$ as:

$$a_{ibt} = \sum_{s,c,k} w_{iskc} T_{bskct}. \tag{4.3}$$

In Section 2.4 we discussed the type of variation in the data that we rely on by providing an example of household viewing behaviour with respect to three popular soap operas. Figure 4.2 shows the number of adverts aired during Coronation Street and during Hollyoaks by the two most advertised brands – Walkers Regular and Pringles. The third soap opera, Eastenders is aired on BBC and therefore has no adverts shown during it. The figure illustrates that both brands are advertised during the two shows, but the level and timing of adverts varies. This generates differential time series variation across households in their exposure to the adverts of each brand. We control for brand-time-demographic shocks to demands, and we exploit this differential across household advertising variation in estimation.

Figure 4.2: *Advertisements aired by two largest brands*




*Note: The two top figures show the number of adverts aired on ITV during Coronation Street, including those aired directly before or directly after; the two bottom figures show those aired on Channel 4 during Hollyoaks; the two left hand figures show the number of Walkers Regular adverts aired; the two right hand figures show the number of Pringles adverts aired.*

For this sort of variation to be correlated with the idiosyncratic demand shocks, $\epsilon_{ijt}$, one would have to believe these demand shocks exhibit a complicated cyclical correlation with soap watching behaviour, so it is sometime best to advertise to Coronation Street viewers, sometimes best to advertise to Hollyoaks viewers or sometime best to advertise to both. Moreover, the pattern would have to be differential across Walkers Regular and Pringles (given the different patterns of advertising) and it must be forecastable by advertisers. We believe it is much more likely that this kind of variation in advertising is driven by firm strategies (e.g. the type of pulsing strategies described in Dubé et al. (2005)) or by the discretion channels have to choose exactly when adverts air – typically advertisers purchase a number of impressions within a given demographic group and time period (e.g. month) with precise scheduling decisions left to stations (see Crawford et al. (2012)).

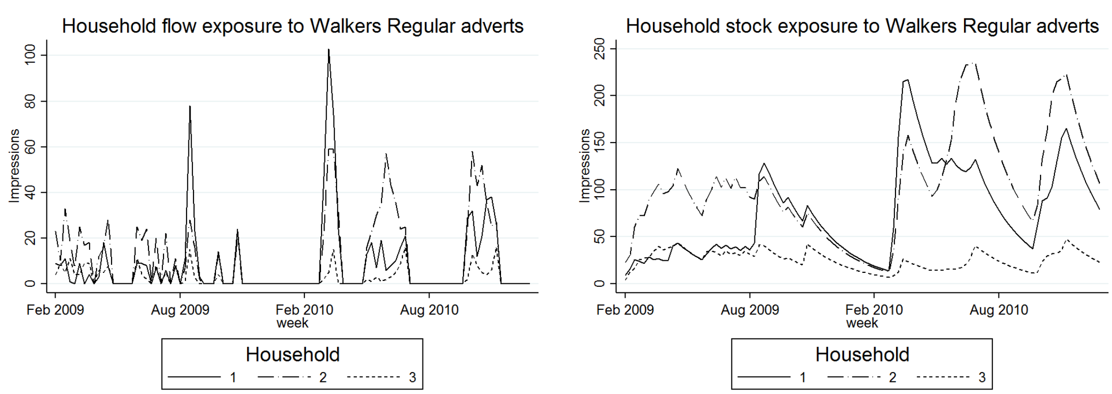
To make the model empirically tractable we assume that the dynamic effect of advertising on demand is such that the state variables of advertising exposure are equal to a discounted sum of current (up until the day we observe the purchase being made) and past advertising exposure, as in Erdem et al. (2008),

$$\mathfrak{a}_{ibt} \equiv \mathcal{A}\left(a_{ibt}, a_{ibt-1}, .., a_{ib0}\right) = \sum_{n=0}^{t-t_0} \delta^n a_{ibt-n}.$$

$\mathfrak{a}_{ibt}$ can be interpreted as a household specific stock of advertising goodwill that decays over time at rate $\delta$ per week, but that can be increased by exposure to more advertising. This means that the dimension of the state space for advertising exposure remains finite, as $\mathfrak{a}_{ibt} = \mathcal{A}\left(\mathfrak{a}_{ibt-1}, a_{ijt}\right) = \delta\mathfrak{a}_{ibt-1} + a_{ibt}$. In estimation we set $\delta = 0.9$ implying that an advertising impression two weeks ago has 90% of the effect of one seen one week ago.[11] We use data on purchases starting in June 2009 and have data on advertising flows starting from February 2009, meaning that the effects of initial conditions are minimal.

To illustrate the differential variation in exposure of households to advertising, in Figure 4.3, we take three example households from our data and plot their exposure to advertising of Walkers Regular. The left hand panel shows the flow measure of exposure and the right hand side shows the stock measure. Household 2 is more exposed than the other two households to Walkers Regular advertising from February to August 2009 and after May 2010. Household 1 has greater exposure from August 2009 to May 2010. At almost all points in time, household 3 has the lowest exposure to advertising. These differences, driven by variation in the TV shows and stations these the households watch and the days and times they tend to watch TV, leads to rich differential variation in stocks of advertising exposure.

Figure 4.3: *Advertising flow and stocks for Walkers Regular brand for three example households*




*Note: The left hand side plots exposure to Walkers Regular adverts per week,* $a_{ibt}$ *from equation (4.3), for three example households; the right hand side plots the stock of exposure to Walkers Regular adverts,* $\mathfrak{a}_{ibt}$.

We allow for diminishing returns to advertising; it seems natural that the incremental effect of an additional impression is less for consumers that have already seen a large number of adverts. We follow Dubé et al. (2005) and Shapiro (2015) by including a concave transformation of the advertising state variable; as

[11]We experiment with stocks computed using different decay parameters and find qualitatively similar results for $\delta$ not close to 0 and not too close to 1. $\delta = 0$ and $\delta = 1$ are rejected by the data.

Dubé et al. (2005) point out, under certain circumstances this allows firms' advertising problem to have a well-behaved optimum. We therefore transform the own advertising variable, $\mathfrak{a}_{ibt}$, and the sum of competitor advertising variable, $\sum_{l\neq b}\mathfrak{a}_{ilt}$, using the inverse hyperbolic sine function, $\tilde{a}=\ln(a+\sqrt{a^2+1})$.

## 4.2 Purchase data

The purchase data are from the Kantar Worldpanel for the period June 2009 to October 2010. Our data are unusual in that we have information on households' purchases for food at home *and* individuals' purchases for food on-the-go. For each household we observe *all* food purchases made and brought into the home (we refer to these as "food at home" purchases). We also have information from a sample of individuals drawn from these households that record all food purchases made for consumption "on-the-go" (we refer to these as "food on-the-go" purchases) during the same period. Food at home purchases are by definition made for future consumption (the product has to be taken back home to be recorded), while food on-the-go purchases are made for immediate consumption. Individuals participating in the on-the-go panel include both adults and children aged 13 or older.

We use information on 266,328 transactions over the period June 2009 to October 2010; this includes 147,530 food at home purchase occasions and 118,798 food on-the-go purchase occasions, made by 2,496 households and 2,112 individuals. We define a purchase occasion as a week.

For the food at home segment this is any week in which the household records buying groceries. We say that a household selected the outside option when it does not record purchasing any potato chips for home consumption. Potato chips are purchased on 41% of food at home purchase occasions.

For the food on-the-go segment a purchase occasion is any week in which the individual records purchasing any food on-the-go; when an individual bought food on-the-go, but did not purchase any potato chips, we say they selected one of the outside options. Potato chips are purchased on 27% of food on-the-go purchase occasions.

We define two outside options. One is the unhealthy outside option that corresponds to purchasing junk food (but not potato chips), which includes chocolate, confectionery, cakes, pastries and ice cream. The other is a healthy outside option that corresponds to purchasing food other than junk foods. For the food at home segment this includes all other non-junk foods purchased in the supermarket; for the food on-the-go segment this includes healthy snacks such as fruit, yoghurt and nuts. Our definition of the outside options means that we assume that changes in pricing or advertising in the potato chips market may change consumers' propensity to buy potato chips, but not their propensity to go shopping.

From other data we know that 14% of potato chips are bought on-the-go, with the remaining share purchased for food at home (Living Cost and Food Survey).

### 4.2.1 Product definition

Purchase data is at the UPC or barcode level, containing information on purchases of over 1800 unique potato chip UPCs. We aggregate these UPCs into 37 products over which we estimate demand. We define a potato chip product as a brand-pack size combination (the products are listed in Table 4.2); in terms of product definition the main form of aggregation is across different flavours. In the UK potato chip market, price and advertising does not vary across flavours and variation in nutrients across flavour within brand is minimal (and far out weighed by variation across brands). For instance, the brand Pringles has 78 separate UPCs. Of these, four UPCs (original flavour, salt and vinegar, sour cream and onion, and barbecue) account for over 55% of Pringles' transactions. For the brand Pringles we define two products – Pringles 150-300g and Pringles 300g+ based on the consumer's total purchase of the brand on a purchase occasion. In some cases – for example, Walkers Other – we also aggregate over a set of minor brands (with market shares less that 4%).[12]

Potato chips for consumption at home are almost entirely purchased in large supermarkets as part of the households main weekly shopping,[13] whereas those for consumption on-the-go are mostly purchased in small convenience stores.[14] The set of products available in large supermarkets (for food at home) differs from the set of products available in convenience stores (for food on-the-go). Some brands are not available in convenience stores (for example, generic supermarket brands), and purchases made at large supermarkets are almost entirely large or multi-pack sizes, while food on-the-go purchases are almost always purchases of single packs. We restrict the choice sets in each segment to reflect this. This means that the choice sets for food at home and on-the-go occasions do not overlap; most brands are present in both segments, but not in the same pack size. Table 4.2 shows the set of products available and the market shares in each market segment. The table makes clear that Walkers is, by some distance, the largest firm in the market – its products account for 46% of all potato chips sold in the food at home segment and 55% of that sold in the food on-the-go segment.

While the products on offer for food at home and food on-the-go purchase occasions are disjoint, there may nonetheless be linkages in demand between the segments. We assume that when the main shopper is taking a purchase decision in the supermarket for future consumption, they do not consider possible future on-the-go purchases that might be made by members of the household. However, we do consider the possibility that food on-the-go purchase decisions are influenced by recently made food at home purchases.

[12] The aggregation over flavours means that if Pringles and Walkers sold salt and vinegar flavour and KP did not we would potentially miss out on the closer substitution possibilities between Pringles and Walkers for consumers who have a strong taste for salt and vinegar. However, in the UK the dominant flavours are salted (or regular), salt and vinegar and cheese and onion; almost all potato chip products come in these flavours and other flavours tend to have small market shares.

[13] 91% of these purchases are from large supermarket chains.

[14] We use the term small convenience stores to refer to small branches of national chain stores such as Tesco Metro and Sainsbury's Express, plus independent corner stores and news agents; these account for 53% of sales, with the rest coming from shops in the workplace or college, vending machines and other retailers.

When modelling the on-the-go demand of individuals, we include a dummy variable in the payoff function of the inside options indicating whether the main shopper of the household the individual belongs to made a food at home potato chip purchase in the previous week.[15] This allows for the possibility that a recent food at home purchase lowers (or increases) the probability an individual purchases potato chips while on-the-go. We test the impact that recent food at home purchase have on the market demand curve for food on-the-go products and find that it is essentially zero (the impact on market demands is economically very small and not statistically significantly different from zero).

#### 4.2.2 Prices

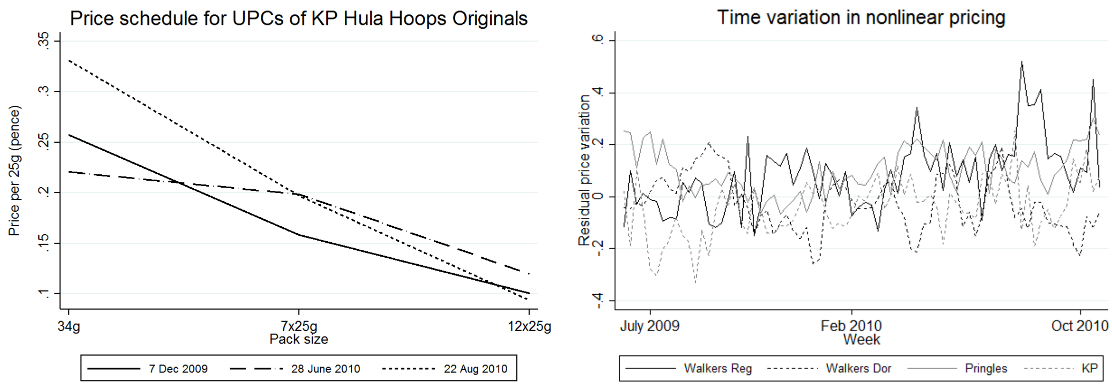
Our data contain prices for each transaction, a transaction is the purchase of an individual UPC (or barcode). These transaction level prices are well measured in our data. As explained in Section 4.2.1, we aggregate UPCs into 37 products. In estimation we use the price of each product measured in pounds sterling (£s), the average of these prices across weeks are shown in Table 4.2. We measure these product prices as the mean across transactions for the UPCs that comprise the product in that week; these transaction prices can vary within a week due to within week price changes and some differences in pricing across stores.

As outlined in Section 2.4, we follow an identification strategy suggested by Bajari and Benkard (2005); we include brand-time effects in the model and identify the effect of price on demand by exploiting differential time series variation in product level prices within brand across different pack sizes (i.e. non-linear pricing).

In the left hand panel of Figure 4.4 we show an example of this sort of price variation in the underlying transaction prices. For KP Hula Hoops Originals we show the price per 25g of the most common pack sizes, 34g, 7x25g and 12x25g, in the retailer Tesco on three separate dates. The figure shows that nonlinear pricing exists – the price schedule slopes downwards – and the shape of the schedule changes over time. This sort of price variation is common in the market. In the right hand panel of Figure 4.4 we summarise the time series variation in nonlinear pricing across the four major potato chip brands, Walkers Regular, Walkers Doritos, Pringles and KP. The time series are generated by regressing product price on brand-week and pack size-week effects, and plotting the residual for the largest size product of each brand. The figure makes clear that there is differential time series variation across brands.

[15] See Appendix B for precise details.

Figure 4.4: *Price variation*




*Note: The left hand side figure plots price per 25g for the most popular pack sizes (or UPCs) belonging to "KP Hula Hoops". The right hand side plots residual prices variation of the four main brands after removing brand-week and size-week effects.*

We assume that, conditional on the controls in the demand model, this variation in prices is exogenous. A problem would arise if in a particular week households had demand shocks for a specific pack size of a brand, but not for other packs of the same brand, and this was forecasted by firms in the market.[16] Possible drivers of this differential movement in prices within brand are cost variations that are not proportional to pack size, differential pass-through of cost shocks and differences in how brand advertising affects demands for different pack sizes (in Section 4.3 we show advertising has a much stronger impact on demand for large packs). It is unlikely that within brand, pack size specific, demand shocks, unrelated to advertising but anticipated by firms are the main driver of the form of price variation we exploit. In Section 4.6 we show robustness to this assumption by including a control function for price.

[16]We allow all preference parameters to vary by whether the purchase occasion is for the food at home or food on-the-go, so these shocks would only cause a problem if they happened within either segment.

Table 4.2: *Quantity share and mean price*

| | | | Food at home | | Food on-the-go | |
|---|---|---|---|---|---|---|
| Firm | Brand | Size | Quantity Share | Price (£) | Quantity Share | Price (£) |
| *Walkers* | | | 45.91% | | 55.34% | |
| | Regular | 34.5g | | | 28.14% | 0.45 |
| | | 50g | | | 7.45% | 0.63 |
| | | 150-300g | 1.77% | 1.24 | | |
| | | 300g+ | 24.22% | 2.77 | | |
| | Sensations | 40g | | | 2.01% | 0.59 |
| | | 150-300g | 0.43% | 1.25 | | |
| | | 300g+ | 1.80% | 2.52 | | |
| | Doritos | 40g | | | 4.68% | 0.45 |
| | | 150-300g | 1.28% | 1.19 | | |
| | | 300g+ | 3.21% | 2.45 | | |
| | Other | <30g | | | 4.68% | 0.45 |
| | | 30g+ | | | 8.38% | 0.61 |
| | | <150g | 0.68% | 1.24 | | |
| | | 150-300g | 3.74% | 1.76 | | |
| | | 300g+ | 8.78% | 3.17 | | |
| *Pringles* | Pringles | | 6.90% | | | |
| | | 150-300g | 1.32% | 1.09 | | |
| | | 300g+ | 5.58% | 2.60 | | |
| *KP* | KP | | 19.62% | | 22.70% | |
| | | 50g | | | 22.70% | 0.52 |
| | | <150g | 0.21% | 0.85 | | |
| | | 150-300g | 4.81% | 1.18 | | |
| | | 300g+ | 14.60% | 2.38 | | |
| *Tayto* | Golden Wonder | | 1.54% | | 4.23% | |
| | | <40g | | | 3.12% | 0.38 |
| | | 40-100g | | | 1.11% | 0.72 |
| | | <150g | 0.10% | 1.29 | | |
| | | 150-300g | 0.24% | 1.39 | | |
| | | 300g+ | 1.20% | 2.71 | | |
| *Asda* | Asda | | 3.37% | | | |
| | | <150g | 0.09% | 0.95 | | |
| | | 150-300g | 0.90% | 0.95 | | |
| | | 300g+ | 2.38% | 2.29 | | |
| *Tesco* | Tesco | | 6.51% | | | |
| | | <150g | 0.19% | 0.82 | | |
| | | 150-300g | 1.78% | 0.91 | | |
| | | 300g+ | 4.54% | 2.07 | | |
| Other | Other | | 16.15% | | 17.73% | |
| | | <40g | | | 12.15% | 0.49 |
| | | 40-100g | | | 5.58% | 0.66 |
| | | <150g | 0.93% | 1.05 | | |
| | | 150-300g | 3.86% | 1.31 | | |
| | | 300g+ | 11.36% | 2.56 | | |

*Notes: Quantity share refers to the quantity share of potato chips in the segment accounted for by that product. Price refer to the mean price across markets.*

### 4.2.3 Nutrient characteristic

The motivation for restricting advertising in junk food markets is to improve health outcomes. Therefore we are particularly interested in the nutrient characteristics of the products. Table 4.3 shows the main nutrients in potato chips. We control for the nutrient characteristics using an index that combines the individual nutrients into a single score and that is used by UK government agencies. It is based on the nutrient profile model developed by Rayner et al. (2005) (see also Rayner et al. (2009) and Arambepola et al. (2008)) and is used by the UK Food Standard Agency, and by the UK advertising regulator Ofcom to categorize food products for regulatory purposes. For potato chips the relevant nutrients are the amount of energy, saturated fat, sodium and fiber that a product contains per 100g. Products get points based on the amount of each nutrient they contain; 1 point is given for each 335kJ per 100g, for each 1g of saturated fat per 100g, and for each 90mg of sodium per 100g (or, equivalently, 0.225g of salt per 100g). Each gram of fiber per 100g reduces the score by 1 point. The UK Food Standard Agency uses a threshold of 4 points or more to define "less healthy" products, and Ofcom has indicated this is the relevant threshold for advertising restrictions (Ofcom (2007)).

Table 4.3 also shows the nutrient profile score. There is considerable variation across brands; Walkers Regular has the lowest score (10), and the brands Pringles and KP have the highest score (18). This is a large difference. To give some context, if all other nutrients were the same then an 8g difference in saturated fat (per 100g of product) would lead to a difference of 8 points in the nutrient profile score; in the UK the guideline daily amount of saturated fat is 20g per day for woman and 30g per day for men. Note also that potato chips lie far above the "less healthy" threshold of 4 and the possibility that reformulation could bring them below the threshold is unlikely.

Table 4.3: *Nutrient characteristics of brands*

| Brand | Nutrient profiling score | Energy (kj per 100g) | Saturated fat (g per 100g) | Salt (g per 100g) | Fiber (g per 100g) |
|---|---|---|---|---|---|
| Walkers Regular | 10 | 2164 | 2.56 | 1.48 | 4.04 |
| Walkers Sensations | 11 | 2021 | 2.16 | 1.78 | 4.25 |
| Walkers Doritos | 12 | 2095 | 2.86 | 1.65 | 3.02 |
| Walkers Other | 15 | 2017 | 2.50 | 2.04 | 3.14 |
| Pringles | 18 | 2160 | 8.35 | 1.55 | 2.74 |
| KP | 18 | 2157 | 5.87 | 2.10 | 2.70 |
| Golden Wonder | 16 | 2124 | 4.03 | 2.30 | 3.77 |
| Asda | 15 | 2125 | 4.13 | 1.88 | 3.31 |
| Tesco | 15 | 2141 | 4.63 | 1.92 | 3.57 |
| Other | 12 | 2083 | 3.84 | 1.75 | 4.06 |

*Notes: See text for definition of the nutrient profiling score; a higher score indicates a less healthy product.*

We allow for two outside goods. The unhealthy outside option includes purchases of chocolate, confectionery, cakes, pastries and ice cream. The mean nutrient score of these foods is 20, which is above even the most unhealthy potato chips brands. If a ban on advertising potato chips predominantly leads to switching towards these alternative "junk foods" then it is possible the policy might reduce the nutritional quality of foods purchased. The healthy outside option comprises all other (non-junk) foods – including fruit and vegetables, yoghurt and nuts – and has a mean nutrient score of 2, well below even the most healthy potato chip product.

### 4.2.4 Household demographics

Table 4.4 provides details of the numbers of households we observe making food at home purchases, the number of individuals making food on-the-go decisions and the number of purchase occasions. Households and individuals can switch between demographic groups over time, for example if a child is born in a household, or if a grown up child turns 18.

Table 4.4: *Household types*

| Demographic group | | | Number of | | Number of purchase occasions | |
|---|---|---|---|---|---|---|
| | | | households | individuals | food at home | food on-the-go |
| Composition | skill level | income | | | | |
| No children | high | high | 413 | 302 | 20747 | 14761 |
| | | medium | 270 | 223 | 11962 | 9669 |
| | | low | 245 | 225 | 11800 | 10147 |
| | low | medium-high | 193 | 152 | 9477 | 7200 |
| | | low | 289 | 234 | 14369 | 10488 |
| Pensioners | | | 242 | 134 | 13273 | 6683 |
| Children | high | high | 367 | 323 | 18976 | 15368 |
| | | medium | 276 | 244 | 12923 | 10766 |
| | | low | 147 | 126 | 6448 | 5315 |
| | low | medium-high | 282 | 256 | 13971 | 12060 |
| | | low | 277 | 257 | 13584 | 11976 |
| Child purchase | | | | 95 | | 4365 |
| Total | | | 2496 | 2112 | 147,530 | 118,798 |

*Notes: Households with "children" are households with at least one person aged below 18, "Pensioners" refers to a households with no more than two people, no-one aged below 18 and at least one person aged above 64; "No children" refers to all other households. "Child purchase" refers to someone aged below 18 making a food on-the-go purchase. Skill levels are defined using socioeconomic groups. "High" comprises people in managerial, supervisory or professional roles, "low" refers to both skilled and unskilled manual workers and those who depend on the state for their income. Income levels are defined by terciles of the within household type income per person distribution. The total number of households and individuals is less than the sum of the number in each category because households may switch group over time.*

We allow all coefficients, including the distribution of the random coefficients, to vary across the demographic groups shown in Table 4.4. Households are distinguished along three characteristics: (i) household composition, (ii) skill or education level of the head of household, based on socio-economic status, and (iii) income per household member. For individuals observed making food on-the-go purchases we categorize them based on their income, education and income of their household, with the exception of individuals aged below 18 (which we group together as a separate category). As argued in Sections 2.3 and 2.4, allowing preference variation across this dimension will allow for the possibility of important differences in demand shape and, because we also allow variation in the brand-time effects across demographic groups, it will control for time varying demographic specific shocks to brand demands.

## 4.3 Empirical estimates

We estimate the demand model using maximum simulated likelihood. We report the full set of estimated coefficients, along with the market own and cross price elasticities and marginal cost estimates in Appendix D. Here we focus on what the estimates imply for how advertising affects the shape of demand. We show that advertising has rich effects on demands and that allowing for advertising to affect demand in a flexible way in the choice model is therefore important. We describe how advertising impacts on consumers' willingness to pay for the nutrient characteristic, price elasticities and patterns of cross brand and cross pack size substitution.

### 4.3.1 The empirical effects of advertising on demand

One potential impact of advertising is to change consumers' willingness to pay for a characteristic (see equation (2.3)). We allow for this possibility by including interactions between both advertising and price and advertising and the nutrient characteristic in the payoff function, and the coefficients on these are statistically significant.

We compute the willingness to pay for a one point improvement (reduction) in the nutrient profiling score. A one point reduction would be achieved, for instance, by a 1g reduction in saturated fat per 100g of product. Table 4.5 shows how advertising affects the willingness to pay. We take as the base case a consumer with zero exposure to advertising and show the difference between their willingness to pay and that of a consumer at the 10th, 50th and 90th percentile of the advertising exposure distribution. We do this separately for food at home and food on-the-go purchase occasions. 95% confidence intervals are given in brackets.[17]

For both food at home and food on-the-go higher exposure to advertising lowers consumers' willingness to pay for a more healthy product. For food at home, a consumer at the 10th percentile of the exposure distribution is willing to pay 4.7 pence (or 2.3% of the mean price) less than a consumer not exposed to advertising; a household at the 90th percentile of the exposure distribution is willing to pay 9.2 pence (or 4.5% of the mean price) less. For food on-the-go a similar relationship exists but it is less strong; a consumer at the 10th percentile of the advertising exposure distribution has willingness to pay for a marginally more healthy product that is 0.4 pence (or 0.9% of the mean price) less than a consumer with zero advertising

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

exposure, while a consumer at the 90th percentile has a lower willingness to pay of 0.6 pence (or 1.2% of the mean price). Table 4.5 makes clear that one thing that advertising does is lower consumers' willingness to pay for an increase in the healthiness of potato chips and that allowing for interactions of advertising with price and the nutrient characteristic in the demand model is empirically important.

Table 4.5: *Effect of advertising on willingness to pay for an increase in healthiness (a 1 point reduction in nutrient profiling score)*

| | | Position in advertising exposure distribution | | |
|---|---|---|---|---|
| | Difference relative to zero exposure: | 10th percentile | Median | 90th percentile |
| Food at home | Willingness to pay in pence | -4.7 | -7.2 | -9.2 |
| | | [-6.8, -3.1] | [-10.7, -4.4] | [-14.0, -5.5] |
| | % of mean price | -2.3 | -3.5 | -4.5 |
| | | [-3.3, -1.5] | [-5.2, -2.1] | [-6.8, -2.7] |
| Food on-the-go | Willingness to pay in pence | -0.4 | -0.6 | -0.6 |
| | | [-1.0, -0.2] | [-1.3, -0.3] | [-1.5, -0.3] |
| | % of mean price | -0.9 | -1.1 | -1.2 |
| | | [-2.0, -0.5] | [-2.6, -0.5] | [-2.9, -0.5] |

*Notes: Numbers shows how willingness to pay varies with advertising exposure. Numbers in rows 1 and 3 show the difference in willingness to pay in pence for a one point reduction in the nutrient profiling score for a consumer at the 10th, 50th and 90th percentile of the advertising exposure distribution relative to a consumer with zero advertising exposure. Numbers in rows 2 and 4 show differences as a percentage of the mean price of potato chips on the purchase occasion (i.e. food at home or food on-the-go occasion). We base numbers for the distribution of advertising exposure on the brand Walkers Regular. 95% confidence intervals are given in square brackets.*

The interaction between advertising and price in the payoff functions also allows for the possibility that advertising shifts consumers' price sensitivities. We find that for the food at home segment (which represents 86% of the market) advertising leads to a reduction in consumers' sensitivity to price. In order to illustrate the strength of this effect we do the following. For each of the food at home products that belong to the three most highly advertised brands, we compute the own price elasticity of market demand at the observed advertising levels in each month. We report the mean elasticities, averaging across months, in the top panel of Table 4.6. For each brand we unilaterally set the flow of advertising of that brand to zero and recompute the own price elasticities (i.e. what the own price elasticity for the Walkers Regular products would have been if that brand was not advertised in that month). The bottom panel of Table 4.6 shows the resulting mean percent change in own price elasticities (relative to observed advertising) for each product, with a positive number showing that the absolute value of the elasticity increases. For instance, the mean market own price elasticity of the most popular product, Walkers Regular 300g+, is -2.61. Shutting off advertising in the current market for Walkers Regular results in demand for Walkers Regular 300g+ becoming more elastic, with an average increase in the absolute value of the own price elasticity of 2.65%. The effect is also to make demand for the smaller 150g-300g pack more elastic, although the strength of the effect is less. A similar pattern holds for the other brands.

Table 4.6: *Effect of advertising on market own price elasticities*

| | Walkers Regular | Pringles | KP |
|---|---|---|---|
| *Own price elasticity in observed equilibrium* | | | |
| <150g | | | -1.22 |
| | | | [-1.25, -1.18] |
| 150g-300g | -1.63 | -1.45 | -1.57 |
| | [-1.68, -1.57] | [-1.51, -1.40] | [-1.62, -1.52] |
| 300g+ | -2.61 | -2.66 | -2.53 |
| | [-2.73, -2.50] | [-2.78, -2.54] | [-2.62, -2.43] |
| *% reduction in price elasticity under zero market advertising* | | | |
| <150g | | | 1.13% |
| | | | [0.86, 1.44] |
| 150g-300g | 1.78% | 1.74% | 1.25% |
| | [1.44, 2.07] | [1.38, 2.14] | [0.97, 1.56] |
| 300g+ | 2.65% | 2.48% | 1.72% |
| | [2.14, 3.09] | [2.01, 3.03] | [1.30, 2.14] |

*Notes: The top panel reports the mean market own price elasticity for each pack size available in the food at home segment for the brands Walkers Regular, Pringles and KP. For each of these brands we unilaterally set current market advertising to zero and we compute the change in own price elasticities. The bottom panel shows the percent reduction for each elasticity. 95% confidence intervals are given in square brackets.*

We undertake a similar exercise to illustrate the impact advertising has on brand demand. For each brand we simulate what demand would have been if that brand had not been advertised in that month (and all other brands' advertising had remained at observed levels). In Table 4.7 we report the results for the most highly advertised brands. If Walkers unilaterally stopped advertising its Regular brand quantity demanded for that brand would fall by 1.60%, demand for Pringles would increase by 0.24%, while demand for most other brands, and for potato chips overall, would fall. Unilaterally shutting down Pringles' advertising results in a larger reduction in the quantity of that brand demanded of 4.45%, demand for Walkers Regular is unaffected, and demand for most other brands either is unaffected or falls. The overall effect is to reduce potato chips demand by 0.41%.

Table 4.7 makes clear that, for a number of brands, advertising is cooperative (if one brand stops advertising in a month, other brands see a fall in demand). The fact that we find evidence of cooperative effects of advertising underlines the importance of allowing advertising to enter demand in a flexible way that does not unduly constrain the impact of advertising on demand a priori; if we had only included own brand advertising in the payoff function and omitted the competitor advertising effect the functional form assumptions would have ruled out cooperative advertising effects.

Table 4.7: *Effect of advertising on brand demand*

| | Walkers Regular | Pringles | KP |
|---|---|---|---|
| *% change in row brand demand if column brand market advertising is set to zero* | | | |
| Walkers Regular | -1.60 | -0.06 | 0.05 |
| | [-2.13, -0.95] | [-0.15, 0.08] | [-0.01, 0.14] |
| Walkers Sensations | -0.51 | -0.14 | -0.17 |
| | [-0.72, -0.37] | [-0.24, -0.06] | [-0.23, -0.09] |
| Walkers Doritos | -0.24 | -0.06 | -0.05 |
| | [-0.40, -0.06] | [-0.15, 0.01] | [-0.11, 0.01] |
| Walkers Other | 0.32 | -0.05 | 0.13 |
| | [0.15, 0.49] | [-0.17, 0.08] | [0.06, 0.21] |
| Pringles | 0.24 | -4.45 | 0.06 |
| | [0.07, 0.43] | [-5.07, -3.75] | [-0.03, 0.17] |
| KP | -0.03 | -0.12 | -1.29 |
| | [-0.16, 0.10] | [-0.22, 0.03] | [-1.73, -0.94] |
| Golden Wonder | -1.05 | -0.26 | -0.81 |
| | [-1.19, -0.92] | [-0.35, -0.12] | [-0.96, -0.69] |
| Asda | -0.31 | -0.29 | -0.33 |
| | [-0.43, -0.14] | [-0.37, -0.17] | [-0.41, -0.19] |
| Tesco | -0.44 | -0.35 | -0.48 |
| | [-0.57, -0.27] | [-0.42, -0.22] | [-0.59, -0.34] |
| Other | 0.17 | -0.15 | 0.23 |
| | [0.04, 0.36] | [-0.31, 0.06] | [0.10, 0.35] |
| *% change in total potato chips demand if column brand market advertising is set to zero* | | | |
| | -0.43 | -0.41 | -0.22 |
| | [-0.53, -0.34] | [-0.46, -0.32] | [-0.25, -0.19] |

*Notes: For each brand Walkers Regular, Pringles and KP, in each market, we unilaterally set current brand advertising expenditure to zero. Numbers in the table report the resulting percentage change in quantity demanded for all brands and for the potato chips market as a whole. Numbers are means across markets. 95% confidence intervals are given in square brackets.*

Table 4.8 shows how unilaterally setting market advertising to zero for each of the most advertised brands affects quantity demanded (measured in 1000s of kilograms) for each of the pack sizes available for food at home. For all three brands it is demand for the largest pack size that declines when advertising expenditure is set to zero; demand for smaller packs either does not change by a statistically significant amount or increases slightly. This highlights that an important effect of brand advertising is to lead consumers to switch to the larger pack size of that brand.

Table 4.8: *Effect of advertising on demand by pack size*

| | Walkers Regular | Pringles | KP |
|---|---|---|---|
| *Change in own brand demand by pack size if flow of brand advertising is set to zero* | | | |
| <150g | | | 0.57 |
| | | | [0.03, 0.91] |
| 150g-300g | 1.24 | -1.46 | 1.56 |
| | [-2.88, 6.04] | [-3.37, 0.26] | [-1.69, 3.89] |
| 300g+ | -78.54 | -36.39 | -32.80 |
| | [-98.20, -56.92] | [-40.86, -31.15] | [-40.62, -25.07] |
| *Change in food at home demand for brand if flow of brand advertising is set to zero* | | | |
| | -77.30 | -37.86 | -30.67 |
| | [-99.51, -52.96] | [-44.23, -31.33] | [-42.27, -20.26] |

*Notes: For each brand Walkers Regular, Pringles and KP, in each market, we unilaterally set current brand advertising expenditure to zero. Numbers in the table are measured in 1000s of kilograms and report the change in quantity demands for all pack sizes of the brand available on food at home purchase occasions. Numbers are means across markets. 95% confidence intervals are given in square brackets.*

## 4.4 Counterfactual analysis of advertising ban

We compare the observed market equilibrium to one in which advertising is banned. Specifically, we set the advertising stocks of all firms to zero. This would be the situation after advertising has been banned for long enough for the stock to fully depreciate; with $\delta = 0.9$ it would take less than a year for stocks to depreciate to 4% of their original value prior to the ban. We find the new equilibrium in all markets (months) and report the means across markets.

### 4.4.1 Impact on market equilibrium

One effect that advertising has on consumer demand is to lower consumers' sensitivity to price (see Table 4.6). Banning advertising therefore leads to tougher price competition. The (quantity weighted) average price in the market falls by 4%. This fall is driven by price reductions for products in the food at home segment that belong to the most heavily advertised brands. Table 4.9 shows the mean market price in the observed equilibrium with advertising and in the counterfactual equilibrium in which all advertising is banned; we show this for the food at home products belonging to the three most advertised brands. The ban results in a fall in price for all products in Table 4.9. Walkers reduces the price of its most popular brand by the most, reducing the price of the 150-300g pack by 15p (or 12%) and the 300g+ pack by 17p (or 6%). Walkers also reduces the price of products belonging to the other brands it offers. The brands for which there is little advertising (e.g. Asda and Tesco) see small increases in their equilibrium prices post ban (not shown in Table). Equilibrium prices in the smaller food on-the-go segment do not change much following the advertising ban.

Table 4.9: *Effect of advertising ban on equilibrium prices*

| | Walkers Regular | | Pringles | | KP | |
|---|---|---|---|---|---|---|
| | Pre ban equilibrium | Advertising banned | Pre ban equilibrium | Advertising banned | Pre ban equilibrium | Advertising banned |
| <150g | | | | | 0.86 | 0.82 |
| | | | | | | [0.81, 0.84] |
| 150g-300g | 1.26 | 1.11 | 1.11 | 1.05 | 1.19 | 1.14 |
| | | [1.09, 1.13] | | [1.03, 1.08] | | [1.13, 1.16] |
| 300g+ | 2.79 | 2.62 | 2.60 | 2.50 | 2.38 | 2.31 |
| | | [2.58, 2.64] | | [2.47, 2.52] | | [2.30, 2.33] |

*Notes: Numbers show the mean price across markets in £s. "Pre ban equilibrium" refers to the prices observed in the data; "Advertising banned" refers to counterfactual prices when advertising is banned. 95% confidence intervals are given in square brackets.*

Table 4.10 summarizes the overall impact of an advertising ban on total monthly expenditure on potato chips and the total quantity of potato chips sold.[18] The first column shows the average of each variable across markets in the observed pre ban equilibrium, the second column shows values in the counterfactual when advertising is banned but prices are held constant, and the final column shows the values in the new equilibrium when advertising is banned and firms reoptimise prices.

Table 4.10: *Effect of advertising ban on purchases*

| | Pre ban | Advertising banned | |
|---|---|---|---|
| | equilibrium | no price response | with price response |
| Expenditure (£m) | 100.85 | 85.62 | 87.11 |
| | [99.78, 101.91] | [82.44, 88.26] | [84.25, 89.77] |
| *% change* | | -15.10 | -13.62 |
| | | [-17.83, -12.67] | [-16.18, -11.18] |
| Quantity (mKg) | 14.80 | 12.55 | 13.36 |
| | [14.64, 14.98] | [12.05, 12.97] | [12.96, 13.71] |
| *% change* | | -15.24 | -9.72 |
| | | [-17.93, -12.61] | [-11.83, -7.40] |

*Notes: Percentage changes are shown below variables. "No price response" refers to the situation where advertising is banned and prices are held at their pre ban level; "with price response" refers to the situation where advertising is banned and firms reoptimise their prices. Expenditure refers to total expenditure on potato chip and quantity refers to the total amount of potato chips sold. Numbers are means across markets. 95% confidence intervals are given in square brackets.*

In the pre ban equilibrium (in which advertising is allowed) total monthly expenditure on potato chips was around £100m and total quantity sold was 15m kg. The impact of the ban if we hold prices constant is to induce a 15.1% fall in expenditure and a 15.2% fall in quantity sold. The reduction in quantity is mainly

[18] To gross the numbers up from our sample to the UK market we need a measure of the total market size $M_t$ and how it is split between food at home and food on-the-go segments. From Mintel we know that total annual potato chip expenditure in the UK is around £1200m (http://www.marketingmagazine.co.uk/article/1125674/sector-insight-crisps-salty-snacks) and from the Living Cost and Food Survey we know that 14% of potato chips by volume were purchased as food on-the-go. Based on this information we can compute the implied potential market size and the size of each segment of the market.

driven by consumers purchasing potato chips less frequently. When we account for the fact that oligopolistic firms will respond to the advertising ban by adjusting prices we find that expenditure falls by 13.6% and total quantity sold falls by 9.7%. The reason for this smaller reduction in the quantity of potato chips sold is that a number of firms – including Walkers, the dominant firm in the market – respond to the advertising ban by lowering their prices. Important in driving this result is that our demand specification is flexible enough to capture the fact that advertising leads consumers to have demands that are less price sensitive.

#### 4.4.2 Impact on health

The key motivation for advocates of advertising restrictions in junk food markets is to lower consumption of nutrients associated with diet related health problems (see for instance, WHO (2010) and Gortmaker et al. (2011)). Whether banning advertising does reduce consumption of targeted nutrients will depend on both how advertising affects demand, including demand substitutions across products, and on the equilibrium pricing response of firms operating in the market. It will also depend on what alternatives consumers substitute to if they switch out of the market altogether.

We first focus on the impact of the advertising ban on nutrients obtained from potato chips in Table 4.11. The top panel describes the impact of the ban on the total monthly quantity of energy, saturated fat and salt that households buy as potato chips. The bottom panel describes the impact on the nutrient content of the potato chips that households buy.

Holding prices at their pre ban level, the advertising ban leads to a reduction in the total quantity of energy (by 15.2%), saturated fat (by 16.3%) and salt (by 15.4%) consumers purchase from potato chips. Conditional on purchasing potato chips, consumers also buy healthier varieties; the nutrient score of purchases falls by 0.5% (which corresponds to an increase in healthiness), and the quantity of saturated fat and salt per 100g of potato chip purchases fall by 1.1% and 0.2%. Abstracting from the equilibrium response of firms, the advertising ban appears successful in improving the nutritional content of consumers' purchases of potato chip.

However, the improvement in nutrients purchased as potato chips is partially offset by firms reducing prices in response to the ban. The full effect of the ban (accounting for the pricing response of firms) is to lower energy (by 9.7%), saturated fat (by 11.9%) and salt (by 10.3%) purchased as potato chips. The reductions are smaller than when prices are held at their pre ban level. However, the pricing response of firms reinforces the improvements in nutritional characteristics of products purchased. Conditional on purchase, the nutrient score of purchases now falls (i.e. improves) by 1.2% and the saturated fat and salt content per 100g of potato chip purchases falls by 2.4% and 0.6%. This is because the products that see the biggest fall in price (e.g. the Walkers Regular products) are among the more healthy (least unhealthy) products available in the market.

Table 4.11: *Effect of advertising ban on nutrient purchases*

| | Pre ban equilibrium | Advertising banned no price response | with price response |
|---|---|---|---|
| Energy (bn kj) | 313.70 | 265.94 | 283.23 |
| | [310.22, 316.37] | [256.46, 274.18] | [274.70, 290.29] |
| *% change* | | -15.23 | -9.71 |
| | | [-17.33, -12.55] | [-11.45, -7.18] |
| Saturates (1000 kg) | 584.79 | 489.78 | 515.24 |
| | [576.73, 589.84] | [472.66, 506.86] | [498.46, 528.92] |
| *% change* | | -16.25 | -11.89 |
| | | [-18.05, -13.56] | [-13.57, -9.66] |
| Salt (1000 kg) | 264.94 | 224.18 | 237.67 |
| | [261.89, 266.95] | [216.29, 231.02] | [230.45, 243.13] |
| *% change* | | -15.38 | -10.29 |
| | | [-17.41, -12.78] | [-12.01, -7.84] |
| Nutrient score | 13.78 | 13.72 | 13.62 |
| | [13.74, 13.80] | [13.66, 13.74] | [13.56, 13.65] |
| *% change* | | -0.46 | -1.19 |
| | | [-0.83, -0.13] | [-1.55, -0.92] |
| Saturates intensity (g/100g) | 3.95 | 3.90 | 3.85 |
| | [3.93, 3.97] | [3.87, 3.92] | [3.83, 3.87] |
| *% change* | | -1.19 | -2.41 |
| | | [-1.73, -0.72] | [-2.90, -2.03] |
| Salt intensity (g/100g) | 1.79 | 1.79 | 1.78 |
| | [1.79, 1.79] | [1.78, 1.79] | [1.77, 1.78] |
| *% change* | | -0.17 | -0.63 |
| | | [-0.37, 0.01] | [-0.83, -0.48] |

*Notes: Percentage changes are shown below variables. "No price response" refers to the situation where advertising is banned and prices are held at their pre ban level; "with price response" refers to the situation where advertising is banned and firms reoptimise their prices. Nutrient score reports the mean nutrient profiling score for potato chip purchases; a reduction indicates consumers are switching to more healthy potato chips. Numbers are means across markets. 95% confidence intervals are given in square brackets.*

Table 4.11 makes clear that a ban on advertising in the potato chip market would improve the nutritional quality of purchases of potato chips. Part of this improvement is due to people switching out of the potato chip market (by purchasing potato chips less often). An overall assessment of the health consequences of the policy also depends on what these consumers switch to instead. To address this question we have included in the model a less healthy outside option and a more healthy outside option. As described in Section 4.2.3, the less healthy outside option consists of other junk foods, which are typically less healthy than potato chips, while the more healthy outside option comprises non-junk foods.

Table 4.12 summarises the impact of the advertising ban on the consumers' probabilities of selecting potato chips, the less healthy outside option and the more healthy outside option. Prior to the advertising ban, the mean probability of a consumer purchasing potato chips on a given purchase occasion is 35%, the probability that they instead select the less healthy outside option is 39% and the probability they select the more healthy outside option is 26%. The full effect of the ban (taking into account the pricing response of firms) is to lower the probability of a consumer purchasing potato chips by 4.0 percentage points to 31%. Consumer substitution from the potato chip market to other less healthy junk foods is stronger than substitution away from junk food products; after the ban the probability of selecting the less healthy outside option rises by 2.7 percentage points while the increase for the more healthy outside option is 1.4 percentage points.

Table 4.12: *Substitution to alternatives*

| | Pre ban equilibrium | Advertising banned no price response | with price response |
|---|---|---|---|
| Probability of selecting potato chips (%) | 35.34 | 30.07 | 31.31 |
| | [34.85, 35.61] | [28.82, 31.13] | [30.14, 32.60] |
| *Change* | | -5.27 | -4.03 |
| | | [-6.25, -4.16] | [-5.03, -2.80] |
| Probability of selecting less healthy outside option (%) | 38.93 | 42.44 | 41.61 |
| | [38.61, 39.45] | [41.72, 43.41] | [40.75, 42.53] |
| *Change* | | 3.51 | 2.67 |
| | | [2.87, 4.15] | [2.01, 3.24] |
| Probability of selecting more healthy outside option (%) | 25.72 | 27.49 | 27.09 |
| | [25.44, 26.02] | [27.00, 28.10] | [26.54, 27.70] |
| *Change* | | 1.77 | 1.36 |
| | | [1.28, 2.17] | [0.87, 1.78] |

*Notes: Percentage point changes are shown below variables. "No price response" refers to the situation where advertising is banned and prices are held at their pre ban level; "with price response" refers to the situation where advertising is banned and firms reoptimise their prices. Numbers are means across markets. 95% confidence intervals are given in square brackets.*

While the overall effect of the ban is to lower the probability of a consumer purchasing any junk food (the probability of selecting the healthy outside option increases), the ban also has the effect of increasing the likelihood that consumers that do purchase junk food buy products other than potato chips. These alternative snacks are, on average, less healthy than potato chips (their mean nutrient score is 20 compared to around 14 for potato chips), so this mitigates the positive health effects of the policy from looking only at potato chip consumption. While the effect of the ban is to reduce the probability of purchasing any junk food (potato chips or the less healthy outside option) by 1.4 percentage points, it also leads to an increase worsening) in the average nutrient score of purchases conditional on purchasing a junk food.

Overall, therefore, the positive health effects of the ban on advertising potato chips that comes from lowering potato chip demand are partially offset by the equilibrium pricing response of firms and by consumer substitution to other junk foods. A ban with broader scope, for example imposed on all junk food markets, as well as affecting more of the unhealthy items in consumers' shopping baskets, would likely suffer less from these offsetting effects by inducing less consumer substitution to other unhealthy products.

### 4.5 Measuring consumer welfare

Economists are generally interested in measuring the impact of policy change on traditional economic measures of welfare. In our case this includes the effect on consumer welfare and the profits of firms that manufacture and sell potato chips.[19] Our aim in specifying the demand model presented in Section 2 is to ensure the specification is flexible enough to capture the impact of pricing and advertising on demand regardless of which view one takes about advertising. However, to understand the effect of the advertising ban on consumer welfare we have to take a stance on which view of advertising is most appropriate (is it informative about product characteristics, persuasive or a characteristic). We consider how to measure consumer welfare under the views that advertising is persuasive or that it is a product characteristic. Figure 4.5 shows prominent examples of potato chip advertising.

Our welfare measures do not take into account any long run health consequences that results from the ban that are not taken into account by consumers at the point of purchase. However, the numbers in Tables 4.11 and 4.12 could be combined with estimates from the medical literature to say something about monetary consequences of long term health effects.

The persuasive view of advertising has a long tradition in the advertising literature (Robinson (1933), Kaldor (1950)). More recently, the behavioural economics literature (see Bernheim and Rangel (2005)) has suggested advertising might lead consumers to act as non-standard decision makers; advertising providing environmental "cues" to consumers. While policies that improve cognitive processes are potentially welfare enhancing if the environmental cues have information content, persuasive advertising might distort choices in ways that do not enhance welfare. Bernheim and Rangel (2009) argue that *"choices made in the presence of those cues are therefore predicated on improperly processed information, and welfare evaluations should be guided by choices made under other conditions."* The welfare implications of restricting advertising that acts to distort decision making has been explored by Glaeser and Ujhelyi (2010), who are particularly concerned with firm advertising (or misinformation in their terms) in food markets, while Mullainathan et al. (2012) consider the broad policy framework in public finance applications when consumers make decisions that are inconsistent with their underlying welfare.

[19] Profits of firms in the advertising industry may also be affected. Though we have less to say about this, we can state the total advertising budgets, which represent an upper bound on advertisers' profits.

Figure 4.5: *Example adverts for potato chip brands*


*Notes: The advertisement on the top left shows supermodel Elle Macpherson eating Walkers potato chips; the one on the lower left shows an ex-professional football player and TV personality Gary Lineker with the FA Cup (football) trophy full of Walkers potato chips; the top right shows one of a series of adverts for KP Hola Hoops aimed at children, and the bottom right shows a model with Golden Wonder Skins.*

As pointed out by Dixit and Norman (1978), the welfare effects of changes in advertising will depend on whether one uses pre or post advertising tastes to evaluate welfare. When assessing the welfare implications of banning persuasive advertising it is natural to assess welfare changes using undistorted preferences (i.e. the parameters in the consumer's payoff function in the absence of advertising). This mirrors the distinction made by Kahneman et al. (1997) between decision and experience utility; in their terms, advertising affects choice and therefore decision utility, but it does not affect underlying experience utility.

Under the persuasive view of advertising, decisions made when advertising is non-zero maximize a payoff function that does not coincide with the consumer's utility function. Consumers will choose the product that provides them with the highest payoff $\bar{v}_{ijt}$ as in equation (2.1), but the underlying experience utility is based on the consumer's product valuation in the absence of advertising.

$$\widehat{v}_{ijt} = \alpha_{1i} p_{jt} + \psi_{1i} \mathbf{x}_j + \xi_{ib(j)} + \tau^d_{b(j)t} + \epsilon_{ijt}. \tag{4.4}$$

In this case the consumer's expected utility at the advertising state and price vectors $(\mathfrak{a}_{it}, \mathbf{p}_t)$ is given by evaluating the choice made by maximising the payoff function (2.1) at preferences described by equation (4.4):

$$\widehat{W}_i\left(\mathfrak{a}_{it}, \mathbf{p_t}\right) = \mathbb{E}_\epsilon\left[\widehat{v}_{ij^*t}\right].$$

where we define $j^* = \arg\max_j\{\bar{v}_{ijt}\}$. In this case, following the terminology of Kahneman et al. (1997), $\widehat{v}$ is the experience utility while $\bar{v}$ is the decision utility of the consumer. Noting that

$$\widehat{v}_{ijt} = \bar{v}_{ijt} - \left[\lambda_i \mathfrak{a}_{ib(j)t} + \alpha_{2i}\mathfrak{a}_{ib(j)t} p_{jt} + \psi_{2i}\mathfrak{a}_{ib(j)t} n_{b(j)} + \rho_i \left(\sum\nolimits_{l\neq b(j)} \mathfrak{a}_{ilt}\right)\right],$$

we can write $\widehat{W}_i\left(\mathfrak{a}_{it}, \mathbf{p}_t\right)$ as:

$$\begin{aligned}
\widehat{W}_i(\mathfrak{a}_{it}, \mathbf{p_t}) =& \mathbb{E}_\epsilon[\bar{v}_{ij^*t}] - \mathbb{E}_\epsilon\left[\lambda_i \mathfrak{a}_{ib(j)t} + \alpha_{2i}\mathfrak{a}_{ib(j)t} p_{jt} + \psi_{2i}\mathfrak{a}_{ib(j)t} n_{b(j)} + \rho_i \left(\sum\nolimits_{l\neq b(j)} \mathfrak{a}_{ilt}\right)\right] \\
=& \mathbb{E}_\epsilon\left[\max_j\{\bar{v}_{ijt}\}\right] - \mathbb{E}_\epsilon\left[\lambda_i \mathfrak{a}_{ib(j)t} + \alpha_{2i}\mathfrak{a}_{ib(j)t} p_{jt} + \psi_{2i}\mathfrak{a}_{ib(j)t} n_{b(j)} + \rho_i \left(\sum\nolimits_{l\neq b(j)} \mathfrak{a}_{ilt}\right)\right] \\
=& W_i(\mathfrak{a}_{it}, \mathbf{p_t}) - \sum_{j>0} s_{ijt}\left[\lambda_i \mathfrak{a}_{ib(j)t} + \alpha_{2i}\mathfrak{a}_{ib(j)t} p_{jt} + \psi_{2i}\mathfrak{a}_{ib(j)t} n_{b(j)} + \rho_i \left(\sum\nolimits_{l\neq b(j)} \mathfrak{a}_{ilt}\right)\right],
\end{aligned}$$

where $s_{ijt}$ is given by equation (2.2) and, up to an additive constant,

$$\begin{aligned}
W_i\left(\mathfrak{a}_{it}, \mathbf{p_t}\right) \equiv& \mathbb{E}_\epsilon\left[\max_j\{\bar{v}_{ijt}\}\right] \\
=& \ln\Bigg[\exp\left(\xi_{i\underline{0}j} + \psi_{1i} x_{\underline{0}} + \tau^d_{\underline{0}t}\right) + \sum_{j>0}\exp\Bigg(\alpha_{1i} p_{jt} + \psi_{1i}\mathbf{x}_j + \xi_{ib(j)} + \tau^d_{b(j)t} + \\
& \left[\lambda_i \mathfrak{a}_{ib(j)t} + \alpha_{2i}\mathfrak{a}_{ib(j)t} p_{jt} + \psi_{2i}\mathfrak{a}_{ib(j)t} n_{b(j)} + \rho_i \left(\sum\nolimits_{l\neq b(j)} \mathfrak{a}_{ilt}\right)\right]\Bigg)\Bigg],
\end{aligned}$$

using the standard closed form (Small and Rosen (1981)) when the error term $\epsilon$ is distributed i.i.d. type I extreme value.

This says that when a consumer's choices are distorted by advertising, expected utility is equal to expected utility if advertising was in the consumer's utility function, minus a term reflecting the fact that the consumer is making choices that do not maximize her experience utility function.

Denote by $\mathbf{p}^0$ price in the counterfactual equilibrium in which there is no advertising (defined in Section 3.2). Evaluating the impact of banning advertising under the welfare standard of $\widehat{v}_{ijt}$, the difference in consumer welfare between the equilibrium with advertising and the one in which advertising is banned can be decomposed as:

$$\begin{aligned} W_i\left(\mathbf{0},\mathbf{p_t^0}\right)-\widehat{W}_i\left(\mathfrak{a}_{it},\mathbf{p_t}\right)=&W_i\left(\mathbf{0},\mathbf{p_t}\right)-\widehat{W}_i\left(\mathfrak{a}_{it},\mathbf{p_t}\right) \quad \text{(choice distortion effect)} \\ &+W_i\left(\mathbf{0},\mathbf{p_t^0}\right)-W_i\left(\mathbf{0},\mathbf{p_t}\right) \quad \text{(price competition effect)}, \end{aligned} \tag{4.5}$$

where we use the fact that $\widehat{W}_i\left(\mathbf{0},\mathbf{p}\right)=W_i\left(\mathbf{0},\mathbf{p}\right)$.

Under this persuasive view of advertising, advertising has the effect of inducing the consumer to make suboptimal choices. Banning advertising removes this distortion to decision making, which benefits consumers. We label this the "choice distortion effect". However, banning advertising also affects consumer welfare through the "price competition effect" channel. The sign of this effect will depend on the change in pricing equilibrium. The price competition effect is independent of the view we take about advertising since firms' behaviour depends only on decision utilities of consumers.

An alternative to the persuasive view of advertising is that it is a characteristic of the product that consumers value (Stigler and Becker (1977) and Becker and Murphy (1993)). In this case, in the terminology of Kahneman et al. (1997), advertising would enter both experience and decision utilities. The welfare effect of banning advertising would be given by the more standard term $W_i\left(\mathbf{0},\mathbf{p_t^0}\right)-W_i\left(\mathfrak{a}_{it},\mathbf{p_t}\right)$ and the choice distortion term in the equation (4.5) would be replaced by a term reflecting the impact on welfare of removing the advertising characteristic from the market, $W_i\left(\mathbf{0},\mathbf{p_t}\right)-W_i\left(\mathfrak{a}_{it},\mathbf{p_t}\right)$.

The identification of this characteristic effect is influenced by the normalisation of the outside option utility. We include own brand and competitor advertising in the payoff function of inside goods, but the alternative specification where own brand advertising appears in the payoff of inside goods and total advertising appears in the payoff of the outside option would give rise to observationally equivalent demand. Although observationally equivalent, these two specifications would lead to different welfare predictions under the characteristics view.[20] However, as advertising does not enter the experience utility under the persuasive view, this problem does not exist in this alternative welfare definition.

We focus on welfare measures of the direct monetary costs for consumers and firms of an advertising ban. To measure the monetary costs to a consumer we convert the welfare changes to compensating variation (dividing by the marginal utility of income):

$$CV_i\left(\mathfrak{a}_{it},\mathbf{p_t},\mathbf{p_t^0}\right)=\frac{1}{\alpha_{0i}}\left[W_i\left(\mathbf{0},\mathbf{p_t^0}\right)-\widehat{W}_i\left(\mathfrak{a}_{it},\mathbf{p_t}\right)\right]. \tag{4.6}$$

[20] See Appendix C for details.

Aggregate compensating variation is given by integrating across the observable and unobservable consumer level heterogeneity,

$$CV\left(\mathfrak{a}_t, \mathbf{p_t}, \mathbf{p_t^0}\right) = \int CV_i\left(\mathfrak{a}_{it}, \mathbf{p_t}, \mathbf{p_t^0}\right) f(\pi|d) f(d) \mathrm{d}\pi \mathrm{d}d. \tag{4.7}$$

Table 4.13 shows the impact of the ban on consumer welfare under the persuasive view of advertising (column 1) and the characteristic view (column 2). The first four rows describe the impact of the ban on consumer welfare, row 5 gives the change in profits (inclusive of the reductions in advertising expenditure) and the final row gives the overall welfare effect (equal to the sum of compensating variation and changes in profits). The difference between the persuasive and characteristic views is that in the former the compensating variation includes the "choice distortion effect", while in the latter this is replaced with the "characteristics effect".

Table 4.13: *Effect of advertising ban on welfare*

| | Persuasive view | Characteristic view |
|---|---|---|
| Choice distortion effect (£m) | 15.0 | |
| | [14.2, 16.1] | |
| Characteristic effect (£m) | | -23.2 |
| | | [-25.4, -20.4] |
| Price competition effect (£m) | 3.7 | 3.7 |
| | [3.1, 4.3] | [3.1, 4.3] |
| *Total compensating variation (£m)* | 18.7 | -19.5 |
| | [17.7, 20.4] | [-21.3, -16.7] |
| *Change in profits (£m)* | -5.1 | -5.1 |
| | [-6.0, -3.7] | [-6.0, -3.7] |
| **Total change in welfare (£m)** | 13.6 | -24.6 |
| | [12.7, 15.1] | [-27.0, -20.4] |

*Notes: Total compensating variation is equal to the sum of the choice distortion effect or characteristic effect and the price competition effect. Total change in welfare is equal to the sum of total compensating variation and change in profits. Profits are inclusive of savings from no advertising expenditure. Numbers are means across markets. 95% confidence intervals are given in square brackets.*

Focusing first on the persuasive view, the advertising ban benefits consumers as they no longer make decisions distorted by advertising and because it leads to lower prices for a number of products in the market; the "choice distortion effect" leads to a £15 million per month increase in consumer welfare and the "price competition effect" raises consumer welfare by a further £4 million. The ban increases total consumer welfare by £19 million per month. However, banning advertising leads to a reduction in firms' profits of £5 million.[21] Under the persuasive view of advertising, the effect of the ban is thus to raise total welfare by around £14 million.

[21] See Appendix D for a breakdown by firms.

Under the alternative characteristic view of advertising the "choice distortion effect" is replaced by the "characteristic effect". The characteristic effect is influenced by the normalisation of the outside option utility. Under our adopted normalisation, where own brand and competitor advertising enter the payoff function of inside goods, the characteristic effect leads to a reduction in consumer welfare of £23 million. This outweighs the price competition effect, meaning that under this view total welfare is reduced by £25 million.

### 4.6 Robustness

In this section we test the robustness of our results to two potential concerns. First, we use a control function approach to correct for any potential remaining endogeneity in advertising and price. Second, we consider firms as setting prices collusively, rather than according to Nash-Bertrand competition.

In Section 2.4 we argued that we were able to isolate plausibly exogenous variation in advertising exposure and prices. Nevertheless, concern may remain that our estimates are contaminated by endogeneity. Our first robustness check is therefore to repeat our analysis implementing a control function approach (see Blundell and Powell (2004) and for multinomial discrete choice models Petrin and Train (2010)). We estimate a control function for both advertising and price.

For advertising we estimate a first stage regression of household $i$'s period $t$ advertising exposure for brand $j$ (denoted $a_{ijt}$ and defined by equation 4.3), on time varying brand effects and an instrument (interacted with brand effects). We use the average advertising price per second in period $t$ for the stations and times that consumer $i$ reported watching TV as the instrument. Variation in advertising prices is likely to drive changes in potato chip advertising. However, as potato chips are only a small part of the TV advertising market, demand shocks to potato chip demand (not captured by our brand-time-demographic effects) are unlikely to induce changes in advertising prices. The F-stat for a test of the (ir)relevance of this instrument leads us to very strongly reject the hypothesis of no relationship between the advertising exposure of the consumer and advertising prices.

As an instrument for product price, we use past prices. Product prices in the UK potato chip market are set nationally, and over the time period of our data there is very little variation in product attributes, products or sets of competitors, which are other commonly used instruments. Lagged prices will control for any contemporaneous correlation between idiosyncratic demand shocks and current price. Unsurprisingly, our price instruments are highly correlated with price (conditional on exogenous variables included in the demand model).

Table 4.14: *Effect of advertising on demand: with control functions*

| | Main specification | | | With control functions | | |
|---|---|---|---|---|---|---|
| | Walkers Regular | Pringles | KP | Walkers Regular | Pringles | KP |
| *% change in row brand demand if column brand market advertising is set to zero* | | | | | | |
| Walkers Regular | -1.60 | -0.06 | 0.05 | -2.05 | -0.12 | 0.05 |
| | [-2.13, -1.01] | [-0.14, 0.09] | [-0.01, 0.15] | [-2.36, -1.23] | [-0.15, 0.06] | [-0.01, 0.17] |
| Walkers Sensations | -0.51 | -0.14 | -0.17 | -0.44 | -0.20 | -0.21 |
| | [-0.69, -0.37] | [-0.21, -0.05] | [-0.24, -0.09] | [-0.58, -0.32] | [-0.21, -0.05] | [-0.22, -0.06] |
| Walkers Doritos | -0.24 | -0.06 | -0.05 | -0.16 | -0.14 | -0.07 |
| | [-0.38, -0.06] | [-0.14, 0.05] | [-0.13, 0.05] | [-0.28, -0.01] | [-0.13, 0.05] | [-0.12, 0.07] |
| Walkers Other | 0.32 | -0.05 | 0.13 | 0.41 | -0.13 | 0.13 |
| | [0.17, 0.49] | [-0.13, 0.10] | [0.05, 0.24] | [0.24, 0.53] | [-0.14, 0.08] | [0.06, 0.27] |
| Pringles | 0.24 | -4.45 | 0.06 | 0.24 | -4.50 | 0.00 |
| | [0.09, 0.43] | [-5.77, -3.49] | [-0.02, 0.19] | [0.08, 0.43] | [-5.71, -3.41] | [-0.03, 0.17] |
| KP | -0.03 | -0.12 | -1.29 | 0.03 | -0.22 | -1.40 |
| | [-0.14, 0.10] | [-0.20, 0.03] | [-1.98, -0.78] | [-0.05, 0.17] | [-0.22, 0.01] | [-2.10, -0.78] |
| Golden Wonder | -1.05 | -0.26 | -0.81 | -0.90 | -0.32 | -0.75 |
| | [-1.21, -0.91] | [-0.35, -0.16] | [-0.96, -0.67] | [-1.02, -0.72] | [-0.36, -0.15] | [-0.82, -0.58] |
| Asda | -0.31 | -0.29 | -0.33 | -0.30 | -0.38 | -0.39 |
| | [-0.43, -0.18] | [-0.37, -0.19] | [-0.43, -0.19] | [-0.41, -0.18] | [-0.37, -0.18] | [-0.42, -0.20] |
| Tesco | -0.44 | -0.35 | -0.48 | -0.47 | -0.43 | -0.53 |
| | [-0.56, -0.31] | [-0.42, -0.22] | [-0.59, -0.35] | [-0.54, -0.32] | [-0.42, -0.23] | [-0.59, -0.35] |
| Other | 0.17 | -0.15 | 0.23 | 0.23 | -0.24 | 0.21 |
| | [0.04, 0.35] | [-0.25, 0.06] | [0.14, 0.38] | [0.12, 0.40] | [-0.27, 0.03] | [0.15, 0.42] |
| *% change in own pack size demand if brand market advertising is set to zero* | | | | | | |
| <150g | | | 0.89 | | | 1.35 |
| | | | [0.08, 1.52] | | | [0.05, 1.57] |
| 150g-300g | 0.34 | -1.01 | 0.36 | 0.47 | -0.51 | 0.85 |
| | [-0.58, 1.37] | [-2.17, 0.03] | [-0.39, 0.95] | [-0.37, 1.28] | [-2.30, -0.04] | [-0.34, 1.02] |
| 300g+ | -2.63 | -5.16 | -1.79 | -3.09 | -5.33 | -1.87 |
| | [-3.29, -1.89] | [-6.58, -4.22] | [-2.64, -1.16] | [-3.32, -1.92] | [-6.56, -4.11] | [-2.72, -1.15] |
| *% reduction in own price elasticity if brand market advertising is set to zero* | | | | | | |
| <150g | | | 1.13 | | | 1.21 |
| | | | [0.86, 1.44] | | | [0.77, 1.31] |
| 150g-300g | 1.78 | 1.74 | 1.25 | 1.94 | 1.83 | 1.34 |
| | [1.44, 2.07] | [1.38, 2.14] | [0.97, 1.56] | [1.33, 1.94] | [1.29, 1.93] | [0.87, 1.40] |
| 300g+ | 2.65 | 2.48 | 1.72 | 3.04 | 2.69 | 1.98 |
| | [2.14, 3.09] | [2.01, 3.03] | [1.30, 2.14] | [1.99, 2.88] | [1.82, 2.68] | [1.22, 1.98] |

*Notes: The first row refers to the model specification. Main specification refers to the demand specification outlined in Section 2. Control function refers to demand estimates when control functions for advertising and price are used. For brands in the second row (Walkers Regular, Pringles and KP), in each market, we unilaterally set current brand advertising to zero. Numbers in the first panel report the resulting percentage change in quantity demanded for all brands. Numbers in the second panel report the percentage change in own demands for pack sizes available on food at home purchase occasions for the brand in the second row. The third panel reports the percent reduction in the market own price elasticity for each pack size available in the food at home segment for the brand in the second row. Numbers are means across markets. 95% confidence intervals are given in square brackets.*

We re-estimate the full model. In Table 4.14 we summarise the effect on demands that would result if Walkers Regular, Pringles and KP, separately and unilaterally, ceased advertising in one market (month). We report the average effect across all markets. The top panel shows percent changes in brand level demands. The second panel shows the percentage change in demand for the smaller and larger food at home pack sizes that would result for that brand if the flow of advertising was set to zero. The final panel reports the percent reduction in the value of own price elasticities that would result for each pack size if the flow of advertising was set to zero. We show the results for our main specification (mirroring the information in Tables 4.6, 4.7 and 4.8), and for the control function specification. The numbers make clear that our findings that advertising is partially predatory and partially cooperative, that it leads consumers to switch to larger pack sizes and it acts to make demand more price elastic hold across both specifications. The control function specification, like our baseline model, also predicts that an advertising ban holding prices constant leads to a reduction in energy, saturated fat and salt purchases, but that firms respond to the ban by lowering prices. Our main conclusions are unaffected.

In our supply model, presented in Section 3.2, we made the assumption that firms set their prices according to a per period Nash-Bertrand game. An alternative to this assumption is that firms set prices collusively. We test the Nash-Bertrand assumption against this alternative. To do this we recover marginal costs under the assumption of collusive pricing. These marginal costs do not make economic sense; across all product-months 56.5% of the costs recovered under collusive pricing are negative (while, in contrast, only 2.7% of the marginal costs recovered under the Nash-Bertrand assumption have negative point estimates and these are not statistically significantly different from zero). This is evidence against collusive pricing (and in favour of the alternative of Nash-Bertrand pricing). We formally test between the marginal costs inferred under Nash-Bertrand and collusive pricing using the non-nested tests developed in Vuong (1989) and Rivers and Vuong (2002). Under the assumption of a linear additive cost function (in size, brand and market fixed effects) we reject the model of collusion in favour of Nash-Bertrand pricing with a statistic of 9.09, much above its 5% critical value of 1.64. The test is robust to other cost equation specifications and always rejects collusion.

# 5 Summary and Conclusions

In this paper we develop a model of demand and supply in a market where firms compete over prices and advertising. We allow advertising to affect demands in a flexible way; allowing for past advertising to affect current demand, for the possibility of predatory or cooperative effects, and for advertising to affect consumer price sensitivities and willingness to pay for characteristics. We apply the model to the UK potato chip market using detailed data on households' exposures to brand advertising and novel transaction level data on purchases of food taken into the home and food bought on-the-go for immediate consumption. Our estimates highlight that allowing for a flexible relationship between advertising and demand is empirically important; we find evidence that advertising is, at least in part, cooperative, it acts to lower consumer sensitivity to price and it lowers consumers' willingness to pay for more healthy products. It also acts to attract new consumers into the market and to trade up to larger pack sizes.

We use the model to simulate the impact of an advertising ban on market equilibrium. We find that banning advertising, holding prices fixed, lowers potato chip demand, as well as total purchases of potato chip calories, saturated fat and salt. However, these health gains are partially offset for two reasons. Firstly, some firms respond to the ban by lowering prices, which leads to an offsetting increase in potato chip demand. Secondly, some consumers switching out of the market choose to substitute to other less healthy junk foods.

In our main analysis we remain agnostic about how exactly advertising affects consumers' underlying utilities, instead focusing on allowing advertising to flexibly shift demand. However, to calculate the impact of the advertising ban on consumer welfare we must take a view. We consider the change in welfare under different assumptions about how advertising affects experience utility. We show how to evaluate consumer welfare under the view that advertising is persuasive, acting to distort consumer decision making, leading them to take decisions that are inconsistent with their underlying preferences. Under this view of advertising the ban acts to raise consumer and total welfare. In the counterfactual equilibrium consumers no longer make distorted decisions and benefit from lower prices.

In this paper our focus has been on the impact of an advertising ban on a market with a set of well established and known brands. An interesting avenue for future research would be to consider an alternative counterfactual; for instance how would firms' pricing and advertising strategies respond to the introduction of a tax. The framework we develop in this paper could potentially be used to study such a question, although solving for the set of counterfactual equilibria would present considerable challenges. In markets with a reasonable degree of product churn, entry and exit considerations may play a more prominent role than in the potato chips market. In such a case, the ex ante evaluation of an advertising ban could be extended to study the effects of a ban on industry structure. Advertising may constitute a barrier to entry, and banning advertising may facilitate entry of competitors who would not need to invest in building up large advertising stocks.[22] While in the particular market studied in the paper, this consideration is not of first-order concern, in other less mature markets it may be more important. This represents a promising direction for future research.

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[22] See, for instance Doraszelski and Markovich (2007), Chamberlin (1933), Dixit (1980), Schmalensee (1983) and Fudenberg and Tirole (1984)).

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# Appendices for "The effects of banning advertising in junk food markets"

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# A Dynamic oligopoly competition in prices and advertising

In Section 3.2 of the paper we argue that because i) prices do not directly affect future demand or the evolution of the state variables and ii) we observe the advertising state variables, optimal price are determined by a static equilibrium pricing condition, and for the purposes of considering an advertising ban, we can restrict our attention to this optimality condition. Here we outline an example of a fully dynamic oligopoly game which implies additional optimality conditions (not required in our case) that will characterise dynamic equilibrium advertising strategies. This is one example of many games that is consistent with the validity of focusing only on the price first order conditions for our counterfactual of considering an advertising ban. We abstract from explicitly considering entry and exit for notational simplicity, but as will become clear, identification of marginal costs of products present in the market is independent of whether we allow for entry and exit of firms or products.

Before turning to discuss a fully dynamic oligopoly game in advertising we discuss some reduced form evidence supporting no dynamics in prices.

## A.1 Omitted unobserved heterogeneity or habits?

In models of habit formation (e.g Meghir and Weber (1996)) intertemporal nonseparabilities result in past consumption having a causal impact on current consumption. We consider the reduced form relationship between current quantity purchased and past purchase decisions by estimating the reduced form regression:

$$q_{it} = \sum_{k=1}^{8} \beta^k w_{it}^k + \tau_t + c_i + e_{it}, \tag{1.1}$$

where $q_{it}$ is the quantity of potato chips household $i$ purchased in week $t$, and $w_{it}^k$ are dummy variables equal to one if the last time household $i$ purchased potato chips was $k$ weeks ago, $\tau_t$ are week effects and $c_i$ are household fixed effects.

The coefficient $\beta^k$ can be interpreted as capturing habits, i.e. the effect of past purchases on the quantity of potato chips purchased today, conditional on unobserved heterogeneity and aggregate time effects, with the baseline being not purchasing potato chips any time in the last two months. We estimate this separately by demographic group.

We first estimate equation (1.1) *without the unobserved heterogeneity term*, $c_i$. The estimated coefficients in Table A.1 shows considerable evidence of a strong association between past purchase behaviour and current behaviour; having purchased potato chips recently is associated with purchasing more potato chips now.

However, as Heckman (1981) and others have argued, this association seen in Table A.1 could be driven by omitted unobserved heterogeneity, reflecting spurious state dependence, rather than structural state dependence. Therefore, in Table A.2 we include $c_i$, and see that once we include heterogeneity in the form of household fixed effects the relationship between recent past purchases of potato chips and the current purchase level is very small, and almost everywhere not statistically different from zero.

Table A.1: *Relationship between current and past purchases: no unobserved preference heterogeneity*

| Dep var: quantity purchased | No kids, high income, high skill | No kids, medium income, high skill | No kids, low income, high skill | No kids, high-medium income, low skill | No kids, low income, low skill | Pensioners | Kids, high income, high skill | Kids, medium income, high skill | Kids, low income, high skill | Kids, high-medium income, low skill | Kids, low income, low skill |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Purchased: | | | | | | | | | | | |
| 1 week ago ($\beta^1$) | 0.101*** | 0.135*** | 0.128*** | 0.113*** | 0.150*** | 0.0733*** | 0.137*** | 0.165*** | 0.161*** | 0.151*** | 0.179*** |
| | (0.00266) | (0.00407) | (0.00447) | (0.00481) | (0.00447) | (0.00342) | (0.00487) | (0.00627) | (0.0106) | (0.00986) | (0.00772) |
| 2 weeks ago ($\beta^2$) | 0.0836*** | 0.0905*** | 0.104*** | 0.0850*** | 0.112*** | 0.0610*** | 0.110*** | 0.133*** | 0.133*** | 0.121*** | 0.138*** |
| | (0.00348) | (0.00494) | (0.00555) | (0.00595) | (0.00543) | (0.00427) | (0.00552) | (0.00724) | (0.0119) | (0.0105) | (0.00865) |
| 3 weeks ago ($\beta^3$) | 0.0641*** | 0.0639*** | 0.0694*** | 0.0613*** | 0.0854*** | 0.0399*** | 0.0850*** | 0.110*** | 0.102*** | 0.0875*** | 0.103*** |
| | (0.00427) | (0.00578) | (0.00620) | (0.00687) | (0.00665) | (0.00475) | (0.00635) | (0.00879) | (0.0135) | (0.0116) | (0.00960) |
| 4 weeks ago ($\beta^4$) | 0.0519*** | 0.0443*** | 0.0567*** | 0.0396*** | 0.0749*** | 0.0354*** | 0.0730*** | 0.0722*** | 0.0878*** | 0.0713*** | 0.0776*** |
| | (0.00465) | (0.00632) | (0.00747) | (0.00783) | (0.00778) | (0.00529) | (0.00731) | (0.00988) | (0.0164) | (0.0128) | (0.0114) |
| 5 weeks ago ($\beta^5$) | 0.0483*** | 0.0280*** | 0.0403*** | 0.0381*** | 0.0481*** | 0.0299*** | 0.0502*** | 0.0599*** | 0.0528** | 0.0545*** | 0.0489*** |
| | (0.00561) | (0.00611) | (0.00792) | (0.00936) | (0.00832) | (0.00579) | (0.00857) | (0.0112) | (0.0172) | (0.0144) | (0.0124) |
| 6 weeks ago ($\beta^6$) | 0.0164** | 0.0272*** | 0.0292*** | 0.0212* | 0.0341*** | 0.0161** | 0.0490*** | 0.0536*** | 0.0834*** | 0.0176 | 0.0422** |
| | (0.00511) | (0.00766) | (0.00843) | (0.00845) | (0.00885) | (0.00537) | (0.00998) | (0.0133) | (0.0235) | (0.0159) | (0.0145) |
| 7 weeks ago ($\beta^7$) | 0.0262*** | 0.0208** | 0.0268** | 0.0135 | 0.0450*** | 0.0217*** | 0.0225* | 0.0362** | 0.0257 | 0.0185 | 0.0231 |
| | (0.00576) | (0.00797) | (0.00946) | (0.00904) | (0.0113) | (0.00629) | (0.00981) | (0.0138) | (0.0242) | (0.0163) | (0.0155) |
| 8 weeks ago ($\beta^8$) | 0.0187** | 0.0414*** | 0.0248* | 0.0201 | 0.0332** | 0.0144* | 0.0237* | 0.00924 | 0.0208 | 0.0171 | 0.0142 |
| | (0.00661) | (0.0107) | (0.00971) | (0.0108) | (0.0124) | (0.00637) | (0.0120) | (0.0126) | (0.0280) | (0.0188) | (0.0153) |
| Time-group effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Household effects | No | No | No | No | No | No | No | No | No | No | No |
| Number observations | 20011 | 11405 | 10985 | 8867 | 13140 | 11995 | 18143 | 12564 | 6264 | 13422 | 13036 |

*Notes: Each column is a separate regression of the quantity of potato chips a household purchases in a week (at home and on-the-go) on eight indicator variables indicating whether the household purchased any potato chips in the previous week, two weeks ago, etc. for each of the previous 8 weeks. Household fixed effects are not included. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, ***, $p < 0.001$.*

Table A.2: *Relationship between current and past purchases: unobserved preference heterogeneity included*

| Dep var: quantity purchased | No kids, high income, high skill | No kids, medium income, high skill | No kids, low income, high skill | No kids, high-medium income, low skill | No kids, low income, low skill | Pensioners | Kids, high income, high skill | Kids, medium income, high skill | Kids, low income, high skill | Kids, high-medium income, low skill | Kids, low income, low skill |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Purchased: | | | | | | | | | | | |
| 1 week ago ($\beta^1$) | 0.00247 | -0.00713 | 0.00257 | 0.00162 | 0.00774 | -0.00726 | 0.00941 | 0.0127 | 0.0311* | -0.000953 | 0.0104 |
| | (0.00433) | (0.00635) | (0.00677) | (0.00728) | (0.00739) | (0.00500) | (0.00764) | (0.0115) | (0.0150) | (0.0122) | (0.0106) |
| 2 weeks ago ($\beta^2$) | 0.0103* | -0.00116 | 0.0179* | 0.00733 | 0.0102 | 0.00343 | 0.0186* | 0.0231* | 0.0340* | 0.0117 | 0.0197 |
| | (0.00435) | (0.00621) | (0.00693) | (0.00759) | (0.00742) | (0.00482) | (0.00788) | (0.0115) | (0.0159) | (0.0121) | (0.0108) |
| 3 weeks ago ($\beta^3$) | 0.00802 | -0.00554 | 0.00398 | 0.00349 | 0.00828 | -0.00427 | 0.0129 | 0.0277* | 0.0211 | 0.00493 | 0.0138 |
| | (0.00447) | (0.00654) | (0.00693) | (0.00846) | (0.00808) | (0.00523) | (0.00756) | (0.0115) | (0.0151) | (0.0122) | (0.0122) |
| 4 weeks ago ($\beta^4$) | 0.00906 | -0.00871 | 0.00571 | -0.00429 | 0.0122 | -0.00129 | 0.0161 | 0.00959 | 0.0195 | 0.0103 | 0.00715 |
| | (0.00483) | (0.00698) | (0.00785) | (0.00884) | (0.00829) | (0.00554) | (0.00828) | (0.0115) | (0.0181) | (0.0146) | (0.0134) |
| 5 weeks ago ($\beta^5$) | 0.0152** | -0.0130* | -0.000740 | 0.00431 | -0.00263 | -0.00157 | 0.00567 | 0.0113 | 0.00163 | 0.00804 | -0.00417 |
| | (0.00509) | (0.00618) | (0.00855) | (0.0103) | (0.00834) | (0.00587) | (0.0101) | (0.0123) | (0.0198) | (0.0141) | (0.0128) |
| 6 weeks ago ($\beta^6$) | -0.00757 | -0.00745 | -0.00335 | -0.00404 | -0.00664 | -0.0102 | 0.0141 | 0.0174 | 0.0410 | -0.0182 | -0.0000541 |
| | (0.00480) | (0.00809) | (0.00788) | (0.00981) | (0.0111) | (0.00551) | (0.0106) | (0.0135) | (0.0222) | (0.0160) | (0.0150) |
| 7 weeks ago ($\beta^7$) | 0.00655 | -0.00674 | 0.000714 | -0.00709 | 0.0105 | -0.00155 | -0.00457 | 0.00828 | -0.00405 | -0.0117 | -0.0103 |
| | (0.00611) | (0.00843) | (0.00905) | (0.00903) | (0.0109) | (0.00552) | (0.0109) | (0.0154) | (0.0207) | (0.0159) | (0.0163) |
| 8 weeks ago ($\beta^8$) | 0.00464 | 0.0184 | 0.00755 | 0.00454 | 0.00485 | -0.00345 | -0.0000289 | -0.0115 | 0.00454 | -0.00577 | -0.00901 |
| | (0.00606) | (0.0105) | (0.00997) | (0.0112) | (0.0127) | (0.00597) | (0.0114) | (0.0120) | (0.0226) | (0.0208) | (0.0175) |
| Time-group effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Household effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 20011 | 11405 | 10985 | 8867 | 13140 | 11995 | 18143 | 12564 | 6264 | 13422 | 13036 |

*Notes: Each column is a separate regression of the quantity of potato chips a household purchases in a week (at home and on-the-go) on eight indicator variables indicating whether the household purchased any potato chips in the previous week, two weeks ago, etc. for each of the previous 8 weeks. Household fixed effects are included. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, ***, $p < 0.001$.*

## A.2 A fully dynamic oligopoly game in advertising

We model demand as depending on individual stocks of advertising exposure, $\mathfrak{a}_{it} = (\mathfrak{a}_{i1t}, ..., \mathfrak{a}_{iBt})$ and collect the vectors of all consumer specific advertising states into $\mathfrak{a}_t$. Firms do not directly choose $\mathfrak{a}_t$, as this depends also on the TV watching behaviour of households. We denote by $\mathbf{e}_{bt}$ the vector of advertising choices made by a firm for brand $b$ at time $t$. This includes how many adverts to air on each station on each time-slot. We denote the cost of this advertising by $C(\mathbf{e}_{bt})$.

Before describing the details of the dynamic oligopoly game, we start by writing the objective function of a firm as a function of strategic variables, prices and advertising, and the vectors of state variables. The firm owning product $j$ chooses the product's price, $p_{jt}$, and advertising, $\mathbf{e}_{b(j)t}$ in each period $t$. The intertemporal variable profit of firm $f$ at period 0 is:

$$\sum\nolimits_{t=0}^{\infty} \beta^t \left[ \sum\nolimits_{j \in \mathcal{J}_f} (p_{jt} - c_{jt}) \, s_j \left( \mathfrak{a}_\mathbf{t}, \mathbf{p_t}, \boldsymbol{\tau_t} \right) M_t - \sum\nolimits_{b \in \mathcal{B}_f} C(\mathbf{e}_{bt}) \right], \tag{A.1}$$

As outlined in Section 4.1.3 of the main paper we assume $\mathfrak{a}_{ibt} = \delta \mathfrak{a}_{ibt-1} + a_{ibt}$ where $a_{ibt}$ denotes the households current period advertising exposure. $a_{ibt}$ will be a function of $\mathbf{e}_{bt}$ as well as the household's TV watching behaviour. The stock $\mathfrak{a}_{ibt}$ will be a function of current and past advertising choices $\mathbf{e}_{bt}, \mathbf{e}_{bt-1}, ....$

Suppose that at each period $t$ all firms observe the total market size, $M_t$, the vector of all firms' marginal costs $\mathbf{c_t}$, and the aggregate demand shocks $\boldsymbol{\tau_t}$. Denote the information set $\theta_t = (M_t, \mathbf{c_t}, \boldsymbol{\tau_t})$. Suppose that firms form symmetric expectations about future shocks according to the assumption: Marginal costs and market size follow independent Markov processes such that for all $t$, $E_t\left[c_{jt+1}\right] = c_{jt}$, $E_t\left[M_{t+1}\right] = M_t$ and $E_t\left[\boldsymbol{\tau_{t+1}}\right] = \boldsymbol{\tau_t}$.

The majority of the empirical literature restricts attention to pure Markov strategies (see, inter alia, Ryan (2012), Sweeting (2013) and Dubé et al. (2005)). This restricts firms' strategies to depend only on payoff relevant state variables, $(\mathfrak{a}_\mathbf{t-1}, \theta_t)$. For each firm $f$, a Markov strategy $\sigma_f$ is a mapping between the state variables $(\mathfrak{a}_{t-1}, \theta_t)$, and the firm $f$ decisions $\left\{p_{jt}\right\}_{j \in \mathcal{J}_f} \left\{\mathbf{e}_{bt}\right\}_{b \in B_f}$, which consist of choosing prices and advertising expenditures for the firm's own products $(\sigma_f\left(\mathfrak{a}_{t-1}, \theta_t\right) = (\{p_{jt}\}_{j \in \mathcal{J}_f} \{\mathbf{e}_{bt}\}_{b \in B_f}))$.

There is no guarantee that a Markov Perfect Equilibrium (MPE) in pure strategies of this dynamic game exists. In a discrete version of this game, existence of a symmetric MPE in pure strategies follows from the arguments in Doraszelski and Satterthwaite (2003, 2010), provided that we impose an upper bound on advertising strategies. Ericson and Pakes (1995) and Doraszelski and Satterthwaite (2003) provide general conditions for the existence of equilibria in similar games, but as our model set up differs, the conditions cannot be directly applied in our case. If we assume the technical conditions for the existence of a subgame perfect Markov Perfect Equilibrium of this game are satisfied, we can use necessary conditions to characterise an equilibrium (Maskin and Tirole (2001)). However, we do not need to assume that an equilibrium is unique, and indeed it is perfectly possible that this game has multiple equilibria.

In this dynamic oligopoly game, each firm $f$ makes an assumption on the competitors' strategy profiles denoted $\sigma_{-f}$, where $\sigma_{-f}\left(\mathfrak{a}_{t-1},\theta_t\right)=\left(\sigma_1\left(\mathfrak{a}_{t-1},\theta_t\right),..,\sigma_{f-1}\left(\mathfrak{a}_{t-1},\theta_t\right),\sigma_{f+1}\left(\mathfrak{a}_{t-1},\theta_t\right),..,\sigma_F\left(\mathfrak{a}_{t-1},\theta_t\right)\right)$. Equilibrium decisions are generated by a value function, $\pi_f^*(.,.)$, that satisfies the following Bellman equation

$$\pi_f^*\left(\mathfrak{a}_{t-1},\theta_t\right)=\max_{\left(\{p_{jt}\}_{j\in\mathcal{J}_f},\{\mathbf{e}_{bt}\}_{b\in\mathcal{B}_f}\right)}\left\{\sum_{j\in\mathcal{J}_f}\left(p_{jt}-c_{jt}\right)s_j\left(\mathfrak{a}_t,\mathbf{p_t},\boldsymbol{\tau_t}\right)M_t-\sum_{b\in\mathcal{B}_f}C(\mathbf{e}_{bt})+\beta E_t\left[\pi_f^*\left(\mathfrak{a}_t,\theta_{t+1}\right)\right]\right\},$$

where $\pi_f^*\left(\mathfrak{a}_t,\theta_{t+1}\right)$ is the next period discounted profit of firm $f$, given the future advertising states. The Bellman equation is conditional on a specific competitive strategy profile $\sigma_{-f}$. A MPE is then a list of strategies, $\sigma_f^*$ for $f=1,..,F$, such that no firm deviates from the action prescribed by $\sigma_f^*$ in any subgame that starts at some state $\left(\mathfrak{a}_{t-1},\theta_t\right)$.

Assuming that the technical conditions for the profit function to be differentiable in price and have a single maximum are satisfied, we can use the first order conditions of firm $f$ profit with respect to prices for each $j\in\mathcal{J}_f$:

$$s_j\left(\mathfrak{a}_t,\mathbf{p_t},\boldsymbol{\tau_t}\right)+\sum_{j'\in\mathcal{J}_f}\left(p_{j't}-c_{j't}\right)\frac{\partial s_{j'}\left(\mathfrak{a}_t,\mathbf{p_t},\boldsymbol{\tau_t}\right)}{\partial p_{jt}}=0 \tag{A.2}$$

We can identify price-cost margins using the condition (A.2) provided this system of equations is invertible, which will be the case if goods are "connected substitutes" as in Berry and Haile (2014). Another set of conditions for the optimal choice of advertising flows exists and characterises the equilibrium relationship between advertising flows, prices and all state variables including past advertising. We however do not need to use such a condition for identifying marginal costs since the price first order conditions are sufficient. Thus, we do not need to impose differentiability of the profit function with respect to advertising, nor continuity, we only need to use the necessary first order condition on price, which depends on the observed state vector $\mathfrak{a}_t$. In addition, if we allowed for entry and exit of firms we still would be able to identify marginal costs using equation (A.2); entry and exit would change optimal advertising and the set of the firms in the market (both of which we observe), but it would not change the form of the price first order condition for active firms.

As shown by Dubé et al. (2005) and Villas-Boas (1993), this type of dynamic game can give rise to alternating strategies or pulsing strategies in advertising, corresponding to each MPE profile $\sigma$. However, the identification of marginal costs, $c_{jt}$, does not depend on the equilibrium value function $\pi_f^*$ for a given level of observed optimal prices and advertising $(\mathbf{p_t},\mathbf{e_t})$. First order conditions will depend on equilibrium strategies only through observed prices and advertising decisions, and marginal costs will simply be the solution of the system of equations (A.2). Therefore we can identify marginal costs without making assumptions about the uniqueness of dynamic equilibria, whether firms' value function are differentiable, or whether the same equilibria is played in each market.

# B Demand linkages between segments

We denote the set of potato chip products available for food at home purchase occasions as $\Omega_{in}$ and the set available for food on-the-go purchase occasions as $\Omega_{out}$. The two sets of products are disjoint; $\Omega_{in} \cap \Omega_{out} = \varnothing$.

We denote the set of households we observe making decisions on food at home purchase occasions by $\mathbb{I}_{in}$ and the set of individuals we observe making decisions for food on-the-go purchase occasions by $\mathbb{I}_{out}$. The individuals who we observe making food on-the-go decisions are drawn from the households that we observe making food at home decisions (although the individuals need not be the household main shopper).

We allow for the possibility that the demands of individuals on food on-the-go purchase occasions are influenced by recent food at home purchases made by the household the individual belongs to. Specifically we define a dummy variable indicating whether the household the consumer belongs to was observed purchasing potato chips on a food at home purchase occasion in the preceding week – we denote this variable by $fi_{it}$. We include this variable in the payoff function of potato chip products targeted at on-the-go consumption. This allows for the possibility that a recent food at home purchase lowers (or increases) the probability an individual purchases potato chips while on-the-go. The payoff functions associated with the various purchase options are then:

$$
\begin{aligned}
\bar{v}_{ijt} =& \alpha_{1i} p_{jt} + \psi_{1i} \mathbf{x}_j + \\
& \left[ \lambda_i \mathfrak{a}_{ib(j)t} + \alpha_{2i} \mathfrak{a}_{ib(j)t} p_{jt} + \psi_{2i} \mathfrak{a}_{ib(j)t} n_{b(j)} + \rho_i \left( \sum\nolimits_{l \neq b(j)} \mathfrak{a}_{ilt} \right) \right] + \xi_{ib(j)} + \tau^d_{b(j)t} + \epsilon_{ijt} \quad \forall j \in \Omega_{in} \\
\bar{v}_{ijt} =& \alpha_{1i} p_{jt} + \psi_{1i} \mathbf{x}_j + \phi_i fi_{it} + \\
& \left[ \lambda_i \mathfrak{a}_{ib(j)t} + \alpha_{2i} \mathfrak{a}_{ib(j)t} p_{jt} + \psi_{2i} \mathfrak{a}_{ib(j)t} n_{b(j)} + \rho_i \left( \sum\nolimits_{l \neq b(j)} \mathfrak{a}_{ilt} \right) \right] + \xi_{ib(j)} + \tau^d_{b(j)t} + \epsilon_{ijt} \quad \forall j \in \Omega_{out} \\
\bar{v}_{i\underline{0}t} =& \xi_{i\underline{0}j} + \psi_{1i} x_{\underline{0}} + \tau^d_{\underline{0}t} + \epsilon_{i\underline{0}t} \\
\bar{v}_{i\bar{0}t} =& \epsilon_{i\bar{0}t},
\end{aligned}
$$

and the purchase decision of consumers in each market segment is then:

$$\forall\ i \in \mathbb{I}_{in} : \text{select } j \text{ if } \quad \bar{v}_{ijt} \geq \bar{v}_{ij't} \quad \forall\ j' \in (\Omega_{in} \cup \{\underline{0}, \overline{0}\})$$

$$\forall\ i \in \mathbb{I}_{out} : \text{select } j \text{ if } \quad \bar{v}_{ijt} \geq \bar{v}_{ij't} \quad \forall\ j' \in (\Omega_{out} \cup \{\underline{0}, \overline{0}\})$$

# C Expected utility under characteristics view of advertising

Our model specification leads, under the characteristic view of advertising, to expected utility given (up to an additive constant) by:

$$W_i\left(\mathfrak{a}_{it}, \mathbf{p_t}\right) = \ln\Bigg[\exp\left(\xi_{i\underline{0}j} + \psi_{1i}x_{\underline{0}} + \tau^d_{\underline{0}t}\right) + \sum_{j>0}\exp\Bigg(\alpha_{1i}p_{jt} + \psi_{1i}\mathbf{x}_j + \xi_{ib(j)} + \tau^d_{b(j)t} + \left[\lambda_i\mathfrak{a}_{ib(j)t} + \alpha_{2i}\mathfrak{a}_{ib(j)t}p_{jt} + \psi_{2i}\mathfrak{a}_{ib(j)t}n_{b(j)} + \rho_i\left(\sum\nolimits_{l\neq b(j)}\mathfrak{a}_{ilt}\right)\right]\Bigg)\Bigg]$$

An alternative to our model specification is:

$$\widetilde{v}_{ijt} = \alpha_{1i}p_{jt} + \psi_{1i}\mathbf{x}_j + \left[\tilde{\lambda}_i\mathfrak{a}_{ib(j)t} + \alpha_{2i}\mathfrak{a}_{ib(j)t}p_{jt} + \psi_{2i}\mathfrak{a}_{ib(j)t}n_{b(j)}\right] + \xi_{ib(j)} + \tau^d_{b(j)t} + \epsilon_{ijt} \tag{C.1}$$

$$\widetilde{v}_{i\underline{0}t} = \xi_{i\underline{0}j} + \psi_{1i}x_{\underline{0}} + \tau^d_{\underline{0}t} + \tilde{\rho}_i\left(\sum\nolimits_l \mathfrak{a}_{ilt}\right) + \epsilon_{i\underline{0}t} \tag{C.2}$$

$$\widetilde{v}_{i\overline{0}t} = \tilde{\rho}_i\left(\sum\nolimits_l \mathfrak{a}_{ilt}\right) + \epsilon_{i\overline{0}t}. \tag{C.3}$$

Note:

$$\widetilde{v}_{ijt} - \widetilde{v}_{i\overline{0}t} = \alpha_{1i}p_{jt} + \psi_{1i}\mathbf{x}_j + \left[\tilde{\lambda}_i\mathfrak{a}_{ib(j)t} - \tilde{\rho}_i\left(\sum\nolimits_l \mathfrak{a}_{ilt}\right) + \alpha_{2i}\mathfrak{a}_{ib(j)t}p_{jt} + \psi_{2i}\mathfrak{a}_{ib(j)t}n_{b(j)}\right] + \xi_{ib(j)} + \tau^d_{b(j)t} + (\epsilon_{ijt} - \epsilon_{i\overline{0}t})$$

$$\widetilde{v}_{i\underline{0}t} - \widetilde{v}_{i\overline{0}t} = \xi_{i\underline{0}j} + \psi_{1i}x_{\underline{0}} + \tau^d_{\underline{0}t} + (\epsilon_{i\underline{0}t} - \epsilon_{i\overline{0}t})$$

Setting $\widetilde{\lambda}_i = \lambda_i - \rho_i$ and $\widetilde{\rho}_i = -\rho_i$ shows that $\widetilde{v}_{ijt} - \widetilde{v}_{i\overline{0}t} = \bar{v}_{ijt} - \bar{v}_{i\overline{0}t}$, while clearly $\widetilde{v}_{i\underline{0}t} - \widetilde{v}_{i\overline{0}t} = \bar{v}_{i\underline{0}t} - \bar{v}_{i\overline{0}t}$. Hence this alternative specification yields observationally equivalent demand to our main specification.

However, expected utility under equations (C.1)-(C.3) is given by

$$\begin{aligned}
\widetilde{W}_i\left(\mathfrak{a}_{it},\mathbf{p_t}\right) = & \ln\left[\sum\nolimits_{j>0}\exp\left[\quad \alpha_{1i}p_{jt}+\psi_{1i}\mathbf{x}_j+\left[\tilde{\lambda}_i\mathfrak{a}_{ib(j)t}+\alpha_{2i}\mathfrak{a}_{ib(j)t}p_{jt}+\psi_{2i}\mathfrak{a}_{ib(j)t}n_{b(j)}\right]+\xi_{ib(j)}+\tau^d_{b(j)t}\right]\right.\\
&\left.+\exp\left[\xi_{i\underline{0}j}+\psi_{1i}x_{\underline{0}}+\tau^d_{\underline{0}t}+\tilde{\rho}_i\left(\sum\nolimits_l\mathfrak{a}_{ilt}\right)\right]+\exp\left[\tilde{\rho}_i\left(\sum\nolimits_l\mathfrak{a}_{ilt}\right)\right]\right]\\
= & \ln\left[\sum\nolimits_{j>0}\exp\left[\quad \alpha_{1i}p_{jt}+\psi_{1i}\mathbf{x}_j+\xi_{ib(j)}+\tau^d_{b(j)t}+\left[\widetilde{\lambda}_i\mathfrak{a}_{ib(j)t}+\alpha_{2d}\mathfrak{a}_{ib(j)t}p_{jt}+\rho_i\left(\sum\nolimits_l\mathfrak{a}_{ilt}\right)+\psi_{2d}\mathfrak{a}_{ib(j)t}n_{b(j)}\right]\right]\right.\\
&\left.+\exp\left[\xi_{i\underline{0}j}+\psi_{1i}x_{\underline{0}}+\tau^d_{\underline{0}t}+\tilde{\rho}_i\right]\right]-\rho_i\left(\sum\nolimits_l\mathfrak{a}_{ilt}\right)\\
= & W_i\left(\mathfrak{a}_{it},\mathbf{p_t}\right)-\rho_i\quad\sum\nolimits_l\mathfrak{a}_{ilt}
\end{aligned}$$

Therefore the two specifications, giving rise to identical demand, lead to different welfare conclusions. Under the characteristic view of advertising, welfare is not identified without an assumption about whether competitor advertising is included in inside product utilities or whether total advertising is included in outside option utility.

# D Additional Tables

## D.1 Coefficients Estimates

Table D.1: *Coefficient estimates for food at home - part 1*

| | | No kids, high inc., high sk. | No kids, medium inc., high sk. | No kids, low inc., high sk. | No kids, high-medium inc., low sk. | No kids, low inc., low sk. | Pensioners |
|---|---|---|---|---|---|---|---|
| *Random coefficients* | | | | | | | |
| Means | Price | -0.0168 | 0.5908 | 0.1717 | 0.6665 | 0.3769 | 0.5577 |
| | | 0.0703 | 0.0600 | 0.0887 | 0.0576 | 0.0576 | 0.0680 |
| | Brand advertising | 0.2087 | -0.2060 | 0.0391 | -0.1066 | 0.0135 | -0.3212 |
| | | 0.0919 | 0.1140 | 0.1201 | 0.1301 | 0.0957 | 0.1429 |
| | Competitor advertising | 0.1272 | 0.0243 | 0.0262 | 0.2519 | 0.1346 | 0.1530 |
| | | 0.0344 | 0.0416 | 0.0481 | 0.0545 | 0.0355 | 0.0485 |
| Std. deviations | Price | 0.4901 | 0.3969 | 0.3681 | 0.2828 | 0.2458 | 0.3620 |
| | | 0.0300 | 0.0256 | 0.0306 | 0.0190 | 0.0153 | 0.0297 |
| | Brand advertising | 0.2517 | 0.4010 | 0.4891 | 0.2589 | 0.4447 | 0.5222 |
| | | 0.0183 | 0.0517 | 0.0270 | 0.0200 | 0.0268 | 0.0332 |
| | Competitor advertising | 0.3845 | 0.4451 | 0.3625 | 0.3988 | 0.3943 | 0.3231 |
| | | 0.0131 | 0.0187 | 0.0149 | 0.0173 | 0.0157 | 0.0140 |
| | Nutrient score | 0.0577 | 0.0517 | 0.0536 | 0.0572 | 0.0663 | 0.0578 |
| | | 0.0020 | 0.0023 | 0.0025 | 0.0024 | 0.0028 | 0.0023 |
| | Walkers | 1.1359 | 1.0317 | 0.9544 | 0.8573 | 1.1725 | 1.6661 |
| | | 0.0583 | 0.0463 | 0.0470 | 0.0709 | 0.0502 | 0.0767 |
| *Fixed coefficients* | | | | | | | |
| | Size | 0.0157 | 0.0225 | 0.0159 | 0.0226 | 0.0197 | 0.0179 |
| | | 0.0008 | 0.0011 | 0.0010 | 0.0012 | 0.0009 | 0.0011 |
| | Size squared | -0.0157 | -0.0209 | -0.0139 | -0.0202 | -0.0174 | -0.0163 |
| | | 0.0011 | 0.0014 | 0.0012 | 0.0015 | 0.0011 | 0.0014 |
| | Price*Brand advertising | 0.0609 | 0.0745 | 0.0332 | 0.1033 | 0.0968 | 0.1496 |
| | | 0.0182 | 0.0234 | 0.0224 | 0.0259 | 0.0184 | 0.0281 |
| | Nutrient score*Brand advertising | -0.0183 | 0.0023 | -0.0124 | -0.0017 | -0.0103 | 0.0021 |
| | | 0.0056 | 0.0067 | 0.0067 | 0.0075 | 0.0056 | 0.0089 |
| | Pringles | -0.7571 | -1.2205 | -0.8833 | -1.0926 | -1.1005 | -1.1489 |
| | | 0.2000 | 0.2626 | 0.2627 | 0.2811 | 0.2435 | 0.3148 |
| | Walkers Regular | -0.1795 | 0.1177 | 0.2999 | 0.1940 | 0.3344 | -0.1314 |
| | | 0.1787 | 0.2097 | 0.1825 | 0.2314 | 0.1566 | 0.2654 |
| | Walkers Sensations | -1.3215 | -1.7494 | -2.2248 | -1.3587 | -2.3061 | -2.7820 |
| | | 0.0855 | 0.1146 | 0.1309 | 0.1306 | 0.1201 | 0.1735 |
| | Walkers Doritos | -1.6412 | -1.7466 | -2.2237 | -1.7334 | -2.3937 | -3.1287 |
| | | 0.0787 | 0.0894 | 0.1101 | 0.1127 | 0.0986 | 0.1573 |
| | Walkers Other | 0.0132 | 0.1402 | -0.0665 | 0.2579 | 0.0318 | -0.3358 |
| | | 0.0687 | 0.0821 | 0.0901 | 0.1011 | 0.0833 | 0.1035 |
| | KP | -0.5126 | -0.7673 | -0.4281 | -0.3918 | -0.5677 | -1.2660 |
| | | 0.0650 | 0.0820 | 0.0824 | 0.0982 | 0.0765 | 0.1026 |
| | Golden Wonder | -2.6271 | -2.8302 | -2.6358 | -1.9780 | -2.3935 | -2.3342 |
| | | 0.1197 | 0.1554 | 0.1425 | 0.1467 | 0.1189 | 0.1426 |
| | Asda | -2.2531 | -2.6026 | -2.5739 | -2.6312 | -2.2339 | -3.2279 |
| | | 0.0894 | 0.1128 | 0.1194 | 0.1422 | 0.0967 | 0.1547 |
| | Tesco | -1.9697 | -2.0158 | -1.9980 | -2.1284 | -2.0374 | -1.8927 |
| | | 0.0835 | 0.1004 | 0.1068 | 0.1266 | 0.0952 | 0.1161 |
| | Unhealthy Outside | 4.1946 | 3.5160 | 3.9868 | 4.2590 | 4.0322 | 3.8942 |
| | | 0.1739 | 0.2328 | 0.2371 | 0.2684 | 0.2017 | 0.2507 |
| | Healthy Outside | 3.3431 | 2.4587 | 2.7485 | 3.1482 | 2.5344 | 2.6580 |
| | | 0.1883 | 0.2630 | 0.2654 | 0.2951 | 0.2323 | 0.2716 |
| Brand-time effects | | Yes | Yes | Yes | Yes | Yes | Yes |
| Region effects | | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes: Each column represents a separate estimation (one for each consumer type group), standard errors are reported below coefficient estimates. Random coefficients have normal distributions except for the price coefficient which is log normal.*

Table D.2: *Coefficient estimates for food at home - part 2*

| | | Kids, high inc., high sk. | Kids, medium inc., high sk. | Kids, low inc., high sk. | Kids, high-med inc., low sk. | Kids, low inc., low sk. |
|---|---|---|---|---|---|---|
| *Random coefficients* | | | | | | |
| Means | Price | 0.3305 | 0.4212 | 0.2525 | 0.3532 | 0.2703 |
| | | 0.0526 | 0.0534 | 0.0904 | 0.0563 | 0.0623 |
| | Brand advertising | -0.3341 | -0.3529 | 0.0380 | -0.2641 | -0.1703 |
| | | 0.0811 | 0.1013 | 0.1321 | 0.0906 | 0.0929 |
| | Competitor advertising | -0.0442 | 0.0179 | -0.1184 | 0.1590 | 0.0578 |
| | | 0.0329 | 0.0387 | 0.0427 | 0.0361 | 0.0364 |
| Std. deviations | Price | 0.3260 | 0.3863 | 0.3666 | 0.3732 | 0.3502 |
| | | 0.0199 | 0.0245 | 0.0353 | 0.0244 | 0.0232 |
| | Brand advertising | 0.2786 | 0.3606 | 0.1624 | 0.2977 | 0.2810 |
| | | 0.0233 | 0.0233 | 0.0203 | 0.0181 | 0.0196 |
| | Competitor advertising | 0.2816 | 0.3429 | 0.3401 | 0.2588 | 0.1338 |
| | | 0.0117 | 0.0162 | 0.0176 | 0.0148 | 0.0125 |
| | Nutrient score | 0.0497 | 0.0458 | 0.0507 | 0.0582 | 0.0511 |
| | | 0.0022 | 0.0026 | 0.0030 | 0.0028 | 0.0029 |
| | Walkers | 1.0012 | 0.8024 | 1.1057 | 1.0026 | 0.9034 |
| | | 0.0474 | 0.0397 | 0.0635 | 0.0424 | 0.0542 |
| *Fixed coefficients* | | | | | | |
| | Size | 0.0199 | 0.0202 | 0.0202 | 0.0217 | 0.0183 |
| | | 0.0008 | 0.0009 | 0.0013 | 0.0009 | 0.0008 |
| | Size squared | -0.0174 | -0.0173 | -0.0170 | -0.0191 | -0.0135 |
| | | 0.0010 | 0.0011 | 0.0016 | 0.0011 | 0.0010 |
| | Price*Brand advertising | 0.0393 | 0.0562 | 0.0563 | 0.0638 | 0.0595 |
| | | 0.0172 | 0.0209 | 0.0266 | 0.0184 | 0.0196 |
| | Nutrient score*Brand advertising | 0.0170 | 0.0188 | -0.0060 | 0.0050 | 0.0085 |
| | | 0.0046 | 0.0056 | 0.0074 | 0.0050 | 0.0051 |
| | Pringles | -1.7730 | -0.9653 | -1.8418 | -0.3797 | -0.5909 |
| | | 0.2238 | 0.2091 | 0.4839 | 0.1745 | 0.2082 |
| | Walkers Regular | 0.0204 | 0.3537 | 0.3962 | 1.0984 | 0.8195 |
| | | 0.1447 | 0.1594 | 0.2060 | 0.1287 | 0.1351 |
| | Walkers Sensations | -1.6537 | -1.9435 | -1.6145 | -1.7102 | -2.2232 |
| | | 0.0855 | 0.1122 | 0.1517 | 0.0979 | 0.1318 |
| | Walkers Doritos | -1.6270 | -1.6347 | -1.6377 | -1.5902 | -1.5503 |
| | | 0.0703 | 0.0848 | 0.1211 | 0.0777 | 0.0847 |
| | Walkers Other | 0.1389 | 0.3509 | 0.3917 | 0.5388 | 0.4517 |
| | | 0.0674 | 0.0803 | 0.1120 | 0.0706 | 0.0781 |
| | KP | -0.4334 | -0.2258 | 0.0335 | -0.0662 | 0.0402 |
| | | 0.0562 | 0.0681 | 0.0945 | 0.0654 | 0.0685 |
| | Golden Wonder | -2.9515 | -3.1130 | -2.3539 | -2.4497 | -1.9833 |
| | | 0.1196 | 0.1588 | 0.1832 | 0.1164 | 0.1095 |
| | Asda | -2.4922 | -1.9399 | -1.4080 | -2.1574 | -1.6769 |
| | | 0.0833 | 0.0890 | 0.1184 | 0.0895 | 0.0881 |
| | Tesco | -1.7888 | -1.6075 | -1.2958 | -1.7677 | -1.3378 |
| | | 0.0724 | 0.0857 | 0.1202 | 0.0849 | 0.0854 |
| | Unhealthy Outside | 3.7751 | 4.1851 | 3.5957 | 4.7109 | 4.6910 |
| | | 0.1635 | 0.2005 | 0.2495 | 0.1893 | 0.1840 |
| | Healthy Outside | 2.3760 | 2.6866 | 1.8465 | 2.9409 | 2.7740 |
| | | 0.1961 | 0.2371 | 0.3285 | 0.2367 | 0.2388 |
| Brand-time effects | | Yes | Yes | Yes | Yes | Yes |
| Region effects | | Yes | Yes | Yes | Yes | Yes |

*Notes: Each column represents a separate estimation (one for each consumer type group), standard errors are reported below coefficient estimates. Random coefficients have normal distributions except for the price coefficient which is log normal.*

Table D.3: *Coefficient estimates for food on-the-go - part 1*

| | | No kids, high inc., high sk. | No kids, medium inc., high sk. | No kids, low inc., high sk. | No kids, high-medium inc., low sk. | No kids, low inc., low sk. | Pensioners |
|---|---|---|---|---|---|---|---|
| *Random coefficients* | | | | | | | |
| Means | Price | 2.2190 | 2.2697 | 2.3476 | 2.3585 | 2.5566 | 1.6297 |
| | | 0.0644 | 0.0784 | 0.0793 | 0.0848 | 0.0642 | 0.1860 |
| | Brand advertising | -0.0643 | 0.5110 | -0.3377 | -1.1439 | 0.4329 | 0.7301 |
| | | 0.1597 | 0.1962 | 0.2075 | 0.2305 | 0.2080 | 0.2992 |
| | Competitor advertising | -0.0041 | -0.2862 | 0.1747 | 0.3013 | -0.6367 | -0.2117 |
| | | 0.0602 | 0.0759 | 0.0637 | 0.0684 | 0.0845 | 0.0898 |
| Std. deviations | Price | 0.3643 | 0.2421 | 0.2943 | 0.2033 | 0.3216 | 0.2193 |
| | | 0.0257 | 0.0228 | 0.0262 | 0.0183 | 0.0207 | 0.0444 |
| | Brand advertising | 0.4108 | 0.3986 | 0.5150 | 0.5199 | 0.4596 | 0.3688 |
| | | 0.0354 | 0.0243 | 0.0326 | 0.0359 | 0.0337 | 0.0332 |
| | Competitor advertising | 0.4466 | 0.5901 | 0.3492 | 0.6635 | 0.7329 | 0.5360 |
| | | 0.0200 | 0.0240 | 0.0204 | 0.0308 | 0.0272 | 0.0299 |
| | Nutrient score | 0.1053 | 0.1032 | 0.0916 | 0.1391 | 0.0870 | 0.1060 |
| | | 0.0039 | 0.0046 | 0.0035 | 0.0061 | 0.0030 | 0.0065 |
| *Fixed coefficients* | | | | | | | |
| | Food in purchase | 0.1080 | -0.0917 | 0.0588 | 0.0116 | -0.0360 | 0.2286 |
| | | 0.0564 | 0.0713 | 0.0684 | 0.0809 | 0.0712 | 0.0958 |
| | Size | 0.1673 | 0.2222 | 0.1214 | 0.0511 | 0.1738 | 0.0925 |
| | | 0.0129 | 0.0172 | 0.0169 | 0.0207 | 0.0191 | 0.0257 |
| | Size squared | -1.6745 | -2.1109 | -1.2073 | -0.3290 | -1.3660 | -1.1047 |
| | | 0.1247 | 0.1683 | 0.1620 | 0.1929 | 0.1803 | 0.2469 |
| | Price*Brand advertising | -0.7900 | -1.2331 | 0.1955 | 0.3814 | -1.1697 | -1.3569 |
| | | 0.2538 | 0.3016 | 0.3268 | 0.3221 | 0.3295 | 0.4508 |
| | Nutrient score*Brand advertising | 0.0308 | 0.0095 | 0.0077 | 0.0472 | 0.0241 | 0.0016 |
| | | 0.0071 | 0.0099 | 0.0095 | 0.0113 | 0.0099 | 0.0158 |
| | Walkers Regular | 0.0596 | 0.2551 | 0.0877 | 0.8054 | 0.7231 | 0.1321 |
| | | 0.1507 | 0.2017 | 0.1886 | 0.2173 | 0.1987 | 0.2941 |
| | Walkers Sensations | -1.2068 | -1.6118 | -1.7029 | -3.0508 | -2.5429 | -2.6812 |
| | | 0.1146 | 0.1943 | 0.1768 | 0.3990 | 0.3381 | 0.3588 |
| | Walkers Doritos | -1.9873 | -1.2532 | -1.5789 | -1.4638 | -0.9979 | -1.8196 |
| | | 0.1188 | 0.1385 | 0.1432 | 0.1712 | 0.1444 | 0.2133 |
| | Walkers Other | -0.1507 | 0.4051 | -0.2114 | -0.3048 | 0.2143 | -0.7124 |
| | | 0.0703 | 0.0973 | 0.0984 | 0.1267 | 0.1126 | 0.1368 |
| | KP | -0.0773 | -0.4113 | -0.3293 | -0.2600 | -0.2299 | -0.6847 |
| | | 0.0855 | 0.1261 | 0.1228 | 0.1546 | 0.1362 | 0.1730 |
| | Golden Wonder | -2.5480 | -1.5341 | -2.8857 | -2.4053 | -2.1619 | -1.7653 |
| | | 0.1173 | 0.1442 | 0.1706 | 0.1783 | 0.1736 | 0.1833 |
| | Unhealthy Outside | 0.8079 | 2.3118 | 0.3405 | -1.5001 | -1.1891 | 1.7083 |
| | | 0.3646 | 0.4562 | 0.4289 | 0.4932 | 0.5247 | 0.5919 |
| | Healthy Outside | 0.0550 | 2.9034 | -0.7107 | -1.0354 | -0.8878 | 1.3293 |
| | | 0.3894 | 0.4648 | 0.4384 | 0.5015 | 0.5258 | 0.6293 |
| Brand-time effects | | Yes | Yes | Yes | Yes | Yes | Yes |
| Region effects | | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes: Each column represents a separate estimation (one for each consumer type group), standard errors are reported below coefficient estimates. Random coefficients have normal distributions except for the price coefficient which is log normal.*

Table D.4: *Coefficient estimates for food on-the-go - part 2*

| | | Kids, high inc., high sk. | Kids, medium inc., high sk. | Kids, low inc., high sk. | Kids, high-med inc., low sk. | Kids, low inc., low educ | Kid purchaser |
|---|---|---|---|---|---|---|---|
| *Random coefficients* | | | | | | | |
| Mean | Price | 2.0420 | 2.1705 | 2.1833 | 2.4339 | 2.0701 | 1.0912 |
| | | 0.0986 | 0.0910 | 0.1269 | 0.0623 | 0.0981 | 0.2652 |
| | Brand advertising | 0.1278 | -0.8830 | 0.2564 | -1.2480 | 0.2307 | 0.6294 |
| | | 0.1640 | 0.2019 | 0.2827 | 0.1709 | 0.1985 | 0.3003 |
| | Competitor advertising | 0.1729 | -0.0785 | -0.1309 | 0.3942 | 0.2405 | -0.1968 |
| | | 0.0451 | 0.0548 | 0.0672 | 0.0513 | 0.0536 | 0.0834 |
| Std. deviation | Price | 0.2554 | 0.2919 | 0.2728 | 0.2664 | 0.2951 | 0.6586 |
| | | 0.0353 | 0.0321 | 0.0381 | 0.0159 | 0.0382 | 0.1239 |
| | Brand advertising | 0.1962 | 0.4618 | 0.5295 | 0.6286 | 0.3516 | 0.6029 |
| | | 0.0228 | 0.0394 | 0.0432 | 0.0250 | 0.0252 | 0.0469 |
| | Competitor advertising | 0.6945 | 0.5500 | 0.4217 | 0.6502 | 0.4362 | 0.6032 |
| | | 0.0282 | 0.0240 | 0.0277 | 0.0238 | 0.0203 | 0.0334 |
| | Nutrient score | 0.1203 | 0.1015 | 0.0996 | 0.1375 | 0.0944 | 0.1281 |
| | | 0.0058 | 0.0051 | 0.0065 | 0.0051 | 0.0041 | 0.0093 |
| *Fixed coefficients* | | | | | | | |
| | Food in purchase | 0.0814 | 0.0599 | 0.1095 | 0.2164 | 0.0853 | 0.1042 |
| | | 0.0514 | 0.0601 | 0.0850 | 0.0576 | 0.0633 | 0.0966 |
| | Size | 0.1912 | 0.1438 | 0.1823 | 0.1835 | 0.0763 | 0.0214 |
| | | 0.0163 | 0.0164 | 0.0237 | 0.0159 | 0.0193 | 0.0269 |
| | Size squared | -2.0272 | -1.5028 | -1.8581 | -1.8859 | -0.9120 | -0.3758 |
| | | 0.1612 | 0.1568 | 0.2278 | 0.1555 | 0.1896 | 0.2783 |
| | Price*Brand advertising | -0.7210 | 0.5037 | -0.4771 | 1.3611 | -0.8152 | -0.5570 |
| | | 0.2902 | 0.3097 | 0.4575 | 0.2643 | 0.3229 | 0.4339 |
| | Nutrient score*Brand advertising | 0.0204 | 0.0419 | -0.0058 | 0.0230 | 0.0033 | -0.0104 |
| | | 0.0067 | 0.0085 | 0.0126 | 0.0076 | 0.0094 | 0.0137 |
| | Walkers Regular | 0.4663 | 0.3221 | 0.0503 | 0.0041 | -0.1471 | 0.4407 |
| | | 0.1505 | 0.1893 | 0.3086 | 0.1728 | 0.2022 | 0.3577 |
| | Walkers Sensations | -1.2745 | -1.7250 | -1.9443 | -2.2908 | -1.8475 | -1.3808 |
| | | 0.1407 | 0.1795 | 0.2456 | 0.1908 | 0.2049 | 0.3256 |
| | Walkers Doritos | -0.7651 | -1.2350 | -0.6725 | -1.1384 | -1.3102 | -0.6640 |
| | | 0.0995 | 0.1230 | 0.1422 | 0.1062 | 0.1411 | 0.2342 |
| | Walkers Other | -0.0661 | -0.1207 | -0.0818 | -0.2598 | -0.4489 | 0.0791 |
| | | 0.0851 | 0.0923 | 0.1249 | 0.0849 | 0.1063 | 0.1708 |
| | KP | 0.3141 | -0.1246 | -0.2311 | -0.3781 | -0.1436 | 0.9850 |
| | | 0.0959 | 0.1097 | 0.1509 | 0.1031 | 0.1241 | 0.1925 |
| | Golden Wonder | -2.4898 | -2.5407 | -2.9543 | -3.1530 | -1.7497 | -1.1466 |
| | | 0.1458 | 0.1543 | 0.2276 | 0.1493 | 0.1391 | 0.2310 |
| | Unhealthy Outside | 3.1550 | 0.8663 | 1.8230 | 0.9019 | 1.3096 | 2.0650 |
| | | 0.3835 | 0.3936 | 0.5767 | 0.4102 | 0.4381 | 0.6551 |
| | Healthy Outside | 2.2844 | 0.3361 | 1.3153 | 0.0188 | 0.9685 | 1.5527 |
| | | 0.3846 | 0.4039 | 0.5963 | 0.4183 | 0.4575 | 0.6757 |
| Brand-time effects | | Yes | Yes | Yes | Yes | Yes | Yes |
| Region effects | | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes: Each column represents a separate estimation (one for each consumer type group), standard errors are reported below coefficient estimates. Random coefficients have normal distributions except for the price coefficient which is log normal.*

## D.2 Price elasticities

Table D.5: *Own and cross price elasticities*

*Selected food at home products*

| | Walkers Regular | | Walkers Sensations | | Walkers Doritos | | Walkers Other | | | Pringles | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 150-300g | 300g+ | 150-300g | 300g+ | 150-300g | 300g+ | 150-300g | 300g+ | <150g | 150-300g | 300g+ |
| Walkers Regular:150-300g | -1.6252 | 0.4191 | 0.0159 | 0.0373 | 0.0282 | 0.0595 | 0.0512 | 0.1086 | 0.1752 | 0.0187 | 0.0592 |
| Walkers Regular:300g+ | 0.0748 | -2.6133 | 0.0107 | 0.0370 | 0.0196 | 0.0623 | 0.0348 | 0.0881 | 0.2052 | 0.0134 | 0.0651 |
| Walkers Sensations:150-300g | 0.0900 | 0.3400 | -1.7804 | 0.0479 | 0.0310 | 0.0632 | 0.0486 | 0.1040 | 0.1697 | 0.0163 | 0.0508 |
| Walkers Sensations:300g+ | 0.0661 | 0.3638 | 0.0150 | -2.9423 | 0.0226 | 0.0650 | 0.0357 | 0.0884 | 0.1934 | 0.0124 | 0.0548 |
| Walkers Doritos:150-300g | 0.0947 | 0.3684 | 0.0182 | 0.0427 | -1.6728 | 0.0668 | 0.0494 | 0.1065 | 0.1743 | 0.0179 | 0.0559 |
| Walkers Doritos:300g+ | 0.0687 | 0.4005 | 0.0127 | 0.0423 | 0.0229 | -2.8249 | 0.0360 | 0.0900 | 0.2008 | 0.0134 | 0.0608 |
| Walkers Other:<150g | 0.0953 | 0.3615 | 0.0160 | 0.0374 | 0.0273 | 0.0578 | -1.6400 | 0.1171 | 0.1891 | 0.0192 | 0.0608 |
| Walkers Other:150-300g | 0.0834 | 0.3776 | 0.0141 | 0.0384 | 0.0242 | 0.0597 | 0.0481 | -2.1122 | 0.2029 | 0.0173 | 0.0639 |
| Walkers Other:300g+ | 0.0599 | 0.3913 | 0.0103 | 0.0376 | 0.0178 | 0.0596 | 0.0347 | 0.0904 | -3.0477 | 0.0128 | 0.0666 |
| Pringles:150-300g | 0.0552 | 0.2216 | 0.0085 | 0.0207 | 0.0156 | 0.0340 | 0.0305 | 0.0665 | 0.1117 | -1.4524 | 0.0960 |
| Pringles:300g+ | 0.0404 | 0.2479 | 0.0062 | 0.0214 | 0.0114 | 0.0360 | 0.0223 | 0.0570 | 0.1333 | 0.0219 | -2.6616 |
| Unhealthy outside option | 0.0341 | 0.1248 | 0.0059 | 0.0132 | 0.0107 | 0.0217 | 0.0196 | 0.0405 | 0.0626 | 0.0144 | 0.0415 |
| Healthy outside option | 0.0391 | 0.1347 | 0.0070 | 0.0151 | 0.0114 | 0.0219 | 0.0179 | 0.0365 | 0.0546 | 0.0118 | 0.0326 |

*Food on-the-go products*

| | Walkers Regular | | Walkers | Walkers | Walkers Other | | KP | GW | | Other | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 34.5g | 50g | 40g | 40g | <30g | 30g+ | 50g | <40g | 40g+ | <40g | 40g+ |
| Walkers Regular:34.5g | -3.2867 | 0.3119 | 0.0466 | 0.1161 | 0.1958 | 0.2070 | 0.4459 | 0.0645 | 0.0119 | 0.3670 | 0.1082 |
| Walkers Regular:50g | 0.7708 | -4.8376 | 0.0497 | 0.1137 | 0.1739 | 0.2139 | 0.4226 | 0.0550 | 0.0127 | 0.3372 | 0.1121 |
| Walkers Sensations:40g | 0.6127 | 0.2617 | -4.5445 | 0.1211 | 0.1749 | 0.2199 | 0.4895 | 0.0726 | 0.0170 | 0.3291 | 0.0888 |
| Walkers Doritos:40g | 0.6726 | 0.2634 | 0.0538 | -4.4182 | 0.1935 | 0.2316 | 0.5528 | 0.0796 | 0.0162 | 0.3402 | 0.0986 |
| Walkers Other:<30g | 0.6791 | 0.2419 | 0.0460 | 0.1158 | -3.8517 | 0.2388 | 0.5395 | 0.0772 | 0.0142 | 0.3711 | 0.1060 |
| Walkers Other:30g+ | 0.6420 | 0.2661 | 0.0518 | 0.1244 | 0.2134 | -4.8103 | 0.5447 | 0.0666 | 0.0153 | 0.3584 | 0.1123 |
| KP:50g | 0.6026 | 0.2294 | 0.0503 | 0.1283 | 0.2108 | 0.2372 | -3.7453 | 0.0753 | 0.0148 | 0.3616 | 0.1054 |
| Golden Wonder:<40g | 0.6303 | 0.2132 | 0.0541 | 0.1332 | 0.2132 | 0.2043 | 0.5280 | -3.2817 | 0.0244 | 0.3147 | 0.0877 |
| Golden Wonder:40g+ | 0.5536 | 0.2381 | 0.0569 | 0.1220 | 0.1842 | 0.2217 | 0.4939 | 0.1092 | -5.0471 | 0.2932 | 0.0980 |
| Other:<40g | 0.6884 | 0.2557 | 0.0470 | 0.1115 | 0.2034 | 0.2189 | 0.5094 | 0.0615 | 0.0122 | -3.9393 | 0.1174 |
| Other:40g+ | 0.7017 | 0.2954 | 0.0443 | 0.1126 | 0.2004 | 0.2378 | 0.5075 | 0.0598 | 0.0144 | 0.4068 | -5.3570 |
| Unhealthy outside option | 0.1981 | 0.0630 | 0.0135 | 0.0384 | 0.0705 | 0.0657 | 0.1823 | 0.0300 | 0.0046 | 0.1146 | 0.0271 |
| Healthy outside option | 0.2505 | 0.0814 | 0.0157 | 0.0268 | 0.0516 | 0.0489 | 0.0942 | 0.0196 | 0.0031 | 0.1049 | 0.0260 |

*Notes: The top panel gives matrix of price elasticities in the food at home segment for the set of products produced by the two firms that advertise most. The bottom panel gives matrix of price elasticities in the food on-the-go segment. Each cell contains the price elasticity of demand for the product indicated in column 1 with respect to the price of the product in row 1. Numbers are means across markets.*

## D.3 Marginal costs estimates

Table D.6: *Marginal costs*

| | Price (£) | Cost (£) | Margin |
|---|---|---|---|
| *Selected food at home products* | | | |
| Walkers Regular:150-300g | 1.11 | 0.32 | 0.72 |
| | | [0.28, 0.36] | [0.68, 0.75] |
| Walkers Regular:300g+ | 2.60 | 1.61 | 0.38 |
| | | [1.56, 1.65] | [0.37, 0.40] |
| Walkers Sensations:150-300g | 1.26 | 0.09 | 0.93 |
| | | [0.04, 0.15] | [0.89, 0.97] |
| Walkers Sensations:300g+ | 2.79 | 1.36 | 0.51 |
| | | [1.29, 1.43] | [0.49, 0.54] |
| Walkers Doritos:150-300g | 1.30 | 0.15 | 0.91 |
| | | [0.10, 0.20] | [0.87, 0.95] |
| Walkers Doritos:300g+ | 2.58 | 1.23 | 0.53 |
| | | [1.17, 1.28] | [0.51, 0.55] |
| Walkers Other:<150g | 1.20 | 0.07 | 0.95 |
| | | [0.02, 0.12] | [0.90, 0.98] |
| Walkers Other:150-300g | 2.48 | 1.13 | 0.54 |
| | | [1.07, 1.19] | [0.52, 0.57] |
| Walkers Other:300g+ | 1.24 | 0.08 | 0.94 |
| | | [0.03, 0.14] | [0.89, 0.98] |
| Pringles:150-300g | 1.77 | 0.51 | 0.71 |
| | | [0.46, 0.58] | [0.68, 0.74] |
| Pringles:300g+ | 3.17 | 1.68 | 0.47 |
| | | [1.61, 1.75] | [0.45, 0.49] |
| *Food on-the-go products* | | | |
| Walkers Regular:34.5g | 0.45 | 0.27 | 0.39 |
| | | [0.26, 0.28] | [0.37, 0.42] |
| Walkers Regular:50g | 0.64 | 0.44 | 0.31 |
| | | [0.42, 0.45] | [0.29, 0.33] |
| Walkers Sensations:40g | 0.60 | 0.41 | 0.33 |
| | | [0.39, 0.42] | [0.31, 0.35] |
| Walkers Doritos:40g | 0.54 | 0.36 | 0.34 |
| | | [0.34, 0.37] | [0.32, 0.37] |
| Walkers Other:<30g | 0.45 | 0.28 | 0.38 |
| | | [0.27, 0.29] | [0.36, 0.40] |
| Walkers Other:30g+ | 0.61 | 0.42 | 0.31 |
| | | [0.41, 0.43] | [0.29, 0.33] |
| KP:50g | 0.51 | 0.38 | 0.27 |
| | | [0.37, 0.38] | [0.25, 0.28] |
| Golden Wonder:<40g | 0.39 | 0.27 | 0.31 |
| | | [0.26, 0.27] | [0.29, 0.33] |
| Golden Wonder:40g+ | 0.71 | 0.57 | 0.21 |
| | | [0.55, 0.58] | [0.19, 0.22] |
| Other:<40g | 0.49 | 0.36 | 0.26 |
| | | [0.35, 0.37] | [0.25, 0.28] |
| Other:40g+ | 0.66 | 0.52 | 0.21 |
| | | [0.51, 0.53] | [0.20, 0.22] |

*Notes: The top panel gives numbers for the food at home segment for the set of products produced by the two firms that advertise most. The bottom panel gives numbers for the food on-the-go segment. Margins are defined as $(p - mc)/p$. Numbers are means across markets. 95% confidence intervals are given in square brackets.*

## D.4 Profits

Table D.7 disaggregates the impact of the ban by firm and reports the average impact across months. The first panel reports pre ban numbers, showing the average price, total quantity of potato chips sold and total variable profits. The second panel details the percent change in quantity sold and variable profits resulting from the ban if firms do not re-optimize their prices in response. The final panel shows the impact on prices, quantity and variable profits following the ban in equilibrium, when firms are allowed to re-optimize prices.

Table D.7: *Advertising ban: Impact by firm*

| | Walkers | Pringles | KP | Golden Wonder | Asda | Tesco | Other |
|---|---|---|---|---|---|---|---|
| *Pre ban* | | | | | | | |
| Price (£) | 1.76 | 1.85 | 1.33 | 1.47 | 1.40 | 1.27 | 1.51 |
| | [1.76, 1.77] | [1.85, 1.85] | [1.33, 1.34] | [1.46, 1.48] | [1.40, 1.40] | [1.27, 1.27] | [1.51, 1.51] |
| Quantity (mKg) | 7.01 | 0.85 | 2.74 | 0.27 | 0.42 | 0.81 | 2.70 |
| | [6.92, 7.15] | [0.83, 0.89] | [2.67, 2.78] | [0.25, 0.29] | [0.39, 0.43] | [0.79, 0.84] | [2.62, 2.76] |
| Profits (£m) | 26.94 | 2.12 | 7.22 | 0.65 | 0.92 | 1.77 | 8.01 |
| | [25.55, 28.45] | [2.06, 2.29] | [6.81, 7.55] | [0.60, 0.71] | [0.88, 0.98] | [1.68, 1.86] | [7.53, 8.38] |
| *Post ban: No firm response* | | | | | | | |
| % change in quantity | -12.70 | -22.17 | -16.28 | -19.31 | -12.96 | -15.51 | -18.44 |
| | [-15.29, -9.65] | [-24.49, -18.72] | [-18.22, -13.53] | [-22.49, -14.39] | [-15.86, -6.91] | [-18.32, -9.09] | [-21.19, -15.37] |
| % change in profits | -10.28 | -10.06 | -14.73 | -21.28 | -14.23 | -16.85 | -16.10 |
| | [-12.75, -7.18] | [-13.99, -6.69] | [-16.78, -12.04] | [-24.63, -17.09] | [-17.01, -8.23] | [-19.49, -10.46] | [-18.89, -12.87] |
| *Post ban: With firm response* | | | | | | | |
| % change in price | -6.09 | -3.99 | -1.90 | 3.13 | 1.76 | 1.62 | -6.35 |
| | [-7.00, -5.09] | [-5.40, -2.83] | [-2.99, -0.31] | [0.82, 5.47] | [1.24, 2.11] | [1.00, 2.13] | [-7.46, -5.21] |
| % change in quantity | -3.54 | -18.32 | -14.81 | -24.71 | -20.00 | -22.05 | -11.45 |
| | [-5.21, -0.70] | [-20.72, -15.16] | [-16.84, -12.35] | [-29.14, -19.24] | [-22.89, -13.99] | [-24.73, -15.91] | [-13.86, -8.38] |
| % change in profits | -10.90 | -14.19 | -18.27 | -24.41 | -19.08 | -21.54 | -18.60 |
| | [-13.22, -7.83] | [-18.08, -10.47] | [-20.05, -15.46] | [-27.51, -20.24] | [-21.54, -12.63] | [-23.89, -14.79] | [-21.41, -15.48] |

*Notes: "No firm response" refers to case of an advertising ban when prices are held at their pre ban level; "Firm response" refers to case of an advertising ban when firms reoptimize their prices. Price refers to the quantity weighted mean price set by the firm, quantity refers to the total amount of produce sold and profits are variable profits. Numbers are means across markets. 95% confidence intervals are given in square brackets.*

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