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VOLUNTARY RESTRICTIONS ON TELEVISION ADVERTISING FOR CARBONATED SOFT DRINKS: THE IMPACT ON CONSUMER DEMAND

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Abstract

The health implications and costs associated with increasing levels of obesity are a widespread global issue. In the United States, there is a growing interest in identifying methods to reduce obesity levels. Particular focus has been given to advertisements for unhealthy foods, especially advertisements directed at young children as a number of studies conclude that advertising influences the perceptions, requests and short-term consumption behavior of young children.

Recently, several of the largest global food producers began voluntary self-regulation of their advertisements to children under the age of 12. The group of participants includes the two largest carbonated soft drink (CSD) manufacturers. We estimate the demand for CSDs in the US over 15 markets using a large, detailed household level data set. We test to see if the advertising restriction had any immediate impact on CSD purchases. Contrary to expectations, we find that purchases increase for several of the CSD brands. This can be explained to some extent by a reduction in prices, however there are likely marketing factors not observed in our analysis that impact purchases as well.

While these advertising restrictions do not appear to reduce purchases, there may be other long term benefits associated with reducing children's exposure to advertising to unhealthy food products.

Keywords: advertising restrictions, demand system, carbonated soft drinks

JEL Codes: Q18 D12

1. Introduction

Over the past decade, serious attention has been given to food products that contain ingredients which contribute to negative health outcomes, particularly obesity and obesity related diseases. The ingredients of concern often include, but are not limited to excessive calories, sugar, fat (particularly transfat and saturated fat) and cholesterol. Most food products contain some levels of the previously mentioned items, but they also deliver other vitamins and healthful nutrients so their consumption is of less concern. Foods that deliver high doses of negative inputs but offer no other nutritional value, however, are increasingly becoming an issue.

Advertising of such unhealthy foods has therefore drawn harsh criticism. In response to perceived excess consumption of unhealthy foods, public interest groups, government agencies and researchers are considering either banning or restricting advertising of these products. The obvious intention of banning or restricting advertising is to limit consumption and deter initiation of new consumers, often young adults and children. The criticism of advertising is especially strong when it is specifically directed at children, generating a high level of anxiety concerning the well-being of young people (Friestad and Wright, 2005; Oates, Blades and Gunter, 2003). As a result, advertising to children has been a focal point of efforts to restrict advertising of unhealthy foods.

Restricting advertising to children is expected to lead to a reduction in consumption of unhealthy foods and therefore a reduction in childhood obesity. To this point, however, causality between advertising and obesity in children has not been clearly established. Chou, Rashad and Grossman (2008) find a positive relationship between children viewing TV ads for fast food restaurants, obesity and the probability of being overweight, but they do not find causality. Baylis and Dhar (2007) examine a ban on television advertising to children in Quebec and fast food consumption. They find that the ban decreased the probability of going to a fast food restaurant, although there was no difference in expenditures if the decision was made to go to the restaurant. In terms of advertising itself, Holt et al (2007) find that children were not exposed to more food advertisements in 2004 than in 1977 and they find no evidence that children are seeing more advertising for low nutrition foods over the same time period. Zywicki, Holt and Ohlhausen (2004) further emphasize that food marketing to children has not grown during the same time that obesity has increased. In terms of advertising bans, Livingstone (2006) finds limited evidence to the effectiveness of advertising bans on consumption and obesity. Eagle et al (2004) also find insufficient evidence to substantiate the link between advertising directed at children and nutrition.

Even if restricting advertising to children leads to a decrease in purchases of unhealthy foods, other factors need to be considered. Following an advertising restriction, firms might also reduce their prices which would increase demand (Kuchler et al 2005). Additionally, reducing advertising to children frees up expenditures for advertising to adults who are more likely to make household purchases. As identified by Holt et al, although children observe 50 percent of their food advertising during children's shows, the other 50 percent is viewed during shows directed at adults. More importantly, Grimm, Harnack and Story (2004) find that youths whose parents regularly drank CSDs were almost three times more likely to consume CSDs than those whose parents did not drink soft drinks. Finally, the persistence of brand equity in well-established markets may make advertising restrictions ineffective, at least in the short-run.

The focus of this study is to examine the effect of a recent voluntary restriction of advertising directed at children, on consumer demand for regular carbonated soft drinks (CSDs). CSDs are heavily advertised in the US, offer no nutritional value and are generally stigmatized for contributing to obesity among both children and adults. As such, they provide an important opportunity to examine the relationship of advertising and consumption of an unhealthy product.

We analyze household CSD purchases for 15 markets in the United States for nearly three years by specifying a demand system of the seven largest selling regular CSDs. Using our demand model, we test for a structural break in household purchases due to a voluntary restriction of children-directed advertising on CSD consumption. Contrary to expectation, we estimate a significant *increase* in consumption for five of the CSDs and a significant decrease for only one. The increase in consumption may be explained in part by the fact that prices drop for three of the products following the advertising restriction. However, changes in consumption may be effected by the other elements of the brand marketing mix which are not observed in our data set.

In the popular press and in some academic literature, advertising of unhealthy foods is regarded normatively as bad. Not only in the sense that some advertising may be unsolicited, unwanted or just annoying, but because it induces individuals to make purchases that they otherwise would not. As such, a reduction in advertising is viewed by many in the public as inherently a good policy option because it may reduce consumption of an unhealthy product. In this analysis we find that corresponding price decreases lead to an increase in consumption, generating an undesirable result from a public policy perspective. At the same time, however, there may be long term benefits to such advertising restrictions that are not measured in our data set.

2. The Carbonated Soft Drinks Industry

In the United States, the CSD market is an oligopoly dominated by three major firms, Coca-Cola Company, PepsiCo Inc and Dr. Pepper-Snapple Group Inc. Each one of these manufacturers offers similar competing product lines which includes a regular CSD (Coke, Pepsi and Dr. Pepper), at least one diet version of their regular CSD and at least one clear CSD as well (Sprite, Mountain Dew, and Seven Up are the largest for each manufacturer). Overall, the six major regular brands make up 26.8 percent of the market used in this study (Table 1) in terms of quantity sold in ounces[1].

Table 1. Market Share of Three Largest CSD Manufacturers in 15 US Markets

Parent Company	Brand	Percentage of total areas sales (oz)
Coca-Cola Company	Coca-Cola	9.7%
	Sprite	2.3%
PepsiCo, Inc	Pepsi	8.7%
	Mountain Dew	2.4%
Dr. Pepper-Snapple Group	Dr. Pepper	2.6%
	7-up	1.1%
	Total	26.8%

source: AC Nielsen Scantrack data

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[1] The market in this study includes 15 designated marketing areas (DMA): Atlanta, Baltimore, Boston, Chicago, Detroit, Hartford-NewHaven, Houston, Kansas City, Los Angeles, Miami-Ft. Lauderdale, New York, Philadelphia, San Francisco-Oakland-San Jose, Seattle Tacoma, Springfield-Holyoke, and Washington D.C.-Hagerstown.

In addition to their major brands, the CSD manufacturers introduce (and remove) variations of their CSD products. For example, CSDs containing chocolate, vanilla or berry flavors. Often product variations are offered seasonally, such as with Pepsi Lemon NFL Kick-off which was offered before the 2008 NFL season.

The CSD industry is a heavily advertised industry with the majority of advertising expenditures going to television advertising and the majority of television advertising allocated to the major brand products listed in Table 1. In 2006, Coca-Cola spent $80k on advertising for Coca-Cola in our study market, but only $24k on Sprite and $30k on all other regular CSDs (Table 2). The share of expenditures favored Coca-Cola even more heavily in 2007 and 2008. In addition, in 2006 Coco-Cola had only five other regular CSDs that they advertised on television and only three and two in 2007, 2008 respectively (Table 3). Similar results are found for PepsiCo Inc and Dr. Pepper-Snapple Group Inc. Not only do the major CSD brands receive the largest share of advertising expenditures, they are also advertised the most frequently. Whereas some seasonal or promotional CSDs are advertised for a single period of time, the major brands benefit from advertising pulsing strategies in which repetitive pulses of advertising occur with a certain frequency throughout the year.

Table 2. Advertising Expenditures for Regular CSDs by Manufacturer and Brand

	expenditures by year (1,000's $)			expenditures by year (percentage)		
Coca-Cola Company	**2006**	**2007**	**2008**	**2006**	**2007**	**2008**
Coca-Cola	$ 80,072	$ 78,245	$ 73,495	59%	83%	79%
Sprite	$ 24,291	$ 9,681	$ 16,522	18%	10%	18%
All other Coke brands	$ 30,276	$ 6,900	$ 2,779	22%	7%	3%
Total	$ 134,640	$ 94,827	$ 92,797			
PepsiCo, Inc						
Pepsi	$ 32,505	$ 21,550	$ 26,290	46%	47%	58%
Mountain Dew	$ 12,218	$ 14,893	$ 11,861	17%	33%	26%
All other Pepsi brands	$ 25,707	$ 9,349	$ 7,147	36%	20%	16%
Total	$ 70,431	$ 45,792	$ 45,298			
Dr. Pepper-Snapple Group						
Dr. Pepper brand	$ 31,112	$ 26,504	$ 30,629	54%	58%	61%
Seven-Up	$ 20,570	$ 14,720	$ 18,406	36%	32%	37%
All other Dr. Pepper brands	$ 5,448	$ 4,337	$ 1,279	10%	10%	3%
Total	$ 57,131	$ 45,562	$ 50,314			

source: The Nielsen company

Table 3. Number of Regular, Non-Brand Leading Products Advertised by Manufacturer

Parent Company	**count of advertised brands**		
	2006	**2007**	**2008**
Coca-Cola Company	5	3	2
PepsiCo, Inc	5	8	7
Dr. Pepper-Snapple Group	2	2	2

source: The Nielsen company

In Figure 1 we plot the aggregate advertising gross ratings points (GRPs) for all regular CSDs owned by Coca-Cola, broken down by adults (over 12) and children (under12). GRPs are a measure of the number of people who see an advertisement times the frequency that it is viewed. As shown, the GRPs for children tend to follow the GRPs for adults, with the level of advertising for adults almost consistently higher than that for children. In addition, adult advertising is generally during prime-time advertising spots and thus are more expensive. The summer time advertising tends to be more active and there are also two peaks which appear to correspond to the Winter Olympics (February 2006) and Summer Olympics (August 2008), for which Coca-Cola is sponsor. In Table 4, we show the yearly average GRPs for all regular CSDs, by age group and parent company. As can be seen for all three companies, the majority of GRPs are for ages 12 and older.

In summary, while the three major firms in the CSD industry offer numerous products, their sales are largely with their name brands. In addition, their television advertising efforts reflect the importance of maintaining a select group of name brand products.

Figure 1. Coca-Cola Advertising GRPs for All Regular CSDs by Adults and children

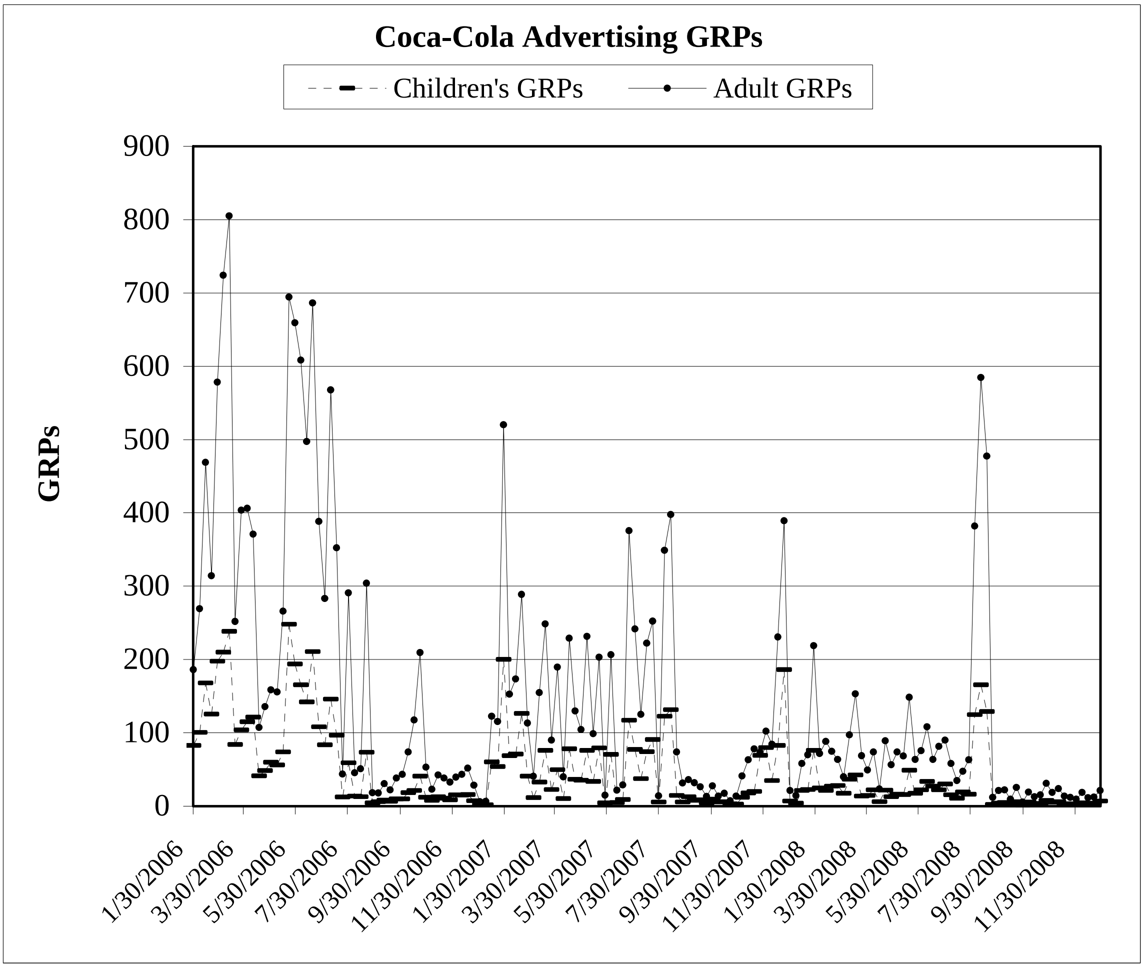

Table 4. Average Yearly GRPs for all regular CSDs by Manufacturer and Age Group

	age groups				
Coca-Cola Company	**age: 2-5**	**age: 6-11**	**age: 12-17**	**age: 18-24**	**age: 25+**
2006 average	52.27	65.07	130.36	128.11	132.65
2007 average	32.90	42.77	69.71	72.65	81.43
2008 average	17.83	23.72	36.55	43.56	62.28
PepsiCo, Inc					
2006 average	30.78	37.31	87.19	87.49	87.50
2007 average	21.34	26.29	64.46	77.31	62.06
2008 average	22.32	30.89	75.52	77.74	60.17
Dr. Pepper-Snapple Group					
2006 average	40.39	52.23	124.11	114.20	85.19
2007 average	27.24	34.37	77.66	84.28	71.35
2008 average	24.04	31.83	62.51	63.38	57.63

source: The Nielsen company

3. Data

Because we are interested in the impact of an advertising restriction on consumer purchases, we focus on the six major brands for the three largest manufacturers. Within our group of products, Coca-Cola owns Coke and Sprite, PepsiCo owns Pepsi and Moutain Dew and Dr. Pepper-Schweppes owns Dr. Pepper and Seven-Up. We also include a category for regular private label CSDs[2].

The time series used in this research captures an interesting shift in industry behavior, the introduction of the Children's Food and Beverage Advertising Initiative (CFBAI). The CFBAI is a self-regulation program designed by the Better Business Bureau that aims to reduce advertisements of unhealthy food products to children under the age of 12. This is a cross-industry effort and the two largest CSD manufacturers (Coca-Cola and Pepsi) voluntarily enacted these restrictions by the end of 2007. Coca-Cola was one of four companies to completely stop advertising to children. Pepsi agreed to restrict their under 12 advertising to products that meet their SmartSpot nutrition guidelines (http://www.pepsico.com/Download/PepsiCo_Pledge.pdf). Regular CSDs do not meet these guidelines. To our knowledge, Dr. Pepper Schewppes did not participate in the CFBAI during the time period used in our analysis. The CFBAI provides a natural experiment to estimate the impact of how advertising restrictions may impact household purchasing behavior as well as consumer welfare. Since Dr. Pepper Schweppes is not participating in the CFBAI, three of the products in our study are not included in the advertising restriction. Our advertising data set provides weekly measures of National advertising GRPs by Parent Company and product brand for five different age groups from January 2006 to December 2008 (152 weeks)[3]. To match our data to the advertising restriction we aggregate our five age groups into a group for children (under 12), teenagers (12-17) and adult (18 and older).

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[2] The private label brand may be different for each market.

We examine household level expenditures for carbonated soft drinks for the same 152 weeks in 15 different markets. Within each household, we have measures of purchase quantity and price as well as demographic variables (Table 5). For each year, we have a sample over roughly 14k households. The average size and composition of the households is constant and the level of education is on the upper end, as is household income. The sample is also predominantly white and non-Hispanic.

For our analysis, we aggregate households together to get estimates of market demand. To scale the households in the data to represent the market, we employ a projection factor provided by AC Nielsen. Since there are weeks in which certain products were not purchased, we aggregate our data into 4-week periods to remove zeros and create a balanced panel. We compile the weekly television advertising gross rating points (GRPs) for the CSDs in the same markets that we have purchasing data.

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[3] National advertising includes network, cable and syndicated advertising.

Table 5. Demographic Characteristics of Households in Data Set

Demographic characteristic	**year**		
	2006	**2007**	**2008**
Number of households	13,951	13,935	14,067
Houshold size (average)	2.37	2.34	2.3
number of children <12 (average)	0.2	0.22	0.21
number of children 12-18 (average)	0.2	0.22	0.21
Hispanic (percentage)	7.4%	7.3%	7.2%
White (percentage)	76%	76%	76%
Black/African American (percentage)	14%	14%	14%
Asian (percentage)	5%	5%	5%
Other (percentage)	6%	6%	5%
Educational attainment groups			
Grade School (percentage)	0.2%	0.1%	0.2%
Some High School (percentage)	1.2%	1.2%	1.1%
Graduated High School (percentage)	14.7%	14.9%	14.8%
Some College (percentage)	28.5%	29.3%	28.9%
Graduated College (percentage)	35.6%	35.1%	35.3%
Post College Grad (percentage)	19.8%	19.4%	19.7%
Income levels			
Under $5,000	0.7%	0.8%	0.9%
$5,000-$7,999	0.8%	0.8%	0.9%
$8,000-$9,999	0.8%	0.8%	0.8%
$10,000-$11,999	1.1%	1.2%	1.1%
$12,000-$14,999	1.9%	1.6%	1.8%
$15,000-$19,999	3.4%	3.2%	2.8%
$20,000-$24,999	5.0%	4.6%	4.5%
$25,000-$29,999	5.1%	5.2%	4.9%
$30,000-$34,999	6.5%	6.0%	5.5%
$35,000-$39,999	5.6%	5.7%	5.3%
$40,000-$44,999	6.2%	5.9%	5.9%
$45,000-$49,999	6.3%	5.9%	5.9%
$50,000-$59,999	10.1%	9.8%	10.2%
$60,000-$69,999	10.2%	8.8%	8.3%
$70,000-$99,999	19.6%	21.2%	20.7%
$100,000 & Over	16.5%	18.5%	20.4%

source: AC Nielsen Scantrack data

We initially examine the data to see if the CFBAI advertising restriction (referred to as advertising break from here on) had any impact on consumption. We estimate a simple linear model with average household purchases of all CSDs in each of the *m* markets during time *t* (Q_{mt}) as the dependent variable. Our regressors include a weighted average price (p_{mt}), weighted average per household member income (M_{mt}), demographic variables (z_{mt}), time, market-level fixed effects and a dummy variable indicating the beginning of the advertising restriction (*R*). Leaving off the time and fixed effects for simplicity, the model is specified as:

$$Q_{mt} = \alpha p_{mt} + \beta M_{mt} + \delta M_{mt} + \gamma R + \phi z_{mt} + \varepsilon_t \, . \tag{1}$$

Prices and income are deflated by market price indices and an error term is included. We estimate equation 1 using OLS (Table 6). The summer dummy variable shows an increase in sales during summer months as expected. The price and income term are also significant and the expected sign. While household size is not significant, the number adults in the household have a positive effect on household purchases. Our parameter of interest, the advertising break, is negative but not significant. This could be due to the aggregation of all products together since only two of the manufacturers participated in the CFBAI. Based on this simple linear model, the CFBAI does not appear to have a significant impact on household purchases.

Table 6. Linear Model of Average Purchase Quantity of CSDs

variable	estimate	std. error	p-value
time	0.55	0.09	0.00
summer dummy	6.60	1.51	0.00
intercept	234.29	37.08	0.00
price	-58.74	6.89	0.00
income	0.01	0.00	0.01
household size	-3.82	9.25	0.68
education level	3.09	7.42	0.68
number of children <12	-1.64	12.26	0.89
number of adults	26.22	10.72	0.02
advertising break	-1.87	2.00	0.35
adj. R-Squared		0.633	

CSD manufacturers may also choose to change their pricing behavior along with a voluntary advertising restriction. We examine if corresponding to the advertising restriction, there are any identifiable changes in CSD prices. To this end, we estimate a simple linear model regression with CSD prices as the dependent variable.

Table 7. Linear Model of CSD Prices

brand	variable	estimate	std. error	p-value
Private label	olympics dummy	-0.029	0.031	0.361
	summer dummy	-0.009	0.024	0.720
	advertising break	-0.026	0.024	0.279
	adjust R-squared		0.472	
Sprite	olympics dummy	0.121	0.059	0.040
	summer dummy	-0.086	0.030	0.005
	advertising break	-0.002	0.047	0.963
	adjust R-squared		0.262	
Coca-Cola	olympics dummy	0.093	0.048	0.055
	summer dummy	-0.145	0.024	<.0001
	advertising break	-0.150	0.032	<.0001
	adjust R-squared		0.578	
Pepsi	olympics dummy	-0.007	0.044	0.877
	summer dummy	-0.099	0.019	<.0001
	advertising break	-0.065	0.029	0.023
	adjust R-squared		0.42	
Seven-Up	olympics dummy	0.212	0.136	0.121
	summer dummy	0.075	0.051	0.146
	advertising break	0.178	0.076	0.019
	adjust R-squared		0.155	
Dr. Pepper	olympics dummy	-0.033	0.052	0.520
	summer dummy	-0.142	0.030	<.0001
	advertising break	0.008	0.056	0.880
	adjust R-squared		0.247	
Mountain Dew	olympics dummy	-0.064	0.074	0.385
	summer dummy	-0.011	0.052	0.841
	advertising break	0.105	0.063	0.095
	adjust R-squared		0.284	

As regressors, we again use time, market-level fixed effects and a dummy variable indicating the beginning of the advertising restriction.

$$P_{mt} = \alpha + \gamma R + \phi z_{mt} + \varepsilon_t \tag{2}$$

We simultaneously estimate all of the CSD prices using a seemingly unrelated regression (SUR). Looking at the results (Table 7), we find that prices for Coca-Cola, Sprite and Pepsi significantly decrease following the advertising break. This is not surprising since Coke and Pepsi are the largest advertisers and Coke owns Sprite. Dr. Pepper had no significant change whereas Seven-Up, which is owned by Dr. Pepper had a significant increase in price. In addition, private label prices also decrease perhaps indicating private label response to their competition. Although we find no significant change in the average quantity demanded for regular CSDs, the decrease in price for some individual brands suggests that estimating a demand model for individual brands may provide improved results.

4. Determining the welfare effect of an advertising restriction

The effect of an advertising restriction on consumers can be measured in terms of consumer welfare, particularly using compensating variation. Compensating variation (CV) can be used to explain how a change in price or quality impacts consumer welfare. In this case, we are looking at both a change in price and a change in quality through advertising. The CV is written as:

$$CV = e(p_1, \psi_1, u_1) - e(p_{0,} \psi_0, u_1) \tag{3}$$

where the expenditure function $e(\;)$ is expressed in terms of prices before and after the restriction, p_0 and p_1 respectively, and utility is constant at the level after the advertising restriction, u_1. The level of CSD advertising before and after the restriction is represented using ψ_0 and ψ_1. Note that this includes both television advertising and all other forms of advertising used by the CSD manufacturers. We do not account for all forms of advertising in this analysis, but the CFBAI restrictions include other forms of advertising media. As such, the ψ term represents an inclusive measurement of how the entire advertising regime of the major CSD manufacturers changes.

To separate out the effect of CSD prices on welfare after the advertising restriction, we separate our measure of CV into two parts, an advertising effect (AE) and a price effect (PE).

$$\begin{aligned} AE &= e(p_1,\psi_1,u_1) - e(p_{1,}\psi_0,u_1) \\ PE &= e(p_1,\psi_0,u_1) - e(p_{0,}\psi_0,u_1) \end{aligned} \qquad (4)$$

An interpretation of the price effect is unequivocal for economic goods; as the price decreases (increases) compensating variation increases (decreases). As previously discussed, firms can increase, decrease or do nothing to their prices following an advertising restriction.

While calculating the advertising effect of the CV term is relatively straightforward, interpreting the result depends on whether or not advertising is strictly persuasive or complementary[4]. There is an extensive literature which defines all advertising as persuasive (Bagwell 2007), and concludes that advertising is unnecessary; generates too much consumption; and is welfare reducing unless accompanied by an adequate price reduction[5]. Without persuasive advertising, consumers would consume the *correct* amount of any good. In there well-known paper, Dixit and Norman (1978) insist that if advertising changes tastes and preferences, the increase in consumer surplus should *not* be included in welfare calculations. Given the current climate regarding obesity and health and the derisive view of advertising, some public opinion may regard advertising of CSDs to be nothing better than persuasive; i.e. having a negative impact on consumer welfare.

Alternatively, advertising is also characterized in the literature as being complementary to the product it advertises and therefore potentially welfare increasing. Although not the first to identify advertising as complementary (again, see Bagwell for an extensive review of the literature), Becker and Murphy (1993) identify how advertising can enter a meta-utility function as a complement to the good being advertised. Consumers benefit from product advertising according to Becker and Murphy as advertising “give[s] favorable notice” to the good being advertised. Advertising for Coca-Cola that relies strictly on presenting favorable imagery (happy young adults consuming the product) would be considered useless if not harmful to the persuasive camp but welfare enhancing to the complementary camp.

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[4] Although advertising is also described as informative, informative television advertising of CSDs could considered complementary to the product as well. As such, we consider only the complementary and persuasive views of CSD television advertising.

[5] As noted in Bagwell, in order for advertising to improve consumer welfare it is necessary, but not sufficient that prices decrease. In fact, even with a price decrease, there may still be excessive advertising from a welfare perspective.

Clearly there is potential for a lengthy debate on the merits of different forms of advertising, but that is beyond the scope of this paper. If the function of advertising is persuasive, then a restriction on advertising will generate non-positive advertising effects in terms of our welfare measure. Put another way, consumers will not need to be compensated for the restriction of advertising. This is because persuasive advertising causes excessive consumption thereby reducing consumer surplus. If the function of advertising is complementary, however, then restricting advertising would generate non-negative advertising effects. This is because the advertising enhances the utility derived from the product being advertised. Removing this complementary good would reduce welfare and consumers would need to be compensated to be just as well off.

It is important to note, however, that persuasive advertising is expected to affect preferences. Therefore the constant utility assumption is violated and restricts our ability to accurately estimate consumer welfare related to persuasive advertising. In terms of drawing conclusions from this analysis, we therefore assume stable preferences and that advertising is complementary with the caveat that in is entirely possible and plausible that the welfare effect due to advertising should not be considered.

Additionally, this welfare analysis does not include the impact of health costs. Although an advertising restriction can potentially be welfare reducing as measured by compensating variation, it may still reduce consumption which can potentially improve consumer health. Estimating the benefit to consumer health is difficult for several reasons. First, we do not possess any information about the health status of any individuals in our data set. Further, even with knowledge of health status, it is not entirely clear how marginal consumption of CSDs will impact long-term health. Consumers can substitute from CSDs to other unhealthy or healthy goods. Finally, consumers may transfer their health costs to society. As such, we do not consider consumer health costs in this analysis.

5. Estimating the impact of an advertising restriction on demand

We estimate a system of demand equations consisting of the seven CSD products to examine how the voluntary advertising restriction impacted consumption. Specifically, we specify the LQ-IDS model originated by LaFrance (1990).The LQ-IDS model is consistent with economic theory and by meeting certain specifications can be estimated as an incomplete demand system avoiding the need to assume weak complementarity or two stage budgeting as done in many previous studies (see for example work by Hausman, Leonard and Zona 1994 and Hausman and Leonard 2002). An incomplete demand system implicitly satisfies homogeneity and requires no adding up restrictions, therefore eliminating the need to include parameter restrictions during estimation. Additionally, an incomplete demand system eschews the dropping of an equation as with the AIDS modeling approach.

The model we estimate is derived from an expenditure function that is linear in income and quadratic in prices which satisfies integrability and allows for exact welfare measures. Specifically, the expenditure function is specified as:

$$e(p,\tilde{p},s,u) = \alpha' p + p'\delta s + 0.5 p'\beta p + \theta(\tilde{p},s,u)e^{\gamma' p}, \qquad (5)$$

where *p* is a vector of CSD prices, $\tilde{p}$ is the numeraire price index and *s* is a vector of demographic variables. The term $\theta(\tilde{p},s,u)$ is the constant of integration and is increasing in utility, *u*, but otherwise cannot be identified. The indirect utility function can be solved using the expenditure function to get:

$$v(p,\tilde{p},m,s) = (m - \alpha' p - p'\delta s - 0.5 p'\beta p)e^{-\gamma' p}. \qquad (6)$$

Substituting equation (6) into (5) the system of demand equations for the LQ-IDS model can be derived written as:

$$q = \alpha + \delta s + \beta p + \gamma(m - \alpha' p - p'\delta s - 0.5 p'\beta p), \qquad (7)$$

where *q* is the vector of quantities, α and γ are vectors of parameters, δ is a matrix of parameters associated with the vector of demographic variables and β is a symmetric matrix of price parameters. In this system, homogeneity is satisfied by normalizing all prices and income by the numeraire price.

The quantity is calculated as the total ounces purchased for each brand within a given market-time period divided by the number of households who made those purchases. The quantity reflects an average quantity purchased across all UPCs of a given brand. The prices are calculated as a weighted average according to:

$p_{imt} = \sum_h \left(\frac{q_{iht}}{\sum_h q_{iht}} \cdot p_{iht} \right)$, where *i* indexes brand, *h* indexes household, *t* indexes the time period and *m* indexes the market area. In addition, we multiply the initial household price p_{iht} by the state tax for soft drinks, which in some states is higher than the state tax for food items.

In addition to an intercept term, we include time, a measure of the number of participants in the market during period *t*, fixed effects for each DMA, a dummy variable for summer months and a dummy variable indicating the occurrence of the summer and winter Olympics. We include a measure of the highest level of education achieved by an adult in the household, the number of children (under 12), teenagers (12-18) and adults (over 18). Finally, we include a dummy variable to indicate the advertising break. To help reduce aggregation bias, we follow Blundell et al (1993) and weight all the demographic variables by $\mu_h = \frac{purchases_{ht}}{\sum_h purchases_{ht}}$; i.e. the weighed average of purchases of all households participating in the market during time *t*.

Our measure of advertising is not a direct measure of advertising. That is, we don’t observe how many times each household observes an advertisement, just that some given households is in an area with some level of advertising stimulus. We incorporate advertising into equation 7 by interacting GRPs for each age group with the measure of the age group. For example, advertising to children enters the demand equation as: $adv_{child} = GRP_{child} \cdot child$. This suggests that a household with a large number of children is more likely to be impacted by advertising GRPs than a household with fewer children. Equation 7 then becomes:

$$q = \alpha + \delta s + \eta\, adv + \beta p + \gamma(m - \alpha' p - p'\delta s - p'\eta\, adv + -0.5\, p'\beta p)\,, \qquad (8)$$

where η is a vector of parameters and *adv* is a vector of advertising values with each element corresponding to children’s advertising GRPs, teenager advertising GRPs, and adult advertising GRPs.

Within each market, prices are likely to be endogenous. As such, we follow the approach used by Hausman and Leonard (2002) and Nevo (2001) for balanced panels. This involves including market specific fixed effect and prices in all other markets as instruments. In addition we include the demographic variables and their interaction terms.

6. Results

We initially estimate the demand system using nonlinear 3SLS and test for auto-correlation as well, but find no indication of autocorrelation being a problem. We also test for unit roots in the CSD purchase quantities using an augmented Dickey-Fuller test, but find no significant evidence. To account for potential heterogeneity we then estimate our demand system using nonlinear GMM and the previously described instruments. We calculate Hansen's J-statistic and fail to reject the null hypothesis that the instruments are uncorrelated with the error term. We first estimated equation 8 but found that the advertising terms were not significant for the equations. Additionally, these terms made convergence more difficult for the model. We discuss the results of equation 7 which does not include the impact of advertising GRPs.

The results of the demand system are presented in Table 8. The Olympics dummy variable is significant and negative for five of the products suggesting reduced purchases during the Coca-Cola sponsored event. Surprisingly, there Coca-Cola also show a slight decrease in purchases during that period. For all but two of the equations, the summer dummy variable is significantly positive, indicating an increase in summer sales. The household demographic variables are significant and varying in sign for the different products and do not appear to indicate a consistent effect. The income variable is positive and significant for most of the products; for the private label it is significantly negative, suggesting that households with higher income move away from private label sodas.

The own price terms are all significant and negative, as would be expected. However, they are much smaller in magnitude than would be expected for CSDs. Although not shown, the implied uncompensated price elasticities are in the range of inelastic to unitary elastic. CSDs are generally accepted as relatively elastic, contrary to these findings. Given this strange result, we considered the possibility of having weak instruments which might bias our results. Ideally, we would use cost data for each brand, but do not have access to such data. We also tried using the prices of similar *diet* soft drinks in all other markets as instruments instead. For example, to instrument for the price of Coca-Cola, we used the price of diet Coca-Cola in all other markets. Since regular and diet brands are similarly priced in retail stores, we hoped that this would provide a good instrument. However, the results were similar. Although the price coefficients appear low, they are significant as are many other variables in the model. The adjusted R-squared values also suggest most of the models perform well. It is not clear if better instruments for these seemingly biased price coefficients would change the implications of the model.

Table 8. Results from the demand system model

	Private Label		Coca-Cola		Dr. Pepper		Mountain Dew		Pepsi		Seven-Up		Sprite	
variable	**estimate**	**p-value**	**estimate**	**p-value**	**estimate**	**p-value**	**estimate**	**p-value**	**estimate**	**p-value**	**estimate**	**p-value**	**estimate**	**p-value**
olympics dummy	-9.963	<.0001	-3.896	0.050	-8.593	0.010	-4.248	0.240	-9.757	0.004	-7.001	0.001	2.835	0.410
summer dummy	6.036	<.0001	4.723	<.0001	-2.611	0.229	15.436	<.0001	14.207	<.0001	0.852	0.686	4.231	0.009
intercept	64.174	0.079	483.371	<.0001	584.335	<.0001	106.030	0.003	290.304	<.0001	274.083	0.005	406.411	<.0001
time	0.492	<.0001	0.546	<.0001	-0.309	0.021	0.562	<.0001	0.726	<.0001	-0.093	0.374	-0.104	0.148
ed	4.768	0.606	-12.995	0.240	-48.193	0.043	38.584	<.0001	-0.480	0.973	-28.100	0.262	-10.124	0.504
kids	11.3381	0.0019	-6.46633	0.1423	39.8975	<.0001	4.57447	0.5366	34.2158	<.0001	-35.2692	<.0001	1.73873	0.759
teens	23.007	<.0001	-10.888	0.011	-54.901	<.0001	55.750	<.0001	32.843	<.0001	0.375	0.964	9.125	0.105
adults	30.985	<.0001	6.294	0.092	41.732	<.0001	4.727	0.515	50.142	<.0001	32.546	<.0001	-14.054	0.002
advertising break	-6.793	<.0001	4.446	0.004	9.291	0.002	-4.699	0.090	6.565	0.002	7.886	0.002	6.420	<.0001
Income	-0.009	<.0001	0.007	0.001	0.039	<.0001	0.003	0.319	0.019	<.0001	-0.003	0.495	0.002	0.462
Price coefficients														
private label	-40.830	<.0001	20.238	<.0001	-25.993	0.003	-3.571	0.517	35.376	<.0001	0.462	0.949	12.829	0.025
Coca-Cola	9.280	0.002	-75.744	<.0001	-26.794	0.001	-19.967	0.001	0.128	0.976	-18.681	0.003	-41.275	<.0001
Dr. Pepper	-1.773	0.458	-1.018	0.651	-46.452	<.0001	14.679	<.0001	6.575	0.018	-2.304	0.514	-6.080	0.073
Mountain Dew	5.984	<.0001	-9.266	<.0001	7.519	0.060	-57.390	<.0001	-9.458	<.0001	-0.684	0.840	2.886	0.115
Pepsi	-3.394	0.260	-6.131	0.165	15.655	0.142	27.783	0.006	-86.768	<.0001	-9.165	0.216	5.799	0.292
Seven-Up	2.83679	0.0083	-1.78686	0.2456	0.45234	0.8702	6.59282	0.0166	9.93825	<.0001	-14.6706	<.0001	-3.64706	0.0166
Sprite	-2.81928	0.2094	5.54	0.0445	-13.3814	0.0215	-0.52806	0.8635	-12.004	0.001	8.23736	0.0812	-32.6026	<.0001
adj R-squared	0.4		0.593		0.289		0.281		0.484		0.08		0.195	

The estimate for the advertising break is significantly positive for five of the equations. This indicates that following the advertising restriction, average quantity purchased increased. For private label products, average quantity purchases decreased at the 10 percent significance level. The increase in purchases is a surprising result. We might expect a priori that a reduction in advertising directed at children would result in a decrease in purchases by households. The linear regression on prices (Table 7) does suggest a significant decrease in price for some of the products. However, comparing just the mean prices before and after the advertising break we find that for all products except Coca-Cola, the average price across all markets was higher (note that this is a simple comparison, not a statistical one). It is possible that some other marketing variable that is not measured in this analysis changed following the advertising break and is having a significant impact on purchases.

6.1. The price and advertising effect

We use our parameter estimates to calculate the price and advertising effects corresponding to the advertising break (equation 4). The welfare measures are calculated using the average prices before and after the advertising break. Given the average increase in prices, our calculated price effect is positive (Table 9). This indicates that the average household would need to be compensated $0.48 per 4-week period following the change in prices. Following the advertising restriction, this suggests that consumers became worse off in terms of the price effect, however only by a small amount.

The advertising effect is roughly 0.60 per 4-week period. Taking the view that advertising is complementary suggests that consumers are worse off. That is because the *quality* of the product has changed as advertising for the product changed. From the persuasive view consumers are no worse off in this case, and in fact, are probably better off because they will consume the proper amount of CSDs. In either case, the 0.60 value is seemingly negligible over a 4-week period. Even the total CV estimate is low over a 4-week period.

Table 9. Welfare calculations, Price and advertising effect

Welfare term		
AE	$	0.60
PE	$	0.48
CV	$	1.08

7. Conclusions

Several of the world’s largest food manufacturers have recently agreed to limit or restrict their advertising directed at children. This is primarily in response to growing concern with childhood obesity. In this paper, we examine the impact on voluntary advertising restrictions undertaken by the two largest CSD manufacturers. Estimating a demand system for the seven largest CSDs, we find that contrary to expectations, purchases for several CSDs increased following the voluntary advertising restriction. This may be partially explained by changes in prices, but there are other factors not observed in our data that explain the increase as well. Although increased purchasing of CSDs does not necessarily indicate increased consumption by children in the household, this effect seems undesirable from a public policy perspective.

Since adults make the majority of household purchases, targeting childhood advertising may have limited impact on household purchase behavior. In fact, manufacturers may compensate for reduced advertising by promoting products in other ways, such as with lower prices. At the same time however, there may be a long term benefit to reducing the number of advertisements children see. Especially in terms of reducing the impact of brand identification of unhealthy products. Although we do not have the ability to test for such long term implications, they are an important consideration.

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