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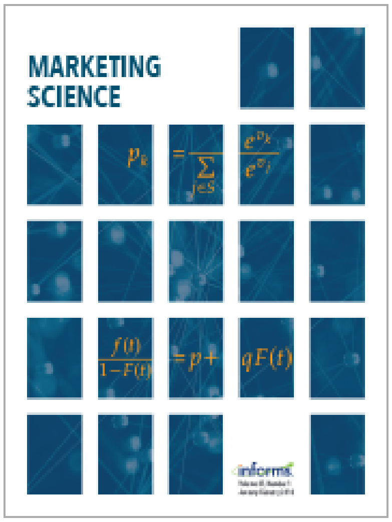

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Super Bowl Ads

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Abstract. We explore the effects of television advertising in the setting of the National Football League's Super Bowl telecast. The Super Bowl is well suited for evaluating advertising because viewers pay attention to the ads, more than 40% of households watch the game, and variation in ad exposures is exogenous because a brand cannot choose how many impressions it receives in each market. Viewership is primarily determined based on local preferences for watching the two competing teams. We combine Super Bowl ratings data with weekly sales data in the beer and soda categories to document three primary findings about advertising. First, the relationship between Super Bowl viewership and sales in the week leading up to the game reveals the brands customers buy to consume during the game. We find some brands are consumed while watching the game while others are not, but this is unrelated to whether a brand ever advertised during the Super Bowl or advertises in a specific year. This rejects the theory that advertising works by serving as a complement to brand consumption. Second, we find that post–Super Bowl sales effects of ad viewership are concentrated in weeks with subsequent sporting events. This suggests Super Bowl advertising builds a complementarity between the brand and sports viewership more broadly. Finally, we collect data on National Collegiate Athletic Association basketball tournament viewership to test this theory and find that the complementarity between a brand's sales and viewership of the tournament is enhanced by Super Bowl ad viewership. Together, these findings identify advertising as a determinant of why some brands outperform others for particular consumption occasions such as sports viewership.

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1. Introduction

The Super Bowl is the premier advertising event of the year. Four of the five most watched telecasts ever were Super Bowls. The 2012 broadcast was the most watched telecast in history, with 54% of U.S. households tuning in. The cost of airing a 30-second spot during the game has grown to near $5 million (Lynch 2015). The two biggest spenders have been Anheuser-Busch (Budweiser) and Pepsi (Associated Press 2009), both well-known brands whose existence and tastes presumably do not need to be communicated. This highlights one of the most puzzling questions in advertising. Can continued heavy advertising by established brands pay off, and if so, why?

Answers to this question begin with the observation that both Budweiser and Pepsi also outperform their rivals in selling beverages for consumption during the game, despite Pepsi's generally inferior market position relative to Coca-Cola in carbonated beverages. The notion that a brand may dominate during particular consumption occasions is discussed by Fennell (1997) and was the focus of a study designed by Miller Brewing Company analyzed by Yang et al. (2002). Such associations for a particular brand among similar products are unlikely to arise exogenously. Fennell (1997) argues that generating such associations is and should be the goal of advertisers. We find evidence that Super Bowl advertising generates associations between the brand and sports viewership occasions broadly. From an economic perspective, the association manifests itself as a complementarity (more sports viewership leads to more consumption of the branded product, and, intuitively, more cans of beer may generate more sports viewership). This alters the conventional economic understanding of advertising's role in forming complements to branded consumption.

To facilitate the economic analysis of advertising, Becker and Murphy (1993) propose a framework for considering advertisements themselves as complements to the consumption of advertisers' products. In fact, Becker and Murphy (1993, p. 948) reference the example of beer advertising and consumption during football games as "obvious" to this complementarity. Our analysis, and the suggestion of Fennell (1997), however, places the complementarity with watching the game, rather than the advertisements during the game. We reject the Becker and Murphy (1993) theory by documenting that (i) some advertising brands never realize consumption complementary with viewership of the game, (ii) advertising brands' consumption complementarity with Super Bowl viewership is invariant to whether the brand advertises in a given year or not, and (iii) some nonadvertising brands also realize complementary consumption.

Our study of brand advertising and the choice of application began with the recognition that we needed to find naturally occurring exogenous sources of variation in advertising exposure because television ad experiments were not feasible and most observational studies suffer from substantial endogeneity problems. Sports turn out to be an ideal place to look for such exogeneity because the disparate fortunes of local teams can increase or decrease the viewership of nationally broadcast games and their advertisements. The Super Bowl provides further identification benefits within the context of sports. First, selection into advertising or not is particularly limited because most Super Bowl ad spots are sold before the season even begins.[1] Second, while typical advertising effects may be quite small and difficult to detect, Super Bowl ads are presumably the most impactful given their heightened attention. McGranaghan et al. (2016) documents that both the number of viewers in a room and the attention to the television increases during Super Bowl advertising breaks, whereas typical advertising exhibits diminished attention throughout commercial breaks. Thus, if there is a single advertising event large enough to shift preferences for established brands, the Super Bowl is it. Consider the following example. When the Green Bay Packers returned to the Super Bowl in 2011 after a 13-year absence, an additional 14% of households in Milwaukee watched the game. That exposed more Wisconsinites and Packers fans elsewhere to perennial advertisers. If those ads are effective, we should see perennial Super Bowl advertisers exhibit a corresponding increase in their sales.

We construct a panel data set consisting of nearly 200 media markets and six years of Super Bowl ratings and sales data from Nielsen. The relationship between Super Bowl viewership and the sales data in the week leading up to the Super Bowl reveals the brands consumers purchase to consume while watching the game. The exclusive beer advertiser, Budweiser, realizes sales for consumption during the game, but so do nonadvertising brands. In the soda category, Pepsi always realizes sales for consumption during the game, whether advertising or not, and Coke never realizes sales for consumption during the game despite advertising in all but the first year of our data. This rejects the notion that advertising works by creating a complementarity between consuming the brand and viewing the ad.

Next, we measure the effect of ad viewership on post–Super Bowl sales. Without an obvious horizon for the effects, we measure the effect separately for each week following the game. While the first few weeks appear to follow a typical decay pattern, the advertising effects show resurgence in weeks when shoppers make purchases to consume during subsequent major sports broadcasts. This pattern suggests the hypothesis that Super Bowl advertising may build a complementarity with sports viewership more broadly. To test this, we collected market-week-level data on viewership of the National Collegiate Athletic Association (NCAA) basketball tournament and interacted it with the Super Bowl ad exposures. We found that purchases for consumption during viewership of the NCAA tournament were augmented if the brand's Super Bowl ad viewership was high.

Brand complementarity with a consumption occasion such as sports, as opposed to advertising itself, is intuitive. Ads themselves may be reasonably less memorable than the associations they promote. The brand strength of the beverages considered here clearly entails persistence, making it almost odd to tie the complementarity to ad viewership directly. A more generous interpretation of the Becker and Murphy (1993) theory might suggest memories of the ads persist to complement subsequent consumption. Yet memories are not observable, nor do they provide meaningful variation that shifts sales in the economically meaningful ways Becker and Murphy (1993) sought by introducing the theory of complements. On the other hand, brand consumption clearly exhibits complementary relationships with consumption occasions, as indicated by consumers stocking up for Super Bowl parties and other occasions. As consumer interest in these complementary associations the brand has built grows or falls, so will the fortunes of the associated brands.

Brand complementarity with the consumption occasion also implies greater brand rivalry than complementarity with the ad. Under Becker and Murphy (1993), any brand advertising during a sporting event should be able to exhibit the complementarity, especially during the Super Bowl, which is viewed by nearly half of all U.S. households and certainly includes customers loyal to each brand. When the advertising works to build a complementarity with particular consumption occasions, it may be difficult for both of the primary competitors advertising during the same program/game to make any progress on the association. We see this in our data. Across the years when both Coke and Pepsi advertised during the same Super Bowl, the advertising effects either disappear or were greatly diminished. In fact, throughout our data, Coke is never observed to have improved its purchases for consumption during the Super Bowl. Given Coke's absence from Super Bowl advertising prior to 2007, it may be nearly impossible for it to capture an association with the Super Bowl without acquiring the exclusivity Budweiser and Pepsi have secured in the past. Coke's Super Bowl advertising effects therefore manifest in associations with other sporting events, such as the NCAA tournament.

Moving the complementarity from the ads themselves to consumption occasions also better reconciles the economics and psychology of advertising. Advertising's role in building both functional and nonfunctional associations for brands is taught in marketing courses throughout the country, yet has lacked a clear role in the economics of advertising. Viewing advertising as building complements between brands and associations can explain both the within-market cross-time relationship between sports viewership and branded consumption and geographic variation in consumption that might occur in this category or others where preferences for associations such as sports might systematically vary.

Brand complementarity with consumption or use occasions can also better extend to examples of durable goods such as automobiles, where brands try to associate themselves with "greenness" or ruggedness (one of Aaker's (1997) brand personality dimensions). Similarly, as consumer interest in these associations varies across markets or over time, so should the preferences for the brands who have built those associations. This is consistent with greater Toyota Prius sales in markets such as California, which is known for relatively strong environmental concerns. A recent news article and quotes by a Ford vice president highlight that demand for their F-150 truck is greatest in regions with oil and gas fracking (e.g., Texas and Pennsylvania) and agriculture (e.g., California; Williams 2014). Brand battles for a dominant association with these categories is evidenced by recent Chevrolet commercials highlighting their truck beds' greater durability in rugged use occasions such as dumping landscaping blocks or dropping a tool box into the bed (Snavely 2016). Consumers who anticipate such occasions or perceive or want to project a similarly rugged lifestyle will value the brands who have best associated themselves with these occasions.

An additional economic implication of Super Bowl ads building brand complements with sports derives from our finding in the soda category where the "creative" of the advertising rarely emphasizes sports. This suggests that the context in which the ad airs can play an important role in generating the complementarity. This has implications for market structure in the advertising industry. The recent deconcentration of consumer viewing habits both within television and to the abundant online alternatives threatens to commoditize the advertising market. However, if the context in which the ad is viewed is an important part of its effectiveness and the associations it builds, as we find here, then television channels, publishers, and websites can differentiate themselves to advertisers based on the content they produce or acquire and distribute.

It is also useful to consider our findings in the context of studies of advertising effectiveness. The challenges of measuring advertising effects are nicely described by Lewis and Rao (2015). Considering field experiments for Internet advertising, their primary point is that effective advertising can involve very small changes in sales. Yet, detection of small effects requires a very large sample size if there is considerable variance in sales. They point out that this same "statistical power" issue led television ad effectiveness studies to report findings at the 80% confidence level (e.g., Lodish et al. 1995). These challenges have been overcome by recent experimental studies on direct mail advertising (Bertrand et al. 2010) and Internet advertising (Sahni 2015), but there is still a dearth of studies analyzing television advertising with credible sources of exogenous variation. Our Super Bowl analysis overcomes these concerns about statistical power because of the large potential effects and the market-level data, which include millions of households and shift inference to within market, where variance in outcomes has been shown to be small (Bronnenberg et al. 2009).

There are also a couple of papers that explore Super Bowl advertising specifically. Reiley and Lewis (2013) studies the effect of Super Bowl ads on search behavior and finds a significant spike within seconds of the airing. Such immediate search effects do not necessarily imply sales effects and would include viewers' desires to either see the commercial again or follow up on something from the ad. The only other paper tying exogenous variation in Super Bowl ad exposures to sales is that by Stephens-Davidowitz et al. (2017). They apply a modified version of our identification approach to the case of movies. They find significant positive effects for movies released well after the Super Bowl. Effects in movies likely represent a strong informative[2] or free-sample component, whereas our focus is on the effects and mechanism of advertising by familiar brands with established advertising stocks (as in Nerlove and Arrow 1962, Dubé et al. 2005, Doganoglu and Klapper 2006, Doraszelski and Markovich 2007) that we argue maintain an association between a brand and consumption occasions.

The remainder of this paper proceeds as follows. The next section describes the data sources. Section 3 presents the estimates, and Section 4 concludes.

2. Data

We analyze the relationship between within-market variation in Super Bowl ratings and within-market variation in Super Bowl advertisers' sales. The ratings data for the top 56 designated market areas (DMAs) is publicly released in some years,[3] but was purchased from Nielsen. We also obtained access to the AdViews database to collect Super Bowl ratings for the remainder of the DMAs, allowing us to include up to 195 markets. AdViews also provides weekly advertising exposures for brands as well as market-level exposures to ads during National Football League (NFL) broadcasts leading up to the Super Bowl.

Data on store-level revenue and volume, as well as trade data (feature and display), come from the Kilts Center's Nielsen Retail Scanner Data.[4] The timeline for our analysis is the 2006–2011 time frame for which we observe all of these data sources.

2.1. Super Bowl Advertising and Ratings

We focus on the Super Bowl advertising by beer and soda brands. Anheuser-Busch has spent the most on Super Bowl advertising and has been the exclusive beer advertiser for the Super Bowl for the entire time span of our data. Pepsi spends the second most and ran an advertisement in every Super Bowl in our data except 2007 and 2010. In 2007 they sponsored the halftime show instead.[5] The withdrawal from 2010 was based on a widely publicized refocus of their advertising efforts toward a social media campaign. Coca-Cola advertised every year from 2007 to 2011, but prior to that had not advertised since 1998. We later discuss potential concerns about selectivity in the advertising decisions in the carbonated beverage category.

While there is little to no variation in our data regarding who advertises during a Super Bowl, Figure 1 depicts substantial variation both across and within the top 56 DMAs in the exposures to the Super Bowl ads.[6] The bars at the bottom represent the average ratings for each DMA as measured on the axis to the right. The average is 45.3% of a market viewing the Super Bowl, with cross-market variation from 36.4% to 53.4%. The dots above represent the year-by-year deviations from the DMA mean ratings as measured on the axis to the left. The DMAs are ordered left to right with increasing variance in the ratings such that the DMA with the smallest variation across years sees movement of roughly ±2.5% around its average rating of 47.7%. Many DMAs experience ratings dispersion of 10 points or more, while the most variable DMAs experience ratings dispersion of 17 points. Overall, this paints a picture of large swings in terms of how many people are watching the Super Bowl and getting exposed to the ads.

From the advertisers' perspective, this variation in exposure is out of their control. It is based on local variation in the preferences for watching the Super Bowl. While it is impossible to decompose all of the factors generating viewership swings for the Super Bowl, we have tried to identify some of the most significant elements. Figure 2 illustrates the role of local preferences for the teams in the Super Bowl in generating ratings. The horizontal axis represents the percentage of the people in the DMA who "liked" the two teams in the Super Bowl on Facebook as of April 2013.[7] The vertical axis plots the associated ratings for the Super Bowl. The relationship is clearly nonlinear, with more than 45% of the population watching whenever at least 5% of the market likes the teams. Among those observations with less than 5% liking the team, there is still a correlation of 0.33 with the observed ratings. This illustrates that preferences for the teams playing is still a significant driver of viewership even outside the home cities.

This certainly does not explain all of the variation in ratings, as Facebook is not demographically representative, and we should ideally have these preference

Figure 1. (Color online) Super Bowl Ratings by DMA: Average and Year-Specific Deviations

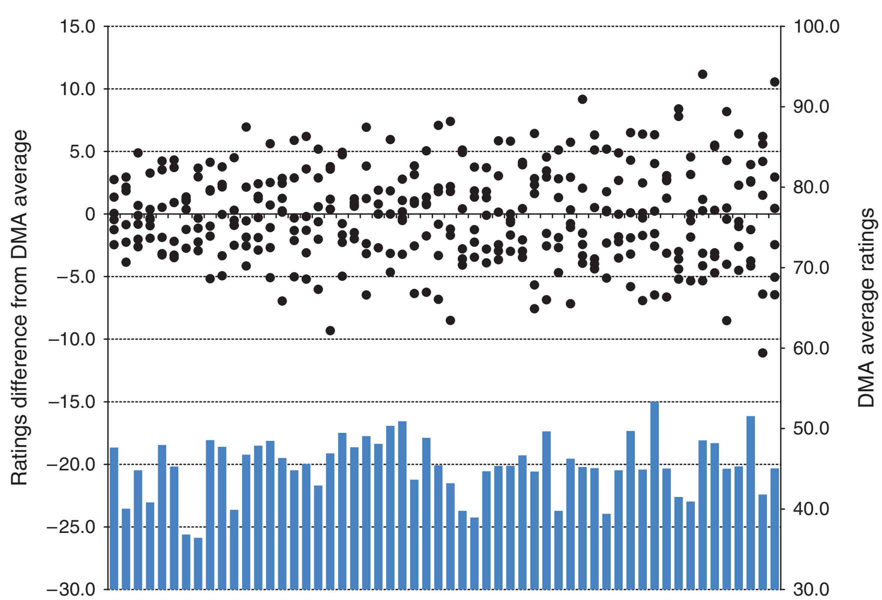
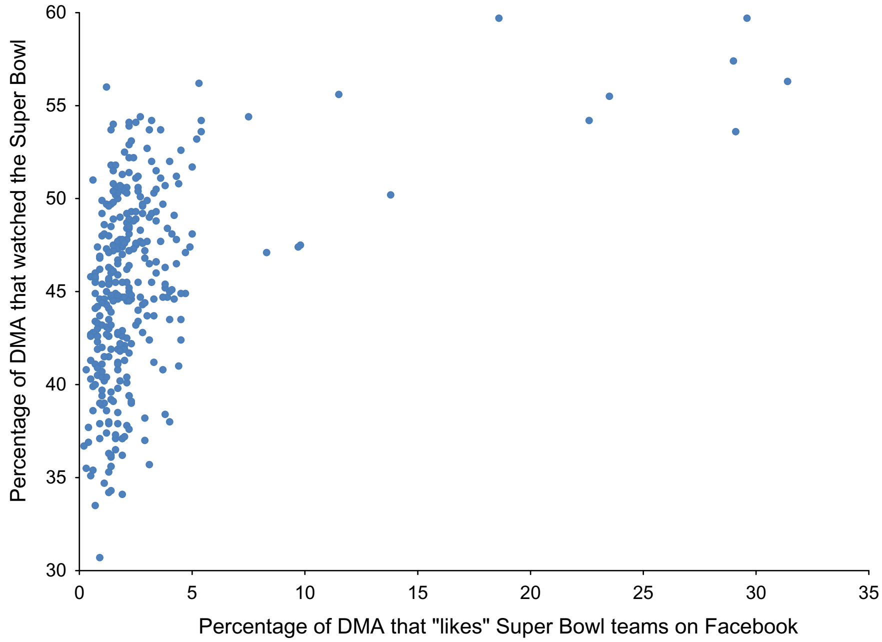


Figure 2. (Color online) Super Bowl Ratings by DMA: Average and Year-Specific Deviations



measures at the beginning of our data. To quantify the explanatory power, we ran a simple regression of log ratings on the log of the percentage of the DMA liking the team. The R-squared is 0.24. Including both DMA and year fixed effects, we find that the percentage liking the team explains 12% of the within-DMA variation in ratings. Year fixed effects alone explain about 42% of the within-market variation. The remainder of the variation may arise from other unobserved components of the local preferences for the game. Some of that variation occurs because we often measure likability of the teams well after the game was actually played.

2.2. Retail Scanner Data

Nielsen's Retail Scanner Data provide unit sales, prices, display, and feature information at the universal product code (UPC) level for each store and week. While the UPCs can be aggregated at many levels (e.g., diet/light versus regular, subbrand, or pack size), we report our analysis aggregating sales to the brand level, as we expect that to internalize all of the effects of advertising.

We consider the top four brands (based on volume) in each category while aggregating the remaining brands in a composite named "Other."[8] In beer, the focal brands are Budweiser, Miller, Coors, and Corona. These four brands also represent the top four purchasers of NFL impressions in weeks prior to the Super Bowl. In soda, the focal brands are Coke, Pepsi, Dr Pepper, and Mountain Dew. These brands also purchased the most NFL impressions prior to the Super Bowl.

We aggregate the store-level data to the geographic level at which we observe ratings, i.e., the DMA. We consider up to 20 weeks after the Super Bowl, as well as the first five weeks of the year leading up to the game on the first Sunday in February. The first week after the Super Bowl includes Super Bowl Sunday. For each week in the data, we have included the DMA-level gross rating points (GRPs) for each brand's advertising as reported by Nielsen's AdViews. GRPs/100 are the number of impressions per household. We also consider the cumulative GRPs during NFL games leading up to the Super Bowl (Pre-SB NFL GRPs). This accounts for brand impressions that would be correlated with Super Bowl ratings because the Super Bowl competitors also drew large audiences in previous rounds of the playoffs. The outcome measures we focus on are volume and revenue. We similarly analyze these on a per-household basis, where we calculate a constant number of households over the six years in our data based on the GRPs and impressions reported in the advertising data.

Table 1 reports the outcomes and marketing decisions for the 20 weeks following the Super Bowl. In the beer category, Budweiser clearly dominates their market with a revenue and volume per household that is comparable to the combination of all brands outside of the top four.[9] The revenue and volume numbers represent only those households that might be covered by the Nielsen sales data and thus translate into a number smaller than the actual revenue and volume per household. The data are not necessarily representative, as some stores, such as Walmart, are not included in the Kilts data. Prices are comparable across the brands with the exception of Corona, an imported beer priced nearly four cents per ounce more. The beers are featured roughly 5% of the time (volume weighted), except for those in the Other category, which includes

Table 1. Weekly Summary Statistics: 20 Post–Super Bowl Weeks

Beer					
Variable	Budweiser	Miller	Coors	Corona	Other
Revenue per HH	0.322	0.114	0.091	0.057	0.332
Volume 6 *pk*	0.077	0.028	0.021	0.008	0.074
Price per oz	0.059	0.058	0.061	0.098	0.061
Feature	0.050	0.050	0.053	0.052	0.024
Display	0.054	0.047	0.049	0.053	0.024
GRPs/100	0.007	0.004	0.002	0.001	0.004
Pre-SB NFL GRPs/100	0.164	0.058	0.095	0.009	0.026
Soda					
Variable	Coke	Pepsi	Dr Pepper	Mtn Dew	Other
Revenue per HH	0.381	0.268	0.111	0.144	0.537
Volume 6 *pk*	0.209	0.158	0.060	0.077	0.288
Price per oz	0.026	0.025	0.027	0.028	0.027
Feature	0.093	0.105	0.021	0.041	0.036
Display	0.082	0.089	0.069	0.077	0.047
GRPs/100	0.007	0.007	0.003	0.002	0.004
Pre-SB NFL GRPs/100	0.006	0.020	0.012	0.001	0.001

Notes. For beer, observations are across 173 DMAs and 20 weeks. DMAs with alcohol restrictions or negligible sales are omitted. For soda, observations are across 191 DMAs and 20 weeks. Some DMA-years are missing. HH, Household.

smaller brands that may be unlikely to promote themselves in store circulars. Display rates are comparable to feature rates. Budweiser advertises 75% more than its closest competitor Miller, with 0.007 impressions per capita. If no household saw an ad more than once, this would translate to less than 1% of households seeing a Bud ad in an average week. This highlights the importance of the Super Bowl, which reaches 45% of households. Budweiser also purchased the most advertising impressions in NFL games leading up to the Super Bowl. Coors came in second at just over half of what Budweiser purchased.

In the soda category, Coke and Pepsi are the market leaders, but the Other category is substantially larger than either of these brands in terms of both revenue and volume per household. Pricing in soda is comparable across all brands. Major brands are featured 9% to 10% of the time, while the Other brands are featured about 4% of the time. Displays occur 7% to 9% of the time for major brands and just under 5% of the time for Other brands. Pepsi is the leader in terms of advertising purchased. Pepsi also purchased the most advertising during previous rounds of the NFL playoffs, with Dr Pepper following with nearly twice the NFL advertising as Coke.

3. Empirical Analysis

Our analysis is divided into three pieces. First, we analyze the brands consumers buy for consumption while viewing the Super Bowl to test whether branded consumption is complementary with watching the game or watching the brand's ad during the game. Second, we estimate whether viewership of the game (and hence the included ads) disproportionately increases post–Super Bowl sales for advertisers relative to nonadvertisers. These findings suggest Super Bowl ad effectiveness occurs in weeks when consumers make purchases for consumption during subsequent sporting events. Finally, we collect additional data on viewership of the NCAA basketball tournament to test whether viewership of a Super Bowl ad increases the brand's ability to capture more of the purchases that complement viewership of the basketball games. The series of results identify advertising as a determinant of brand-specific complementarities between beverage consumption and viewership of sports.

Each of these analyses considers how brand outcomes (volume or revenue per household) in a given week and market relate to the market's Super Bowl viewership. Market fixed effects crucially focus inference on the year-to-year changes in Super Bowl viewership documented in Section 2 to arise from changes in preferences for watching the two teams who qualified for the championship. We also include year fixed effects to avoid the possibility that aggregate viewership and brand sales happened to be higher in one of the six years of our data. Finally, we include covariates describing the brand's local marketing activities in the focal week or prior to the Super Bowl.

We therefore estimate the following descriptive regression to analyze the relationship between the volume or revenue per household (Y) and an indicator for whether brand j advertises in the Super Bowl in year y (A_{jy}), and the fraction of the population that watched the Super Bowl in market m in year y (R_{my}):

$$Y_{jmyw} = \alpha_1 A_{jy} R_{my} + \delta R_{my} + X_{jmyw}\beta + \gamma_{\text{FE}} + \xi_{jmyw}, \quad (1)$$

where j indexes the focal brand, m the market (DMA), and y the year, and w represents the week relative to the Super Bowl, with $w = 0$ being the Sunday to Saturday week leading up to Super Bowl Sunday. The term δ measures how variation in Super Bowl viewership affects the brand's outcomes, and α_1 measures any additional impact of viewership when brand j advertises in year y. We include weekly brand-market-specific covariates, X_{jmyw}, to account for past and concurrent marketing efforts that after the game could represent endogenous responses to the variation in ratings. Most of these are marketing variables summarized in Section 2. The term γ_{FE} is the set of fixed effects discussed above. When we pool multiple brands into the same analysis for comparison, we interact the above market and year fixed effects with brand indicators.

We also estimate a pooled regression that recovers the average advertising effect, α_1, across a fixed number of weeks. The primary reason for this is to test for the significance of an average effect when only some week-specific effects are significant and to quantify an advertising elasticity that covers a span of weeks after the game. In these cases, we introduce an additional fixed effect for the week number relative to the Super Bowl.

3.1. Is Super Bowl Beverage Consumption Complementary to the Advertising or the Game?

We test for complementarities between consumption of a brand and viewership of the Super Bowl. In the absence of direct data on consumption during the game, we use observed purchases in the week leading up to the game. The culture around Super Bowl parties and consumption of beer, other beverages, and snacks suggests complementarities exist. Our emphasis is to focus on differential Super Bowl week purchases across brands of relatively homogenous goods (mass-produced beers and colas/carbonated beverages). Specifically, we consider why some brands might realize greater Super Bowl week sales increases than others. Two differentiable theories can explain this. Yang et al. (2002) argue that brands differ in their associations with certain consumption occasions. Presumably branding activities such as advertising play a role in this development, but they do not explore that in their analysis. We test this conjecture directly in Section 3.3. On the other hand, Becker and Murphy (1993) suggest a complementarity between brand consumption and viewership of the ad. The testable implications of their theory are that brands advertising during the game should receive a greater increase in consumption than nonadvertisers. We illustrate below that (i) brands that have never advertised during the game also realize sales increases for consumption during the game; (ii) Coca-Cola, who advertised in the game for the last five years of our data, never realizes Super Bowl sales for consumption during the game; and (iii) Pepsi's and Coke's Super Bowl sales are invariant to whether or not they advertise in a given year. These results are inconsistent with the Becker and Murphy (1993) theory, but supportive of the idea from Yang et al. (2002) that some brands do, and others do not, have associations with consumption occasions such as watching the Super Bowl.

To document the complementarities that exist, we apply Equation (1) to volume-per-household outcomes in the beer and soda categories. The *Ratings* coefficient in columns (1) and (2) of Table 2 illustrate that Budweiser realizes substantial increases in volume per household in the Sunday through Saturday leading up to Super Bowl Sunday in those markets where realized Super Bowl ratings are higher. Both coefficients being close to 0.1 indicates a 10-point increase in the ratings for the game increases the amount of Budweiser consumed per household by one six-pack for every 100 households. Note that this is likely an underestimate, as we do not observe all sales because some large stores such as Walmart are omitted from the data. Column (2) differs from column (1) in that it controls for marketing variables. We find price to be the only statistically significant factor. Columns (3) and (4) illustrate that nonadvertising brands also realize statistically significant increases in beer volume purchased in anticipation of viewership, yet the effects are about a third of the size. Finally, columns (5) and (6) pool all brands together to illustrate that the incremental effect for Budweiser is about 0.07, or 7 extra six-packs per thousand households when ratings increase by 10 points.[10] The *Ratings* $\times$ *Ad* coefficients in these specifications have p-values of 0.065 and 0.049, respectively. This leaves little doubt as to Budweiser's superior sales for consumption during the game.

Becker and Murphy (1993, p. 948) state that "the complementarity is obvious with beer advertising on television during football games since many people drink beer as they watch a televised game." We argue that only the latter part of this statement is necessarily true. People drink many brands of beer, whether advertised or not, when they watch the big game. These results provide stronger support for the complementarity of beer brands generally with the consumption occasion. In fact, though not reported here, the only one of the top four beer brands that does not exhibit a statistically significant game-week volume increase with the Super Bowl ratings is Corona, which has historically emphasized beach settings as its associated consumption occasion.

Table 2. Volume of Beer Purchases in Anticipation of Super Bowl Viewership

	Volume in week leading up to Super Bowl					
Variables	(1) Bud	(2) Bud	(3) Non-Bud	(4) Non-Bud	(5) All	(6) All
Ratings	0.094*	0.103*	0.030*	0.032*	0.030*	0.032*
	(0.045)	(0.041)	(0.013)	(0.013)	(0.013)	(0.012)
Ratings × Ad					0.064	0.071*
					(0.035)	(0.036)
Marketing						
GRPs		−0.006		−0.034		−0.058
		(0.114)		(0.158)		(0.108)
NFL GRPs		−0.017		−0.019		−0.016
		(0.027)		(0.018)		(0.024)
Price		−3.717**		−0.680**		−1.080**
		(0.994)		(0.125)		(0.234)
Price × Other				−1.841**		−1.446**
				(0.500)		(0.537)
Feature		−0.008		−0.001		−0.004
		(0.034)		(0.005)		(0.008)
Display		−0.007		0.009		0.008
		(0.033)		(0.005)		(0.007)
Observations	888	888	3,552	3,552	4,440	4,440
R-squared	0.101	0.280	0.102	0.287	0.102	0.233
Number of brand-DMAs	173	173	692	692	865	865

Notes. Fixed effects are included at the brand-market and brand-year levels. Standard errors are clustered at the market level.
$^{*}p < 0.05$; $^{**}p < 0.01$.

The large incremental effects for the advertiser, Budweiser, may still, however, be consistent with Becker and Murphy (1993), but we cannot specifically test this as we do not see Budweiser abstaining from advertising during any given year. We therefore turn to the soda category, where we document both that one of the primary advertisers realizes no such game-week volume increases and that the game-week sales are invariant to whether or not the brands are advertising in the Super Bowl.

Columns (1) and (3) of Table 3 show that Coca-Cola realizes no statistically significant change in soda volume in the week leading up to the Super Bowl. This holds whether or not Coca-Cola advertised during the game, and the direction of the coefficients suggests that tighter standard errors would, if anything, imply a negative relationship. This is fully inconsistent with the Becker and Murphy (1993) theory. Clearly, from the beer analysis and the results from Pepsi, which we discuss next, our data can identify consumption in anticipation of viewership. One might argue that because Coca-Cola had not advertised prior to 2007, consumers were unaware Coca-Cola would be advertising. Yet Coca-Cola's entry was likely publicized and their many loyal customers would have been attuned to this by the second year, or at least by the end of the five consecutive years we observe them advertising in our data. Yet, we have separately tested whether Coca-Cola might realize an increase over time in game-week sales in the presence of higher ratings and found that their performance in game-week in markets with higher ratings declines across years.

Pepsi, on the other hand, is seen to realize volume increases comparable to Budweiser's. Columns (2) and (4) test Pepsi's game-week volume sales relationship with ratings both excluding and including marketing variables. The effects are large and statistically significant in column (2) and marginally significant in column (4), with a p-value of 0.13. These results hold in columns (7) and (8) when we pool all soda brands together and test for a difference between Pepsi and others. Pepsi is shown to have a statistically significant greater game-week sales volume of roughly 0.13 without controlling for marketing activity. This diminishes to 0.084 after controlling for marketing activity, yet still has a p-value of 0.059. The marketing activity accounts for typical marketing mix variables as well as concurrent advertising (GRPs) and advertising during prior NFL games in the playoffs or regular season (NFL GRPs). An effect of 0.1 would once again be an extra six-pack per hundred households when the ratings increase by 10 points. Columns (5) and (6) and the top row of columns (7) and (8) document that no other brand is observed to realize significant volume increases in the week before the game. Note that the Other brands include non-Pepsi-branded Pepsi-Cola

Table 3. Volume of Soda Purchases in Anticipation of Super Bowl Viewership

	Volume in week leading up to Super Bowl							
Variables	(1) Coke	(2) Pepsi	(3) Coke	(4) Pepsi	(5) Not Coke/Pepsi	(6) Not Coke/Pepsi	(7) All	(8) All
Ratings					0.034	0.037	0.036	0.039
					(0.032)	(0.035)	(0.032)	(0.037)
Ratings × Ad					0.005	−0.002		
					(0.009)	(0.007)		
Ratings × Coke	−0.076		−0.072				−0.112	−0.116
	(0.077)		(0.072)				(0.072)	(0.077)
Ratings × Ad × Coke	−0.020		−0.030				−0.020	0.013
	(0.038)		(0.033)				(0.038)	(0.032)
Ratings × Pepsi		0.166**		0.091			0.130**	0.084
		(0.064)		(0.060)			(0.047)	(0.044)
Ratings × Ad × Pepsi		−0.024		−0.025			−0.024	−0.009
		(0.030)		(0.027)			(0.030)	(0.031)
Marketing								
GRPs			−0.112	0.665		−1.161*		0.418
			(0.253)	(0.432)		(0.470)		(0.263)
NFL GRPs			−1.243**	0.613*		−0.026		0.182
			(0.362)	(0.249)		(0.074)		(0.146)
Price			−21.211**	−14.240**		−4.916**		−9.759**
			(1.807)	(1.947)		(0.726)		(0.969)
Price × Other						−1.516		3.408**
						(1.114)		(1.226)
Feature			0.060	−0.053		0.017		0.070**
			(0.037)	(0.041)		(0.019)		(0.022)
Display			0.012	0.077		0.008		−0.009
			(0.046)	(0.052)		(0.022)		(0.023)
Observations	1,002	1,002	1,002	1,002	3,006	3,006	5,010	5,010
R-squared	0.088	0.134	0.485	0.312	0.180	0.300	0.131	0.299
Number of brand-DMAs	195	195	195	195	585	585	975	975

Notes. Fixed effects are included at the brand-market and brand-year levels. Standard errors are clustered at the market level.
$^{*}p < 0.05$; $^{**}p < 0.01$.

company sodas that are typically jointly promoted in stores along with Pepsi.

The contrasting Super Bowl week performance of Coke and Pepsi supports our conjecture that advertising is about building associations with consumption occasions and that Pepsi's substantially longer tenure advertising in the game has created that Super Bowl association, while Coca-Cola has not. This highlights a fundamental difference between a theory of advertising that itself is a complement versus our argument that the complementarity is with the occasion and firms advertise to "own" that. Under complementarity with the ad, Coca-Cola's loyal customers should have made purchases for consumption during Coke Super Bowl ads, regardless of Pepsi's history of advertising in the Super Bowl. Yet, if brands seek to build complementarities with certain consumption occasions, Coke's Super Bowl advertising, which ran side by side with Pepsi in all but one year, may have been unable to build a long-run Coca-Cola association with the Super Bowl.

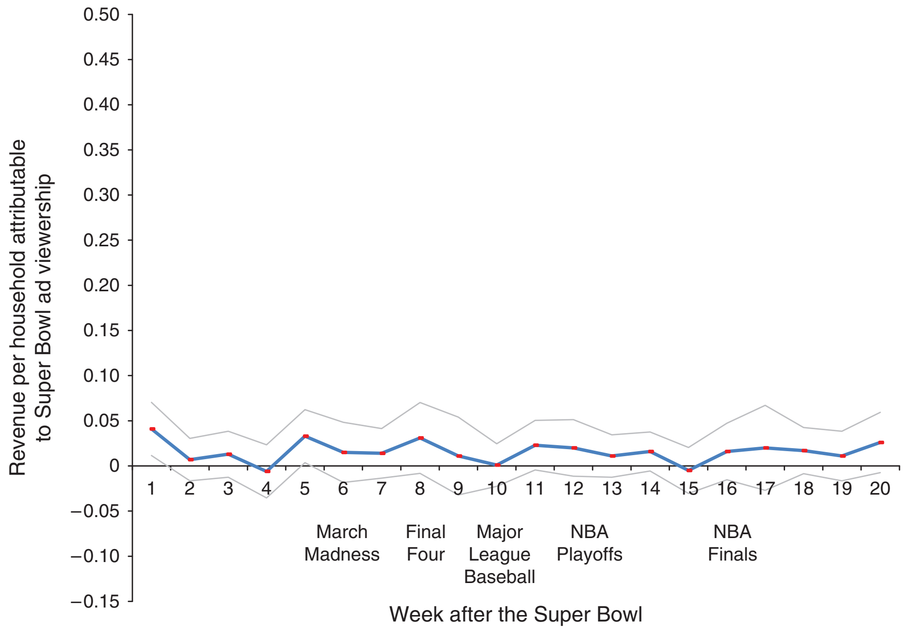
This section has documented complementarity of the brands with the consumption occasion following Yang et al. (2002) and has cast considerable doubt on the advertising as complements theory. Next, we turn to documenting the effects of the Super Bowl ads.

3.2. Super Bowl Advertising Effectiveness

In this section, we evaluate whether the year-to-year variation in within-market viewership of the Super Bowl yields greater sales for advertisers than nonadvertisers in post–Super Bowl weeks. We begin by considering the path of advertising effectiveness across post–Super Bowl weeks. This documents that the Super Bowl advertising effects are concentrated in weeks with subsequent sporting events. To estimate elasticities that account for weeks with and without spikes in effectiveness, we then estimate regressions that pool across multiple post–Super Bowl weeks.

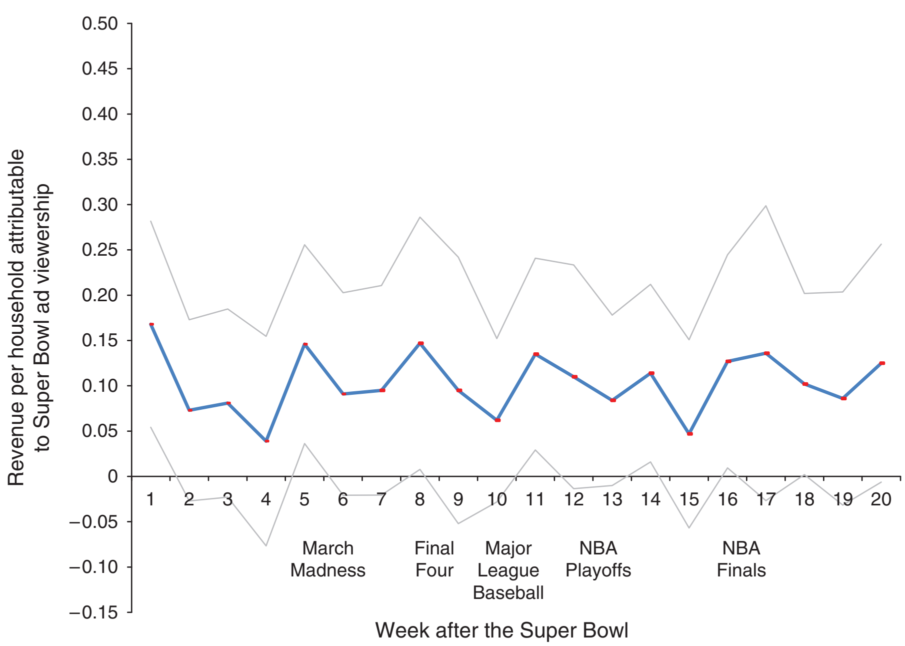
3.2.1. Post–Super Bowl Weekly Advertising Effects. To avoid arbitrarily defining the window of Super Bowl advertising effectiveness, we estimate the effect separately for each of the first 20 weeks following the Super

Figure 3. (Color online) Super Bowl Advertising Effect on Volume by Week After the Super Bowl: Budweiser



Bowl. The weekly regression for our analysis mirrors column (5) from Table 2, except that $w > 0$. Figure 3 plots the coefficient α_1 (*Ratings* × *Bud*) from each week-specific estimation of Equation (1) to show the differential effect of Super Bowl viewership on advertisers' versus nonadvertisers' sales volume per household. The estimate of α_1 begins positive in week 1 and converges to zero by week 4. However, the effect increases to be statistically significant in week 5. The coefficient remains positive yet insignificant until week 10, after which it bumps up again. To reflect whether these volume increases also imply improved returns, Figure 4 changes the dependent variable to revenue per household, and we see significant effects occurring in weeks 5, 8, 11, 14, and 16. These effects are quite large within the week they occur in that the α_1 coefficients for volume and revenue in week 5 of 0.03 and 0.15 indicate that a 10-point increase in ratings would increase volume and revenue by about 3.9% and 4.7%, respectively.

Figure 4. (Color online) Super Bowl Advertising Effect on Revenue by Week After the Super Bowl: Budweiser



In seeking to understand why these advertising effects would show a resurgence in these particular weeks, we found they coincide with subsequent sporting events. We discuss these events in more detail after documenting similar patterns in the soda category.

We address the average effectiveness, elasticities, and a full set of estimates and alternative specifications in Section 3.2.2.

Next, we consider the weekly effectiveness of the Super Bowl ads for the soda category. In soda, we restrict the analysis to Coke and Pepsi as they are most similar and are both observed in and out of the Super Bowl. To allow the effects to vary by whether a competitor is also advertising during the same game, we include an additional interaction we denote as α_2 in the following expanded estimation equation, and as *Ratings* × *Ad* × *Ad* in the tables that follow. The estimating equation for advertising effects in the soda category is therefore

$$Y_{jmyw} = \alpha_1 A_{jy} R_{my} + \alpha_2 A_{jy} A_{ky} R_{my} + \delta R_{my} + X_{jmyw}\beta + \gamma_{\text{FE}} + \xi_{jmy}, \tag{2}$$

where A_{ky} is an indicator for whether a competitor ran a Super Bowl ad that year. The term A_{ky} does not enter separately because there is no year in which no competitor offered an ad, so the effect of just a competitor advertising is reflected in δ. Figure 5 plots α_1 to document the pattern of Super Bowl advertising effectiveness in the soda category over the post–Super Bowl weeks. The effect is significantly positive in week 2, then declines until a resurgence in weeks 6, 8, 11, and 16, with weeks 8 and 11 being statistically significant. Rerunning the analysis with revenue as the dependent variable in Figure 6, weeks 2, 6, 8, 11, 12, and 16 show statistically significant positive effects of Super Bowl ad viewership.

In soda there is clearly a large spike in effectiveness in week 8, which corresponds with both the NCAA Final Four and the opening week of the Major League Baseball season. The confidence intervals indicate that this is significantly greater than the advertising effect in the preceding weeks. Other spikes in weeks 6, 11, and 16 correspond with the beginning of the NCAA basketball tournament, the NBA Playoffs, and the NBA Finals.

We note that we did not hypothesize this timing and resurgence of effects, but we do use these suggestive patterns to formally test the relevance of Super Bowl ads for consumption during sports in Section 3.3.

3.2.2. Average Effect of Super Bowl Ads. Before moving on to explicit tests of the effectiveness arising from the Super Bowl building an association with sports viewership more broadly, we pool these weekly observations into regressions that allow us to test for average effectiveness, estimate proper elasticities, and show the full set of estimates from a variety of specifications. We focus on a two-month (eight-week) window because this time frame provides robustness across nearly all specifications we have tried,[11] and this summarizes the average effects up to the highest peak of advertising effectiveness in each category.

Figure 5. (Color online) Super Bowl Advertising Effect on Volume by Week After the Super Bowl: Coke and Pepsi Advertising Alone

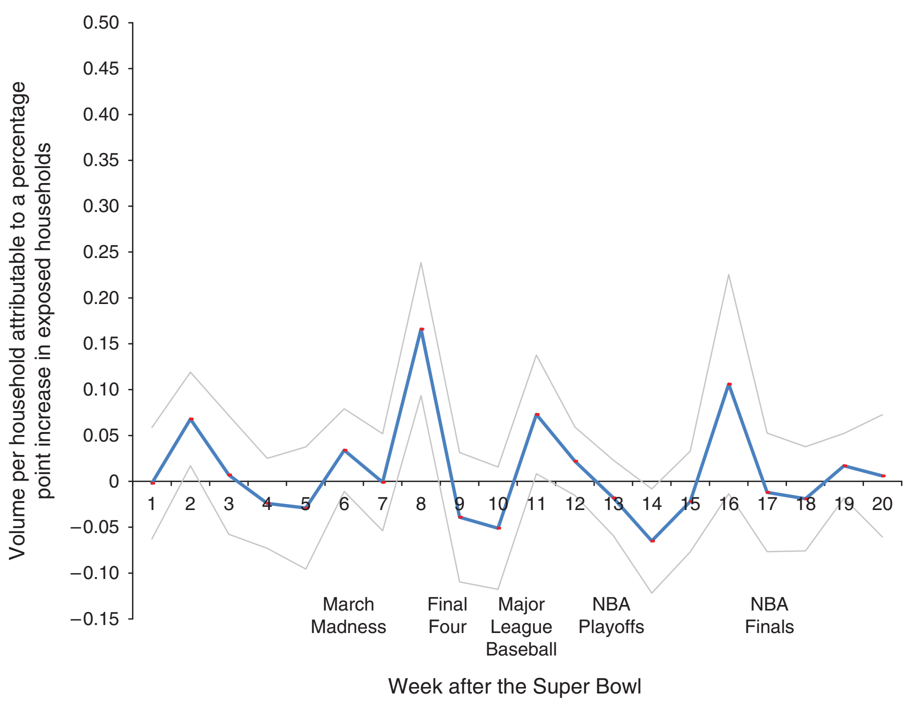
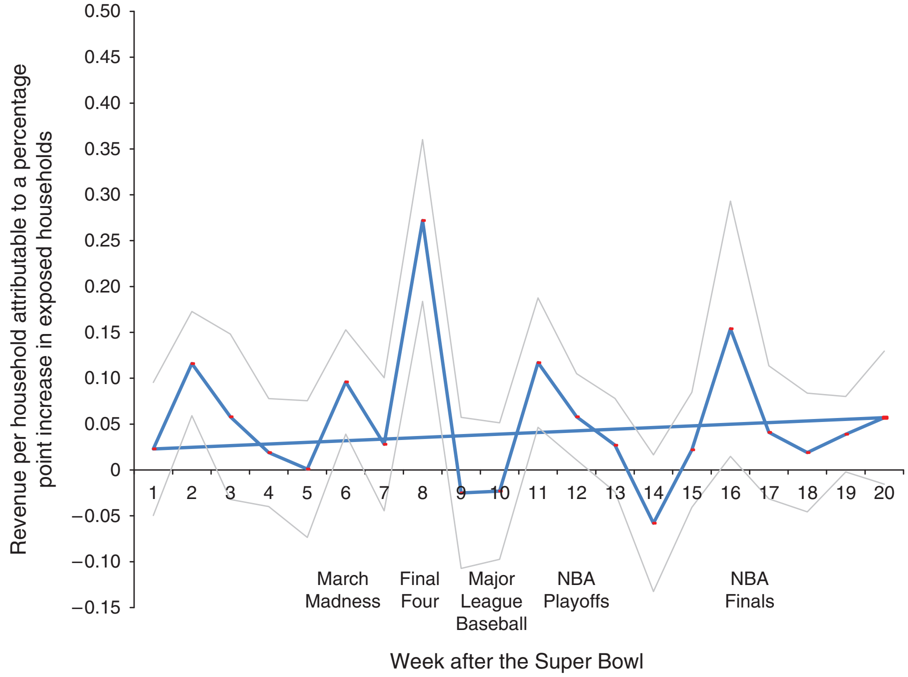


Figure 6. (Color online) Super Bowl Advertising Effect on Revenue by Week After the Super Bowl: Coke and Pepsi Advertising Alone



In this analysis, we separately enter each week into the regressions, rather than aggregating the weekly data. This allows the effects of weekly marketing variables to exhibit their contemporaneous relationships with outcomes. We begin by separately considering advertising and nonadvertising brands. Then, we combine them in a regression to establish statistical significance of the differential performance of the advertising brands relative to nonadvertisers. These latter regressions represent the average effect of the weekly regressions plotted in Figures 3–6.

The first specification in Table 4 considers only Budweiser observations and evaluates how their weekly volume per household varies with ratings for the Super Bowl. The 0.018 $Ratings \times Ad$ coefficient indicates that Budweiser receives a volume increase of nearly two six-packs per thousand households for every 10-point increase in Super Bowl ratings (i.e., ratings are measured as the fraction of the population who watched the game). In column (2) we add covariates and find this effect to increase to 0.026 with a p-value of 0.05. The fit of the regression increases with the inclusion of significant predictors such as price and feature. Note that we cannot interpret the coefficients on the marketing variables causally because we do not have exogenous variation in these. Nevertheless, they make clear that the primary marketing variables of the firm are not exhibiting an endogenous response to the Super Bowl ad viewership that is driving the estimates. Specifications (3) and (4) replicate the preceding regressions for all non-Budweiser brands. There is no evidence of a significant increase or decrease in these brands' performance that can be attributed to Super Bowl viewership. Specifications (5) and (6) pool all brands together to illustrate this significant difference for the advertising brand, Budweiser, relative to competitors. Specification (5) is roughly the average effect over the first 8 weeks plotted in Figure 3. These effects in columns (5) and (6) imply an advertising elasticity of about 0.1.

Table 5 replicates this analysis using revenue per household as the dependent variable. The same pattern of effects holds through these regressions, with p-values of 0.076 and 0.052 in columns (1) and (2) and p-values less than 0.015 when testing the difference between Bud and others in columns (5) and (6). The revenue coefficients near 0.1 indicate that a 10-point ratings increase earns Budweiser an average of an extra penny per household per week over the first two months following the game. Our focus is not to derive a return on investment, but to provide some perspective, one could multiply that by 124 million U.S. households and average ratings of 45 to project a revenue increase of just under USD$45 million. That is, however, an underestimate, because we do not observe Budweiser sales at bars or some large missing stores such as Walmart, but normalize by all households in the market. Comparing that with a cost of roughly $3 million per ad during our data and as many as nine ads in a year, it is clear Budweiser should find this advertising profitable.

Table 4. Effects of Super Bowl Viewership and Advertising on Beer Volume

	8 weeks post–Super Bowl included					
Variables	(1) Bud only	(2) Bud only	(3) Non-Bud	(4) Non-Bud	(5) All brands	(6) All brands
Ratings			−0.000	0.001	−0.000	0.001
			(0.006)	(0.006)	(0.006)	(0.006)
Ratings × Ad	0.018	0.026			0.019*	0.019*
	(0.012)	(0.013)			(0.009)	(0.009)
Marketing						
GRPs		0.030		−0.008		−0.009
		(0.020)		(0.010)		(0.011)
NFL GRPs		0.001		−0.004		0.000
		(0.005)		(0.004)		(0.004)
Price		−2.927**		−0.353**		−0.627**
		(0.501)		(0.043)		(0.087)
Price × Other				−0.849**		−0.624**
				(0.221)		(0.215)
Feature		0.040**		0.002		0.005*
		(0.012)		(0.001)		(0.002)
Display		−0.015		0.007		0.005
		(0.015)		(0.004)		(0.005)
Observations	7,104	7,104	28,411	28,411	35,515	35,515
R-squared	0.222	0.361	0.155	0.225	0.164	0.219
Number of brand-DMAs	173	173	692	692	865	865

Notes. Fixed effects are included at the brand-market, brand-year, and week levels relative to the Super Bowl. Standard errors are clustered at the market level.
$^{*}p < 0.05$; $^{**}p < 0.01$.

Table 5. Effects of Super Bowl Viewership and Advertising on Beer Revenue

	8 weeks post–Super Bowl included					
Variables	(1) Bud only	(2) Bud only	(3) Non-Bud	(4) Non-Bud	(5) All brands	(6) All brands
Ratings			0.007	0.011	0.007	0.009
			(0.035)	(0.035)	(0.035)	(0.036)
Ratings × Ad	0.112	0.126			0.105*	0.108*
	(0.063)	(0.065)			(0.043)	(0.043)
Marketing						
GRPs		−0.025		−0.075		−0.094*
		(0.080)		(0.043)		(0.046)
NFL GRPs		0.017		−0.032		−0.001
		(0.021)		(0.021)		(0.017)
Price		−6.296**		−1.026**		−1.579**
		(1.464)		(0.156)		(0.274)
Price × Other				−0.744		−0.353
				(0.912)		(0.866)
Feature		0.164**		0.011		0.025**
		(0.043)		(0.006)		(0.009)
Display		−0.066		0.021		0.014
		(0.065)		(0.013)		(0.019)
Observations	7,104	7,104	28,411	28,411	35,515	35,515
R-squared	0.353	0.401	0.326	0.342	0.325	0.341
Number of brand-DMAs	173	173	692	692	865	865

Notes. Fixed effects are included at the brand-market, brand-year, and week levels relative to the Super Bowl. Standard errors are clustered at the market level.
$^{*}p < 0.05$; $^{**}p < 0.01$.

Table 6. Effects of Super Bowl Viewership and Advertising on Soda Volume

	8 weeks post–Super Bowl included					
Variables	(1) Coke/Pepsi	(2) Coke/Pepsi	(3) Not Coke/Pepsi	(4) Not Coke/Pepsi	(5) All brands	(6) All brands
Ratings	−0.017	−0.023	−0.012	−0.001	−0.014	−0.005
	(0.024)	(0.023)	(0.016)	(0.016)	(0.018)	(0.017)
Ratings × Ad	0.027**	0.037**	0.004	−0.002	0.016**	0.014**
	(0.010)	(0.008)	(0.003)	(0.003)	(0.005)	(0.004)
Ratings × Ad × Ad	−0.023*	−0.035**			−0.017*	−0.019**
	(0.009)	(0.008)			(0.008)	(0.007)
Marketing						
GRPs		−0.101*		−0.045		−0.155**
		(0.047)		(0.062)		(0.044)
NFL GRPs		−0.170		0.052		−0.050
		(0.135)		(0.035)		(0.074)
Price		−14.109**		−4.430**		−8.426**
		(0.854)		(0.350)		(0.551)
Price × Other				−1.823		2.252*
				(1.114)		(1.069)
Feature		0.082**		0.077**		0.123**
		(0.025)		(0.015)		(0.021)
Display		−0.030		0.012		−0.027
		(0.026)		(0.012)		(0.018)
Observations	16,032	16,032	24,048	24,048	40,080	40,080
R-squared	0.076	0.379	0.082	0.230	0.071	0.281
Number of brand-DMAs	390	390	585	585	975	975

Notes. Fixed effects are included at the brand-market, brand-year, and week levels relative to the Super Bowl. Standard errors are clustered at the market level.
$^{*}p < 0.05$; $^{**}p < 0.01$.

Next, we report the average effects for the soda category in Table 6. The first specification similarly considers only the major Super Bowl advertising brands: Coke and Pepsi. The *Ratings × Ad* coefficient of 0.027 represents a statistically significant increase in advertisers' sales of 2.7 six-packs per thousand households for each 10-point increase in ratings. When both brands advertise in the Super Bowl in the same year, that gain almost completely disappears. A nonadvertising competitor realizes an insignificant decrease of 0.017. In specification (2), we add covariates and find slightly larger effects with a similar lost effect in the presence of competition. Specifications (3) and (4) repeat the analysis for brands other than Coke and Pepsi. In this case, the advertising brand is Dr Pepper in 2010, who realizes an insignificant increase in volume per household of 0.004. Nonadvertising brands realize insignificant decreases in volume per household comparable to Coke or Pepsi when they do not advertise. Specifications (5) and (6) pool all brands together, resulting in an advertising effect between that found for Coke and Pepsi and that found for the smaller Dr Pepper. The competitive effect is present in these specifications as well. The advertising elasticity implied by Coke or Pepsi advertising alone in the Super Bowl is between 0.03 and 0.08, depending on whether the effect in specification (6) or (2) is used.

Table 7 replicates this analysis using revenue per household as the dependent variable. The same pattern of effectiveness holds with advertising GRPs, price, and feature being the marketing variables showing a statistically significant relationship. The relationship for GRPs is negative, but since we do not have causal variation in the GRPs, this may reflect that ads were more likely to be broadcast or viewed where soda brands had trouble generating sales. This highlights the importance of exogenous variation for measuring advertising effects, such as our focus on Super Bowl advertising. The primary difference in the revenue analyses relative to volume is that only about half the gain from advertising during a Super Bowl is lost when both Coke and Pepsi advertise in the same game.

Both the volume and revenue regressions show that advertising in the Super Bowl can be profitable, but that there are substantial competitive effects. These highly competitive advertising effects are consistent with our suggestion that brands use advertising to compete for associations with particular consumption occasions. If both brands advertise head-to-head, it would seem challenging for either brand to make progress in "owning" the relevant associations.

Table 7. Effects of Super Bowl Viewership and Advertising on Soda Revenue

	8 weeks post–Super Bowl included					
Variables	(1) Coke/Pepsi	(2) Coke/Pepsi	(3) Not Coke/Pepsi	(4) Not Coke/Pepsi	(5) All brands	(6) All brands
Ratings	−0.059	−0.064	−0.051	−0.044	−0.054	−0.046
	(0.037)	(0.038)	(0.038)	(0.039)	(0.036)	(0.036)
Ratings × Ad	0.077**	0.087**	0.012*	0.007	0.047**	0.044**
	(0.013)	(0.014)	(0.006)	(0.006)	(0.008)	(0.007)
Ratings × Ad × Ad	−0.036*	−0.053**			−0.020	−0.025*
	(0.015)	(0.012)			(0.013)	(0.011)
Marketing						
GRPs		0.034		−0.493**		−0.177**
		(0.068)		(0.119)		(0.060)
NFL GRPs		−0.368		0.077		−0.125
		(0.214)		(0.068)		(0.114)
Price		−14.505**		−4.310**		−8.523**
		(0.925)		(0.374)		(0.577)
Price × Other				0.423		4.711**
				(1.501)		(1.502)
Feature		0.140**		0.099**		0.170**
		(0.033)		(0.020)		(0.028)
Display		−0.041		0.021		−0.027
		(0.035)		(0.015)		(0.022)
Observations	16,032	16,032	24,048	24,048	40,080	40,080
R-squared	0.093	0.315	0.390	0.437	0.215	0.335
Number of brand-DMAs	390	390	585	585	975	975

Notes. Fixed effects are included at the brand-market, brand-year, and week levels relative to the Super Bowl. Standard errors are clustered at the market level.

$^{*}p < 0.05$; $^{**}p < 0.01$.

3.3. Advertising and the Complementarity Between Brands and Sports

Section 3.1 rejects the Becker and Murphy (1993) theory that advertising itself is a complement in the case of Super Bowl advertising, but here we ask whether advertising builds complementarity between the brand and sports viewership more broadly. We developed this hypotheses based on the temporal patterns observed in Section 3.2 and test it by collecting subsequent sports viewership data.

Specifically, we collected data on viewership of the NCAA basketball tournament, which can span across weeks 4 through 10, depending on the year. We chose to focus on the NCAA tournament for two reasons. First, it occurs the soonest after the game, such that the effects have the potential to be the greatest. Second, NCAA broadcasts are aired during network television such that the viewership is measurable in the Nielsen ratings data. Major League Baseball, for example, would have been difficult to analyze because teams primarily air their games on local/regional cable networks where ratings data are unavailable to us.

To include the effects of NCAA viewership in our model, we run regressions that pool weekly observations as in Section 3.2 but use the entire time span of our data. The empirical specification is extended to include the NCAA viewership variable by itself, then interacted with the major brands in the category, and finally interacted with all of the Super Bowl ratings related coefficients from above. To be clear, the hypothesis is that if Super Bowl advertising builds a complementarity between the brand and sports viewership more broadly, the interaction *NCAA × Ratings × Ad* should be positive.

Our estimates are reported in Table 8. We begin in specification (1) with the beer category and a replication of the analysis from Section 3.2 with the entire 20 week time span of our data. Specification (2) adds covariates, and we find the *Ratings × Ad* coefficient to still be significant. Specification (3) introduces the NCAA viewership data, with the interaction of *Ratings × Ad* with NCAA viewership in the fifth row. It is positive and statistically significant, indicating support for the viewership of Super Bowl advertising building a complementarity between the brand and sports viewership. Column (4) adds covariates in, and the results are unchanged. Columns (5) to (7) repeat this analysis for Coke and Pepsi observations. Similarly, we see that the *NCAA × Ratings × Ad* coefficient is significantly positive. In line with the competitive effects documented above, the *NCAA × Ratings × Ad × Ad* coefficient shows this relationship disappears when both competitors advertise in the Super Bowl. We replicate this analysis

Table 8. Testing Super Bowl Ad Viewership Interaction with NCAA Viewership on Volume

	20 weeks post–Super Bowl included							
Variables	(1) Beer	(2) Beer	(3) Beer	(4) Beer	(5) Coke/Pepsi	(6) Coke/Pepsi	(7) Coke/Pepsi	(8) Coke/Pepsi
Ratings	−0.001	−0.001	−0.000	0.001	−0.031	−0.029	−0.026	−0.031
	(0.006)	(0.007)	(0.006)	(0.007)	(0.026)	(0.029)	(0.027)	(0.030)
Ratings × *Ad*	0.016	0.017	0.015	0.016	0.011	0.016*	−0.004	0.008
	(0.009)	(0.009)	(0.009)	(0.009)	(0.007)	(0.007)	(0.008)	(0.008)
Ratings × *Ad* × *Ad*					−0.004	−0.006	0.007	−0.000
					(0.009)	(0.000)	(0.000)	(0.000)
NCAA × *Ratings*			−0.086**	−0.088**			−0.252**	−0.013
			(0.022)	(0.022)			(0.109)	(0.069)
NCAA × *Ratings* × *Ad*			0.121**	0.118**			0.579**	0.309**
			(0.022)	(0.022)			(0.109)	(0.080)
NCAA × *Ratings* × *Ad* × *Ad*							−0.406**	−0.257**
							(0.076)	(0.057)
NCAA			0.041**	0.044**			0.220**	0.110**
			(0.008)	(0.008)			(0.027)	(0.026)
NCAA × *Bud*			−0.077**	−0.076**				
			(0.009)	(0.009)				
NCAA × *Pepsi*							−0.171**	−0.078**
							(0.024)	(0.020)
Marketing								
GRPs		−0.102**		−0.088**		0.113*		0.034
		(0.028)		(0.028)		(0.053)		(0.055)
NFL GRPs		0.003		0.002		−0.104		−0.100
		(0.004)		(0.004)		(0.137)		(0.137)
Price		−0.710**		−0.715**		−14.710**		−14.670**
		(0.091)		(0.091)		(0.915)		(0.914)
Price × *Other*		−0.382*		−0.372*				
		(0.182)		(0.183)				
Feature		0.008**		0.008**		0.095**		0.095**
		(0.003)		(0.003)		(0.025)		(0.025)
Display		0.004		0.004		0.001		0.001
		(0.005)		(0.005)		(0.033)		(0.033)
Observations	88,795	88,795	88,795	88,795	40,080	40,080	40,080	40,080
R-squared	0.251	0.285	0.255	0.288	0.107	0.398	0.111	0.399
Number of brand-DMAs	865	865	865	865	390	390	390	390

Notes. Fixed effects are included at the brand-market, brand-year, and week levels relative to the Super Bowl. Standard errors are clustered at the market level.
$^{*}p < 0.05$; $^{**}p < 0.01$.

using revenue as the dependent variable in Table 9 and find a similar pattern of results.

To summarize these findings, Super Bowl advertising increases a brand's ability to capture sales when consumer's make purchases for consumption during subsequent sporting events.

3.4. Discussion and Caveats

There are some selection possibilities that deserve discussion. We conduct our analysis using variation in ratings alone, conditional on a Super Bowl ad being aired. The deviations in the two soda brands' typical advertising decisions are not likely candidates for a selection bias. Coca-Cola did not advertise in the first year in our data (2006), but advertised in all subsequent years. As they had not advertised since 1998, it does not appear that they cherry-picked the year in our data in which they did not advertise. Furthermore, the brand-year fixed effect would pick up any common demand shock to Coca-Cola in 2006 that might have led them to not advertise. The fixed effects therefore force selection concerns to imply that a brand chose to advertise or not based on its expectations of the cross-market distribution of Super Bowl viewership relative to that occurring in other years. Suppose the brand has little potential to convert customers in politically left-leaning "blue" states; then, it might withdraw from the Super Bowl in a year when the competing teams will be from San Francisco and New York. This clearly cannot describe Coca-Cola's extended absence pre-2007 and persistence in the game ever since. Pepsi, on the other hand, has been absent in only one year, 2010. There is, however, a lot of information about this exit.

Table 9. Testing Super Bowl Ad Viewership Interaction with NCAA Viewership on Revenue

	20 weeks post–Super Bowl included							
Variables	(1) Beer	(2) Beer	(3) Beer	(4) Beer	(5) Coke/Pepsi	(6) Coke/Pepsi	(7) Coke/Pepsi	(8) Coke/Pepsi
Ratings	0.003	0.003	0.008	0.008	−0.071	−0.070	−0.071	−0.075
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.041)	(0.039)	(0.042)
Ratings × Ad	0.103*	0.109*	0.099*	0.104*	0.052**	0.059**	0.034**	0.049**
	(0.044)	(0.045)	(0.044)	(0.045)	(0.009)	(0.011)	(0.009)	(0.011)
Ratings × Ad × Ad					−0.005	−0.015	0.012	−0.003
					(0.014)	(0.010)	(0.014)	(0.010)
NCAA × Ratings			−0.393**	−0.400**			−0.167	0.091
			(0.085)	(0.085)			(0.102)	(0.086)
NCAA × Ratings × Ad			0.438**	0.431**			0.712**	0.420**
			(0.086)	(0.086)			(0.135)	(0.110)
NCAA × Ratings × Ad × Ad							−0.662**	−0.499**
							(0.106)	(0.091)
NCAA			0.184**	0.193**			0.295**	0.171**
			(0.036)	(0.036)			(0.036)	(0.037)
NCAA × Bud			−0.282**	−0.277**				
			(0.036)	(0.035)				
NCAA × Pepsi							−0.214**	−0.108**
							(0.032)	(0.027)
Marketing								
GRPs		−0.363**		−0.318**		0.196**		0.086
		(0.120)		(0.117)		(0.069)		(0.072)
NFL GRPs		0.006		0.005		−0.328		−0.321
		(0.018)		(0.018)		(0.210)		(0.210)
Price		−1.855**		−1.873**		−15.739**		−15.682**
		(0.314)		(0.313)		(0.974)		(0.972)
Price × Other		0.701		0.738				
		(0.827)		(0.829)				
Feature		0.035**		0.035**		0.140**		0.141**
		(0.010)		(0.010)		(0.032)		(0.032)
Display		0.011		0.011		0.005		0.005
		(0.018)		(0.018)		(0.041)		(0.041)
Observations	88,795	88,795	88,795	88,795	40,080	40,080	40,080	40,080
R-squared	0.352	0.364	0.355	0.367	0.095	0.318	0.100	0.320
Number of brand-DMAs	865	865	865	865	390	390	390	390

Notes. Fixed effects are included at the brand-market, brand-year, and week levels relative to the Super Bowl. Standard errors are clustered at the market level.
$^{*}p < 0.05$; $^{**}p < 0.01$.

Pepsi decided to shift both its Super Bowl budget and a significant portion of the rest of its marketing budget to fund a social media campaign (the Pepsi Refresh campaign) that gave grants to proposals to help local communities, the environment, etc. A Harvard Business School case and the news articles it cites nicely describe this decision as about shifting emphasis to social causes and not about a poor Super Bowl opportunity. In fact, they announced the decision before the end of the NFL's regular season.[12] It is therefore highly unlikely that this was driven by an accurate expectation of which of the NFL teams would eventually make it to the Super Bowl. Pepsi did return the following year when the Pepsi Refresh campaign failed to live up to Pepsi's expectations.

It is possible that advertisers could alter other factors about their advertising in response to the anticipated distribution of Super Bowl viewership. They could change the creative execution of the ad, but the expense of developing creative for Super Bowls suggests this is unlikely in the weeks just before the game. They could also alter the number of spots aired during the game. We can observe this and have run specifications with this included, but prefer to focus our analysis around the ratings data whose variation is exogenous. The brands could also alter the particular products they choose to advertise in the game. Pepsi occasionally advertises Diet Pepsi or Pepsi Max, and Anheuser-Busch has used some of its many spots in a year to include other brands such as Michelob or Stella Artois. These could have also been chosen strategically based on the anticipated distribution of viewership. While we cannot rule out these selection decisions, we are skeptical they exist. They may bias upward the estimates of the Super Bowl ad effect in beer, but its unlikely they account for a majority of it. In soda, it is hard to imagine that such selection decisions would be driving the link between Super Bowl viewership and sales in the particular weeks exhibiting spikes in Figure 6, and that these timed spikes would only occur in years the soda brand is advertising.

It may also be argued that the post–Super Bowl performance of advertisers in high-viewership markets reflects a lasting effect from their greater consumption during the game. Such an effect could be rationalized by habit persistence or switching costs, but (i) such behavior is known to be difficult to identify in aggregate data, (ii) the above effects are much greater than others have found for packaged goods (see Dubé et al. 2010), and (iii) it is also inconsistent with some of the greatest effects occurring five or eight weeks later. Furthermore, we observe nonadvertising beer brands realizing Super Bowl consumption during the game, but not post–Super Bowl sales effects of Super Bowl viewership.

Finally, there might be some concern about measurement error in the market-level ratings data. This does not, however, seem to be a problem, as we are finding large effects. We could have used the Facebook likings of the competing teams as an instrument to remove such errors, but the first-stage incremental fit is too small and greatly increases standard errors (for a discussion of the problems with using weak instruments when there is little endogeneity concern, see Rossi 2014). We also tested for measurement error by allowing coefficients to be interacted with the number of households in the market. Smaller markets in the data should exhibit more measurement error as there are fewer local Nielsen panelists to form the share of household viewership numbers. We did not, however, find this to affect the results.

4. Conclusion

Advertising is one of the most important instruments a brand can use to market its products, yet advertising's efficacy and the mechanisms behind it are highly disputed. The benefits for a new product are clear, as consumers might otherwise be unaware of its existence and features. For established brands, the incentive to spend on uninformative advertising such as that observed in the Super Bowl has been questioned. Using exogenous variation in the viewership of the Super Bowl, we document that established brands can realize substantial advertising effects with elasticities on the order of 0.03 to 0.1.

The pattern of Super Bowl advertising effectiveness over time also uncovers the source of effectiveness and competitive implications. Advertising can build or reinforce a complementarity between a brand and potential consumption occasions. Consumption of beer, snacks, and other items while watching sports is easily observed in society. Previous work suggests this arises from the desire to consume a brand while watching its ad. We document that both advertising and nonadvertising brands realize this complementarity, and that some advertising brands never do. Rather, our results provide what we believe is the first evidence illustrating that advertising plays a role in the complementarity between sports viewership and consumption and that it can link the complementarity to a particular brand. Competition for such a strong branding association in the soda category is, however, shown to be dissipative, which can rationalize Budweiser's procurement of exclusivity in Super Bowl advertising.

Finally, we uncovered the above advertising effects and patterns by exploiting data variation in the Super Bowl context that may have parallels more broadly. The key to our identification is that within-market variation in exposures to a national broadcast represents valuable exogenous variation. The national broadcast prevents market-specific targeting of the advertising and thereby eliminates a primary source of endogeneity. One might imagine applying our strategy to a cross section, but the distribution of viewership could be cross-sectionally associated with the distribution of consumption (e.g., markets that watch a lot of football also consume a lot of beer). By analyzing within-market, cross-time variation, such correlations are removed. Interestingly, such a correlation can safely be the source of the advertising decision as long as the advertising decision covers multiple time periods or is invariant across time, as we see for Budweiser and most years of Coke's and Pepsi's strategies. This logic suggests other applications such as the common purchase of national advertising in "upfronts" months before an event or television program's "season" begins. Week-to-week variation in viewership of Monday Night Football or even dramas could be reasonably exogenous as long as there is not spurious correlation between the weekly viewership and consumption or purchase on subsequent days. The challenge in these settings is to address the reach and frequency dynamics that likely persist across weeks, yet that we could safely ignore across the 12 months between Super Bowls. This, and the challenges of integrating other advertising, therefore represents some of the work still needed to fully incorporate these insights into the marketing mix models measurement firms estimate.

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Endnotes

[1] Competition for spots in 2010 led 80% of capacity to be sold out eight months in advance (Crupi 2012).

[2] Ackerberg (2001) and others document informative advertising effects arising for new products.

[3] Nielsen actually releases data for the top 55 DMAs, but because of entry and exit from the top 55, we have 56.

[4] A previous version of this paper was circulated using the IRI Marketing data set described by Bronnenberg et al. (2008). We switched to the Nielsen data because of an exact match in the definition of the geographic region and the ability to increase the number of DMAs in our analysis from roughly 33 to 56. The Nielsen data also allow us to include the smaller DMAs where statistical power is stretched.

[5] We ran our analysis also coding this as an advertisement, and while the coefficients changed some, the substantive conclusion remained the same.

[6] We focus our descriptives of the ratings data on the top 56 markets because the ratings data for smaller DMAs include a correctable measurement error described to us by the data provider. Specifically, reported ratings for smaller markets represent an average across four weeks of viewership during the particular time slot. This lowers the reported ratings as all other airings during the time slot experience less viewership than the Super Bowl. Nevertheless, the Super Bowl's size represents the majority of variation in this measure and thus enables us to capture the Super Bowl effect. We are able to correct for the measurement error because we know the true variance of the Super Bowl ratings from the larger markets and therefore the error induced by this data collection aspect. These corrections are detailed in the code, and we also include a simple proof of concept program illustrating that our approach recovers the appropriate parameters.

[7] While a better measure would include how many local people liked the teams before the respective Super Bowl, we are unaware of a historical source of such information that can date back to 2006.

[8] To avoid overweighting large markets in selecting the top brands, we first ranked brands within market and week and then selected those whose modal ranks were highest.

[9] The number of households is calculated and held fixed over time based on the median value reported by Nielsen for the DMA across all six years.

[10] We allow the price coefficient to be different for the aggregation of all non–top four brands via the *Price* × *Other Brands* interactions because variation in this price also reflects variation in the relative volume of brands sold within the week.

[11] Some results are significant for both shorter and longer windows. These are available on request.

[12] A *Wall Street Journal* article titled "Pepsi Benches its Drinks" detailed the move on December 17, 2009, which is three weeks before the end of the regular season (Vranica 2009).

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