Effects of Advertising and Product Placement on Television Audiences

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Abstract: Digital video recorder proliferation and new commercial audience metrics are making television networks' revenues more sensitive to audience losses from advertising. There is currently limited understanding of how traditional advertising and product placement affect television audiences. We estimate a random coefficients logit model of viewing demand for television programs, wherein time given to traditional advertising and product placement plays a role akin to the "price" of consuming a program. Our data include audience, advertising, and program characteristics from more than 10,000 network-hours of prime-time broadcast television from 2004 to 2007. We find that the median effect of a 10% rise in traditional advertising time is a 15% reduction in audience size. We find evidence that creative strategy and product category factors are important determinants of viewer response to traditional advertising. When we control for program episode quality, we find that product placement time decreases viewer utility. In sum, our results imply that networks should give price discounts to those advertisers whose ads are most likely to retain viewers' interest throughout the commercial break.

Keywords: Advertising, Advertisement Avoidance, Branded Entertainment, Choice Modeling, Endogeneity, Industrial Organization, Media, Product Placement, Television

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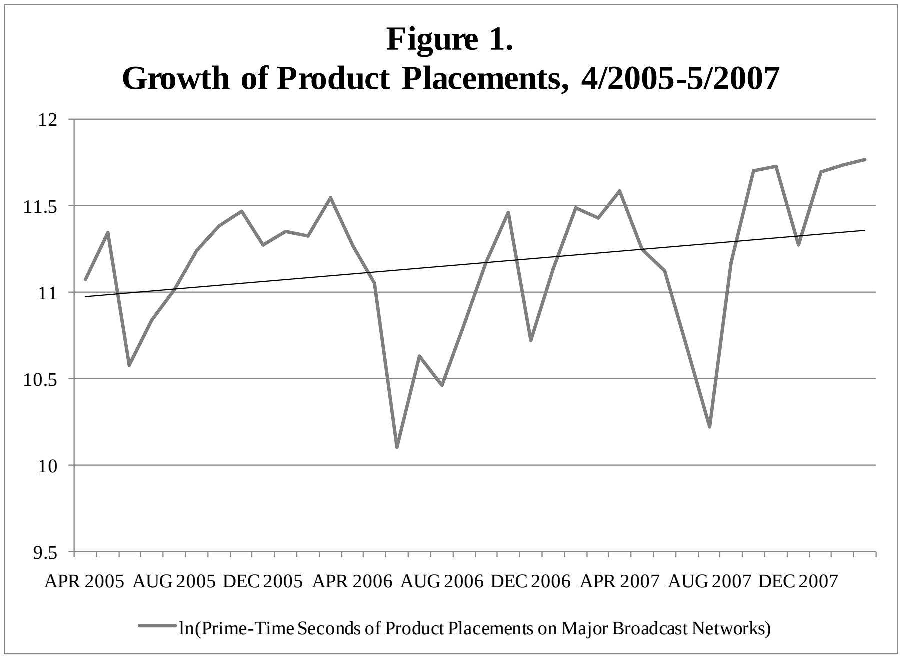
Television viewing is the dominant leisure activity in America. In a telephone survey Americans reported watching 2.6 hours of television per day, more than half of total leisure time.[1] Other measures suggest time spent viewing is even higher. Nielsen Media Research estimates the average adult watches 4.9 hours of television per day.[2]

Television is the most important medium for advertisers. In 2007 the television industry earned $67.8 billion in advertising revenues. Those revenues grew 35% from 2001 to 2007, and accounted for 48% of cumulative advertising expenditures. While some other advertising media (e.g., internet display advertising) grow at higher percentage rates due to smaller revenue bases, television advertising grew more than any other medium from 2001 to 2007.[3]

Traditionally, broadcast television networks have provided viewers with nominally free programs in exchange for their attention and sold that attention to advertisers based on program audience measurements. The structure of the industry suggests that viewers have a relative preference for programs or non-television activities over watching advertising. If this were not the case, networks would presumably refrain from producing such costly programming.

The traditional television business model has been weakened by two recent trends. First, viewers are acquiring digital video recorders (DVRs), which enable them to easily fast-forward past advertisements in recorded and “near-live” programming. The DVR was introduced in 2000, and 23% of American households owned one as of April 2008.[2] Figure 1 shows that broadcast networks have responded to DVR growth in part by increasing product placements (“unskippable advertising”) in their shows by about 40% in the three years to March 2008. Second, improvements in audience tracking technologies have changed business practices. Digital cable boxes and DVRs allow continuous tracking of channel tuning, leading advertisers to demand increasingly granular data about how many viewers watched a particular ad, rather than the program during which the ad appeared. Since September 2007, ad deals have been based on programs’ average commercial minute rating,[4] rather than program rating. Many analysts expect more granular advertisement ratings to be used in the future.

[1] Source: Bureau of Labor Statistics, “American Time Use Survey,” 2006.
[2] Source: Data reported online at *www.tvb.org*. Accessed May 2008.
[3] Source: TNS Media Intelligence custom report. In 2007 advertisers spent $28.0 billion on magazines, $26.2 billion on newspapers, $11.4 billion on internet display advertising, $3.9 billion on outdoor advertising, and $3.4 billion on radio.
[4] A commercial minute is any minute (e.g., 8:12:00 p.m.-8:12:59 p.m.) in which a part of a commercial is aired. The new standard, called “C3,” also includes DVR viewing up to 3 days after the program air date.



Thus viewers are better able to avoid advertisements than ever before. And networks are more likely to be financially penalized for advertisement avoidance than ever before. Our purpose in this paper, then, is to understand the effects of advertising and product placements on television audiences.

This understanding is important in practice for several reasons. First, it can inform networks' sales strategy, influencing which advertisers they seek to sell commercial time to. Second, it can influence networks' pricing. It may be optimal to raise ad prices for advertisers whose ads cause larger audience losses than average, or offer discounts to advertisers whose ads cause smaller audience losses. Third, viewer welfare is directly enhanced if networks can reduce viewer disutility from advertising. And if this reduction raises networks' advertising revenues, there may be an indirect effect on viewer welfare in the form of increased program investments.

We estimate a random coefficients logit model of television viewing demand using data from the television seasons ending in 2005, 2006, and 2007. In this model, the amount of time given to advertising and product placement is the "price" the viewer must pay to consume a program. We find that a 10% increase in advertising time causes a median audience loss of about 15%. When we control for program episode quality, we find that product placement time reduces audience sizes. Audience reaction to individual advertisements is driven by advertising content and product category.

The paper proceeds as follows. In the next section, we discuss salient features of the industry and the recent academic literature. We present a structural model of television viewing behavior in section 2 and discuss the data we use to estimate the model in section 3. In section 4 we describe the estimation procedure. We present the results in section 5 and discuss their implications in section 6.

1. Industry background and relevant Literature

This paper is primarily related to two disparate strands of the literature: advertisement avoidance and television viewing demand.

Several papers document the strategies television viewers use to avoid commercials. Danaher (1995) investigated Nielsen Peoplemeter data in New Zealand and found that audience figures fell by a net 5% during ad breaks, due to a 10% audience loss to switching and a 5% audience gain from viewers leaving other channels. However, the context of the study was a three-channel environment in which simultaneous ad breaks were commonplace. Using Peoplemeter data from the Netherlands, Van Meurs (1998) found that channel switching decreased audience size during advertising breaks by a net 21.5%. Tse and Chan (2001) called viewers at home immediately after commercial breaks ended and found that, of households watching television, 80.8% reported avoiding commercials or diverting their attention in some manner. These finding are buttressed by the large literature on advertising wear-in and wear-out. For example, Siddarth and Chattopadhyay (1998) found the probability that a household switches channels during a particular ad is “J-shaped” with a minimum at 14 exposures.

Other researchers have used eye-tracking technology to measure advertisement avoidance in the lab. Woltman Elpers, et al. (2003) found that subjects stopped watching 59.6% and 76.1% of all commercials in two experiments. They found that commercial watching increases with entertainment content and decreases with information content. Teixeira, Wedel, and Pieters (2008) estimated the effects of commercial characteristics on commercial avoidance. Their findings include an inverted “U”-shaped relationship between advertisement attention and visual complexity, and a positive effect of brand presence and duration on viewer switching. They used the estimates to calculate what pattern of brand appearances minimizes commercial avoidance, finding that, holding on-screen brand time constant, brand pulsing can reduce commercial avoidance substantially.

Advertising avoidance notwithstanding, until September 2007 advertising sales contracts were based on program ratings. Thus, the forms of advertising avoidance that most directly impacted network revenues were switching channels or turning off the television, as these are the two strategies that most likely to decrease a program rating.

Quite separate from advertisement avoidance, there is a large literature on predicting viewer demand for television programs. Rust and Alpert (1984) were the first to use a discrete choice model to explain viewing behavior, demonstrating that contrary to previous findings, programs are important predictors of network audiences. More recently, Shachar and Emerson (2000) introduced cast demographic variables in viewing demand estimation and showed that viewers are more likely to watch programs that feature people who are demographically similar to themselves. Goettler and Shachar (2001) estimated a multidimensional ideal point demand system to calibrate a model of optimal program scheduling, finding that networks' adherence to scheduling "rules of thumb" (e.g. no situation comedies after 10 p.m.) was suboptimal. Anand and Shachar (2005) used data on viewers' exposure to television program "tune-ins" and subsequent viewing choices to identify tune-in effectiveness. They found that tune-ins are informative in nature: they make viewers more likely to watch programs that confer high subjective utility, and more likely to avoid programs that confer low subjective utility. Yang, Narayan, and Assael (2006) estimate a model in which husbands and wives have joint latent viewing preferences, finding that wives' viewing behavior depends more strongly on husbands' viewing status than vice versa.

A few studies have measured audience sensitivity to advertising levels, controlling for characteristics of media content. Wilbur (2008b) estimated indirect network effects on both sides of the television industry, finding that a highly-rated broadcast network lost about 25% of its audience in response to a 10% increase in advertising time. Kaiser and Wright (2006) estimated a two-sided equilibrium model of viewers and advertisers of women's magazines, finding that ads increased reader utility of magazines. Depken and Wilson (2004) estimated magazine-specific audience responses to advertising and found substantial heterogeneity across magazines, including many positive and many negative significant effects. The process by which advertising leads to increased or decreased viewership/readership has not been fully explored, but could depend on consumer demographics and heterogeneity, media content and usage, and advertising content, targeting, and intrusiveness. Goeree (2008) found that advertising exposure and impact varies across demographic groups and advertising media, so it seems reasonable to expect that advertising avoidance also varies across consumer demographics and media.

We also study audience responses to product placement. The first on-screen product placement occurred shortly after the invention of the movie, when in 1896 the Lumiere brothers filmed women washing clothes with Lever Brothers' Sunlight Soap placed in a prominent position. Lever Brothers provided Swiss film distribution in exchange for the favorable treatment. A commonly cited successful placement was the appearance of Reese's Pieces in the film *E.T. the Extraterrestrial*, to which Hershey's attributed a 65% rise in sales. Less commonly discussed is the placement of Coors Lite in the same film, to which no sales rise was attributed (Newell, Salmon and Chang 2006).

Balasubramanian, Karrh, and Parwardhan (2006) review the behavioral literature on product placement, attributing the many discrepancies among published findings to brand, consumer, and placement heterogeneity, and the difficulty of reproducing product placement stimuli in laboratory settings. An interesting framework is proposed by Russell (2002). She finds that placements have differential effects on consumers' memory and brand attitudes. Obtrusive placements are most likely to be remembered, but they positively influence consumers' attitude toward the brand only when they are congruent with the plot, and can harm brand attitudes when they are incongruent with the plot. These findings seemingly refute Ephron's (2003) conjecture about product placement: "If you notice, it's bad. But if you don't, it's worthless."

Finally, there is a large recent theoretical literature on two-sided media markets. Prominent among these papers is Anderson and Coate (2005), which shows that television markets can fail by providing too many ads when available programs are poor substitutes, or too few when viewers are quick to switch and advertisers' profits are large relative to viewers' disutility of ads. Dukes and Gal-Or (2003) model both the market for advertising sales and its subsequent effects on a product market. They show that media outlets can benefit by selling exclusive advertising, since this softens product-market competition and raises advertisers' willingness to pay. Liu, Putler, and Weinberg (2004) show that networks' program investments may decrease with entry of additional networks. Our paper is relevant to this literature insofar as our results inform the assumptions it makes about how viewers respond to advertising of various types. The literature is reviewed by Anderson and Gabscewicz (2006).

To our knowledge, our study is the first to estimate the effect of product placements on viewer switching using field data. In addition, we examine the responsiveness of television audiences to advertising using a dataset that is an order of magnitude larger than any studied previously. Finally, we add to current knowledge on what advertisement characteristics influence audience responsiveness to advertising.

2. A Model of Television Viewing Behavior

In this section we describe our model of television viewing demand. We follow previous literature by assuming that each television viewer watches one network at a time, and model program viewership in a discrete choice framework. Given the aggregate nature of our data, we use a random coefficients logit model in the spirit of Berry, Levinsohn, and Pakes (1995, hereafter "BLP").

We make a few notes here about terminology. Traditionally, a *rating* is the fraction of all potential viewers who watched a given program. A *share* is the fraction of all viewers watching television who watched a given program. Our data measure program ratings, so we use this terminology throughout the paper. Similarly, we use the term "product placement" to refer to the inclusion of brands or products within television programs, which is sometimes called "branded entertainment," "plugs," or "tie-ins." We refer to blocks of time sold to advertisers as "traditional advertising" or simply "advertising." We use the terms "program" and "show" interchangeably. Finally, an "ad creative" is a set of visual and audio stimuli encoded in a video file.

We index networks with *n* and programs with *j*. A viewer chooses from $n = 1...N_t$ networks airing top-100 programs within half hour *t*.[5] Viewer utility is determined by time effects, program and network characteristics, advertising and product placement, and preference parameters. There exists a one-to-one mapping from network-half hours (*nt*) to program-half hours (*jt*).[6]

The indirect utility viewer *i* derives from watching network *n* in half hour *t* is given by

$$u_{int} = v(p_{nt}, q_{nt}; \alpha_i) + X_{nt}\beta_i + \xi_{nt} + \varepsilon_{int} \tag{1}$$

[5] Our audience datasource is a set of weekly "top 100" programs, described further in section 3.
[6] We could alternatively think of a consumer choosing a program-half hour combination. To be consistent with previous literature we model the viewer's decision as choosing a network-half hour.

where p_{nt} is the number of seconds of product placements on network *n* during half-hour *t*, q_{nt} is the number of seconds of traditional advertising on network *n* during half-hour *t*, α_i is a vector of utility parameters, and $v(p_{nt}, q_{nt}; \alpha_i)$ is the utility obtained from advertising and product placement. In section 5, we report results for several specifications of $v(p_{nt}, q_{nt}; \alpha_i)$.

The X_{nt} vector contains program, network, and time data. These include program characteristics (genre, whether the airing was a new episode); network-day dummies, to capture networks' historical schedule strengths and weaknesses; half-hour effects, to allow television utility to vary over the course of the night; and season-week dummies, to allow the utility of watching television to vary over weeks and years. Many previous studies (e.g., Moshkin and Shachar 2002) demonstrate the importance of state dependence in television viewing, so we also include the network's audience rating for the same weekday-half hour in each of the previous five weeks.[7]

In entertainment categories like television shows, observed product characteristics are often inadequate to capture product quality. For example, both *Friends* and *Coupling (US)* were half-hour situation comedies featuring 6-member casts of Caucasian actors, but *Friends* lasted eight seasons while *Coupling (US)* was canceled after 11 episodes. The ξ_{nt} term represents characteristics of the program that are unobserved to the researcher but known to viewers, advertisers, and networks. We include program dummies in the model to estimate the mean utility of program characteristics. We discuss ξ_{nt} in more detail in section 4.1.

Equation 2 defines the distribution of the random utility parameters.

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Phi \upsilon_i, \quad \upsilon_i \sim N(0, I_K) \tag{2}$$

The υ_i term represents viewer tastes that are not observed by the econometrician and is a *K*-dimensional vector drawn from a multivariate standard normal distribution. We assume that the υ_i are independently normally distributed across the population with mean zero, variance one,

[7] Many programs are serial in nature, so previous weeks' ratings are likely to predict demand for the current program. The nature of our data prevents us from using programs' lead-in and lead-out audiences, as would otherwise be standard.

and zero covariance. The Φ term is a diagonal KxK scaling matrix of parameters to be estimated.[8] We assume that the υ_i are independent of ε_{int}.

The number of parameters K can be as large as the combined dimensions of α_i and β_i, but is typically chosen to be smaller, as estimation time increases exponentially in K. We could include individual demographics drawn from population-level distributions in Equation (2), but given that we do not have meaningful variation in viewer demographics over markets or time, it is not clear that these effects would be separately identified from Φ. However, as we discuss in section 4, we estimate a restricted model separately for each demographic group in our data and hence our parameter estimates vary over demographic groups.

The ε_{int} term is a mean zero stochastic term distributed i.i.d. type I extreme value across viewers, networks, and time periods. Choices are invariant to scaling of utility by a viewer-specific constant, so we fix the standard deviation of ε. If we impose the restriction $\Phi = 0_K$, we have specified a multinomial logit model.

We can rewrite equation 1 as

$$u_{int} = \delta_{nt} + \mu_{int} + \varepsilon_{int} \tag{3}$$

where $\delta_{nt} = v(p_{nt}, q_{nt}; \alpha) + X_{nt}\beta + \xi_{nt}$ captures the base utility every viewer derives from network n at time t. The composite random shock, $\mu_{int} + \varepsilon_{int}$, captures viewer preference heterogeneity.

Viewers may elect to watch a program outside the top 100, or engage in a non-television activity. The value of the best available alternative (the "outside option") is given by

$$u_{i0t} = \xi_{0t} + \varepsilon_{i0t} \tag{4}$$

Given that we cannot identify relative utility levels, we normalize ξ_{0t} to zero. The conditional probability that viewer i watches network n at time t is

$$s_{int} = \frac{e^{\delta_{nt} + \mu_{int}}}{1 + \sum_{l}^{N_t} e^{\delta_{lt} + \mu_{ilt}}} \tag{5}$$

[8] Including random coefficients ensures that predicted switching patterns will be based on similarity in observed characteristics, rather than based solely on similarity in audience ratings.

and the set of simulated viewers, defined as a vector of demographics and program specific shocks, for whom network *n* at time *t* maximizes utility are described by parameters and variables in the set

$$A_{nt} = \{(\upsilon_i, (\varepsilon_{int})) \mid u_{int} > u_{imt}, \forall m \neq n\}. \quad (6)$$

Then, assuming ties occur with zero probability, the audience rating for network *n* at time *t* is the integral over the mass of "viewers" in the region A_{nt}:

$$s_{nt} = \int_{A_{nt}} s_{int} dF(\upsilon) \quad (7)$$

where $F(\upsilon)$ denotes the cumulative distribution function of υ. Notice that network *n*'s audience rating is a function of network and program characteristics and advertising for all programs.

3. Data

To estimate the model we use data from two sources: TNS Media Intelligence (TNS) and the Television Bureau of Advertising (TVB). The TNS data are extensive and contain program genre classifications, detailed traditional advertising data at the level of the individual commercial, and detailed product placements at the level of the individual product placement. The TVB data report television audience ratings at the date-network-program level for the top 100 national programs that aired during prime time evening hours each week (8-11 P.M.) during which networks earn 61% of their advertising revenues.

Since programs typically change on half-hour increments, our unit of observation is the date-network-half-hour, e.g. January 1, 2007, ABC, 8:00-8:30 P.M. We discuss each component of the data in more detail, and present descriptive statistics in section 3.5.

3.1 *Program Data*

Program characteristics data come from TNS and consist of program name, genre, network, and date of each airing. We observe each advertisement within each program, so we are able to construct start and end times for each program-date.

The networks in the data are ABC, CBS, CW, FOX, NBC, UPN, and WB. ABC, CBS, and NBC broadcasted national programs 8-11 (all times are P.M., Eastern Standard Time), seven nights a week. FOX broadcasted national programs 8-10 on all seven nights. UPN broadcasted 8-10 Monday through Friday, and WB broadcasted 8-10 Sunday through Friday. WB and UPN merged and began broadcasting as the CW Network in September 2006. CW broadcasted 8-10 Sunday through Friday in the 2006-07 season. FOX started a new network called My Network Television in 2006. However none of its program audiences were large enough to be included in the top 100 in any week of our sample.

There were a few programs that appeared on more than one network over the course of the sample. When this occurred, we defined a separate program-network for each instance of the program.

Our unit of observation is a date-network-half-hour, but a network occasionally aired more than one program per half-hour slot. This affected less than 1% of the half-hours in our sample and was usually related to sports programming. For example, a game ran longer than its scheduled timeslot, or a half-hour included both a "pre-game show" and part of a game (two separate programs for which we observe separate audience ratings). We therefore had to choose which program's audience rating to assign to some date-network-half-hours shared by two programs. We followed a two-step procedure. If exactly one of the two programs did not appear in any other half-hours, then we assigned that program's audience rating to the half-hour. If both programs spanned multiple half-hours, then we assumed the program that contained more advertising during the date-network-half-hour in question accurately reflected the true audience rating. It was never the case that neither program spanned multiple half-hours.[9]

TNS assigns each program exclusively to one genre. Numerous studies (e.g. Rust and Alpert 1984, Goettler and Shachar 2001) illustrate the importance of program genre in predicting program viewing demand. Table 1 lists the genres ordered by the frequency of the network-half-hours in which they are programmed in the sample. Genres range from News Magazine to Wrestling. But the striking feature of the data is its relative lack of dispersion. Four genres—Drama/Adventure, Slice-of-Life, Situation Comedy, and Police/Suspense/Mystery—accounted for 76.4% of prime-time network program-hours. At the other end of the distribution, 30 genres account for just 7.02%.

[9] Some programs leave our sample during the sample period (for example, they are canceled). We assume this variation in the set of programs available to watch is exogenous, a common assumption made in this literature.

Genre	Frequency	Genre	Frequency
Drama/Adventure	34.21%	Game Show	1.66%
Slice-of-Life (or "Reality")	16.08%	Professional Football - Game	1.14%
Situation Comedy	14.70%	Award/Pageant/Parade/Celebration	1.04%
Police/Suspense/Mystery	11.45%	Variety - General	0.99%
Feature Film	5.49%	Professional Baseball - Game	0.98%
News Magazine	5.11%	College Football - Game	0.55%
Wrestling	2.08%	Other	4.51%

Table 1. Genre Frequency

3.2. *Traditional Advertising Data*

We use advertising data from TNS Media Intelligence's "Stradegy" database. This database provides advertisers, advertising agencies, and other marketers with "competitive advertising intelligence." It is widely subscribed within industry.

For all advertisements that aired during the sample period, we observe the brand advertised (e.g. Coca-Cola Classic), the network, start time, and length of the ad, and a name given to the ad creative. In addition, TNS manually classified each brand as belonging to a category (e.g. Regular Carbonated Soft Drinks), an industry (Beverages), a subsidiary (Coca-Cola USA) and a parent company (Coca-Cola Co.).

Networks aired about 250,000 advertisements during our sample period. These included about 29,000 different ad creatives for 5,000 brands spanning 350 categories in 50 industries. We construct daily network-half-hour measures of the frequency of the most common ad creatives and most commonly advertised product categories, and measure their effects on viewer utility. We report the results in section 5.2.

We have data on the average price of a 30-second commercial for each program on each date. Networks report these date-program average advertising costs to TNS and Nielsen after their programs air. These data allow media buyers to estimate costs of future media plans. If networks over-report these costs, they have a greater ability to give advertisers perceived discounts when negotiating ad prices, but they may limit their programs' potential advertising demand. We are not aware of any evidence of systematic under- or over-reporting, perhaps because of the repeated nature of transactions in this industry. (These are not "rate card" data.)

We do not observe advertisements networks aired for their upcoming programs ("tune-ins" or "promos"), as TNS' ad-recording software was not able to distinguish tune-ins from network programs. Time given to tune-ins is a potentially important omitted variable. A 2001 report found that networks aired 4:07 minutes of tune-ins per half-hour. This compared with 9:44 minutes of advertising, and tune-ins and traditional advertising time had a correlation of -0.31 (AAAA/ANA 2001). In section 4.1, we discuss potential endogeneity issues arising from not observing tune-ins and how we control for these in estimation.

3.3. *Product Placement Data*

TNS Media Intelligence began recording product placement information on March 28, 2005. In their database, a product placement is a visual, audio, or audio-visual representation of a brand or product, whether explicit or implied. Common examples include detailed prize descriptions on a game show, a logo on the t-shirt of a reality show contestant, or a partially identifiable truck driven by a police officer in a dramatic series.

For each product placement, we observe the brand placed, the brand characteristics defined in section 3.2, and the product placement characteristics listed in Table 2. In the median placement, an identifiable product or package is shown in the foreground with no other brands or products on the screen. Products are integrated into the program in just 16% of all placements.

	Variable			Notes
Type	Verbal Only		17.0%	
	Direct Visual Only		51.2%	Brand/product is clearly identifiable
	Implied Visual Only		24.5%	Brand/product is not clearly identifiable
	Verbal & Direct Visual		5.3%	
	Verbal & Implied Visual		2.0%	
Appearance	Product or Package shown		63.9%	
	Brand Name shown		11.4%	
	Brand Mark shown		4.6%	
	Billboard or Graphic Overlay		3.1%	
	No Visual		17.0%	
Interaction	Interaction w/ Real Life Persona		21.6%	
	Interaction w/ Fictional Character		37.4%	
	No Interaction		41.0%	
Visual Interaction Type	Brand Interaction		7.9%	E.g. a character wears a shirt with a Nike logo
	Product Interaction (Proper Use)		33.2%	
	Product Interaction (Improper Use)		1.0%	
	No Interaction		57.8%	
Integration	Integration as a Prize or Reward		1.3%	Characters who successfully completed a game or contest were given the brand as a reward
	Integrated Directly into Game/Contest		2.8%	The brand/product was featured during the game/contest
	Integrated Partially Into Game/Contest		1.3%	The brand/product was used during the game/contest
	Integration as a Sponsorship		8.2%	The brand was presented as a sponsor of the program
	Other Integration		2.6%	E.g. the brand was integrated with the plot of a dramatic program
	No Integration		83.9%	
Visibility	Fully Visible		39.8%	
	Partially Visible		40.6%	
	Not Applicable		19.6%	
Clutter	No Clutter		58.1%	
	Clutter		24.9%	At least 1 other brand/product appeared on screen during a visual product placement
	Not Applicable		17.0%	
Visual Location	Foreground		60.7%	
	Background		22.2%	
	Not Applicable		17.0%	
Length	in Seconds	Mean	23.4	
		Med.	9.0	
		St.D.	42.3	
		Max	920.0	

Table 2. Product Placement Descriptive Statistics.

As with advertising, we aggregate over placements to construct measures of product placement at the date-network-half-hour level.

Networks typically do not reveal placement terms, so no available datasource reports product placement prices. Our understanding of the industry is that product placements are sometimes paid in cash, sometimes bartered, and sometimes are not paid. Payment is more likely when plot integration or character interaction occurs, in which case the integration or interaction almost always depicts the brand or product favorably and/or prominently.

In the product placement data, we observe episode names for regular programs. Therefore, for the second and third television seasons in our data, we were able to construct an indicator of whether each episode had appeared previously in the television season.[10] We call this variable *NewEps*. It stands to reason that new program episodes are more attractive to viewers than previously-aired episodes ("re-runs"), so we use this information in predicting viewing demand.

3.4 *Television Audience Data*

Only a handful of television audience datasets have been available to academic researchers in the past 20 years. Most of those contain individual viewers' program choices over a limited number of days and programs. Our data contrast with others in that we have an unusually large number of time periods and programs, but we do not have cross-sectional variation over individuals or markets.

We collected our audience data from weekly "top 100" program lists found on the TVB website (tvb.org). Each list ordered the 100 highest-rated programs that week and included the programs' national audiences, as measured by Nielsen Media Research.[11]

Weekly top-100 program lists were available for three demographic groups in each of three 35-week television "seasons," 2004-05, 2005-06, and 2006-07. Each season began on the third Monday of September and ended on the third Sunday in May. The demographic groups are those traditionally used to measure television audiences: adults aged 18-49, adults aged 25-54, and households. The unit of observation is a date-network-program, so we assign each date-program rating to the network-half-hour in which that program aired. We observe an audience rating for each demographic group whose top-100 list included that program. We do not observe a program's audience rating if it falls short of the 100th-highest audience rating in the week it aired. This truncation issue affects 20% of the date-network-half hours in household audiences and 22% of observations in the other demographic groups.[12]

3.5. *Descriptive Statistics*

[10] We were not able to observe this for the first season since the product placement data sample did not begin until March 2005.

[11] Audience ratings are collected passively using Peoplemeters, which continuously measure television usage and tuning, and periodically require viewers to actively "log in" to verify whom is in the room. Date/program ratings are calculated as the average program rating over quarter-hours in which the program aired.

[12] We are following the majority of the empirical marketing literature by using data on the programs with the largest audience sizes to estimate the model. This truncation issue is common in many settings, such as scanner panel datasets wherein the product set is usually restricted to the highest-selling brands or stock-keeping units.

Table 3 displays advertising and audience descriptive statistics by network. CBS had the largest audience measured in households, by far, with an average rating of 8.24, followed by ABC (6.55) and NBC (6.33). Yet FOX led in advertisers' most desired demographic, adults 18-49 (4.15), followed by CBS (3.93) and ABC (3.77). This lead in adults 18-49 yielded Fox's premiere position in advertising revenues per half hour.

WB and UPN had audiences and advertising revenues about half as large as the big four networks. It is surprising to compare the CW network's performance to WB and UPN. CW had smaller audiences than either of its constituent networks, and lower average advertising revenues than UPN. It would appear that the WB-UPN merger was unprofitable, unless it produced substantial unobserved program cost savings.

ABC sold the most advertising time in the sample, with an average of 370 seconds of ads per half-hour. It was followed by WB (349), CW (340), UPN (334), NBC (318), CBS (309), and FOX (296). There was a great deal of dispersion around these means, with standard deviations about 25% as large as means of advertising time.

Table 4 shows the raw correlations between the major variables. Notably, the correlation between advertising and product placement is close to zero. This may suggest product placements' fit with program narrative is the primary determinant of how many product placements to include in a program, rather than revenue maximization. It is also notable that product placement time is positively correlated with audience ratings, with correlations ranging from 0.13 to 0.17.

Network		Count	Mean	St. Dev.	Min.	Max.
ABC						
	Advertising Seconds	4337	370.48	87.70	15	900.0
	Advertising Dollars	4337	$1,767,586	$1,604,577	$0	$28,800,000
	Product Placement Seconds	3241	42.58	128.52	0	3,537.0
	Household Audience Rating	4089	6.55	3.34	1.9	25.4
	Adults 18-49 Audience Rating	3976	3.77	2.29	0.95	16.5
	Adults 25-54 Audience Rating	4053	4.29	2.52	1.21	17.7
CBS						
	Advertising Seconds	4357	308.80	87.91	30	1,320.0
	Advertising Dollars	4357	$1,787,248	$1,713,685	$0	$38,200,000
	Product Placement Seconds	3240	110.78	209.73	0	1,850.0
	Household Audience Rating	3926	8.24	3.23	2.3	42.6
	Adults 18-49 Audience Rating	3896	3.93	2.12	1.05	35.2
	Adults 25-54 Audience Rating	3918	4.90	2.43	1.28	37.1
CW						
	Advertising Seconds	840	340.28	80.19	90	630.0
	Advertising Dollars	840	$568,699	$356,235	$0	$2,250,000
	Product Placement Seconds	840	84.50	174.66	0	1,652.0
	Household Audience Rating	392	2.71	0.46	1.8	4.2
	Adults 18-49 Audience Rating	396	1.72	0.41	1.1	3.0
	Adults 25-54 Audience Rating	306	1.70	0.31	1.1	2.5
FOX						
	Advertising Seconds	2763	295.75	80.04	40	1,200.0
	Advertising Dollars	2763	$1,809,352	$2,379,358	$0	$62,400,000
	Product Placement Seconds	2060	141.25	311.82	0	7,378.0
	Household Audience Rating	2484	6.20	4.38	1.81	41.1
	Adults 18-49 Audience Rating	2480	4.15	3.20	1.11	33.2
	Adults 25-54 Audience Rating	2479	4.38	3.52	1.05	35.6
NBC						
	Advertising Seconds	4371	318.34	81.89	0.2013889	1,305.0
	Advertising Dollars	4371	$1,585,175	$1,242,212	$0	$10,100,000
	Product Placement Seconds	3257	129.73	332.07	0	4,714.0
	Household Audience Rating	4176	6.33	2.35	1.91	16.4
	Adults 18-49 Audience Rating	4059	3.45	1.54	1.04	10.0
	Adults 25-54 Audience Rating	4126	4.03	1.73	1.3	11.4
UPN						
	Advertising Seconds	1398	334.09	67.61	120	720.0
	Advertising Dollars	1398	$507,876	$355,769	$36,000	$1,922,400
	Product Placement Seconds	858	127.11	189.06	0	1,557.0
	Household Audience Rating	645	2.81	0.54	1.81	4.7
	Adults 18-49 Audience Rating	647	1.71	0.39	1	3.2
	Adults 25-54 Audience Rating	580	1.70	0.33	1.02	3.2
WB						
	Advertising Seconds	1679	348.80	73.15	90	690.0
	Advertising Dollars	1679	$714,339	$272,382	$98,400	$2,235,300
	Product Placement Seconds	1032	69.02	119.15	0	1,049.0
	Household Audience Rating	756	2.94	0.67	1.69	5.4
	Adults 18-49 Audience Rating	795	1.84	0.46	0.85	3.0
	Adults 25-54 Audience Rating	740	1.85	0.43	0.99	2.9

An observation is a date-network-half hour. Advertising and product placement data are from TNS; audience data are from TVB. Product placement data begins March 28, 2005, 27 weeks later than the advertising data.

Table 3. Descriptive Statistics

	Ad Sec.	PP Sec.	Ad Doll.	HH	A18-49	A25-54
Ad Seconds	1.00					
Product Placement Seconds	-0.04	1.00				
Ad Dollars	0.33	0.12	1.00			
Household Rating	0.02	0.13	0.66	1.00		
Adults 18-49 Rating	0.05	0.17	0.72	0.92	1.00	
Adults 25-54 Rating	0.04	0.16	0.70	0.96	0.99	1.00
Drama/Adventure	0.02	-0.05	-0.03	0.02	0.02	0.04
Police/Suspense/Mystery	-0.10	-0.08	0.02	0.18	0.07	0.11
Situation Comedy	0.06	0.04	-0.04	-0.18	-0.11	-0.13
Slice-of-Life ("Reality")	0.03	0.30	0.08	0.05	0.14	0.10

Table 4. Correlations among Key Variables

Slice-of-Life and Situation Comedy genres contain more advertising and product placement time than Drama/Adventure and Police/Suspense/Mystery programs. While audiences across demographic groups are highly correlated, genre preferences depend on demographics. Household-level audiences are more likely to watch police programs than adults 18-49 (0.18 correlation to 0.07), while adults 18-49 are more likely to watch reality programs than the households audience (0.14 to 0.05).

4. Estimation

In this section we discuss potential endogeneity issues and how we address them, what variation in the data allows us to identify the model, and the estimation technique.

4.1 *Endogeneity*

The error term in the model is ξ_{nt}, which represents program characteristics that may be known to the networks and viewers but are unobserved by the econometrician. We specify

$$\xi_{nt} = \xi_j + \Delta\xi_{nt} \tag{8}$$

where ξ_j is the mean of unobserved characteristics for program *j*, and the $\Delta\xi_{nt}$ term represents deviations from this mean over time periods in which the program airs. (Recall that there is a one-to-one mapping from *nt* into *jt*, so we could equivalently write $\Delta\xi_{jt}$ in place of $\Delta\xi_{nt}$.) We use the serial nature of the data to estimate ξ_j by including program-specific fixed effects. The $\Delta\xi_{nt}$ could capture unobserved temporal variation in program quality as some episodes of a program may be more entertaining than others. It could also capture variation in time given to tune-ins. To address this, we include ad price per viewer and its lags in the viewer utility function as this variable is likely to be correlated with tune-in seconds.[13] We include *NewEps*, network-weekday and season-week dummies in X_{nt} to try to reduce variation in $\Delta\xi_{nt}$ due to episode quality, networks' historical schedule strength, and temporally variable factors like weather.

Television networks may know their programs' and episodes' quality, including those aspects captured in $\Delta\xi_{nt}$, and may take it into account when setting traditional advertising and product placement levels. As a result we have a potential endogeneity problem in that advertising choices may be functions of $\Delta\xi_{nt}$. However it should be noted that if networks had complete information about programs' and episodes' quality, we likely would see a lower rate of new program failure in the data.

We use three sets of instruments to address potential remaining endogeneity issues: (1) lags of traditional advertising time, (2) lags of product placement time, and (3) functions of competitors' program characteristics. Regarding the first two sets of instruments, traditional advertising time and product placement seconds are autocorrelated (1-week correlations of 0.42 and 0.44, respectively), so lags are good proxies for current advertising time and product placements. Their exclusion from the viewer utility function is justified if networks are myopic when setting traditional advertising time and product placements.[14] The intuition motivating the third set of instruments follows Goeree (2008) and is similar to that used by BLP to correct for endogeneity of price in differentiated products markets. Rivals' program characteristics enter the network's profit function and therefore influence the network's choice of ad and product placement time, since the optimal amount of advertising to do on a program depends upon the characteristics of all of the programs aired by rivals. Hence, characteristics of rivals' programs and various combinations of these characteristics can be used to instrument for endogenous advertising in that they are correlated with advertising aired during program *j* but not with program *j*'s unobserved quality. These instruments are given by g_{nt}, where *g* is the number of

[13] We originally treated ad price per viewer as an instrument, but instrumental variables validity tests reported in Appendix 1 indicated that their exclusion from viewer utility was not justified.

[14] Our approach is similar to much of the marketing literature (e.g., Villa-Boas and Winer 1999) which uses lagged values of strategic variables to proxy for contemporaneous values.

competing networks offering a program with characteristic *g* within date/half-hour *t*. The characteristics *g* that we consider are *NewEps* and genre effects. Finally, for validity of these instruments and to identify the taste parameters (discussed in the next section), we assume (as in BLP and Nevo, 2000) that the observed and unobserved program characteristics are mean independent.[15]

4.2. *Identification*

We discuss informally what variation in the data identifies the parameters. Associated with each network-half hour is a mean utility, δ_{nt}, which is chosen to match observed and predicted audience ratings. Audience levels identify the show, network-day, week, and half-hour effects. Holding these characteristics constant, correlations between audience, advertising, and product placement over time identify the mean utility parameters associated with advertising and product placement.

In practice we cannot estimate a separate dummy for every show in the sample. Thus we assign a show dummy to as many shows as possible, where the remaining shows are described by *NewEps*, network-day, season-week, half-hour, and genre effects. Some genre effects are dropped because they are highly collinear with the set of show dummies for the shows belonging to that genre. We are able to separately identify show effects from network-time effects because of the rich scheduling variation over the three-year sample period. The taste parameters, β and α, associated with non-time changing X_{nt} are identified using a minimum distance procedure outlined in the next section. The idenfication strategy follows Nevo (2000) who shows that the two-step estimation technique we employ, together with the assumption that the ξ_{nt} are mean independent of other program characteristics, allows for identification of the mean random coefficient.[16]

Identification of the taste distribution parameters, Φ, relies on patterns of viewer substitution between shows. While the means are identified by audience sizes, the standard deviations are identified by the "stickiness" of how those audience sizes change when faced with

[15] Given that we observe variation in the programs offered in different time slots, these instruments are valid even though we estimate program fixed effects.

[16] As Nevo (2000) shows, this procedure is equivalent to a GLS regression where the independent variable consists of the estimated program effects. The number of "observations" in this regression is the number of programs.

variation in show competition, advertising, and product placements on competing networks within the same half-hour.

4.3. *Estimation*

The econometric technique follows recent studies of differentiated products, such as BLP (1995) and Nevo (2000). We estimate the model using the Generalized Method of Moments (GMM). The moments match the predicted demographic audience ratings for network-half hours *nt* to the corresponding observed ratings.

Following the literature, we assume that the demand unobservables (evaluated at the true parameter values) are mean independent of a set of exogenous instruments, *Z*. To estimate the restricted model we follow Berry (1994). Setting $\Phi = 0_K$, the model in section 2 reduces to a multinomial logit with an ordinary least squares (OLS) estimating equation of

$$\ln s_{nt} - \ln s_{0t} = \delta_{nt} = v(q_{nt}, p_{nt}; \alpha) + X_{nt}\beta + \xi_j + \Delta\xi_{nt} \tag{9}$$

where s_{0t} is the audience rating of the outside good (one minus the sum of the "inside" ratings). To estimate the parameters we interact the error term $\Delta\xi_{nt}$ with a set of instruments, *Z*. In our first set of OLS regressions, Z includes program dummies, season-week dummies, network-weekday dummies, half-hour dummies, genre dummies, *NewEps*, five (weekly) lags of audience rating and ad price per viewer, product placement characteristics, and the observed data in $v(p_{nt}, q_{nt}; \alpha)$. In the instrumental variables (IV) specifications, we drop the observed data in $v(p_{nt}, q_{nt}; \alpha)$ and add five lags of traditional advertising time and five lags of product placement time into *Z*.

To estimate the full set of random coefficients, we add the competitors' program characteristics described above to *Z* along with the lags of advertising and product placement time, and adopt the two-step estimator proposed by BLP. The first step is to match the model's predicted ratings to observed ratings. We seek the vector $\delta(S_t^{obs}, \theta)$ that implicitly solves

$$S_t^{obs} - s_t(\delta, \theta) = 0, \tag{10}$$

where S_t^{obs} and s_t are N_t-vectors of observed and predicted audience ratings respectively and θ represents the complete parameter set. For each guess of θ, we start with an initial set of mean utilities δ_{nt}^{0}, calculate $s_{nt}^{0}(\delta_{nt}^{0},\theta)$, construct a new guess $\delta_{nt}^{1}(S,\theta)=\delta_{nt}^{0}\dfrac{S_{nt}^{obs}}{s_{nt}(\delta_{nt}^{0})}$, and repeat these last two steps r times until $\max\left\|\delta_{nt}^{r}(S_{t}^{obs},\theta)-\delta_{nt}^{r-1}(S_{t}^{obs},\theta)\right\|_{\infty}$ is close to zero (10^{-14} in our application). We then calculate the structural error term substituting $\delta_{nt}^{r}(S_{t}^{obs},\theta)$ for δ_{nt}. The error term is given by

$$\Delta\xi_{nt}(\theta)=\delta_{nt}^{r}(S_{t}^{obs},\theta)-(v(q_{nt},p_{nt};\alpha_{i})+X_{nt}\beta+\xi_{j}). \tag{11}$$

We search over θ to minimize the GMM objective function

$$(Z'\Delta\xi)'\Omega^{-1}(Z'\Delta\xi), \tag{12}$$

where $\Delta\xi=\{\Delta\xi_{nt}\}$ is the Nx1 error term, and Ω is a weighting matrix. As an initial guess we set $\Omega=Z'Z$ to get a consistent estimate of $\hat{\Omega}=(Z'\Delta\xi)(Z'\Delta\xi)'$, which we use in the final parameter estimation.

The BLP estimation routine has the desirable property that it is linear in preference means, which greatly speeds computation by reducing the number of parameters that enter the objective function nonlinearly. However it is still nonlinear in the standard deviations of the preference distributions, and computation time increases exponentially with the number of nonlinear parameters to be estimated. We restrict the number of parameters interacting with unobserved viewer heterogeneity to two: those multiplied by the terms p_{nt} and q_{nt} (i.e. K=2). To simulate individual television viewers, we invert the Normal distribution at 500 multivariate Halton draws for each random utility parameter, and use antithetic acceleration to produce 500 more draws to reduce simulation variance.[17] Thus our total number of simulated viewers is 1,000. The data we use in estimation is the final seven weeks of the 2004-05 season, since product placement data were not available until March 28, 2005; and weeks 6-35 of the 2005-06 and 2006-07 seasons, since we have five weekly lags of audience and ad price per viewer in our utility specification.[18]

[17]For more on antithetic acceleration see Stern (1997, 2000). Geweke (1988) shows if antithetic acceleration is implemented during simulation, then the loss in precision is of order 1/N (where N is the number of observations), which requires no adjustment to the asymptotic covariance matrix.

[18] We used OLS results for starting values for parameter means, and evaluated the objective function at 1000 points in a grid search to find starting values for the random coefficients. We found many local minima, but when drawn over the range of grid points we sampled, the objective function looks convex to the eye in both dimensions of θ. Computation time was about five days on a 3.2 GHz computer using serial processing.

5. Results

In section 5.1 we estimate several versions of the multinomial logit (MNL) model using the method described in section 4.3. The ease of MNL estimation makes it helpful for specification testing. We first explore how the proposed endogeneity controls affect the results and various specifications of $v(p_{nt}, q_{nt}; \alpha)$. In section 5.2, we answer some substantive questions, such as how advertising utility varies with advertisement category and ad creative. Section 5.3 reports our random coefficient estimates and estimated audience elasticities of advertising.

5.1. *Multinomial Logit Results*

In section 4 we proposed to use show dummies to control for unobserved program characteristics. Without show dummies, we would expect advertising responsiveness to be biased upward, since networks would include higher ad levels in programs with higher unobserved quality. As table 5 shows, without show dummies we find that both advertising and product placements have significant, positive effects on utility. This is counterintuitive as it suggests viewers enjoy watching advertising on average. When we add show dummies, the point estimates fall markedly, and advertising time is again significant, but this time with the opposite sign. These results indicate that show dummies mitigate some of the endogeneity issues associated with advertising.

	Results without show dummies	**Results with show dummies**
Ad Seconds	1.15E-04	-9.77E-05
	(3.00)	(3.03)
Product Placement Seconds	2.81E-05	-1.75E-05
	(2.25)	(1.38)
Adjusted R^2	0.73	0.82

T-statistics in parentheses. Dependent variable is the log-transform of the audience rating among adults 18-49.

Table 5. Effects of program dummies on advertising utility estimates.

Our other endogeneity controls are instrumental variables for intertemporal variation in unobserved program characteristics and unobserved tune-in levels. We present the results of instrumental variables robustness checks in Appendix 1. To summarize, we found that lags of advertising and product placements are valid instruments for advertising and product placement time, but their use does not materially affect the estimates. In light of these findings, we proceed with OLS estimation on efficiency grounds (see Appendix 1 for more detail).

Next we consider what specification for $v(p_{nt}, q_{nt}; \alpha)$ best fits the data. We know of no extant theory available to guide our selection. It seems reasonable to expect that viewers' marginal utility of advertising and product placement may be nonlinear. We followed two common procedures to select a functional form; both led to the same conclusion. First, we used splines with varying numbers of knots to estimate the shape of the advertising and product placement utility function. Second, we added powers of each term to a linear specification and stopped when the next power added was not statistically significant. Both methods indicated that $v(p_{nt}, q_{nt}; \alpha)$ should be cubic in traditional advertising time, and quadratic in product placement time. We found no evidence of interactions between advertising and product placement.

Figure 2 shows the estimated marginal utility of advertising for each of the three demographic groups. The household demographic group is less averse to advertising than the other two demographic groups, but there is no apparent difference between adults 18-49 and adults 25-54. The differences emphasize how much more ad-averse adults 18-54 are than other viewers, since the households demographic group includes adults 18-49 and adults 25-54. Ad utility is everywhere decreasing, with an inflection point at 407 seconds. Just 16% of observed ad levels exceed this inflection point.

Figure 3 shows viewers' estimated response to product placement seconds. Product placement utility is concave, but increasing and positive over most of the variable's range. Households appear to respond the most positively to product placement, followed by adults 25-54 and adults 18-49.

While we have included several endogeneity controls, the product placement results still may be biased. It could be the case that product placements are naturally accommodated by certain types of program scenes that contain unobserved characteristics that are attractive to viewers. For example, if high-budget program scenes are more likely to attract viewers, and contain increased levels of product placement, our finding of positive product placement utility could be spurious. Such content could vary over episodes within a program and therefore escape the control provided by our program dummies. This problem seems unlikely to affect our advertising utility estimates since advertising content is seldom influenced by program content.

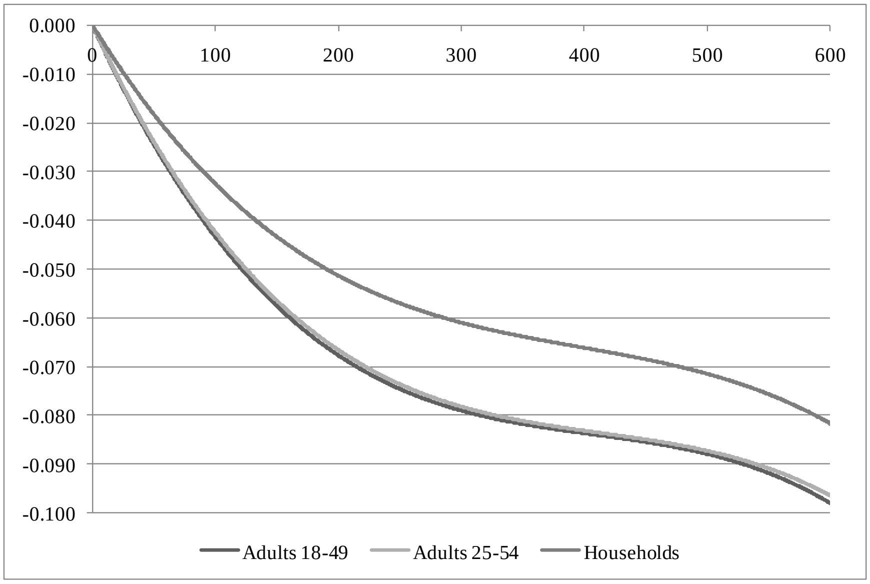


Figure 2. Estimated Marginal Utility of Ad Seconds

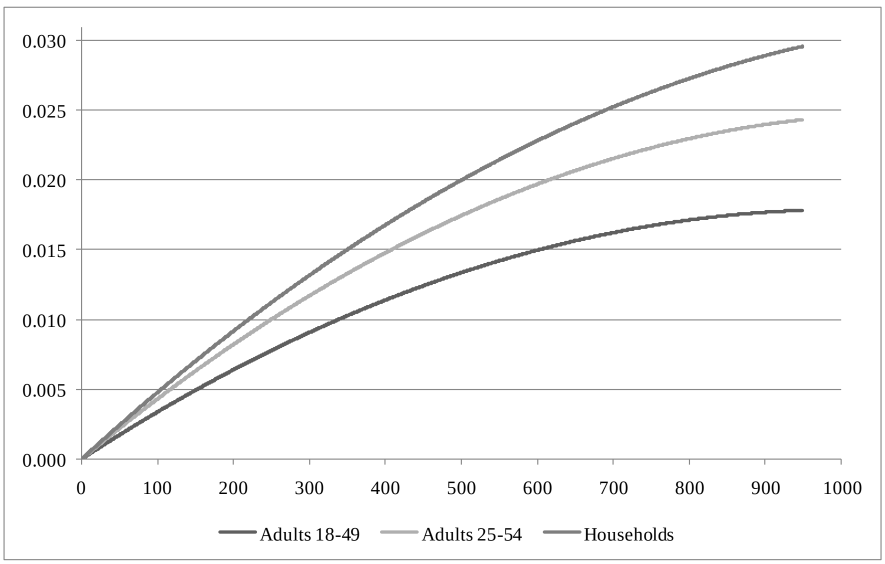


Figure 3. Estimated Marginal Utility of Product Placements

We collected some additional data to investigate this possibility. The website TV.com aggregates viewers' ratings of television programs and episodes. We supplemented these data with information from our sample, so we were able to separately control for episode quality and product placement. When we did this, we found that the estimated effect of product placement time on utility was negative and significant. We describe the procedure and results in detail in Appendix 2.

Adults 25-54 appear to have a nearly equal reaction to ads as adults 18-49. Households are the least valuable audience metric and seem to be least negatively affected by traditional advertising, and most positively affected by product placements. From here on, we focus on models estimated using audience data for adults 18-49, as they are the group valued most highly by advertisers.

Table 6 presents parameter estimates measuring the impact of product placement characteristics on viewer utility. We include in X_{nt} the product placement characteristics described in section 3.1. Specifically, the X_{nt} term includes x_{lnt}, the fraction of product placement seconds on network *n* during half-hour *t* that have characteristic *l*. In this way we are able to separately control for the amount of placements during the program and the types of placements observed. The estimates are small in magnitude or not statistically significant suggesting that product placement characteristics are not driving program viewing decisions.

	Variable	**Point Est. (T-Stat)**		**Variable**	**Point Est. (T-Stat)**
Type	Verbal Only	.06 (0.9)	Integration	Integration as a Prize or Reward	.00 (0.1)
	Direct Visual Only	-.02 (0.7)		Integrated Directly into Game/Contest	.04 (1.0)
	Implied Visual Only	-.03 (1.1)		Integrated Partially Into Game/Contest	-.09 (1.5)
	Verbal & Direct Visual	-.04 (1.0)		Integration as a Sponsorship	.02 (0.8)
	Verbal & Implied Visual	--		Other Integration	.04 (1.8)
Appearance	Product or Package shown	.04 (0.8)		No Integration	--
	Brand Name shown	.02 (0.4)	Visibility	Fully Visible	-.01 (0.5)
	Brand Mark shown	.05 (1.1)		Partially Visible	-.02 (0.6)
	Billboard or Graphic Overlay	.05 (0.8)		Not Applicable	--
	No Visual	--	Clutter	No Clutter	.00 (0.0)
Interaction	Interaction w/ Real Life Persona	-.08 (1.3)		Clutter	--
	Interaction w/ Fictional Character	-.04 (0.7)	Visual Interaction Type	Brand Interaction	.06 (0.9)
	No Interaction	--		Product Interaction (Proper Use)	.04 (0.6)
Visual Location	Foreground	.01 (0.6)		Product Interaction (Improper Use)	.08 (1.1)
	Background	--		No Interaction	--

Table 6. Product Placement Characteristics Estimates

5.2. *Some Substantive Results*

In this section we report results from some multinomial logit regressions that exploit the richness of the data. The questions we consider are: how do the effects of advertising on audience sizes vary by product category? How do they vary by ad creative? We also investigated whether advertising utility varied over months in the sample, but we did not find any supporting evidence.

Ad Utility by Product Category

To estimate the effect of product category advertising on utility we set

$$v(p_{nt}, q_{nt}; \alpha) = \sum_c p_{cnt}\alpha_c^p + \sum_c q_{cnt}\alpha_c^q \tag{13}$$

where p_{cnt} is the product placement time given to brands in category *c* on network *n* in half-hour *t*, and q_{cnt} is the corresponding ad time.

Table 7 gives the significant estimates of α_c^p and α_c^q. Our priors were that beer and movie ads, and possibly car ads, would positively impact utility. The results are consistent with these expectations, as the highest significant category ad effects include movies, DVDs, light beer, regular beer, and four automotive categories. More surprising was the appearance of finance-related categories, including banks, insurance, and financial services. We reviewed some of these ads to try to understand the results further. Our general sense is that these ads contain higher entertainment value and production budgets than the typical ad, perhaps because they must capture consumer attention for products that might not otherwise be enjoyable to think about. The most-liked categories were corporate computing and participatory sports, though both represent a very small share of total advertising dollars. Corporate computing was dominated by a highly entertaining branding campaign by IBM, while the highest-spending brand in participatory sports was 1-800-SKYDIVE.[19]

The estimates indicate that viewers are averse to advertising in a variety of categories. Many are low-involvement categories like toothpaste, candy, cookies, and mouthwash. Others may have negative product associations such as diapers, vegetable juices, bleach, or pharmacies. Prescription medications and wireless telecommunications are the two highest spending categories that negatively impact viewer utility. Prescription medication ad utility may be impacted by US Food and Drug Administration rules regarding disclosure of medication side effects.

Table 8 displays the estimates for product placement category effects. The results lend some credence to the possibility that our product placement results are affected by endogeneity. Some of the highest category effect estimates are beer and soft drinks, which may correlate with

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[19] Positive effects may be interpreted as categories whose ads discourage viewer switching in such a way as to increase Nielsen audience measurements, or capture the attention of viewers leaving other channels who then continue viewing the network.

depictions of social settings, and cosmetics, which may be correlated with scenes containing female models.

Ad Utility by Advertising Creative

Our other substantive question is how individual advertisements vary in their effect on viewer utility. We respecify ad utility as

$$v(p_{nt}, q_{nt}; \alpha) = p_{nt}\alpha_1 + p_{nt}^2\alpha_2 + q_{0nt}\alpha_3 + q_{0nt}^2\alpha_4 + q_{0nt}^3\alpha_5 + \sum_{h=1}^{H} q_{hnt}\alpha_h \tag{15}$$

where q_{hnt} is the number of ad seconds devoted to creative *h* on network *n* at time *t*, α_h is the effect of creative *h* on utility, and q_{0nt} is the amount of all ad time given to creatives that are not in the set 1…*H*. We choose ad creatives to include in *H* by following two steps. First, TNS creative names sometimes include an integer at the end, to indicate that the creative is a minor departure from a previously-logged commercial for the same brand. Typically these departures are :15-second versions of a :30-second ad, or a change in on-screen text in an otherwise identical ad. We drop this integer to pool across variations within an ad creative, yielding about 24,000 ad creatives in the sample. Second, we define a dummy variable for each of the 350 ad creatives that occurred on television most frequently during our restricted sample period. Thus *H*=350. Each ad described by a creative-specific utility parameter appeared at least 42 times.

Positive Category Advertising Effects[a]

Category	Point Est. (T-Stat)	% All Ad Seconds	% All Ad Dollars
Computers, Corporate	0.0026 (3.0)	0.07%	0.11%
Participatory Sports	0.0024 (2.8)	0.03%	0.06%
Light Beer & Ale	0.0024 (2.8)	0.40%	0.78%
Regular Beer & Ale	0.0023 (5.6)	0.13%	0.30%
Ice Cream	0.0014 (2.2)	0.18%	0.23%
Home Audio Equipment	0.0013 (2.2)	0.29%	0.39%
Financial Products and Services	0.0013 (2.6)	0.32%	0.36%
Cars, European	0.0012 (2.7)	0.46%	0.62%
Courier Services	0.0012 (3.3)	0.35%	0.53%
Cars, Domestic	0.0012 (2.7)	0.75%	0.98%
Motion Pictures	0.0011 (4.5)	5.76%	6.28%
Insurance	0.0010 (8.7)	0.31%	0.36%
Diet Carbonated Soft Drinks	0.0009 (2.0)	0.50%	0.65%
Pre-Recorded Video & DVDs	0.0008 (2.0)	1.86%	1.92%
Banks, S&Ls	0.0007 (2.7)	0.70%	0.75%
Light Trucks, Asian	0.0006 (2.0)	1.83%	2.04%
Light Trucks, Domestic	0.0005 (2.7)	2.48%	3.28%

Negative Category Advertising Effects[a]

Category	Point Est. (T-Stat)	% All Ad Seconds	% All Ad Dollars
Prescription Medications	-0.0002 (-2.7)	7.06%	6.33%
Wireless Telecom Providers	-0.0003 (-2.6)	6.09%	6.05%
Toothpaste & Whiteners	-0.0007 (-2.1)	0.59%	0.57%
Stationery, Greeting Cards	-0.0009 (-3.4)	0.48%	0.37%
Candy & Mints	-0.0011 (-2.9)	0.62%	0.53%
Real Estate Agencies	-0.0012 (-3.0)	0.54%	0.46%
Cookies & Crackers	-0.0012 (-2.3)	0.32%	0.28%
Mouthwashes & Breath Fresheners	-0.0013 (-2.9)	0.37%	0.30%
Diapers (Adult, Infant And Toddler)	-0.0016 (-2.3)	0.14%	0.11%
Bleach & Fabric Softeners	-0.0018 (-2.4)	0.12%	0.10%
Spectator Sporting Events	-0.0019 (-2.5)	0.14%	0.09%
Shoe Stores	-0.0019 (-2.0)	0.14%	0.11%
Apparel	-0.0020 (-2.1)	0.08%	0.09%
Pharmacies	-0.0025 (-3.0)	0.08%	0.07%
Vegetable Juices	-0.0027 (-2.3)	0.07%	0.06%

[a] Only effects significant at the 95% confidence level are shown, for categories that spent >= .05% of total advertising dollars.

Table 7. Category Advertising Utility

Positive Category Product Placement Effects[a]			**Negative Category Product Placement Effects**[a]		
Category	**Point Est. (T-Stat)**	**% All PP Seconds**	**Category**	**Point Est. (T-Stat)**	**% All PP Seconds**
Gelatins and Puddings	0.0014 (2.0)	0.10%	Apparel	-0.0003 (-2.7)	1.64%
Regular Beer & Ale	0.0007 (2.0)	0.42%	Pre-Recorded Video	-0.0003 (-4.6)	1.09%
Cosmetics & Beauty Aids	0.0006 (2.1)	0.46%	Corporate Advertising	-0.0004 (-2.4)	0.53%
Regular Carbonated Soft Drinks	0.0003 (4.7)	10.37%	Magazines	-0.0005 (-2.0)	0.91%
Sneakers	0.0002 (3.0)	3.14%	Cars, Domestic	-0.0007 (-2.0)	0.48%
Motion Pictures	0.0002 (2.7)	1.53%	Wireless Telecom Providers	-0.0007 (-4.2)	1.77%
			Internet Service Providers	-0.0008 (-4.7)	0.89%
			Credit Cards	-0.0012 (-2.4)	0.29%
			Prepared Dinners & Entrees	-0.0022 (-2.7)	0.09%
			Employment Agencies	-0.0054 (-3.3)	0.12%
			Medical Supplies	-0.0070 (-2.3)	0.04%

[a] Only effects significant at the 95% confidence level are shown.

Table 8. Category Product Placement Utility

Of the 350 ad creative parameters, 35 were estimated to be significant at the 95% confidence level. Table 9 displays the creative names, brands, parameter estimates, and t-statistics for each of those creatives. It also shows what fraction of all ads and ad dollars in the sample each creative accounted for.

We interpret these results with caution. We presume that most of the ad creatives in the sample have some effect on viewer utility, and we would be able to measure all of their effects if we had individual-level viewing data. We are looking here at the tails of the distribution of ad creative utility, among the ads that appeared most frequently.

With those caveats in mind, it is interesting to note what these ads do not have in common. It does not appear that brand identity is a primary driver of ad creative utility, as two brands (Verizon Wireless and Old Navy) have ad creatives with significant positive effects, as well as ad creatives with significant negative effects. However, none of the significant creative effects contradict the positive and negative category-specific effects presented above.

We watched the ads in Table 9 to try to get a general sense of what creative elements drive the results. We noticed that ads with significant positive effects tended to be upbeat and affirmative, and to feature actors that appeared younger than about 40 years old. One advertisement featured a popular celebrity (Denzel Washington) and another had a song from a popular band (Kings of Leon).

TNS Ad Creative Name[a]	Brand	Point Est. (T-Stat)	% of all ads	% ad dollars
It's Ok To Look	Match.Com Dating Service	.005 (2.1)	.04%	.02%
Man Gets Locked Out In Bathrobe	Burlington Coat Factory Men	.005 (2.2)	.04%	.02%
Biggest Sale Of The Year	JC Penney	.004 (2.1)	.03%	.02%
No Title Assigned - #3726541	Boys & Girls Club/Psa	.003 (2.4)	.04%	.04%
Man Drives Family To Gaze At Stars	Toyota Trucks Sequoia	.003 (3.3)	.09%	.11%
Tunics/Women Dance On Boat	Old Navy Clothing Store	.003 (2.4)	.05%	.07%
Duck Helps Couple Get By	Aflac Medical Insurance	.003 (2.2)	.04%	.04%
Trainer Gets Pumped Up From Song	Verizon Wireless Service	.002 (2.3)	.05%	.05%
Vehicle Drives On Building Edges	Ford Trucks Edge	.002 (2.0)	.04%	.09%
Molly's Chambers/Couple Dances	Volkswagen Autos Jetta	.002 (3.0)	.06%	.10%
Truck Performs Seesaw Ramp Trick	Toyota Trucks Tundra	.002 (2.4)	.06%	.08%
Woman Wakes Up In The Dark	Lunesta Sleep Rx	-.001 (-2.2)	.08%	.15%
Woman Had Mysterious Symptoms	Requip Restless Legs Syndrm Rx	-.001 (-2.0)	.04%	.07%
People...To Do/Prescription Assistance	Humira Rheumatoid Arthritis Rx	-.001 (-2.6)	.04%	.07%
No Title Assigned - #3978969	Foundation/Better Lf/Psa	-.002 (-2.2)	.08%	.08%
Bubbles Flow Over Bottle & Teeth	Listerine Whitening Rinse	-.002 (-2.1)	.05%	.04%
Effortless Meticuless Fabuless	Target Disc Multi-Pdts	-.002 (-2.1)	.04%	.06%
Father Says He Got Hosed	Verizon Wireless Service	-.002 (-2.1)	.05%	.04%
Lust For Life/Women In Europe	Royal Caribbean Cruises	-.002 (-2.6)	.06%	.07%
Family Shareplan/Man Talks To Family	Verizon Wireless Service	-.002 (-2.3)	.05%	.04%
Women Walk Around City In Shorts	Old Navy Clothing Store	-.002 (-2.2)	.04%	.06%
Breast Meal/2Pc Meal/3 Strip Meal	KFC Restaurant	-.002 (-2.3)	.05%	.05%
Woman Acquires Boxes To Be Mailed	USPS.com	-.003 (-2.5)	.05%	.03%
Man Offers People Fast Relief	Zantac 150	-.003 (-2.1)	.03%	.03%
Man Works At Vineyard	Claritin Allergy Remedy	-.003 (-2.4)	.07%	.05%
National Sales Race	Nissan Autos Altima & Sentra	-.003 (-2.0)	.04%	.03%
Push It/I365 Nextel Phone	Sprint PCS Wireless Service	-.003 (-2.0)	.03%	.03%
Tuscan Garlic Chicken	Olive Garden Restaurant	-.003 (-2.1)	.06%	.05%
No Hassle Rewards/Man Skis In Summer	Capital One Mastercard & Visa	-.003 (-3.0)	.05%	.04%
No Hassle Rewards/D Spade Answers No	Capital One Mastercard & Visa	-.003 (-2.3)	.05%	.06%
People Rinse Their Mouth With Product	Listerine Mouthwash	-.003 (-2.2)	.04%	.03%
1500 Whenever Mins/Cheerleader On Phone	T-Mobile Wireless Service	-.003 (-4.3)	.09%	.09%
A Night In...Castle Giveaway/Letterbox	Disneyparks.Com Online	-.004 (-3.3)	.04%	.03%
The Difference Between Services	Blockbuster.Com Store Online	-.004 (-3.6)	.04%	.04%
Men & Ellen At Reception Are Gellin	Dr Scholls Massaging Gel Insoles	-.004 (-2.3)	.05%	.03%

[a]Only ad creative effects significant at the 95% level are shown.

Table 9. Ad Creative Utility

Ad creatives with significant negative effects were more likely to feature actors older than forty, convey negative messages, and depict scenes of frustration. Some contained what could be subjectively termed annoying stimuli, such as intentionally bad dancing ("Push It/I365 Nextel Phone"), high-pitched, rapid speech ("1500 Whenever Mins/Cheerleader on Phone"), or actors using made-up words in conversation ("Men and Ellen at Reception are Gellin").

The results suggest that, consistent with Woltman Elpers et al. (2003) and Teixeira et al. (2008), creative characteristics drive viewer acceptance of advertising. While we find these effects to be interesting, they are suggestive at best. We think there is scope for future research to use field data to measure the effects of ad creative characteristics on viewers' advertising utility.

5.3. *Random coefficients logit results*

In this section we present results from the full random coefficients logit model, including the estimated elasticities of advertising. Our advertising utility specification is given by[20]

$$v(p_{nt}, q_{nt}; \alpha_i) = p_{nt}\alpha_{1i} + p_{nt}^2\alpha_2 + q_{nt}\alpha_{3i} + q_{nt}^2\alpha_4 + q_{nt}^3\alpha_5 . \tag{16}$$

The main results are shown in Table 10. The point estimates of advertising and product placement have the same signs as those estimated in the multinomial logit model, but are not estimated as precisely. Most of the significant effects are those associated with the program dummies, network-day dummies, and half-hour dummies. Table 11 presents the highest estimated program effects. The top programs seem reasonable: *American Idol*, *Desperate Housewives*, *Grey's Anatomy*, and *Lost*.

Table 12 shows the network-weekday point estimates. One of the highest significant point estimates is NBC's Thursday night, which is the only network-day to be branded in recent years ("Must See TV").

The primary reason to estimate the random coefficients logit model is that its estimated audience elasticities of advertising do not exhibit the well-known independence of irrelevant alternatives problem. The advertising elasticities generated by this model are

$$\frac{\partial s_{nt} q_{mt}}{\partial q_{mt} s_{nt}} = \begin{cases} -\dfrac{q_{nt}}{s_{nt}} \displaystyle\int \frac{\partial v_i}{\partial q_{nt}} s_{int}(1-s_{int})dF(\upsilon_i), \text{ if } m = n \\ \dfrac{q_{mt}}{s_{nt}} \displaystyle\int \frac{\partial v_i}{\partial q_{nt}} s_{int} s_{imt} dF(\upsilon_i), \text{ if } m \neq n \end{cases} . \tag{17}$$

The elasticities in equation 17 contain s_{int}, the probability that simulated individual *i* picks

[20] We first included random coefficients for all five elements of α_i. However, this resulted in a much larger objective function value, and the local minima problem was more prounounced. Given the high correlations among powers of p_{nt} and q_{nt}, it may be impractical to expect variation in the data to allow us to separately identify more than one element of α_i for each variable. As a result we simplified the specification to that in equation 16.

Regressor	Coeff. Est. (T-Stat)	Stat)
Ad Sec.	-.00113 (-0.2)	0.1 (0.0)
(Ad Sec.)^2	.00000 (0.0)	
(Ad Sec.)^3	.00000 (0.1)	
PP Sec.	.00000 (-0.1)	0.3 (0.0)
(PP Sec.)^2	.00000 (-0.6)	
NewEps	1.48984 (0.6)	
1-week lag s_{nt}	.04335 (0.5)	
2-week lag s_{nt}	.01432 (0.3)	
3-week lag s_{nt}	.00989 (0.1)	
4-week lag s_{nt}	.01269 (0.3)	
5-week lag s_{nt}	.01376 (1.2)	
Constant	.18429 (1.3)	
GMM Objective		8.4558
Pseudo R^2		0.7499

Note: lags of s_{nt} are the the previous week's audience rating on network n at the same weekday/half-hour as t

Table 10. Random Coefficients Logit Parameter Estimates

Program	Coeff. Est. (T-Stat)
Program: American Idol	6.8E-1 (2.2)
Program: Desperate Housewives	5.9E-1 (4.6)
Program: Grey's Anatomy	5.3E-1 (5.4)
Program: Lost	5.2E-1 (3.2)
Program: House	4.4E-1 (1.7)
Program: 20/20	3.4E-1 (2.0)
Program: 24	3.3E-1 (2.6)

Table 11. Program Effect Estimates

Regressor	Coeff. Est. (T-Stat)	Regressor	Coeff. Est. (T-Stat)
ABC-Mon	0.18 (1.3)	FOX-Mon	0.24 (2.5)
ABC-Tue	0.13 (1.5)	FOX-Tue	0.20 (1.2)
ABC-Wed	0.11 (1.4)	FOX-Wed	0.27 (2.7)
ABC-Thu	0.15 (1.8)	FOX-Thu	0.11 (1.0)
ABC-Fri	-0.23 (-1.8)	FOX-Fri	-0.31 (-1.9)
ABC-Sat	-0.29 (-2.0)	FOX-Sat	0.39 (0.7)
CBS-Sun	0.25 (0.9)	NBC-Sun	0.05 (0.3)
CBS-Mon	0.48 (2.7)	NBC-Mon	0.27 (2.6)
CBS-Tue	0.20 (1.5)	NBC-Tue	0.23 (0.7)
CBS-Wed	0.15 (1.5)	NBC-Wed	0.07 (0.8)
CBS-Thu	0.45 (1.6)	NBC-Thu	0.40 (3.1)
CBS-Fri	0.04 (0.2)	NBC-Fri	-0.03 (-0.2)
CBS-Sat	0.08 (0.3)	NBC-Sat	-0.13 (-0.7)
FOX-Sun	0.49 (2.5)	WB-Thu	-0.26 (-1.8)

Note: ABC-Sun was chosen to be the excluded night. With one exception (WB-Thu), all CW-, UPN-, and WB-Weekday interactions were dropped due to scarcity of top-100 audience observations on those nights.

Table 12. Network-Weekday Effects

alternative *n* at time *t*, given a change in ad time q_{mt}. Therefore substitution patterns are not driven by aggregate market shares irrespective of program characteristics, as in the multinomial logit model, but instead they are calculated as the aggregation of simulated discrete choices. Also notable is that the model produces a different elasticity for each network-half hour.

Table 13 displays the median estimated audience elasticities of advertising. It indicates that if a broadcast network increases its advertising time by 10%, its median audience loss is about 15%. The cross-elasticities are roughly comparable in nature across the "inside" networks and the outside option, but since the market share of the outside option is much larger than the sum of the ratings of the inside networks, this implies that when viewers leave an audience in response to an additional advertisement, they usually turn away from broadcast television altogether (tuning to a cable network, for example) rather than switching to another top-100 program.

Network	ABC	CBS	CW	FOX	NBC	UPN	WB	Outside Option
ABC	-1.49	0.06	0.08	0.06	0.06	0.06	0.09	0.04
CBS	0.08	-1.53	0.05	0.05	0.05	0.05	0.03	0.05
CW	0.03	0.03	-1.49	0.03	0.03	–	–	0.02
FOX	0.06	0.06	0.00	-1.45	0.06	0.06	0.05	0.05
NBC	0.07	0.06	0.04	0.06	-1.51	0.06	0.03	0.04
UPN	0.02	0.02	--	0.02	0.02	-1.56	0.04	0.02
WB	0.02	0.02	--	0.02	0.02	0.02	-1.51	0.03

[a] Table entry *i,j* reports the estimated elasticity of option j's national audience in response to a 10% increase in network i's observed advertising level. Reported elasticities are the medians of the distribution of national audience elasticities over days and half-hours.

Table 13. Estimated Audience Elasticities of Advertising.

It is interesting to compare our elasticity estimates to those of Wilbur (2008b). He estimated a similar model using four weeks of audimeter/diary audience data from a cross-section of local markets. He found that a 10% rise in advertising time caused a median 25% audience loss on highly-rated networks, and larger own-elasticities for low-rated networks. Our elasticities are smaller and more homogeneous by comparison, though still substantial. The difference in our estimates can perhaps be attributed to the unreliability of diary data, which places a much higher burden on the audience member than the Peoplemeter technology used to produce our sample.

6. Discussion

In light of the increasing importance of advertisement avoidance, we estimated a model of television viewing demand in which viewing decisions depend on program characteristics, scheduling factors, advertising time and characteristics, and product placement time and characteristics. Our key findings are that a 10% increase in advertising reduces a network's audience by a median 15%, and audience responses to advertising seem to be driven by product category and ad content. When we control for episode quality, we find that product placement has a negative effect on viewer utility.

Our findings imply that networks ought to price discriminate among advertisers in order to maximize audience retention throughout their commercial breaks. There are three ways this could be done in practice. The simplest way would be to give ad price breaks to advertisers in categories which have traditionally been associated with high-utility ad creatives, such as beer, autos, movies, and finance-related categories. Accordingly, higher prices could be charged to those advertisers in categories that historically cause larger audience losses.

A more nuanced way to implement this would be to set up a system whereby advertisers submit their creatives to standardized tests of audience acceptance. For example, an ad creative could be vetted by an online consumer panel or inserted into network programming online (e.g., on Hulu.com), and observed viewer reactions would be used to measure viewer response to the ad. Given enough consumers in the panel and a standard approach toward testing creatives, a formula could be devised to adjust the advertiser's price. The attraction of this idea is that it would give advertisers an increased incentive to produce engaging advertising, and could possibly correct the currently unpriced externality in which an ad's audience loss harms subsequent advertisers in the commercial break.

A third approach would be to base ad prices on more granular television audience measurements, such as second-by-second ratings currently extractable from the universe of digital cable boxes and digital video recorders (Wilbur 2008a). This would give advertisers the strongest incentives to avoid causing audience losses. However, it would be the most difficult to implement, since ownership of the most granular viewing data resides with multiple parties with potentially conflicting interests, and the television industry has historically been slow to agree upon and implement new metrics.

We view all three of these suggestions as realistic. The first can feasibly be implemented right away, while the second probably needs to be refined after a design and testing phase. The third suggestion is the most difficult to set up, but would have the most positive impact on the television industry's collective health in the long run. It would also likely have the greatest effect on viewer welfare, which is consequential in an industry with such a large share of gross domestic leisure time.

Like all models, ours has several limitations which suggest directions for future research. We have not modeled viewer uncertainty about advertising and product placement time, as Anand and Shachar (2004, 2005) did in a related context. This is difficult to do reliably using aggregate rating data, but may be feasible using the approaches of Chen and Yang (2007) or Musalem, Bradlow and Raju (forthcoming). We also have not controlled for order of advertisement presentation. Finally, while we have used the best audience data available to us, there is scope for estimating a similar model using more granular data, such as commercial minute ratings or second-by-second set-top box data.

Appendix 1. Instrument Validation.

We follow the methodology of Bound, Jaeger, and Baker (1995) and Staiger and Stock (1997) to validate our use of lags of ad seconds and product placement seconds as instruments for current ad seconds and product placement time. There are three steps to this procedure. The first step is to use F-tests to determine whether the proposed instruments jointly explain the endogenous variables. The second step is to use F-tests to determine whether the proposed instruments can be justifiably excluded from the viewer utility function. The third step is to use a Hausman specification test to gauge the difference between the OLS and IV estimates. The first two steps of this procedure formalize the standard instrumental-variables intuition that valid instruments should be (1) correlated with the endogenous regressor, and (2) uncorrelated with the error term in the second-stage equation. The third step checks whether IV estimation changes the point estimates of the endogenous regressors. If it does not change the estimates, we retain OLS estimates on efficiency grounds.

Table A1 displays the results of the first two steps. The first column of the table presents results from the first-stage regression of advertising seconds on the proposed instruments and the exogenous variables in the viewer utility function. Lags of advertising seconds are significant and the F-test rejects the null hypothesis that the candidate instruments jointly do not explain the dependent variable at a high confidence level. The second column of the table indicates that the instruments jointly explain product placement seconds to a similar degree. The third column tests the exclusion restrictions. The F-statistic fails to reject the null that the instruments do not jointly explain the log-transformed program ratings. Thus we conclude that lags of advertising and product placement time are valid instruments for current advertising and product placement time.

The final step of the validation process is to compare the parameter estimates under OLS and IV. If there is no significant difference, OLS results are preferred on efficiency grounds. The Hausman test fails to reject the null that the OLS estimates are preferred to the IV estimates. Thus the use of these instruments does not change the estimated effects of the potentially endogenous variables enough to justify the loss of efficiency associated with IV estimation.

Instrument	First-stage Est. in AdSec Eqn.	First-stage Est. in PP Eqn.	Second-Stage Est. in Viewer Demand Eqn.
	(T-Stat)	(T-Stat)	(T-Stat)
Ad Seconds			
1st Lag	0.16 (17.38)	-0.03 (-1.53)	4.5E-5 (1.39)
2nd Lag	0.13 (13.64)	0.01 (0.34)	4.4E-6 (0.14)
3rd Lag	0.09 (9.89)	-0.02 (-0.99)	8.0E-6 (0.25)
4th Lag	0.09 (9.33)	0.00 (0.2)	-1.7E-5 (-0.54)
5th Lag	0.09 (10.47)	0.01 (0.62)	-3.3E-5 (-1.07)
Product Placement Seconds			
1st Lag	2.0E-3 (0.6)	0.06 (7.18)	-2.9E-5 (-2.51)
2nd Lag	4.2E-3 (1.29)	0.03 (3.5)	-2.5E-6 (-0.22)
3rd Lag	-5.7E-3 (-1.57)	0.03 (3.28)	1.7E-5 (1.4)
4th Lag	-2.5E-3 (-0.7)	0.03 (3.81)	-8.5E-6 (-0.68)
5th Lag	4.1E-4 (0.11)	0.04 (4.53)	1.8E-6 (0.14)
Null Hypothesis	No joint effect	No joint effect	No joint effect
R^2 in unrestricted model	0.4383	0.6307	0.8315
R^2 in restricted model	0.3316	0.6231	0.8313
Joint Significance F-Stat	173.26	18.73	1.08
99% Critical Value	2.32	2.32	2.32
P-Value	**0**	**1.71E-34**	**0.37**
Result	Reject Null	Reject Null	Don't Reject Null

Table A1. Instrumental Variables Validity Checks

Appendix 2. Estimating Product Placement Utility with Episode Quality Controls

We are concerned that, despite our controls for endogeneity, the product placement utility estimates may be positively biased. It could be that occasions for product placement in a program episode correlate with unobserved episode characteristics that increase viewer utility. The program effects control for variation in unobserved program characteristics across programs in the sample, but not across episodes within a program. It is this latter variation that may be correlated with product placement. If we had an independent measure of program quality that varied over episodes within a program, we could control for unobserved episode quality and measure the effect of product placement independently of episode quality.

We were able to find such a measure in an online database, TV.com. This site states that "TV.com is home to millions of television fans contributing and connecting via their favorite shows. From program ratings and episode reviews to forum posts and blogs, the fans provide almost all of the site's content…" The site is a wiki in which viewers can list, review, and assign quality "scores" to television programs and episodes. Each program and episode in the database has been scored on a 1-10 scale by TV.com users. Popular programs' episodes are often rated by 400 or more users. The website says 72.3% of its users are between the ages of 18 and 49, and they watch an average of 21 television hours per week. Thus we think their ratings may be a reasonable proxy for episode utility experienced by adults aged 18-49. The benefit of using these data is that they contain average episode quality scores, which will allow us to control for the endogeneity issue discussed in the previous paragraph.

The TV.com data are rich but incomplete and often inaccurate. The website's program database is missing many of the less popular programs in our sample. For those less popular programs that are included, viewer ratings data are very sparse. The episode database seems to have even more problems. Even popular programs have duplicate episode listings and are missing some new episodes. Some episodes' air dates are listed incorrectly. We considered using data from another wiki, tv.yahoo.com, but this database seemed to have even more omissions and duplicates than TV.com. We therefore concluded it would be infeasible to add the episode-level TV.com data into the TNS/TVB sample.

Instead, we supplemented some of the usable TV.com data with the TNS/TVB data. The data contain fewer flaws for popular programs, so we identified the most-frequently-programmed show in each of the four most common genres in the TNS/TVB sample: *24*, *CSI*, *Scrubs*, and *Extreme Makeover*. We then narrowed the airings of these programs to new episodes in the 2005-2006 and 2006-2007 seasons. We downloaded episode quality scores for all of the program/dates on which TV.com and TNS agreed a new episode appeared. This gave us a sample of 159 program-episodes. We supplemented this with episode-level advertising, product placement, audience, and characteristics data from our TNS/TVB sample.

We used these data to estimate a multinomial logit model at the program-episode level in which the dependent variable is the log-transformation of observed program/episode ratings and outside share data. The independent variables are the average number of advertising seconds per half-hour, average number of product placement seconds per half-hour, average previous week's audience in the same network-half hours (to control for state dependence), a scalar indicating how many new episodes of the program had previously been aired in the same season (to control for narrative arc), program dummies, a dummy for the 2005-06 season, and weekday dummies. We also tried including calendar-month dummies, product placement characteristics, powers of advertising and product placement time, and interactions between program dummies and product placement time, but none of these increased the adjusted R^2 enough to justify the degrees of freedom they cost.

Table A2 shows our results. The primary result of interest is the effect of product placement on utility, which is estimated to be negative and significant at the 95% confidence level. This finding is robust to basic specification changes. It appears that our product placement estimates reported in section 5 are positively biased.

The effects of advertising and episode quality score on utility are not estimated to be significant. Ad price per viewer, included to control for unobserved tune-in levels, is negative and significant. The weekday effects, season dummy, and program effects are all significant, yielding a high degree of fit. State dependence is not estimated to be significant, perhaps due to its correlation with the program and weekday dummies.

In sum, we conclude that our product placement results in the full model are likely biased upwards. However, we are not able to control for this bias in the full sample.

Regressor	**Coeff. Est. (T-Stat)**
Product Placement Seconds	-.0002 (-2.2)
Ad Seconds	.0008 (1.3)
TV.com Episode Score	-.0271 (-1.0)
Ad Price per Viewer	-1.8E-7 (-3.8)
Previous week audience	-.0005 (-0.1)
Episode Number	-.0164 (-9.0)
05-06 Season	.1555 (5.3)
24	-.6976 (-5.2)
Extreme Makeover	-1.1232 (-10.1)
Scrubs	-.8832 (-17.3)
Monday	-.2052 (-1.9)
Tuesday	-.6860 (-6.8)
Thursay	-.5693 (-6.8)
Constant	-1.5852 (-4.7)
Adjusted R^2	0.8766
Number of observations	159

The dependent variable is $\ln(s_{nt})-\ln(s_{0t})$, where s_{nt} is audience share among Adults 18-49, and t indexes network-time periods in which valid episode rating data could be obtained from tv.com for the programs *24*, *CSI*, *Extreme Makeover*, and *Scrubs*.

Table A2. Program-Episode Utility Effects

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