The Effectiveness and Targeting of Television Advertising

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Television networks spend about 16% of their revenues on tune-ins, which are previews or advertisements for their own shows. In this paper, we examine two questions. First, what is the informational content in advertising? Second, is this level of expenditures consistent with profit maximization? To answer these questions, we use a new and unique micro-level panel dataset on the television viewing decisions of a large sample of individuals, matched with data on show tune-in advertisements. The difference in effectiveness of advertisements between "regular" shows (about which viewers are assumed to have substantial information a priori) and "specials" (about which they have very little) reveals the value of information in advertisements and the different roles that information can play. The number of exposures for each individual is likely to be correlated with their preferences, since networks target their audiences. We address this endogeneity problem by controlling for observed, and integrating the unobserved, characteristics of individuals, and find that the estimated effects of tune-ins are still large. Finally, we find that actual expenditures on tune-ins closely match the predicted optimal levels of spending.

1. Introduction

Advertising expenditures by television networks are substantial. In 1995, for example, the three major networks spent approximately

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16% of their revenues on tune-in advertisements,[1] more than twice as much as firms in other industries. The networks also rank among the top ten firms in the economy in terms of dollars of advertising expenditures.[2] This raises an obvious question: are networks spending too much on advertising?[3] Indeed, one may suspect that networks underestimate their advertising costs, since these are mostly opportunity costs; consequently, advertising expenditures might exceed the optimal amount. Answering this question requires an understanding of the effects of tune-ins on individuals' viewing choices, since advertising revenues are a function of show ratings, which are aggregations of individual viewing decisions. In this study, we estimate these effects using a new and unique micro-level panel dataset on the television viewing decisions of a large sample of individuals, matched with data on show tune-ins.

The second question that we address in this paper is of more general interest: what is the informational value of advertising? A spirited debate on whether advertising is ''informative'' or ''persuasive'' has gone on for some time.[4] Understanding the relative importance of informing and persuading has both positive and normative implications. However, distinguishing these effects empirically is difficult. We base our solution to this identification problem on the following logic: if advertising has information content, then the effects of tune-ins on viewing decisions should differ across shows according to individuals' prior information about each show. For example, individuals may possess very little information about the timing and attributes of shows that are aired once—(*specials*) compared to shows that are aired frequently (*regulars*).[5] We estimate the differential effects of tune-ins on viewing decisions for these two

1. ''Tune-in'' usually refers to an advertisement *for* a television show. Advertisements for TV shows represent a cost for the networks, and other advertisements supply their revenues. The ads we focus on in this paper are of the first type.

2. The networks usually air 12 minutes of commercials during each hour of programming. In 1995, they used about 2 of these 12 minutes on tune-ins for their shows. Since advertising revenues represent almost all of the networks' revenues, and tune-ins represent most of their advertisement effort, we proxy the share of revenues spent on advertisements as 16%. We then estimate their spending on advertising in dollars, using these numbers and data on networks' revenues.

3. Roberts and Samuelson (1988) use a different approach than ours to answer a similar question in the context of the tobacco industry.

4. Early work on this can be traced to Galbraith (1967) and Solow (1967); Tirole (1989, pp. 289–290) labels these as the ''partial'' view versus the ''adverse'' view of advertising. For models dealing explicitly with the informational effects of advertising, see Butters (1977) and Grossman and Shapiro (1984).

5. This is similar to the oft-cited distinction between ''search'' goods and ''experience'' goods, although not identical, since regular shows have features common to both types of goods.

kinds of shows. If there were no informational content in advertising, then the effects of tune-ins should not differ across such shows with different preexisting ''information stocks.'' Thus, the product variation in the data provides us with a clear way to identify the informational value of advertising.[6]

Our estimates of the effects of tune-ins may be biased, since networks generally *target* their tune-ins for each show towards certain groups of individuals. For example, tune-ins for comedies are more often aired during other comedies, thus targeting individuals most likely to watch comedies in the first place. If these unobserved differences in individual preferences are not controlled for, the effects of tune-ins on viewership will be upward biased. We deal explicitly with this endogeneity problem in the estimation below. To our knowledge, no other micro-level study addresses this issue in any detail.[7]

This is the first study focusing explicitly on the effects of tune-in advertisements on individual behavior.[8] There are two main advantages of examining the effects of advertising in the TV industry. First, advertising is undertaken by firms using, in general, various instruments (price discounts, promotions, etc.) and various media (television, billboards, magazines, etc.). These different forms of advertising may be substitutes or complements in consumption[9]: for example, the marginal effectiveness of magazine ads may depend on the amount of advertising generated by other means, concurrently or in the past. In order to accurately estimate the marginal effectiveness of a particular form of advertising or assess the relative efficacy of alternative forms of advertising, one would require data on the amount of advertising via other forms; this is usually difficult to obtain. This issue is of less concern in the TV industry for two reasons: first, almost all advertising by networks is in the form of tune-ins; second, the price of TV services is zero from an individual's standpoint. Hence, we do not need to consider issues arising from the existence of multiple advertising inputs.

6. A few previous studies attempt to distinguish informative effects from persuasive effects in advertising, either by subjective measurement of the information content in ads (Resnik and Stern, 1978) or by econometric identification techniques similar to ours (Ackerberg, 1995). All these studies focus on single-product returns of advertising.

7. The targeting of advertising may be important in contexts of both repeat and nonrepeat purchase, and hence is likely to be an issue of general concern.

8. See, for example, Berndt (1991) or Tellis and Weiss (1995) for surveys of the literature on the effects of advertising.

9. Strictly, the advertising itself is not consumed; rather, ads may convey information that is of value in making decisions.

Second, previous studies suggest that the returns to advertising may differ across products.[10] These differences are useful in revealing the different roles of advertising in influencing individual choice. However, it is difficult to compare results across studies, given nonuniformity in datasets, methodologies, or products under examination. Since our dataset contains information for multiple TV shows that, in principle, differ substantially in their attributes, we can examine such cross-product differences within a common setting. Our focus here is only on characterizing the variation between regulars and specials; we plan to further exploit the product variation in the dataset in future research on this issue.

The rest of the paper is organized as follows. We first describe the datasets used, since this assists in understanding the structure of the model. In Section 2, we describe the construction of the dataset and present descriptive statistics on the sample population, viewership patterns, show characteristics, and characteristics of tune-ins. In Section 3, we present the model used to estimate the effects of tune-ins, and discuss identification issues. We discuss the results in Section 4, and their implications for network strategies in Section 5. In Section 6, we discuss issues for further study.

2. The Datasets

We use three datasets in this study. The first includes data on the viewing choices of about 17,000 individuals during one week in November 1995. The second describes the attributes of the shows offered to these individuals by the four leading networks during this week. The number of tune-ins for each show and the time of their airing constitute the third data set.

Nielsen Media Research maintains a sample of over 5000 households nationwide by installing a Nielsen People Meter (NPM) for each television set in the household. Using 1990 Census data, the sample is designed to reflect the demographic composition of viewers nationwide. The sample is revised regularly, ensuring, in particular, that no single household remains in the sample for more than two years.

The NPM uses a special remote control to record arrivals and departures of individual viewers, as well as the channel being watched on each television set. Although the NPM is calibrated for

10. For example, Batra et al. (1995) summarize the variation in estimated returns across products examined in prior studies. For conflicting results regarding the existence of diminishing returns to advertising, see Simon and Arndt (1980) and Rao and Miller (1975).

measurements each minute, the data set available to Nielsen clients provides a record of whether or not each viewer tuned into each of the alternatives during each quarter hour.

The raw dataset records whether or not an individual was watching television in each quarter hour, and if so, her choice of network. An individual who was watching television, but did not choose any network, is coded as watching a nonnetwork channel. This might be a cable channel, PBS, or a local independent channel. Each quarter hour is defined as a time slot.

We use the data for *prime time*, 8:00 to 11:00 P.M., for the five weekdays starting Monday, November 6, 1995. Thus, we observe viewers' choices in 60 time slots. Table I presents the programming of the four major networks (ABC, CBS, NBC, and FOX) over this time period. This study confines itself to east-coast viewers, to avoid problems arising from ABC's Monday night programming. ABC features Monday Night Football, broadcast live across the country; depending on local starting and ending times of the football game, ABC affiliates across the country fill their Monday night schedule with a variety of other shows. Adjusting for these programming differences by region would unnecessarily complicate this study. Finally, viewers who never watched television during weeknight prime time and those younger than six years of age are eliminated from the sample. From this group, we randomly select 1675 individuals. Their viewing choices provide an adequate and rich set of information that is used in the estimation.

Most individuals chose not to watch TV (55.5%) in any given time slot, and many preferred to watch a nonnetwork channel (18.4%). NBC was the most watched network, with 8.9% of the individuals tuned in, on average, in a given time slot, followed by ABC (7.7%), CBS (6.1%), and FOX a distant fourth (3.6%). The highest-rated show during the week under consideration was *ER* (a medical drama on NBC), with a 21% share,[11] while the CBS news magazine *48 Hours* had the lowest rating with a 2.9% share. An interesting aspect of viewing behavior was the persistence in choices of individuals. Two out of any three viewers in any given time slot watched the same channel in the previous time slot. The degree of persistence was even higher across time slots spanned by a single show, and varied according to demographic characteristics.[12]

11. "Share" is defined here to be the fraction of all individuals (including those who do not watch TV) who are tuned in to the show in the given time slot.

12. Shachar and Emerson (1996) examine the phenomenon of persistence in more detail, using the same dataset.

TABLE 1.
TELEVISION SCHEDULE, NOVEMBER 6-10, 1995

Day	Network	8:00	8:30	9:00	9:30	10:00	10:30
Mon.	ABC	The Marshal		Pro Football: Philadelphia at Dallas			
	CBS	The Nanny	Can't Hurry Love	Murphy Brown	High Society	Chicago Hope	
	NBC	Fresh Prince of Bel-Air	In the House	Movie: She Fought Alone			
	FOX	Melrose Place		Beverly Hills 90210		Affiliate Programming: News	
Tue.	ABC	Roseanne	Hudson Street	Home Improvement	Coach	NYPD Blue	
	CBS	The Client		Movie: Nothing Lasts Forever			
	NBC	Wings	News Radio	Frasier	Pursuit of Happiness	Dateline NBC	
	FOX	Movie: Bram Stoker's Dracula				Affiliate Programming: News	
Wed.	ABC	Ellen	The Drew Carey Show	Grace Under Fire	The Naked Truth	Prime Time Live	
	CBS	Bless this House	Dave's World	Central Park West		Courthouse	
	NBC	Seaquest 2032		Dateline NBC		Law & Order	
	FOX	Beverly Hills 90210		Party of Five		Affiliate Programming: News	
Thu.	ABC	Movie: Columbo: It's All in the Game				Murder One	
	CBS	Murder, She Wrote		New York News		48 Hours	
	NBC	Friends	The Single Guy	Seinfeld	Caroline in the City	E.R.	
	FOX	Living Single	The Crew	New York Undercover		Affiliate Programming: News	
Fri.	ABC	Family Matters	Boy Meets World	Step by Step	Hangin' With Mr. Cooper	20/20	
	CBS	Here Comes the Bride		Ice Wars: USA vs The World			
	NBC	Unsolved Mysteries		Dateline NBC		Homicide: Life on the Street	
	FOX	Strange Luck		X-Files		Affiliate Programming: News	

The purpose of this study is to examine the effects of tune-ins on viewing decisions. In Section 3, we present the viewing-choice model that we use to estimate these effects. The structure of this model is similar to that of Shachar and Emerson (1996), which found that demographic characteristics of a show's cast and of individuals,

TABLE II.
SUMMARY STATISTICS: INDIVIDUAL DEMOGRAPHIC CHARACTERISTICS

Variable[a]	Mean	Std. Dev
Kids	0.0794	0.2704
Teens	0.0627	0.2425
Gen-X	0.2400	0.4272
Boom	0.2764	0.4474
Old	0.4191	0.4936
Female	0.5319	0.4991
Male	0.4681	0.4991
Family	0.4304	0.4953
Adult	0.8579	0.3492
Income	0.8333	0.2259
Educat	0.7421	0.2216
Urban	0.4149	0.4929
Basic	0.3642	0.4813
Premium	0.3588	0.4798

[a] Definitions (dummy variables, unless otherwise specified): ''Kids'': individual is between the ages of 7 and 11. ''Teens'': individual is between the ages of 12 and 17. ''Gen-X'': individual is between the ages of 18 and 34. ''Boom'': individual is between the ages of 35 and 49. ''Old'': individual is age 50 or older. ''Female'': individual is a female. ''Male'': individual is a male. ''Family'': individual lives in a household with a female older than 18 and her kids. ''Adult'': individual is older than 18. ''Income'': there are six levels of income on the unit interval. ''Educat'': there are five categories of education on the unit interval. ''Urban'': individual lives in an urban area. ''Basic'': individual has basic cable. ''Premium'': individual has premium cable.

as well as five show attributes—action, comedy, romance, suspense, and fiction—are important in explaining viewing decisions. We briefly describe each of these variables below.

Table II defines all the individual demographic variables and presents their summary statistics. Show demographics are described in Table III. In Table IV, we present the various attributes for each show, each of which is normalized to lie between 0 and 1. These attributes were subjectively measured by four research assistants who both watched the entire tapes of the week's shows, and used preexisting knowledge about the shows in constructing these measures.[13]

13. For details on the construction of these attribute measures, see Shachar and Emerson (1996).

TABLE III. SUMMARY STATISTICS: CAST DEMOGRAPHICS OF SHOWS

Show Cast	Mean	Std. Dev.
Gen-X	0.3438	0.4787
Boom	0.2813	0.4532
Family	0.1719	0.3802
Male	0.4531	0.5017
Female	0.2500	0.4364
Black	0.0727	0.2603

Definitions (all dummy variables): ''Gen-X'': the main characters in the show are between the ages of 18 and 34. ''Boom'': the main characters in the show are between the ages of 35 and 49. ''Family'': the main characters in the show are members of a family. ''Male'': the main characters in the show are male. ''Female'': the main characters in the show are female. ''Black'': the main characters in the show are black.

TABLE IV. SHOW ATTRIBUTES

Show	Network	Action	Comedy	Fiction	Romance	Suspense
Fresh Prince of Bel-Air	NBC	0.11	1.00	0.67	0.50	0.20
Melrose Place	FOX	0.33	0.00	0.67	0.75	0.80
The Marshal	ABC	0.56	0.00	0.67	0.38	0.60
The Nanny	CBS	0.00	1.00	0.67	0.63	0.20
Can't Hurry Love	CBS	0.00	1.00	0.67	0.88	0.20
In The House	NBC	0.22	1.00	0.67	0.25	0.20
Pro Football	ABC	1.00	0.14	0.00	0.00	1.00
Beverly Hills, 90210	FOX	0.22	0.43	0.67	1.00	0.60
She Fought Alone	NBC	0.67	0.29	0.33	0.75	0.80
Murphy Brown	CBS	0.11	1.00	0.67	0.50	0.20
High Society	CBS	0.00	1.00	0.67	0.38	0.20
Chicago Hope	CBS	0.67	0.14	0.33	0.63	0.80
Roseanne	ABC	0.00	1.00	0.67	0.75	0.20
Bram Stoker's Dracula	FOX	0.67	0.00	1.00	0.63	0.80
Wings	NBC	0.11	1.00	0.67	0.75	0.20
The Client	CBS	0.22	0.14	0.33	0.25	0.60
NewsRadio	NBC	0.00	1.00	0.67	0.38	0.20
Hudson Street	ABC	0.00	1.00	0.67	0.88	0.20
Nothing Lasts Forever	CBS	0.33	0.00	0.67	0.63	0.80
Home Improvement	ABC	0.22	1.00	0.67	0.75	0.20
Frasier	NBC	0.00	1.00	0.67	0.63	0.20
Pursuit of Happiness	NBC	0.00	1.00	0.67	0.88	0.20
Coach	ABC	0.00	1.00	0.67	0.63	0.20
Dateline NBC	NBC	0.22	0.00	0.00	0.00	0.40
NYPD Blue	ABC	0.56	0.14	0.33	0.63	0.80
Bless This House	CBS	0.00	1.00	0.67	0.50	0.20
Ellen	ABC	0.00	1.00	0.67	0.25	0.20

TABLE IV.
(CONTINUED)

Show	Network	Action	Comedy	Fiction	Romance	Suspense
Beverly Hills, 90210	FOX	0.22	0.43	0.67	1.00	1.00
Seaquest 2030	NBC	1.00	0.00	1.00	0.13	0.80
The Drew Carey Show	ABC	0.11	1.00	0.67	0.00	0.20
Dave's World	CBS	0.00	1.00	0.67	0.50	0.20
Dateline NBC	NBC	0.11	0.00	0.00	0.00	0.80
Party of Five	FOX	0.00	0.29	0.67	1.00	0.20
Grace Under Fire	ABC	0.00	1.00	0.67	0.38	0.20
Central Park West	CBS	0.22	0.14	0.67	0.75	0.80
The Naked Truth	ABC	0.11	1.00	0.67	0.88	0.20
Law and Order	NBC	0.67	0.43	0.33	0.13	1.00
Courthouse	CBS	0.33	0.29	0.67	0.88	0.80
Prime Time Live	ABC	0.78	0.14	0.00	0.25	0.80
Murder, She Wrote	CBS	0.44	0.14	0.67	0.38	0.80
Living Single	FOX	0.00	1.00	0.67	0.75	0.40
Columbo: It's All in the Game	ABC	0.44	0.43	0.67	0.75	0.80
Friends	NBC	0.00	1.00	0.67	0.88	0.60
The Crew	FOX	0.00	1.00	0.67	0.63	0.20
The Single Guy	NBC	0.00	1.00	0.67	0.88	0.20
Seinfeld	NBC	0.11	1.00	0.67	0.63	0.60
New York News	CBS	0.56	0.14	0.33	0.50	0.60
New York Undercover	FOX	0.89	0.29	0.33	0.50	1.00
Caroline in the City	NBC	0.00	1.00	0.67	1.00	0.20
48 Hours	CBS	0.22	0.00	0.00	0.25	0.40
ER	NBC	1.00	0.29	0.33	0.50	0.80
Murder One	ABC	0.33	0.00	0.33	0.50	0.80
Strange Luck	FOX	0.78	0.29	1.00	0.50	0.80
Family Matters	ABC	0.22	1.00	0.67	0.50	0.20
Unsolved Mysteries	NBC	0.44	0.00	0.33	0.00	1.00
CBS Friday Night Movie	CBS	0.33	1.00	0.00	0.50	0.20
Boy Meets World	ABC	0.22	1.00	0.67	0.50	0.20
Ice Wars: USA vs The World	CBS	0.78	0.14	0.00	0.00	0.60
X-Files	FOX	1.00	0.29	1.00	0.25	1.00
Step by Step	ABC	0.00	1.00	0.67	0.75	0.20
Dateline NBC	NBC	0.22	0.14	0.00	0.25	0.40
Hangin' with Mr. Cooper	ABC	0.22	1.00	0.67	0.50	0.20
Homicide: Life on the Street	NBC	0.67	0.29	0.33	0.13	1.00
20/20	ABC	0.22	0.13	0.00	0.13	0.40

The variable Tune In_{jt} indicates whether there was a tune-in advertisement for a show jt (i.e., a show on network j in a given time slot t) in each time slot during the week. Obviously, there are no tune-ins for a show in any time slot subsequent to when it is aired. Table V presents the shows ordered by their number of tune-ins.

TABLE V.
SHOW TUNE-INS

Show	Network	Day	Tune-Ins
The Nanny	CBS	Monday	0
The Marshal	ABC	Monday	0
Melrose Place	FOX	Monday	0
Fresh Prince of Bel-Air	NBC	Monday	0
Pro Football	ABC	Monday	1
Home Improvement	ABC	Tuesday	2
Roseanne	ABC	Tuesday	2
Coach	ABC	Tuesday	2
Beverly Hills, 90210	FOX	Monday	2
Family Matters	ABC	Friday	2
Wings	NBC	Tuesday	2
NYPD Blue	ABC	Tuesday	2
X-Files	FOX	Friday	2
Murphy Brown	CBS	Monday	2
Hudson Street	ABC	Tuesday	2
Can't Hurry Love	CBS	Monday	2
In The House	NBC	Monday	2
Chicago Hope	CBS	Monday	2
Ellen	ABC	Wednesday	3
Bram Stoker's Dracula	FOX	Tuesday	3
Dateline NBC	NBC	Wednesday	3
Boy Meets World	ABC	Friday	3
Seaquest 2030	NBC	Wednesday	3
Step by Step	ABC	Friday	3
Unsolved Mysteries	NBC	Friday	3
Hangin' with Mr. Cooper	ABC	Friday	3
Grace Under Fire	ABC	Wednesday	3
High Society	CBS	Monday	3
The Naked Truth	ABC	Wednesday	3
Dateline NBC	NBC	Friday	3
Courthouse	CBS	Wednesday	4
Strange Luck	FOX	Friday	4
NewsRadio	NBC	Tuesday	4
The Client	CBS	Tuesday	4
Homicide: Life on the Street	NBC	Friday	4
Frasier	NBC	Tuesday	4
New York Undercover	FOX	Thursday	4
Living Single	FOX	Thursday	4
Law & Order	NBC	Wednesday	4
She Fought Alone	NBC	Monday	4
The Drew Carey Show	ABC	Wednesday	4
Bless This House	CBS	Wednesday	4
Nothing Lasts Forever	CBS	Tuesday	5
Columbo: It's All in the Game	ABC	Thursday	5
Pursuit of Happiness	NBC	Tuesday	5
Dateline NBC	NBC	Tuesday	5

TABLE V.
(CONTINUED)

Show	Network	Day	Tune-Ins
Beverly Hills, 90210	FOX	Wednesday	5
The Crew	FOX	Thursday	5
Central Park West	CBS	Wednesday	5
Murder, She Wrote	CBS	Thursday	6
Dave's World	CBS	Wednesday	6
Party of Five	FOX	Wednesday	6
Prime Time Live	ABC	Wednesday	6
CBS Friday Night Movie	CBS	Friday	6
Seinfeld	NBC	Thursday	6
Friends	NBC	Thursday	6
The Single Guy	NBC	Thursday	7
Ice Wars: USA vs The World	CBS	Friday	7
Caroline in the City	NBC	Thursday	7
Murder One	ABC	Thursday	8
New York News	CBS	Thursday	8
20/20	ABC	Friday	8
ER	NBC	Thursday	9
48 Hours	CBS	Thursday	10

Since the data contain information only on tune-ins that were aired on prime time starting on Monday, it is not surprising that the shows on Monday have fewer tune-ins than do shows aired later in the week. Interestingly, the three shows with the largest number of tune-ins were aired in the same time-slot, Thursday at 10:00 P.M. This may indicate the strategic use of tune-ins by networks.

The variable Count_{ijt} indicates the number of times that an individual i was exposed to a tune-in for a show jt. This variable was created by matching the Nielsen data on individuals' viewing choices with the information in Tune In_{jt}. In principle, the effect of tune-ins can then be estimated by examining the effects of this variable on individual viewing decisions, after controlling for other characteristics. The resulting estimates will be biased in general, however. The following example illustrates the source of this bias.

Eight tune-in advertisements for the ABC news magazine *20/20* aired during the following time slots and shows: Monday 10:30 (*Monday Night Football*); Tuesday 9:45 (*Coach*); Tuesday 10:15 (*NYPD Blue*); Wednesday 9:15 (*Grace Under Fire*); Wednesday 10:15 (*Prime Time Live*); Thursday 9:15 (*Movie*: *Columbo*); Thursday 10:15 (*Murder One*); and Friday 9:45 (*Hangin' with Mr. Cooper*). In Table VI, we estimate a probit model to test the hypothesis that individuals who

TABLE VI.
AN EXAMPLE TO ILLUSTRATE TARGETING[a]

Variable	Coefficient	Standard Error
Lead-In	1.4938	0.1371
Monday Night Football	0.0321	0.1666
Coach	0.3149	0.1544
NYPD Blue	0.1452	0.1561
Grace Under Fire	−0.0920	0.1489
Prime Time Live	0.9942	0.1388
Columbo	−0.0267	0.2048
Murder One	0.7413	0.2089
Constant	−1.7985	0.0663
No. of observations	1675	
Log likelihood	−386.44	

[a] Dependent variable: the decision to watch *20/20*.

were exposed to any of these tune-ins had a higher propensity to watch *20/20*. The dependent variable is equal to one if a person watched *20/20*, and zero otherwise. The explanatory variables are: (1) a dummy variable set equal to one if the person was watching ABC in the previous time slot (i.e., at 9:45 on Friday), and zero otherwise (this captures the "lead-in" effect), and (2) for each tune-in, a dummy variable equal to one for individuals who watched the tune-in and zero for those who did not.

The estimation results reveal that not all tune-ins were effective. For example, viewers exposed to the tune-in while watching *NYPD Blue* did not have a higher propensity *ex post* to watch *20/20*. On the other hand, some tune-ins—those aired during *Coach*, *Prime Time Live*, and *Murder One*, for example—were indeed effective. However, these results do not necessarily indicate that the advertisements during these shows were effective, since there is an alternative explanation. The networks probably do not choose the timing of their tune-ins randomly; rather, they may air the ad for a show during other shows with similar characteristics in order to target a particular audience. One of the ads for *20/20* occurred during the ABC news magazine *Prime Time Live*. As Table VI shows, being exposed to an ad during *Prime Time Live* had the strongest explanatory power among the exposure variables, increasing the viewing probability by almost 21% (with a t-value of about 7). This may merely indicate, however, that some viewers may like news magazines more than others and thus have a higher *ex ante* propensity to watch both *Prime Time Live* and *20/20*. Since such preferences are unobserved, an individual's exposure to tune-ins for *20/20* aired during *Prime Time Live* is endogenous[14]; hence, the estimate of its effect is biased.

To summarize, since the networks air their tune-ins during shows with a viewing audience that has a higher *ex ante* propensity to watch the promoted show, the effect of exposure to an ad on viewing decisions reflects both the effectiveness of the ad and the targeting of the network. We explicitly deal with this endogeneity problem in the model below.

3. Model, Estimation, and Identification

In each time slot t, individual i makes her viewing choice C_{it} from among six options. She may either choose to watch a particular show on any of the four networks, watch nonnetwork (including cable) TV, or not watch TV (i.e., pursue some outside alternative). Each of these alternatives is indexed by j, with $j = 1$ indexing the outside option, $j = 2, \ldots, 5$ corresponding to the four networks ABC, CBS, NBC, and FOX, respectively, and $j = 6$ denoting cable TV and other nonnetwork channels. An individual i is assumed to derive utility from alternative j in time slot t given by U_{ijt}. Time slots are defined every 15 minutes. The structure we impose on U_{ijt} is given by the following:

$$
\begin{aligned}
U_{ijt} = \eta_t &+ Z_{jt}(X_i\beta + \alpha_i) \\
&+\left(\tau_1^r \text{ Count}_{ijt} + \tau_2^r \text{ Count}_{ijt}^2\right)(1 - \text{Special}_{jt}) \\
&+\left(\tau_1^s \text{ Count}_{ijt} + \tau_2^s \text{ Count}_{ijt}^2\right)\text{Special}_{jt} \\
&+(Y_{i,\text{net},t}\Delta)I\{C_{i,t-1} = j\} + \varepsilon_{ijt} \qquad \text{for} \quad j = 2, \ldots, 5,
\end{aligned}
$$

$$U_{i,\text{out},t} = \eta_{\text{out}} + Y_{i,\text{out},t}\gamma_{\text{out}} + \delta_{\text{out}} I\{C_{i,t-1} = 1\} + \alpha_i^{\text{Out}} + \varepsilon_{i,\text{out},t},$$

$$U_{i,\text{non},t} = \eta_{\text{non}} + Y_{i,\text{non},t}\gamma_{\text{non}} + \delta_{\text{non}} I\{C_{i,t-1} = 6\} + \alpha_i^{\text{Non}} + \varepsilon_{i,\text{non},t},$$

where X_t is an $l \times l$ diagonal matrix of individual demographics, Z_{jt} is a $1 \times l$ row vector of show characteristics, Special_{jt} is a dummy

14. Based on the characteristics of demand, the networks probably choose both how many tune-ins to air for each show, and where to locate (or target) these tune-ins. Most previous studies of advertising ignore the targeting issue, and focus on the endogeneity problem arising from the choice of number of ads. While this is clearly an issue of concern when using aggregate-level data, the use of individual-level data avoids this problem, since the optimal number of tune-ins by networks is not chosen separately for each individual.

variable that is equal to one if the show on network j at time t is a special, and I is the indicator function. $Y_{i,\text{net},t}$ is a vector of show and individual characteristics such as show continuity and gender; $Y_{i,\text{out},t}$ and $Y_{i,\text{non},t}$ are vectors of individual characteristics such as income, location, age, education, and family size. The detailed structure of utilities is provided in the Appendix.

We allow for switching costs in individual behavior, as captured by the parameters δ_{out}, δ_{non} and the vector of parameters Δ. For example, individuals watching cable TV in a particular time slot may continue to watch it in the subsequent time slot due to switching costs, thus inducing state dependence. We estimate the switching costs in the decision to watch network TV, watch cable TV, or not watch TV at all, and allow the switching costs to vary for males (relative to females), and for continuation shows (i.e., shows that span more than one time slot).

The match between individual characteristics[15] X_i and show characteristics Z_{jt} may be an important component of preferences as well. For example, males may be more likely to watch sports shows, teens to watch *Beverly Hills 90210*, and women to watch shows with female casts, less action, and more romance. Such differences in viewing behavior are used to identify the parameters β. The choice of which interaction variables for show and individual characteristics, $Z_{jt} X_i$, to include is essentially ad hoc.[16] These variables are defined only for the various network alternatives, $j = 2, \ldots, 5$.

Individuals also may differ in their unobserved preferences, α_i, over various kinds of shows. For example, some individuals may like to watch comedies, while others prefer dramas. Moreover, such heterogeneity may be important even after controlling for simple observed differences in preferences across people, as captured by X_i. If tune-ins for comedies are primarily placed in other comedies, viewers who are more likely to watch comedies in the first place will be exposed to more tune-ins. Separating the effects of tune-ins from these unobserved differences in preferences is important for obtaining unbiased estimates of tune-in effects.

15. These include age, education, gender, income, and family status here.

16. A more comprehensive set of interaction variables is included in Shachar and Emerson (1996). Our choice of which variables to include here is motivated in part by the results of the estimation there.

We assume a simple discrete distribution for these unobserved preferences, where individuals are any of K types. Thus

$$\alpha_i = \begin{cases} \alpha_1 & \text{with probability } p_1 \\ \alpha_2 & \text{with probability } p_2 \\ \vdots & \\ \alpha_k & \text{with probability } 1 - \Sigma_{l=k} p_l. \end{cases}$$

Here α_1 is a parameter vector—$\{\alpha_1^{\text{Action}}, \alpha_1^{\text{Comedy}}, \alpha_1^{\text{Romance}}, \alpha_1^{\text{Suspense}}, \alpha_1^{\text{Fiction}}\}$—that indicates the preferences of individuals of type 1 for shows characterized according to their level of action, comedy, etc; similarly, α_2 represents the preferences of type-2 individuals, and so on. The parameters $\alpha_1, \alpha_2, \ldots, \alpha_K$ are identifiable if there is any systematic pattern in the viewing decisions of one group of individuals relative to others. Identification of the probability of each of these types in the population, $p_1, p_2, \ldots, p_K$, is straightforward.

The focus of this estimation is on the effects of tune-ins on viewing behavior. We measure an individual's exposure to tune-ins for a given show, Count_{ijt}, simply as the number of ads for that show that she is exposed to over the week.[17] A quadratic term in exposure allows for a simple nonlinear structure for the effects of counts on viewing decisions. Differences in the decision to watch a show among individuals exposed to different counts of tune-ins are used to identify the parameters τ_1 and τ_2.

Not all individuals with preferences of a given type, α_k, will watch exactly the same shows during the week; hence, there will be variation in the exposure of tune-ins among individuals of any given type. For example, some individuals of type 1 may be exposed to more tune-ins for a particular comedy than for others of the same type, simply due to idiosyncratic variation in viewing decisions. Similarly, there will also be variation in the exposure to tune-ins for a particular show among individuals of each of the other types. This variation allows us to identify the effects of tune-ins, after allowing

17. Since the tune-in data are available only for the same week as the shows were aired, there is measurement error in Count_{ijt}. For example, the shows on Monday will have fewer tune-ins than those later in the week. In principle, it is possible to estimate a different tune-in parameter τ for shows aired on different days of the week. Estimates obtained during a preliminary stage of this research—allowing for linear effects of tune-ins only, and without distinguishing between regular shows and specials—did not reveal significant differences in tune-in effects for shows on different days. In view of these results, since we are primarily concerned here with differences between regular shows and specials, we do not explicitly correct for this measurement error when constructing the likelihood function.

for individuals' preferences to vary in unobserved ways. The results of the estimation, with and without controlling for unobserved heterogeneity, are presented in Section 4 below.

In order to estimate the variation in the effects of tune-ins according to individuals' prior information about a show, we separate shows into two categories, *specials* (new, one-time shows) and *regulars*. Individuals may be presumed to know more about a regular show's characteristics—its time slot, its cast, whether it is a comedy, etc.—than about a special. If the effect of tune-ins does not depend on their informational content, these effects should not differ between specials and regulars, i.e., τ_1^s and τ_2^s would be equal to τ_1^r and τ_2^r. Thus, this provides a source of identification of the informational content in advertising relative to other effects, such as persuasion or signaling (Milgrom and Roberts, 1986).

The informational content of tune-ins may be of two kinds. First, tune-ins may simply increase awareness about the existence of a show. Second, they may provide information about the show's *attributes*.[18] Individuals are likely to possess much more information about both the existence and attributes of regular shows than about those of specials. For regular shows, then, the role of tune-ins may be simply to serve as reminders of the show's existence and its attributes. Since most of this information could easily be conveyed via a few tune-ins, the informational value for an individual would diminish as the number of tune-ins viewed increases. For specials, however, tune-ins may be important both in informing people about the existence of such a show and in conveying information about its attributes. Here, a single tune-in is unlikely to be nearly as effective; instead, a series of tune-ins may be necessary to convey information about the different aspects of a new show. For the same reason, although diminishing marginal effectiveness of tune-ins should apply here as well, the rate at which these returns diminish is likely to be smaller than for regular shows. According to this simple characterization of the informational content in tune-ins, the marginal value of tune-ins should be larger for regular shows (relative to specials) at low levels of tune-ins, but should decline more rapidly as well. More generally, however, the identification strategy is based on the logic that if tune-ins convey information, their effectiveness is likely to

18. A similar distinction between the informational roles of advertising has been made in the previous literature. Butters (1977), for example, focuses on the role of advertising in conveying information about a product's existence and its price. Grossman and Shapiro (1984) augment this to consider information about a product's other attributes (such as location) as well.

differ across shows for which viewers possess different preexisting stocks of information. We return to a discussion of these different effects in our presentation of the results.

3.1. The Likelihood Function

For the econometrician, the viewing choice is probabilistic, since we do not observe ε_{ijt}. The random variables ε_{ijt} are assumed to be independent across individuals i and time slots t, having the generalized extreme-value distribution

$$F(\varepsilon_1, \ldots, \varepsilon_6) = \exp\left(-e^{\varepsilon_1} - \left(\sum_{k=2}^{6} (e^{\varepsilon_k})^{1/(1-\sigma)} \right)^{1-\sigma} \right),$$

where ε_j denotes the vector of disturbances for choice j (the subscripts for individuals and timeslots are suppressed here). As McFadden (1978) illustrates, under these conditions, the viewing choice probability is

$$P(C_{it} = 1) = \frac{e^{\overline{U}_1}}{e^{\overline{U}_1} + \left[\Sigma_{k=2}^{6}(e^{\overline{U}_k})^{1/(1-\sigma)}\right]^{1-\sigma}}$$

$$P(C_{it} = j) = \frac{(e^{\overline{U}_j})^{1/(1-\sigma)}\left[\Sigma_{k=2}^{6}(e^{\overline{U}_k})^{1/(1-\sigma)}\right]^{-\sigma}}{e^{\overline{U}_1} + \left[\Sigma_{k=2}^{6}(e^{\overline{U}_k})^{1/(1-\sigma)}\right]^{1-\sigma}} \qquad \text{for} \quad j = 2, \ldots, 6,$$

where $\overline{U}_j = U_j - \varepsilon_j$. This specification is commonly referred to as the "nested multinomial logit," and relaxes the assumption of independence of irrelevant alternatives (IIA) imposed by the standard multinomial logit specification. For example, it appears reasonable to assume that an individual first decides whether or not to watch TV; conditional on doing so, she then chooses between the various channels. The nested logit model we specify here can be thought of as capturing this two-level representation of the viewing decision. Moreover, since the multinomial logit specification is nested within this model (and obtains when $\sigma = 0$), one can explicitly test which specification better describes the data.

While the disturbances (ε) are independent across time slots, the viewing choices are not, because of the switching costs. Thus, the conditional probability of each viewer's history of choices for the entire week, $C_i = (C_{i1}, \ldots, C_{iT})$, is simply the product of the conditional probabilities of each of his or her choices made at each quarter hour. That is, for a type-k person,

$$f_i(C_i|\Omega_{it}; \alpha^k, \theta) = \prod_{t=1}^{T} P(C_{it} = j|\Omega_{it}, C_{i,t-1}; \alpha^k, \theta), \tag{3.1}$$

where $\Omega_{it} = \{Z_{jt}, X_i, \text{Count}_{ijt}, \text{Special}_{jt}, Y_{i,\text{out},t}, Y_{i,\text{non},t}, Y_{i,\text{non},t}\}$ (all observed individual and show characteristics as well as the lagged choices), and the vector θ includes of all the parameters in the model other than the α's.

Since we do not observe each viewer's type, we integrate out these unobservable preferences. The resulting marginal distribution is

$$f_2(C_i|\Omega_i; \theta, \alpha, P) = \sum_{k=1}^{K} f_1(C_i|\Omega_i; \theta, \alpha^k) \cdot p_k \tag{3.2}$$

where P is a vector of type probabilities, $p_1, \ldots, p_K$, for K viewer types.

Because the ε_{itj} and the type probabilities are independent across individuals, the likelihood function is simply the product of the probabilities of each individual's history of viewing choices. The parameters $\theta, \alpha_1, \ldots, \alpha_K$, and P are chosen to maximize the log-likelihood function given by

$$\log L(\theta, \alpha, P) = \sum_{i=1}^{N} \log f_2(C_i|\Omega_i; \theta, \alpha, P), \tag{3.3}$$

where N denotes the number of individuals.

The estimates of the structural parameters obtained are discussed below.

4. Results

Most of the estimates in Table VII are motivated and discussed elsewhere.[19] We present them briefly here and then turn to a thor-

19. See Shachar and Emerson (1996).

TABLE VII.
Effects of Tune-Ins without Correcting for Targeting Bias[a]

Parameter	Coeff.	Std. Error	Parameter	Coeff.	Std. Error
τ_1^r	0.4236	0.0238	η_{ABC}	−0.7966	0.0621
τ_2^r	−0.0429	0.0047	η_{CBS}	−0.9352	0.0627
τ_1^s	0.2404	0.0463	η_{NBC}	−0.7288	0.0620
τ_2^s	−0.0149	0.0119	η_{FOX}	−1.0097	0.0759
σ	0.2759	0.0272	$\eta_{Special}$	0.0234	0.0369
			η_{non9}	−0.1373	0.0322
β^{X_Kids}	0.2007	0.1148	η_{non10}	−0.0317	0.0408
β^{X_Teens}	0.2448	0.1148	$\eta_{8:15}^{out}$	0.6733	0.0914
$\beta^{X\_Gen X}$	0.3703	0.0585	$\eta_{8:30}^{out}$	0.6459	0.0862
β^{X_Boom}	0.3549	0.0549	$\eta_{8:45}^{out}$	0.6849	0.0936
β^{X_Old}	−0.0285	0.0473	$\eta_{9:00}^{out}$	0.5061	0.0840
β^{B_Kids}	−0.3174	0.1295	$\eta_{9:15}^{out}$	0.7912	0.0908
β^{B_Teens}	−0.2571	0.0952	$\eta_{9:30}^{out}$	0.8525	0.0866
$\beta^{B\_Gen X}$	0.1733	0.0541	$\eta_{9:45}^{out}$	0.9644	0.0931
β^{B_Boom}	0.3569	0.0490	$\eta_{10:00}^{out}$	0.9323	0.0820
β^{B_Old}	0.1351	0.0429	$\eta_{10:15}^{out}$	1.2245	0.0965
β^{Fa_Fa}	0.3267	0.0526	$\eta_{10:30}^{out}$	1.4854	0.0939
β^{Fa_NoFa}	0.0275	0.0466	$\eta_{10:45}^{out}$	1.4315	0.0991
β^{Black_Income}	−0.2440	0.0424			
β^{Fe_Fe}	0.0939	0.0333	δ_{out}	3.7657	0.0563
β^{Fe_Ma}	−0.0227	0.0371	δ_{non}	2.0182	0.0808
β^{Ma_Fe}	−0.1010	0.0338	δ_{net}	1.2474	0.0605
β^{Ma_Ma}	0.0177	0.0360	δ_{cont}	1.8249	0.0744
			δ_{samp}	−0.3564	0.0492
γ_{Kids}	−0.6079	0.0955	δ_{drama}	0.4200	0.0825
γ_{Teens}	0.6241	0.2263	δ_{news}	−0.5545	0.0634
$\gamma_{Gen X}$	−1.1669	0.0919	δ_{sport}	−0.8934	0.0685
γ_{Boom}	−1.2977	0.0929	δ_{MA}	−0.1093	0.0172
γ_{Old}	−1.5139	0.0863			
γ_{Income}	0.3087	0.0422			
$\gamma_{Education}$	0.0775	0.0477			
γ_{Urban8}	−0.0041	0.0375			
γ_{Urban9}	−0.1308	0.0380			
$\gamma_{Urban10}$	−0.2476	0.0356			
γ_{Basic}^{non}	0.3949	0.0215			
$\gamma_{Premium}^{non}$	0.5182	0.0245			
γ_{Teens}^{non}	0.6241	0.2263			
γ_{Male}^{non}	0.1499	0.0219			

TABLE VII.
(CONTINUED)

Parameter	Coeff.	Std. Error	Parameter	Coeff.	Std. Error
β^{A}_Kids	0.1550	0.2240	β^{F}_Old	−0.3592	0.1331
β^{A}_Teens	0.0659	0.2318	β^{F}_Female	0.1113	0.0656
β^{A}_Gen X	−0.0736	0.1623	β^{F}_Education	−0.0984	0.1455
β^{A}_Boom	0.0771	0.1613	β^{R}_Kids	−0.2842	0.2102
β^{A}_Old	0.0050	0.1445	β^{R}_Teens	0.1819	0.1838
β^{A}_Female	−0.0735	0.0790	β^{R}_Gen X	0.2911	0.1444
β^{A}_Education	0.3907	0.1726	β^{R}_Boom	−0.0216	0.1436
β^{C}_Kids	0.5123	0.1108	β^{R}_Old	0.0351	0.1325
β^{C}_Teens	0.7446	0.2113	β^{R}_Female	0.2115	0.0689
β^{C}_Gen X	0.3239	0.0875	β^{R}_Education	−0.3061	0.1489
β^{C}_Boom	0.3719	0.0894	β^{S}_Kids	−0.3442	0.2191
β^{C}_Old	0.1754	0.0827	β^{S}_Teens	0.4525	0.3347
β^{C}_Female	−0.0504	0.0442	β^{S}_Gen X	0.2839	0.1550
β^{C}_Education	0.3868	0.0840	β^{S}_Boom	0.1793	0.1541
β^{F}_Kids	0.3692	0.2011	β^{S}_Old	0.2932	0.1437
β^{F}_Teens	0.1985	0.2106	β^{S}_Female	−0.0229	0.0747
β^{F}_Gen X	−0.4724	0.1462	β^{S}_Education	0.0938	0.1619
β^{F}_Boom	−0.2680	0.1479			

[a] Dependent variable: decision by individual i to view alternative j in time slot t.

ough discussion of the effectiveness of tune-in ads. We first report the results without controlling for differences in unobserved preferences across individuals.

First, note that the estimate of σ is significantly different from zero ($\hat{\sigma} = 0.28$, std. error $= 0.03$). In other words, we can reject the simple multinomial logit model in favor of the nested logit specification.

The precise structure of the utility and most of the parameters (η, γ, δ, and Δ) are included in the Appendix. Briefly, we find that the utility from the outside alternative is a declining function of age, and is positive in income and education. The utility from the nonnetwork alternative is higher for individuals with basic cable, and still higher for those who subscribe to premium channels. Men and teens have a higher utility from the nonnetwork alternative as well. We also find strong evidence for switching costs, as evidenced by the parameters δ. In particular, the transition propensities of viewers appears to decrease during the finales of dramas, men appear to switch away marginally more than women, and older viewers switch slightly less often than younger viewers.

The β parameters suggest that "likes attract." In particular, individuals prefer shows whose cast demographics are similar to their own. For example, shows with a generation-X cast are most preferred by generation-X viewers, and baby boomers like to watch shows with baby boomers in the cast. Similarly, viewers prefer to watch shows about people of their own gender, and families like shows about families more than people who live alone. Finally, low-income people prefer shows with blacks in a central role (note that we have used the income variable for individuals as a proxy for their race).

Viewers in different age groups do not differ much in their preference for "action." However, younger viewers like comedies as well as shows with a high fiction level. Generation-Xers tend to watch romantic shows, whereas kids do not. Kids also do not like to watch shows with a high element of suspense, relative to other viewers. Finally, women like watching romantic shows more than men; and educated people like action and comedy, but do not appreciate romance.

4.1. Effects of Tune-Ins

We now turn to the effect of the tune-in variables, which are the focus of this study. We find that the utility from a show is a positive, concave function of the number of times the individual was exposed to its ads, indicating that while tune-ins are effective, they have diminishing returns. The first exposure to an ad for a regular show increases the probability of watching the shows by more than 41%; the second exposure increases this probability by an additional 29%, and the third by about 17%. We interpret the strong response to the first few ads for regular shows as an *awareness* effect: viewers already know how much they like a given show, and the main purpose of the ad is to remind them of the timing of the show, for example. Note that one exposure to an ad may not be enough to achieve this effect, since viewers, while exposed, may often ignore the television during commercial breaks. Furthermore, some people may need more than one reminder in order not to forget.[20] Thus, the second and the third exposures have a positive (but smaller) effect on the individual's probability of watching the promoted show.

Figure 1 presents the effect of the Count variable on the utility from regular shows (the solid line) and from specials (the dashed line). The difference between these curves is striking. While the first

20. See also Olney, et al. (1991).

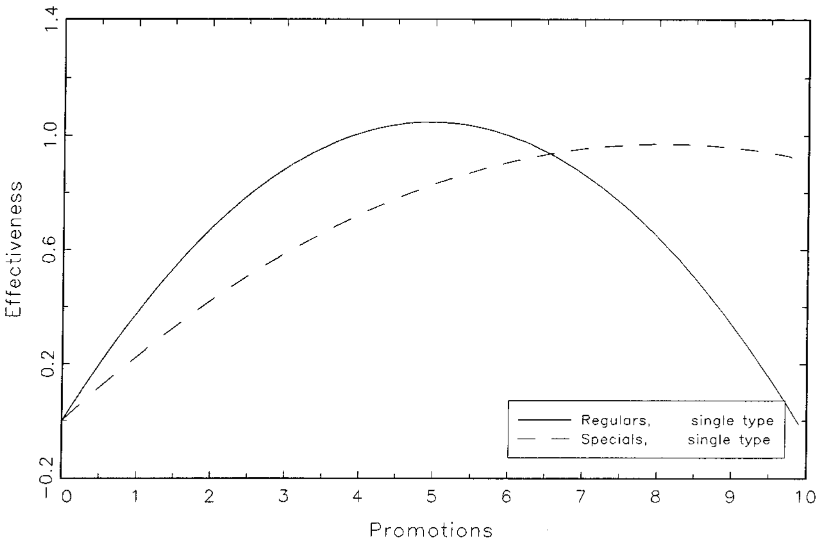

FIGURE 1. EFFECTS OF PROMOTIONS ON VIEWING DECISIONS

ad for a special is quite effective—it increases the probability of watching the shows by about 23%—it is not as effective as the first ad for a regular show. Since viewers are not familiar with specials, the first couple of ads obviously do not serve as reminders; rather, they are likely to inform viewers about the show's attributes, such as its degree of comedy or action. Therefore, their effect is not likely to be as strong as for the regular shows. For the same reason, however, their effectiveness may not diminish as quickly as for regular shows, given that they serve as sources of information. This interpretation is strongly supported by the data, as demonstrated by Figure 1.

The sixth tune-in for a regular show and those following it have a negative effect on the viewing probability. This effect, previously recognized in the advertising literature, is referred to as *wearout*. The reason for wearout may be either that after a while viewers stop attending to the advertising (Calder and Sternthal, 1976), or that excessive exposure generates irritation.[21]

21. The effectiveness of exposures may vary according to their timing as well; for example, recent exposures may have a greater effect on an individual's viewing decisions than those further in the past. We have tested this hypothesis and found no evidence of this form of wearout in the data.

4.2. Controlling for the Targeting Bias

The estimates of tune-in effectiveness may be biased, as discussed above, since the variable capturing an individual's exposure to tune-ins is probably endogenous. In order to correct for this, we estimate the effect of ads, while allowing for K-types of viewers (as outlined in Section 3), each with potentially different preferences over the shows' attributes (such as comedy and action).

We report the results of the estimation with six types of viewers in Table VIII.[22] As expected, the effectiveness of tune-ins decreases when we control for unobserved heterogeneity of preferences over the show types, as demonstrated in Figure 2. This confirms the bias in our previous estimates of the effectiveness of ads, induced by the networks' targeting strategies. However, notice that (1) tune-ins are still strongly effective, and (2) the difference between the effects of tune-ins for specials and regular shows is similar to that estimated earlier.

The six types of viewers differ substantially in their viewing patterns. These differences can be illustrated by examining the types' distinct preferences and their viewing choices. To infer these choices, we distribute each individual in our sample to one of the types. The prior distribution for each individual over the various types is defined by the estimated probabilities $p_1, \ldots, p_k$. Based on their viewing history and using Bayes's rule, we then estimate the posterior type probability for each individual, and assign her to the group for which her posterior type probability is the highest.

The types are ordered in Table VIII according to their size.[23] The largest type (31.2%) rarely watch television. Only 6% of them watch the highest-rated show for this type, the football game. The second largest type (22.3%) prefer to watch shows with a high level of suspense and romance, but dislike comedies, relative to other types. Thus, it is not surprising that their top five shows are *ER* (watched by 36% of them), the *CBS Tuesday Night Movie*, *Beverly Hills 90210* (which had, relatively, high levels of action and suspense during this week's episodes), the football game, and *NYPD Blue*. Moreover, each of these shows is on a different network, indicating that these viewers are not loyal to any particular network. Further, although *Seinfeld* is

22. We did not test for a seventh type, since adding the fifth and sixth types barely affected the estimated tune-in effects.

23. Group sizes are based on the estimated probabilities of an individual belonging to each type, $p_1, \ldots, p_6$. These are calculated directly from the estimates $\mu_1, \ldots, \mu_6$ in Table VIII, where $p_k = e^{\mu_k}/(1 + \Sigma_{k=1}^{K} e^{\mu_k})$ for $k = 1, \ldots, 6$ and μ_2 is normalized to 0.

TABLE VIII.
EFFECTS OF TUNE-INS AFTER CORRECTING FOR TARGETING BIAS[a]

Parameter	Coeff.	Std. Error	Parameter	Coeff.	Std. Error
τ_1^r	0.2817	0.0218	η_{ABC}	−0.3568	0.0866
τ_2^r	−0.0271	0.0047	η_{CBS}	−0.4686	0.0855
τ_1^s	0.1515	0.0447	η_{NBC}	−0.2725	0.0866
τ_2^s	−0.0017	0.0117	η_{FOX}	−0.5467	0.0943
σ	0.3437	0.0267	$\eta_{Special}$	−0.0014	0.0349
			η_{non9}	−0.0766	0.0308
β^{X_Kids}	0.1874	0.1078	η_{non10}	0.0531	0.0401
β^{X_Teens}	0.1981	0.1081	$\eta_{8:15}^{out}$	0.6580	0.0920
$\beta^{X\_Gen\ X}$	0.3529	0.0552	$\eta_{8:30}^{out}$	0.6400	0.0881
β^{X_Boom}	0.3161	0.0512	$\eta_{8:45}^{out}$	0.6649	0.0943
β^{X_Old}	−0.0595	0.0448	$\eta_{9:00}^{out}$	0.5166	0.0856
β^{B_Kids}	−0.3474	0.1209	$\eta_{9:15}^{out}$	0.7920	0.0925
β^{B_Teens}	−0.2865	0.0885	$\eta_{9:30}^{out}$	0.8797	0.0887
$\beta^{B\_Gen\ X}$	0.1499	0.0510	$\eta_{9:45}^{out}$	0.9714	0.0942
β^{B_Boom}	0.3187	0.0459	$\eta_{10:00}^{out}$	0.9646	0.0824
β^{B_Old}	0.1251	0.0410	$\eta_{10:15}^{out}$	1.2548	0.0962
β^{Fa_Fa}	0.2937	0.0518	$\eta_{10:30}^{out}$	1.5415	0.0938
β^{Fa_NoFa}	0.0264	0.0457	$\eta_{10:45}^{out}$	1.4911	0.0992
β^{Black_Income}	−0.2367	0.0392			
β^{Fe_Fe}	0.0670	0.0314	δ_{out}	3.8251	0.0538
β^{Fe_Ma}	−0.0478	0.0362	δ_{non}	1.6594	0.0730
β^{Ma_Fe}	−0.1026	0.0317	δ_{net}	1.1345	0.0578
β^{Ma_Ma}	−0.0008	0.0338	δ_{cont}	1.6245	0.0734
			δ_{samp}	−0.3111	0.0475
γ_{Kids}	−0.9996	0.1416	δ_{drama}	0.3953	0.0790
γ_{Teens}	−0.5950	0.2496	δ_{news}	−0.4910	0.0614
$\gamma_{Gen\ X}$	−1.7083	0.1282	δ_{sport}	−0.7673	0.0656
γ_{Boom}	−1.8195	0.1266	δ_{MA}	−0.1056	0.0175
γ_{Old}	−2.1334	0.1181			
γ_{Income}	0.3235	0.0766			
$\gamma_{Education}$	0.1185	0.0856			
γ_{Urban8}	−0.0235	0.0475			
γ_{Urban9}	−0.1476	0.0484			
$\gamma_{Urban10}$	−0.2704	0.0470			
γ_{Basic}^{non}	0.4101	0.0361			
$\gamma_{Premium}^{non}$	0.5602	0.0397			
γ_{Teens}^{non}	0.8986	0.2104			
γ_{Male}^{non}	0.1769	0.0360			

TABLE VIII.
(CONTINUED)

Parameter	Coeff.	Std. Error	Parameter	Coeff.	Std. Error
β^{A}_Kids	0.1937	0.2236	α_1^{Action}	0.1401	0.1400
β^{A}_Teens	0.1650	0.2305	α_1^{Comedy}	0.4598	0.1302
β^{A}_Gen X	−0.0656	0.1651	$\alpha_1^{Fiction}$	0.2722	0.1275
β^{A}_Boom	0.0630	0.1672	$\alpha_1^{Romance}$	−0.3854	0.1356
β^{A}_Old	0.0342	0.1516	$\alpha_1^{Suspense}$	0.1979	0.1982
β^{A}_Female	−0.0764	0.0744	α_1^{Out}	1.7193	0.1494
β^{A}_Education	0.3736	0.1680	α_1^{Non}	0.9639	0.1517
β^{C}_Kids	0.1314	0.1492	μ_1	0.3378	0.1291
β^{C}_Teens	0.4152	0.2287	α_3^{Action}	0.1932	0.1395
β^{C}_Gen X	−0.0868	0.1225	α_3^{Comedy}	1.1469	0.1266
β^{C}_Boom	−0.0483	0.1229	$\alpha_3^{Fiction}$	0.3612	0.1233
β^{C}_Old	−0.3540	0.1139	$\alpha_3^{Romance}$	−0.6130	0.1302
β^{C}_Female	−0.0645	0.0515	$\alpha_3^{Suspense}$	0.1126	0.1890
β^{C}_Education	0.2572	0.1051	α_3^{Out}	0.6302	0.1449
β^{F}_Kids	0.2804	0.2003	α_3^{Non}	−0.1078	0.1367
β^{F}_Teens	0.1170	0.1979	μ_3	−0.4366	0.1928
β^{F}_Gen X	−0.5761	0.1480	α_4^{Action}	−0.3724	0.2090
β^{F}_Boom	−0.3761	0.1485	α_4^{Comedy}	0.5388	0.1713
β^{F}_Old	−0.5217	0.1396	$\alpha_4^{Fiction}$	0.6029	0.1707
β^{F}_Female	0.0759	0.0630	$\alpha_4^{Romance}$	−0.4624	0.1625
β^{F}_Education	−0.1878	0.1401	$\alpha_4^{Suspense}$	0.0708	0.2587
β^{R}_Kids	−0.1527	0.2193	α_4^{Out}	1.4438	0.1862
β^{R}_Teens	0.4126	0.1959	α_4^{Non}	−0.5828	0.2042
β^{R}_Gen X	0.4142	0.1493	μ_4	−0.6657	0.1739
β^{R}_Boom	0.1525	0.1524	α_5^{Action}	−0.4131	0.1893
β^{R}_Old	0.2640	0.1432	α_5^{Comedy}	0.9339	0.1451
β^{R}_Female	0.2514	0.0677	$\alpha_5^{Fiction}$	0.0462	0.1521
β^{R}_Education	−0.0160	0.1484	$\alpha_5^{Romance}$	−0.7290	0.1552
β^{S}_Kids	−0.2444	0.2275	$\alpha_5^{Suspense}$	−0.6439	0.2273
β^{S}_Teens	0.6766	0.3426	α_5^{Out}	−0.1076	0.1447
β^{S}_Gen X	0.3690	0.1741	α_5^{Non}	−0.1996	0.1359
β^{S}_Boom	0.3096	0.1777	μ_5	−0.7673	0.2102
β^{S}_Old	0.3824	0.1688	α_6^{Action}	0.3193	0.1832
β^{S}_Female	−0.0301	0.0749	α_6^{Comedy}	−0.1016	0.1595
β^{S}_Education	0.0194	0.1606	$\alpha_6^{Fiction}$	0.0430	0.1499
			$\alpha_6^{Romance}$	−0.2205	0.1850
			$\alpha_6^{Suspense}$	−0.0609	0.2472
			α_6^{Out}	0.3020	0.1872
			α_6^{Non}	0.9792	0.1749
			μ_6	−0.8578	0.1619

[a] Dependent variable: decision by individual i to view alternative j in time slot t.

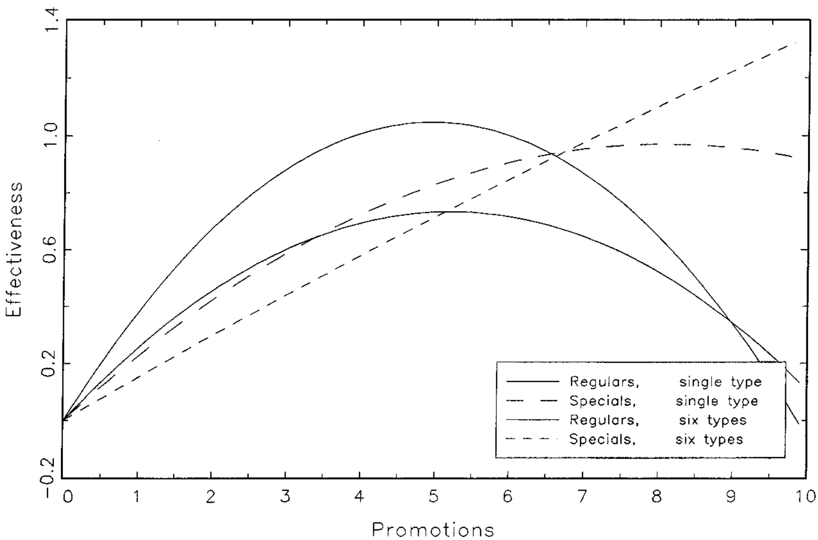

FIGURE 2. EFFECTS OF PROMOTIONS ON VIEWING DECISIONS

their sixth most popular show, they clearly favor dramas—*Seinfeld* is the only sitcom in their top-ten list.

The third largest type (14.4%) like sitcoms. Except for *ER*, all the top 15 shows watched by this group are sitcoms. Although this type also have a relatively high level of utility from the outside alternative, they watch network television frequently—for example, the tenth highest rated show for this week is watched by 18.7% of them. This is probably because network television offers exactly the product—sitcoms—that they are looking for. The fourth (11.5%) and the fifth (10%) types like comedy as well. The fourth type tend to watch significantly less TV than the third, whereas the fifth type are less tolerant toward nonsitcoms than the other types—there are no dramas among their top ten shows. The last type (9.4%) like action and dislike comedy. It is thus not surprising that their favorite show is the football game (with a 17% share). Moreover, their high nonnetwork utility is probably due to the vast offering of live sport events on cable TV.

To summarize, individuals of the first and last types spend less time watching network television than the others. Individuals of types 3, 4, and 5 almost only watch sitcoms, and type-2 individuals almost only watch dramas. These results suggest that viewers do not tend to prefer a variety of shows, and are consistent with the findings of Goettler and Shachar (1996). Moreover, since the networks frequently air a tune-in for a drama during other dramas and for a sitcom during other sitcoms, the estimate of the tune-in effectiveness would be upward-biased without controlling for the differences between these types. The differences between the other types are of significance as well. For example, type-1 individuals are less likely to watch *any* television show and thus are less exposed to tune-ins. Without controlling for differences in preferences between these individuals and others, the relationship between the number of exposures to tune-ins and the propensity to watch television would also influence our estimate of τ's.

5. Are Network Strategies Optimal?

In this section, we return to the question that we presented at the outset: do networks' expenditures on advertising exceed the profit-maximizing level? To answer this, we first present a simple model, which we solve for the optimal (profit-maximizing) number of tune-ins for each show; then, we compare this with the actual number of tune-ins chosen by the network.

Network j should choose the number of tune-ins for show k that maximizes its expected profit function. If the network airs C_k tune-ins—each of length L_k (in seconds), on average—for show k, it loses advertising fees that depend on the ratings of the shows during which these tune-ins aired. Here, we do not solve for the network's decision of *when* to air each tune-in; thus, we proxy these lost advertising fees for each tune-in by

$$P \cdot \text{Rating}_j \cdot L_k$$

where P is the fee that advertisers pay for an expected exposure of one viewer for one second.[24] Thus, for C_k tune-ins, the network's lost fees are $P \cdot \text{Rating}_j \cdot L_k \cdot C_k$. We proxy for Rating_j as the *average* rating of network j (over all time slots).

The network's expected revenues from airing C_k tune-ins for show k will depend on the effect of these tune-ins on the ratings for that show. Let $E(\text{Rating}_k | C_k)$ denote the expected number of viewers for show k, given C_k. Then expected revenues are given by

$$P \cdot \text{AD}_k \cdot E(\text{Rating}_k | C_k)$$

24. Note that an increase in the amount of tune-in time for a show—which depends on C_k—reduces the supply of advertising time, which may result in a decline in P as well. We ignore this effect here.

where AD_k is the length (in seconds) of commercial advertising time available during show k.[25] Thus, the network's profit function is

$$\pi_{jk} = P \cdot AD_k \cdot E(\text{Rating}_k | C_k) - P \cdot (C_k L_k) \cdot \text{Rating}_j$$

We substitute for L_k using actual figures during this week for each show, and base $E(\text{Rating}_k | C_k)$ on our estimation results. We then solve for the profit-maximizing number of tune-ins for each show and each network.[26]

We estimate the optimal number of tune-ins, C_k^*, to be 4 for almost all the 58 regular shows, and higher for all the specials.[27] The reason for the lack of variation in C_k^* across the shows can be explained as follows. From the first-order condition, the marginal profit is equal to zero when

$$\frac{dE(\text{Rating}_k | C_k)/dC_k}{\text{Rating}_k} = \frac{L_k}{AD_k} \tag{5.1}$$

Consider, for example, this optimization for a sitcom. For most such shows, $L_k/AD_k = \frac{1}{30}$. If the average network rating (over all its shows), Rating_j, is close enough to the expected rating for a show, $E(\text{Rating}_k)$—which is indeed the case for most of these shows—then the expression on the left-hand side in equation (5.1) gives the percentage effect of the marginal tune-in on the expected rating of the show. For a regular show, this was estimated to be 10% of the fourth tune-in, and about 0% for the fifth tune-in; this suggests that the fourth tune-in would be profitable for almost all sitcoms, but the fifth would not. A similar argument holds for nonsitcom regular shows as well.

Without further distinguishing regular shows according to their information stock (some shows are better known than others) and according to the effectiveness of tune-ins across such shows, we cannot explain the source of actual variation in C_k. (It should be

25. This is equal to 6 minutes for each 30-minute segment.

26. In reality networks do not advertise their shows on the other networks. This is a rule of the game, and we take it as such. Examining the logic of this rule is beyond the scope of this study.

27. The optimal number of tune-ins for specials is 8. However, since the variance of the estimate of τ_2^s is high, the variance of the estimated optimal number of tune-ins is high as well. Notice also that while we estimate the effectiveness of tune-ins for specials to be a concave function, we cannot reject the hypothesis that the effectiveness of tune-ins for specials is a linear or a convex function (i.e., we cannot reject the hypothesis $\tau_2^s \geq 0$). Thus, we would not like to make too much of this result.

noted, however, that this variation is small.) Our model nevertheless has two important predictions. First, regular shows should have a smaller number of tune-ins than specials. Second, regular shows should have about 4 tune-ins, on average. As it turns out, network strategies are closely consistent with these implications: the average number of tune-ins for specials is 5 (with a standard deviation of 1.4), and for regular shows is 3.8 (with a standard deviation of 2.25). It is not surprising that observed strategies are consistent with our first prediction. But the consistency with our second prediction is revealing, because it indicates that network executives appear to be on target in assessing the effect of tune-ins on viewers' choices.

The model we have presented here is stylized.[28] Nevertheless, these results do suggest that network expenditures on advertising are similar to the levels that maximize their respective profits.

6. Conclusion

While the expenditures on tune-in advertisements by TV networks may appear excessive, we find that they are similar to what is predicted by a simple model of profit maximization by the networks. Exposure to a maximum of four tune-ins for a show has a dramatic effect on an individual's decision to watch that show. We also find that the effectiveness of advertising differs between specials and regular shows. Since the main difference between these kinds of shows is in the prior information that individuals possess about each, this result is indicative of informational content in advertising.

While we have established here the value of information in advertising, it would be interesting to examine the nature of this information in more detail. The differential effectiveness of advertising between specials and regular shows suggests that advertising conveys at least two distinct types of information—information about a show's existence and information about its attributes. In order to identify each of these effects, it would be useful first to construct a

28. One issue that we have not explicitly modeled, for example, is the role of advertisements as *signals* (see Milgrom and Roberts, 1986); according to this, shows with many ads are inferred to be of higher quality, which in turn increases the propensity to watch the show. We are not concerned with the signaling hypothesis, however, for various reasons. First, it predicts that the effectiveness of ads should increase with the number of exposures, contrary to the wearout effect observed in the data. Second, our results rest on the difference in the effectiveness of specials versus regular shows, not on the distinction between the persuasive effect and the signaling effect, which may be viewed as one of interpretation. Finally, clarifying whether ads are signals or simply persuasive, though likely to affect the socially efficient level of advertisements, should not change the implications for profit maximization.

model that explicitly incorporates the uncertainty about the alternatives in an individual's choice set as well as the utility derived from each alternative. The dataset we use may also be appropriate in structurally estimating such a model. The resulting estimates concerning the relative importance of each type of information may be useful in determining a firm's strategy, as well as in normative analysis.

Finally, our estimates of the effects of tune-ins allow for the possibility of networks targeting particular audiences in scheduling their tune-ins. Since such strategies imply that an individual's exposure to tune-ins may be correlated with her unobserved preferences, estimates that do not correct for this endogeneity will be upward biased. Indeed, we find the magnitude of this bias to be large in the context of TV tune-ins. Similar biases are likely to exist in the estimates obtained from previous studies that analyze the effects of advertising on the demand for yogurt, beer, tobacco, and other goods. The methodology we present in this paper may be extended to these other contexts.

Appendix

Here we present the complete structure of the utility function. First, we define all the variables that we use:

- Variables defining individual characteristics:

Kids_i	7–11 years old at November 1995
Teens_i	12–17 years old
Gen X_i	18–34 years old
Boom_i	35–49 years old
Old_i	50 years old and over
Income_i	On unit interval, 0 = less than \$10,000, 0.20 = between \$10,000 and \$15,000, 0.40 = between \$15,000 and \$20,000, 0.60 = between \$20,000 and \$30,000, 0.80 = between \$30,000 and \$40,000, 1 = \$40,000 and over
Education_i	On unit interval, 0 = 0–8 years grade school, 0.25 = 1–3 years of high school, 0.50 = 4 years of high school, 0.75 = 1–3 years of college, 1 = 4 or more years college
Urban8PM_i	Lives in one of 25 largest metropolitan areas, and the time is between 8:00 P.M. and 9:00 P.M.
Urban9PM_i	Lives in one of 25 largest metropolitan areas, and the time is between 9:00 P.M. and 10:00 P.M.

Urban10PM_i	Lives in one of 25 largest metropolitan areas, and the time is between 10:00 P.M. and 11:00 P.M.
Basic_i	Basic cable service
Premium_i	Basic and premium service
Male_i	Male
Female_i	Female
Family_i	Lives with his or her family

- Variables defining show characteristics:

Gen X_Show_{jt}	Main characters are between the ages of 18 and 34
Boom_Show_{jt}	Main characters are between the ages of 35 and 49
Family_Show_{jt}	Main characters are members of a family
Male_Show_{jt}	Main characters are male
Female_Show_{jt}	Main characters are female
Black_Show_{jt}	Main characters are black

- Variables concerning show continuity:

Continue_{jt}	Show continuity (middle of show)
Sample_{jt}	First quarter hour of show
Drama_{jt}	Last quarter hour of drama
Sports_{jt}	Sports show
News_{jt}	News show
Hour Break_{jt}	The 9:00 and 10:00 breaks for the nonnetwork alternative

Next, we present the specific structure of the utilities:

$$
\begin{aligned}
U_{i,\text{out},t} = {} & \eta_{\text{out},t} + \text{Kids}_i \cdot \gamma^{\text{Kids}} + \text{Teens}_i \cdot \gamma^{\text{Teens}} + \text{Gen X}_i \cdot \gamma^{\text{Gen X}} \\
& + \text{Boom}_i \cdot \gamma^{\text{Boom}} + \text{Old}_i \cdot \gamma^{\text{Old}} \\
& + \text{Income}_i \cdot \gamma^{\text{Income}} + \text{Education}_i \cdot \gamma^{\text{Education}} \\
& + \text{Urban8PM}_i \cdot \gamma_{\text{Urban8}} + \text{Urban9PM}_i \cdot \gamma_{\text{Urban9}} \\
& + \text{Urban10PM}_i \cdot \gamma_{\text{Urban10}} + \delta_{\text{out}} I\{C_{i,t-1} = 1\} \\
& + \alpha_i^{\text{Out}} + \varepsilon_{i,\text{out},t},
\end{aligned}
$$

$$
\begin{aligned}
U_{i,\text{non},t} = {} & \eta_{\text{non}\,9} \cdot I\{9 \text{ P.M.} \leq t < 10 \text{ P.M.}\} + \eta_{\text{non}\,10} \\
& \cdot I\{10 \text{ P.M.} \leq t < 11 \text{ P.M.}\} \\
& + \text{Basic}_i \cdot \gamma^{\text{non}}_{\text{Basic}} + \text{Premium}_i \cdot \gamma^{\text{non}}_{\text{Premium}} \\
& + \text{Male}_i \cdot \gamma^{\text{non}}_{\text{Male}} + \text{Teens}_i \cdot \gamma^{\text{non}}_{\text{Teens}} + \delta_{\text{non}} I\{C_{i,t-1} = 6\} \\
& + \alpha_i^{\text{Non}} + \varepsilon_{i,\text{non},t},
\end{aligned}
$$

$$
\begin{aligned}
U_{i,j,t} = {} & \eta_j + \eta^{\text{Special}} \cdot \text{Special}_{jt} \\
& + \text{Gen X\_Show}_{jt} \cdot (\text{Kids}_i \cdot \beta^{\text{X\_Kids}} + \text{Teens}_i \cdot \beta^{\text{X\_Teens}} \\
& + \text{Gen X}_i \cdot \beta^{\text{X\_Gen X}} + \text{Boom}_i \cdot \beta^{\text{X\_Boom}} + \text{Old}_i \cdot \beta^{\text{X\_Old}}) \\
& + \text{Boom\_Show}_{jt} \cdot (\text{Kids}_i \cdot \beta^{\text{B\_Kids}} + \text{Teens}_i \cdot \beta^{\text{B\_Teens}} \\
& + \text{Gen X}_i \cdot \beta^{\text{B\_Gen X}} + \text{Boom}_i \cdot \beta^{\text{B\_Boom}} + \text{Old}_i \cdot \beta^{\text{B\_Old}}) \\
& + \text{Family\_Show}_{jt} \\
& \cdot \left[\text{Family}_i \cdot \beta^{\text{Fa\_Fa}} + (1 - \text{Family}_i) \cdot \beta^{\text{Fa\_NoFa}}\right] \\
& + \text{Black\_Show}_{jt} \cdot \text{Income}_i \cdot \beta^{\text{Black\_Income}} \\
& + \text{Female\_Show}_{jt} \cdot (\text{Female}_i \cdot \beta^{\text{Fe\_Fe}} + \text{Male}_i \cdot \beta^{\text{Fe\_Ma}}) \\
& + \text{Male\_Show}_{jt} \cdot (\text{Female}_i \cdot \beta^{\text{Ma\_Fe}} + \text{Male}_i \cdot \beta^{\text{Ma\_Ma}}) \\
& + \text{Action}_{jt} \cdot (\text{Kids}_i \cdot \beta^{\text{A\_Kids}} + \text{Teens}_i \cdot \beta^{\text{A\_Teens}} \\
& + \text{Gen X}_i \cdot \beta^{\text{A\_Gen X}} + \text{Boom}_i \cdot \beta^{\text{A\_Boom}} + \text{Old}_i \cdot \beta^{\text{A\_Old}} \\
& + \text{Female}_i \cdot \beta^{\text{A\_Female}} + \text{Education}_i \cdot \beta^{\text{A\_Education}} + \alpha_i^{\text{Action}}) \\
& + \text{Comedy}_{jt} \cdot (\text{Kids}_i \cdot \beta^{\text{C\_Kids}} + \text{Teens}_i \cdot \beta^{\text{C\_Teens}} \\
& + \text{Gen X}_i \cdot \beta^{\text{C\_Gen X}} + \text{Boom}_i \cdot \beta^{\text{C\_Boom}} + \text{Old}_i \cdot \beta^{\text{C\_Old}} \\
& + \text{Female}_i \cdot \beta^{\text{C\_Female}} + \text{Education}_i \cdot \beta^{\text{C\_Education}} + \alpha_i^{\text{Comedy}}) \\
& + \text{Fiction}_{jt} \cdot (\text{Kids}_i \cdot \beta^{\text{F\_Kids}} + \text{Teens}_i \cdot \beta^{\text{F\_Teens}} \\
& + \text{Gen X}_i \cdot \beta^{\text{F\_Gen X}} + \text{Boom}_i \cdot \beta^{\text{F\_Boom}} + \text{Old}_i \cdot \beta^{\text{F\_Old}} \\
& + \text{Female}_i \cdot \beta^{\text{F\_Female}} + \text{Education}_i \cdot \beta^{\text{F\_Education}} + \alpha_i^{\text{Fiction}}) \\
& + \text{Romance}_{jt} \cdot (\text{Kids}_i \cdot \beta^{\text{R\_Kids}} + \text{Teens}_i \cdot \beta^{\text{R\_Teens}} \\
& + \text{Gen X}_i \cdot \beta^{\text{R\_Gen X}} + \text{Boom}_i \cdot \beta^{\text{R\_Boom}} + \text{Old}_i \cdot \beta^{\text{R\_Old}} \\
& + \text{Female}_i \cdot \beta^{\text{R\_Female}} + \text{Education}_i \cdot \beta^{\text{R\_Education}} + \alpha_i^{\text{Romance}}) \\
& + \text{Suspense}_{jt} \cdot (\text{Kids}_i \cdot \beta^{\text{S\_Kids}} + \text{Teens}_i \cdot \beta^{\text{S\_Teens}}
\end{aligned}
$$

$$
\begin{aligned}
&+\mathrm{Gen\,X}_i \cdot \beta^{\mathrm{S\_Gen\,X}} + \mathrm{Boom}_i \cdot \beta^{\mathrm{S\_Boom}} + \mathrm{Old}_i \cdot \beta^{\mathrm{S\_Old}} \\
&+\mathrm{Female}_i \cdot \beta^{\mathrm{S\_Female}} + \mathrm{Education}_i \cdot \beta^{\mathrm{S\_Education}} + \alpha_i^{\mathrm{Suspense}}) \\
&+\left(\tau_1^r \cdot \mathrm{Count}_{ijt} + \tau_2^r \cdot \mathrm{Count}_{ijt}^2\right) \cdot (1 - \mathrm{Special}_{jt}) \\
&+\left(\tau_1^s \cdot \mathrm{Count}_{ijt} + \tau_2^s \cdot \mathrm{Count}_{ijt}^2\right) \cdot \mathrm{Special}_{jt} \\
&+\Big[\delta_{\mathrm{net}} + (\delta_{\mathrm{cont}} + \delta_{\mathrm{sample}} \cdot \mathrm{Sample}_{jt} + \delta_{\mathrm{news}} \cdot \mathrm{News}_{jt} \\
&+\delta_{\mathrm{drama}} \cdot \mathrm{Drama}_{jt} + \delta_{\mathrm{sport}} \cdot \mathrm{Sport}_{jt} + \delta_{\mathrm{MA}} \cdot \mathrm{Male}_i) \cdot \mathrm{Continue}_{jt}\Big] \\
&\cdot I\{C_{i,t-1} = j\} + \varepsilon_{ijt} \qquad \text{for} \quad j = 2, \ldots, 5.
\end{aligned}
$$

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