An Empirical Model of Television Advertising and Viewing Markets

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Abstract

Television networks compete for both viewers and advertisers. Recent theoretical work has modeled the impact of viewers’ and advertisers’ network usage on the other group. Empirical work has not kept pace.

I estimate viewer demand for television programs as a function of program characteristics, audience flow, day and time effects, and time given to advertising. I find audiences are highly responsive to advertising quantities. When a highly-rated network increases its advertising level 10%, the model predicts it loses about 30% of its audience; a low-rated network loses 70-90% of its viewers.

I separately estimate advertiser demand for program audiences as a function of audience size, quantity of advertising sold, and program characteristics. I find the price elasticity of advertising demand is -2.9, and the audience elasticity of advertising demand is 0.83.

The results indicate that advertiser preferences are at least as important as viewer preferences when networks choose programs. Viewers’ two most preferred program genres, Action/Drama and News, account for just 16% of network program-hours. Advertisers’ two most preferred genres, Reality and Scripted Comedy, account for 47% of network program-hours.

I use viewer and advertiser demand estimates in conjunction with a game-theoretic model of television network competition to speculate how advertisement-avoidance technology will impact market equilibria. The model suggests that ad-avoidance tends to increase equilibrium advertising levels and decrease network revenues.

Key Words: Advertising; Broadcasting; Demand Estimation; Empirical Industrial Organization; Endogeneity; Entertainment Marketing; Television; Two-Sided Markets
1. Introduction

Television continues to be advertisers’ most important advertising medium. It accounts for about a quarter of all advertising volume in the United States. Household television viewing increased every year between 1996 and 2004, to more than eight hours per day.¹

The television industry is an example of a two-sided market. Networks compete to attract viewers’ attention, and then sell that attention to advertisers. A network has to get both sides of the market on board to be successful. Advertisers and marketers have long understood the two-sided nature of the industry, and recent theoretical treatments have started modeling the interplay of advertiser and viewer preferences. Yet there has not been any empirical study of the industry that considers cross-group externalities: the effect the number of advertisers has on audience size, and the effect that audience size has on advertiser demand.²

This paper proposes an equilibrium model of the television industry. Networks set advertising levels to coordinate viewers and advertisers. I estimate the model using data from four sources: US broadcast television networks’ audience shares in 50 geographic television markets, advertising quantities and prices per half-hour, program characteristics, and audience demographics collected by the US Census. There is clear evidence of cross-group externalities. A 10% increase in advertising level typically reduces audience size 30%-93%, with more popular networks experiencing smaller audience losses. In turn, a 10% increase in audience size typically raises advertisement price 8.3%.

Viewer and advertiser preferences for program characteristics are compared to networks’ programming choices. Viewers most prefer to watch Action Drama and News programs. Advertisers most prefer to buy time during Scripted Comedy and Reality programs. Advertiser preferences seem to be at least as important to network programming choices as viewer preferences. Comedies and Realities constitute 48% of network programming, while Action and News programs account for just 16%. Analyzing either side of the market in isolation would suggest networks were failing to satisfy their customers’ tastes.

¹ Sources: Universal McCann and Nielsen Media Research data reported at www.tvb.org.
² Controlling for advertising levels is necessary to obtain unbiased viewer demand estimates. For example, a popular program will contain a lot of ads, so the estimate of its popularity would be biased downwards when advertising is unobserved. This issue is similar to a situation in which demand for a consumer product is estimated in the absence of price data. Similarly, controlling for audience size and ad quantity is necessary to obtain unbiased advertiser demand estimates.
A current topic in the television industry is how digital video recorders will impact network advertising revenues (see, e.g., Garfield 2005). I solve a counterfactual to provide educated speculation about these effects. I use the viewer and advertiser demand estimates to calibrate a model of network conduct and infer unobserved tune-in levels.\(^3\) I then solve for new market equilibria given a hypothetical advertisement-avoidance technology. I find that ad-avoidance technology leads to increasing advertising levels and falling network revenues.

The next section reviews the academic literature on television viewing and advertising markets. I then describe the model of viewer utility, advertiser demand, and network supply of advertisements. Section four describes the data, endogeneity, and estimation. Section five discusses empirical results. In section six I describe the counterfactual and present its results. The paper concludes with a summary and directions for future research.

2. Relevant Literature

This paper contributes to the literature on television and advertising markets. Much of the recent work has been based on theoretical advances in our understanding of “two-sided markets.” Two-sided markets are generally characterized as industries in which platforms enable interactions between distinct groups of agents, and try to get the various sides “on board” (Rochet and Tirole, 2004).\(^4\) The pioneering treatments in the two-sided markets literature are Armstrong (forthcoming), Caillaud and Jullien (2001, 2003), and Rochet and Tirole (2003, forthcoming). For advertisement-supported media, the most important insight from the two-sided markets literature is that ad prices reflect both the value of reaching a given audience, and the marginal effect of the advertisement sale on total audience size. A key assumption in these models concerns agents’ platform uses. Television viewers are usually assumed to singlehome—that is, to only watch one television network at a time. Advertisers are often assumed to multihome—that is, to use multiple networks and programs to reach viewers.

Advertisers and marketers have long understood the two-sided nature of the television industry, but academics have only recently used models of two-sided markets to describe

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\(^3\) Tune-ins are advertisements for future network programs. They are known in the industry as promos.

\(^4\) Examples of two-sided markets include computer software (operating-system manufacturers coordinate software users and developers) and credit cards (credit-card companies coordinate merchants and consumers). Two-sided markets are also called “multi-sided platform industries.”
advertising media. Anderson and Coate (2006) investigate the nature of market failure and entry in the broadcasting industry. They find that the market can provide suboptimally low or high quantities of advertising. Overadvertising can occur because the broadcaster’s disincentive to sell ads is its marginal audience loss. This audience loss does not account for nonswitching viewers’ ad disutility. Underadvertising can occur when programs are close substitutes and viewers are very ad-averse. This leads broadcasters to compete for viewers by lowering ad levels to such an extent that the advertising market is underserved. Dukes and Gal-Or (2003) model interactions between viewers, broadcasters, and advertisers, and also consider the effects of informative advertising on competition in product markets. They show that when increased advertising leads to better-informed consumers, product-market competition intensifies. Networks and advertisers can then benefit from exclusive-advertising contracts. Liu, Putler, and Weinberg (2004) consider the effects of competition between television networks on networks’ incentives to invest in program quality. They show that increased network competition can lead to diminished program investments and lower viewer welfare.

There is also some empirical evidence on two-sided media markets. Kaiser and Wright (2006) apply Armstrong’s (forthcoming) model to competition in the women’s magazines industry. They find evidence that readers value magazine advertisements, and that magazine advertisers value reader exposures still more. Their estimates show that an increase in magazine readers’ demand raises advertising rates, while a boost in magazine advertisers’ demand lowers magazine cover prices. Rysman (2004) estimates a model of competition between yellow-pages directories. He finds that competition both reduces directory ad prices and alters directories’ nonlinear pricing functions, disproportionately benefiting large advertisers.

This work also relates to the long traditions of examining each side of the television market in isolation. The first academic paper to estimate viewer demand for television programs was Lehmann (1971). Rust and Alpert (1984) pioneered the use of discrete choice models to estimate viewer preferences. In the recent literature, Shachar and Emerson (2000) added interactions between viewer and program characteristics to the model. They find that the match between viewers and the demographic characteristics of the characters on the programs they watch is a good predictor of viewing choices. Danaher and Mawhinney (2001) and Goettler and Shachar (2001) each model viewers’ preferences—the first set of authors with a latent class logit
model, and the second with a multidimensional ideal-point framework—with the purpose of calibrating models of optimal program scheduling. Godes and Mayzlin (2004) show that the amount of online “buzz” and its dispersion across online communities are associated with higher ratings for new television programs. Several papers have used Bayesian frameworks to model viewer uncertainty about television program content. Anand and Shachar (2004) estimate the effects of previous program consumption on agents’ beliefs about future programs. They find this uncertainty-reduction mechanism has a greater effect on viewing choices than unobserved heterogeneity. Anand and Shachar (2005) estimate the effects of tune-in exposure on viewers’ information sets and program choices. They find that tune-in exposures have both persuasive and informative effects. Tune-ins’ informative effects increase the efficiency of viewer/program matches. Yang, Narayan, and Assael (2006) estimate a random-effects Tobit model to investigate preference interdependencies between married viewers. They find that husbands’ effects on wives’ viewing intentions exceed wives’ impacts on husbands’ viewing intentions.

The advertising side of the television industry has received less attention than the viewing side. Crandall (1972) and Bowman (1976) estimated advertiser demand for television audiences, but neither paper used data on advertising levels. Two recent working papers, Goettler (1999) and Wildman, McCullough, and Kieschnick (2004), also estimate the relationship between audience size and advertisement price. But neither paper used data on advertising quantities. Another related literature is the series of studies measuring viewer responsiveness to advertising. Siddarth and Chattopadhayay (1998) found that viewers’ propensity to change channels during a commercial is J-shaped in the number of times they are exposed to the commercial, with a minimum at fourteen exposures.

This paper contributes to the literature by estimating demand on both sides of the television industry. The importance of the two-sided approach is underscored when viewer and advertiser preferences are compared to networks’ programming choices. The present analysis includes one of the first efforts to measure the sensitivity of television audience size to the time devoted to national advertising within a program. It also contains the first estimate of the price elasticity of advertising demand. The model’s estimates are applied in a counterfactual to gain some insight into how ad-avoidance technology may affect market equilibria.
3. A Model of Television Advertisers, Networks, and Viewers

This section describes the model of viewer utility, advertiser demand, and network supply of television commercials. The viewer and advertiser models presented in sections 3.1 and 3.2 are used in model estimation. The model of network behavior in section 3.3 is used in conjunction with parameter estimates in two ways. First, its implications are used to infer unobserved tune-in levels. Second, it underpins the counterfactual analysis in section 6.

3.1. Viewers

Television viewers typically watch one program at a time. Thus researchers typically use discrete choice models to estimate viewer demand for television programs. I use a random-coefficients logit to model television viewers. I choose this model because it best suits the available data. Its primary benefits are extensive controls for unobserved viewer heterogeneity, and reliance on consumer characteristics to identify substitution patterns.

Each viewer \( i \) in city \( m \) is assumed to either watch one of \( J-1 \) broadcast television networks (which are indexed by \( j \)), to watch some other television channel (denoted option \( J \)), or to engage in some non-television pursuit at each half-hour \( t \). Let viewer \( i \)'s utility from watching network \( j \) in city \( m \) at time \( t \) be

\[
u_{ijmt} = q_{jt} \alpha^*_i + x_{mij} \beta^*_i + \xi_{jt} + \eta_{mjt} + \epsilon_{ijmt},
\]

where \( q_{jt} \) is the number of seconds of advertising on network \( j \) during half-hour \( t \); \( x_{mij} \) is a vector that includes the observable characteristics of the show on network \( j \) at time \( t \) (e.g., genre), audience flow effects,\(^5\) and market, day and time dummies; \( \alpha^*_i \) and \( \beta^*_i \) are viewer \( i \)'s taste parameters; \( \xi_{jt} \) captures mean tastes for the unobserved characteristics of the program airing on network \( j \) during time \( t \); \( \eta_{mjt} \) measures a deviation from mean tastes for unobserved show

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\(^5\) Moshkin and Shachar (2004) present evidence that state dependence plays an important role in television viewing choices. I do not observe viewer state dependence. Therefore I use network \( j \)'s audience size in market \( m \) at times \( t-1 \) and \( t+1 \) to control for audience flow. The industry terms for these audiences are the lead-in and lead-out.
characteristics common to viewers in city \( m \) at time \( t \);\(^6\) and \( \varepsilon_{imjt} \) is viewer \( i \)'s idiosyncratic taste for network \( j \)'s time-\( t \) program.

To define viewer \( i \)'s taste parameters, let

\[
\begin{bmatrix}
\alpha_{im}^* \\
\beta_{im}^*
\end{bmatrix} = \begin{bmatrix}
\alpha \\
\beta
\end{bmatrix} + \Pi D_m + \Sigma v_{im}, \quad D_m \sim P_{Dm}^*(D), \quad v_{im} \sim P_{v}^*(v),
\]

where \( \alpha \) and \( \beta \) are mean tastes for ad quantity and program characteristics, \( D_m \) is a vector of viewer demographic characteristics (income, age, and age\(^2\)), \( P_{Dm}^*(D) \) is the market-specific joint distribution of viewer demographics, and \( v_{im} \) is a vector of unobserved preference heterogeneity. I make the standard assumption that the components of \( v_{im} \) are independently distributed normal. \( \Pi \) is a parameter matrix that measures how tastes for program characteristics and advertising vary with observed viewer demographics, and \( \Sigma \) is a diagonal matrix that measures the relative importance of unobserved viewer preference heterogeneity.

If viewer \( i \) watches any non-broadcast network, her utility is given by

\[
u_{im,lt} = x_{mlt} \beta_i + \xi_{jlt} + \eta_{mlt} + \pi_j D_m + \sigma_j v_{im} + \varepsilon_{im,lt},
\]

where \( x_{mlt} \) contains audience flow, market, day, and time effects, \( \xi_{jlt} \) is the mean value of the best available non-broadcast network at time \( t \), and \( \eta_{mlt} \) is a deviation from mean preferences for non-broadcast TV networks shared by viewers in city \( m \) at time \( t \).

The utility of the non-television option (option 0) is

\[
u_{im,0t} = \xi_{0lt} + \eta_{m0t} + \pi_0 D_m + \sigma_0 v_{im} + \varepsilon_{m0t},
\]

where \( \xi_{0lt} \) and \( \eta_{m0t} \) are normalized to zero (and the \( \xi_{jlt} \)'s and \( \eta_{mlt} \)'s are identified relative to this normalization), and \( \pi_0 D_m + \sigma_0 v_{im} \) is interpreted as a fixed effect that measures the time-invariant component of viewer \( i \)'s value of the non-television option.

I assume viewers act to maximize utility. Thus, the set of demographics and preference shocks that leads viewer \( i \) in city \( m \) to watch network \( j \) at time \( t \) is

\[
A_{njt} = \{ (D_m, v_{im}, \varepsilon_{im,t}) | u_{imjt} > u_{im,k}, \forall k \neq j \},
\]

\(^6\) The effect of unobserved regional differences in speech and culture on viewer preferences for unobserved show characteristics is assumed to be the primary determinant of \( \eta_{njt} \).
where \( \varepsilon_{imjt} \) is a vector of the \( \varepsilon_{imjt} \)’s. If the idiosyncratic error terms are distributed identically and independently, the viewing share of network \( j \) in market \( m \) at time \( t \) is given by

\[
 s_{mjt} = \int_{A_{mjt}} dP^*_v(\varepsilon) dP^*_v(v) dP^*_{lim}(D).
\]

I assume the idiosyncratic error terms \( \varepsilon_{imjt} \) are distributed \( i.i.d. \) Type I Extreme Value and integrate out over them in the standard fashion. Thus the predicted share can be re-written as

\[
 s_{mjt} = \int_{A_{mjt}} dP^*_v(v, D) dP^*_v(v) dP^*_{lim}(D),
\]

where \( dP^*_v(v, D) \) is the standard multinomial logit share function. Equation (3) will be used to estimate viewer demand for television programs. The integral on the right-hand side does not have a closed-form solution, so simulation will be used to approximate it.

### 3.2. Advertisers

I model advertisers through their aggregate demand for advertising on a given program. Derivation of advertiser demand from first principles would be preferable. But it is complicated by an assignment problem in the matching of advertisers to their preferred audiences.

I consider here a simple example to illustrate the assignment problem. Consider a single advertiser with utility function \( \sum_{s \in S} V_s \), where \( V_s \) is the number of viewers watching show \( s \) and \( S \) is the set of shows purchased by the advertiser. There are two audiences available: audience \( A \) consists of 9 viewers, and audience \( B \) of 16 viewers. Viewers are homogeneous and audiences do not overlap. If the advertiser only purchases audience \( A \), its willingness to pay for \( A \) is 3 \( (= \sqrt{9}) \). If the advertiser only purchases audience \( B \), its willingness to pay for \( B \) is 4 \( (= \sqrt{16}) \). If the advertiser purchases both audiences, its willingness to pay for \( B \) is \( B \)’s marginal contribution to total advertiser utility: 2 \( (= \sqrt{16} + 9 - \sqrt{9}) \). The assignment problem is the dependence of the advertiser’s willingness to pay for audience \( B \) on whether it purchases audience \( A \).
The assignment problem in the advertising marketplace could potentially be addressed using a two-sided, many-to-many matching routine. But many-to-many matching models have unresolved technical challenges regarding the stability and uniqueness of the equilibrium assumptions. I am not aware of any papers that estimate many-to-many matching models. I therefore use a reduced-form assumption in the place of a structural model of advertiser behavior. I assume there exists an aggregate demand curve for advertising during each program and represent that curve with a linear specification.

Advertiser demand for a particular television audience is influenced by many factors, including audience size, viewer demographics, and program characteristics that influence the efficacy of the program’s advertising message delivery. I assume that aggregate inverse demand for advertising is given by

\[ p_s = q_s \lambda_q + V_s \lambda_r + d_s \lambda_d + x_s \lambda_x + \phi_s, \]  

where \( p_s \) is the price of an ad during show \( s \), \( q_s \) is the show’s ad level, \( V_s \) is the number of viewers watching show \( s \), \( d_s \) is a vector of viewer demographics, \( x_s \) represents program characteristics that affect advertising effectiveness, the \( \lambda \)'s are advertiser preference parameters, and \( \phi_s \) is an error term. Possible sources of error include unobserved audience demographics or measurement error in ad price.

The drawback of assuming equation (4) is linear is the lack of clarity in the underlying assumptions about advertiser preferences and behavior, and the attendant risk of specification error. Its advantage is that it obviates the large theoretical and computational burdens of using a many-to-many matching routine to estimate advertiser demand parameters. I conclude that the linear form of (4) is a justifiable simplification. As shown in section 5.3, the assumed functional form is found to explain 87% of the variation in advertisement prices.

3.3. Networks

The complexity of networks’ strategic interactions requires strong assumptions about their behavior. Due to the strength of these assumptions and the limitations of the data, the model of

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7 Two-sided matching has been studied since Gale and Shapley (1962). These models are used most often to analyze labor markets, marriage markets, and school choice. Roth and Sotomayor (1990) provide a detailed introduction.
8 I tested several alternate specifications, including Cobb-Douglas. Model fits and qualitative results were similar across all models tested.
network competition is not used to estimate demand parameters. It is only used to infer missing
data and in the counterfactual described in section six.

I assume networks compete in three stages. In the first stage, networks choose their
programs; in the second stage, networks schedule their programs; and in the third stage, networks
set ad quantities. I focus here on competition in the final stage, in which program costs are
sunk, and program schedules have been finalized.

Tune-ins are not observed in the data. But they account for about 25% of non-program
material so it is important to account for them in the counterfactual simulation. I assume
networks set advertisement and tune-in levels to maximize current-period advertising revenues.
A higher number of tune-ins in the current period will inform viewers of upcoming
programming, but tune-ins may reduce audience size since some viewers flip channels during
tune-ins. Those audience losses reduce current-period advertising revenues.

I assume that a network’s benefit from a viewer’s tune-in exposure is constant at $\tau_s$
during each show $s$. $\tau_s$ is the marginal effect of exposure to one tune-in on the probability any
given viewer will watch the advertised show, times the network’s profit from the increase in the
advertised show’s audience.

If we denote the number of tune-ins aired during show $s$ as $r_s$, the network’s stage-three
profits can be written as the sum of its advertising revenues and tune-in benefits during the show:

$$\pi_j = \max_{(q_s, r_s) \in s} \sum_{s \in S} [q_s p_s + r_s V_s \tau_s],$$

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9 The timing of the game is consistent with reality. The first stage takes place before the upfront market, when
networks renew returning shows, and buy new ones. The second stage takes place at the start of the upfront, when
networks announce their program schedules. The third stage occurs during the remainder of the upfront and scatter
markets. Yet it should be noted that networks replace and reschedule shows during the season and typically sell
about 20% of their primetime advertising inventory after the upfront (Reynolds 2006).

10 The ad-quantity-setting assumption is standard in the literature. Networks can control the number of minutes of
advertising in a program by editing it appropriately. The upfront contains considerable uncertainty about advertising
demand and protracted price negotiations with advertisers in which advertisers are known to pay nonuniform prices.
This information seems inconsistent with an assumption that networks set a single price per show. Anderson and
Coate (2006) show that ad price and ad quantity games yield identical results when viewers pay no subscription fees.
But the inclusion of tune-ins in the model makes this framework more similar to Crampes, Haritchabalet, and Jullien
(2005). These authors find that an ad price setting assumption yields equilibrium advertising levels and prices
equivalent to the ad quantity game, but higher media profits and subscription prices. If networks set ad prices, the
empirical implication is that the inferred tune-in levels presented in section 5.5 will be too small.


12 This tune-in benefit could vary across shows for the same reasons that advertising demand varies across shows:
some shows deliver advertising more effectively than others, and some viewers are more valuable than others.
where $S_j$ is network $j$’s catalogue of shows.

Substituting ad demand (4) into equation (5) and differentiating with respect to $q_s$ and $r_s$ yields

$$p_s + q_s \lambda_q + q_s \lambda_v \frac{\partial V_s}{\partial q_s} + r_s \frac{dV_s}{dq_s} \tau_s = 0, \text{ and}$$

$$q_s \lambda_v \frac{\partial V_s}{\partial r_s} + V_s \tau_s + r_s \frac{\partial V_s}{\partial r_s} \tau_s = 0.$$  

(6) 

(7)

The first two terms in equation (6) are similar to marginal revenue in any monopoly or oligopoly first-order condition. The third term captures the two-sided nature of the market, the decrease in advertisement price through the audience loss (\(\frac{\partial V_s}{\partial q_s}\)) engendered by commercial sales. The fourth term is the marginal effect of the network’s advertising sales on its gross tune-in benefit. The first-order condition taken with respect to $r_s$ contains similar logic. The first term is the marginal effect of a tune-in on advertising revenues, and the second two terms are the network’s marginal benefit of airing a tune-in.

I make the additional assumption that viewers are equally averse to advertisements and tune-ins. Tune-ins are more likely to be relevant to the mean viewer than advertisements. But they are also repeated more frequently in short periods of time, so they are accordingly more likely to wear out. This assumption is very strong, but it is only used to infer unobserved tune-in levels. It is not used in the estimation. It implies that the marginal effect of ad sales on audience size is equal to that of airing tune-ins: \(\frac{\partial V_s}{\partial q_s} = \frac{\partial V_s}{\partial r_s}\). Equations (6) and (7) then imply a third relationship:

$$p_s + q_s \frac{\partial p_s}{\partial q_s} = V_s \tau_s.$$  

(8)

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13 A computer simulation was conducted to investigate the existence, stability, and uniqueness of the equilibria of this oligopoly game. Assuming \(\frac{\partial V_s}{\partial q_s}\) is strictly negative, two equilibria exist: one is an interior, stable equilibrium in which all networks play nonzero advertising levels. In the other equilibrium, networks advertising quantities go to infinity and audience sizes go to zero.
Equation (8) says that, holding audience size constant, the network will choose advertising and tune-in levels to equate its marginal benefit from each activity. Equations (7) and (8) will be used in conjunction with advertiser and viewer demand parameter estimates to make inferences about unobserved supply parameters and tune-in levels.

4. Data, Endogeneity, and Estimation

I start here with the overview of the empirical strategy depicted in Figure 1. The model has three sets of primitives: assumptions about viewers, advertisers, and networks. These primitives are used to generate four sets of results. First, the viewer demand model is estimated. Second, viewer demand parameters provide instruments to estimate advertiser demand for audiences.\(^\text{14}\) Third, the two sets of parameter estimates are used in conjunction with the model of network competition to make inferences about missing data. Fourth, all assumptions, empirical results, and data inferences are used to derive the counterfactual results.

In this section, I describe in turn the data, viewer demand-side endogeneity and estimation, advertiser demand-side endogeneity and estimation, and the inference procedure. The counterfactual is discussed in section 6 and described in detail in the technical appendix.

4.1. Data

The model is estimated using data on television audiences, viewer demographics, advertisements, and program characteristics from four sources. The unit of observation is a network-day-time period. For each observation, the data report seconds of national advertising, the average cost of a 30-second commercial, the characteristics of the program, and household audience share in each of 50 television markets.

The sample includes the programs and ads aired by the six most-watched US broadcast television networks (ABC, CBS, FOX, NBC, UPN, and WB) between 8:00 p.m. and 10:00 p.m.,

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\(^{14}\) The two sides of the model are estimated separately for two reasons. The computation time required for the viewer demand model was extensive, and increased exponentially with the dimensionality of the parameter space. Second, the program quality estimates must be averaged over program half-hours to account for networks’ strategic considerations before they can be used as instruments to identify advertiser demand. Berry and Waldfogel (1999) found in a similar context that simultaneous estimation of the two sides of the market yield results that are “nearly identical” to separate estimation.
Monday to Friday, April 24 to May 21, 2003. I describe each component of the data in turn, report descriptive statistics, and conclude by describing some limitations of the dataset.

Audience share data come from Nielsen Media Research (NMR) “Viewers in Profile” reports covering the 50 largest US Designated Market Areas (DMAs). More than 90% of US television households are represented in the sample. NMR collected household audience data in each market with a sample of “audimeters,” set-top boxes that record viewing choices and transmit data to Nielsen via telephone lines. The data report audiences by half-hour, day, and network affiliate.

Two important characteristics of the audience data merit discussion. First: if a household watched a program for five not-necessarily-consecutive minutes during a 15-minute period, Nielsen includes that household in the program’s audience. (The data are reported at the half-hour level, as the average of the two fifteen-minute blocks in each half-hour.) It is therefore possible for a household in Nielsen’s sample to watch a program, avoid commercials perfectly with a remote control, and still be counted among the program’s audience. This would suggest the household is extremely ad-averse, but its ad-aversion would not be detectable in the data. To the extent this occurs, I will underestimate viewers’ true ad disutility. However the main purpose here is to measure how Nielsen’s audience measurements change with advertising levels, since those measurements were the currency of the advertising marketplace in 2003.

Second, Nielsen excluded DVR households from its sample in 2003. The Yankee Group estimated DVR penetration at 2% of US households in mid-2003. Therefore, viewer demand parameters can be interpreted as describing the tastes of the remaining 98% of US TV households.

The viewing data used in this paper should be contrasted with the datasets used in prior literature to aid interpretation of the estimation results. Many previous studies have used 1980’s- or 1990’s-era individual-level viewing data collected by Nielsen Peoplemeters for thousands of viewers. This dataset is relatively coarse in comparison: it consists of aggregated choices of households in 50 geographic markets. It is also relevant to consider that the households that

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15 Saturdays and Sundays were excluded because UPN does not broadcast on either day, and WB does not broadcast on Saturdays. 10-11:00 p.m. was excluded because FOX, UPN, and WB do not broadcast at that time. I also exclude two nights in which programs with unpredictable ad levels aired: a presidential address, on Thursday, May 1; and a NBA basketball game, on Thursday, May 15.
accept peoplemeters may differ from the households that accept audimeters and diaries. Diaries require viewers to manually record the programs they view each week, while Peoplemeters require viewers to “log in” once or twice per hour. The relative disadvantage of the current dataset is that it is not a panel of individual viewers, so viewer persistence is not directly observed. The relative advantage of this dataset is its size. The sample on which it is based is large (NMR sampled 1,000-1,500 households in each of the 50 DMAs) and its four-week time period and six broadcast networks are unusually large.

Audience demographic data were collected from US Census 1% IPUMS files for each Consolidated Metropolitan Statistical Area corresponding to a DMA. The demographics I use are viewers’ age and household income.

Data on ad quantities and prices come from TNS Media Intelligence/CMR. For each program in the sample, I observe the time given to national advertising and the estimated price of a 30-second commercial during the show. The estimated prices were recorded from network reports of “the estimated cost of a 30-second spot” after the program aired. These data are commonly used by advertisers and agencies to budget for future advertising campaigns.\(^{16}\)

Program characteristics were recorded by the author from videotapes of network programming made during the sample period. The videotapes were supplemented with data from a website, *TVTome*. Observable program characteristics include genre, thematic elements, main and supporting characters’ demographics\(^{17}\) (including gender, race, age, and family structure), program age, setting, and current and past Emmy nominations.

Advertisement quantities exhibit substantial intratemporal variation in the sample. The mean ad level per half-hour is 5:15 minutes, and the average difference between the maximal and minimal network ad levels within a half-hour is 2:49 minutes. Programs that are more attractive to viewers, relative to within-time-period competition, typically contain more ads. Broadcasters

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\(^{16}\) There is evidence that ad transaction prices are not uniform across advertisers. Advertisers can secure lower prices by procuring quantity discounts (Auletta 1992) and strong media negotiators (Bloom 2005). Networks keep transaction prices strictly confidential to avoid weakening their negotiating positions. The assumption that ad prices are constant within a program will only be a problem if advertisement prices are systematically correlated with the preferences of advertisers receiving discounts. Fournier and Martin (1983) is the only paper I know of that analyzes a sample of actual advertisement transaction prices but it does not present any evidence on this question.

\(^{17}\) A main character is defined as a character on which major plotlines are based.
had limited themselves to six ad minutes per hour until an antitrust suit in 1982 but non-program
time has more than doubled since then.

Table 1 reports the means and standard deviations of ad price, ad quantity, cost per
thousand households (CPM), and audience size, by network and day. Some interesting results
emerge. ABC aired the most national advertising during the sample, averaging 6:07 minutes of
national ads per half-hour, while FOX aired the least, 4:44 minutes per half-hour. FOX and NBC
shared the highest average CPM ($28), while UPN charged the least ($19). FOX attracted the
largest average audience, followed by CBS, NBC, ABC, WB, and UPN.

Figure 2 shows average nightly audiences by network and day. The three highest-rated
networks’ nightly audiences varied considerably over days of the week. FOX dominated
Tuesday and Wednesday with its American Idol franchise, but was near average otherwise. CBS
and NBC both attracted large audiences on Thursday night. The bottom three networks’
audiences showed much less variation, with standard deviations less than half as large as CBS,
FOX, and NBC.

Figure 3 shows how networks’ prices per viewer moved over the course of the average
week. NBC was the only network to consistently charge in the upper echelon of per-viewer
prices. CBS’ take per viewer dipped precipitously on Tuesday, while FOX’s CPM fell
dramatically on Thursdays. The three lowest-rated networks all charged per-viewer prices with
lower means and less variation.

Table 2 lists the program characteristics, their definitions, and descriptive statistics,
weighted by total half-hours of programming in the sample. The table shows that the two most
commonly programmed genres, by far, were Scripted Comedy and Psychological Drama.
African-Americans appeared in prominent roles in nearly half of all shows, while other
minorities were cast in leading roles less frequently (9%). The average program in the sample
was 3.3 years old, was nominated for 1.4 Emmys in 2003, and had been nominated for 3.6
Emmys in previous years.

Table 3 shows the correlations between program audience size, advertising time, ad price,
and genre. Ad price and audience size are highly collinear, with a correlation of 0.81.
Advertising time is slightly negatively correlated with audience size (-0.06). Ad time is also
negatively correlated with ad price (-0.10). Some of the genre correlations are interesting.
Scripted Comedy is the only genre positively correlated with advertising time but is not correlated with audience size or ad price. The Reality genre, by contrast, was the most positively correlated with ad price (0.26) and was positively correlated with audience size (0.14), but it was negatively correlated with ad time (-0.1).

It is important to note that local advertising and national tune-ins remain unobserved. The 2001 Television Commercial Monitoring Report (TCMR) reports detailed information for all non-program material based on one week of data from November, 2001. It shows that the average half-hour of programming contained 8:22 minutes of non-program material, of which 4:52 minutes were national advertisements, 2:03 minutes were national tune-ins, and 1:24 minutes were local advertising time. Local ad time is determined by long-term contracts between networks and affiliates. It is nearly uncorrelated with national advertising time. In the TCMR sample, this correlation was -0.09. Non-program time does not vary across markets. Its effects on viewer utility should be captured by $\xi_{jt}$. Networks do not set local advertising time based on contemporaneous program quality, so its omission is unlikely to bias estimates of viewer responsiveness to advertising.

The TCMR data suggest the absence of tune-in data may be more important. The program dummies, $\xi_{jt}$, will capture the mean effect of tune-in levels across a program’s episodes. This suggests a possible bias in programs’ estimated attractiveness to viewers. I am left without a way to test the magnitude of the bias, but I suspect that program characteristics will be stronger drivers of estimated program quality than tune-in levels.

4.2. Viewer Demand Endogeneity and Estimation

In the estimation of the viewer demand model presented in section 3.1, mean tastes for unobserved program characteristics $\xi_{jt}$ and market-specific deviations from mean tastes for unobserved program characteristics $\eta_{mjt}$ are unobserved by the econometrician. Yet these data are likely to be known by the television network and taken into account when it sets its prices.

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18 Local advertising time within a national broadcast is constant across affiliated stations. Affiliates vary in how much time they sell to local advertisers, use to promote their own programs, or air public service announcements.

19 I thank an anonymous reviewer for pointing this out.
advertising level $q_{jt}$. To avoid bias in the advertising response parameters, I use program
dummies to estimate $\xi_{jt}$. Thus the correlation between $q_{jt}$ and $\xi_{jt}$ exists between observable
variables, rather than between an observed variable and an error.$^{20}$

There is a further concern that the network has knowledge of the market-specific tastes
for unobserved program characteristics $\eta_{mjt}$ and uses that knowledge in setting its advertising
level. There are two reasons this could be the case. First, larger markets’ tastes matter more
because large markets contain more viewers. Second, even after controlling for audience size and
demographics (like age and income), the network might have preferences over the geographic
distribution of the viewers in an audience.

To correct for the first concern, I premultiply $\eta_{mjt}$ in equation (3) with

$$\tilde{\omega}_m \equiv \frac{\omega_m}{\sum_{n=1}^{M} \omega_n},$$

where $\omega_m$ is the number of households in city $m$ and $M$ is the number of cities in the sample.
Thus, by construction, the program-specific fixed effect is estimated to be the mean effect of
unobserved program characteristics across all households in the sample rather than the mean
effect across DMAs in the sample. The data is defined at the market level, rather than the
household level, so this premultiplication is necessary to ensure the effects captured by $\xi_{jt}$ and
$\eta_{mjt}$ are consistent with their definitions in section 3.1.

There is not a similarly parsimonious strategy to control for the second concern listed
above. I acknowledge this as a possible objection, but I think it is not a first-order issue. While
individual advertisers are certain to have preferences over geographic distributions of audience
members, if those preferences are very strong, they are likely to buy audiences in the “spot”
television market (advertising on local stations) in place of national advertising. Additionally,
geographic preferences are likely to vary across advertisers, and network incentives are
influenced by the cumulative preferences of all advertisers in the market.

$^{20}$ This approach is similar to that used by Nevo (2000, 2001). The program dummies $\xi_{jt}$ are identified: every
program airs in 50 DMAs in each time period, and airs in multiple time periods in the sample.
I now describe the algorithm and the moments used to estimate the structural parameters of the viewer demand model presented in section 3.1. The estimation routine is similar to that introduced by Berry, Levinsohn, and Pakes (1995; hereafter, “BLP”) and described in detail by Nevo (2000, 2001). The main idea of this estimation routine is to numerically solve the market share functions defined by equation (3) for programs’ mean utility levels, and to use these imputed mean utilities in a moment condition. Use of this algorithm confers two primary benefits. It defines the objective function as a smooth function of the parameters, which reduces simulation error. And it significantly reduces the number of parameters to be estimated nonlinearly. This speeds computation greatly.\(^2^1\)

To facilitate explanation of the estimation routine, I define some new notation. Let \(N\) be the number of city/day/time/network market shares observed in the sample, and let \(P\) be the number of programs in the sample. Let \(H\) be a \(NxP\) matrix of program dummies and \(\psi\) be the \(Px1\) vector of mean program utilities that are constant across viewers and time periods in which the program airs. Let two partitions of \(x_{mj}\) be labeled \(x_{jt}\), which includes program dummies, and \(\tilde{x}_{mj}\), which contains the data that varies across markets and/or time periods within a program.\(^2^2\) Label two partitions of \(\beta\) with \(\beta_1\), which interacts with \(x_{jt}\), and \(\beta_2\), which interacts with \(\tilde{x}_{mj}\). Denote the set of parameters to be estimated using GMM with \(\theta = \{\psi, \alpha, \beta_2, \Pi, \Sigma\}\.\(^2^3\)

Define the mean utility that viewers in city \(m\) derive from watching network \(j\) at time \(t\) as \(\delta_{mj} = \psi_p + q_j \alpha + \tilde{x}_{mj} \beta_2 + \tilde{\omega}_m \eta_{mj}\), where \(\psi_p\) is the non-ad, mean utility (NAMU) of the program on network \(j\) at time \(t\).

The integral that defines the predicted market share function (equation 3) has no closed form solution. I use simulation to approximate it. I draw simulated viewer demographics \(D_{im}\) from the city-specific nonparametric marginal distributions defined by the IPUMS data, and I draw \(\nu_j\) from a standard multivariate normal distribution. The predicted audience share of network \(j\) at time \(t\) in market \(m\) is then the fraction of the simulated viewers in the market for

\(^{21}\) The method traditionally used to estimate random coefficient logit models is to define the objective function as the difference between the predicted market shares and the observed market shares. The advantages of the BLP estimation algorithm listed here are relative to the traditional estimation method.

\(^{22}\) \(\tilde{x}_{mj}\) contains the advertising level (which varied over networks, days and half-hours, but not DMAs), audience flow effects, the last-half-hour dummy, and day-, time-, and market-specific fixed effects.

\(^{23}\) \(\beta_1\) will be estimated using the minimum-distance procedure explained below.
whom network j’s time-t program maximizes utility, conditional on the time-t programs aired by all networks and a guess of the parameter set θ.

I use the contraction mapping suggested by BLP to solve for the J-vector of mean utilities \( \tilde{\delta}_{mt}(\theta) \) that, for a given value of \( \theta \), equate predicted market shares to observed market shares in market m at time t,

\[
S_{mt}\left(\tilde{\delta}_{mt}(\theta)\right) = S_{mt}.
\]

I then construct the error term, the market-specific deviation from mean tastes for network j’s time-t broadcast, as

\[
\tilde{\eta}_{mjt}(\theta) = \frac{1}{\tilde{\omega}_m} (\tilde{\delta}_{mjt}(\theta) - \psi_p - q_j \alpha - \tilde{x}_{mjt} \beta_2).
\]

Next, I construct the moment conditions, \( EX'\tilde{\eta}(\theta) = 0 \), where \( X \) is a matrix of instruments defined below, and \( \tilde{\eta}(\theta) \) is a \( N \)-vector of the \( \tilde{\eta}_{mjt}(\theta) \)’s. The GMM estimate of \( \theta \) is

\[
\hat{\theta} = \arg\min_{\theta} \tilde{\eta}(\theta)'X'\left(X'X\right)^{-1}X'\tilde{\eta}(\theta),
\]

where \( A \) is a positive-definite weighting matrix.

I use the minimum-distance procedure suggested by Nevo (2000) to decompose the program-level mean utilities \( \psi \) into the taste parameters associated with observed program characteristics (\( \beta_i \)) and unobserved program characteristics (\( \xi \)). Let \( X_p \) be a \( P \times K \) matrix of program characteristics and let \( \psi \) be the \( P \times 1 \) vector of estimated mean program utilities. Then, since \( \psi = X_p \beta + \xi \), the estimate of \( \beta \) is computed as \( \hat{\beta} = \left(X_p'\hat{\Omega}^{-1}X_p\right)^{-1}X_p'\hat{\Omega}^{-1}\hat{\psi} \), and \( \hat{\xi} = \hat{\psi} - X_p \hat{\beta} \), where \( \hat{\Omega} \) is the estimated covariance matrix of \( \hat{\psi} \). This minimum-distance procedure is analogous to a GLS regression wherein the dependent variable is the set of estimated program mean utilities, the independent variables are the programs’ observed characteristics, and the number of observations is equal to the number of programs in the sample.

The columns of the \( X \) matrix must all be orthogonal to the vector of markets’ deviations from mean program utility, \( \eta \). The obvious candidates for inclusion in \( X \) are the program dummies. These are valid instruments because the inclusion of \( \tilde{\omega}_m \) ensures that the mean program utilities are mean-independent of \( \eta \). \( X \) also includes the market, day, and time

\[\text{24}
\]

The most efficient choice of \( A \) is the covariance matrix of the moments. I follow the standard method of setting \( A = X'X' \) to obtain a consistent estimate of \( \theta \). I then use this estimate to construct a consistent estimate of the asymptotically efficient weighting matrix, \( E X'\tilde{\eta}(\hat{\theta})\tilde{\eta}(\hat{\theta})'X \), which is used to obtain the final estimate of \( \theta \).
dummies, and interactions between some elements of \( x_{mjit} \) and moments of the market-specific distributions of viewer demographics. For each variable \( k \) whose effect on utility varies with consumer demographics, and for each observable viewer demographic \( d \), I include \( X_d^k \), a \( N \)-vector whose \( n^{th} \) element is \( x_{j}^k Ed_{im} \), where \( Ed_{im} \) is the expected value of viewer demographic \( d \) in market \( m \). These interactions are equal in number to the number of parameters to be estimated in \( \Pi \) and \( \Sigma \). Note that the audience flow effects cannot be used, as they are highly likely to be correlated with market-specific tastes for unobserved program characteristics. To meet necessary identification conditions, I also include a \( NxJ \) matrix \( Q \), whose \( n^{th} \) row contains the time-\( t \) ad levels of the associated network and its \( J-1 \) competitors. Inclusion of advertising levels in \( X \) is justified by the discussion at the beginning of this subsection.

I impose some zero-restrictions on \( \Pi \) and \( \Sigma \) to limit the number of parameters that enter the GMM objective function nonlinearly.\(^{25} \) Three regressors are assumed to interact with viewer demographics: the viewer’s taste for the outside option, her taste for non-broadcast-network television, and her disutility of advertisements. The first two variables were chosen to improve the reliability of predicted substitution patterns among various options, and the third variable improves the reliability of predicted audience changes resulting from varying levels of advertisements.

### 4.3. Advertiser Demand Endogeneity and Estimation

Advertiser demand parameters are estimated using instrumental variables. A limited-information approach is used, in place of a full-information approach based on the network supply model presented in section 3.3, for two reasons. First, the assumptions underlying the model in section 3.3 are strong and therefore potentially unreliable. Second, there are not good instruments available for the unobserved elements in the networks’ first order conditions. I proceed here by describing the endogeneity concerns in advertisement demand estimation, the instruments used, a data manipulation, and the estimation strategy.

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\(^{25} \) If there are \( d \) elements in \( D_n \), each observable program characteristic whose effect on utility varies with viewer demographics adds \( d + 1 \) nonlinear parameters. This is a problem because computation time increases at an increasing rate in the number of parameters that enter the objective function nonlinearly.
The error in the advertisement demand equation, $\phi_s$, is assumed to primarily reflect unobserved program and audience characteristics that influence advertiser demand for ads.\textsuperscript{26} For example, $\phi_s$ might reflect viewers’ level of “engagement” with the program, or it might represent the fraction of audience members who drink cola. The network is likely to have partial knowledge of $\phi_s$ and take it into account when setting its advertising level. Thus $q_s$ could be correlated with $\phi_s$; and, because audience size depends on $q_s$, $V_s$ could also be correlated with $\phi_s$. (Note, this second correlation is due solely to the direct dependence of $V_s$ on $q_s$. There is no obvious reason to think that audience size is systematically related to advertiser preferences for unobserved program and audience demographics.)

Instruments are required to obtain unbiased estimates of the advertiser demand parameters in equation (4). Instruments must meet two requirements for validity: they should be correlated with $V_s$ and $q_s$, and uncorrelated with advertiser preferences for unobserved audience demographics $\phi_s$. I follow the typical strategy of using program characteristics as instruments. I use two sets of program characteristics as instruments: the observed program characteristics thought to influence advertiser demand, $x_s$, and the non-ad, mean utility (NAMU) of the program and its within-time-period competition estimated by the viewer demand model. (In the notation of section 4.2, the NAMU is $\hat{\psi}_p$ or $X_p \hat{\beta}_1 + \hat{\xi}$. ) These instruments meet the first requirement for validity: they enter directly into program share functions in equation (3), so they are correlated with $V_s$. They are correlated with $q_s$ because the network’s optimal advertising level depends partly on its audience size, as illustrated by equations (6) and (7). They can also be assumed to meet the second requirement of valid instruments, that they are uncorrelated with advertiser preferences for unobserved program and audience characteristics. NAMU is the mean utility of program consumption across all viewers, which only influences advertiser preferences through the size of the audience the program garners. And the program characteristics $x_s$ are included in

\footnote{$\phi_s$ could also be assumed to reflect measurement error in advertisement prices. This is not as troubling as advertiser preferences for unobserved program and audience characteristics. The ad price data is reported by networks after the program airs, and is used by media buyers to plan future purchases; if it were consistently unreliable, we would probably observe regular complaints from media buyers.}
ad demand (4), so $\phi_s$ by definition consists of advertiser preferences for those program and audience characteristics that are not included in $x_s$.

Before estimating advertiser demand parameters I modify the data to account for how the market operates. Audiences are sold and prices are reported at the program level, but networks distribute ads within a program based on strategic considerations. Longer programs tend to contain more ads in their latter stages, as viewers are relatively more ‘captive’ at that point and the program is less likely to attract new viewers from competing networks. This phenomenon is likely to be an important source of variation in the advertisement price/quantity relationship. To account for it, I average each program’s audience characteristics over the half-hours in which the program aired, so the unit of observation is a network/day/program, rather than a network/day/half-hour.\footnote{For example, a two-hour movie is treated as one observation, as is a half-hour program. Breaking the movie up into four half-hour increments would fail to account for networks’ strategic distribution of advertisements across half-hours within the movie.}

To estimate advertisement demand parameters, I interact the instruments described above with the ad demand function residual and use GMM to solve the moment conditions. Let $Z_s$ be a vector that includes the set of instruments for show $s$ described above; and let $Z$ be a matrix constructed by stacking the $Z_s$’s. Then the moments are $EZ'\phi = 0$, where $\phi$ is a vector of the $\phi_s$’s. The GMM estimates of advertisement demand and supply parameters are

$$\hat{\lambda} = \arg\min_{\lambda} \phi' Z B^{-1} Z' \phi,$$

where $B$ is the covariance matrix of the moments. Following standard practice, I set $B = Z' Z$ to obtain a consistent estimate of the asymptotically efficient weighting matrix, which I then use to re-estimate the model and obtain the final results.

### 4.4. Network Supply Inferences

I use demand parameter estimates in conjunction with networks’ first-order conditions to infer unobserved tune-in levels and benefits. I start with equation (8), the condition that says the profit-maximizing network will air tune-ins and ads to equate its marginal benefits from each activity. Solving equation (8) for $\tau$ gives
\[ \hat{\tau}_s = \frac{p_s + q_s \hat{\lambda}_q}{\hat{V}_s}. \]  

(10)

We can use \( \hat{\tau}_s \) to make inferences about tune-in levels. From either of the network’s first-order conditions (equations 6 and 7) it can be shown that

\[ \hat{\tau}_s = \frac{q_s \hat{\lambda}_q \frac{\partial V_s}{\partial q_s} + V_s \hat{\lambda}_q}{-\frac{\partial V_s}{\partial q_s} \hat{\tau}_s}. \]  

(11)

In the next section, I check whether inferred per-viewer tune-in benefits and tune-in levels seem reasonable by comparing inferred tune-in levels with data reported in the TCMR. I find that they are largely consistent with prior expectations, and use them in the counterfactual exercise described in section 6.

5. Empirical Findings

In this section, I report and discuss estimation results. I begin with estimation of a multinomial Logit model (MNL) of viewer demand for television programs. I then present the results from the full random coefficients Logit (RCL). In section 5.3 I report advertiser demand parameter estimates. Section 5.4 compares advertiser and viewer preferences for program characteristics to networks’ observed programming choices. In section 5.5, I report inferences about unobserved network tune-in levels.

5.1. Viewer Demand: Multinomial Logit Results

In this section, I present empirical results based on OLS estimation of the multinomial Logit model. The MNL is a special case of the full Random Coefficients Logit model wherein parameter matrices \( \Pi \) and \( \Sigma \) are restricted to zero. While the MNL has unrealistic substitution patterns, its ease of computation makes it a good tool for comparing results from various specifications.

In the specifications reported below advertising quantity \( (q_{jt}) \) enters viewer utility linearly. I estimated several alternative models but found no evidence that ad levels have nonlinear effects on utility. Nor was there any evidence that the number of commercial breaks
affects program audience size (controlling for ad quantity). I therefore maintain the assumption that viewers’ marginal utility of advertising is linear in advertising seconds.\textsuperscript{28}

Table 4 reports estimation results from eight MNL specifications. Parameter estimates are computed from OLS regressions of transformed log shares, $\log(s_{mj}) - \log(s_{m0})$, on alternate mean utility specifications. The specifications are permutations of including program-specific fixed effects, market dummies, and market-size-indices $\bar{\omega}_m$. Program dummies control for correlation between ad levels and unobserved program quality, market dummies approximate the way the full model controls for unobserved viewer heterogeneity (since simulated viewers’ demographics are drawn from market-specific distributions), and market-size-indices control for the effects of market size on networks’ ad quantity decisions.

The MNL model fits the data very well: the Adjusted $R^2$ ranges from 0.79 to 0.91. These high fits suggest there is not much unobserved viewer heterogeneity for the random coefficients to explain.

Table 4 shows that the point estimate of advertising time on viewer utility is negative across all specifications. Inclusion of program dummies has the effect of making this point estimate significant and quadrupling it. This is consistent with standard models of consumer demand. Failure to control for unobserved product characteristics biases the price coefficient towards zero. These findings, and the improved fit of the model, validate the endogeneity controls described in section 4.2. They show that networks know their programs’ qualities and take them into account when setting advertising levels, so a model that ignores this strategic behavior will yield biased parameter estimates.

The finding that higher aggregate advertising levels are associated with smaller program audiences is intuitive. But it contrasts with Kaiser and Wright’s (2006) finding that women’s magazine readership grows with the number of advertising pages the magazines contain. The difference in the sign of the effect might be attributed to the mediums’ varying level of consumer control over their advertising exposures. Magazine readers are free to choose how much time they spend with each ad based on how much they value it. Television viewers have less perfect

\textsuperscript{28} It should be recalled that the data are relatively insensitive to viewer zapping of commercial breaks. This is not a test of whether the number of ad breaks affects viewer zapping. See Danaher (1995) or Zufryden, Pedrick, and Sankaralingam (1993) for studies of viewer zapping.
control over their advertising exposure. It should also be noted that some segments of viewers may like television advertising; Rojas-Mendez and Davies (2005) find that present- and future-oriented people are relatively more likely to be receptive to advertising than those who are past-oriented.

Audience flow effects and the last-half-hour dummy are included to control for viewing persistence. Numerous studies find evidence of this phenomenon. Among these, Shachar and Emerson (2000) find that viewers’ switching costs grow as they become more experienced with a program, and are higher when they have fewer new programs to sample on competing networks. Moshkin and Shachar (2002) find that uncertainty reduction through program consumption plays a larger role in explaining viewing persistence than state dependence. Zhou (2004) shows that networks tend to air more and longer commercial breaks toward the end of a popular program. Table 4 shows that the lead-in and lead-out effects are positive and significant. The last-half-hour dummy is positive but not significant. The insignificance of this effect is likely due to small audience losses at the end of a program being offset by smaller numbers of viewers tuning in (Shachar and Emerson 2000).29 The level of aggregation of viewers in the current dataset makes this model a less reliable judge of the presence of state dependence than other studies that observe individual viewers’ behavior. The interested reader is referred to Moshkin and Shachar (2002).

5.2. Viewer Demand: Random Coefficients Logit Results
I present here estimation results of the full random coefficients Logit model of viewer demand. The model fit the data quite well. A goodness-of-fit statistic30 rejects the null hypothesis that all parameter estimates are zero at a very high confidence level. The model’s pseudo $R^2$ is 0.86. The Root Mean Square Error is 1.12, and the average relative error is 0.22.

Table 5a shows the parameter estimates of the random utility parameters. The mean effect of advertising seconds is negative and significant. The heterogeneity parameters associated

29 These results are not a formal test of viewer persistence. A proper test would require data on the numbers of viewers in each market who tune in and tune away from each network in each time period. I only observe the net change in audience size. I thank an anonymous reviewer for pointing this out.

30 This statistic is defined as $\hat{\Theta}^{1/2} \hat{\Theta} \hat{\Theta}^{1/2}$, where $\hat{\Theta}$ is the estimated covariance matrix of $\hat{\Theta}$. This statistic has a value of $8.41e+9$ and is distributed chi-square with 141 degrees of freedom.
with tastes for advertising are not significant, indicating that market-level differences in age and income do not affect audiences’ advertising responsiveness.

The mean taste for non-broadcast-network programming is negative. This indicates that the “TV-Off” option is generally preferred to non-broadcast options like cable networks. There are two reasons for this. First, the TV-off market share exceeded the non-broadcast-TV market share in 77% of the DMA/time-periods in the sample. Second, advertising quantities on cable networks are not observed, so their effect is captured by the “Non” dummy. The random utility parameters associated with option \( J \) were not significant.\(^{31}\)

Table 5a indicates that unobserved heterogeneity plays a large role in tastes for the non-television option. The other eight random utility parameter estimates are not significant. I considered removing the random effects from the demand model. I tested the null hypotheses that \( \Pi = 0 \), \( \Sigma = 0 \), and \( \{\Pi = 0\} \cap \{\Sigma = 0\} \). All hypotheses were rejected at the 1% confidence level by Newey-West “D” tests and Wald tests. Yet some parameter estimates are imprecisely estimated. I therefore do not use the random utility parameter estimates to construct unobserved audience demographics \( d_e \).

Table 5b reports the effects of audience flow, program, and time characteristics. Many previous studies have found that audience flow effects are very strong predictors of audience ratings. Consistent with this research, the lead-out effect is very large, positive, and significant. The lead-in effect is not significant, but this is probably due to its high correlation (0.88) with the lead-out effect.

The day effects indicate that viewers exhibit a statistically significant preference for watching television on Thursday and Friday nights. This corresponds to intuition observing that most television viewers are more likely to engage in leisure pursuits like television on Friday nights. The large Friday effect contrasts with the broadcast networks’ tendency to air low-quality programs on Friday nights (this is explored further in section 5.4). The Friday result contrasts with Goettler and Shachar (2001), who found that the only significant day effect was a positive tendency of children to watch television on Friday night.

\(^{31}\) Goettler and Shachar (2001) find that tastes for non-broadcast-network programming correlate positively with viewer income levels below $20,000 and negatively with viewer ages in the ranges of 2-11, 18-24, and 65+. They use individual level data, a better setting for testing these hypotheses than the DMA-level data used here. I thank an anonymous reviewer for pointing this out.
The half-hour parameter estimates indicate that the 8:00-8:30 p.m. (EST) time block is preferred to the 8:30-9:00 block. The 9:00-9:30 block is preferred to both of the preceding half-hours, while the 9:30-10:00 block is not statistically different from the 8:00-8:30 utility. These results agree with Goettler and Shachar (2001), who find that television utility peaks in the first quarter of each hour, and declines steadily after 9:30.

Program genre is a powerful predictor of audience size. Viewers’ preference order is Action Drama, News, Psychological Drama, Reality, Movie, and Scripted Comedy. News is the only genre whose effect is not significantly different from Psychological Drama.

These genre results differ from Shachar and Emerson’s (2000) results that viewers’ preference order is Sports, followed by Sitcom, Movie, News, Psychological Drama, and Action Drama. They also contrast with Yang, Narayan, and Assael (2006), who find that male viewers’ preference order is Drama, News, Comedy, and female viewers’ preference order is Drama, Comedy, News. I speculate that these differences in results are caused by three factors. First, there was nearly complete turnover in network programs between the samples. Second, the current data sample includes two smaller networks (WB and UPN), no Sports programs, many Reality programs, and a different set of Movies. Third, consumer tastes and program production technology may have changed between the years the samples were recorded (1996/1997 and 2003).

I find that main character demographics influence audience size. Viewers prefer programs that include African American and 18- to 34-year-old main characters. Main characters in other age groups and of other minority races have no significant effect on audience size. Inclusion of married or single-parent main characters had no significant effect on audience size. Programs without female main characters fared slightly better, while exclusion of male main characters had no significant effect. These last two results are reminiscent of Yang, Narayan, and Assael’s (2006) finding that husbands exert stronger influence on wives’ viewing than vice versa.

Cast demographics also influence viewers’ program choices. Programs featuring all-white casts drew slightly smaller audiences. Higher levels of minority cast representation and

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32 The only programs to appear in all three samples were 20/20, 48 Hours, America’s Most Wanted, Dateline, Law and Order, Primetime Live, and the Simpsons.
female cast representation do not affect audience size. The interested reader is referred to Shachar and Emerson (2000) for evidence that viewers strongly prefer to watch programs whose casts are demographically similar to themselves.

Program setting and thematic elements influence viewers’ choices. Viewers most prefer programs with House settings, followed by Apartment, TV Studio, Outdoors, and Workplace. Workplace scenes may be unpopular because they involve tension that interferes with viewers’ recreational use of television, while House and Apartment scenes may be popular for the opposite reason. Three of four setting effects are significant, but they are relatively small in magnitude. Of the thematic effects, Sci-Fi has a large and positive impact on viewership, but Cop and Supernatural are not significant.

Past Emmy award nominations increase a program’s attractiveness to viewers. 2003 Emmy nominations were not announced until after the sample concluded, and actually correlate negatively with program viewership. This suggests that Emmy nominations play an important role in signaling program quality to both viewers and networks. The negative effect of current-year Emmy nominations more likely reflects unfavorable timeslots and tune-in support given to unproven new shows. I am not aware of any other studies that measure the impact of program setting, thematic elements, or award nominations on audience size.

Two of five networks effects are significant. Viewers prefer ABC to the excluded network (CBS), and prefer CBS to UPN. The preference of ABC over CBS is consistent with Shachar and Emerson (2000), who find the network preference order to be NBC, ABC, FOX, CBS. But I do not find evidence that NBC is preferred to any other network besides UPN. Network effects likely represent two factors: networks’ abilities to cross-promote their programs, and affiliates’ signal strengths. The most likely explanation for NBC’s fall is its inability to replace its most popular programs (e.g., Seinfeld) during the time between the two samples.

Table 5c reports market-specific fixed effects. The excluded DMA is Louisville, Kentucky. Television utilities vary considerably across markets, and are significantly different from the excluded DMA in 24 of 49 markets. The highest point estimates are found in such diverse markets as San Francisco-Oakland-San Jose, Greenville-Spartanburg-Asheville, Sacramento-Stockton-Modesto, West Palm Beach-Fort Pierce, and Atlanta. There are no clear correlations between television utility and DMA size or location.
Table 5d shows median own- and cross-advertising elasticities by network. Audience sizes are very sensitive to advertising levels. For example, if CBS were to increase its advertising levels 10%, its median audience loss would be 30%, while ABC audiences would increase 8.3%. The three lowest-rated networks have the most elastic audience demand, but audience elasticity is not uniformly related to network audience shares. ABC had a higher average program rating than the WB, but a substantially more elastic viewer demand (-9.05 to -7.12). This is probably because the WB tended to provide narrower niche programming than ABC.

Higher-rated networks’ audiences were generally less responsive to advertising quantity. This is because programs are differentiated vertically as well as horizontally. Programs with high levels of vertical differentiation garner larger, more diverse audiences and have fewer good substitutes. This logic also underlies why all six broadcast networks are more likely to lose audience share to the non-television option than to the non-broadcast-network television option. Cable programs tend to exhibit high levels of horizontal differentiation and low levels of vertical differentiation. Therefore cable programs are unlikely to be better substitutes for broadcast programming than other broadcast networks’ programs.

5.3. **Advertiser Demand Parameter Estimates**

Advertisement demand parameters were estimated using the instruments and the procedure described in section 4.4. In the advertisement demand regression I include program characteristics that can be presumed to influence audience receptivity to advertisements or proxy for unobserved demographics valued by advertisers. These included:

- **Network dummies**: to account for networks’ varying abilities to bundle desirable program audiences with smaller audiences.
- **Genre**: viewers’ mood at the time of exposure to advertising affects ad message processing. (Goldberg and Gorn 1987)
- **Main Character and Cast demographics**: Shachar and Emerson (2000) found that people like to watch programs about characters demographically similar to themselves, so cast demographics should correlate with audience demographics.
• A “special” dummy: irregularly-scheduled programs typically preempt networks’ weakest programs.\textsuperscript{33}

• Thematic elements: these may correlate with viewer psychographics, which advertisers use to target ad messages.

• Program Age: networks typically renew their best programs, so program age may reflect viewers’ and advertisers’ past appraisals of a show.

• Award nominations and past award nominations: these seem likely to indicate the degree to which viewers are emotionally involved in a show, and to correlate with desirable viewer demographics.

• Weekday: many consumers shop on the weekend and have limited memories, so many advertisers prefer to air their commercials later in the week (Auletta 1992).

Table 6 reports advertiser demand parameter estimates. The model fit the data very well, with a pseudo $R^2$ of 0.87, an average relative error of 0.248, and a root mean square error of 39,509 (the dependent variable’s mean is 142,813). Most of the results conform to the hypotheses above.

The direct effect of advertising quantity on ad price was negative and significant and implied a mean marketwide price elasticity (holding audience size constant) of \(-2.93\).\textsuperscript{34} This is substantially more elastic than other authors’ findings; Crandall (1972) estimated a marketwide price elasticity of \(-0.45\), and Bowman (1976) found elasticities (using two different specifications) of \(-0.73\) and \(-0.92\). These differences in results are likely due to increased competition: the number of broadcast networks has increased from three to six, cable networks and other media have entered into competition for advertising dollars, and broadcasters are no longer allowed to collude by setting a cap on advertising minutes.

The effect of audience size on ad price is positive and significant, with a mean elasticity of 0.83. This figure is substantial, especially given the large variation in audience sizes. It also punctuates the importance of considering both sides of the television industry in this paper, showing that ad revenues are dependent on audience sizes, just as audience size is highly responsive to advertising levels.

\begin{footnotesize}
\textsuperscript{33} An example of a special in the data is \textit{Miss Dog Beauty Pageant}, which aired Thursday, May 22, on FOX.
\textsuperscript{34} The bounds of the 95\% confidence interval for this statistic are \(-2.40\) and \(-3.53\).
\end{footnotesize}
The genre parameter estimates show that advertisers value Reality programs most, followed by Scripted Comedy, Psychological Drama, News, Movie, and Action Drama. Reality programs receive, \textit{ceteris paribus}, $146,000 more per spot than shows in the Action genre, a difference that is larger than the mean ad price. This helps to explain the rapid proliferation of Reality programs after their introduction in the mid-1990s.

Why do Reality programs earn so much more than other shows? Their distinguishing characteristics are unscripted action, nonprofessional cast members, competitive themes, and increased ability to accommodate product placement. It might be that advertisers are seeking to take advantage of companion advertising to complement their product placement, or to “jam” rival advertisers’ product placements. It also could be that viewers’ feeling of identifying with the nonprofessional program cast enhances their receptivity to ad messages. This question certainly deserves further study. Comedies earn more than average because they generate positive feelings among viewers, which reduces resistance to persuasion and increases liking, a feeling that can be transferred to advertising (Goldberg and Gorn 1987).

Cast demographics also affected ad prices. Programs featuring African American main characters earned slightly more than average, while programs featuring other minorities earned far more than average. This latter finding might be due to the relative scarcity of non-white and non-African-American actors working on television. Shows with married or single-parent main characters earned more than average. Advertisers pay significantly less for programs featuring 50\% or greater minority cast representation, but programs with 25\%-50\% minority casts charge a premium. The first result likely reflects the audience demographics of 50+\% minority cast programs, since nearly all of these shows feature African-American casts, and African-American viewers tend to earn less than average.

Program thematic elements influence advertiser demand. “Cop” shows earn slightly more than average, as do programs with supernatural elements. But science fiction programs earn $60,000 less per spot than do other shows. This is perhaps due to incongruities between programming and advertising content.

Irregularly-scheduled programs earn less per ad but there does not appear to be any advertising premium associated with program age. The effect of current-year Emmy nominations (which were not announced until after the sample was complete) was quite large, suggesting that
advertisers are able to predict program quality well. Past Emmy nominations increased advertiser demand but their effect was much smaller. These results give evidence of the “halo of quality” effect conferred by highly-involving programs on their advertising.

Thursday programs command a $41,766 premium over Monday programming. Next came Friday ($12,303), followed by Wednesday ($7,340), and Tuesday ($3,152). Consumers save some shopping trips (e.g., autos or movies) for the weekend, so advertisers seek to send messages on Thursdays. The relative preference for Friday over Wednesday, while much smaller, does not conform to conventional wisdom, and is discussed further in the next subsection.

5.4. Comparing Advertiser and Viewer Demand Parameter Estimates

It is interesting to compare advertiser and viewer preferences for program characteristics to networks’ programming decisions. Viewer preferences reflect program characteristics’ entertainment value, while advertiser preferences are more likely to measure the effect of program characteristics on advertising delivery. Networks’ revenues count on getting both sides of the market on board, so they must take both sets of preferences into account when they make program and scheduling decisions.35

I now compare viewer and advertiser preferences for program genres. Viewers’ most preferred genre was Action Drama, with a 95% confidence interval of [.04,.18]; followed by News ([-.06,.15]), Psychological Drama (restricted to zero), Reality ([-.18,-.03]), Movie ([-.30,-.11]), and Scripted Comedy ([-.27,-.16]). It is striking that viewers’ three most preferred genres account for only 42% of network schedules. The reason why becomes clear when we see that advertisers’ preferences over genre is nearly opposite viewers’ preference list. Advertisers most prefer to buy time during Reality programs ([72049,74479]), followed by Scripted Comedy ([38053,39880]), Psychological Drama (restricted to zero), News ([19454,-16061]), Movie ([23246,-17299]), and Action Drama ([74212,-71159]). Now it becomes more clear why Reality and Scripted Comedy programs account for 47% of network programming: they

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35 I focus here on program genre and day-of-the-week effects. Further insights about main character and cast demographics, thematic elements, and award nominations can be drawn by comparing tables 2, 5b, and 6. For example, viewers exhibit a significant preference for Science Fiction programming, while advertisers strongly prefer to avoid it. Accordingly Science-Fiction elements are present in just 6% of network program-hours.
command large premiums over other genres. Analyzing either side of the market in isolation might suggest that networks were failing to satisfy their customers’ tastes.

It is also interesting to consider the interplay between consumers’ and advertisers’ preferences over days of the week. Viewers’ preferred evening for television is Friday ([.21,.133]), followed by Thursday ([.06,.59]). Advertisers’ most preferred night is Thursday ([40642,42892]), followed by Friday ([11196,13410]), Wednesday ([6159,8523]), Tuesday ([2021,4285]), and Monday (restricted to zero). The estimation results suggest that networks schedule stronger programs as the week progresses, peaking on Thursday before falling sharply on Friday. The average program NAMU on Monday was -.20, -.15 on Tuesday, -.14 on Wednesday, -.07 on Thursday, and -.28 on Friday.

It is easy to see why network competition for viewers has historically been fiercest on Thursday night. Advertisers are willing to pay a significant premium on Thursday nights, while viewers are more likely than average to watch television.

What is less intuitive is Friday night, when networks aired lower-quality programs. Yet this is viewers’ most preferred night to watch television, as freedom from going to work or school the next day allows many viewers extra leisure time. And advertisers are even willing to pay slightly more for Friday night slots than for nights earlier in the week. But there are several strategic factors that may explain broadcast networks’ lack of strong shows on Friday nights. First, viewers as a group are more likely to watch on Friday nights, but any individual viewer may be more likely to have occasional social opportunities that would preempt involvement with a regular television series. Second, the value of tune-ins is lower on Friday nights. With the networks’ strongest programs on Thursday nights, tune-ins are more likely to be remembered on Mondays, Tuesdays, and Wednesdays. Third, broadcast networks face stronger-than-average competition from cable networks on Friday nights. For example, the USA and Sci-Fi cable networks usually debut original programming on Fridays. Cumulative broadcast audiences fall from 45.8% to 29.3% from Thursday night to Friday night, but non-broadcast networks’ share rises from 22.4% to 28.9%. This final reason is perhaps the most compelling. Flint (2006) notes that networks scheduled strong programs like *Dallas*, *Miami Vice*, and *Dukes of Hazzard* on

36 This is supported by the observation that nonserial shows (e.g., movies) are often programmed on Friday nights.
Friday nights in the 1980’s, before cable networks offered strong competition. He also notes that broadcast networks strengthened their Friday-night schedules in the 2005-2006 television season.

5.5. Network Tune-In Inferences

I use advertiser demand parameter estimates to infer networks’ per-viewer tune-in benefits and tune-in levels in the manner described in section 4.4. Figure 4 contains a histogram of $\hat{\tau}$, the imputations of networks’ tune-in benefits (per thousand households) across shows. $\hat{\tau}$ was unrestricted, but the imputations were strictly positive, with a mean of $19.50. The minimum tune-in benefit was $3.16, for the WB’s Reba on Friday night at 9:00; this show aired on a low-rated network on a night before that network goes dark. The maximum tune-in benefit was on NBC’s Wednesday-night Law & Order; this show aired at 9 p.m. the night before the network’s “Must See TV” Thursday night line-up. Other programs have similarly intuitive places in the distribution of tune-in benefits, lending credence to the findings, with programs on higher-rated networks having much higher per-viewer tune-in benefits.

I also checked the reasonableness of the imputed tune-in benefits by measuring their correlation with the mean program utilities estimated by the viewer demand model. This potential correlation was the reason why I did not use the structural model of network competition to estimate advertiser demand parameters. The correlation has the hypothesized sign and turns out to be quite large: 0.48.37

These checks suggest the imputed network tune-in benefits are reasonable, so I proceed by imputing networks’ tune-in levels. Figure 5 depicts the histogram of imputed tune-in levels. The distribution appears to be approximately lognormal. Like imputed tune-in benefits, imputed tune-in levels are strictly positive, despite the absence of non-negativity restrictions. The programs with the highest inferred tune-in levels are the season finales of American Idol (FOX) and Everybody Loves Raymond (CBS). The lowest tune-in inferences corresponded to second-hour, Friday-night programs on low-rated networks: Reba and Grounded for Life on the WB, and movies on UPN.

37 This correlation is significant at the 1% confidence level.
A useful check on inference reasonableness is the TCMR data, which reports tune-in levels and ad levels for one week in November 2001. The mean imputed tune-in level in this analysis is 2.63 minutes, 0.58 minutes more than the mean of 2.05 in the TCMR data, while the average national ad level in my data (5.4 minutes) exceeds the TCMR mean level by 0.55 minutes.

The imputed tune-in levels are slightly larger than those reported in the TCMR, but the difference is small and is matched by a similar difference in observed advertising levels. The difference seems reasonable because of the seasonal differences in the samples: the TCMR data were collected in November, in the midst of the fall season when program lineups are mostly stable. The data used in this study were collected in May, shortly before networks significantly alter program schedules for the summer months. Greater schedule variability suggests higher returns to tune-ins, and consequently more tune-ins in equilibrium. I proceed with the assumption that the imputed tune-in levels are reasonable, and use them in the counterfactual exercise described in the next section.

6. Gaining Insight into the Effects of Ad-Avoidance Technology Proliferation
Advertisement-avoidance technology (AAT) proliferation could have two possible effects on equilibrium advertising time. First, viewer channel switching is networks’ primary incentive to keep advertising levels low. It might be that AAT’s primary effect is to reduce networks’ audience losses from advertising, because AAT users fast-forward past ad messages rather than switching channels. Falling disincentives to advertise would lead networks to increase their advertising time. Rises in ad time would make AAT more valuable to ad-averse viewers. AAT penetration and rising ad time could positively reinforce each other.

The other possibility is that AAT penetration’s primary effect is to lower advertisers’ willingness to pay for viewers using AAT. This would make non-AAT users more scarce, and this increased scarcity will lead to higher per-viewer advertising prices. Networks might respond by competing more intensely for non-ad-avoiding viewers. This competition would take the form of lower advertising levels. Falling ad levels could dampen the advertisement-avoidance benefits of AAT ownership and therefore slow its rate of growth.
I use a counterfactual to gain insight about the question of how AAT affects the industry. I solve the estimated model of network competition to test the sensitivity of ad levels to a hypothetical AAT. I report predicted equilibrium ad quantities, ad revenues, and audience sizes, given plausible assumptions about the effects of ad-avoidance technology on viewer and advertiser behavior.

I model an AAT that allows each viewer to view or record one program per half-hour. I consider here a pure ad-avoidance technology that gives all ad-averse television viewers an identical, proportional reduction in ad disutility. I do not model non-ad-avoidance aspects of the digital video recorder, such as enhanced program information or ability to record multiple networks at once. I also do not consider the effects of AAT use on networks’ program scheduling or quality investments. The exercise here is a counterfactual: how would market equilibria in May 2003 have been different if \( x \%) of viewers had access to the assumed ad-avoidance technology? The results should be interpreted as educated speculation, rather than as prediction.

The effects of the hypothetical AAT are governed by three parameters, and which viewers have the technology (the “technology distribution rule”). The parameters are

\[
\begin{align*}
\gamma_1 & \quad \text{Ad-avoiders’ proportional reduction in ad nuisance} \\
\gamma_2 & \quad \text{The proportion of ad-avoiders in the viewing population} \\
\gamma_3 & \quad \text{Advertisers’ valuation of an ad-avoider’s exposure to a commercial, relative to a non-ad-avoider’s exposure}
\end{align*}
\]

I describe in detail how the model’s primitives are respecified to account for AAT and show how to solve for the resulting equilibrium in the Technical Appendix.

There is no published research to guide the selection of values for the unobserved parameters, and it is not possible to estimate them from the available data. I therefore use ranges of values that seem reasonable. I report the sensitivity of the counterfactual results to the assumptions used. I assume that the proportional reduction of advertising disutility resulting from AAT use is 0.67, that \( \gamma_2 \) is small,\(^{38}\) and that AAT is first adopted by the most ad-averse

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\(^{38}\) Wilbur (2007) reviews research on advertising exposure and finds three reasons that advertisers might attach some value to ad-skipping viewers. First, viewer learning has been shown to increase with advertising exposure speed. Second, there is evidence that advertising can have latent effects on consumers’ consideration sets, even when
viewers in the population. The counterfactual results are most sensitive to assumptions about $\gamma_2$ and $\gamma_3$, so I report predictions for various combinations of those parameters.\(^{39}\)

Figure 6 shows mean predicted advertising time (advertising seconds plus tune-in seconds) for various assumptions about $\gamma_2$ and $\gamma_3$.\(^{40}\) An increase in AAT penetration from 5% to 35% increases equilibrium advertising time by about 14%. This indicates the attenuation in audience sensitivity to advertising outweighs the viewer-scarcity effect described above. Ad time also increases with advertiser valuations of AAT-using viewers. When ad-skippers are more valuable, networks have an incentive to sell more ads, to take advantage of ad-skippers’ less elastic viewing demand.

Figure 7 shows how mean audience sizes and effective audience sizes change with AAT penetration. Cumulative audience sizes rise as AAT proliferates, as AAT users watch more television. Those rises are negatively impacted by AAT users’ value to advertisers, because networks increase ad levels when ad-avoiders are relatively more valuable. However, networks’ “effective” audience size falls with AAT penetration. The bottom set of lines in Figure 7 show the value of the expanded audience sizes when translated to non-ad-avoider equivalents.\(^{41}\) Ad-avoiders’ fast-forwarded exposure to commercials represents an unavoidable loss of audience value.

Figure 8 shows that network revenues fall with AAT penetration. The size of the fall depends on advertiser valuations of ad-skippers. A conservative estimate (1 non-AAT user is worth 100 AAT users) indicates network revenues fall 38% when AAT use climbs to 35%. A liberal estimate (1 non-AAT user is worth 5 AAT users) indicates network revenues fall 22%. The main implication of this result for marketers is a likely decrease in network incentives to invest in program quality. But it is important to note that I have not accounted for program consumers do not remember the advertising. Third, the heightened attention required to fast-forward past ads has been linked to increased consumer awareness and recall.

\(^{39}\) The model’s predictions change very little with assumptions about $\gamma_1$ and the technology distribution rule because these two assumptions primarily affect viewers with AAT. These viewers are not highly valued by advertisers so their actions have little effect on networks’ strategies.

\(^{40}\) Predictions are based on the first week of data due to large computational costs.

\(^{41}\) As an example, assume an audience contains 10 viewers with AAT, and ten viewers without, and that $\gamma_3 = .10$. The cumulative audience size is 20, but the “effective” audience size is 11, since each of the viewers with AAT is worth one-tenth as much as a viewer without AAT.
scheduling; networks might respond to AAT by decreasing intertemporal competition among high-quality programs. (For example they might move some good shows to Monday or Friday night.) There is also a question about the extent to which falling ad revenues will be distributed among the networks and their content providers, and other possible strategic changes in advertising content and delivery.

7. Conclusion and Discussion

Television networks operate in a multi-sided platform environment, choosing programs to match both advertisers’ and viewers’ preferences. This paper estimates viewer demand for television programs as a function of program characteristics, audience flow, advertising quantity, and day and time effects. The analysis finds that a 10% increase in advertising time tends to decrease audience size by about 30% on a highly-rated broadcast network, and 70-90% on a low-rated broadcast network. It also estimates a model of advertiser demand for television programs, as a function of audience size, ad quantity, and program characteristics. Advertisement prices are highly responsive to advertising quantity (elasticity of -2.9) and audience size (elasticity of 0.8). These results indicate the advertising market has become substantially more competitive than in the 1970’s.

Estimated advertiser and viewer preference parameters were compared to networks’ programming choices. It was found that viewers’ two most preferred genres (Action Drama and News) account for just 16% of network program schedules. Advertisers’ two most preferred genres (Reality and Scripted Comedy) occupy 47% of network timeslots. It is clear that advertiser preferences are at least as important as viewer preferences to network programmers.

I investigated a counterfactual to isolate the effect of an assumed advertisement-avoidance technology on viewer and advertising market equilibria. This exercise offers educated speculation about the effects of digital video recorder proliferation on market equilibria. The model suggests that proliferation of a hypothetical ad-avoidance technology increases equilibrium advertising levels, and decreases network advertising revenues.

A limitation of the present analysis is that the market-level audience data used in this paper mask viewer zapping behavior. (But it should be noted that the program audience ratings used as currency in the advertising market also mask viewer zapping behavior.) It will be
interesting to see how the results would vary using individual level data or ad break ratings in place of program ratings.

This paper can be extended in several interesting ways. Networks’ program scheduling decisions could be endogenized. Advertisers could be modeled from first principles to solve the assignment problem described in section 3.2. It would be interesting to model the third side of the television industry: networks’ program acquisition and expenditure. And it would be interesting to consider how AAT penetration impacts the value of advertising exposures, as opposed to the number of ads that AAT users avoid.
Technical Appendix: Model Respecification

In this technical appendix, I lay out the details of the respecification of the estimated model of viewer demand, advertiser demand, and network supply of programs and television commercials. The respecification shown here assumes that AAT is first adopted by the most ad-averse viewers in the population. Any alternate technology distribution rule is a straightforward extension to what is presented here. I denote viewers with AAT with a superscript \( a \), and other viewers with a superscript \( n \). I rewrite ad-avoider \( i \)'s utility of watching network \( j \) at time \( t \) in city \( m \) as

\[
u_{imjt}^a = [q_{jt} + r_{jt} - \hat{r}_{jt}] \hat{\alpha}_{im}^a + x_{mjt} \hat{\beta}_{im} + \hat{\varepsilon}_{jt} + \hat{\eta}_{mjt} + \varepsilon_{imjt},
\]

where \( \hat{\alpha}_{im}^a, \hat{\beta}_{im}, \hat{\varepsilon}_{jt} \), and \( \hat{\eta}_{mjt} \) are viewer demand parameter estimates, \( r_{jt} \) is the network’s tune-in level, \( \hat{r}_{jt} \) is the network’s inferred tune-in level (as defined by equation 11 in section 4), and \( 1(\hat{\alpha}_{im} < 0) \) is an indicator function that equals one if the estimated effect of advertising on viewer \( i \)'s utility is negative. The difference \( r_{jt} - \hat{r}_{jt} \) is added to ad quantity to allow for the possibility that the network may change its tune-in level in response to AAT proliferation. Type-\( n \) viewers’ utility can be rewritten as

\[
u_{imjt}^n = [q_{jt} + r_{jt} - \hat{r}_{jt}] \hat{\alpha}_{im}^n + x_{mjt} \hat{\beta}_{im} + \hat{\varepsilon}_{jt} + \hat{\eta}_{mjt} + \varepsilon_{imjt}.
\]

AAT should also affect the utility of the non-broadcast-network option, as type-\( a \) viewers who choose this option are more likely to watch advertisement-supported cable networks than ad-free alternatives like PBS. I assume that an ad-avoider’s utility from option \( J \) at time \( t \) increases by the same amount as the average network option at the same time:

\[
u_{imjt}^a = \hat{\varepsilon}_{jt} + \hat{\eta}_{mjt} + \hat{\sigma}_j \Delta m_{jt} + \hat{\sigma}_j V_j + \varepsilon_{imjt} - \hat{\alpha}_j^*(1 - \gamma_1)1(\hat{\alpha}_j^* < 0) \frac{1}{J-1} \sum_{j=1}^{J-1} [q_{jt} + r_{jt} - \hat{r}_{jt}].
\]

The utility from the non-television option remains unchanged. I construct predicted market share functions for each type of viewer, \( \hat{s}_{mjt}^a \) and \( \hat{s}_{mjt}^n \), in the manner described in section 3.1.

Network \( j \)'s total audience at time \( t \) depends on its share of each type of viewer, and the proportion of ad-avoiders in its audience (\( \gamma_2 \)). Thus

\[
V_{jt} = \sum_m [(1 - \gamma_2)\hat{s}_{mjt}^n + \gamma_2\hat{s}_{mjt}^a] N_m,
\]

where \( N_m \) is the number of viewers in city \( m \).

\( \gamma_3 \) captures advertisers’ value of an ad-avoiding viewer, relative to a non-ad-avoider. If the exposure of an ad-avoider to the advertiser’s message is worthless, \( \gamma_3 \) will be zero; or, if
such an exposure is worth half as much as the exposure of a non-ad-avoider to the advertiser’s message, then $\gamma_3 = .5$. I use $\gamma_3$ to construct the “effective” audience size, which is the number of type-$n$ viewers in the audience, plus the number of type-$a$ viewers, weighted by advertisers’ relative valuation of this latter group. Effective audience size is

$$\hat{V}_{jt} = \sum_m [(1 - \gamma_2)\hat{s}_{mj}^n + \gamma_2 \gamma_3 \hat{s}_{mj}^a]N_m.$$ 

I then rewrite ad price in terms of effective audience size,

$$\tilde{p}_s = q_s \hat{\lambda}_q + \hat{V}_s \hat{\lambda}_V + x_s \hat{\lambda}_x + \phi_s$$

where the $\hat{\lambda}$’s are advertiser demand estimates and $\phi$ is interpreted as unobserved audience demographics.

Next, I use the respecified viewer and advertiser demand functions to rewrite network $j$’s advertising/tune-in equilibrium condition for show $s$ (originally given by equation 8) as

$$\tilde{p}_s + q_s \hat{\lambda}_q - \hat{V}_s \hat{\tau}_s = 0.$$ 

(8')

I solve the $J-1$ equilibrium conditions defined by equation (8') for new equilibrium ad levels. I then use these ad levels and network first-order conditions to predict new tune-in levels,

$$r_s = \frac{q_s \hat{\lambda}_V - \hat{V}_s}{\frac{\partial \hat{V}_s}{\partial q_s}}.$$ 

(11')

Equilibrium predictions about ad prices, audience sizes, and tune-in levels are calculated as functions of predicted ad levels. For a guess of the $q_s$’s and $r_s$’s, the steps to find the new equilibrium in a given time period are:

1) Calculate predicted audience shares, $\hat{s}_{mj}^n$ and $\hat{s}_{mj}^a$, for all networks;

2) Calculate the effective audience size, $\hat{V}_{jt}$, and its derivative, $\frac{\partial \hat{V}_{jt}}{\partial q_{jt}}$, for all networks;

3) Calculate new ad prices $\tilde{p}_s$;

4) Use equation (8') to find new predicted advertising levels;

5) Calculate new tune-in predictions using equation (11'); and

6) Numerically optimize over the $q_s$’s, repeating steps (1)-(5) for each guess of the equilibrium ad levels, to solve the system of network advertising/tune-in equilibrium conditions.
References


Bloom, Jonah (2005), “First, Know that Prices for Identical Buys Vary as much as 25%,” *Advertising Age,* March 2.


### Table 1.
Descriptive Statistics: Ad Price, Ad Quantity, CPM, and Audience Size, by Network and Day

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<thead>
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<th></th>
<th>All Nets</th>
<th>ABC</th>
<th>CBS</th>
<th>FOX</th>
<th>NBC</th>
<th>UPN</th>
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<td>(6)</td>
<td>(13)</td>
<td>(7)</td>
<td>(8)</td>
<td>(6)</td>
<td>(7)</td>
</tr>
<tr>
<td>Thursday</td>
<td>24</td>
<td>25</td>
<td>30</td>
<td>15</td>
<td>35</td>
<td>19</td>
<td>18</td>
</tr>
<tr>
<td></td>
<td>(11)</td>
<td>(13)</td>
<td>(13)</td>
<td>(7)</td>
<td>(7)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Friday</td>
<td>19</td>
<td>16</td>
<td>20</td>
<td>26</td>
<td>20</td>
<td>11</td>
<td>23</td>
</tr>
<tr>
<td></td>
<td>(7)</td>
<td>(3)</td>
<td>(10)</td>
<td>(8)</td>
<td>(3)</td>
<td>(1)</td>
<td>(3)</td>
</tr>
<tr>
<td>All Nights</td>
<td>24</td>
<td>22</td>
<td>23</td>
<td>28</td>
<td>28</td>
<td>19</td>
<td>21</td>
</tr>
<tr>
<td></td>
<td>(9)</td>
<td>(7)</td>
<td>(11)</td>
<td>(9)</td>
<td>(8)</td>
<td>(6)</td>
<td>(5)</td>
</tr>
<tr>
<td><strong>Audience Size (000)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Monday</td>
<td>5,846</td>
<td>5,779</td>
<td>8,862</td>
<td>6,119</td>
<td>6,928</td>
<td>2,699</td>
<td>4,690</td>
</tr>
<tr>
<td></td>
<td>(2386)</td>
<td>(1275)</td>
<td>(2369)</td>
<td>(1723)</td>
<td>(1569)</td>
<td>(250)</td>
<td>(549)</td>
</tr>
<tr>
<td>Tuesday</td>
<td>6,376</td>
<td>5,299</td>
<td>8,291</td>
<td>11,303</td>
<td>5,703</td>
<td>2,768</td>
<td>4,895</td>
</tr>
<tr>
<td></td>
<td>(3087)</td>
<td>(546)</td>
<td>(551)</td>
<td>(2932)</td>
<td>(1509)</td>
<td>(819)</td>
<td>(670)</td>
</tr>
<tr>
<td>Wednesday</td>
<td>6,613</td>
<td>6,678</td>
<td>5,409</td>
<td>12,574</td>
<td>8,551</td>
<td>3,260</td>
<td>3,210</td>
</tr>
<tr>
<td></td>
<td>(4036)</td>
<td>(1134)</td>
<td>(589)</td>
<td>(4984)</td>
<td>(2552)</td>
<td>(725)</td>
<td>(1362)</td>
</tr>
<tr>
<td>Thursday</td>
<td>6,723</td>
<td>4,281</td>
<td>13,098</td>
<td>4,269</td>
<td>12,737</td>
<td>3,807</td>
<td>2,144</td>
</tr>
<tr>
<td></td>
<td>(4659)</td>
<td>(1336)</td>
<td>(2547)</td>
<td>(1150)</td>
<td>(828)</td>
<td>(334)</td>
<td>(411)</td>
</tr>
<tr>
<td>Friday</td>
<td>4,206</td>
<td>5,722</td>
<td>5,610</td>
<td>4,131</td>
<td>5,574</td>
<td>1,940</td>
<td>2,260</td>
</tr>
<tr>
<td></td>
<td>(1734)</td>
<td>(549)</td>
<td>(932)</td>
<td>(916)</td>
<td>(901)</td>
<td>(290)</td>
<td>(248)</td>
</tr>
<tr>
<td>All Nights</td>
<td>5,868</td>
<td>5,693</td>
<td>7,716</td>
<td>8,058</td>
<td>7,361</td>
<td>2,793</td>
<td>3,584</td>
</tr>
<tr>
<td></td>
<td>(3294)</td>
<td>(1182)</td>
<td>(2825)</td>
<td>(4573)</td>
<td>(2752)</td>
<td>(791)</td>
<td>(1379)</td>
</tr>
</tbody>
</table>

Numbers in parantheses are standard deviations

1 averaged over half-hours, 8:00-10:00 p.m., and weeks

2 measured in households; averaged over half-hours, 8:00-10:00 p.m., and weeks

3 Thursday, May 1, and Thursday, May 15, were removed from the sample

Sources: Nielsen Media Research; TNS Media Intelligence/CMR
Table 2.  
Variable Definitions and Descriptive Statistics

<table>
<thead>
<tr>
<th>variable name</th>
<th>description</th>
<th>mean</th>
<th>st. dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adv Seconds</td>
<td>Seconds of national advertisements aired during the program</td>
<td>308</td>
<td>(75)</td>
</tr>
<tr>
<td>ScriptedComedy</td>
<td>=1 if the show is a scripted comedy</td>
<td>.31</td>
<td>(.46)</td>
</tr>
<tr>
<td>ActionDrama</td>
<td>=1 if the show is a scripted drama that contains action scenes</td>
<td>.10</td>
<td>(.30)</td>
</tr>
<tr>
<td>PsychDrama</td>
<td>=1 if the show is a scripted drama that does not contain action scenes</td>
<td>.26</td>
<td>(.44)</td>
</tr>
<tr>
<td>Reality</td>
<td>=1 if the show is unscripted</td>
<td>.16</td>
<td>(.36)</td>
</tr>
<tr>
<td>News</td>
<td>=1 if the show is a news program or a newsmagazine</td>
<td>.06</td>
<td>(.24)</td>
</tr>
<tr>
<td>Movie</td>
<td>=1 if the show is a movie</td>
<td>.11</td>
<td>(.31)</td>
</tr>
<tr>
<td>African-American</td>
<td>=1 if at least one African-American main character</td>
<td>.44</td>
<td>(.50)</td>
</tr>
<tr>
<td>Other Nonwhite</td>
<td>=1 if at least one non-white, non-African American main character</td>
<td>.09</td>
<td>(.29)</td>
</tr>
<tr>
<td>MC&lt;18</td>
<td>=1 if at least one main character is under 18</td>
<td>.20</td>
<td>(.40)</td>
</tr>
<tr>
<td>MC18-34</td>
<td>=1 if at least one main character is between 18 and 34 years old</td>
<td>.67</td>
<td>(.47)</td>
</tr>
<tr>
<td>MC35-49</td>
<td>=1 if at least one main character is between 35 and 49 years old</td>
<td>.62</td>
<td>(.49)</td>
</tr>
<tr>
<td>MC50+</td>
<td>=1 if at least one main character is over 50 years old</td>
<td>.17</td>
<td>(.38)</td>
</tr>
<tr>
<td>Married</td>
<td>=1 if at least one main character is married to another character</td>
<td>.19</td>
<td>(.40)</td>
</tr>
<tr>
<td>Single Parent</td>
<td>=1 if at least one main character is single and has children</td>
<td>.10</td>
<td>(.30)</td>
</tr>
<tr>
<td>Female Only</td>
<td>=1 if none of the main characters are male</td>
<td>.09</td>
<td>(.29)</td>
</tr>
<tr>
<td>Male Only</td>
<td>=1 if none of the main characters are female</td>
<td>.23</td>
<td>(.42)</td>
</tr>
<tr>
<td>50+% Nonwhite</td>
<td>=1 if 50% or more of the show’s cast is non-white</td>
<td>.20</td>
<td>(.40)</td>
</tr>
<tr>
<td>25+% Nonwhite</td>
<td>=1 if 25-49% of the show’s cast is non-white</td>
<td>.39</td>
<td>(.49)</td>
</tr>
<tr>
<td>10+% Nonwhite</td>
<td>=1 if 10-24% of the show’s cast is non-white</td>
<td>.55</td>
<td>(.50)</td>
</tr>
<tr>
<td>50+%Female</td>
<td>=1 if 50% or more of the show’s cast is female</td>
<td>.46</td>
<td>(.50)</td>
</tr>
<tr>
<td>25+%Female</td>
<td>=1 if 25-49% of the show’s cast is female</td>
<td>.74</td>
<td>(.44)</td>
</tr>
<tr>
<td>House</td>
<td>=1 if the show contains scenes set in a character’s house</td>
<td>.23</td>
<td>(.42)</td>
</tr>
<tr>
<td>Apartment</td>
<td>=1 if the show contains scenes set in a character’s apartment</td>
<td>.06</td>
<td>(.23)</td>
</tr>
<tr>
<td>Workplace</td>
<td>=1 if the show contains scenes set in a business or workplace</td>
<td>.34</td>
<td>(.48)</td>
</tr>
<tr>
<td>Outdoors</td>
<td>=1 if the show contains outdoor scenes</td>
<td>.49</td>
<td>(.50)</td>
</tr>
<tr>
<td>Studio</td>
<td>=1 if the show contains scenes set in a TV studio</td>
<td>.20</td>
<td>(.40)</td>
</tr>
<tr>
<td>Cop</td>
<td>=1 if the show has some law enforcement element</td>
<td>.10</td>
<td>(.31)</td>
</tr>
<tr>
<td>Sci-Fi</td>
<td>=1 if the show contains elements of science fiction (i.e. Star Trek)</td>
<td>.06</td>
<td>(.24)</td>
</tr>
<tr>
<td>Supernatural</td>
<td>=1 if the show contains supernatural elements (i.e. angels, witchcraft)</td>
<td>.07</td>
<td>(.26)</td>
</tr>
<tr>
<td>Age</td>
<td># of years since the show’s debut</td>
<td>3.28</td>
<td>(3.5)</td>
</tr>
<tr>
<td>2003EmmyNoms</td>
<td>2004 Emmy Nominations</td>
<td>1.4</td>
<td>(3.1)</td>
</tr>
<tr>
<td>Past Emmy Noms</td>
<td>All pre-2004 Emmy Nominations</td>
<td>3.6</td>
<td>(11.9)</td>
</tr>
<tr>
<td>ABC, CBS, FOX, NBC, UPN, WB</td>
<td>Network-specific dummy variables</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mon, Tue, Wed, Thu, Fri</td>
<td>Day-specific dummy variables</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1stHH, 2ndHH, 3rdHH, 4thHH</td>
<td>Dummy variables for 1st half-hour of prime time, 2nd half-hour of prime time, 3rd, 4th, etc.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Audience Size</td>
<td>Adv Price</td>
<td>Adv Seconds</td>
</tr>
<tr>
<td>-------------------------</td>
<td>---------------</td>
<td>-----------</td>
<td>-------------</td>
</tr>
<tr>
<td>Audience Size</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adv Price</td>
<td>0.81</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>Adv Seconds</td>
<td>-0.06</td>
<td>-0.10</td>
<td>1.00</td>
</tr>
<tr>
<td>Comedy</td>
<td>0.00</td>
<td>0.02</td>
<td>0.44</td>
</tr>
<tr>
<td>Action</td>
<td>0.04</td>
<td>0.02</td>
<td>-0.19</td>
</tr>
<tr>
<td>Drama</td>
<td>-0.12</td>
<td>-0.16</td>
<td>-0.23</td>
</tr>
<tr>
<td>Reality</td>
<td>0.14</td>
<td>0.26</td>
<td>-0.10</td>
</tr>
<tr>
<td>News</td>
<td>0.00</td>
<td>-0.09</td>
<td>-0.13</td>
</tr>
<tr>
<td>Movie</td>
<td>-0.05</td>
<td>-0.07</td>
<td>-0.02</td>
</tr>
</tbody>
</table>

Table 3. Correlations between Audience Size, Ad Price, Ad Seconds, and Program Genres
### Table 4.
Multinomial Logit Viewer Demand Parameter Estimates

<table>
<thead>
<tr>
<th></th>
<th>(i)</th>
<th>(ii)</th>
<th>(iii)</th>
<th>(iv)</th>
<th>(v)</th>
<th>(vi)</th>
<th>(vii)</th>
<th>(viii)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Advertising Seconds</td>
<td>-5.9E-5</td>
<td>-2.2E-4</td>
<td>-5.7E-5</td>
<td>-2.2E-4</td>
<td>-5.4E-5</td>
<td>-2.2E-4</td>
<td>-4.9E-5</td>
<td>-2.1E-4</td>
</tr>
<tr>
<td></td>
<td>(4.7E-5)</td>
<td>(4.6E-5)</td>
<td>(4.3E-5)</td>
<td>(4.2E-5)</td>
<td>(4.7E-5)</td>
<td>(4.6E-5)</td>
<td>(4.3E-5)</td>
<td>(4.1E-5)</td>
</tr>
<tr>
<td>Lead-In Audience</td>
<td>5.133</td>
<td>4.756</td>
<td>4.735</td>
<td>4.288</td>
<td>5.293</td>
<td>4.920</td>
<td>4.832</td>
<td>4.380</td>
</tr>
<tr>
<td></td>
<td>(0.083)</td>
<td>(0.081)</td>
<td>(0.077)</td>
<td>(0.075)</td>
<td>(0.085)</td>
<td>(0.084)</td>
<td>(0.078)</td>
<td>(0.075)</td>
</tr>
<tr>
<td></td>
<td>(0.083)</td>
<td>(0.082)</td>
<td>(0.078)</td>
<td>(0.075)</td>
<td>(0.084)</td>
<td>(0.082)</td>
<td>(0.077)</td>
<td>(0.074)</td>
</tr>
<tr>
<td></td>
<td>(3.378)</td>
<td>(0.027)</td>
<td>(3.125)</td>
<td>(0.030)</td>
<td>(3.406)</td>
<td>(0.026)</td>
<td>(3.093)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Last Half-Hour(^a)</td>
<td>-4.6E-3</td>
<td>3.9E-3</td>
<td>-8.1E-3</td>
<td>2.0E-3</td>
<td>2.0E-3</td>
<td>0.010</td>
<td>-3.4E-3</td>
<td>5.6E-3</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.011)</td>
<td>(9.3E-3)</td>
<td>(9.8E-3)</td>
<td>(0.010)</td>
<td>(0.01)</td>
<td>(9.1E-3)</td>
<td>(9.7E-3)</td>
</tr>
<tr>
<td>Includes Program Dummies?</td>
<td>---</td>
<td>yes</td>
<td>---</td>
<td>yes</td>
<td>---</td>
<td>yes</td>
<td>---</td>
<td>yes</td>
</tr>
<tr>
<td>Includes Market Dummies?</td>
<td>---</td>
<td>---</td>
<td>yes</td>
<td>yes</td>
<td>---</td>
<td>---</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Weighted by Market Size?</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.791</td>
<td>0.813</td>
<td>0.821</td>
<td>0.844</td>
<td>0.864</td>
<td>0.876</td>
<td>0.897</td>
<td>0.911</td>
</tr>
</tbody>
</table>

* = Significant at the 1% level

\(^a\) Indicates whether a program was in its last half-hour only for those programs that lasted 60 minutes or longer

Notes: Reported here are OLS regressions wherein the dependent variable is log(smjt)-log(sm0t)

Number of Observations: 23,588

All Specifications included Day (Tues, Weds, Thurs, Fri) and Half-hour (8:30, 9:00, 9:30) Dummies

When Program Dummies are not included, observable program characteristics (genre, setting, main character and cast demographics, age, and current and past award nominations) and a constant are included
<table>
<thead>
<tr>
<th></th>
<th>Means (β’s)</th>
<th>Standard Deviations (σ’s)</th>
<th>actions with Demographic Variables (π’s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Income</td>
</tr>
<tr>
<td>Advertising Seconds</td>
<td>-1.5E-3 **</td>
<td>-0.478</td>
<td>-4.1E-5</td>
</tr>
<tr>
<td></td>
<td>(2.1E-4)</td>
<td>(9.269)</td>
<td>(4.9E-5)</td>
</tr>
<tr>
<td>Non-Broadcast-Network</td>
<td>-10.024 **</td>
<td>-0.501</td>
<td>7.1E-14</td>
</tr>
<tr>
<td></td>
<td>(1.387)</td>
<td>(0.935)</td>
<td>(1.1E-4)</td>
</tr>
<tr>
<td>TV-Off</td>
<td>0a</td>
<td>1.819 **</td>
<td>0b</td>
</tr>
<tr>
<td></td>
<td>(0.479)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

GMM Objective

χ² Goodness-of-Fit (degrees of freedom)

Pseudo R²

Number of Observations: 23,588

** Significant at the 1% confidence level

a The mean utility of "TV-Off" is normalized to zero. It is not separately identified from the mean utilities of the "inside" options.

b Interactions between "TV-Off" and interactions with consumer demographics are, in practice, very difficult to estimate separately from the market-specific fixed effect. They are set to zero.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate (std. error)</th>
<th>Variable</th>
<th>Estimate (std. error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lead-in</td>
<td>3.144 (2.152)</td>
<td>Main Characters: Male Only b</td>
<td>0.112 ** (0.037)</td>
</tr>
<tr>
<td>Lead-out</td>
<td>20.917 ** (6.055)</td>
<td>Cast: 50+% NonWhite b</td>
<td>-0.062 (0.044)</td>
</tr>
<tr>
<td>Last Half-Hour  ~</td>
<td>0.026 (0.038)</td>
<td>Cast: 25+% NonWhite b</td>
<td>-0.046 (0.040)</td>
</tr>
<tr>
<td>Tuesday</td>
<td>-0.439 (0.507)</td>
<td>Cast: 10+% NonWhite b</td>
<td>-0.094 ** (0.047)</td>
</tr>
<tr>
<td>Wednesday</td>
<td>0.176 (0.099)</td>
<td>Cast: 50+%Female b</td>
<td>-0.046 (0.038)</td>
</tr>
<tr>
<td>Thursday</td>
<td>0.322 ** (0.136)</td>
<td>Cast: 25+%Female b</td>
<td>0.060 (0.047)</td>
</tr>
<tr>
<td>Friday</td>
<td>0.772 ** (0.287)</td>
<td>Setting: House b</td>
<td>0.151 ** (0.040)</td>
</tr>
<tr>
<td>2nd Prime-Time Half-Hour</td>
<td>-0.246 ** (0.092)</td>
<td>Setting: Apartment b</td>
<td>0.042 (0.057)</td>
</tr>
<tr>
<td>3rd Prime-Time Half-Hour</td>
<td>0.124 ** (0.042)</td>
<td>Setting: Workplace b</td>
<td>-0.112 ** (0.027)</td>
</tr>
<tr>
<td>4th Prime-Time Half-Hour</td>
<td>0.105 (0.070)</td>
<td>Setting: On Location b</td>
<td>-0.073 ** (0.026)</td>
</tr>
<tr>
<td>Constant b</td>
<td>1.664 (6.644)</td>
<td>Special b</td>
<td>0.080 (0.041)</td>
</tr>
<tr>
<td>Genre: Scripted Comedy b</td>
<td>-0.214 ** (0.028)</td>
<td>Cop b</td>
<td>5.8E-3 (0.039)</td>
</tr>
<tr>
<td>Genre: Action Drama b</td>
<td>0.112 ** (0.037)</td>
<td>Sci-Fi b</td>
<td>0.286 ** (0.065)</td>
</tr>
<tr>
<td>Genre: Reality b</td>
<td>-0.105 ** (0.037)</td>
<td>Supernatural b</td>
<td>0.035 (0.040)</td>
</tr>
<tr>
<td>Genre: News b</td>
<td>0.046 (0.053)</td>
<td>SeasonFirstAired b</td>
<td>-2.9E-3 (3.3E-3)</td>
</tr>
<tr>
<td>Genre: Movie b</td>
<td>-0.203 ** (0.047)</td>
<td>2003 Emmy Nominations b</td>
<td>-0.042 ** (5.5E-3)</td>
</tr>
<tr>
<td>Main Characters: African-American b</td>
<td>0.139 ** (0.039)</td>
<td>Past Emmy Nominations b</td>
<td>0.012 ** (1.1E-3)</td>
</tr>
<tr>
<td>Main Characters: Other Nonwhite b</td>
<td>-0.032 (0.040)</td>
<td>ABC b</td>
<td>0.177 ** (0.042)</td>
</tr>
<tr>
<td>Main Characters: &lt;18 years old b</td>
<td>0.027 (0.045)</td>
<td>FOX b</td>
<td>0.040 (0.038)</td>
</tr>
<tr>
<td>Main Characters: 18-34 years old b</td>
<td>0.144 ** (0.031)</td>
<td>NBC b</td>
<td>-0.026 (0.036)</td>
</tr>
<tr>
<td>Main Characters: 35-49 years old b</td>
<td>0.043 (0.026)</td>
<td>UPN b</td>
<td>-0.125 ** (0.049)</td>
</tr>
<tr>
<td>Main Characters: Married b</td>
<td>-0.052 (0.038)</td>
<td>WB b</td>
<td>0.020 (0.050)</td>
</tr>
<tr>
<td>Main Characters: Single Parent b</td>
<td>-0.012 (0.031)</td>
<td>Minimum-Distance χ^2</td>
<td>1.23E+07</td>
</tr>
<tr>
<td>Main Characters: Female Only b</td>
<td>-0.035 (0.035)</td>
<td>Minimum-Distance Pseudo R^2</td>
<td>0.6447</td>
</tr>
</tbody>
</table>

** Significant at the 1% confidence level
a Parameters are GMM estimates, except where noted.
b Minimum-distance estimate
c Defined only for those programs whose duration exceeds 30 minutes
<table>
<thead>
<tr>
<th>Market</th>
<th>Size (000 Households)</th>
<th>Estimate (std. error)</th>
<th>Market</th>
<th>Size (000 Households)</th>
<th>Estimate (std. error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>New York, NY</td>
<td>9343</td>
<td>2.98 **</td>
<td>San Diego, CA</td>
<td>1004</td>
<td>0.00</td>
</tr>
<tr>
<td>Los Angeles, CA</td>
<td>6834</td>
<td>-0.08</td>
<td>Hartford &amp; New Haven, CT</td>
<td>1566</td>
<td>2.72 **</td>
</tr>
<tr>
<td>Chicago, IL</td>
<td>3782</td>
<td>3.00 **</td>
<td>Charlotte, NC</td>
<td>1248</td>
<td>0.17</td>
</tr>
<tr>
<td>Philadelphia, PA</td>
<td>3748</td>
<td>0.33</td>
<td>Raleigh-Durham (Fayetteville), NC</td>
<td>1324</td>
<td>3.03 **</td>
</tr>
<tr>
<td>San Francisco-Oakland-San Jose, CA</td>
<td>3866</td>
<td>3.22 **</td>
<td>Nashville, TN</td>
<td>1023</td>
<td>0.04</td>
</tr>
<tr>
<td>Boston, MA (Manchester, NH)</td>
<td>2354</td>
<td>0.07</td>
<td>Milwaukee, WI</td>
<td>957</td>
<td>2.87 **</td>
</tr>
<tr>
<td>Dallas-Ft. Worth, TX</td>
<td>2611</td>
<td>2.82 **</td>
<td>Cincinnati, OH</td>
<td>1309</td>
<td>-0.11</td>
</tr>
<tr>
<td>Washington, DC (Hagerstown, MD)</td>
<td>3598</td>
<td>0.27</td>
<td>Kansas City, MO</td>
<td>1091</td>
<td>2.78 **</td>
</tr>
<tr>
<td>Atlanta, GA</td>
<td>2246</td>
<td>3.14 **</td>
<td>Columbus, OH</td>
<td>1111</td>
<td>-0.06</td>
</tr>
<tr>
<td>Detroit, MI</td>
<td>2481</td>
<td>0.36</td>
<td>Greenville-Spartanburg, SC-Asheville, NC-Anderson, SC</td>
<td>1124</td>
<td>3.22 **</td>
</tr>
<tr>
<td>Houston, TX</td>
<td>2009</td>
<td>2.92 **</td>
<td>Salt Lake City, UT</td>
<td>780</td>
<td>-0.35</td>
</tr>
<tr>
<td>Seattle-Tacoma, WA</td>
<td>1788</td>
<td>0.02</td>
<td>San Antonio, TX</td>
<td>862</td>
<td>2.59 **</td>
</tr>
<tr>
<td>Tampa-St. Petersburg</td>
<td>1837</td>
<td>0.09</td>
<td>Grand Rapids-Kalamazoo-Battle Creek, MI</td>
<td>950</td>
<td>-0.25</td>
</tr>
<tr>
<td>Minneapolis-St. Paul, MN</td>
<td>1908</td>
<td>0.17</td>
<td>West Palm Beach-Fl. Pierce, FL</td>
<td>1390</td>
<td>3.15 **</td>
</tr>
<tr>
<td>Cleveland-Akron (Canton), OH</td>
<td>2380</td>
<td>3.12 **</td>
<td>Birmingham (Anniston and Tuscaloosa), AL</td>
<td>831</td>
<td>0.26</td>
</tr>
<tr>
<td>Phoenix (Prescott), AZ</td>
<td>1930</td>
<td>0.02</td>
<td>Norfolk-Portsmouth-Newport News, VA</td>
<td>690</td>
<td>2.94 **</td>
</tr>
<tr>
<td>Miami-Ft. Lauderdale, FL</td>
<td>1981</td>
<td>2.83 **</td>
<td>New Orleans, LA</td>
<td>731</td>
<td>-0.07</td>
</tr>
<tr>
<td>Denver, CO</td>
<td>1991</td>
<td>-0.08</td>
<td>Memphis, TN</td>
<td>886</td>
<td>2.68 **</td>
</tr>
<tr>
<td>Sacramento-Stockton-Modesto, CA</td>
<td>2328</td>
<td>3.20 **</td>
<td>Buffalo, NY (Including Canadian Audiences)</td>
<td>795</td>
<td>1.84 **</td>
</tr>
<tr>
<td>Orlando-Daytona Beach-Melbourne, FL</td>
<td>1688</td>
<td>0.25</td>
<td>Oklahoma City, OK</td>
<td>768</td>
<td>2.69 **</td>
</tr>
<tr>
<td>Pittsburgh, PA</td>
<td>1656</td>
<td>2.60 **</td>
<td>Greensboro-High Point-Winston Salem, NC</td>
<td>973</td>
<td>0.05</td>
</tr>
<tr>
<td>St. Louis, MO</td>
<td>1349</td>
<td>0.04</td>
<td>Harrisburg-Lancaster-Lebanon-York, PA</td>
<td>974</td>
<td>2.48 **</td>
</tr>
<tr>
<td>Portland, OR</td>
<td>1229</td>
<td>2.99 **</td>
<td>Providence, RI-New Bedford, MA</td>
<td>2138</td>
<td>-0.26</td>
</tr>
<tr>
<td>Baltimore, MD</td>
<td>2611</td>
<td>0.17</td>
<td>Albuquerque-santa Fe, NM</td>
<td>659</td>
<td>2.87 **</td>
</tr>
<tr>
<td>Indianapolis, IN</td>
<td>1319</td>
<td>2.88 **</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

** Significant at the 1% confidence level
### Table 5d.
**Median Own- and Cross-Advertising-Level Audience Elasticities**

<table>
<thead>
<tr>
<th>Network</th>
<th>ABC</th>
<th>CBS</th>
<th>FOX</th>
<th>NBC</th>
<th>UPN</th>
<th>WB</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABC</td>
<td>-9.05</td>
<td>0.37</td>
<td>0.32</td>
<td>0.37</td>
<td>0.43</td>
<td>0.31</td>
</tr>
<tr>
<td>CBS</td>
<td>0.83</td>
<td>-3.03</td>
<td>0.35</td>
<td>0.42</td>
<td>0.42</td>
<td>0.32</td>
</tr>
<tr>
<td>FOX</td>
<td>0.75</td>
<td>0.37</td>
<td>-2.81</td>
<td>0.40</td>
<td>0.42</td>
<td>0.34</td>
</tr>
<tr>
<td>NBC</td>
<td>0.80</td>
<td>0.39</td>
<td>0.35</td>
<td>-3.10</td>
<td>0.44</td>
<td>0.34</td>
</tr>
<tr>
<td>UPN</td>
<td>0.59</td>
<td>0.27</td>
<td>0.27</td>
<td>0.30</td>
<td>-9.68</td>
<td>0.27</td>
</tr>
<tr>
<td>WB</td>
<td>0.70</td>
<td>0.36</td>
<td>0.31</td>
<td>0.38</td>
<td>0.39</td>
<td>-7.12</td>
</tr>
<tr>
<td>Non-Broadcast-Network TV</td>
<td>0.33</td>
<td>0.16</td>
<td>0.16</td>
<td>0.17</td>
<td>0.19</td>
<td>0.15</td>
</tr>
<tr>
<td>Outside Option (TV-Off)</td>
<td>0.90</td>
<td>0.24</td>
<td>0.28</td>
<td>0.24</td>
<td>0.81</td>
<td>0.64</td>
</tr>
</tbody>
</table>

*Table entry \(i,j\) reports the estimated elasticity of option \(i\)’s national audience, given a 30-second increase in network \(j\)’s observed advertising level. Reported elasticities are the medians of the distribution of national audience elasticities over days and half-hours.*
Table 6. Advertisement Demand Parameter Estimates

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate (std. error)</th>
<th>Variable</th>
<th>Estimate (std. error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Advertising Seconds</td>
<td>-1,302.4 ** (127.1)</td>
<td>Main Char: Single Parent</td>
<td>7,144.7 ** (500.8)</td>
</tr>
<tr>
<td>Audience Size</td>
<td>19.4 ** (6.3)</td>
<td>Cast: 50+% NonWhite</td>
<td>-88,517.6 ** (691.7)</td>
</tr>
<tr>
<td>Network: ABC</td>
<td>-14,307.7 ** (1679.5)</td>
<td>Cast: 25+% NonWhite</td>
<td>36,147.8 ** (631.1)</td>
</tr>
<tr>
<td>Network: FOX</td>
<td>-15,960.4 ** (662.2)</td>
<td>Special</td>
<td>-36,644.9 ** (842.9)</td>
</tr>
<tr>
<td>Network: NBC</td>
<td>-16,261.2 ** (681.3)</td>
<td>Theme: Cop</td>
<td>6,678.1 ** (791.2)</td>
</tr>
<tr>
<td>Network: UPN</td>
<td>-7,228.7 ** (1094.7)</td>
<td>Theme: Sci-Fi</td>
<td>-60,251.8 ** (1132.4)</td>
</tr>
<tr>
<td>Network: WB</td>
<td>-57,648.9 ** (667.5)</td>
<td>Theme: Supernatural</td>
<td>4,119.5 ** (685.9)</td>
</tr>
<tr>
<td>Genre: Scripted Comedy</td>
<td>38,966.3 ** (466.0)</td>
<td>SeasonFirstAired</td>
<td>110.6 (71.3)</td>
</tr>
<tr>
<td>Genre: Action Drama</td>
<td>-72,658.6 ** (778.8)</td>
<td>2003 Emmy Nominations</td>
<td>12,949.7 ** (99.0)</td>
</tr>
<tr>
<td>Genre: Reality</td>
<td>73,264.1 ** (619.8)</td>
<td>Past Emmy Nominizations</td>
<td>229.4 ** (18.3)</td>
</tr>
<tr>
<td>Genre: News</td>
<td>-17,757.6 ** (865.7)</td>
<td>Day: Tues</td>
<td>3,152.7 ** (577.5)</td>
</tr>
<tr>
<td>Genre: Movie</td>
<td>-20,272.5 ** (1517.0)</td>
<td>Day: Weds</td>
<td>7,340.9 ** (603.0)</td>
</tr>
<tr>
<td>Main Char: African American</td>
<td>1,058.8 ** (519.1)</td>
<td>Day: Thurs</td>
<td>41,766.7 ** (573.9)</td>
</tr>
<tr>
<td>Main Char: Other Nonwhite</td>
<td>52,127.7 ** (711.4)</td>
<td>Day: Fri</td>
<td>12,303.1 ** (564.7)</td>
</tr>
<tr>
<td>Main Char: Married</td>
<td>16,958.8 ** (532.7)</td>
<td>Constant</td>
<td>83,812.4 ** (13486.1)</td>
</tr>
<tr>
<td>Pseudo R²</td>
<td>0.8747</td>
<td>Average Relative Error</td>
<td>0.248</td>
</tr>
</tbody>
</table>

Notes: Number of observations = 262. Dependent variable is advertisement price.
Figure 1.
Layout of Empirical Strategy

- Viewer Demand Model
- Advertiser Demand Function (equation 4)
- Model of Network Competition

1. Viewer Demand Parameter Estimates
2. Advertiser Demand Parameter Estimates
3. Tune-in Inferences
4. Counterfactual Results

Instruments
Figure 2. Average Nightly Audience Size, by Network

Figure 3. Average Nightly Cost Per Thousand Households, by Network
Figure 4: Histogram of Imputed Tune-In Benefits (per 1,000 households)

Figure 5: Histogram of Imputed Tune-In Levels
Figure 6. Mean Equilibrium Advertising Seconds per Network Half-hour, by AAT Penetration (assuming $\gamma_1=.667$ and most ad-averse viewers have AAT)

Note 1: If advertisers' relative ad-avoider valuation ($\gamma_3$) is .10, advertisers are indifferent between reaching ten viewers with AAT and reaching one viewer without AAT.

Note 2: These results assume that AAT use reduces viewers' advertising disutility by 2/3.

Figure 7. Mean Equilibrium Audience and "Effective" Audience per Network Half-hour, by AAT Penetration (assuming $\gamma_1=.667$ and most ad-averse viewers have AAT)

Note 1: If advertisers' relative ad-avoider valuation ($\gamma_3$) is .10, advertisers are indifferent between reaching ten viewers with AAT and reaching one viewer without AAT.

Note 2: These results assume that AAT use reduces viewers' advertising disutility by 2/3.
Figure 8. Mean Equilibrium Advertising Revenues per Network Half-hour, by AAT Penetration (assuming $\gamma_1=0.667$ and most ad-averse viewers have AAT)

Note 1: If advertisers' relative ad-avoider valuation ($\gamma_3$) is 0.10, advertisers are indifferent between reaching ten viewers with AAT and reaching one viewer without AAT.

Note 2: These results assume that AAT use reduces viewers' advertising disutility by 2/3.