Digital Video Recorders and the Future of Television

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Work in Progress; Comments Welcome

Abstract

Every so often, a new technology changes media consumers' control over the amount of advertising to which they are exposed. Advertisers, media firms, and regulators will benefit from an empirical methodology to forecast the degree to which such technologies will affect their business.

This paper introduces such a methodology. I model the two-sided nature of advertiser-supported media markets: media platforms (networks) compete both for media consumers (viewers) and for advertisers. The profit-maximizing network will choose an advertising level such that the marginal revenue of its last ad just offsets the value of its marginal audience loss.

I apply the methodology to the television industry to predict the effects of digital video recorder (DVR) proliferation on equilibrium ad prices, clutter, and audiences. Four key findings are (1) viewers dislike ads, but ads' effects on utility are relatively small; (2) TV ad prices are driven more by audience size than demographic composition; (3) networks exercise a great deal of market power in the market for television advertisements; and (4) given reasonable beliefs about unobserved parameter values, when 25% of households use DVRs to avoid ads, the average price of a 30-second ad will fall by 13%, ad levels will fall by 8%, and the average television audience will increase by 2%.

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"The television business cannot exist, unless consumers are willing to give time for marketers." Jamie Kellner, Chairman/CEO, Turner Broadcasting System[1]

"People like commercials." –Stanley Hubbard, CEO, Hubbard Broadcasting, responding to the threat of digital video recorders[2]

1. INTRODUCTION

For decades, no medium has delivered large audiences to advertisers as consistently as broadcast television. A new technology, the digital video recorder (DVR),[3] enables viewers to avoid advertisements and threatens to harm networks, advertisers, and even the viewers themselves. In theory, if every viewer had a DVR and used it to skip ads, ad prices would fall to zero, and networks would have no incentive to put programs on the air.

And yet, similar arguments were used to predict the end of television after the introduction of the remote control and the videocassette recorder (VCR). But these arguments described reality poorly: despite ever-diminishing audiences, broadcast networks' advertising revenues rose from $9.96 billion in 1990 to $15 billion in 2002.[4]

[1] Quoted by CNN.com, December 5, 2002.
[2] Quoted by *Broadcasting & Cable*, April 21, 2003, page 20.
[3] A.k.a. TiVo, a.k.a. Personal Video Recorder (PVR).
[4] Source: TVB.org; figures exclude WB and UPN.

This paper introduces a model of an advertisement-supported media industry in which media platforms compete for media consumers and advertisers, and a method to forecast the effects of ad-avoidance technology. The example used to illustrate the method is how the DVR will change the television industry, so I will refer to media platforms as "networks" and media consumers as "viewers."[5]

The model stems from a simple observation: if viewers dislike ads, then additional advertisements necessarily cause audience losses. A profit-maximizing network will sell ads until the marginal revenue of its last ad just equals the value of its marginal audience loss.

To quantify the network's tradeoff, I model both sides of the television industry. I estimate viewer demand for TV programs (to predict the marginal audience losses accruing to additional advertisements) and advertiser demand for TV audiences (to predict networks' marginal benefits of selling ads, and to calculate the value of ads' marginal audience losses). I use networks' first-order conditions to infer conduct in the ad market. Then, the viewer and advertiser demand functions are re-specified to include the effects of ad-avoidance

[5] Internet websites are also affected by ad-avoidance technology; for example, the Google toolbar for Internet Explorer blocks "pop-up" ads. It seems reasonable to suspect that any advertiser-supported, digital communications medium might be affected by ad-avoidance technology at some point.

technology; and networks' first-order conditions are solved to predict new ad quantities,[6] ad prices, and audience sizes.

Predictions depend on beliefs about four unobserved variables: the effectiveness of the ad-avoidance technology; the proportion of ad-avoiders in the viewing population; advertisers' valuation of ad-avoiding viewers (relative to non-ad-avoiders); and the permanence of audience flow effects on DVR users. I report predictions for several sets of beliefs about these variables.

The advantage of the method used in this paper is that, unlike many recent surveys of DVR users, results are not biased by sample selection. Current DVR users are "early adopters," and as such, presumably different from the majority of the television viewing population. Accordingly, we should not make generalizations based on their behavior.

I present several empirical results. TV viewers dislike advertisements, but viewers' marginal disutility of ads is relatively small. Advertiser demand for ads on any given show is downward-sloping, and depends much more on audience size than on demographic characteristics. Networks exercise a great deal of market power in the market for television advertisements. Predictions about how DVRs will affect market variables vary by beliefs. For example, if DVR usage

[6] Ad quantities, or ad levels, are called "clutter" in the advertising literature; I use the three terms interchangeably.

reduces marginal disutility of ads by one-third, and advertisers value five ad-avoiding viewers the same as one non-ad-avoider, I find that DVR penetration of 25% will induce networks to lower ad quantities by 8%, cut ad prices by 13%, and the average television audience will increase by 2%.

In the next section, I describe DVR technology, the television industry, and the relevant academic literature. Section 3 contains the model. Section 4 discusses instruments used to identify viewer and advertiser demand, and section 5 describes the data. Section 6 presents demand parameter estimates and inferences about networks' market power. Section 7 shows how to re-specify the model to accommodate ad-avoidance, and predictions about how DVR proliferation will affect the TV industry. Section 8 concludes.

2. BACKGROUND

In this section, I describe DVR features, how DVR proliferation will affect television industry economics, recent trends in advertising clutter, how TV ads are bought and sold, and the relevant academic literature.

2.1. *What's all the hoopla?*

It is common to hear anecdotes of DVR owners who claim the device has changed their lives, [7] while non-owners seem unimpressed by the device's features. A DVR is basically a VCR with a hard drive—meaning that many of its functions have been widely available for years—but a number of subtle advantages seem to add up to a big difference.

Unlike a VCR, a DVR is "always on," continuously storing the previous 30 minutes (or so) of TV programming, so live TV can always be paused or rewound. Many DVR users start watching TV after their program of interest begins, so they can fast-forward through the commercials.

Fast-forwarding is faster on a DVR than on a VCR: a two-minute commercial break can be skipped in as little as five seconds. A DVR stores programs digitally, so DVR owners never have to purchase, rewind, insert, remove, or store bulky videotapes. And, whereas VCRs are notoriously difficult to program, DVRs allow users to record programs by selecting them from a grid of TV listings.

Until recently, DVRs were confined to standalone, difficult-to-install boxes, available only from consumer electronics retailers and satellite television providers. In the near future, DVR-equipped set-top boxes will

[7] As one TiVo owner was quoted by the *New York Times*: "Before we got the TiVo, my son was getting C's and D's in school because he was staying up late to watch his shows and going to school half-awake"…[Now he is getting enough sleep and his grades have risen to A's and B's.]…"We watch TV together as a family after dinner… And my son even has enough time to get a job. So it's improved his sense of the value of time. And it's improved my relationship with him."

be available to most digital cable subscribers for a monthly fee, as well as to users of Microsoft's Windows XP Media Center Edition operating system.

2.2 *Economics of Television Advertisements.*

Television networks operate in a two-sided market.[8] Networks offer viewers "free" programs in exchange for their attention, and sell that attention to advertisers. Viewers' true cost of consuming a television program is the amount of time they spend watching commercials.

The structure of the industry suggests that the average viewer dislikes watching the average ad; if not, networks would have little reason to air programs. Because of viewer distaste of ads, the television network faces a tradeoff when choosing its advertising level: additional commercials may increase revenues, but will induce some viewers to leave the audience. The profit-maximizing network will sell ads until the marginal revenue of its last ad sold equals the value of the audience losses accruing to that ad.

Because viewers pay for programs by enduring commercials, avoiding ads with a TiVo is equivalent to a fall in price. As with any price

[8] Also called a multi-sided platform industry, a two-sided market is one in which two groups of participants interact via competitive intermediaries. (Armstrong 2002) Other examples include operating systems (operating systems coordinate users and software developers), payment mechanisms (credit card companies coordinate retailers and shoppers), and academic journals (journals coordinate authors and readers). For a general treatment of such markets, see Rochet and Tirole (2001). Wright (2004) gives an excellent summary of conventional economic wisdom that does not apply in a two-sided market setting.

reduction, we should expect a positive income effect (viewers will watch more TV because avoiding ads increases their total stock of free time) and a positive substitution effect (viewers will watch more TV, because it takes less time, relative to other activities).

The effect of DVR proliferation on clutter is less clear. Increasing scarcity of non-ad-avoiding viewers might lead networks lower ad quantities to compete more fiercely for audience share. On the other hand, some DVR users will fast-forward past ads, rather than leaving the audience; and smaller audience losses mean lower disincentives for additional ads. It is difficult to predict which effect will dominate.

Several consultancies expect DVR ownership to increase rapidly. The Yankee Group predicts the number of DVRs in American households will rise from 3.5 million in March 2004 to 24.7 million in 2007. Forrester Research expects there to be 25 million DVR Households by the end of 2006.

2.3. *Advertising Clutter: Current Data and Recent Trends*

A common misconception holds that there is little or no variation in advertisement quantities. In truth, there is substantial variation: in this paper's sample, the average difference between the highest and lowest network ad levels, within a prime-time[9] half-hour, is 2:49 minutes. (For comparison, the mean advertising level is 5:10 minutes.) A similar

[9] Prime time is defined as 8:00pm-11:00pm, Mon-Saturday, and 7:00pm-11:00pm, Sunday.

pattern emerges from data on total non-program minutes[10] reported in the *2001 Television Commercial Monitoring Report* (TCMR). The strongest programs in any given timeslot normally contain more advertisements than the weakest.

Ad levels once were fixed: until 1980, broadcasters limited themselves to 6 minutes of non-program content per prime-time hour. Although tacitly supported by the Federal Communications Commission, this practice was discontinued after the US Department of Justice brought an antitrust suit against the industry. Although the US does not regulate prime-time advertising levels, many other nations do, including the UK, France, Germany, and Japan. (Motta and Polo 1997)

After the antitrust ruling, network advertising levels rose slowly, from 3:24 minutes of national ads per half-hour in 1982, to 3:39 in 1988 (Owen and Wildman, 1992). As increasing competition for viewers' attention eroded network audiences during the 1990's, ad levels rose more rapidly: total commercial time (national and local) increased from 4:51 minutes in 1991 to 6:02 minutes in 2001 (TCMR).

2.4. *The Market for Television Advertisements*

Television advertisements are bought and sold in an unusual fashion. Networks present their new and returning programs to advertisers in May of each year. During the next few weeks, advertisers

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[10] Non-program minutes include ads, tune-ins, and public service announcements.

review scripts and watch clips to try to predict new shows' audiences, while networks gather data on advertisers' budgets. Each network then produces a "rate card," its starting point for price negotiations with advertisers. After negotiations begin, the market usually "breaks" in early summer, with networks selling about 70-80% of the coming year's commercial time within a few weeks. This period is known as the *upfront* market.

Ads unsold during the upfront may be sold any time before the broadcast airs, on the *scatter* market. Networks guarantee minimum audiences for ads sold during the upfront,[11] while ad prices in the scatter market are normally linked to the audience delivered.

Networks tend to charge higher prices to more-profitable advertisers, and offer volume discounts. Audiences are typically bundled[12] across days, time periods, and quarters.[13] Ads are purchased in 10-, 15-, 30-, or 60-second increments. There are many interesting issues to be investigated in this market, but data limitations will force me to assume networks charge a uniform price per show.

2.5. *Literature Review*

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[11] When a program fails to meet its minimum guaranteed audience, the network provides its advertisers with *make-goods*, free commercials during other programs to compensate the advertiser. Unfortunately, my data do not distinguish which ads are make-goods.

[12] Networks almost always bundle larger audiences with smaller, a practice known as *packaging*.

[13] The frequency and size of these audience bundles are the primary reason to presume that networks may wield different levels of market power in the market for TV advertisements, made later in this paper.

There have been many studies of the television industry, but few empirical studies of the market for television advertisements. Two recent studies are Goettler (1999) and Kieshnick, McCullough, and Wildman (2003). Both papers estimate the relationship between audience size and advertisement price while, for lack of data, holding ad quantities constant. Goettler finds a convex relationship between ad price and audience size, shows that audience demographics are important determinants of ad price. Kieshnick, et. al., present evidence that networks charge different implicit prices for different types of viewers. To the best of my knowledge, this paper is the first structural econometric model of the television industry with endogenous advertisement quantities.

Several recent theoretical papers have modeled the two-sided nature of the television industry. Anderson and Coate (2003) present a welfare analysis of the industry, showing that equilibrium ad quantities may exceed or fall short of socially optimal ad levels, depending on viewers' disutility of ads relative to advertiser surpluses from contacting viewers. Dukes and Gal-Or (2002) look at the interaction between product markets and advertisement markets. Liu, Putler and Weinberg (2004) study television networks' competition for viewers through choice of program content and quality. Other notable papers include Cunningham and Alexander (2003), Gabszewicz, Laussel and Sonnac (1999) and Nilssen and Sorgard (2003).

This paper is related to the marketing literature on estimating viewer demand for television programs, including Shachar and Emerson (2000) and Rust and Alpert (1984). Other empirical investigations of two-sided markets include Berry and Waldfogel (radio, 2001), Rosse (newspapers, 1970), Rysman (yellow pages, 2003), and Kaiser and Wright (magazines, 2004).

3. MODEL

In this section I lay out the model of viewers, advertisers, and networks that underpins the empirics presented later.

3.1. *Viewers*

Each viewer *i* is assumed to watch one of *j=1...J* networks in each time period *t*, or to engage in some other activity (the "outside option," which includes all non-network-TV pursuits). I assume indirect utility (U_{ijt}) is linear in show characteristics. Let

$$U_{ijt} = q_{jt}\alpha + X_{jt}\beta + \xi_{jt} + \varepsilon_{ijt} \qquad (1)$$

where q_{jt} is the ad quantity aired by network *j* at time *t*, X_{jt} are observable characteristics of the show on network *j* at time *t*, ξ_{jt}

represents the unobserved characteristics of show *jt* that affect all viewers' utility,[14] and ε_{ijt} is viewer i's idiosyncratic taste for show *jt*.

By assuming that viewers maximize utility, and that the idiosyncratic error terms are distributed *i.i.d.* Type 1 Extreme Value; and by normalizing level and scale effects entering into viewer utility of the outside option to zero; I can analytically solve for the multinomial logit market shares,

$$s_{jt} = \frac{e^{q_{jt}\alpha + X_{jt}\beta + \xi_{jt}}}{1 + \sum_{k=1}^{J} e^{q_{kt}\alpha + X_{kt}\beta + \xi_{kt}}} \tag{2}$$

where s_{jt} is the fraction of viewers watching network *j* at time *t*.

If all of the regressors were exogenous, I could use maximum-likelihood to estimate parameters α and β in equation (2). But, because networks know their shows' quality, ξ_{jt}, and take it into account when setting advertisement quantities, q_{jt} is endogenous. To deal with this, I employ Berry's (1994) method to transform the logit share functions:

$$\ln(s_{jt}) - \ln(s_{0t}) = \alpha q_{jt} + X_{jt}\beta + \xi_{jt} \tag{3}$$

where s_{0t} is the fraction of viewers engaging in the outside option at time *t*. The linear form of equation (3) allows for traditional instrumental-

[14] A natural interpretation of ξ_{jt} is unobserved show quality, which (in this case at least) is synonymous with popularity.

variables estimation. Instruments for ad quantity are described in section 4.1.

This model and the results presented in section 6 do not account for unobserved viewer heterogeneity, causing the estimates to exhibit the independence of irrelevant alternatives problem. This is a serious problem, which I will address in a future revision with a mixed logit model (as described in Appendix 1).

3.2. *Advertisers and Networks*

I assume that networks play a three-stage game: in stage one, they simultaneously select their programs; in stage two, they simultaneously schedule their programs; and in stage three, they simultaneously choose ad quantities and prices. This assumption narrows the focus of this study to strategic behavior in the final stage, wherein program selection and scheduling choices are sunk. I now turn to assumptions about demand and costs, in order to formulate a network's profit function.

Advertisers purchase ads to gain access to program audiences. Audiences contain different numbers of viewers ("eyeballs") of different types, and advertiser preferences over eyeball types vary by advertiser and by eyeball type. Therefore, advertisers' inverse demand for ads (hereafter, "ad demand") during a particular show *s* can be written

$$p_s = p\left(q_s, V_s(q), x_p\right), \tag{4}$$

where p_s is the price of one ad during show s; q_s is the number of ads sold during show s; q is a vector of the q_s's; $V(q)$ is either a scalar measure of audience size or a vector of the number of viewers of each type in the audience; and x_p is a vector of show characteristics that affect advertisers' utility. We should expect $\frac{\partial p}{\partial q} \leq 0$ and $\frac{\partial p}{\partial V} > 0$.

The marginal cost (to the network) of selling an ad is probably close to zero. Because nearly all ad sales take place long before a program appears on the air, the length of a show can be edited to accommodate the network's choice of ad quantity.[15]

If marginal costs are zero, networks maximize advertisement revenues. I assume that firms compete in ad levels, and write their objective function as

$$\max_q \sum_{t=1}^{T} q_t p_t \left(q_t, V_t(q), x_p\right) \tag{5}$$

where T is the total number of time periods.

3.3. Network Conduct

Is the market for television advertisements competitive? There are several reasons to believe it is not. First, there are only a few firms that sell large television audiences, and thousands of potential buyers. Spectrum regulations limit entry of local television stations, which constrains the supply of network affiliates and prevents entry of new

[15] And, because the bulk of program production costs are fixed, it should cost little to adjust program duration to accommodate ad sales.

networks. Second, anecdotal evidence suggests that buyers are routinely afraid of being "shut out"—unable to purchase the audiences they want—if they do not move quickly to buy during the upfront.[16] This could enable networks to play large buyers against each other, creating an environment in which buyers' uncertainty increases networks' bargaining power. Third, national advertisers have no real alternatives to large television audiences when they want to reach a very large number of people in a short period of time.

Regardless of all of the above, we would expect to see a departure from marginal-cost pricing in the advertisement market. Efficient pricing in any two-sided market reflects not just marginal costs, but also the additional surplus generated by additional users. Because ad sales have negative externalities (they harm viewers, and audience losses harm other advertisers), advertisers will be "taxed" for their participation in the market. What follows is a method to separately identify networks' market power from the premium advertisers are charged for their ads' negative externalities.[17]

Consider, first, a simple example. A competitive firm produces output y, with cost function $c(y)$, and inverse demand function $p(y)$. The

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[16] See, for example, *Broadcasting & Cable*, August 7, 2000, page 38.

[17] I should emphasize that the presence of market power does not necessarily imply evidence of collusion or even positive economic profits. In a two-sided market, a reduction in competition on one side of the market can intensify competition on the other side of the market, to the point where firms are actually worse off than before. (See Wright 2004.)

firm's profit function is $\max_y yp(y) - c(y)$, with first-order condition (FOC) $p(y) = c'(y)$. Meanwhile, a monopolist (with identical demand, cost, and profit functions) produces where marginal revenue equals marginal cost, with FOC $p(y) + yp'(y) = c'(y)$. To infer market power, a parameter, θ,[18] can be included in the firm's FOC, $p(y) + yp'(y)\theta = c'(y)$, and solved for: $\theta = \frac{c'(y) - p'(y)}{yp'(y)}$. The bounds on θ are the extreme assumptions of price-taking behavior ($\theta = 0$, as in the competitive firm's case), and monopoly-level market power ($\theta = 1$, as in the monopoly case). Higher θ is associated with higher levels of market power.

To adapt this approach to a two-sided market, I write the network's FOC in a general fashion,

$$p_t(q_t, V(q, q'), x_p) + q_t \frac{\partial p_t}{\partial q_t}\theta + q_t \sum_{s=1}^{T} \frac{\partial p_s}{\partial V_s} \frac{\partial V_s}{\partial q_t} = 0 \qquad (6)$$

where θ represents the amount of market power the broadcaster exercises in the advertisement market, and the third term is interpreted as the value of the marginal audience losses accruing to an additional ad.[19] This FOC says that a competitive network will sell ads until its ad price just equals the value of an ad's marginal audience loss ($\theta = 0$), while a monopolistic network will sell ads until the marginal revenue generated

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[18] θ is sometimes written 1+*r* in the conjectural-variations literature, on which this approach is based. See Bresnahan (1989) or Genesove and Mullen (1998).

[19] In estimation, I will assume that, for $|s - t| \geq 2$, $\frac{\partial V_s}{\partial q_t} = 0.$

by an additional ad just equals the value of that ad's marginal audience loss.

To infer networks' market power in the ad market, I solve for θ:

$$\theta = \frac{-p_t(q_t, V(q,q'), x_p) - q_t \sum_{s=1}^{T} \frac{\partial p_s}{\partial V_s} \frac{\partial V_s}{\partial q_t}}{q_t \frac{\partial p}{\partial q}}. \tag{7}$$

All of the terms on the right-hand side of the equation are known, or will be estimated or predicted: *p* and *q* are observed, estimates of $\frac{\partial p}{\partial q}$ and $\frac{\partial p}{\partial V}$ come from advertiser demand for TV advertisements, and $\frac{\partial V}{\partial q}$ will be predicted by the model of viewer demand. Appendix 2 shows how the data identifies θ separately from $\frac{\partial p}{\partial q}$.

A reasonable objection could be made that I have modeled network/ advertiser and network/network interaction insufficiently. I agree, and would direct objectors to the richer model presented in Appendix 1, but there is a reason for the simplicity assumed here. If advertisers' utility is nonlinear in the number of eyeballs they purchase, then their reservation prices for any given show will depend on their other audience purchases. This dependence means that demand for any given show will be ill-defined, making it impossible to write down an analytical demand function, much less a first-order condition.

I report estimates based on the simple model presented here for two reasons: to generate discussion of initial results, and because this model is far easier to estimate than the more-sophisticated model. The value of a method intended for practitioners' use is proportional to practitioners' ability to use it.

4. INSTRUMENTS

In this section I discuss the need for instruments and the instruments I use.

4.1. *Viewer Demand-side Instruments*

A program with a large unobserved quality component will attract more viewers and contain more ads. Therefore, ad quantity q is correlated with unobserved program quality ξ. I propose two instruments for ad quantity.

The first is the network's average ad quantities in all of the other half-hours it programs.[20] This is correlated with ad quantity in the current half-hour because all ad levels are determined, in part, by networks' varying levels of market power. But, because a network's market power is unlikely to be influenced much by any single program's unobserved quality, this instrument should be uncorrelated with ξ.

[20] This instrument is similar to those suggested by Berry, Levinsohn, and Pakes (1995).

The second set of instruments I use are same-night, same-network program characteristics. These characteristics are correlated with ad quantity because networks take audience flow between time periods into account when setting ad levels. They are uncorrelated with unobservable program characteristics because networks do not follow uniform strategies when scheduling their shows. (On some nights, weak shows are buttressed by strong shows, while other nights see programs of similar quality aired consecutively.)

4.2. *Advertisement Demand-side Instruments*

A show with better unobserved audience characteristics will attract more ads, at a higher price. Thus ad quantity is correlated with the ad demand residual. Audience sizes depend on ad quantity, so they are also correlated with the ad demand residual.

I employ two instruments. The first is the audience loss accruing to an additional 30-second advertisement. This audience loss is the network's disincentive to air additional advertisements, and so is correlated with ad quantity (as can be seen by the presence of $\frac{\partial V}{\partial q}$ in equation 6, the network's first-order condition). Predicted audience losses should be uncorrelated with the demand residual as long as viewers' disutility of ads is unrelated to their unobserved demographic characteristics that affect advertiser utility. I also employ network dummy variables as instruments for ad quantity, to proxy for networks' varying levels of market power.

5. DATA

Data for this study comes from three sources. Audience data comes from "Viewers in Profile" (ViP) reports produced by Nielsen Media Research (NMR), covering the 50 largest geographic television markets (called Designated Market Areas, or DMAs), for the four-week "sweeps" period that spanned April 24-May 21, 2003. These reports contain, for each prime-time half-hour, estimated audiences by households and persons, by demographic,[21] watching each of the six major broadcast networks (ABC, CBS, FOX, NBC, UPN, and WB). These 50 DMAs contain 94.7 million television households and 242.8 million people. I aggregate local audience estimates over the 50 DMAs to produce national audience measures; Table 1 contains summary statistics for the audience data. Unfortunately, because this is not panel data, I do not observe the extent to which programs' audiences overlap.

To collect their audience figures, NMR maintains a sample of "audimeters" in each DMA. Audimeters measure television usage and tuning, and upload the data to Nielsen over telephone lines. Nielsen used 370 audimeters in the smallest DMA (Louisville), and 487 in the largest

[21] Demographics include gender and age groups like "Men 18-49."

(New York City). Household audience measurements are based on audimeter data.

NMR also collects a sample of television diaries. Diary sample respondents are picked on a household basis; each member of the household is asked to record her viewing behavior daily, and to return her diary by mail on a weekly basis. Diary samples are larger than audimeter samples: Nielsen collected 1,537 per week in Louisville, and 1,687 in New York. Audience demographics are based on both audimeters and diaries.

While producing these audience estimates, Nielsen excluded DVR-using households from its sample, classifying them as "technically difficult."[22] In May 2003, DVRs were in use in approximately 2.5 million US households.[23]

Nielsen data has been criticized, frequently and intensely, for decades. Television networks claim it systematically undercounts their audiences; advertisers say it designs its methods to suit networks' purposes. In spite of the criticism, Nielsen data is the industry standard, as it produces the best (and, usually, only) audience measurements available.

[22] Nielsen will start including DVR households in its audience sample in 2005. (*MediaDailyNews*, March 4, 2004)
[23] Based on Yankee Group estimates reported at http://www.internetnews.com/stats/article.php/3080851.

Advertisement data comes from TNS Media Intelligence/CMR. For each prime-time national advertisement in the four-week sample period, I observe the date, network, start time, duration, and brand.

Ad prices come from data on the "estimated cost per 30-second commercial" reported by the networks to both Nielsen and TNSMI/CMR. Networks report price estimates for each installment of each program.

Observable program characteristics were recorded from a large number of videotapes recorded during the sample period, supplemented by internet sources, where appropriate. Observable program characteristics consist of genre; main character[24] and cast demographics, including gender, race, age, and family structure; program age;[25] and numbers of current and past Emmy nominations. Table 2 contains variable definitions and descriptive statistics.

6. RESULTS

In this section I discuss estimation of viewer and advertiser demand, results, and inferences about networks' market power.

6.1. *Viewer Demand*

Viewer demand parameters were estimated with Two-Stage Least Squares, using equation (3), the variables listed in table 2, and the

[24] A main character is defined as a character on whom major plotlines are based.
[25] For those movies that were not originally produced for TV, age is defined as the number of years since the movie's theatrical opening.

instruments described in section 4.1. Viewer demand regressions were run separately for audience shares by household, persons, persons by age group, and persons by gender and age group. I include a dummy for *American Idol* because it aired frequently during the sample period,[26] and its audience was markedly larger than those of programs with similar observable characteristics.[27]

Viewer demand parameter estimates for households and persons are presented in Table 3. The estimated effect of advertisements on viewer utility is negative and significant in both specifications. Audience flow is important; lead-in and lead-out effects are positive and significant.

The excluded network is CBS, so the interpretation of network effects are viewers' marginal utility from watching a given network, relative to watching CBS. The negative, significant effects of FOX, NBC, UPN, and WB probably reflect CBS' and ABC's signal strength and channel position.

The excluded day is Sunday. In both specifications, viewers watch less TV on Friday and Saturday nights.

The excluded genre is Scripted Comedy. The results indicate that Psychological Dramas are preferred to Comedies. (This, in part, helps to explain the recent proliferation of Dramas on the airwaves.) Movies tend to do worse than other genres.

[26] Fox aired 9.5 hours of *American Idol*, including 3.5 hours on three consecutive nights.
[27] I.e., *Star Search*.

Interestingly, while viewers are less likely to watch a show with greater minority cast representation, the presence of an African-American main character has a positive and significant effect on viewership. Shows without female main characters do well, as do shows set in character's homes. The older a show is, the more viewers prefer it (an unsurprising result, given that networks only renew their best shows). Past Emmy nominations is a strong indicator of current success, but the effect of 2003 Emmy nominations (which were not announced until September, four months after the sample period) is insignificant.

Tables 4a and 4b present viewer demand parameters, estimated by viewers' age group. The estimated effect of advertisements on utility is negative for all eight age groups, and significant for five of the eight. Audience flow effects are positive and significant for every age group.

Other interesting results emerge. Younger viewers tend to prefer ABC, FOX and WB to CBS, while older viewers prefer the opposite. Aversion to watching television on Friday and Saturday nights is strongest among those under 49. Viewers under 18 are less likely to watch after 9:00pm EST. Viewers under 35 are much less likely to watch News, and much more likely to watch Reality, than those over 50. The presence of a main character over the age of 50 has a negative and significant effect on utility for viewers under 25, while the presence of younger main characters has little effect on older viewers' behavior. Shows that are set in a workplace are much less likely to be watched by those over 65. Finally, the show *American Idol* is much more likely to be watched by those over 50 (and especially those over 65) than by viewers under 35.

Tables 5a and 5b present parameter estimates for men and women, by age group. The model fits the narrower demographic groups less well, perhaps because audience estimates are based on smaller numbers of Nielsen survey respondents. Advertisement Seconds coefficient estimates are negative for all groups; most are not significant. Lead-in and lead-out effects are again positive and significant for all groups.

While viewers' estimated marginal disutility of advertising is always negative and often significant, its effects are not as large as might be expected. Table 6 shows the model's average predicted audience losses accruing to an additional 30-second spot. On average, an additional commercial aired during a program decreases that program's audience by 44,300 households (just 0.7% of the 6.2 million households in the average prime-time network audience), or 103,800 people (1.1% of the average of 9.8 million).

Table 7 shows predicted audience changes when each network unilaterally airs no ads. The average predicted gain is 331,000 households (5.3% more than current viewership), or 916,000 people (a gain of 9.3%).

6.2. *Advertisement Demand*

Estimation of advertiser demand for television advertisements is complicated by several sources of error, including ad price reporting, audience measurement error, multicollinearity, and unobserved audience characteristics.

Audiences are sold and prices reported at the program level, but networks distribute ads within a program based on strategic considerations. To help correct for this, I average program characteristics over half-hours so the unit of observation is a network/day/program.

Advertisers should care about the number of viewers of each demographic type in the audiences they purchase, so ideally I could include the number of eyeballs of various types as regressors in the ad demand equation. Two problems force me to take a different approach: multicollinearity, and measurement error in the NMR data. The former problem arises because a program that is very appealing to viewers in one age group is also likely to be appeal to viewers in other age groups. The latter arises because Nielsen's estimates of the number of people of each type in each audience are based on television viewing diaries; due to human error, these diaries are likely to include more measurement error than the household data (which is measured by audimeters). To address these two problems, I measure audience size in households and include audience demographic compositions as regressors in the demand equation. I define show s's audience composition of demographic d as

$$comp_{ds} = \frac{V_{ds}}{V_s} \tag{8}$$

where V_{ds} is the number of viewers of type d watching show s, and V_s is the number of people, 2 years and older, watching show s. I treat audience demographic compositions as exogenous and audience size as endogenous.

Another source of error is unobserved audience characteristics. While I observe audience estimates by gender and age, unobserved variables like income, education, or race are important. I can partially mitigate this problem by including program characteristics that might correlate with the unobserved audience characteristics. I include *SingleParent* (likely to correlate with viewer income and family structure), *50+%NonWhite* (likely to correlate with race and income), and *PastEmmyNominations* (likely to correlate with viewer education).[28] I also include *ScriptedComedy*, because I expect consumers will be more receptive to advertising when they are laughing. (CITE ADV LIT)

I assume ad demand is linear in ad quantity, audience size, demographic compositions, and program characteristics. I exclude programs broadcast 9-9:30, May 8, 2003, because a presidential address preempted four networks' advertisements. Estimation was performed via Two-Stage Least Squares, with the instruments described in section 4.2.

[28] If the average Emmy nominator has more education than the average viewer, Emmy nominators' tastes are likely to correlate with more-educated viewers' tastes.

Demand parameter estimates are reported for several specifications in Table 8.

The effect of the number of ads sold during a program on ad price is negative and significant in five of the six specifications. There are two possible interpretations for the negative coefficient of ad quantity: variation in advertiser reservation prices, and clutter effects—more ads during a program decreases the effectiveness of any single ad. I think both are likely explanations.

Specification two is included to show that the effect of audience size is significant, while audience-squared is not. I use a linear measure of audience size in subsequent regressions. I also estimated log-log relationships, but the results changed little.

Specifications three and four include demographic audience compositions, by age group and gender/age group. The results suggest that advertisers care most about Women, 35-49, and Men, 25-34. A larger fraction of People, 50-64, in a program's audience will lower its ad price.

One set of results is difficult to interpret. In specification 3, the coefficient estimate of People, 18-24, is estimated to be negative and significant. In specification 4, the effect of Women, 18-24, is negative and insignificant and only one standard deviation below zero, while the effect of Men, 18-24, is positive and nearly two standard deviations above zero. Since People, 18-24, should equal the sum of Men, 18-24, and Women, 18-24, these inconsistencies are surprising. Further investigation reveals inconsistencies in the data. The average number of People, 18-24, in a program's audience is 711,000; and the average difference between People, 18-24, and the sum of Men, 18-24, and Women, 18-24, is 107,000.

Specifications five and six include observable show characteristics that may correlate with unobserved audience characteristics. *ScriptedComedy* has a positive and significant effect, as does *PastEmmyNominations*. Including these variables improves the fit of the model.

6.3. *Market Power Inferences*

To make inferences about the amount of market power network *j* exercises in the market for its audience at time *t*, I use the definition of the market power parameter presented in equation (7),

$$\hat{\theta}_{jt} = \frac{-p_{jt} - q_{jt}\hat{\lambda}_V\left(\frac{\partial V_{j,t-1}}{\partial q_{jt}} + \frac{\partial V_{jt}}{\partial q_{jt}} + \frac{\partial V_{j,t+1}}{\partial q_{jt}}\right)}{q_{jt}\hat{\lambda}_q} \tag{9}$$

where $\hat{\lambda}_V$ and $\hat{\lambda}_q$ are advertiser demand parameter estimates from specification six, and the $\frac{\partial V}{\partial q}$ terms are lead-in, current, and lead-out audience losses accruing to an additional commercial, as predicted by the viewer demand model. Networks' average levels of market power are the averages of all market power inferences in their catalogue of shows, and the industry average is the average over all shows in the sample.

Table 9 reports market power inferences, by network, using demand parameters estimated in specifications five and six. The average market power inferences are very high: 0.8 or 0.7, depending on which advertiser demand specification estimates are used. These are much higher than conjectural-variations inferences made in studies of other industries. I attribute this difference to the industry characteristics described in section 3.3: barriers to entry, networks' bargaining power, and lack of substitutes for network audiences.

It is discouraging that the market power inferences for FOX and NBC exceed the parameter's theoretical bound. It could be that some terms were left out of the network's first-order condition. For example, if airing additional ads at 8:00pm on Monday decreases the network's audience at 8:00 on the following Monday, then more $\frac{\partial V_{s \neq t}}{\partial q_t}$ terms should be included in the network's first-order condition. Inclusion of additional terms would lower market power inferences. Alternatively, it could be that the parameter should be reinterpreted as a measure of networks' strategy: it may measure the vigor with which networks compete for viewers, relative to competition for advertisers' dollars.

More encouraging is the ordering of networks' inferred levels of market power. The top three in total audience size have the three highest inferred levels of market power. NBC and FOX generally have audiences with better demographic characteristics than CBS' older audiences. FOX's ascendancy is ascribable to the mass audiences its *American Idol* franchise attracts. All of the networks' rankings fit my prior expectations, with the exception of UPN and WB—I thought these inferred levels of market power would be close, but I did not know which would be higher.

7. PREDICTIONS

In this section, I show how to re-specify the model to accommodate the effects of ad-avoidance on viewer demand and advertiser demand, and I report predicted changes in clutter, ad prices, and eyeball prices.

7.1. *Model Respecification*

DVR proliferation will change agents' behavior in the model in several ways. Ad-avoiding viewers' advertisement disutility will be reduced; audiences will contain (and therefore advertisers will purchase) DVR users; and the permanence of audience flow effects may be reduced for ad-avoiding viewers.[29] I first change the model to include these effects; and then, for plausible values of unobserved parameters, solve

[29] The logic for this last point is that, if DVR owners record programs for playback by selecting shows from a listing grid, the effect of inertia on viewing choices will be weaker.

networks' first-order conditions to find equilibrium ad quantities, prices, and audiences. The unobserved parameters are:

γ_1 The extent to which DVR usage reduces ad nuisance

γ_2 The extent to which DVR usage reduces audience flow effects

γ_3 The proportion of ad-avoiders in the viewing population

γ_4 Advertisers' marginal valuation of a DVR-using viewer, relative to a non-ad-avoiding viewer

A DVR-using viewer's disutility from ads is reduced by γ_1, and audience flow effects are reduced by γ_2. For these type-*D* viewers, we can rewrite the utility of watching network *j* at time *t* as

$$U_{ijt}^{D} = q_{jt}\hat{\alpha}\gamma_1 + LI_{jt}\hat{\beta}_{LI}\gamma_2 + LO_{jt}\hat{\beta}_{LO}\gamma_2 + X'_{jt}\hat{\beta}' + \hat{\xi}_{jt} + \varepsilon_{ijt} \qquad (1')$$

where LI_{jt} is network *j*'s lead-in audience at time *t*, LO_{jt} is network *j*'s lead-out audience at time *t*, and X'_{jt} are all of the other program characteristics that enter viewer utility, and $\hat{\alpha}$, the $\hat{\beta}$'s, and $\hat{\xi}_{jt}$ are viewer demand model estimates. The utility of those viewers who do not watch television (type *N*) is unchanged. Parameter estimates and unobserved parameters γ can be used to construct market share functions for both types of viewer, $\hat{s}_{jt}^{D}(q)$ and $\hat{s}_{jt}^{N}(q)$, where *q* is a vector of all networks' ad quantities at times *t-1*, *t*, and *t+1*.

Network *j*'s total audience at time *t* depends on its share of each type of viewer, and the number of viewers of each type (γ_3 and $1-\gamma_3$). Thus

$$V_{jt}(q) = \left[(1-\gamma_3)\hat{s}_{jt}^{ND}(q) + \gamma_3 \hat{s}_{jt}^{D}(q)\right]N \tag{10}$$

where $V_{jt}(q)$ denotes audience size and there are *N* total viewers.

Advertisers' willingness-to-pay for a given audience depends on the number of viewers of each type in the audience, and γ_4, their relative valuation of ad-avoiding viewers. I rewrite ad demand as

$$\hat{p}(q) = q\hat{\lambda}_q + \left[(1-\gamma_3)\hat{s}_{jt}^{ND}(q) + \gamma_3\gamma_4 \hat{s}_{jt}^{D}(q)\right]N\hat{\lambda}_V + x_p\hat{\lambda}_x + \hat{\varepsilon}_p \tag{4'}$$

where the $\hat{\lambda}$'s and $\hat{\varepsilon}_p$ denote advertiser demand model estimates.

I rewrite network *j*'s first-order condition with respect to ad quantity q_{jt} (originally given by equation 6) as

$$\hat{p}_{jt}(q_{jt}) + q_{jt}\hat{\lambda}_q\hat{\theta}_{jt} + q\hat{\lambda}_q N\begin{bmatrix}(1-\gamma_3)\left(\frac{\partial\hat{s}_{jt-1}^{ND}}{\partial q_{jt}} + \frac{\partial\hat{s}_{jt}^{ND}}{\partial q_{jt}} + \frac{\partial\hat{s}_{jt+1}^{ND}}{\partial q_{jt}}\right) \\ +\gamma_3\gamma_4\left(\frac{\partial\hat{s}_{jt-1}^{D}}{\partial q_{jt}} + \frac{\partial\hat{s}_{jt}^{D}}{\partial q_{jt}} + \frac{\partial\hat{s}_{jt+1}^{D}}{\partial q_{jt}}\right)\end{bmatrix} = 0. \tag{6'}$$

I solve the set of equations (6') for networks that compete at the each time *t* to find equilibrium ad levels.[30] Predicted ad quantities are used in

[30] Solving (6') for all of the ad quantities that enter it is difficult because of the feedback of ad levels through audience flow effects; ABC's ad level at 10:30pm on Sunday could conceivably affect FOX's 7:00pm Sunday audience. Solving the problem numerically as stated could mean as many as 36 nonlinear equations for 36 unknowns. To improve the precision of the solutions and reduce computation time, I solve (6') for all of the networks on the air at each time *t*, for all times *t*; then, using predicted ad levels, I calculate the partial derivatives of lead-ins and lead-outs with respect to ad quantities, and use those derivatives to re-solve (6') for all of the networks on the air at time *t*, for

equations (4') and (10) to predict equilibrium audience sizes and ad prices.

7.2. *Results*.

The specific values used for the γ's in simulating the effects of ad-avoidance technology on equilibrium variables should come from the researcher's prior beliefs. I present some predictions for values of the γ's that seem plausible to me. I first report predicted equilibrium ad prices, quantities, and adjusted costs per thousand non-DVR households for the case of $\gamma_1 = \frac{1}{3}$ (meaning that DVR usage reduces ad nuisance by one-third) and $\gamma_2 = 1$ (DVR usage does not reduce audience flow effects).

Figure 1 shows predicted clutter levels, by advertisers' relative valuation of DVR households and DVR penetration rate. Three results emerge. First, clutter tends to decrease as DVR penetration increases. This is because greater DVR penetration makes the more-valuable non-DVR households more scarce, forcing networks to compete more fiercely for dwindling numbers of non-DVR viewers. Second, higher advertiser valuation of ad-avoiding viewers is associated with higher ad quantities. This is because higher valuations of DVR viewers compensate networks for the increased scarcity of non-DVR households. Third, the rate at

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all times *t*; and iterate until the routine converges. This way, the problem is never larger than 6 unknowns in 6 equations.

which clutter falls with DVR penetration is inversely related to advertisers' valuation of ad-avoiders.

Figure 2 shows how ad prices change as DVRs proliferate. The lessons are similar to those learned from Figure 1.

One commonly used measure of eyeball price is cost per thousand viewers (CPM). The typical formula for CPM is $CPM = {}^{1000p}\!/_{V}$, where p is ad price and *V* is the size of the audience. When audiences contain significant numbers of DVR owners and non-owners, the CPM is an insufficient measurement of eyeball price, because it does not distinguish between the two groups of viewers. To replace it, I use an adjusted CPM (ACPM), $ACPM = {}^{1000p}\!/_{(V_N + \gamma_4 V_D)}$, where V_D is the number of DVR households in the audience, and V_N is the number of non-DVR households in the audience. Figure 3 shows average predicted ACPMs. It suggests that ACPMs will change little for low levels of DVR usage, but could increase dramatically for higher levels.

Interestingly, in the case of $\gamma_1 = \frac{2}{3}$ and $\gamma_2 = 1$, model predictions change little. This is presumably because, as DVR users' ad nuisance reductions hold for any network they watch, the reduction in ad nuisance only pulls some type-*D* viewers away from the outside option, and changes little else. For brevity, I omit this set of predictions.

The second set of predictions I report are those that correspond to the case of $\gamma_1 = \frac{1}{3}$ and $\gamma_2 = \frac{1}{2}$ (meaning that, for DVR viewers, lead-in and lead-out effects are reduced by half). Average predicted ad quantity, price, revenues, and ACPM are shown in figures 4-6.

Predictions in figures 4-6 are similar to those in figures 1-3 for low levels of γ_4. This is because reduced audience flow effects only affect DVR users, and when DVR users are valued little by advertisers, changes in their behavior matter little. The real differences between the clutter and ad price figures are the slopes of the lines. (Steeper lines indicate better outcomes for the networks.) When DVR usage reduces audience flow effects, DVR viewers' behavior offsets the loss of type-*N* viewers less.

8. DISCUSSION

This paper has made a first attempt to provide advertisers, platform operators, and regulators with a method to predict the effects of advertisement-avoidance technology on a two-sided market. The picture that emerges from the application of this method to the television industry and the DVR suggests that, consistent with most network executives' public statements, networks have little to fear from low levels of DVR penetration. But at higher levels, say 15% or more, if advertisers value DVR users significantly less than non-DVR users, networks will start to see significant revenue losses. Still, this does not necessarily mean lower CPMs, as some advertisers expect.

While the method presented here is far from perfect, it is relatively easy to implement. Some of the shortcomings of this model will be addressed; future work will use a richer model to describe unobserved viewer heterogeneity and networks' and advertisers' behavior. (See Appendix 1.)

Other shortcomings are more difficult to address, and suggest the directions in which this research could be extended. These include changes in program and advertisement form, content and duration; program characteristics and schedules; changes in advertiser or viewer demand over time; and external factors like cable networks' ad prices and quantities.

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APPENDIX 1

A1.1. *A Richer Model of Viewer Demand*

Since the audience data used in this study comes from 50 geographically distinct television markets, I can learn a lot about the distribution of unobserved viewer heterogeneity. For example, I will observe each program's estimated audience among men, 35-49, in Pittsburgh. I can use Current Population Survey data to define the conditional multivariate distribution of characteristics like income, race, and education for men between the ages of 35 and 49 in Pittsburgh. Simulating from this conditional distribution will let me identify taste parameters associated with unobserved viewer demographics.

To model unobserved viewer heterogeneity, I will use the mixed logit (also called random coefficients logit). This model predicts that viewers will substitute between similar shows, and that similar viewers will have similar substitution patterns.

If viewer *i* is a member of age/gender demographic group *d*, her utility of watching network *j* at time t is

$$U_{ijt} = x_{jt}\beta_i - q_{jt}\alpha_i + \xi_{djt} + \varepsilon_{ijt} \qquad \text{(A1)}$$

where β_i and α_i are random coefficients distributed according to

$$\begin{pmatrix}\alpha_i \\ \beta_i\end{pmatrix} = \begin{pmatrix}\alpha \\ \beta\end{pmatrix} + \Gamma D_i + \Lambda v_i \,, \qquad v_i \sim P_v^*(v)\,. \qquad \text{(A2)}$$

D_i is a vector of viewer demographics drawn from the conditional distribution described above, v_i is a vector of unobservable demographics, and α, β, Γ, and Λ are parameters to be estimated. $P_v^*(v)$ will be specified as a mean-zero multivariate distribution.

Each viewer is defined by a set of demographics and idiosyncratic preferences $(D_i, v_i, \varepsilon_{i\cdot t}) \equiv I_{it}$ in each time period (where $\varepsilon_{i\cdot t} = [\varepsilon_{i1t},..,\varepsilon_{iJt}]$), and utility maximization implicitly defines the set of individual attributes that lead viewers in demographic *d* to choose option *j* at time *t*:

$$A_{djt}(X_t, \xi_{d\cdot t}; \Gamma, \Lambda) = \{I_{it} \mid u_{ijt} > u_{ikt} \forall k = 1...J\} \quad \text{(A3)}$$

where X_t is a vector of observable program characteristics at time *t*, and $\xi_{d\cdot t}$ is a vector of the ξ_{djt}'s. If stochastic terms v_i, D_i, and ε_{ijt} are independent, then network *j*'s market share among demographic-*d* viewers at time *t* can be found by integrating over A_{djt},

$$s_{djt}(Xt, \xi dt; \Gamma, \Lambda) = \int_{A_{djt}} dP_\varepsilon^*(\varepsilon) dP_v^*(v) dP_D^*(D)\,. \quad \text{(A4)}$$

A procedure to estimate (A4), while accounting for the correlation of the *q*'s and the ξ's through a nonlinear approximation of instrumental variables techniques, is well established: see Berry, Levinsohn, and Pakes (1995) or Nevo (2000).

A1.2. *A Richer Model of the Market for Television Advertisements*

The primary objections to the model presented in sections 3.2 and 3.3 should be (a) it does not model advertiser substitution between similar audiences and (b) it does not model network/network or network/advertiser interaction in the market for television advertisements. These simplifications are made for a reason: if advertiser preferences are nonlinear in the number of viewers reached, then an advertiser's willingness to pay for any given audience is a function of the other audiences that advertiser purchases. So, unless we assume that audience purchases take place in some exogenously determined order, demand for any particular show is not well defined. In the economics literature, this is called a matching problem.

I present here a model of advertiser demand and advertiser/network interaction in which there is only one type of viewer, and advertisers care only about the number of exposures they purchase.[31] The generalization of this model to multiple viewer demographics is straightforward. Adding reach and frequency to advertiser preferences is possible.

Let there be *A* advertisers and *S* shows. Let n_a^s be the number of ads purchased by advertiser *a* on show *s*. Let N_a be the *S*-vector of the n_a^s's that describe advertiser *a*'s complete set of advertisement purchases, and let N^S be the *A*-vector of the n_a^s's that describe show *s*'s complete set

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[31] *Reach* is the number of viewers who see an advertiser's message, and *frequency* is the average number of times each viewer reached sees the message. Exposures=Reach*Frequency.

of advertisement sales. If advertiser *a* purchases one ad on a single show, *s*, I define the advertiser's utility as

$$U_a(q^s, L^s) = \psi_a V^s(q) + \zeta_a \left[V^s(q)\right]^2 \qquad \text{(A5)}$$

where q^s is the number of commercials sold during show *s*; *q* is a vector of the q^s's; $V^s(q^s)$ is the number of viewers watching show *s*; L^s is a *S*-dimensional vector whose t^{th} element l_t=1 if *t*=*s*, and 0 otherwise; and ψ_a and ζ_a are taste parameters that vary by advertiser.

If advertiser *a* purchases the set of shows described by N_a, its utility is

$$U_a(q, N_a) = \psi_a \sum_{s=1}^{S} n_a^s V^s(q) + \zeta_a \left[\sum_{s=1}^{S} n_a^s V^s(q)\right]^2, \qquad \text{(A6)}$$

and its reservation price for any show in its purchase vector N_a is given by that show's contribution to its utility U_a,

$$MU_a^s(q, N_a) = U_a(q, N_a) - U_a(q, N_a - L^s). \qquad \text{(A8)}$$

The dependence of (A8) on N_a shows that any advertiser's reservation price for any show depends on the other shows it purchases.

In Wilbur (2003) I proposed a matching algorithm to match advertisers to shows. The logic underlying the algorithm is simple: advertisers should be matched to those shows they value most; and shows should be matched first to those advertisers that value them most. The output of the matching algorithm will be a set of vectors N_a from whence advertisers' reservation prices for each show can be determined.

When placed in descending order, these reservation prices form a demand correspondence

$$p^s(q^s) = \{MU_1^s(q, N_1^s), \ldots, MU_A^s(q, N_A^s)\}\,. \qquad \text{(A9)}$$

After the matching algorithm has defined demand for each program, network *j*'s objective function can be written

$$\Pi_j = \max_{\{q^s\}_{s\in S_j}} \sum_{s\in S_j} q^s p^s(q^s) \qquad \text{(A10)}$$

where S_j is the set of shows aired on network *j*.

Iteration of networks' profit-maximizing choices of ad quantities and the matching algorithm will yield predicted ad quantities, prices, and ad purchases. The difference between these predictions and observed variables forms a moment condition that can be estimated with Method of Simulated Moments.

To reduce the number of parameters, I will assume that advertiser demand parameters come from a type-specific distribution (i.e., "auto" or "movie"), and I will estimate the means and variances of those distributions.

APPENDIX 2

It is not necessarily obvious how θ is separately identified from $\frac{\partial p}{\partial q}$. θ is identified by nonproportional shifts in demand. A simple example explains.

Consider the case of two firms operating in different markets. Both firms face inverse demand function $p(q)$ and produce at zero marginal cost. The firms differ only in their conduct: *M* is a monopolist, while *C* behaves competitively. When inverse demand is $p_1(q) = 1 - q$, the firms choose points M_1 and C_1. When demand rises to $p_2(q) = 2 - q$, the firms produce at M_2 and C_2, respectively. The angle between points M_1 and C_1 (or between M_2 and C_2) identifies the slope of demand, while the angle between M_1 and M_2, or between C_1 and C_2, identifies the market power parameter for each firm.

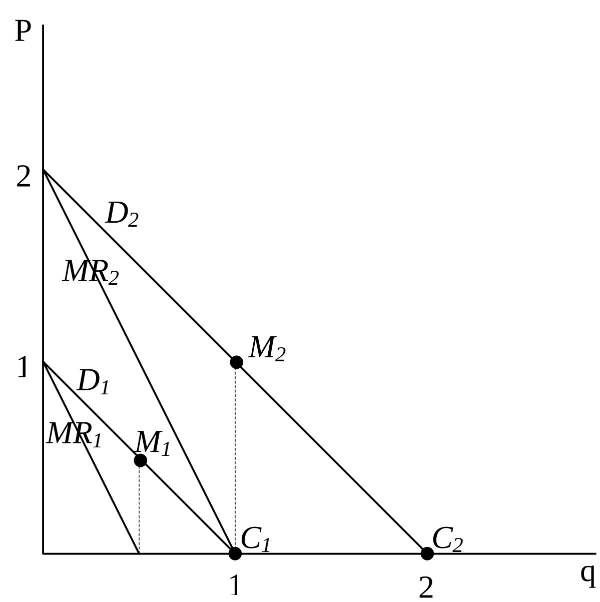


Table 1. Summary Statistics: Audience, Ad Price, and Adv Seconds, by Network and Demographic

	Universe	ABC	CBS	FOX	NBC	UPN	WB
Prime Time Half-Hours	176	176	176	120	176	80	104
Adv Seconds		310	308	307	309	320	301
		(71)	(83)	(78)	(75)	(75)	(71)
Adv Price (per 30 seconds, $000)		138	140	136	149	208	134
		(110)	(110)	(78)	(135)	(183)	(104)
CPM (Households, $)		26	20	27	22	75	48
		(24)	(18)	(22)	(26)	(72)	(41)
Households (000)	94736	5683	7920	6611	7965	2876	3223
		(1473)	(2651)	(4052)	(3443)	(800)	(1320)
People, 2+ (000)	242796	8908	12396	389	12141	4252	4978
		(2187)	(4492)	(274)	(5501)	(1354)	(2383)
Children, 2-5 (000)	13764	203	156	653	178	137	140
		(184)	(137)	(639)	(206)	(81)	(110)
Children, 6-11 (000)	21953	309	195	1000	198	225	254
		(246)	(190)	(687)	(245)	(152)	(150)
Teens, 12-17 (000)	21789	478	400	1224	438	459	647
		(189)	(259)	(874)	(326)	(229)	(335)
Adults, 18-24 (000)	23517	542	503	2132	740	475	686
		(230)	(296)	(1509)	(616)	(250)	(342)
Adults, 25-34 (000)	34384	1167	1119	3155	1783	788	882
		(517)	(784)	(2208)	(1372)	(369)	(512)
Adults, 35-49 (000)	57576	2352	2737	1608	3181	1176	1200
		(698)	(1434)	(1167)	(1739)	(465)	(531)
Adults, 50-64 (000)	40329	2026	3687	1379	3032	708	628
		(697)	(1134)	(780)	(1217)	(325)	(337)
Adults, 65+ (000)	39484	1830	3599	11540	2592	284	541
		(587)	(972)	(7729)	(1037)	(162)	(414)
Women, 18-24 (000)	11787	332	208	690	444	258	502
		(186)	(169)	(538)	(495)	(135)	(251)
Women, 25-34 (000)	17390	707	703	1163	1091	375	534
		(363)	(452)	(938)	(743)	(192)	(319)
Women, 35-49 (000)	29480	1442	1637	1808	2001	593	785
		(491)	(834)	(1432)	(1180)	(225)	(322)
Women, 50+ (000)	38189	1944	3769	1307	2761	453	627
		(592)	(957)	(1035)	(1039)	(192)	(497)
Working Women (000)	45424	1963	2518	2590	2960	882	1206
		(605)	(1083)	(1944)	(1573)	(375)	(583)
Men, 18-24 (000)	11727	182	142	510	228	260	204
		(86)	(128)	(369)	(204)	(222)	(160)
Men, 25-34 (000)	16998	510	568	914	742	366	319
		(200)	(384)	(573)	(499)	(242)	(201)
Men, 35-49 (000)	28093	933	1089	1358	1196	643	441
		(277)	(599)	(829)	(642)	(361)	(244)
Men, 50+ (000)	31633	1254	2281	1107	1857	436	389
		(448)	(780)	(647)	(728)	(266)	(153)

Sources: Nielsen Media Research; TNS Media Intelligence/CMR

Table 2. Variable Descriptions and Descriptive Statistics

variable name	description	mean	st. dev.
Adv Seconds	Seconds of national advertisements aired during the program	308.7	(75.6)
Lead-in	The size of the network's audience in the previous half-hour		
Lead-out	The size of the network's audience in the subsequent half-hour		
ABC, CBS, FOX, NBC, UPN, WB	Network-specific dummy variables		
Mon, Tue, Wed, Thu, Fri, Sat, Sun	Day-specific dummy variables		
7pmEST, 8pmEST, 9pmEST, 10pmEST	Start time-specific dummy variables		
ActionDrama	=1 if the show is a scripted drama that frequently contains action scenes (i.e. chase or fight scenes)	0.13	(0.33)
PsychologicalDrama	=1 if the show is a scripted drama that does not contain action scenes	0.30	(0.46)
Reality	=1 if the show is unscripted	0.14	(0.35)
News	=1 if the show is a news program or a newsmagazine	0.09	(0.28)
Movie	=1 if the show is a movie	0.13	(0.34)
African-American	=1 if at least one African-American main character	0.44	(0.14)
Other NonWhite	=1 if at least one non-White, non-African American main character	0.50	(0.35)
<18 years old	=1 if at least one main character is under 18	0.17	(0.37)
18-34	=1 if at least one main character is between 18 and 34	0.68	(0.47)
Over 50	=1 if at least one main character is over 50 years old	0.28	(0.45)
Married	=1 if at least one main character is married	0.16	(0.36)
Single Parent	=1 if at least one main character is single and has children	0.08	(0.27)
Female Only	=1 if none of the main characters are male	0.11	(0.31)
Male Only	=1 if none of the main characters are female	0.21	(0.41)
50+% NonWhite	=1 if 50% or more of the show's cast is non-White	0.14	(0.35)
25+% NonWhite	=1 if 25-49% of the show's cast is non-White	0.23	(0.42)
10+% NonWhite	=1 if 10-24% of the show's cast is non-White	0.23	(0.42)
50+%Female	=1 if 50% or more of the show's cast is female	0.42	(0.50)
25+%Female	=1 if 25-49% of the show's cast is female	0.36	(0.48)
House	=1 if the show's main set is a character's house	0.18	(0.38)
Apartment	=1 if the show's main set is a character's apartment	0.05	(0.21)
Workplace	=1 if the show's main set is some type of business or	0.37	(0.48)
Studio	=1 if the show's main set is in a TV studio (not a stage)	0.25	(0.44)
Cop	=1 if the show has some law enforcement element	0.22	(0.41)
Sci-Fi	=1 if the show contains elements of science fiction (i.e. Star Trek)	0.04	(0.19)
Supernatural	=1 if the show contains supernatural elements (i.e. angels, witchcraft, "Twilight Zone," etc.)	0.08	(0.28)
SeasonFirstAired	Year the show debuted on TV (or the year the movie was released)	1999	(5.40)
2003 Emmy Noms	2004 Emmy Nominations	1.25	(2.72)
Past Emmy Noms	All pre-2004 Emmy Nominations	4.11	(13.20)
American Idol	=1 if the show is American Idol	0.02	(0.15)

Table 3. Viewer Demand Parameter Estimates, Households and Persons

		Households			Persons, 2+		
		coeff.	s.e.		coeff.	s.e.	
Adv Seconds	Adv Seconds	-0.0003	(8.9E-5)	**	-0.0003	(9.6E-5)	**
	Lead-in Audience	7.0E-5	(3.7E-6)	**	3.6E-5	(2.1E-6)	**
audience flow	Lead-out Audience	5.9E-5	(3.5E-6)	**	4.2E-5	(2.3E-6)	**
	ABC	-0.0275	(0.0226)		-0.0181	(0.0244)	
	FOX	-0.1286	(0.0282)	**	-0.1302	(0.0299)	**
	NBC	-0.1005	(0.0216)	**	-0.1284	(0.0233)	**
	UPN	-0.3159	(0.0358)	**	-0.4122	(0.0379)	**
network effects	WB	-0.3245	(0.0340)	**	-0.3848	(0.0361)	**
	7pmEST	-0.2847	(0.0359)	**	-0.3207	(0.0390)	**
	9pmEST	0.0651	(0.0159)	**	0.0070	(0.0174)	
hour effects	10pmEST	-0.0582	(0.0223)	**	-0.0282	(0.0239)	
	Mon	0.0540	(0.0249)	*	0.0255	(0.0270)	
	Tue	0.1067	(0.0250)	**	0.0444	(0.0270)	
	Wed	0.0818	(0.0250)	**	0.0278	(0.0270)	
	Thu	0.0264	(0.0273)		-0.1259	(0.0293)	**
	Fri	-0.1508	(0.0256)	**	-0.1890	(0.0279)	**
day effects	Sat	-0.2476	(0.0307)	**	-0.2489	(0.0331)	**
	ActionDrama	-0.0020	(0.0302)		-0.0226	(0.0327)	
	PsychologicalDrama	0.0808	(0.0260)	**	0.0721	(0.0282)	*
	Reality	0.0293	(0.0272)		0.0207	(0.0295)	
	News	-0.0044	(0.0362)		-0.0243	(0.0393)	
genre	Movie	-0.0976	(0.0233)	**	-0.1236	(0.0252)	**
	African-American	0.0515	(0.0232)	*	0.0857	(0.0252)	**
	Other NonWhite	0.0254	(0.0223)		0.0226	(0.0242)	
	<18 years old	-0.0258	(0.0263)		-0.0173	(0.0285)	
	18-34	0.0129	(0.0202)		0.0201	(0.0220)	
	Over 50	0.0196	(0.0177)		-0.0054	(0.0191)	
	Married	-0.0150	(0.0302)		0.0086	(0.0328)	
	Single Parent	0.0113	(0.0318)		0.0458	(0.0345)	
Main Character	Female Only	-0.0214	(0.0256)		0.0094	(0.0277)	
Demographics	Male Only	0.0544	(0.0250)	*	0.0887	(0.0272)	**
	50+% NonWhite	-0.1186	(0.0288)	**	-0.1770	(0.0313)	**
	25-49% NonWhite	-0.0345	(0.0270)		-0.0554	(0.0293)	
	10-24% NonWhite	-0.0621	(0.0219)	**	-0.0882	(0.0237)	**
Whole-Cast	50+%Female	0.0281	(0.0212)		0.0108	(0.0230)	
Demographics	25-49%Female	0.1023	(0.0224)	**	0.1012	(0.0243)	**
	House	0.0718	(0.0268)	**	0.0960	(0.0291)	**
	Apartment	0.0705	(0.0414)		0.0989	(0.0448)	*
	Workplace	-0.0365	(0.0206)		-0.0311	(0.0224)	
Setting	Studio	0.0516	(0.0286)		0.0659	(0.0310)	*
	Cop	-0.0345	(0.0228)		-0.0130	(0.0248)	
	Sci-Fi	0.0988	(0.0414)	*	0.0836	(0.0449)	
	Supernatural	-0.0203	(0.0279)		0.0059	(0.0303)	
	SeasonFirstAired	-0.0033	(0.0015)	*	-0.0047	(0.0016)	**
	2003 Emmy Nominations	0.0042	(0.0037)		0.0057	(0.0040)	
Other	Past Emmy Nominations	0.0021	(0.0006)	**	0.0024	(0.0007)	**
Characteristics	American Idol	0.2060	(0.0674)	**	0.1864	(0.0734)	*
	Constant	3.4996	(3.0245)		5.5783	(3.2911)	
	R^2	0.9123			0.9028		

* Significant at the 5% level
** Significant at the 1% level
Number of observations = 832

Table 4a. Viewer Demand Parameter Estimates, by Viewer Age Group

		Kids, 2-5			Kids, 6-11			Teens, 12-17			Adults, 18-24		
		coeff.	s.e.		coeff.	s.e.		coeff.	s.e.		coeff.	s.e.	
Adv Seconds	Adv Seconds	-0.0009	(0.0004)	*	-0.0004	(0.0002)		-0.0006	(0.0001)	**	-5.0E-5	(0.0002)	
aud. flow	Lead-in	0.0018	(0.0002)	**	0.0008	(6.2E-5)	**	0.0006	(3.8E-5)	**	0.0005	(3.3E-5)	**
	Lead-out	0.0011	(0.0002)	**	0.0009	(7.5E-5)	**	0.0006	(3.7E-5)	**	0.0006	(3.6E-5)	**
network effects	ABC	0.2344	(0.0900)	**	0.3746	(0.0581)	**	0.2154	(0.0350)	**	0.1307	(0.0386)	**
	FOX	0.3565	(0.1162)	**	0.2687	(0.0740)	**	0.1409	(0.0468)	**	0.1021	(0.0517)	*
	NBC	0.1422	(0.0890)		-0.0729	(0.0573)		0.0022	(0.0346)		-0.0050	(0.0387)	
	UPN	0.1923	(0.1223)		-0.0005	(0.0784)		0.0815	(0.0472)		0.0375	(0.0526)	
	WB	-0.1066	(0.1143)		0.1156	(0.0731)		0.1979	(0.0444)	**	0.1698	(0.0490)	**
hour effects	7pmEST	-0.9192	(0.1501)	**	-0.4240	(0.0965)	**	-0.4393	(0.0579)	**	-0.1676	(0.0641)	**
	9pmEST	-0.4926	(0.0690)	**	-0.2866	(0.0431)	**	-0.1104	(0.0269)	**	0.0372	(0.0289)	
	10pmEST	-0.6372	(0.0914)	**	-0.7240	(0.0582)	**	-0.2476	(0.0356)	**	0.0227	(0.0396)	
day effects	Mon	-0.3715	(0.1050)	**	-0.1459	(0.0669)	*	-0.0455	(0.0402)		0.0137	(0.0444)	
	Tue	-0.3147	(0.1052)	**	-0.3360	(0.0670)	**	-0.0703	(0.0402)		-0.1280	(0.0445)	**
	Wed	-0.2694	(0.1038)	**	-0.5741	(0.0664)	**	-0.1798	(0.0400)	**	-0.0889	(0.0445)	*
	Thu	-0.1078	(0.1106)		-0.1250	(0.0713)		0.0591	(0.0428)		-0.0060	(0.0479)	
	Fri	0.1210	(0.1064)		-0.1248	(0.0688)		-0.1319	(0.0416)	**	-0.1778	(0.0457)	**
	Sat	-0.4735	(0.1277)	**	-0.4799	(0.0807)	**	-0.3241	(0.0482)	**	-0.2789	(0.0530)	**
genre	ActionDrama	-0.1243	(0.1252)		-0.2073	(0.0807)	**	-0.1392	(0.0487)	**	-0.1378	(0.0539)	*
	PsychDrama	0.1920	(0.1079)		-0.0739	(0.0700)		0.0327	(0.0419)		0.0933	(0.0465)	*
	Reality	0.2705	(0.1126)	*	0.2059	(0.0725)	**	0.1409	(0.0439)	**	0.1363	(0.0486)	**
	News	-0.8830	(0.1482)	**	-0.5258	(0.0958)	**	-0.4018	(0.0576)	**	-0.0899	(0.0642)	
	Movie	-0.0375	(0.0961)		-0.1479	(0.0621)	*	0.0182	(0.0375)		-0.0610	(0.0417)	
Main Char Demos	African-American	0.1833	(0.0972)		0.1833	(0.0624)	**	0.1710	(0.0375)	**	0.0580	(0.0412)	
	Other NonWhite	0.0010	(0.0923)		0.1566	(0.0596)	**	0.0262	(0.0359)		-0.0267	(0.0398)	
	<18 years old	-0.0118	(0.1092)		0.0229	(0.0705)		0.0747	(0.0428)		0.0048	(0.0471)	
	18-34	-0.1632	(0.0842)		-0.0496	(0.0542)		-0.0173	(0.0329)		-0.0064	(0.0365)	
	Over 50	-0.3494	(0.0732)	**	-0.1489	(0.0471)	**	-0.0866	(0.0284)	**	-0.1195	(0.0315)	**
	Married	0.2486	(0.1253)	*	0.1356	(0.0806)		0.0653	(0.0487)		-0.0205	(0.0542)	
	Single Parent	0.1917	(0.1326)		0.0636	(0.0850)		0.1012	(0.0512)	*	0.0819	(0.0568)	
	Female Only	0.1438	(0.1060)		0.0933	(0.0683)		0.0399	(0.0411)		-0.0138	(0.0456)	
	Male Only	-0.0789	(0.1045)		0.1456	(0.0674)	*	0.1031	(0.0407)	*	0.1301	(0.0449)	**
Whole-Cast Demos	50+%NonWhite	-0.5416	(0.1203)	**	-0.3405	(0.0774)	**	-0.2807	(0.0466)	**	-0.1906	(0.0513)	**
	25-49%NonWhite	-0.1251	(0.1145)		-0.0714	(0.0729)		-0.0557	(0.0438)		-0.0487	(0.0483)	
	10-24%NonWhite	-0.0553	(0.0911)		-0.0757	(0.0587)		-0.1069	(0.0353)	**	-0.0973	(0.0390)	*
	50+%Female	-0.0041	(0.0866)		-0.0132	(0.0561)		0.0604	(0.0338)		0.1072	(0.0376)	**
	25-49%Female	0.1104	(0.0936)		0.0837	(0.0600)		0.0916	(0.0362)	*	0.0625	(0.0401)	
Setting	House	0.0600	(0.1108)		0.1184	(0.0717)		0.0956	(0.0433)	*	0.0765	(0.0478)	
	Apartment	0.2482	(0.1714)		0.3126	(0.1101)	**	0.1223	(0.0667)		-0.0250	(0.0747)	
	Workplace	0.1030	(0.0856)		-0.0631	(0.0550)		0.0220	(0.0333)		0.0880	(0.0370)	*
	Studio	0.3150	(0.1183)	**	0.0544	(0.0766)		0.0795	(0.0462)		-0.0194	(0.0513)	
Other Char	Cop	-0.2995	(0.0944)	**	-0.1789	(0.0609)	**	-0.0511	(0.0367)		0.0581	(0.0409)	
	Sci-Fi	-0.3710	(0.1715)	*	0.1056	(0.1106)		0.0013	(0.0667)		0.0858	(0.0739)	
	Supernatural	0.0665	(0.1153)		0.1091	(0.0746)		-0.0023	(0.0449)		-0.0666	(0.0498)	
	SeasonFirstAired	0.0079	(0.0062)		0.0007	(0.0040)		-0.0024	(0.0024)		0.0016	(0.0027)	
	2003 Emmy Nom.	-0.0074	(0.0148)		0.0184	(0.0096)		0.0194	(0.0058)	**	0.0050	(0.0064)	
	Past Emmy Nom.	-0.0016	(0.0026)		-0.0011	(0.0017)		-0.0005	(0.0010)		0.0020	(0.0011)	
	American Idol	-0.6318	(0.2734)	*	-0.2548	(0.1883)		-0.2594	(0.1125)	*	-0.0425	(0.1265)	
	Constant	-20.1956	12.3587)		-6.0289	(7.9351)		0.5183	(4.7848)		-7.5704	(5.3304)	
	R^2	0.6219			0.7908			0.8424			0.8123		

* Significant at the 5% level

** Significant at the 1% level

Number of observations = 832

Table 4b. Viewer Demand Parameter Estimates, by Viewer Age Group

		Adults, 25-34		Adults, 35-49		Adults, 50-64		Adults, 65+	
		coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
Adv Seconds	Adv Seconds	-0.0006	(0.0001) **	-0.0002	(0.0001)	-0.0003	(0.0001) *	-0.0006	(0.0003) *
aud. flow	Lead-in	0.0002	(1.5E-5) **	0.0001	(8.0E-6) **	0.0002	(1.2E-5) **	0.0002	(3.1E-5) **
	Lead-out	0.0003	(1.7E-5) **	0.0002	(9.2E-6) **	0.0002	(1.3E-5) **	0.0002	(3.2E-5) **
network effects	ABC	0.1993	(0.0345) **	0.0679	(0.0265) *	-0.0970	(0.0371) **	-0.0761	(0.0893)
	FOX	0.1554	(0.0440) **	-0.0615	(0.0330)	-0.4858	(0.0507) **	-0.3402	(0.1176) **
	NBC	0.0501	(0.0352)	-0.0552	(0.0263) *	-0.1979	(0.0340) **	-0.0343	(0.0822)
	UPN	0.0396	(0.0480)	-0.3456	(0.0397) **	-0.7092	(0.0587) **	-1.7265	(0.1507) **
	WB	-0.0054	(0.0447)	-0.3683	(0.0373) **	-0.8468	(0.0588) **	-1.2727	(0.1432) **
hour effects	7pmEST	-0.5996	(0.0574) **	-0.3731	(0.0438) **	-0.2153	(0.0540) **	-0.1578	(0.1136)
	9pmEST	0.0907	(0.0258) **	0.0474	(0.0197) *	0.0898	(0.0236) **	-0.1269	(0.0493) **
	10pmEST	0.0619	(0.0355)	0.0256	(0.0276)	-0.0018	(0.0324)	-0.0991	(0.0676)
day effects	Mon	-0.0356	(0.0397)	0.0364	(0.0304)	0.1296	(0.0374) **	0.2797	(0.0789) **
	Tue	0.0203	(0.0398)	0.0578	(0.0305)	0.1571	(0.0374) **	-0.0486	(0.0793)
	Wed	-0.0968	(0.0398) *	-0.0009	(0.0305)	0.0803	(0.0373) *	0.1372	(0.0791)
	Thu	-0.0839	(0.0431)	-0.0895	(0.0332) **	0.0036	(0.0402)	0.0950	(0.0843)
	Fri	-0.4062	(0.0411) **	-0.2402	(0.0313) **	-0.0013	(0.0386)	0.0505	(0.0809)
	Sat	-0.5523	(0.0482) **	-0.3174	(0.0368) **	0.0132	(0.0458)	-0.0814	(0.0966)
genre	ActionDrama	-0.2066	(0.0484) **	-0.0765	(0.0370) *	0.2354	(0.0452) **	0.1928	(0.0953) *
	PsychDrama	0.0567	(0.0415)	0.0693	(0.0317) *	0.2215	(0.0394) **	0.2572	(0.0823) **
	Reality	0.1556	(0.0434) **	0.0823	(0.0332) *	0.0846	(0.0411) *	-0.1230	(0.0859)
	News	-0.2065	(0.0579) **	-0.0387	(0.0443)	0.0417	(0.0534)	0.0866	(0.1130)
	Movie	-0.0789	(0.0372) *	-0.1502	(0.0284) **	-0.1033	(0.0349) **	-0.1913	(0.0734) **
Main Char Demos	African-American	0.0897	(0.0370) *	0.0837	(0.0284) **	0.0905	(0.0348) **	-0.0953	(0.0730)
	Other NonWhite	0.0470	(0.0356)	0.0379	(0.0272)	0.1002	(0.0334) **	-0.1159	(0.0701)
	<18 years old	-0.0492	(0.0419)	-0.0660	(0.0321) *	-0.0155	(0.0393)	0.1491	(0.0825)
	18-34	-0.0297	(0.0325)	-0.0219	(0.0247)	-0.1669	(0.0305) **	0.0873	(0.0641)
	Over 50	-0.0516	(0.0281)	-0.0202	(0.0215)	0.0668	(0.0269) *	0.1924	(0.0571) **
	Married	-0.0136	(0.0485)	0.0129	(0.0369)	0.0042	(0.0454)	-0.1393	(0.0954)
	Single Parent	-0.0573	(0.0510)	0.0096	(0.0388)	0.1766	(0.0478) **	0.1559	(0.1005)
	Female Only	0.0012	(0.0408)	0.0239	(0.0312)	-0.0617	(0.0384)	-0.1485	(0.0807)
	Male Only	-0.0340	(0.0400)	0.0737	(0.0305) *	-0.0847	(0.0374) *	0.2974	(0.0787) **
Whole-Cast Demos	50+%NonWhite	-0.2611	(0.0464) **	-0.1576	(0.0354) **	-0.0684	(0.0425)	-0.2581	(0.0901) **
	25-49%NonWhite	0.0136	(0.0434)	-0.0044	(0.0329)	0.0545	(0.0405)	-0.0939	(0.0852)
	10-24%NonWhite	-0.0247	(0.0351)	-0.0723	(0.0268) **	-0.1393	(0.0328) **	-0.1506	(0.0689) *
	50+%Female	-0.0205	(0.0337)	-0.0184	(0.0258)	-0.0182	(0.0316)	0.2494	(0.0660) **
	25-49%Female	0.0758	(0.0358) *	0.0837	(0.0273) **	0.0174	(0.0336)	0.0896	(0.0705)
Setting	House	0.1040	(0.0428) *	0.1083	(0.0327) **	0.0529	(0.0403)	0.0818	(0.0846)
	Apartment	0.0116	(0.0667)	0.1139	(0.0505) *	0.0849	(0.0622)	-0.1420	(0.1303)
	Workplace	-0.0695	(0.0331) *	-0.0443	(0.0253)	0.0398	(0.0311)	-0.1836	(0.0650) **
	Studio	0.0582	(0.0460)	-0.0119	(0.0352)	0.2114	(0.0429) **	0.0695	(0.0901)
Other Char	Cop	0.0350	(0.0365)	-0.0241	(0.0279)	-0.0770	(0.0345) *	0.1408	(0.0721)
	Sci-Fi	0.2070	(0.0660) **	0.2332	(0.0504) **	-0.0655	(0.0623)	0.2578	(0.1310) *
	Supernatural	0.0014	(0.0446)	0.0320	(0.0342)	0.0146	(0.0419)	0.3156	(0.0880) **
	SeasonFirstAired	-0.0082	(0.0024) **	-0.0030	(0.0018)	0.0014	(0.0022)	-0.0030	(0.0049)
	2003 Emmy Nom.	0.0074	(0.0058)	0.0133	(0.0045) **	0.0214	(0.0054) **	0.0254	(0.0113) *
	Past Emmy Nom.	0.0025	(0.0010) *	0.0022	(0.0008) **	-0.0003	(0.0009)	0.0024	(0.0020)
	American Idol	-0.3216	(0.1100) **	0.0449	(0.0834)	0.2880	(0.0968) **	0.9289	(0.2028) **
	Constant	12.6918	(4.7982) **	2.4848	(3.6556)	-6.2094	(4.4936)	2.3494	(9.8964)
	R^2	0.8676		0.8950		0.9057		0.7951	

* Significant at the 5% level
** Significant at the 1% level
Number of observations = 832

Table 5a. Viewer Demand Parameter Estimates, by Viewers' Gender and Age

		Women, 18-24 coeff.	s.e.	Women, 25-34 coeff.	s.e.	Women, 35-49 coeff.	s.e.	Women, 50+ coeff.	s.e.
Adv Seconds	Adv Seconds	-0.0005	(0.0004)	-0.0002	(0.0002)	-0.0004	(0.0001) **	-0.0005	(0.0002) **
	Lead-in	0.0007	(0.0001) **	0.0004	(2.8E-5) **	0.0002	(1.2E-5) **	0.0002	(1.8E-5) **
aud. flow	Lead-out	0.0007	(0.0001) **	0.0005	(3.0E-5) **	0.0003	(1.4E-5) **	0.0002	(1.9E-5) **
	ABC	0.7862	(0.1043) **	0.1269	(0.0365) **	0.0631	(0.0253) *	0.0201	(0.0541)
	FOX	0.7248	(0.1366) **	0.0694	(0.0459)	-0.1140	(0.0317) **	-0.4752	(0.0759) **
	NBC	0.4564	(0.1050) **	-0.0296	(0.0372)	-0.0713	(0.0251) **	-0.1396	(0.0500) **
network	UPN	0.4791	(0.1404) **	-0.2259	(0.0518) **	-0.5087	(0.0388) **	-0.9021	(0.0917) **
effects	WB	0.9793	(0.1330) **	-0.1304	(0.0473) **	-0.2861	(0.0354) **	-0.9353	(0.0891) **
	7pmEST	-0.9451	(0.1712) **	-0.4334	(0.0606) **	-0.4570	(0.0418) **	-0.0786	(0.0733)
hour	9pmEST	0.0039	(0.0759)	0.0991	(0.0272) **	0.0625	(0.0187) **	-0.0295	(0.0317)
effects	10pmEST	-0.0696	(0.1039)	0.0862	(0.0376) *	0.0405	(0.0261)	-0.0946	(0.0435) *
	Mon	0.0850	(0.1187)	-0.0149	(0.0420)	0.0979	(0.0292) **	0.3388	(0.0511) **
	Tue	-0.2978	(0.1190) *	0.0448	(0.0421)	0.0961	(0.0292) **	0.2573	(0.0513) **
	Wed	-0.2895	(0.1201) *	-0.0689	(0.0423)	-0.0378	(0.0293)	0.2031	(0.0511) **
	Thu	0.0460	(0.1294)	-0.3709	(0.0454) **	-0.0796	(0.0321) *	-0.0710	(0.0547)
day	Fri	-0.3365	(0.1215) **	-0.4017	(0.0432) **	-0.2254	(0.0297) **	0.1415	(0.0520) **
effects	Sat	-1.1301	(0.1405) **	-0.4500	(0.0510) **	-0.3704	(0.0349) **	0.1284	(0.0616) *
	ActionDrama	-0.6746	(0.1439) **	-0.1933	(0.0510) **	-0.0780	(0.0352) *	0.2560	(0.0615) **
	PsychDrama	0.1967	(0.1242)	0.2136	(0.0439) **	0.0747	(0.0303) *	0.3048	(0.0537) **
	Reality	0.1781	(0.1298)	0.1254	(0.0459) **	0.1210	(0.0317) **	0.0765	(0.0557)
	News	-0.7570	(0.1710) **	-0.0250	(0.0610)	-0.0810	(0.0423)	0.1644	(0.0724) *
genre	Movie	0.1469	(0.1114)	-0.0877	(0.0393) *	-0.1432	(0.0272) **	-0.1526	(0.0474) **
	African-American	-0.1574	(0.1099)	0.1062	(0.0392) **	0.1317	(0.0271) **	0.1360	(0.0472) **
	Other NonWhite	0.0231	(0.1064)	0.0664	(0.0376)	0.0123	(0.0259)	0.0783	(0.0454)
	<18 years old	-0.1087	(0.1254)	-0.0863	(0.0443)	-0.0910	(0.0305) **	0.0473	(0.0534)
	18-34	-0.3380	(0.0971) **	0.0022	(0.0342)	-0.0632	(0.0236) **	-0.0672	(0.0413)
	Over 50	-0.3176	(0.0840) **	-0.0492	(0.0297)	0.0125	(0.0205)	0.0924	(0.0371) *
	Married	-0.0324	(0.1444)	-0.0584	(0.0511)	-0.0074	(0.0352)	-0.0921	(0.0616)
Main	Single Parent	-0.0223	(0.1524)	0.0207	(0.0539)	0.0310	(0.0371)	0.2529	(0.0649) **
Char	Female Only	0.2113	(0.1220)	-0.0770	(0.0433)	0.0080	(0.0298)	-0.0924	(0.0522)
Demos	Male Only	-0.0540	(0.1192)	-0.0246	(0.0421)	0.0020	(0.0290)	-0.0531	(0.0509)
	50+%NonWhite	-0.0942	(0.1359)	-0.1461	(0.0485) **	-0.1038	(0.0335) **	-0.0857	(0.0577)
	25-49%NonWhite	0.1640	(0.1297)	-0.1052	(0.0458) *	-0.0514	(0.0314)	-0.0584	(0.0550)
Whole-	10-24%NonWhite	0.1200	(0.1042)	-0.0974	(0.0371) **	-0.1003	(0.0257) **	-0.2551	(0.0445) **
Cast	50+%Female	-0.0121	(0.1005)	0.0449	(0.0360)	0.0202	(0.0247)	0.0928	(0.0430) *
Demos	25-49%Female	-0.2220	(0.1068) *	0.0978	(0.0378) **	0.0690	(0.0261) **	0.0329	(0.0457)
	House	0.0947	(0.1278)	0.1065	(0.0453) *	0.1152	(0.0312) **	0.0624	(0.0548)
	Apartment	0.2598	(0.2020)	0.1246	(0.0709)	0.2146	(0.0483) **	0.1543	(0.0844)
	Workplace	0.0783	(0.0993)	-0.0744	(0.0350) *	0.0022	(0.0241)	0.0150	(0.0422)
Setting	Studio	-0.0689	(0.1375)	0.0900	(0.0485)	-0.0037	(0.0335)	0.2164	(0.0582) **
	Cop	0.3547	(0.1094) **	-0.0143	(0.0387)	-0.0317	(0.0266)	-0.0980	(0.0466) *
	Sci-Fi	-0.0678	(0.1972)	0.2348	(0.0698) **	0.2030	(0.0482) **	-0.2053	(0.0849) *
	Supernatural	-0.2074	(0.1333)	-0.0763	(0.0471)	-0.0469	(0.0326)	0.0597	(0.0569)
	SeasonFirstAired	-0.0104	(0.0071)	-0.0025	(0.0025)	-0.0027	(0.0017)	0.0033	(0.0031)
	2003 Emmy Nom.	0.0166	(0.0172)	0.0127	(0.0062) *	0.0136	(0.0043) **	0.0324	(0.0073) **
Other	Past Emmy Nom.	0.0041	(0.0030)	0.0018	(0.0011)	0.0008	(0.0007)	-0.0010	(0.0013)
Char	American Idol	0.2240	(0.3360)	-0.1790	(0.1157)	0.1372	(0.0804)	0.3929	(0.1317) **
	Constant	16.9344	14.2239)	1.3484	(5.0511)	2.1404	(3.4840)	-10.2644	(6.1874)
	R^2	0.6176		0.8584		0.9121		0.8780	

* Significant at the 5% level
** Significant at the 1% level
Number of observations = 832

Table 5b. Viewer Demand Parameter Estimates, by Viewers' Gender and Age

		Men, 18-24		Men, 25-34		Men, 35-49		Men, 50+	
		coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
Adv Seconds	Adv Seconds	-0.0006	(0.0005)	-0.0004	(0.0003)	-0.0002	(0.0001)	-0.0002	(0.0002)
	Lead-in	0.0014	(0.0003) **	0.0005	(7.9E-5) **	0.0003	(2.4E-5) **	0.0002	(3.4E-5) **
aud. flow	Lead-out	0.0012	(0.0003) **	0.0006	(8.3E-5) **	0.0004	(2.6E-5) **	0.0003	(3.7E-5) **
	ABC	0.9065	(0.1345) **	0.0446	(0.0723)	0.0823	(0.0318) **	-0.2023	(0.0675) **
	FOX	0.6402	(0.1854) **	0.0475	(0.0916)	-0.0537	(0.0393)	-0.3969	(0.0882) **
	NBC	0.3205	(0.1349) *	0.0593	(0.0724)	-0.0440	(0.0315)	-0.1178	(0.0628)
network	UPN	0.3409	(0.1846)	-0.5240	(0.1006) **	-0.1445	(0.0450) **	-1.0954	(0.1073) **
effects	WB	0.7946	(0.1701) **	-0.1887	(0.0958) *	-0.4188	(0.0440) **	-0.8977	(0.1063) **
	7pmEST	-1.1667	(0.2233) **	-0.1498	(0.1200)	-0.4452	(0.0526) **	-0.0730	(0.0988)
hour	9pmEST	0.1285	(0.1003)	0.1952	(0.0539) **	0.0304	(0.0239)	0.1478	(0.0430) **
effects	10pmEST	0.0659	(0.1357)	0.1093	(0.0740)	-0.0118	(0.0332)	0.0369	(0.0589)
	Mon	0.1379	(0.1553)	-0.1543	(0.0833)	-0.0523	(0.0364)	-0.0255	(0.0685)
	Tue	-0.1120	(0.1552)	-0.0030	(0.0833)	0.0245	(0.0365)	0.1024	(0.0686)
	Wed	0.0873	(0.1543)	-0.0028	(0.0829)	-0.0417	(0.0365)	0.1275	(0.0682)
	Thu	0.0703	(0.1652)	0.1815	(0.0907) *	-0.0336	(0.0393)	0.2250	(0.0739) **
day	Fri	-0.3952	(0.1602) *	-0.3688	(0.0867) **	-0.2453	(0.0380) **	0.0285	(0.0709)
effects	Sat	-0.7844	(0.1851) **	-0.2910	(0.1012) **	-0.3027	(0.0445) **	-0.0008	(0.0848)
	ActionDrama	-0.7218	(0.1870) **	-0.2206	(0.1016) *	-0.0497	(0.0443)	0.1109	(0.0829)
	PsychDrama	-0.0218	(0.1617)	-0.0526	(0.0870)	0.0247	(0.0381)	0.0416	(0.0718)
	Reality	-0.0175	(0.1714)	0.1960	(0.0908) *	0.0429	(0.0398)	0.0736	(0.0749)
	News	-0.3168	(0.2212)	-0.2435	(0.1212) *	-0.0709	(0.0530)	-0.0002	(0.0976)
genre	Movie	0.0137	(0.1448)	-0.1291	(0.0777)	-0.1198	(0.0341) **	-0.0655	(0.0639)
	African-American	0.2629	(0.1430)	-0.0639	(0.0777)	0.0980	(0.0341) **	-0.0777	(0.0637)
	Other NonWhite	0.2540	(0.1377)	0.0391	(0.0747)	0.0758	(0.0326) *	0.0376	(0.0612)
	<18 years old	-0.3504	(0.1627) *	0.2001	(0.0880) *	-0.1017	(0.0384) **	0.2607	(0.0719) **
	18-34	-0.1449	(0.1273)	0.0025	(0.0680)	-0.0278	(0.0298)	-0.0376	(0.0557)
	Over 50	-0.3649	(0.1098) **	-0.1119	(0.0589)	-0.0403	(0.0258)	0.0129	(0.0491)
	Married	0.1142	(0.1890)	-0.0812	(0.1016)	0.0848	(0.0444)	-0.0934	(0.0831)
Main	Single Parent	0.4070	(0.1974) *	-0.4117	(0.1066) **	0.0946	(0.0466) *	-0.2833	(0.0875) **
Char	Female Only	0.2764	(0.1583)	0.0631	(0.0853)	0.0757	(0.0373) *	0.0744	(0.0702)
Demos	Male Only	0.1409	(0.1576)	0.1164	(0.0837)	0.0988	(0.0367) **	0.0394	(0.0685)
	50+%NonWhite	-0.6498	(0.1791) **	-0.2542	(0.0972) **	-0.2699	(0.0428) **	-0.1193	(0.0780)
	25-49%NonWhite	0.0636	(0.1689)	0.1859	(0.0904) *	-0.0033	(0.0396)	0.2419	(0.0742) **
Whole-	10-24%NonWhite	-0.4807	(0.1356) **	0.0577	(0.0732)	-0.0653	(0.0320) *	-0.0277	(0.0600)
Cast	50+%Female	-0.2500	(0.1295)	0.0398	(0.0703)	-0.0844	(0.0306) **	-0.0266	(0.0576)
Demos	25-49%Female	-0.1209	(0.1397)	0.0790	(0.0749)	0.1086	(0.0327) **	0.0235	(0.0614)
	House	0.4162	(0.1674) *	0.2047	(0.0896) *	0.1126	(0.0393) **	0.1277	(0.0739)
	Apartment	0.1464	(0.2561)	-0.4212	(0.1380) **	-0.0105	(0.0603)	-0.4540	(0.1135) **
	Workplace	-0.0451	(0.1281)	0.1584	(0.0699) *	-0.0891	(0.0302) **	0.1446	(0.0566) *
Setting	Studio	-0.0286	(0.1770)	0.2396	(0.0964) *	-0.0114	(0.0419)	0.2840	(0.0785) **
	Cop	0.3449	(0.1415) *	0.0084	(0.0762)	-0.0015	(0.0334)	-0.0253	(0.0631)
	Sci-Fi	0.5309	(0.2575) *	0.6002	(0.1381) **	0.2127	(0.0605) **	0.2721	(0.1138) *
	Supernatural	0.1148	(0.1729)	0.1383	(0.0935)	0.1071	(0.0410) **	0.2432	(0.0767) **
	SeasonFirstAired	0.0099	(0.0093)	-0.0051	(0.0050)	-0.0040	(0.0022)	0.0017	(0.0042)
	2003 Emmy Nom.	0.0562	(0.0220) *	0.0179	(0.0122)	0.0035	(0.0053)	0.0320	(0.0099) **
Other	Past Emmy Nom.	0.0007	(0.0039)	0.0065	(0.0021) **	0.0035	(0.0009) **	0.0039	(0.0017) *
Char	American Idol	-0.4299	(0.4184)	-0.2699	(0.2247)	-0.0672	(0.0978)	0.1786	(0.1773)
	Constant	-24.6558	18.5829)	6.1363	10.0299)	4.1320	(4.3917)	-7.2490	(8.3148)
	R^2	0.5162		0.6353		0.8622		0.7623	

* Significant at the 5% level
** Significant at the 1% level
Number of observations = 832

Table 6. Average Predicted Audience Losses Accruing to an Additional 30-second Commercial, by Demographic and Network*

	All Nets	ABC	CBS	FOX	NBC	UPN	WB
Households (000)	-44.3	-41.5	-56.0	-46.6	-55.9	-21.7	-24.1
	(21.0)	(10.1)	(16.7)	(25.0)	(21.6)	(5.9)	(9.5)
People, 2+ (000)	-103.8	-96.9	-133.6	-120.0	-126.7	-44.6	-53.6
	(54.0)	(22.6)	(42.8)	(72.0)	(52.2)	(14.3)	(26.7)
Children, 2-5 (000)	-5.2	-5.3	-4.1	-9.9	-4.6	-3.6	-3.7
	(5.0)	(4.6)	(3.5)	(6.7)	(5.1)	(2.1)	(2.8)
Children, 6-11 (000)	-3.1	-3.3	-2.1	-6.7	-2.1	-2.4	-2.7
	(3.5)	(2.6)	(2.0)	(6.2)	(2.5)	(1.6)	(1.6)
Teens, 12-17 (000)	-8.6	-7.6	-6.4	-15.3	-7.0	-7.3	-10.2
	(6.1)	(2.9)	(4.0)	(9.7)	(5.0)	(3.6)	(5.1)
Adults, 18-24 (000)	-1.0	-0.8	-0.7	-1.7	-1.0	-0.7	-1.0
	(0.7)	(0.3)	(0.4)	(1.1)	(0.8)	(0.4)	(0.5)
Adults, 25-34 (000)	-21.0	-18.6	-17.7	-32.1	-27.1	-12.7	-14.1
	(15.2)	(7.8)	(11.8)	(20.4)	(19.0)	(5.8)	(7.9)
Adults, 35-49 (000)	-14.1	-13.7	-15.7	-17.7	-18.0	-7.0	-7.1
	(8.3)	(3.9)	(7.7)	(11.1)	(9.1)	(2.7)	(3.1)
Adults, 50-64 (000)	-17.0	-15.8	-27.5	-12.5	-22.9	-5.7	-5.1
	(10.4)	(5.1)	(7.5)	(8.6)	(8.3)	(2.6)	(2.7)
Adults, 65+ (000)	-33.8	-31.8	-59.6	-24.1	-43.9	-5.2	-9.7
	(21.9)	(9.7)	(14.5)	(12.9)	(16.3)	(2.9)	(7.3)
Women, 18-24 (000)	-5.3	-4.6	-2.9	-9.0	-5.8	-3.6	-6.8
	(4.6)	(2.5)	(2.3)	(6.2)	(6.0)	(1.8)	(3.2)
Women, 25-34 (000)	-5.4	-4.9	-4.8	-7.6	-7.3	-2.7	-3.7
	(3.8)	(2.4)	(2.9)	(5.4)	(4.4)	(1.3)	(2.2)
Women, 35-49 (000)	-16.3	-16.1	-18.0	-19.3	-21.5	-6.8	-9.0
	(10.0)	(5.2)	(8.5)	(13.5)	(11.5)	(2.5)	(3.6)
Women, 50+ (000)	-30.0	-28.4	-52.3	-19.1	-39.3	-6.9	-9.4
	(19.1)	(8.2)	(11.8)	(14.4)	(13.5)	(2.9)	(7.3)
Working Women (000)	-22.3	-20.5	-25.8	-25.9	-29.8	-9.4	-12.8
	(12.9)	(6.0)	(10.3)	(17.5)	(14.4)	(3.9)	(6.0)
Men, 18-24 (000)	-4.0	-3.1	-2.4	-8.3	-3.8	-4.3	-3.5
	(3.7)	(1.4)	(2.1)	(5.7)	(3.3)	(3.6)	(2.6)
Men, 25-34 (000)	-7.5	-6.6	-7.2	-11.3	-9.3	-4.7	-4.1
	(5.1)	(2.5)	(4.6)	(6.5)	(5.8)	(3.1)	(2.5)
Men, 35-49 (000)	-4.3	-4.1	-4.7	-5.8	-5.2	-2.9	-2.0
	(2.5)	(1.2)	(2.5)	(3.3)	(2.7)	(1.6)	(1.1)
Men, 50+ (000)	-9.7	-8.9	-15.7	-7.9	-12.9	-3.2	-2.9
	(5.9)	(3.0)	(4.9)	(4.4)	(4.7)	(1.9)	(1.1)

* Holding competing programs' advertising levels constant

Table 7. Average Predicted Audience Gains in the Absence of Advertisements, by Demographic and Network*

	All Nets	ABC	CBS	FOX	NBC	UPN	WB
Households (000)	331.1	364.0	394.4	290.7	449.5	148.2	155.1
	(201.4)	(153.8)	(162.9)	(189.0)	(242.3)	(63.2)	(78.2)
People, 2+ (000)	915.8	990.4	1097.8	959.6	1169.7	386.8	439.8
	(558.5)	(387.9)	(458.4)	(660.1)	(631.0)	(154.5)	(250.9)
Children, 2-5 (000)	55.1	64.7	40.7	95.1	50.5	38.7	37.2
	(56.4)	(59.4)	(36.4)	(70.2)	(66.1)	(22.2)	(30.9)
Children, 6-11 (000)	31.0	37.6	19.8	62.0	20.8	23.9	25.9
	(36.0)	(31.2)	(19.9)	(65.0)	(25.8)	(16.4)	(16.8)
Teens, 12-17 (000)	81.9	85.3	57.3	133.0	68.9	68.7	91.1
	(60.5)	(42.5)	(37.8)	(95.9)	(56.1)	(35.1)	(49.7)
Adults, 18-24 (000)	8.6	8.0	6.0	13.7	9.7	5.9	8.2
	(6.8)	(4.4)	(3.6)	(10.2)	(8.6)	(3.3)	(4.3)
Adults, 25-34 (000)	186.4	195.0	143.5	254.7	254.9	106.1	111.8
	(150.7)	(111.5)	(100.8)	(185.0)	(204.1)	(56.5)	(68.6)
Adults, 35-49 (000)	120.3	134.5	124.5	132.5	161.7	56.6	54.4
	(81.7)	(58.5)	(69.4)	(95.3)	(100.1)	(27.8)	(27.6)
Adults, 50-64 (000)	138.9	145.8	213.1	85.5	197.3	45.5	36.5
	(98.0)	(65.2)	(82.2)	(68.9)	(97.6)	(28.1)	(22.7)
Adults, 65+ (000)	293.4	313.6	492.9	174.9	398.6	41.4	74.6
	(217.0)	(139.6)	(184.6)	(111.1)	(200.5)	(27.3)	(63.6)
Women, 18-24 (000)	47.8	48.7	23.7	72.8	56.0	31.8	56.6
	(44.8)	(32.5)	(18.6)	(56.0)	(63.8)	(19.0)	(29.3)
Women, 25-34 (000)	45.2	48.2	37.2	55.3	65.0	20.8	27.4
	(36.6)	(29.5)	(24.2)	(44.4)	(48.3)	(12.1)	(17.1)
Women, 35-49 (000)	135.7	157.1	138.2	137.5	189.2	53.3	65.9
	(97.1)	(75.7)	(73.9)	(110.2)	(122.3)	(26.9)	(33.7)
Women, 50+ (000)	251.1	269.0	418.8	129.8	345.0	54.7	69.3
	(183.5)	(115.2)	(153.1)	(112.5)	(165.3)	(27.8)	(60.8)
Working Women (000)	187.6	200.4	202.0	187.5	266.2	75.3	95.0
	(127.8)	(91.2)	(94.4)	(144.2)	(162.6)	(39.4)	(51.8)
Men, 18-24 (000)	39.8	35.1	22.4	76.8	39.6	43.5	31.7
	(38.0)	(20.4)	(21.9)	(58.6)	(36.6)	(37.0)	(24.4)
Men, 25-34 (000)	67.3	68.9	60.5	91.8	87.9	40.0	34.3
	(49.9)	(33.6)	(40.8)	(61.3)	(63.0)	(28.2)	(21.8)
Men, 35-49 (000)	38.1	41.5	39.1	46.0	47.5	24.6	15.7
	(25.1)	(17.6)	(23.2)	(29.9)	(29.3)	(15.8)	(9.1)
Men, 50+ (000)	84.0	86.6	128.4	58.3	117.1	26.4	22.5
	(58.2)	(39.4)	(52.3)	(38.5)	(57.2)	(18.6)	(11.0)

* Assuming no changes in competing networks' ad levels

Table 8. Advertiser Demand Parameter Estimates (Various Specifications)

Dependent Variable: Ad Price

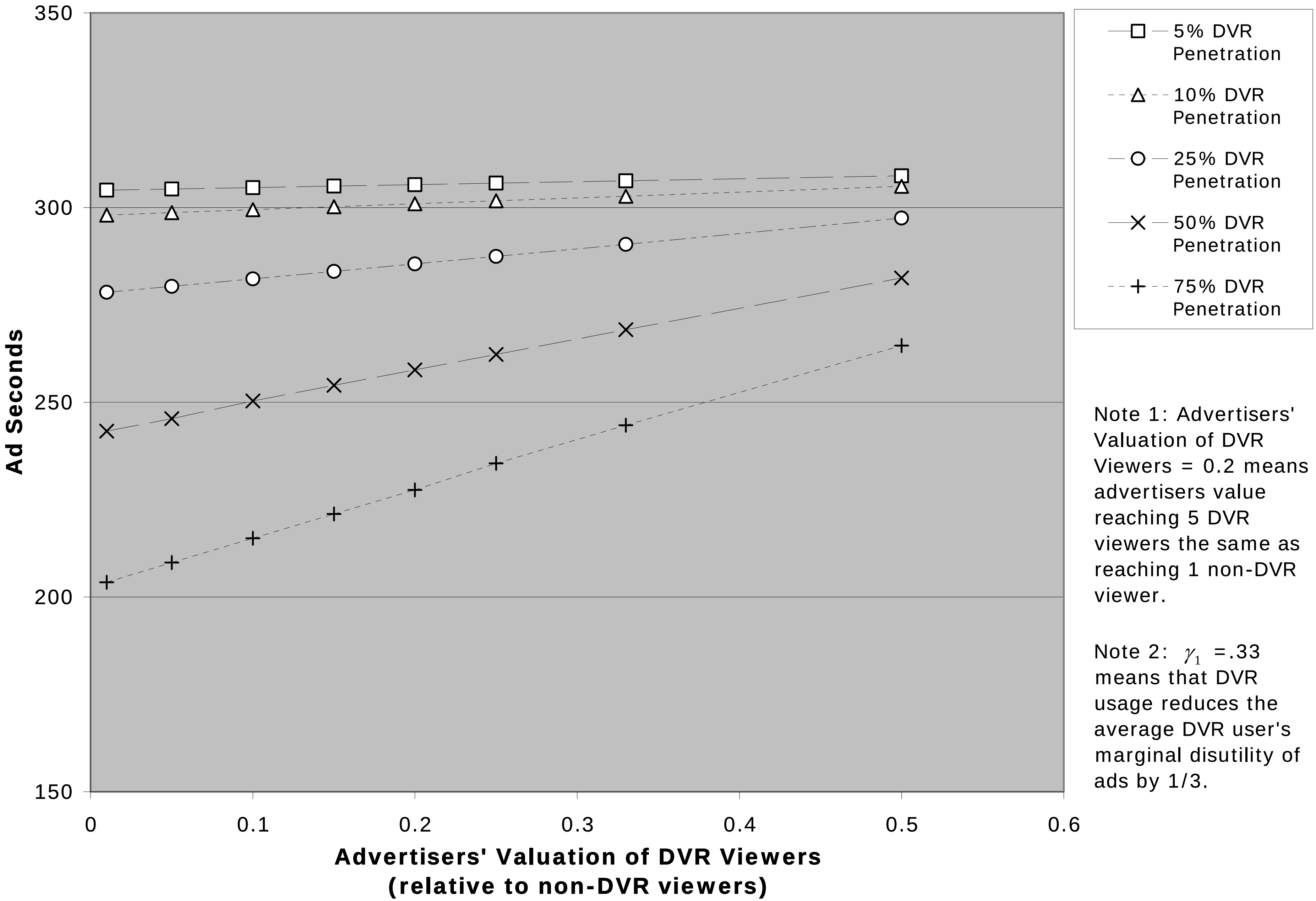
		Specification 1	Spec. 2	Spec. 3	Spec. 4	Spec. 5	Spec. 6
Adv Seconds	Adv seconds	-304.97 *	-256.42	-352.97 *	-432.79 **	-528.57 **	-603.02 **
		(139.48)	(139.84)	(143.67)	(166.90)	(147.10)	(167.34)
Audience	Audience (Households)	30.56 **	22.37 **	31.14 **	30.21 **	29.56 **	28.66 **
		(1.13)	(5.27)	(1.23)	(1.26)	(1.22)	(1.28)
	Audience^2		5.14E-4				
			(3.2E-4)				
Audience Composition, by Age Group	People, 18-24			-5.87e+5 *		-5.42e+5 *	
				(2.4e+5)		(2.3e+5)	
	People, 25-34			3.21e+4		1.52e+5	
				(1.4e+5)		(1.5e+5)	
	People, 35-49			1.15e+5		1.75e+4	
				(1.3e+5)		(1.3e+5)	
	People, 50-64			-3.60e+5 **		-2.30e+5 *	
				(8.8e+4)		(9.3e+4)	
	People, 65+			-1.74e+5		-1.76e+5	
				(9.4e+4)		(9.3e+4)	
Audience Composition, by Gender / Age Group	Women, 18-24				-2.14e+5		-1.97e+5
					(2.2e+5)		(2.1e+5)
	Women, 25-34				9.21e+4		5.25e+5 *
					(2.3e+5)		(2.3e+5)
	Women, 35-49				6.95e+5 **		4.46e+5
					(2.5e+5)		(2.3e+5)
	Working Women				-1.23e+5		-2.64e+5
					(2.6e+5)		(2.5e+5)
	Men, 18-24				6.03e+5		7.47e+4
					(3.2e+5)		(3.2e+5)
	Men, 25-34				5.78e+5 *		3.94e+5
					(2.4e+5)		(2.3e+5)
	Men, 35-49				1.43e+5		1.45e+5
					(2.0e+5)		(2.0e+5)
Observed Program Character-istics	Scripted Comedy					3.99e+4 **	5.04e+4 **
						(9.3e+3)	(9.3e+3)
	Single Parent					-1.59e+4	-1.50e+4
						(1.3e+4)	(1.3e+4)
	50+% NonWhite Cast					-6.94e+3	-6.52e+3
						(9.9e+3)	(9.9e+3)
	Past Emmy Nominations					1.19e+3 **	1.15e+3 **
						(2.3e+2)	(2.4e+2)
	Constant	6.05e+4	7.08e+4	1.95e+5 *	-3.99e+4	2.20e+5 **	6.18e+4
		(4.43e+4)	(4.38e+4)	(8.8e+4)	(5.9e+4)	(8.4e+4)	(6.1e+4)
	R^2	0.657	0.672	0.717	0.701	0.742	0.732

* Significant at the 5% level
** Significant at the 1% level
Number of Observations=375

Table 9. Market Power Inferences, by network

	Advertiser Demand Specification 5	Advertiser Demand Specification 6
Industry	0.80	0.70
ABC	0.58	0.51
CBS	0.93	0.82
FOX	1.24	1.09
NBC	1.08	0.94
UPN	0.29	0.26
WB	0.37	0.32

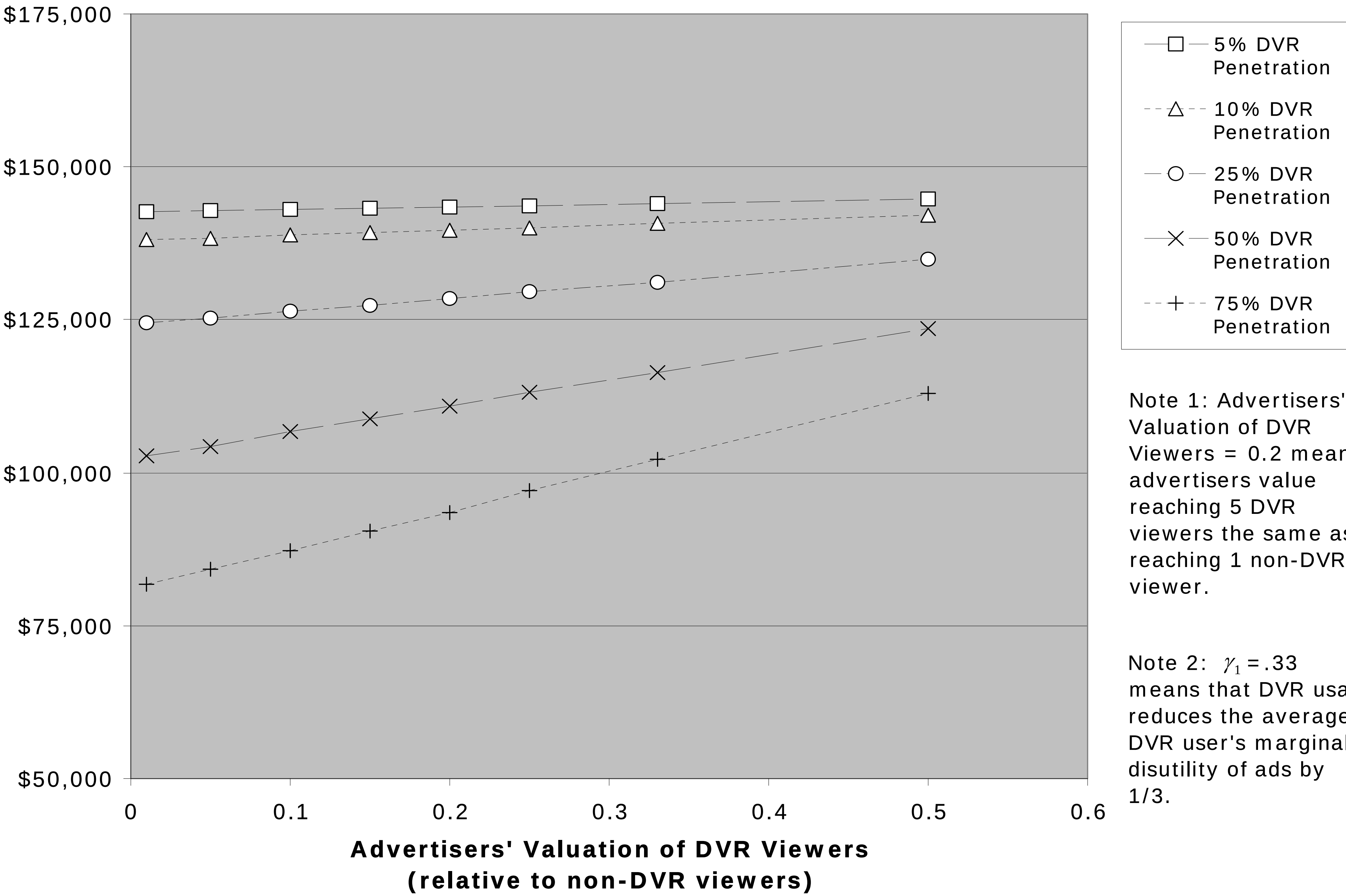
Figure 1. Predicted Clutter per Network Half-hour, by DVR Viewer Valuation (γ_1 =.33, γ_2 =1)



Note 1: Advertisers' Valuation of DVR Viewers = 0.2 means advertisers value reaching 5 DVR viewers the same as reaching 1 non-DVR viewer.

Note 2: γ_1 =.33 means that DVR usage reduces the average DVR user's marginal disutility of ads by 1/3.

Figure 2. Average Predicted Ad Price per 30-Second Spot, by DVR Viewer Valuation (γ_1=.33, γ_2=1)



Note 1: Advertisers' Valuation of DVR Viewers = 0.2 means advertisers value reaching 5 DVR viewers the same as reaching 1 non-DVR viewer.

Note 2: γ_1 =.33 means that DVR usage reduces the average DVR user's marginal disutility of ads by 1/3.

Figure 3. Adjusted Costs Per Thousand Households (γ_1=.33, γ_2=1)

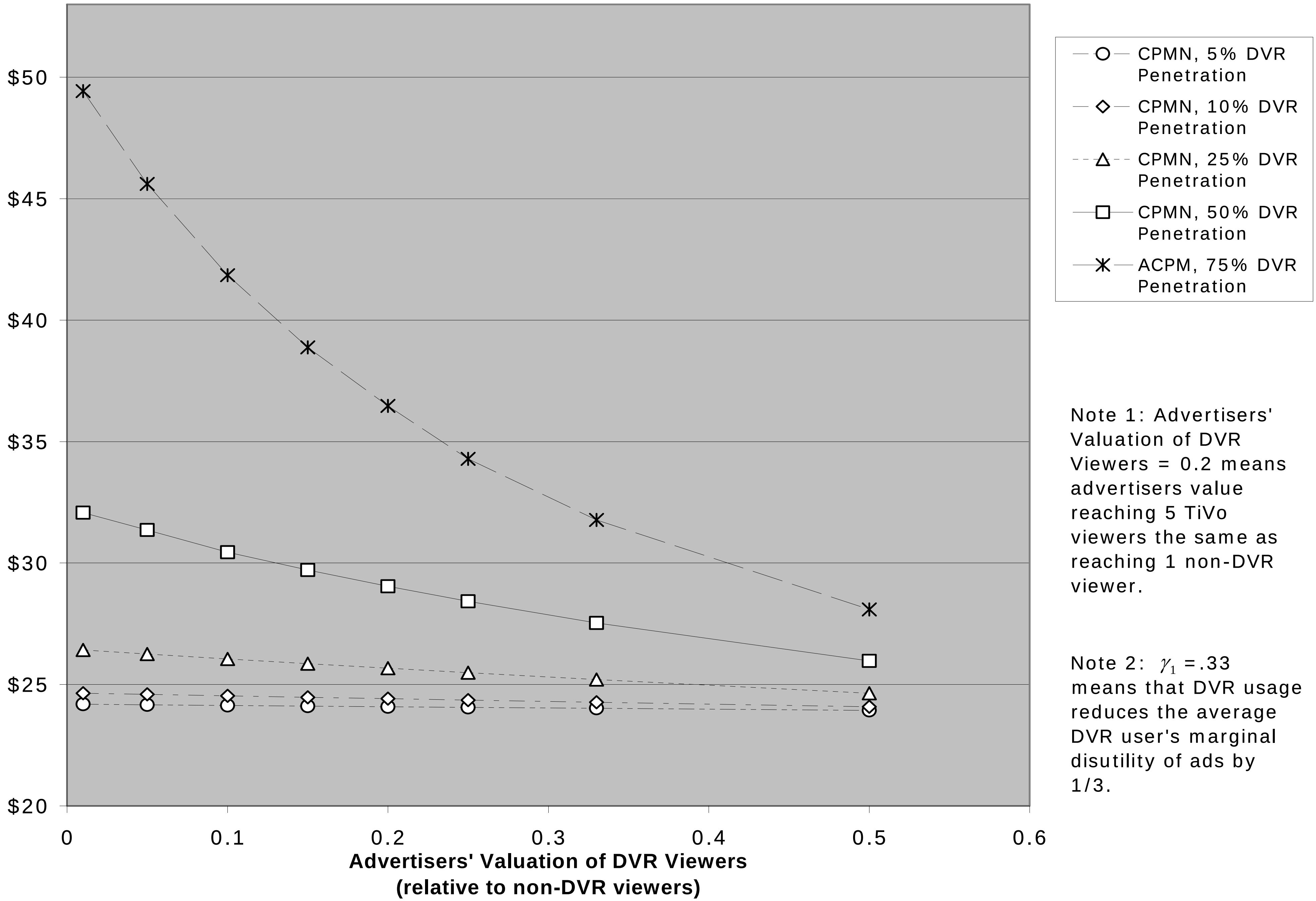
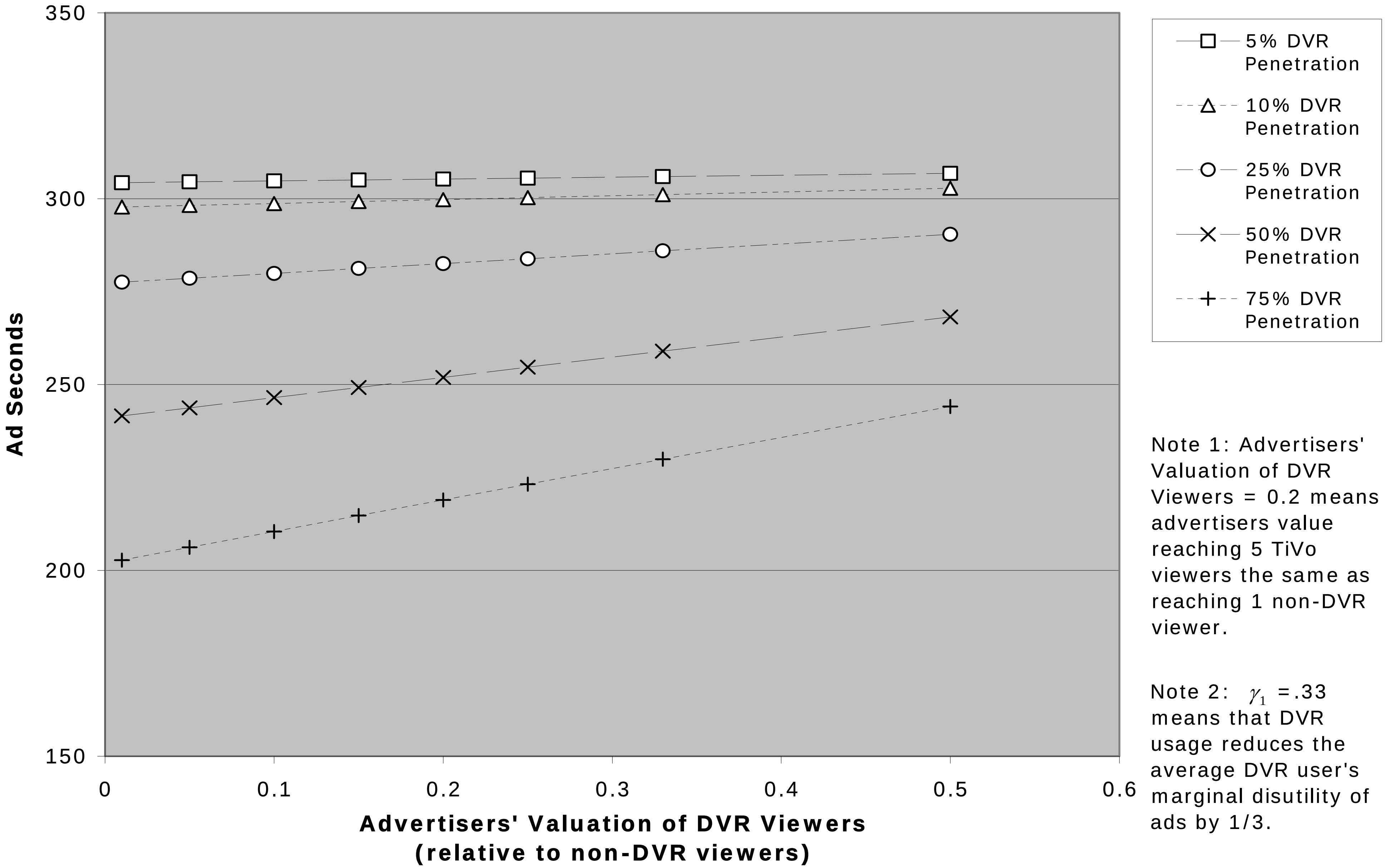


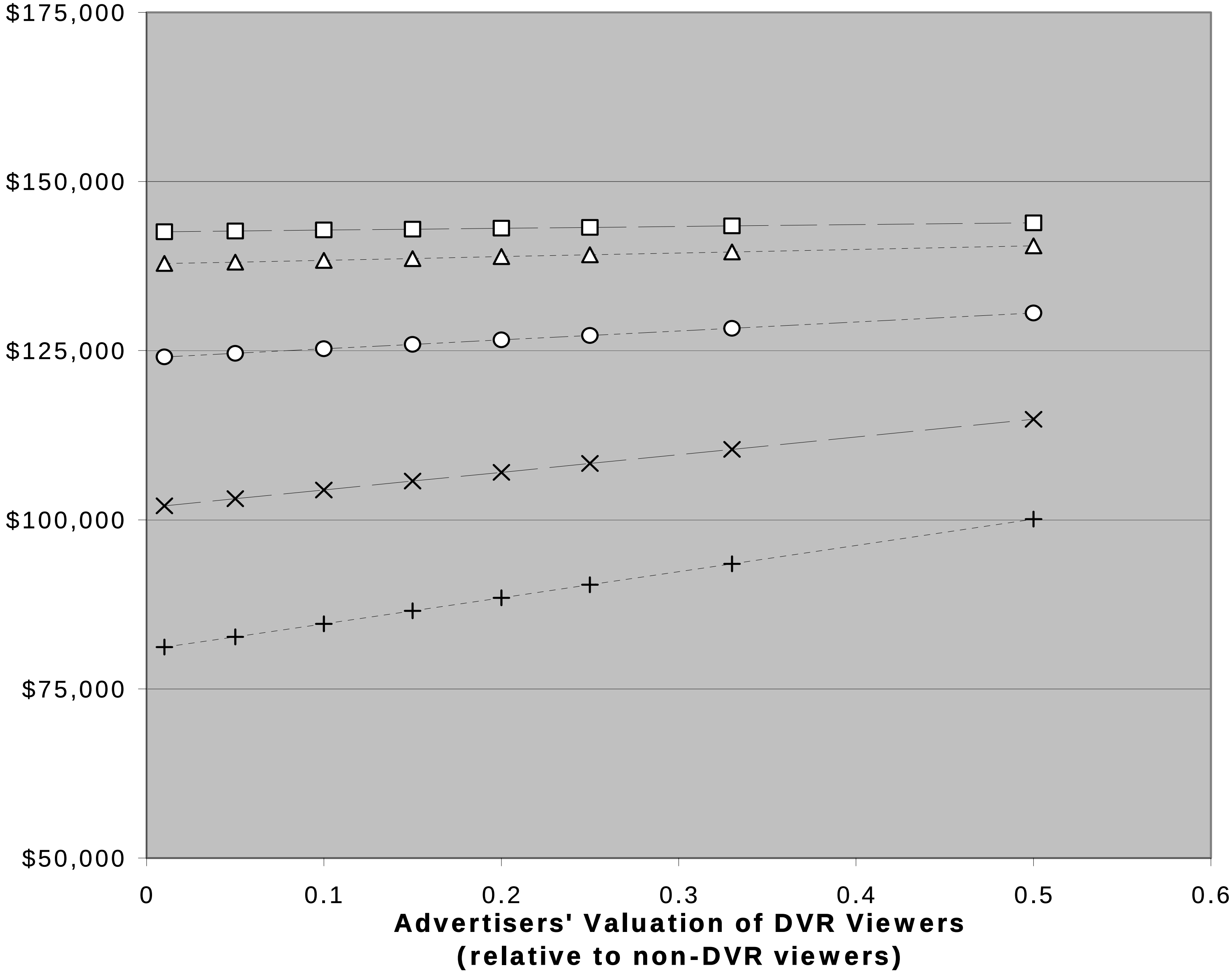
Figure 4. Predicted Clutter per Network Half-hour, by DVR Viewer Valuation (γ_1=.33, γ_2=.5)



Note 1: Advertisers' Valuation of DVR Viewers = 0.2 means advertisers value reaching 5 TiVo viewers the same as reaching 1 non-DVR viewer.

Note 2: γ_1 =.33 means that DVR usage reduces the average DVR user's marginal disutility of ads by 1/3.

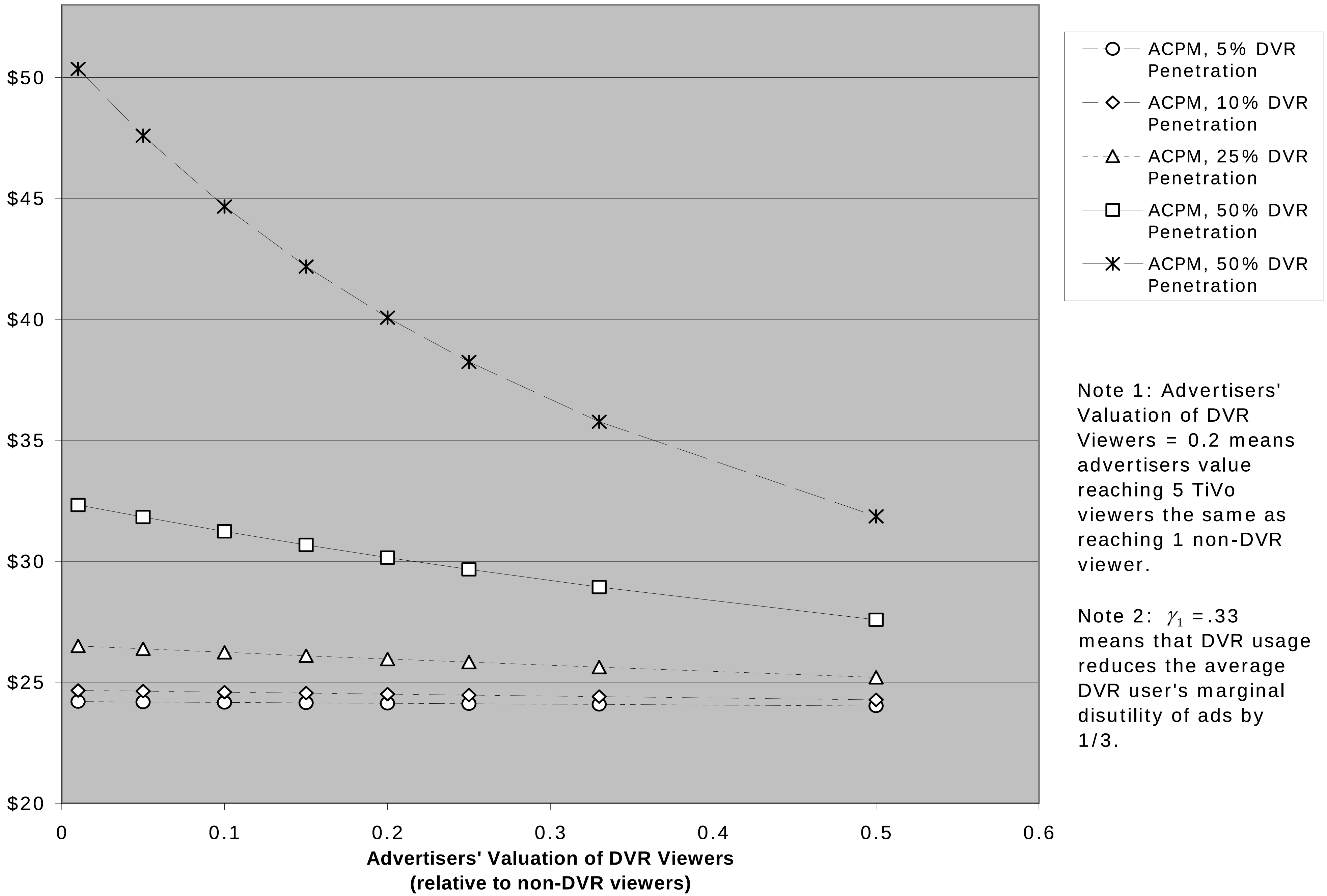
Figure 5. Average Predicted Ad Price per 30-Second Spot, by DVR Viewer Valuation (γ_1=.33, γ_2=.5)



Note 1: Advertisers' Valuation of DVR Viewers = 0.2 means advertisers value reaching 5 TiVo viewers the same as reaching 1 non-DVR viewer.

Note 2: γ_1 =.33 means that DVR usage reduces the average DVR user's marginal disutility of ads by 1/3.

Figure 6. Adjusted Costs Per Thousand Households (γ_1=.33, γ_2=.5)



Note 1: Advertisers' Valuation of DVR Viewers = 0.2 means advertisers value reaching 5 TiVo viewers the same as reaching 1 non-DVR viewer.

Note 2: γ_1 =.33 means that DVR usage reduces the average DVR user's marginal disutility of ads by 1/3.