

The Role of Paid and Earned Media in Building Entertainment Brands: Reminding, Informing, and Enhancing Enjoyment*

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We study the role of social engagement and advertising in building entertainment brands. We develop a structural model of viewing behaviors and apply the model to a new television program setting using a data set that contains both viewing and stated expectations and experiences. We use this model to not only assess the relative impact of advertising exposures and social engagement, but also to distinguish multiple roles that advertising and social engagement might play—reminding (i.e., activating memory), informing (i.e., learning about the quality of the program), or enhancing enjoyment (i.e., gaining additional utility from socializing about the program). We present descriptive analyses and results from our structural model, both of which indicate that advertising effects are largely due to reminding, that social engagement effects are due to a combination of reminding and enhancing enjoyment, and that information comes primarily watching episodes. Our results imply that the average effect of paid media is four times larger than that of earned media, but that if earned media strategies can expand the proportion of frequent socializers, it can have a profound effect on viewership.

Key words: Social engagement, informative effects, reminder effects, entertainment brands, word-of-mouth, Bayesian learning, earned media

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1. Introduction

In recent years word-of-mouth marketing and social engagement with brands have received growing attention from both practitioners and scholars, and increasingly tactics involving social media marketing, brand communities, and buzz agents have become key ingredients to building brands (Iezzi 2010, Keller and Fay 2012). While advertising agencies are frequently hired to create campaigns with “paid” (advertising) and “earned” (word-of-mouth, social media buzz, or publicity) media, the benefits of these earned media strategies is surprisingly unclear with notable anecdotes leaving a disconnect between successful social engagements and successful business outcomes (Keller and Fay 2012, Bollinger et al. 2013).

In this study, we estimate the relative effectiveness of social engagement and advertising. Further, we distinguish three roles that social engagement and advertising can play—reminding, informing, and enhancing enjoyment. Consider the context of this study, television program choices. Reminding occurs when a cue (e.g., commercial) makes the program more salient in a person’s memory and thereby makes the program more likely to be considered for viewing. Informing occurs when the cue provides a signal about how well the brand will match the individual’s tastes. The third role, enhancing enjoyment, involves anticipating future experiences that will be better because one watches the program. In particular, we focus on the enjoyment one anticipates from socializing about the program with others.

We incorporate these three fundamental roles into a structural model of viewing choices, including delayed viewing decisions. We apply the model to data on viewing, social engagement, advertising exposures, and stated expectations. To obtain these data, we follow a panel of over 1700 individuals for seven weeks as they make viewing decisions about a new TV show. We obtain initial beliefs about the program as well as weekly reports of beliefs, cues (advertising, socializing), and viewing.

These data allow us to separate the reminding, informing, and enhancing enjoyment roles without relying purely on functional form assumptions used in the past. For informing effects, we use the correlations between the arrival of cues and the stated expectations, which also implies a relationship between the cues and viewing decisions. The remaining relationship between the cues and viewing decisions is attributed to the reminding role. For the enhancing enjoyment role, socializing more (seeing more ads) gives greater utility than socializing less, and so does watching earlier for a given level of socializing. Hence, we identify the enhancing enjoyment effect of socializing by how early the frequent socializers watch the program compared to the infrequent socializers.

We provide model free evidence, and structural model estimates, and counterfactual analyses that are all consistent. We find that social engagement and advertising have a negligible role in informing individuals about how well the show matches with their tastes, but have a significant role in reminding individuals to watch the program. Social engagements enhance enjoyment through socializing about the program and that this effect is approximately equal in size to the reminding role, whereas advertising does not enhance enjoyment. We find that individuals learn about how much they like the show primarily through viewing experiences. Finally, although we don't account for the cost of increasing social engagement or advertising, the effect of increasing social engagement is generally much smaller than that of advertising. Nonetheless, our results also indicate that increasing the social engagement of an individual can profoundly affect their viewing, and as a result, total viewing. These results suggests that social engagement can be a fundamental means of developing entertainment brands.

These results can shed light on managerial actions such as the allocation of resources between social engagement and traditional advertising efforts. Moreover, the roles shed

light on what kinds of specific strategies may be most useful. Since in our context advertising effects are largely to remind the viewer, advertisements that draw attention and are memorable should be more important than ones that contain information. Similarly, broad-based social engagement strategies may be less valuable than ones focused on attracting highly socially engaged viewers.

2. Relationship to Literature

Our study builds on several related literatures. The first two aim to distinguish various effects of advertising: (1) informative and persuasive effects and (2) direct choice effects and indirect effects that operate through memory, awareness, or consideration. We link these two literatures by using new data to distinguish between reminding and informative effects. We also evaluate these roles for socializing about the show, adding to a third literature on social engagement. Finally, because of the context of our study, we add to the literature on TV viewing choices (Goettler and Shachar 2001) by incorporating into the model the delayed viewing of a program. This extension is important since delayed viewing has become a significant component of viewership for some TV genres (Carter 2011).

2.1. Persuasive and informative effects of advertising

Whereas an active stream of research focuses on pure informative effects (e.g., Szymanowski and Gijbrecchts 2012, Roos 2012), our work is more related to a stream that distinguishes between informative and persuasive (also referred to as prestige, image, or reminding) effects. Akerberg (2001) originally argues that informative effects influence those with limited category experience, whereas those with more category experience are unlikely to be informed by advertising. In contrast, a persuasive effect could influence any individual. This literature has largely used only revealed preference data. Consequently, informative effects are identified by assuming diminishing effects as more signals are received and

attributing the remaining (relatively constant) effects to be persuasive effects. Multiple studies (Ackerberg 2003, 2001, Mehta et al. 2008, Byzalov and Shachar 2004) find an informative effect of advertising, but no persuasive effect. In contrast, other studies have found both an informative and persuasive effect (Narayanan et al. 2005, Narayanan and Manchanda 2009, Anand and Shachar 2011). Hence, the evidence is mixed on advertising exerts persuasive effects, but supports informative advertising effects.

2.2. Consideration and memory effects of advertising

The literature in marketing on consideration sets argues that individuals only consider a subset of all brands for purchase (Shocker et al. 1991, Bronnenberg and Vanhonacker 1996). We focus on recent studies that contrast a direct effect of advertising on preferences against an indirect effect on choice by influencing the consideration set. Terui et al. (2011) found advertising affects product choices both directly and indirectly using scanner panel data. Draganska and Klapper (2011) find similar results using aggregate purchase and brand consideration data. Mitra and Lynch (1995) use experiments and find that advertising both directly influences preferences and increases the chances a brand will be included in the consideration set when the options must be recalled. In contrast, Goeree (2008) argues that advertising operates only through consideration and Clark et al. (2009) separately estimate advertising effects on aggregate measures of awareness and brand preference, and find significant effects only for awareness. Thus, while the evidence on a direct effect is mixed, the memory/consideration effect is supported.

We add to these literatures in two ways. First, we have measures of the person's stated experiences and expectations that provide a new way of calibrating these advertising effects. These measures allow us to attribute (1) informative effects to changes in stated expectations rather than relying solely on the diminishing nature of these effects and (2) reminder

effects to the changes in choice that are unrelated to changes in stated expectations.¹ Second, we develop a structural model that takes advantage of these data and incorporates both informative and memory/consideration effects of advertising. Following Sahni (2011), we build on recent cognitive psychology models of memory (Anderson et al. 2004) and like (Sahni 2011, Goeree 2008) assume that memory determines whether the brand is considered. Much like these papers, choice in our setting involves a large number of brands so that advertising effects on recall are likely to exist (Mitra and Lynch 1995).²

2.3. The role of social engagement

We also consider social engagement effects. Our research question and approach, however, differs from most existing studies on social engagement. Prior scholarly work has tended to focus on the role of social contagion on aggregate adoption (Bass 1969) or associated aggregate data on decisions with aggregate data on paid or earned media (Bruce et al. (2012), Sonnier et al. (2011), Godes and Mayzlin (2004), Stephen and Galak (2012)). A few studies have considered both word-of-mouth and paid advertising. Trusov et al. (2009) study the influence of media coverage and company sponsored events. Onishi and Manchanda (2012) study whether blogs and television ads reinforce or damage each other's role in supporting sales of new products.

In contrast, our interest is on the fundamentals of individual-level decisions. As a result, our study more closely relates to a number of recent papers that consider micro-level adoption decisions. For example, Manchanda et al. (2008) considers the effect of geographically proximate physician adoption (i.e., aggregating local actions) on individual physician adoptions, whereas other studies consider the position in the social network, such as opinion

¹ Importantly, while the memory/consideration effects are sometimes referred to as informative, the theoretical foundations differ from informative effects related to Bayesian learning. Thus, we use informative to refer only to learning and not reminding.

² We also note that our approach to incorporating memory into a learning model is different from that of Mehta et al. (2004), since in our approach memory is a function of marketing activities and influences consideration, rather than adding uncertainty and drift in the belief about the match-value.

leaders (Nair et al. 2010), particular network ties (Iyengar et al. 2011), and joint decisions (Hartmann 2010, Yang et al. 2010). Our focus, however, is on distinguishing multiple roles for social engagement that have been identified for advertising, and on augmenting these roles with the potential to gain direct “social utility” through communications about the program that bring the individual closer to others, allow the individual to express herself (Lovett et al. 2013), or provides a basis of conversation to fill the need to socialize (Rubin et al. 1988).

To this literature, we add the enhancing enjoyment role is also an important role for social engagement.³ This enhancing enjoyment role can lead to long-term brand relationships cemented by social engagement and reflects the focal mechanism discussed in much of the popular literature on why social engagement is so important—i.e., that people become more involved in the brand as a result of the social interaction (Iezzi 2010).

3. Model

A TV program (entertainment brand) is experienced through its episodes, which we index by c . A consumer i can choose to view (once) an episode when it is aired or in time-delay (e.g., via hulu.com or DVR) prior to the next episode airing.⁴ We index the period by t and note that each episode can be viewed in up to J periods, where J is the number of partitions in the window between airings (what we will refer to as the inter-airing period). The original airing period of episode c is denoted $t_{c,A}$. An episode c can be viewed live in the period $t = t_{c,A}$ or viewed in time-delay using a time-shifting technology (TST) in any of the following $J - 1$ periods. The next episode, $c + 1$, is aired in period $t_{c,A} + J$. We assume that when episode $c + 1$ is aired, episode c is no longer considered an option.

³ This role is related to Becker and Murphy’s (1993) model of advertising as complementary good.

⁴ Delayed viewing can occur before or after the next episode is aired. To simplify we ignore the after case, since we observe less than 1% of the sample viewing an episode c after the next episode, $c + 1$, airs. We also do not observe the number of viewings and assume consumers only watch an episode once.

In airing periods, the choice is among engaging in c , another option in P_t , the set of available competing programs (which we will model as a single “other” TV program option), or engaging in some “outside good” activity. For non-airing periods, an individual may watch episode c time-delayed (or not), if she did not already watch episode c .⁵ We denote the viewing decision for individual i at time t as $w_{i,t}$, which takes values c if episode c is watched, P if another program is watched, and 0 otherwise. We also assume that c can only be chosen if it is considered and model whether the consumer i considers watching the focal program at time t . We denote consideration for the focal program as $r_{i,t}$, which takes a value of 1 if considered and 0 otherwise.

In our model, consideration and viewing decisions depend on memory and information. These are developed through cues or signals in the environment, including advertising exposures (ad), social engagements (so), and viewing experiences (ex). We denote the vector of cues, $C_{i,t}$ and the cue types by $k \in ad, so, ex$. If individual i receives a cue of type k in period t , $C_{i,t,k} = 1$, otherwise $C_{i,t,k} = 0$. Each $C_{i,t,k} = 1$ has a corresponding signal, $v_{i,t,k}$. The information set for the decision at time t is denoted $I_{i,t}$ and consists of the union of the new cues and signals received in t and the prior information set, $I_{i,t-1}$.

Our primary interest is in the probability, $P(w_{i,t}, r_{i,t} | I_{i,t}) = P(w_{i,t} | r_{i,t}, I_{i,t})P(r_{i,t} | I_{i,t})$. In the following sections we discuss $P(r_{i,t} | I_{i,t})$ and the components of $P(w_{i,t} | r_{i,t}, I_{i,t})$. These components include the entertainment utility (or match-value), the social utility, and the benefits or costs associated with watching the episode in time delay.

3.1. Consideration and reminder effects

In order for individual i to watch the episode at time t , the program first must be considered, i.e., $r_{i,t} = 1$. Similar to Sahni (2011), we adapt the ACT-R model of Anderson et al.

⁵ We do not model competitive options in non-airing periods because for these periods in our data we only observe not watching rather than which option is chosen. Further, we note that this is an incredibly complex set.

(2004) to allow consideration to depend on the program’s activation level in memory. This memory activation level for the focal program (i.e., index for the probability of considering the focal program) for individual i in period t is

$$\tilde{A}_{i,t} = A_{i,t} + \varepsilon_{i,t}^r = \psi X_{A,i,t} + B_{i,t} + \varepsilon_{i,t}^r \quad (1)$$

where $A_{i,t}$ is the deterministic component of the memory activation level for the episode available at t that is a function of $X_{A,i,t}$, the contextual cues available during airing periods that do not directly affect long-term memory, $B_{i,t}$, the baseline memory activation level, and $\varepsilon_{i,t}^r$, an idiosyncratic, temporary memory shock. The contextual cues we include are “audience flow” effects (Rust and Alpert 1984, Shachar and Emerson 2000): whether in the half-hour period prior to the airing of the focal program the person was (1) watching TV, $1(\text{TV}_{i,t})$, and (2) watching the same channel as the focal program, $1(\text{FOX}_{i,t})$.⁶ The baseline memory activation level is the function $B_{i,t} = \delta B_{i,t-1} + \sum_{k=1}^K \phi_k 1(C_{i,t,k} = 1)$, where ϕ_k is the respective cue strength and δ is the rate of memory decay. Because the airing period is so short compared to the inter-airing periods, we do not depreciate the baseline memory activation level during airing periods (i.e., $\delta = 1$). We assume that $\varepsilon_{i,t}^r$ is distributed with the usual standardized logistic distribution, so that the resulting probability of the consideration event is $P(r_{i,t}|A_{i,t}) = \frac{1}{1+e^{-A_{i,t}}}$.

3.2. Entertainment utility and learning

Television viewing generates utility through the entertainment value of the programming. During airing periods, individuals who are already watching television may be more likely to continue watching because of an active entertainment goal or lower transaction costs. To capture this effect, we include an indicator, $1(\text{TV})$, in all viewing options and β_1 as its linear parameter.

⁶ Here and throughout the paper, we use the notation $1(\cdot)$ as an indicator function.

The entertainment utility of the focal program is obtained from watching the available episode. This utility is a match-value between the individual's tastes and the program and will naturally differ across people. We denote the (average) match-value between individual i and the focal program as μ_i .

Individuals may have uncertainty about their true match-value of the new program, μ_i . The individual has prior beliefs and according to Bayes rule optimally updates these beliefs upon the receipt of new information. We assume the individual i 's initial belief about the true match-value, given the information set, $I_{i,0}$ available at $t = 0$, is distributed normally with mean $\bar{\mu}_{i,0}$ and variance $\hat{\sigma}_{0,\mu_i}^2$. Being exposed to ads, engaging socially, and watching episodes all provide informative, unbiased signals about the true match-value, i.e., $v_{i,t,k} = \mu_i + \epsilon_{i,t,k}$. Following the literature, we assume that the $\epsilon_{i,t,k}$ are distributed normally with mean 0 and variance $\sigma_{v,k}^2$ and that the individual knows these distributions and signal variances. As a result, following standard formulas (DeGroot 1970), the updated (posterior) belief after receiving the signals prior to time t is normally distributed with moments

$$\bar{\mu}_{i,t} = \frac{\hat{\sigma}_{t,\mu_i}^2}{\hat{\sigma}_{t-1,\mu_i}^2} (\bar{\mu}_{i,t-1}) + \sum_{k=1}^K \frac{\hat{\sigma}_{t,\mu_i}^2}{\sigma_{v,k}^2} v_{i,t,k} 1(C_{i,t,k} = 1) \quad (2)$$

$$\hat{\sigma}_{t,\mu_i}^2 = \frac{1}{\frac{1}{\hat{\sigma}_{t-1,\mu_i}^2} + \sum_{k=1}^K \frac{1(C_{i,t,k}=1)}{\sigma_{v,k}^2}} \quad (3)$$

3.3. Social engagement utility

Individuals also gain utility from engaging socially with others about the program. We assume that social contacts, $C_{i,t,so}$ are passive (i.e., exogenous and stochastic) and follow a Bernoulli process. Individuals have heterogeneous propensities, $\bar{q}_i \in [0, 1]$, to engage socially about the program per half week.⁷ Our utility formulation is agnostic about the presence

⁷ Social connections also have an element of choice, but these choices involve complex and idiosyncratic rituals and social networks that constrain choices. We treat socializing as an exogenous fixed propensity. We do not expect in our application that individuals altered the socializing occasions (how often and with whom they speak) in response to this television program. We discuss possible issues with this assumption in Section 5.4.

of a constant social utility (i.e., regardless of the viewing behavior), but since such constant utility does not affect viewing choices, we ignore it. Instead, we focus on the incremental net social utility gained from watching the most recent episode, c . If the current episode is watched, this incremental utility will be generated in each period the individual engages socially until the next episode is aired. Since the individual is uncertain about future social contacts, the individual bases the decision on the expected number of such contacts per period, \bar{q}_i . Hence the utility from socializing given watching in period t is

$$u_{i,t}^{soc} = \omega \bar{q}_i (J - t - t_{c,A}) \quad (4)$$

where ω is the incremental utility per social contact of watching the most recent episode. We assume that \bar{q}_i is known to the individual.⁸

3.4. Time-shifting

If an individual has not already chosen to watch an episode, she can watch the program after the original airing period using a TST. Time-shifting an episode may impose additional costs (monetary, psychological, or time) or generate some benefit from flexibility in scheduling or skipping commercial breaks. We denote this cost/benefit, $\beta_{2,i}$, and use $1(TST_{i,t})$ as an indicator variable set to 1 in periods when the TST-related costs/benefits would be incurred if the show is watched, and 0 otherwise. We note that time-shifting is endogenous, but the time-shifting decision is not forward-looking in our model.

3.5. Viewing decisions and choice likelihoods

The individual bases her viewing decisions on expected utility using her current beliefs.

The expected utility of watching the focal program is

$$u_{c,i,t} = \bar{\mu}_{i,t} + u_{i,t}^{soc} + \beta_1 1(TV_{i,t}) + \beta_{2,i} 1(TST_{i,t}) + \varepsilon_{i,t}^* \quad (5)$$

⁸ We also estimated models in which the expected likelihood of engaging socially was updated (i.e., Bayesian learning about \bar{q}_i). based on new information, but the estimated parameters indicated no meaningful learning. Hence, for simplicity, we dropped this learning from the model.

where $\varepsilon_{i,t}^*$ is an idiosyncratic demand shock for watching the focal program at time t , and the other terms are as described above. The expected utility of choosing an option in the set of competing programs P_t (in an airing period) is

$$u_{P,it} = \alpha_{P,t} + \beta_1 1(TV_{i,t}) + \varepsilon_{i,t}^1 \quad (6)$$

where the $\alpha_{P,t}$ is a week fixed effect to control for competition at airtime and $\varepsilon_{i,t}^1$ is an idiosyncratic demand shock for the set P_t . The outside option has the deterministic component normalized to zero so that, $u_{0,it} = \varepsilon_{i,t}^0$ where $\varepsilon_{i,t}^0$ is an idiosyncratic demand shock to the outside option. We note that in time-shifted viewing decisions, we use the same outside option normalization.

We assume the idiosyncratic errors $\varepsilon_{i,t}^0$, $\varepsilon_{i,t}^1$, and $\varepsilon_{i,t}^*$ are i.i.d. extreme value. Conditioning on $r_{i,t} = 1$ in an airing period, the choice set includes $j \in \{c, P, 0\}$. The corresponding probabilities are

$$P(w_{i,t} = j | r_{i,t}, I_{i,t}) = \frac{e^{u_{j,i,t}}}{\sum_{j' \in \{c, P, 0\}} e^{u_{j',i,t}}}, \quad (7)$$

where $r_{i,t}$ means $r_{i,t} = 1$. Conditioned on not considering c , the choice set includes only $j \in \{P, 0\}$ with corresponding probabilities

$$P(w_{i,t} = j | r_{i,t} = 0) = \frac{e^{u_{j,it}}}{\sum_{j' \in \{P, 0\}} e^{u_{j',it}}}, \quad (8)$$

where we have dropped the $I_{i,t}$. Summing over the consideration outcomes,

$$\begin{aligned} P(w_{i,t} = c | I_{i,t}) &= P(r_{i,t} | I_{i,t}) P(w_{i,t} = c | r_{i,t}, I_{i,t}) \\ P(w_{i,t} = P | I_{i,t}) &= P(r_{i,t} | I_{i,t}) P(w_{i,t} = P | r_{i,t}, I_{i,t}) + (1 - P(r_{i,t} | I_{i,t})) P(w_{i,t} = P | r_{i,t} = 0) \end{aligned} \quad (9)$$

$$P(w_{i,t} = 0 | I_{i,t}) = P(r_{i,t} | I_{i,t}) P(w_{i,t} = 0 | r_{i,t}, I_{i,t}) + (1 - P(r_{i,t} | I_{i,t})) P(w_{i,t} = 0 | r_{i,t} = 0)$$

Conditional on considering episode c , but not yet having watched c , and assuming $t = t_{c,A}$, the probability of watching and not watching c at time $t+k$, for $1 \leq k < J$ is

$$\begin{aligned} P(w_{i,t+k} = c | r_{i,t+k}, I_{i,t+k}, w_{i,t+k-1} \neq c, \dots, w_{i,t} \neq c) &= \frac{e^{u_{c,i,t+k}}}{1 + e^{u_{c,i,t+k}}} \\ P(w_{i,t+k} = 0 | r_{i,t+k}, I_{i,t+k}, w_{i,t+k-1} \neq c, \dots, w_{i,t} \neq c) &= 1 - \frac{e^{u_{c,i,t+k}}}{1 + e^{u_{c,i,t+k}}} \end{aligned} \quad (10)$$

Finally, we note that in the delayed time period decisions, the marginal probability of not viewing is the complement of viewing, which requires considering the program.

4. Data

Our application focuses on *Human Target*, a mid-season action drama entry for FOX in 2010 that was based on a comic book series in which the main character is an ex-assassin turned bodyguard who integrates himself into his clients' lives in order to identify and eliminate the threat. The show obtained a moderate following of over 7 million viewers for all but one episode and over 10 million viewers for the first two episodes. The show was renewed for the Fall 2010 line-up on FOX.

The premier episode was launched on January 17th of 2010. We collected information from a sample of individuals over a seven week period. During this period the program had last minute schedule changes, aired at four different airing times, and faced different competing programs including the Winter Olympics. Because of these changes and unusual events, we incorporate into equation 5 fixed effects, $\alpha_{c,t}$, for weeks 2-6 (week 1 is not identified).

4.1. Sample and Survey Measures

The respondents are from P&G's VocalPoint Online Community. We enrolled individuals prior to the premier episode with an initial survey that gathered information on predispositions for TV viewing and the *Human Target* show. The initial survey was available to approximately 50,000 eligible participants. In total 1720 individuals participated in the initial survey. Participation and payment did not require watching the program.

After each episode was aired, a survey was sent to the panel. The survey notification was sent via email in the mid-point between episode airings and was typically completed within 2 days. The surveys were largely the same with minor changes to adjust for the week (see Appendix B for the questions).

Not surprisingly, a large portion of the panel expressed a low likelihood of watching the initial show. Of the 1720 individuals only 56% indicated there was at least a “good possibility” that they would watch the show and only 13% indicated they would “definitely watch.” We have 1066 completed first surveys (after episode 1) and the total drop-off to the last survey was an additional 31%. The drop-off event is highly correlated with the initial expressed likelihood of watching ($\chi^2 = 4.43$, $df = 1$, $p\text{-value} < .05$). Hence, the drop-off event is likely to be predictive of preferences for the show and should not be ignored. In addition to drop-off, a small proportion of respondents (that otherwise continue to complete surveys) do not complete the survey in any given week, amounting to approximately 2% of total potential surveys over the first five weeks (see Appendix Section E for details on the impact on the choice likelihoods). In total, we have 5,026 completed surveys.

The model free analysis in Section 4.3 uses only completed surveys, but since drop-off has information about preferences, for our regression and structural analysis we include the missing cases. These drop-off (and other missing) cases are given a separate dummy variable and coded as not watching and not receiving any cues. In Section 4.4, we present evidence on the robustness of our results to alternative missing data assumptions.

The initial survey provided data about the initial state of individual-level brand liking and category knowledge. This information includes a measure of the likelihood of watching the first episode, LW_i (measured on an 11 point scale), the average number of action dramas watched per week, $nDrama_i$, aided awareness for *Human Target*, $Aware_i$ (1 or 0), and the tendency to watch programs at broadcast or in time delay using DVR, internet, or VCR), WTD_i (1 for time-delay tendency otherwise 0). We also obtain a rich set of self-reported variables from the weekly surveys as described below:

- **Viewing behaviors.** Respondents indicated what they watched during airing periods or if they later watched in time delay before or after the midpoint of the inter-airing period

($w_{i,t}$). In addition, they indicated what program, if any, they watched in the half-hour prior to the airing period, which provides $1(TV_{i,t})$ and $1(FOX_{i,t})$.

- **Liking and expected liking.** Respondents indicated how much they like episodes they viewed, $Lik_{i,t}$, where t is the period the episode was watched. In addition, regardless of viewing, respondents indicate their expected liking for the upcoming episode, $EL_{i,t}$, where t refers to the period in which the question is asked. Both questions used essentially the same interval scale that ranged between 1 and 11 with 11 the greatest (expected) liking.

- **Advertising exposure and social engagements.** Respondents were asked retrospectively whether they were exposed to any advertisements or had heard from any social contacts (online and offline) about the program. For social contacts, we note that more than 85% of the social contacts in our data are offline. As a result, we interchangeably refer to this measure as social contacts and social engagement, since it reflects the two-sided conversations common in offline word-of-mouth rather than one-sided ones more typical of lurkers in the online world. For those that watched the previous episode, we asked for this information both for the period between the last survey and the airing of the episode and the period after airing and before the current survey. For those that did not watch, we obtained this information for the entire inter-survey period. We use these responses and viewing to form the set of cues, $C_{i,t}$.

- **Change in expected liking due to cues.** Anyone who indicated being exposed to ads or having social contacts was asked how these cues in total affected the expected liking of the upcoming episode, $\Delta EL_{i,t}$, where t refers to the period in which the cues were received. Response categories were increased (1), decreased (-1), or did not change (0) the expected liking.

Finally, to analyze the enhancing enjoyment role, we create two segments based on the propensity to socialize. We calculate the observed average propensity to engage socially

during the study, \bar{q}_i , as a rational expectation for the probability of social contact about the program, q_i (i.e., $\bar{q}_i = E[1(C_{i,t,so} = 1)]$) and segment individuals into high socializers, who engage on average at least one time per four periods, and low socializers, who engage less than one time in four.⁹ The segment sizes are 9% and 91% respectively, and the average socializing propensities for the segments are 0.56 and 0.02 respectively. We use these categories in both our model free and structural analyses. For our model free analysis, we also constructed similar propensity measures for the frequency of advertising exposures.

4.2. Basic description

In Panel 1 of Figure 1 we present the aggregate ratings and the percent of our sample that reported viewing the show. Both series have a similar declining trend that flattens towards the end. We find it encouraging that the self-reported measures from our sample, which is not designed to be representative, demonstrates a similar declining/flattening pattern to the aggregate observed data. In Web Appendix C we present further evidence that our self-reported advertising and social contacts measures have a reasonable connection to aggregate observed behaviors.

The prominence of the declining trend indicates that any model of viewing behaviors should capture this pattern. In Panel 2 we present the percent of our sample that is exposed to advertising or engaging socially by the approximately half-week periods. Advertising exposures are much more common than socializing about the program. While advertising exposures decline meaningfully over the six weeks,¹⁰ socializing declines only slightly and appears to increase towards the end. This suggests that the advertising decline might help to explain the decline in viewing. In contrast, the trend for the average of observed

⁹ We checked the robustness to varying cut-points by using values below and above 0.25.

¹⁰ We confirmed using Kantar Media's AdSpender product that this pattern of decline was strongly correlated with an actual decline in paid advertising over the observation period.

expected liking measures increases for both viewers and non-viewers (plot not depicted). This suggests, the informative effects, which operate through these expectations, may have difficulty explaining the decline in viewership.

Time-shifting is also a prominent feature of viewing among our sample with approximately 40% of episodes watched via TSTs, a portion that is both consistent across episodes and with previous reports.¹¹ Also, these time-shifting behaviors for *Human Target* are highly correlated with individuals' general tendencies to time-shift (WTD_i). For example, 92% of those always watching *Human Target* at airtime also indicating they mostly watch TV at broadcast.

In Web Appendix D, we describe in more detail the variation in the stated expectation and experience measures. To summarize, average within survey variance (across individuals) ranges between 3.4 and 4.3 and average between survey variance (within individual) ranges between 0.9 and 1.2. The pattern of this variation is consistent with updating beliefs in response to new information. For example, across individuals, we find that the variation in $Lik_{i,t}$ is constant over time, the variation in $EL_{i,t}$ increases, and the difference between $EL_{i,t}$ and $Lik_{i,t}$ decreases over time. Further, we present in the Web Appendix Section D.3 example individual-level patterns of data that illustrate the kinds of information available from our survey measures. These patterns again suggest variation in our data exists that can inform the parameters of our structural learning model. Finally, in Web Appendix Section D.4, we address the issues of common method variance and scale usage heterogeneity that could affect our measures, and thus our results. As seen in the appendix, we find that

¹¹ While this rate is somewhat higher than the average rate found in Bronnenberg et al. (2010), they focused on TiVo use and considered many categories, including sports and news programming which are known to have lower rates of time-shifting than comedy and action programming (Bernoff 2004). The prevalence of time-shifting in our data is similar to available industry estimates. For example, Carter (2011) reports that within seven day gains in viewers due to DVRs ranged between 25% and 33% for top shows and Bernoff (2004) found an overall average of 43% of programming with significant time-shifting and 61% with at least some delay. Hence, we take this evidence to indicate the average propensity to use TSTs in our data is within the normal range for an action drama program.

neither issue is a major concern in our data. Hence, we do not explicitly account for these potentially confounding effects in our analysis approach.

4.3. Model free evidence on the multiple roles

In this section, we present preliminary evidence on whether the three roles of informing, reminding, and enhancing enjoyment exist. We then turn to the regression analysis.

4.3.1. Informative effects. We conduct two analyses. The first analysis tests two implications of Bayesian learning from experience: (1) the expected liking for the upcoming episode $EL_{i,c}$ should be positively related to the previous liking $Lik_{i,c-1}$ after controlling for the previous expected liking $EL_{i,c-1}$ and (2) this association should decrease as more signals are received. We estimate the linear regression equation, $EL_{i,c} = \beta_{1,c}EL_{i,c-1} + \beta_{2,c}Lik_{i,c-1} + \epsilon_{i,c}^d$, which is directly analogous to equation 2, where we have not forced the β s to equal the weights from the Bayesian learning model and where the other signals are ignored (i.e., in the $\epsilon_{i,c}^d$).¹² We estimate these coefficients jointly for each of episodes 2-6, since we require lags. We note that the sample size decreases in later episodes since the regression requires observed liking data.

The results are presented in Table 1 with the t-statistics in parentheses. Compatible with Bayesian learning and an informative effect, all variables are positive and significant with p-values less than 0.001, and the average effect of liking decreases over time with most of the decline occurring in the first few episodes.¹³

The second analysis examines the self-reported changes in the expected liking due to advertising and social contact. If the cues provide information then the portion of respondents reporting changes should decrease over time. Figure 2 plots the percent of those

¹² Notice that we are using subscript c instead of t , since we are using the episode ordering and not the exact timing in this regression

¹³ To the extent the signals are correlated (and received), the coefficient on $Lik_{i,c}$ may pick up the other signal effects.

who receive these cues and indicate changing their expected liking of the next episode. Although the pattern in the first few half-periods is decreasing, many of the decreases are not statistically different and increases follow. Taken together, the informative effects appear to be stronger for experience than for advertising and social contact.

4.3.2. Reminding effects To isolate the reminder effect for advertising and social engagement, we consider cases in which the informative effects of these cues are unlikely to increase the likelihood of viewing. To do so, we contrast viewing occasions where cues were received but did not have a positive effect on expected liking (i.e., $\Delta EL_{i,t} \leq 0$) against viewing occasions where the individual did not receive any cues. We split the sample at the average expected liking to control for preferences. The results reported in Table 2 are very supportive of a reminder effect. The receivers of “uninformative” cues are more likely to watch than those who do not receive the cues, regardless of the expected liking. Thus, it appears the cues still serve as a reminder to watch the program.

4.3.3. Social utility The enhancing enjoyment role implies that those who socialize more have a greater incentive to watch earlier than those who socialize less. To evaluate this prediction, Table 3 presents a cross-tabulation of the time delay tendency from the initial survey ($X_{WTD,i}$) by the socializing frequency, (\bar{q}_i). For those that indicate watching programs mostly live, both the high and low \bar{q} groups prefer viewing at the original airing time. However, the high \bar{q} group is more likely to watch at original airing than the low \bar{q} group. For those that indicate watching programs mostly delayed, we confirm the preference for time-shifting with the highest proportions being after the original airing independent of \bar{q}_i . However, we again find that the high \bar{q} group is more likely to watch earlier. These findings are supportive of a role for enhancing enjoyment through social utility.

4.4. Model free regressions

We use linear probability models to evaluate the partial relationships in the data. As the decision variable, we use the choice of whether to watch the program at airtime. Our focal explanatory variables are advertising exposures and social contacts. We include controls for audience flow ($1(TV_{i,t})$ and $1(FOX_{i,t})$), whether the individual watched the program in the previous week (*Watched Last Week*), and week fixed effects (to control for advertising endogeneity, competitive environment, and viewing times). In addition, in one reduced form model, we add indicators for frequent socializing (i.e., \bar{q}_i =high) and frequent advertising exposures as well as a polynomial function of expected liking. Table 4 presents the results.

Column 1 indicates that both advertising and social engagement have significant positive effects with the effect of advertising much larger than that of social engagement. Column 2 adds the control variables, which reduces the effect of both cue variables by approximately 50%. Column 3 adds a polynomial function of expected liking (along with an indicator if it is not observed). The lack of change suggests that the advertising and social engagement variables are not mediated by expected liking. Since the informative effects should operate through expected liking, this is further evidence of weak or non-existent informative effects for these two cue variables. In contrast, the variable *Watch Last Week* decreases significantly, suggesting experiential learning. Interestingly, the lack of informative effects also suggests that these cues operate through reminding effects. In Column 4, we add the indicators for frequent socializers and frequent ad exposures, which are our variables to capture the role of enhancing enjoyment. If individuals anticipate this future utility from enhanced enjoyment of socializing or seeing ads, then we should see positive effects for these variables. We find that frequent ad exposures are slightly negative and not significant, whereas frequent socializing is positive and significant. Further, we find that the

effect of socializing decreases significantly, suggesting that part of the previously estimated effect was due to enhancing enjoyment. These results suggest that social engagement has a role in enhancing enjoyment, but that advertising does not. The last column drops all of our variables related to advertising and social engagement. We find that the R^2 decreases significantly as compared to Model 2, 3, or 4, indicating a significant role for our joint set of variables.

We test the robustness against alternative assumptions in Table 5. We replicate Model 2 from Table 4, where we include the control variables and the direct effects of advertising and social contact, but not the more complicated (and incorrectly specified) additional variables. In Column 1, we verify that the same direction of effects arise in a Logit model. In Columns 2-4, we check our results against alternative missing data assumptions. In Column 2 and 3 we set the missing cases to have not watch and impute the cues. In Column 2 we impute the cues using the distribution conditioned on not watching and in Column 3, we impute the cues using the unconditional distribution. In both cases, we use the empirical distribution of the observed cases. In Column 4, we use case deletion, keeping only individuals who responded in all six weeks (i.e., around $\frac{1}{3}$ of the sample). Under each of these alternative missing data assumptions, we find that the effect sizes decrease, but that the direction and significance of results are the same. Hence, our results appear robust to the missing data issue. In Column 5, we verify that our results hold for a model with fixed effects for each individual. Although previous models already controlled for unobserved heterogeneity, this model provides further evidence that fixed heterogeneity cannot explain our results. Finally, we note that in all of these regressions, our time effects control for any direct effects of the survey itself (e.g., the survey acting as a reminder). Hence, it appears the survey is not eliminating the role of the other variables.

4.4.1. Summary of descriptive evidence This section provides model free evidence that viewing experiences, advertising exposures, and social engagements influence viewing decisions in ways that are compatible with our structural model. These analyses do not model the process or control for the time-varying nature of influences on viewing decisions and accounting for these is important in order to evaluate the relative magnitude of the various effects. For, this we turn to estimating our structural model.

5. Likelihood and Estimation

In this section, we discuss the structural model estimation including heterogeneity and initial beliefs, the measurement model, the full model likelihood, and qualitative arguments for what variation in the data informs our parameter estimates.

5.1. Heterogeneity and initial beliefs

We allow heterogeneity in μ_i , $\bar{\mu}_{i,0}$, $\hat{\sigma}_{0,\mu_i}^2$, and $\beta_{TST,i}$, each of which is a function of key observable factors and a random effect. Specifically, we assume the mixing distribution

$$\pi(\cdot) = f_N(X_{\mu,i}\gamma_\mu, \sigma_\mu^2) f_N(X_{\mu,i}\gamma_{\bar{\mu}}, \sigma_1^2) f_{LN}(X_{\sigma,i}\gamma_\sigma, \sigma_2^2) f_N(X_{TST,i}\beta_{TST}, \sigma_{TST}^2) \quad (11)$$

where f_N and f_{LN} are the normal and lognormal distributions, where the lognormal is parameterized in terms of the (underlying) normal. The parameters of these distributions, the γ s and the variances σ_μ^2 , σ_1^2 , σ_2^2 , and σ_{TST}^2 , are estimated. The X variables (and corresponding parameters) are as follows: $X_{\mu,i}$ includes an intercept ($\gamma_{\mu,0}$ and $\gamma_{\bar{\mu},0}$) and the stated likelihood of viewing the pilot episode, LW_i ($\gamma_{\mu,LW}$ and $\gamma_{\bar{\mu},LW}$); $X_{\sigma,i}$ includes an intercept ($\gamma_{\sigma,0}$) and the number of action dramas viewed in a typical week, $nDrama_i$ ($\gamma_{\sigma,nDrama}$); and $X_{TST,i}$ includes an intercept ($\beta_{TST,0}$) and the indicator for mostly watching in time delay, WTD_i ($\beta_{TST,WTD}$). In addition, we allow observable heterogeneity in the initial memory, $B_{i,1}$, which includes an intercept ($\gamma_{mem,0}$) and $Aware_i$ ($\gamma_{mem,Aware}$). Finally, as described in Section 4.1, we construct segments of high socializing and low socializing groups using observed data .

5.2. Measurement Model

Our data contains fallible measures of expectations and experiences, which we incorporate into our structural estimation via a measurement model. Our measurement model for the (stated) expected liking of the next episode, $EL_{i,t}$, imposes a monotonic function that relates the underlying mean of the match-value belief, $\bar{\mu}_{i,t}$, to the $EL_{i,t}$. Specifically, we assume

$$EL_{i,t} = a_{ME} + \bar{\mu}_{i,t} + \varepsilon_{ME,EL,i,t}$$

where a_{ME} is the scale shifter, $\varepsilon_{ME,EL,i,t} \sim f_N(0, \sigma_{ME}^2)$, and σ_{ME}^2 is the measurement error variance. Similarly, the liking measure, $Lik_{i,t}$, measures the experience signal, $v_{i,t,ex}$ via

$$Lik_{i,t} = a_{ME} + v_{i,t,ex} + \varepsilon_{ME,Lik,i,t}$$

where $\varepsilon_{ME,Lik,i,t} \sim f_N(0, \sigma_{ME}^2)$ and we use the same measurement model parameters since $Lik_{i,t}$ shares essentially the same scale as $EL_{i,t}$.¹⁴ We assume the ordered categorical variable, $\Delta EL_{i,t}$ (the stated change in expected liking) follows an ordered logit model having two cutpoint parameters, $a_{\Delta EL}$ and $b_{\Delta EL}$, and an underlying index $\Delta \bar{\mu}_{i,t} = \hat{\mu}_{i,t} - \bar{\mu}_{i,t-1}$, where $\hat{\mu}_{i,t}$ is the updated belief excluding any experience signal in period t . Thus, the measurement model is¹⁵

$$\begin{aligned} \text{if } \Delta \bar{\mu}_{i,t} < a_{\Delta EL} & \quad \Delta EL_{i,t} = -1 \\ \text{if } b_{\Delta EL} \geq \Delta \bar{\mu}_{i,t} \geq a_{\Delta EL} & \quad \Delta EL_{i,t} = 0 \\ \text{if } b_{\Delta EL} < \Delta \bar{\mu}_{i,t} & \quad \Delta EL_{i,t} = 1 \end{aligned} \tag{12}$$

¹⁴ As noted previously, in Web Appendix Section D.4, based on our examination of the data we find limited evidence for scale usage heterogeneity and common methods variance, and as a result, we do not incorporate them here, i.e., we assume that the measurement errors are i.i.d. and that the error variance and scale shifters are common.

¹⁵ Note that the difference in distributions between the $EL_{i,t}$ or $Lik_{i,t}$ measures and the $\Delta EL_{i,t}$ measures reflect measurement errors and not structural components.

5.3. Simulated likelihood

We apply a simulated maximum likelihood approach to estimate the parameters of our model. We denote the total number of periods, $TP = 17$, where we observe six airing periods, ten inter-airing half periods between airings prior to the sixth airing period, and one half inter-airing period after the sixth episode. The joint individual likelihood given the parameters, θ , the parameter random effects, θ_i , and the information sets, $I_{i,t}$ (which contain the signals and jointly are referred to simply as I) is (see Appendix E for the notation and details related to missing data)

$$L_i(\theta, \theta_i, I) = \prod_{t=1}^{TP} L_{w_{i,t}}(\theta, \theta_i, I_{i,t}) L_{EL,i,t}(\theta, \theta_i, I_{i,t}) L_{Lik,i,t}(\theta, \theta_i, I_{i,t}) L_{\Delta EL,i,t}(\theta, \theta_i, I_{i,t}). \quad (13)$$

The elements in θ_i and $I_{i,t}$ are random effects with distributions that depend on the parameters of interest, θ . We use Monte Carlo integration to integrate out these unobserved variables. To achieve this integration efficiently we use Halton sequences with $NP = 200$ draws. The simulated likelihood that we maximize is approximated via

$$L(\theta) \approx \prod_{i=1}^N \frac{1}{NP} \sum_{m=1}^{NP} L_i(\theta, \theta_i^m, I^m).$$

5.4. Identification

Of primary interest are the parameters relating to the informing, reminding, and enhancing enjoyment roles. We focus our discussion on these roles and on the exogeneity of the cues.

First, similar to the analysis of Section 4.3.3, the utility parameter for socializing about the most recent episode is identified by the interaction between the propensity to engage socially and the timing of the program viewing choice. The parameter captures how much more likely those with a high propensity to socialize are to watch earlier than those with a low propensity to socialize. This identification assumes that individuals are not altering

their socializing behaviors or developing new social connections because of this program.¹⁶ We argue that this is a reasonable assumption given the program’s genre and modest success.

Second, our rich set of stated data provide additional information beyond standard revealed preferences for estimating the learning model parameters. Prior research (Shin et al. 2012) demonstrates that incorporating observed heterogeneity in the initial prior mean and variance result in better recovery of actual learning than revealed preferences alone. Using a similar approach, we incorporate $LW_{i,t}$ and $nDrama_{i,t}$ to help separate the variation due and to (otherwise) unobserved preferences and prior information from the variation arising from changes in viewing due to informative effects. Further, similar to Erdem et al. (2005), we incorporate additional information directly into the likelihood, in our case the measures $Lik_{i,t}$, $EL_{i,t}$, and $\Delta EL_{i,t}$. Unlike in choice data, the $Lik_{i,t}$ provide information directly on the experience signals, $v_{i,t,ex}$, and as a result on their variance, σ_{ex}^2 . This information identifies the scale of this signal variance, allowing us to separate the initial belief variance from all of the other signal variances.¹⁷ We use the standard identification arguments for the remaining parameters, which can be known, for example, up to the ratio of the initial belief variance and one of the signal variances (see for example Shin et al. 2012). For this purpose, the additional data provides similar information to revealed preferences. The $Lik_{i,t}$ measures the unobserved $v_{i,t,ex}$, and provides information on the location of that signal in a similar fashion to choice shares (after an experience). Similarly, $Lik_{i,t}$ also provides information directly on μ_i , the mean of $v_{i,t,ex}$, which is similar in choice data to the role that long run choice shares play. In Bayesian learning models,

¹⁶ We note that the estimated parameter will capture the benefits only from watching the most recent episode, a conservative estimate of the social utility one might get from watching a program.

¹⁷ We can identify this variance and the measurement error variance because we assume $EL_{i,t}$ and $Lik_{i,t}$ are on the same scale.

the changes in average shares over time along with the (decreasing) association between choices and the arrival of informative cues is used to estimate the initial belief variance, $\hat{\sigma}_{0,\mu_i}^2$. We have not only choices, but also the levels of $EL_{i,t}$ and changes from $EL_{i,t-1}$ to $EL_{i,t}$ as well as the direct measures of change, $\Delta EL_{i,t}$.

Third, these self-reported data allow a data-driven separation of the informative and reminding effects. Past studies that have separated informative and persuasive effects (Ackerberg 2001, 2003, Narayanan et al. 2005, 2009) do so based on the diminishing returns to informative effects or observable variables that suggest learning has already occurred, such as extensive experience with a product. The remaining effect of ads (or other cues) after obtaining extensive product experience is attributed to so called persuasive or prestige effects. Netting these effects out for those without extensive experience provides an estimate of the informative effects. In contrast, our approach is almost exactly the opposite. We require the informative effects to operate through changes in the stated expectations and attribute any remaining effects to the reminding process. By doing so, we are using the stated expectation and experience data to identify consideration as the component of the choice process that is not operating through these measures. In Section 4.3.2, we use this essential logic to provide model free evidence that reminding effects exist and in the structural model analysis we impose a specific memory model.

Finally, although we endogenize viewing decisions, we argue that it is reasonable to assume that advertising and social engagement cues are exogenous given the observed variables. Our strategy rests on two inclusions in the model. First, we acknowledge that endogeneity in advertising could arise from demand shocks for the program that are not accounted for in the estimation, but are incorporated into the advertiser's decision to air show promos. In this case, we would see positive correlation between advertising and choices

that would lead to positive bias in the advertising effects. We include in the model time effects for each airing period that control for aggregate demand shocks. This controls for the reverse causality concern that aggregate advertising may decline in response to declining viewing, since the time effects absorb these average level changes. Second, we include observed initial heterogeneity and the time-varying, individual-level observed measures of preference (i.e., $EL_{i,t}$ and $Lik_{i,t}$), which controls for heterogeneity in (expected) tastes. These controls reduce the concern that unobserved heterogeneity is causing our results, and in particular that social engagement effects are biased due to correlation with unobserved preferences. Further, in Appendix F, we test (1) whether social engagement behaviors change in response to the expected liking measure and find no statistical evidence of such changes and (2) whether socializing is restricted to follow watching the most recent episode (i.e., reverse causality) and again find no statistical evidence to support this concern.

6. Structural Model Results

We present estimates from three models in Table 7 and begin with the variables related to the learning and informative effects. The true match-value and initial belief distributions are characterized by the observable heterogeneity parameters in γ_μ and $\gamma_{\bar{\mu}}$ and the unobservable heterogeneity variances, σ_μ and σ_1 . The observable heterogeneity parameters imply that the conditional mean of the μ_i distribution is always above that of the $\bar{\mu}_{i,0}$ distribution, suggesting individuals at the average are increasing the match-value belief as additional signals arrive. This is consistent with the reported evidence in Section 4.2 that expected liking increases over time. However, the variances, σ_μ and σ_1 , indicate that 40% of the population have $\bar{\mu}_{i,0}$ above the μ_i .

The initial variance of the match-value belief, $\hat{\sigma}_{0,\mu_i}^2$, follows a lognormal mixing distribution, which is skewed. The value at the 19th quartile is 3, at the 50th is 6, and at the 81st is

10. This suggests modest uncertainty with a slight skewness in the distribution. The mean parameter, $\gamma_{\sigma, nDrama}$, is significant and negative as expected. When $nDrama_i = 0$, the median value for $\hat{\sigma}_{0, \mu_i}^2$ is 9, whereas it is 4 when $nDrama_i = 4$. These results are consistent with the intuition that category knowledge decreases the variance in the belief.

The signal variances, $\sigma_{v, ad}^2$, $\sigma_{v, so}^2$, and $\sigma_{v, ex}^2$, capture the informativeness of the signals. The ordering of the magnitudes is experience, advertising, and social engagement. The signal variances for advertising and social engagement are so large that their impact is negligible. In contrast, the signal variance for experience is only 2.55 and tightly estimated. This result that experience is informative, but advertising and social contact are not is consistent with the results from our descriptive analysis.

The parameters for the initial memory, $B_{i,0}$, γ_{mem} , present an intuitive story. Both variables are positive and significant as expected indicating that awareness of the program reflects higher initial memory. The depreciation parameter is negative leading to a δ value of approximately 0.001. At this level of depreciation, initial memory is near zero in the period before the second episode airs, and those who were initially aware are only 10% more likely to consider the program in the half-week after the premier episode (assuming no other cues). This suggests memory is short-lived.

The reminding effect parameters, ϕ_{ad} , ϕ_{ex} , and ϕ_{so} , are all positive and significant. Advertising and experience effects are large enough to keep the program in consideration for a full week, while social engagement generates a meaningful impact only in the half-week it occurred. This suggests that all three cues play a role in reminding individuals to watch the program. As for the contextual variables, watching TV in the previous half-hour leads to a significantly lower likelihood of considering the focal program (i.e., $\psi_{TV} < 0$), while watching the FOX channel, ψ_{FOX} , has a positive, but insignificant effect. Taking into account the

positive direct effect of prior television on utility, this implies that those who are already watching television are less likely to view *Human Target* than those who turn on the TV when *Human Target* airs (i.e., they may have turned it on specifically to do so).

The enhancing enjoyment role for social engagement is captured in the social utility parameter, ω . This parameter estimate is positive and significant with a value of 0.42. At this level, the social utility is equivalent to a modest shift (3 points on the 11 point $LW_{i,t}$ scale) in the true match-value. This finding suggests that social engagement can be an important avenue to increase (or hold on to) viewership even when the programming is not particularly well-suited to the tastes of some audience members.

The remaining parameters provide sensible results. The effects for prior TV viewing and time-shifting have the expected direction and significance. Having the television on previously suggests that individuals will more likely continue watching television (whether the focal program or some other programming). The time shifting parameters indicate that those who indicated watching television mostly at broadcast are less likely to watch in time delay than at airing, whereas the opposite is true for individuals who indicate watching television mostly in time delay.

The focal program week fixed effects show no clear pattern and none of the effects are significant. This suggests that the average viewing trend is captured adequately in the model. We suggest that the reason for not needing these fixed effects comes largely from the reminder effects. We also note that the competitor programming fixed effects decrease for the first three weeks, increase in the fourth week, decrease again in the fifth week, and increase again in the sixth.

6.1. Counterfactuals

Using the estimates from the structural model, we develop several counterfactual experiments to evaluate the impact of advertising and social engagement as well as provide an

indication of the magnitude of effects. In each scenario, we simulate 100,000 individuals, using the empirical distribution for all observed variables (resampling from this distribution), and simulate decisions and signals over a full season of the program (12 episodes). We then calculate the elasticity of response using a two point method. To do so, we calculate a baseline and the market share based on the adjustment indicated for the scenario. We report simulations that use either the MLE point estimates of the parameters, or that incorporate the parameter uncertainty by drawing parameter vectors from the asymptotic distribution. In this latter case, we report the 25th and 75th percentiles of the outcome distribution.

Table 7 presents the different scenarios, the baseline each scenario uses, and the calculated elasticity based on the baseline and adjusted scenario. The findings provide insight into the magnitude of each role of advertising and social media. Scenario 1 indicates that the overall advertising elasticity is 0.088 with a relatively small interquartile range. These values are similar to, albeit slightly lower than, prior advertising elasticities found in the literature with a more recent study finding an overall average of 0.12 (Sethuraman et al. 2011).

Scenario 2 forces the reminder effect of advertising to 0 (i.e., $\phi_{ad} = 0$, imposing a change in the structural effect of advertising for illustration purposes). The baseline in this scenario also forces $\phi_{ad} = 0$, but does not increase the advertising exposures. The elasticity of less than 0.001 (with small variation around this estimate) confirms that in our setting the informative effect of advertising is quite small, and thus the reminder effect dominates.

The remaining scenarios provide insight into the effect of social engagements. Scenario 3 proportionately increases both the occurrence of social engagements and the average

propensity to engage socially (i.e., the propensity that influences the expected social utility). Even with both increases in social engagement, the elasticity is only 0.022, approximately one fourth that of advertising. Thus, for similar percent increases in advertising exposures and social engagements, advertising has a much larger effect on viewing.

Scenario 4 increases the social engagement occurrences but not the propensity to engage socially (i.e., violating rationality in order to assess the effects of social engagement). The elasticity is now 0.009, suggesting that more than half of the effect of social engagement is due to social utility, or greater enjoyment through socializing.

Scenario 5 also increases social engagement occurrences while leaving the propensity to engage socially at the baseline and eliminates the reminder effect of social engagements (i.e., $\phi_{so} = 0$). In this scenario, there is no appreciable change in viewing so that the elasticity is always close to zero. This suggests that most of the effect of social engagement is due to a combination of the reminding effect and the social utility effect.

We also conduct another pair of scenarios (not shown in the table) to provide further insight into the potential benefits of social engagement. In the first scenario, we increase the proportion of the population that is in the high frequency socializer group from 9 to 19 percent. This increases both the frequency of social engagements and the social utility for the 10 percent who become high frequency socializers, while leaving the rest of the individuals the same. This change leads total social engagements to increase by approximately 5 percentage points and the viewing shares to increase by 1.8% (1.6% and 1.9% for the 25th and 75th quartiles). We compare this to a similar 5 percentage point increase in advertising exposures and find that this leads to almost the same magnitude of effect on viewing shares (1.8%). These scenarios suggest that although increasing social engagement on average is much less valuable than advertising, increasing the portion of frequent socializers can have a much larger effect on viewership.

6.2. Discussion

Based on the full model, we find that advertising has a large and influential reminding effect, whereas its informative effect appears negligible in our setting. These results are consistent with Clark et al. (2009), who studied a broad range of brands across multiple categories and finds a significant awareness effect of advertising, but not an effect on perceived quality. Those authors refer to this result as supporting an informing role of advertising. Our results allow us to provide further clarification of this point. The “information” is in the form of memory triggers that keep the brand in consideration. This is in contrast to the informative effects that diminish with the accumulation of informative signals that are captured in Bayesian learning models. One contribution of the current study is to make this distinction regarding empirical advertising effects.

Our empirical results also shed light on the multiple roles of social engagement. We find that for our data, social engagement has a moderate (compared to advertising) role in reminding and, like advertising, a negligible role in informing. More interestingly, social engagement plays an important role in enhancing enjoyment for the program. These social utility effects are larger than the reminder effect of social contact, but given the distribution of social encounters in our data set, still represent a smaller average effect than the advertising reminder effects on viewing. By increasing the share of high frequency socializers, however, the resultant effects have an impact on viewing that is similar to an equivalent increase in advertising exposures. Given that *Human Target* attracted a small (approximately 10%) audience of frequent socializers, we suspect these results may be most readily applied to settings with similarly modest numbers of frequent brand socializers.

7. Conclusion

In this paper we develop a structural model of consumers interacting with entertainment brands. The model incorporates both paid (i.e., advertising) and earned (i.e., social engage-

ment) media effects and distinguishes reminding, informing, and enhancing enjoyment roles for these media influences. The model also allows brand engagement decisions to be made both at launch (original broadcast) and later (in time delay), capturing observed and unobserved heterogeneity in preference for the timing of engagement.

We use a unique data set on television viewing that contains viewing as well as observable information on initial heterogeneity and weekly stated expectation and experience data. We find that advertising plays primarily a reminding role, whereas social engagement plays a mix of two roles—reminding and enhancing enjoyment through socializing about the program. Only experience has a meaningful informing role in our context. We find that the effect of a uniform percentage increase in advertising exposures is four times larger than that of the same percentage increase in social contacts. However, we also find that increasing the proportion of frequent socializers can have a profound impact on viewing—an impact as large as a similar increase in advertising exposures—though our analysis does not go as far as establishing the costs of achieving such an increase.

These results suggest that unlike much of the common wisdoms stated by so called “engagement” advertising agencies, traditional advertising can still be very important. Yet engagement strategies, if producing larger bases of frequent socializers about the program, can have a profound impact, if it can be accomplished with less cost than a similar increase in advertising exposures. Our results suggest that managers of entertainment brands should look to ads that draw attention and are memorable rather than provide information and that broad-based social engagement strategies may be less valuable than ones focused on attracting highly socially engaged viewers.

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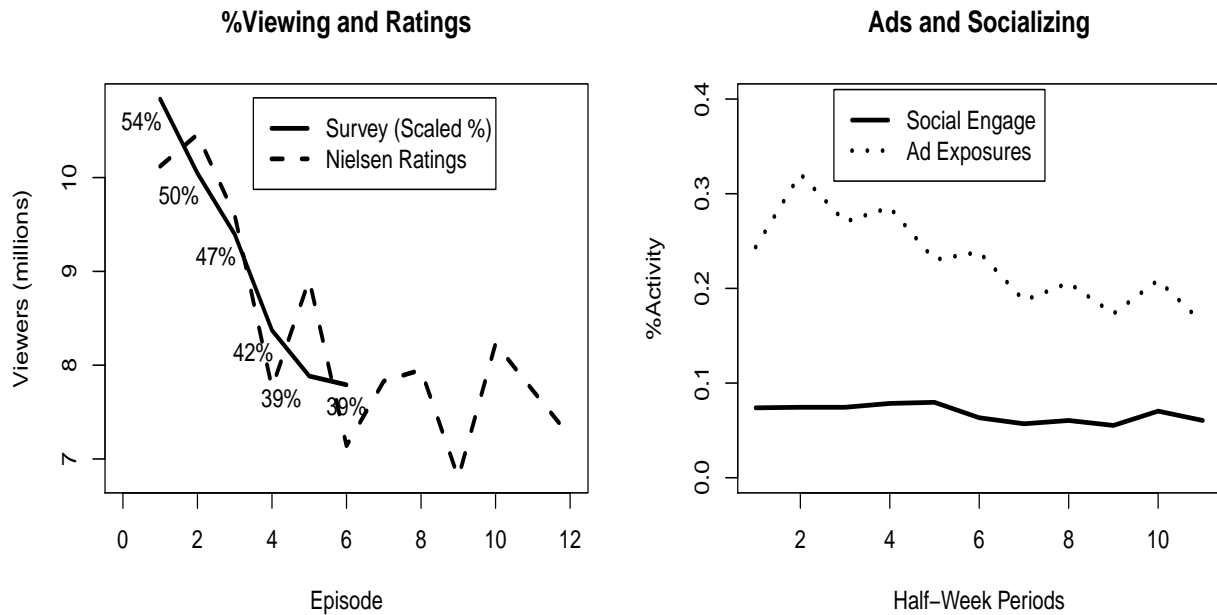


Figure 1 Panel 1: Nielsen Ratings and Viewing: Figure displays the stated viewing versus Nielsen ratings for the show, with the stated viewing % scaled by 20 million viewers to match the scale with the total viewers. Panel 2: Shows the frequency of ad exposures and social engagements over time.

Expectation After Episode	Expected Liking (c-1)	Liking (c)
2 (n=827)	0.296 (17.0)	0.732 (41.7)
3 (n=752)	0.308 (15.7)	0.712 (36.2)
4 (n=695)	0.409 (18.6)	0.606 (27.2)
5 (n=649)	0.449 (18.7)	0.572 (23.7)
6 (n=648)	0.380 (14.1)	0.614 (22.0)

Table 1 Regression of Expected Liking on Prior Liking and Expected Liking

	Expected Liking (avg.)			
	Low ($EL < 8.75$)		High ($EL > 8.75$)	
	Received, $\Delta EL \leq 0$	Did not Receive	Received, $\Delta EL \leq 0$	Did not Receive
Social Engagement	78%	60%	90%	69%
Advertising Exposure	81%	55%	95%	66%

Table 2 Descriptive Evidence on Reminding: The cells are the proportion of the group that watched the focal program.

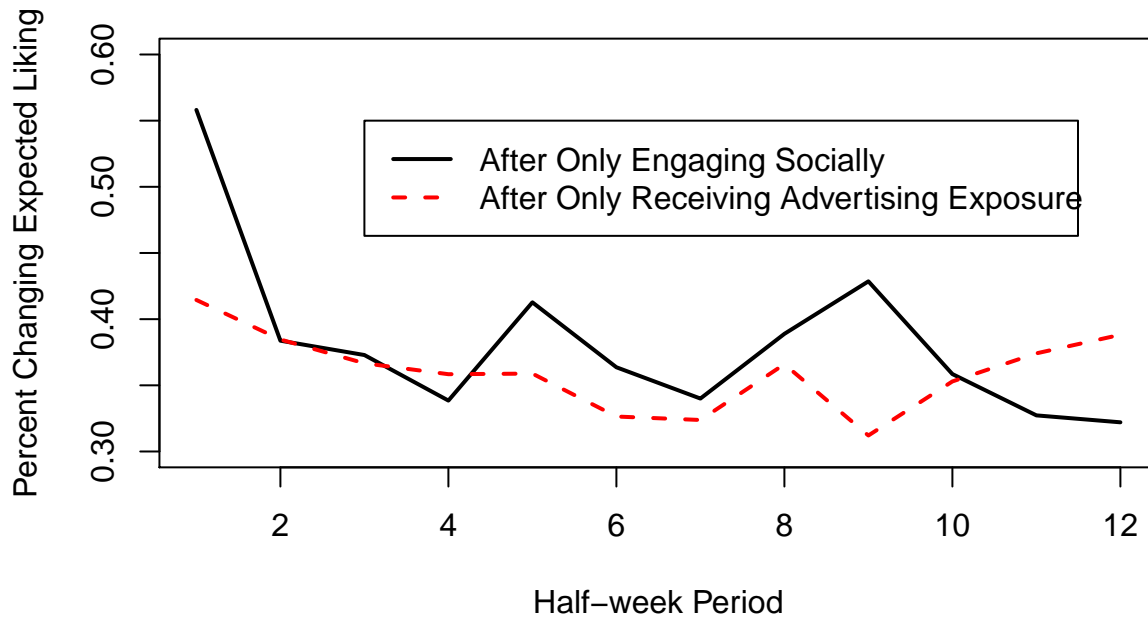


Figure 2 Change in Expected Liking Over Time

Timing Preference?	Social Engagement Propensity (\bar{q}_i)	At Original Airing	First Half of Inter-airing Period	Second Half of Inter-airing Period
Mostly Live	Low (< .25)	72.5%	24.1%	3.4%
Mostly Live	High (> .25)	80.2%	18.6%	1.3%
Mostly Delayed	Low (< .25)	20.1%	77.3%	2.5%
Mostly Delayed	High (> .25)	40.1%	57.7%	1.5%

Table 3 Proportion of viewers over different periods by timing preference and social engagement propensity.

	Model 1	Model 2	Model 3	Model 4	Model 5
Paid(Ad)	0.47 (0.01)**	0.226 (0.01)**	0.216 (0.01)**	0.223 (0.01)**	.
Earned(Social/WOM)	0.26 (0.02)**	0.139 (0.02)**	0.116 (0.02)**	0.077 (0.02)**	.
Watch Last Week	.	0.358 (0.01)**	0.267 (0.02)**	0.268 (0.02)**	0.477 (0.01)**
TV On	.	0.088 (0.01)**	0.088 (0.01)**	0.088 (0.01)**	0.099 (0.01)**
FOX On	.	0.082 (0.01)**	0.079 (0.01)**	0.079 (0.01)**	0.123 (0.01)**
Frequent Ad Exposures	.	.	.	-0.013 (0.01)	.
FrequentSocializers	.	.	.	0.060 (0.02)**	.
Time Effects	No	Yes	Yes	Yes	Yes
Fixed Effects	No	No	No	No	No
EL Polynom.	No	No	Yes	Yes	No
R-squared (avg)	0.259	0.39	0.399	0.400	0.349

Table 4 Reduced Form Regression Analysis on Viewing at Broadcast

Entries are coefficients (t-stat) and significance indicators.

** = p-value <.01, * = p-value <.05, + = p-value <.1

	Model 2a (Logit)	Model 2b (MI)	Model 2c (MI)	Model 2d (MI)	Model 2e (FE)
Paid(Ad)	1.00 (0.07)**	0.046 (0.01)**	0.048 (0.01)**	0.060 (0.02)**	0.22 (0.011)**
Earned(social/WOM)	0.66 (0.10)**	0.032 (0.01)**	0.034 (0.01)**	0.066 (0.02)**	0.12 (0.015)**
Watch Last Week	3.30 (0.11)**	0.475 (0.01)**	0.475 (0.01)**	0.243 (0.05)**	0.06 (0.012)**
TV on	0.82 (0.07)**	0.098 (0.01)**	0.097 (0.01)**	0.226 (0.02)**	0.04 (0.007)**
Fox On	0.51 (0.09)**	0.117 (0.01)**	0.116 (0.01)**	0.098 (0.02)**	0.05 (0.009)**
Time Effects	Yes	Yes	Yes	Yes	Yes
Fixed Effects	No	No	No	No	Yes

Table 5 Regression Robustness Tests

Entries are coefficients (t-stat) and significance indicators.

** = p-value <.01, * = p-value <.05, + = p-value <.1

	Parameter	Coefficient	St. Err.
Informing Role (Bayesian Learning Model)			
True	$\gamma_{\mu,0}$	-1.97	(0.17)***
Match-Value	$\gamma_{\mu,LW}$	0.14	(0.01)***
(μ_i)	σ_{μ}	0.16	(0.03)***
Initial Mean	$\gamma_{\bar{\mu},0}$	-2.81	(0.22)***
of Belief	$\gamma_{\bar{\mu},LW}$	0.18	(0.02)***
$(\bar{\mu}_{i,0})$	σ_1	2.29	(0.1)***
Initial Variance	$\gamma_{\sigma,0}$	2.54	(0.34)***
of Belief	$\gamma_{\sigma,nDrama}$	-0.30	(0.11)**
$(\hat{\sigma}_{0,\mu_i}^2)$	σ_2	0.47	(0.13)***
Signal	$\sigma_{v,ad}^2$	12304	(212)#
Variations	$\sigma_{v,so}^2$	9604	(291)#
	$\sigma_{v,ex}^2$	2.55	(0.09)#
Enjoying Role (Social Engagement Utility)			
Social Utility	ω	0.42	(0.09)***
Reminding Role (Memory and Consideration Model)			
Memory	ϕ_{ad}	9127	(171)***
Cue Strength	ϕ_{so}	4.30	(1.11)***
	ϕ_{ex}	6500	(221)***
Contextual	ψ_{TV}	-3.13	(0.23)***
Cues	ψ_{FOX}	0.35	(0.44)
Initial	$\gamma_{mem,0}$	1998	(318)***
Memory and	$\gamma_{mem,Aware}$	3307	(534)***
Depreciation	$\log((1-\delta)/\delta)$	-6.80	(0.14)***
Controls and Measurement Models			
TV	β_{TV}	2.69	(0.17)***
and	$\beta_{TST,0}$	-0.98	(0.24)***
Time-shifting	$\beta_{TST,WTD}$	3.62	(0.27)***
	σ_{TST}	3.75	(0.20)***
Focal	$\alpha_{c,Week2}$	0.27	(0.22)
Program	$\alpha_{c,Week3}$	0.04	(0.21)
Week	$\alpha_{c,Week4}$	0.22	(0.22)
Fixed	$\alpha_{c,Week5}$	0.18	(0.21)
Effects	$\alpha_{c,Week6}$	0.31	(0.22)
Competitor	$\alpha_{P,Week1}$	-0.95	(0.19)***
Program	$\alpha_{P,Week2}$	-1.42	(0.22)***
Week	$\alpha_{P,Week3}$	-1.69	(0.22)***
Fixed	$\alpha_{P,Week4}$	-1.33	(0.23)***
Effects	$\alpha_{P,Week5}$	-1.63	(0.24)***
	$\alpha_{P,Week6}$	-1.5	(0.25)***
Measurement	a_{ME}	9.79	(0.17)***
Scaling	σ_{ME}	1.67	(0.03)***
	a_{cEL}	-3.77	(0.11)***
	b_{cEL}	0.55	(0.03)***
Log-likelihood (full data)		-29408	

Table 6 Parameter Estimates - * - significant with p-value \leq .05; ** - significant with p-value \leq .01; *** - significant with p-value \leq .001; # - these parameters cannot be zero, so the standard hypothesis test is not meaningful.

Scenario	Baseline Scenario	Elasticity		
		At MLE	25%	75%
1. \uparrow Ads	Baseline	0.088	0.086	0.092
2. \uparrow Ads, $\phi_{ad} = 0$	Baseline + $\phi_{ad} = 0$	0.000	0.000	0.001
3. \uparrow Social Engagements, $\uparrow \bar{q}_i$	Baseline	0.022	0.019	0.024
4. \uparrow Social Engagements	Baseline	0.009	0.009	0.010
5. \uparrow Social Engagements, $\phi_{so} = 0$	Baseline + $\phi_{so} = 0$	0.000	0.000	0.000

Table 7 Counterfactual Scenarios - Baseline is calculated using the existing empirical distribution to simulate 100,000 individuals and the elasticities are calculated using a two point method. The elasticities are calculated at the MLE and at the 25% and 75% of the elasticity distribution.

Appendix A: Sample description

Table 8 presents summary statistics for the sample. These data come from a combination of the initial survey and information previously provided by the panelists to VocalPoint. As apparent in Table 8, the sample has a large range in age, education, and TV viewing behaviors with a tendency towards heavy TV viewing and large numbers of action drama TV shows. We also note that the VocalPoint community is all female. The initial survey questions also indicate relatively low aided awareness of 21% for *Human Target* and an extremely low awareness of the comic book series at 1%. Thus, among the sample this series was not building on a large base of knowledgeable and excited followers of an existing brand, leaving a reasonable basis for widespread learning and informative effects.

Appendix B: Survey Measures

In the initial survey we asked a set of questions to understand individuals' pre-study attitudes, behaviors, and intentions. Below are the relevant questions for each measure:

- WTD_i : "Which way do you most often watch TV? I usually watch TV. . ." The options were "as it is broadcast (not taped or DVR)"; "that I have taped on a VCR"; "that I have recorded on DVR/Tivo"; "on the Internet (network websites, websites, Hulu, etc.)". We score the first option as mostly at broadcast ($WTD_i = 0$) and the others as time-delayed ($WTD_i = 1$).

- $nDrama_i$: "How many action drama shows do you personally watch in a typical week?" The options were 0, 1, 2, 3, 4+ and we score "4+" as a 4.

- $Aware_i$: "Which of the following shows premiering or returning in January or February have you heard of: (Select all that apply)" with a selectable button for 17 cases and a "None of the above" option. We take their selection of *Human Target* (one of the 17 options) as awareness.

- $AwareComic_i$: "Have you or anyone in your family ever read any of the Human Target comic books or graphic novels published by DC Comics? (Select all that apply) ." We coded responses indicating yes to "I have read Human Target comic books" as 1 and 0 otherwise.

- LW_i : "Do you personally plan to watch the premier of 'Human Target' on Jan 17th?" The options were
 - 10 - Certainly will watch (99 chances in 100)
 - 9 - Almost certainly will watch (90 chances in 100)
 - 8 - Very probably will watch (80 chances in 100)
 - 7 - Probably will watch (70 chances in 100)

- 6 - Good possibility will watch (60 chances in 100)
- 5 - Fairly good possibility will watch (50 chances in 100)
- 4 - Fair possibility will watch (40 chances in 100)
- 3 - Some possibility will watch (30 chances in 100)
- 2 - Slight possibility will watch (20 chances in 100)
- 1 - Very slight possibility will watch (10 chances in 100)
- 0 - No possibility will watch (0 chances in 100)

During the weekly surveys that were completed between episode airings, we asked a set of questions which differed due to the different programming during the week and the different episode names. These questions that related to each measure are as described below:

- $1(TV_{i,t})$ and $1(FOX_{i,t})$: “Think back to [Insert Date/Day of week]. What did you watch from [Insert half hour prior to Human Target start time with Central time noted]?” The options indicated channel and program (where appropriate). In addition, we included options for “Did not watch TV anytime during [time period],” “I watched TV then, but I don’t remember what I watched,” and “I don’t remember whether I watched TV during [time period].” We coded the obvious cases as expected and code the watched TV but don’t remember as $1(TV_{i,t}) = 1$ and $1(FOX_{i,t}) = 0$, while the don’t remember case we coded as both zeros.

- $w_{i,t}$: “The [episode number] episode of Human Target titled [Insert title] was about [Insert one sentence description]. Did you watch [episode title] which aired at [airing date/time]?” The options were

1. Yes, I watched it when it was televised
2. Yes, but I watched it after it is was televised using a DVR, Tivo, VCR or the Internet
3. No, but I plan to watch it before the next episode
4. No, I do not plan to watch it
5. Don’t remember whether I watched it or not

We coded item 1 as at broadcast, 2 as in time delay in the first half of the inter-airing period (recall the surveys were completed half-way into the week). For the remaining cases, we asked two additional questions. The first requested what show(s) they watched during the Human Target airtime. Hence, we have the exact alternative show only for those who did not watch Human Target at air time or in the first half of the week (this was due to length limitations in the survey, since the others responded to additional questions). The second follow-up question was asked in the survey in the following week. In this question we asked, ”Which

of the following previously aired Human Target episodes did you watch? (check one box in each row that best describes your situation).” The answer type had as a row the second most recent episode (along with the other previously aired episodes) and as columns options for when the episode was watched. These options were

1. Watched Before Seeing the Most Recent Episode ([Insert current episode title])
2. Watched After Seeing the Most Recent Episode ([Insert current episode title])
3. Watched But Not Sure If I Saw It Before or After [Insert current episode title]
4. Did Not Watch this Episode
5. Not Sure Whether I Watched This Episode

We used the answers to these questions to fill in the other half-week period, coding options 1 and 3 as watching in the second half of the inter-airing period, and the remaining cases as not watching the episode.

We note that option 2 and 3 consisted of a negligible portion of observations.

- $EL_{i,t}$: “If you were to watch the next episode of Human Target ([Insert airing date/time]), how much would you expect to like it?”

- 10 - As much as the best action drama TV episode I have ever seen
- 9 - As much as one of the best action drama TV episodes I have ever seen
- 8 - Much better than the average action drama TV episode I have seen
- 7 - Better than the average action drama TV episode I have seen
- 6 - Slightly better than the average action drama TV episode I have seen
- 5 - As good as the average action drama TV episode I have seen
- 4 - Slightly less than the average action drama TV episode I have seen
- 3 - Less than the average action drama TV episode I have seen
- 2 - Much less than the average action drama TV episode I have seen
- 1 - As little as one of the worst action drama TV episodes I have seen
- 0 - As little as the worst action drama TV episode I have seen

- $Lik_{i,t}$: For those who answered watching the program they also answered, “How much did you like [Insert episode title] the [insert episode number] episode of Human Target?”

- 10 - As much as the best action drama TV episode I have ever seen
- 9 - As much as one of the best action drama TV episodes I have ever seen

- 8 - Much better than the average action drama TV episode I have seen
- 7 - Better than the average action drama TV episode I have seen
- 6 - Slightly better than the average action drama TV episode I have seen
- 5 - As good as the average action drama TV episode I have seen
- 4 - Slightly less than the average action drama TV episode I have seen
- 3 - Less than the average action drama TV episode I have seen
- 2 - Much less than the average action drama TV episode I have seen
- 1 - As little as one of the worst action drama TV episodes I have seen
- 0 - As little as the worst action drama TV episode I have seen

• $C_{i,t,ad}$ and $C_{i,t,so}$: “Think about the time [since/before] you watched [Insert episode title], the [Insert episode number] regular episode of Human Target. During that time, did you hear about the show from any of the following sources? (check all that apply)” The options were

1. Show previews on TV (coded as ad)
2. Show or network website (coded as ad)
3. General websites (e.g., Yahoo, MSN, AOL, IMDB)
4. Media coverage (e.g., TV Guide, Entertainment)
5. Online social networks (e.g., Facebook, Myspace, Twitter) (coded as social engagement)
6. Friends (coded as social engagement)
7. Family (coded as social engagement)
8. Co-workers/colleagues (coded as social engagement)
9. Other [blank to fill in] (please specify)
10. Did not hear from any sources prior to watching

Less than 4% of possible cases contained responses of either 3 or 4 and they didn’t have a significant effect on airtime viewing. As a result, we did not include them in the analysis. The “Other” category was manually coded into one of the existing categories.

• $\Delta EL_{i,t}$: For those who indicate receiving a cue for ads or social engagement we asked, “Sometimes other sources affect how much people expect to like an episode. Overall, how did [Insert sources] change how much you expect to like the next episode of Human Target ([Insert air date/time information with Central time

noted]?” The options were “Increased how much I expect to like it,” “Decreased how much I expect to like it,” and “Did not change how much I expect to like it.”

Appendix C: Relationship between survey measures and other data

In this section, we present evidence to corroborate the data patterns we obtain from the weekly surveys. We begin by checking whether the self-reported advertising cues are internally consistent with other self-reported data from the initial survey. Specifically, the initial survey contains a categorical variable for self-reported weekly hours of TV viewing. We match this general behavior to the frequency of self-reported advertising exposures for the *Human Target* program. Our expectation is that there should be a positive relationship between the two variables, since TV viewing is what leads to exposure to show promos. Table 9 presents the summary. From this table, the relationship is clear. Further, the overall relationship is statistically significant based on a rank correlation test, and the differences between pairs of frequencies are all statistically significant except the pairs (1-4 Hours, 5-8 Hours) and (9-12 Hours, 12+ Hours). The difference between 5-8 Hours and 9-12 Hours is only marginally significant. Based on these results, we suggest that this relationship exists and, given measurement error and the lumpiness of the show promos (i.e., which kinds of shows they air on are not spread evenly across shows), the differences appear sensible.

We next describe the relationship between our self-reported data and outside data. In the text itself, we discuss the similarity between our data and the Nielsen aggregate ratings. We find that both our sample and the Nielsen ratings for the program decline over time and flatten at the end. Despite the fact that our sample is not intended to be representative, it captures a dominant pattern in the data.

We provide two additional comparisons related to our ad exposures and social contact measures. First, we compare the self-reported advertising measure against paid advertising as collected from Kantar media’s AdSpender product. AdSpender provides weekly TV expenditures and monthly expenditures on all media (print, outdoor, internet display, radio, and TV). Looking across all media, we see the largest paid buys occurring in January and February (the month of and after the launch). Continued low levels of paid ads occur, throughout the Spring season, but at much lower spending levels. Looking just at paid network TV where we can see weekly expenditures, we see a two week build-up prior to the show launch totaling nearly 200 paid promos. In the week of the launch, over 500 are aired, in the second week over 200, and in the third week only 121, after which it is 0 until the next fall season. Like the self-reported advertising, these numbers decline, but more sharply. However, AdSpender excludes show promos aired on FOX, which are

not paid. Indeed, in an analysis of eleven programs for which we had both the Ad\$ponder data and AdvIEWS data on when show promos aired, we found that all eleven had a surge of advertising around the premier but also continued promos after that surge. Hence, at least anecdotally, we find such unpaid promos may make up a significant portion of total advertising and continue after the burst of paid ads. This suggests that the self-reported advertising data reflect similar declining trends as the aggregate data.¹⁸

Second, we turn to the self-reported social contact measure. We collect public social media posts (e.g., Twitter posts) during the survey period from the tool Nielsen-McKinsey Incite. This tool collects the posts about the program using a query into a database of text data pulled from public social media sources (i.e., it does not include private Facebook data). The query contained terms related to the TV show “Human Target” (after dropping unrelated posts). Because this data only contains public online social media posts, we construct the most relevant comparison metric from our self-reported data, online social media contacts. We note (1) that our measure includes listening without posting and (2) that these online social contacts represent less than 15% of the total social contacts we measure. Nonetheless, we find a fairly reasonable correspondence with both series presenting a declining trend (see Figure 3). Both patterns decrease over the period and it appears that the self-reported measure that includes listening, not just posting may lag by a week. We take this as suggestive that our self-reported social contact measures have a reasonable correspondence to observed data.

To summarize these results, we find that aggregate movements in the self-reported viewing, advertising, and social contacts measures have a reasonable correspondence with aggregate observed data we were able to collect. In addition, the distribution of advertising frequency has internal consistency with measures of hours of television viewing per week.

¹⁸ Related, to evaluate how common such a burst strategy is, we develop a dataset of six network programs with Spring premiers in 2010 and eleven programs from cable and network TV that had premiers in the Spring of 2012. We collect paid TV promos from Kantar Media’s Ad\$ponder product. Of these programs every one had a similar burst of advertising around the premier week and lasted a few weeks after the premier. This set included both successful programs and ones that were cancelled. Hence, this strategy of bursting around the premier seems quite common among successful and unsuccessful programs. We also obtained a dataset for the same eleven programs of all TV promos (paid and unpaid). Indeed in our analysis of this AdvIEWS data provided by Nielsen, we find that unpaid promos are as frequent or more frequent than paid promos. For instance, for a show launched in April 2012 (ABC’s *Scandal*), we find a similar declining trend in paid advertising to *Human Target* and during the first two months, the number of promos on other channels and promos on ABC appear to be fairly similar. Again, the evidence seems consistent with the declining trend being common practice and not necessarily in response to ratings. This is consistent with anecdotal evidence from television industry executives. Thus, we feel comfortable in assuming declining viewing is not causing the major advertising decline in our case.

Appendix D: Variation in Survey Measures

In this section, we discuss the key survey measures and describe the variation in the measures. In particular, we examine the within and between survey variation in the measures $EL_{i,t}$ and $Lik_{i,t}$, and we present illustrative individual patterns. We then examine two potential concerns commonly raised in survey research—common methods variance and scale usage heterogeneity.

D.1. Within Survey Variation and Correlation

Table 10 presents information related to within survey (across individuals) variation and correlation. We first address how much variation exists in the measures. Both measures contain reasonable amounts of variation with period specific variances ranging from 3.4 to 4.3 and the overall variance of $Lik_{i,t}$ being 3.7 and that of $EL_{i,t}$ being 4.0. More interesting is the time pattern of these variances. Consistent with our expectations, the variance of liking does not have a clear pattern. In contrast, the variance of $EL_{i,t}$ increases over time, which is consistent with heterogeneity in the true match values and learning over time.

Second we consider the correlations. The main concern is that the questions related to $EL_{i,t}$ and $Lik_{i,t}$ are simply too correlated. Of course, given our structural model, the two variables should theoretically be correlated. As a result, when designing the study we aimed to develop scales that give respondents the ability to discriminate fine enough differences so that the variables would not be perfectly correlated. Hence, the two questions were separated within the survey by a number of other questions including open-ended questions, and the scales had 11 points rather than a more typical 5 or 7 points.¹⁹ This design led to Pearson correlations (see Table 10) that are high, as expected with values ranging from 0.87 to 0.92 for the weekly surveys and 0.90 overall.

To get a better sense of the variation, we present data on how different the responses are to the two questions (see Table 10). Specifically, we calculate $\text{abs}(EL_{i,t} - Lik_{i,t})$ and tabulate the portion of cases in each of four categories of these differences—0, 1, 2, and 3+. For this analysis (and the correlations mentioned above), we also include only the cases in which individuals provided both measures in any given week. We find that between 35% and 25% of the sample differ. This suggests there is distinct variation for the two measures. More interestingly, the pattern of these differences is exactly what one would expect if the individuals are

¹⁹ Note also that these scales were pretested by rotating the type of scale between a 5 point, 7 point, and 11 point scale in order to evaluate whether the response and non-response tendencies appeared to differ between these scales for the population we were studying. We did not find evidence of such and neither did the survey administrators, who were interested in this question for their own internal use.

learning from these signals—the expectations match experiences better towards the end of the study period than at the beginning.

D.2. Between Surveys Variation and Correlation

Table 11 presents the information related to between survey variation. The main concern between surveys is that the variables don't have much variation (i.e., are too consistent). Again, the difficulty is that the liking for a show is likely to be relatively consistent over time given a person's true match-value. Our goal then is to illustrate the degree of variation in the data series $EL_{i,t}$ and $Lik_{i,t}$ over time. We present first the average variance within individual. For $EL_{i,t}$ the average is 0.91 for those individuals with all cases observed and 0.97 for those with at least two cases observed. For $Lik_{i,t}$, the average is 1.14 for those with all cases observed and 1.16 for those with at least two cases observed. However, these averages do not tell the full story. For instance, for some individuals the programming matches fairly closely their expectations while for others it does not. As a result, the total range of values can differ across the population of individuals.

To capture the amount of change in the data, Table 11 presents the distribution of the range of answers each individual provides. As above, we present results both for individuals who always provided responses and for individuals who provided at least 2 observations. This distribution suggests that while there are individuals whose responses do not change or change very little, over half of the individuals change their responses by more than two levels over the course of the period. Further, this variation is higher for Liking than for Expected Liking, what we would expect, since expectations should be less variable than experiences.

We next report the correlation between the lagged (periods 1-5) and the current (periods 2-6) values of the variables. We find that the sample with at least two observations has a Pearson correlation of 0.84 for $EL_{i,t}$ and 0.75 for $Lik_{i,t}$. Given the common source of *theoretical* variation, this degree of correlation is not too surprising.

D.3. Example Patterns in Individual-level Data

Below we present individual-level data patterns for three individuals in order to illustrate the role of the survey data. The figures present the expected liking, $EL_{i,t}$ (the dotted lines with circles as markers) over time, the self-reported experiences, $Lik_{i,t}$, if watched (indicated by EpX), and the cues from advertising (ad), owned media/PR (me), and social contact (so). The dotted lines up to the vertical position of these cues indicate whether the cues in total were reported as leading to increases (dotted lines moving to text at

the top of graph), decreases (dotted lines moving to text at the bottom of graph), or no change (no vertical dotted line) in the expected liking, i.e., $cEL_{i,t}$.

From these data, we wish only to point out a few features that are relevant. Individuals expectations change over time and although some of these shifts are coincident with experienced liking or cues, others are not. Assuming these variables are reflective of the actual match value beliefs, it is easy to see how this data provides some individual-level information. In particular, one can see from Panelist 8 that the initial match-value belief, $\bar{\mu}_{i,0}$ is above average and increases to (apparently) stabilize around 10 (one from the top value on the scale), suggesting μ_i is very high. For Panelist 26, the $\bar{\mu}_{i,0}$ appears to be low and increases dramatically to stabilize at a relatively high-level, again suggesting a high μ_i . Panelist 2 appears less unidirectional and doesn't appear to have started too far from the ending belief, suggesting both the μ_i and $\bar{\mu}_{i,0}$ are similar. However, the plots also suggest that the individual-level data is unlikely to calibrate individual learning rates very precisely. That said the rate at which $EL_{i,t}$ responds less to the new experiences and cues will be helpful in this regard. In each of these patterns one might see such diminishing response, though perhaps to varying degrees. Similarly, the data has coincidence of recent cues and watching, suggestive of reminding effects. For instance, for Panelist 8, the individual watches Episodes 1, 2, 5 and 6 after having seen ads recently, but did not watch Episodes 3 and 4 and did not receive any cues that might have triggered memory to watch those episodes. Of course, all of this is merely suggestive and the analyses involving the full sample provide the econometric evaluation of these effects.

D.4. Discussion of Common Methods Variance and Scale Usage Heterogeneity

The first concern, common methods variance refers to a condition in which the measurement approach itself leads to correlations rather than the underlying constructs. To test for the potential size of common methods variance, we follow the spirit of Lindell and Whitney's (2001) "marker" variable approach. The marker variable approach use a variable collected in the survey that is theoretically unrelated to the other variables within the survey. The idea is that this variable contains the common methods variance (e.g., mood effects) and can be used to evaluate the size of this variance (or the magnitude of the correlation arising from this variance). We do not directly observe such a variable, but we have a similar approach to construct such an estimate.

Specifically, we use the variable, $cEL_{i,t}$, which measures the change in expectations due to all cues received. Theoretically, $cEL_{i,t}$ can be correlated with $cEL_{i,k}$ for $k \neq t$ due to persistence in the difference between the

true mean and the belief about the mean. However, we would theoretically expect that the correlation between adjacent pairs, $cEL_{i,t}$ and $cEL_{i,t+1}$ and $cEL_{i,t+1}$ and $cEL_{i,t+2}$ would have similar correlations, with the latter perhaps slightly lower because learning has on average reduced the distance between truth and belief. We propose to measure the extent of common methods variance by comparing the the correlation between $cEL_{i,t}$ and $cEL_{i,t+1}$, which are selected to be adjacent pairs both collected in the same survey against adjacent pairs of $cEL_{i,m}$ and $cEL_{i,m+1}$, which are selected to be in different surveys. By taking the difference between the correlations, we can estimate the influence of common method variance on within survey correlation due to such factors as mood that affects all of the measured variables. Pooling across all available pairs, the between-surveys Spearman correlation is 0.50 and the within-surveys Spearman correlation is 0.69, leading to a difference of 0.19. Estimating the correlations separately for each pair and then taking the difference in the average correlation for the two sets leads to a similar value, 0.18. In contrast, the Spearman correlation is 0.89 for the $EL_{i,t}$ to $Lik_{i,t}$ relationship. In other words, by this estimate of the common methods variance, only approximately 20% of the within-survey correlation could be explained by this issue. Thus, common methods variance appears to be relatively small.

The second concern, scale usage heterogeneity, refers to the situation when different respondents use survey scales differently so that variation across respondents is not as useful. The basic concern is that different individuals use different parts of the scale to communicate the same subjective assessments. For example, if this issue were problematic, two people with the same true subjective evaluation of a program would rate the program differently, say a 6 vs. a 2 simply because of the way they use the scale. In this case, if we ignore scale usage heterogeneity and treat the data as though the 6 and 2 reflect true differences in their opinions, we would falsely assess the person rating a 2 as less likely to watch than the person with a 6.

Most of the literature addressing this concern (e.g., Allenby et al 2001; Johnson 2003) focuses on applications where individuals respond to a large number of identically (or very similarly) formulated scales within a *single survey*. For example, Johnson (2003) considers an application where respondents rate 72 different objects on the same seven-point scale and Allenby et al (2001) consider a case where respondents rate the brand on 10 different dimensions using the same ten-point scale. Such within survey correlation is exactly the concern we addressed above. However, scale usage heterogeneity could potentially influence responses to the same scale across surveys, i.e., correlation in repeated measurements, though generally longitudinal studies are considered less susceptible to measurement effects (e.g., Rindfleish et al. 2008).

Mathematically, addressing scale usage heterogeneity in our setting would require the measurement model to have individual-level parameters for the scale, σ_{ME}^2 , and intercept, a_{ME} . Doing so assumes cross-sectional variation is not informative. Including such individual level parameters would only allow information from variation over time within individual. This is a very conservative assumption and it can be evaluated by checking whether the cross-sectional variation predicts behavior. In our context, we examine whether the lagged expected liking measures, $EL_{i,c-1}$, are related to the watching behaviors, $w_{i,c}$. In Figure 4, we present the mean proportion that watches (along with 1 standard error above and below the mean in dotted lines) for each level of lagged $EL_{i,c-1}$. We see a clear pattern of increasing watching as expected liking increases. In fact, it appears that cross-sectional variation in the $EL_{i,t}$ measure is a good predictor of watching. This suggests that scale usage heterogeneity is not too severe. To provide an even tighter test, we restrict the sample to individuals who respond with the same value to all six $EL_{i,t}$ questions (e.g., an individual always rates the program a 6). Under scale usage heterogeneity, the econometrician would have no information from these responses about the likelihood of watching. Because there are only 89 such individuals, the cells at each level of $EL_{i,t}$ are too small to calculate precise cell means and only 14 observations exist at or below 8. Hence, we split the sample with cut-points at 8, 9 and 10. For each cut-point, we calculate the difference in average viewing rates between those at or below the cut-point and those above it. We find that in each case the difference in viewing shares is greater than 0.25 and significant. Again, under a very tight test, the cross-section is predictive of viewing even when it should have no information under the scale usage heterogeneity assumption.

To summarize, we find that neither common methods variance nor scale usage heterogeneity appear to be major concerns in our data. As a result, in the paper we ignore these problems.

Appendix E: Likelihood notation details

In this appendix, we provide details of the notation and calculations for the full model likelihood. The likelihood components from the measurement model are

$$\begin{aligned}
 L_{EL,i,t}(\theta, \theta_i, I_{i,t}) &= f_N(a_{ME} + \bar{\mu}_{i,t}, \sigma_{ME}^2) \\
 L_{Lik,i,t}(\theta, \theta_i, I_{i,t}) &= f_N(a_{ME} + v_{i,t,ex}, \sigma_{ME}^2) \\
 L_{\Delta EL,i,t}(\theta, \theta_i, I_{i,t}) &= (\Lambda(a_{\Delta EL} - \Delta \bar{\mu}_{i,t}))^{1(\Delta EL_{i,t}=-1)} (1 - \Lambda(b_{\Delta EL} - \Delta \bar{\mu}_{i,t}))^{1(\Delta EL_{i,t}=1)} \\
 &\quad \cdot (\Lambda(b_{\Delta EL} - \Delta \bar{\mu}_{i,t}) - \Lambda(a_{\Delta EL} - \Delta \bar{\mu}_{i,t}))^{1(\Delta EL_{i,t}=0)}
 \end{aligned}$$

where $\Lambda(x) = e^x/(1 + e^x)$.

To write the likelihood of the observed choices we refer back to section 3.5. The likelihoods for an airing and a non-airing period given the set of individual parameters, θ_i and information set, $I_{i,t}$, are

$$L_{w_{i,t=t_{c,A}}}(\theta, \theta_i, I_{i,t}) = \prod_{j \in \{c, P, 0\}} \text{P}(w_{i,t} = j | I_{i,t})^{w_{i,t}=j}$$

$$L_{w_{i,t \neq t_{c,A}}}(\theta, \theta_i, I_{i,t}) = \prod_{j \in \{c, 0\}} \text{P}(w_{i,t} = j | I_{i,t}, w_{i,t-1} \neq c, \dots, w_{i,t_{c,A}} \neq c)^{w_{i,t}=j}$$

respectively, where we drop the obvious dependence on the data. The likelihood for an arbitrary period is then

$$L_{w_{i,t}}(\theta, \theta_i, I_{i,t}) = \left(L_{w_{i,t=t_{c,A}}}(\theta, \theta_i, I_{i,t}) \right)^{1(t=t_{c,A})} \left(L_{w_{i,t \neq t_{c,A}}}(\theta, \theta_i, I_{i,t}) \right)^{1(t \neq t_{c,A})}$$

This leads to the notation used in the joint likelihood of Equation 13.

For some panel members, as described, not all viewing behaviors are observed. This includes cases where the survey was missing (where we assume that the missing data actually means not viewing) and where they indicate watching in time-delay in the first half of the inter-airing period (i.e., not at airtime). Because we do not observe whether a different program was watched or the television was not on, we sum over these possibilities. The consideration probability is unchanged and the non-airing period conditional choice probabilities are unchanged, but the conditional choice probability during airing periods sums over the two non c cases:

$$\text{P}(w_{i,t} = 0 | r_{i,t} = 1, I_{i,t}) = \frac{1 + e^{u_{P,it}}}{1 + e^{u_{c,it}} + e^{u_{P,it}}} \quad (14)$$

$$\text{P}(w_{i,t} = 0 | r_{i,t} = 0, I_{i,t}) = 1 \quad (15)$$

Our likelihood is approximated and involves simulating both the heterogeneity with draws from the mixing distribution and the signals. We need the signals for four purposes—updating the $\bar{\mu}_{i,t}$ according to equation 2 and calculating the likelihood of $EL_{i,t}$, $Lik_{i,t}$, and $\Delta EL_{i,t}$. In each period the role of the signals is simulated by drawing two different quantities—the experience signal (if any) and the combination of the social engagement and advertising exposure signals (if any).

In addition, the transitions of the variance of the belief are updated according to equation 3, which is deterministic given the prior variance belief and the types of signals received (i.e., $C_{i,t}$). These transitions are

$$\hat{\sigma}_{t,\mu_i}^2 = \frac{1}{\frac{1}{\hat{\sigma}_{t-1,\mu_i}^2} + \sum_{k=1}^K \frac{1}{\sigma_{v,k}^2} 1(C_{i,t,k} = 1)} \quad (16)$$

Appendix F: Social Engagement Exogeneity

In this appendix, we conduct several analyses to evaluate whether our assumptions necessary for identifying the social utility effect are reasonable. The first point is whether fixing the social engagement propensity is problematic. As noted in the main text, we also estimated a model in which the occurrence (or not) of social engagement in a period is a signal that informs the future expected propensity to engage socially (i.e., a learning model for the social engagement propensity). This model led to similar results, but found that learning about the socializing propensity is negligible. However, social engagement could be related to changes in expected liking (i.e., the more you come to like the show, the more you talk about it). This led us to calculate the difference in social engagement before and after the measure of expected liking is taken and regress this difference on the change in expected liking (dropping those cases where expected liking does not change). We find a small, positive coefficient of 0.024 that is not statistically significant (p-value of 0.16). We note that this pools over thousands of cases, so if the effect exists, it must be quite small. We take this to suggest that this phenomenon is unlikely to be problematic to our estimation.

The second point is whether causality is reversed. Our argument is that watching earlier leads to more opportunities to talk about the most recent episode, which is why those that socialize more watch earlier. However, if all talking is about the most recent episode (rather than, say, the upcoming episode), then mechanically the earlier the episode is watched, the more the opportunity to talk and thus the more talking that could be observed. This reverses the causality and suggests social utility is not a real effect. To shed light on this possibility, we ran two analyses. In the first the dependent variable is the total amount of socializing between the episode at time t and $t + 1$ and the explanatory variable is whether watching at air time or in time delay in period t . We also control for the expected liking observed at t and use only cases where the program was watched. Using various specifications for the expected liking (including linear and fully non-parametric), we find no significant effects for the timing of watching. This indicates that the timing of watching is not changing the rate at which people socialize about the show. Further, following not watching 4.6% of cases socialize in the inter-airing period. As a second test, we run the analysis in differences to controls for individual fixed effects. We construct the difference between total socializing after episode $t + 1$ and after episode t . We then use as the explanatory variable whether the viewing switched from airing to time delayed, from time delayed to airing, or stayed the same. Again, we find no significant effects for the

timing. Taken together, these analyses suggest that reverse causality in the social engagement effects we find are unlikely to explain our results.

Age	<25 3%	25-34 23%	35-44 31%	45-54 27%	55+ 16%
Education	≤High School 22%	Some College 31%	2 Year Degree 13%	4 Year Degree 21%	Grad School 12%
TV Hours	1-4 11%	5-8 24%	9-12 25%	12+ 40%	
Action Dramas	0 6%	1 15%	2 24%	3 22%	4+ 33%

Table 8 Survey Population Characteristics

	1-4 Hours	5-8 Hours	9-12 Hours	12+ Hours	Overall
Average Frequencies	0.39	0.44	0.50	0.54	0.49
Sample Sizes	104	269	288	466	1127

Table 9 Average Advertising Exposures by TV Watching

	Survey 1	Survey 2	Survey 3	Survey 4	Survey 5	Survey 6	All Surveys
Diff = 0	66%	65%	67%	70%	73%	75%	69%
Diff = 1	25%	26%	25%	23%	19%	19%	23%
Diff = 2	6%	6%	6%	4%	6%	5%	5%
Diff = 3+	3%	3%	2%	3%	3%	1%	2%
Cor(EL,Lik)	0.88	0.87	0.90	0.90	0.88	0.92	0.90
Var(EL)	3.52	3.70	3.73	4.20	4.14	4.34	3.96
Var(Lik)	3.39	3.73	3.67	3.70	3.51	3.36	3.66
Sample Size	932	864	808	720	678	670	4670

Table 10 Within Survey (Across Respondents) Variation and Correlations

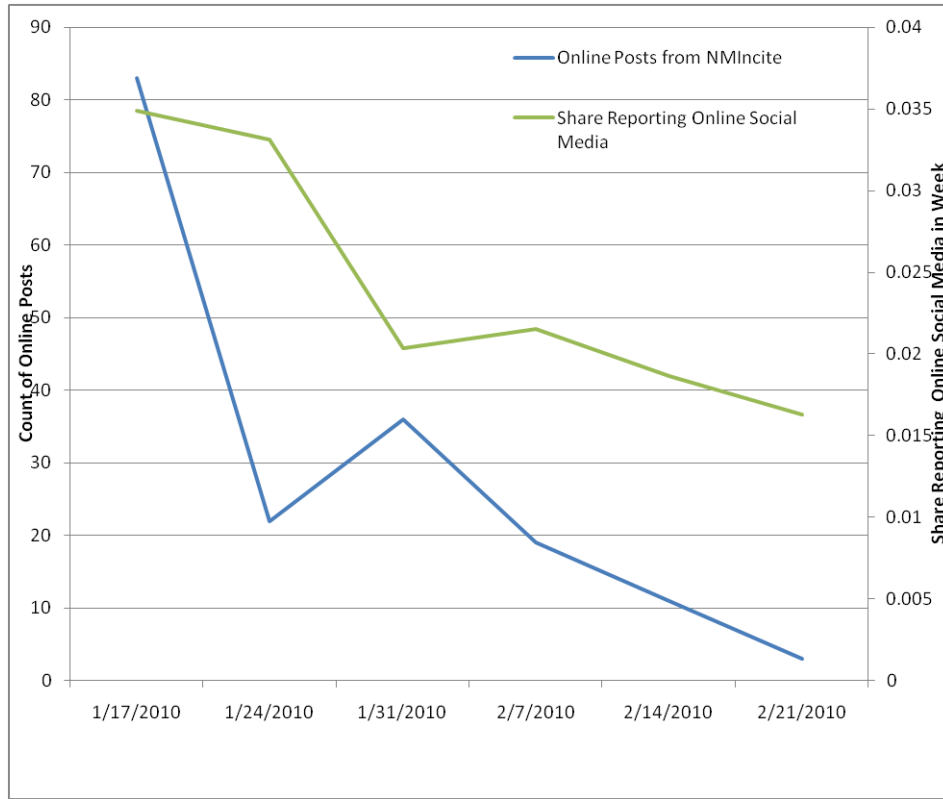
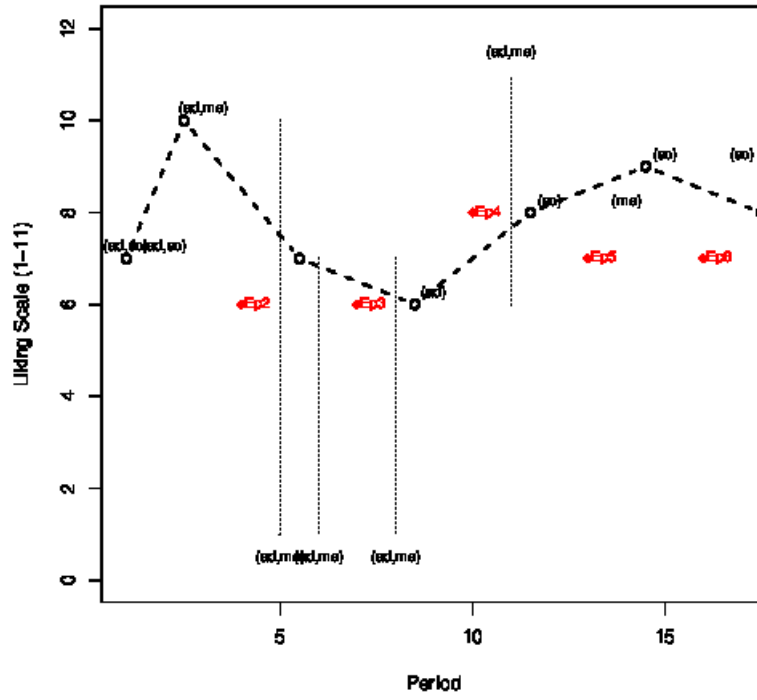


Figure 3 Self-reported Social Media Contacts vs. Public Online Social Media Posts

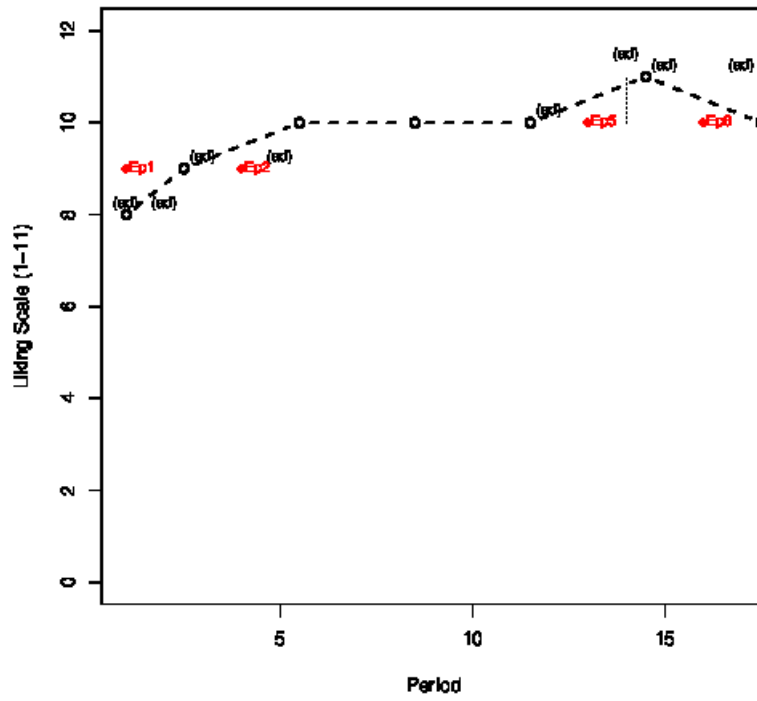
Range is	Expected Liking		Liking	
	6 Obs	2+ Obs	6 Obs	2+ Obs
0	15%	19%	10%	16%
1	31%	32%	26%	28%
2	29%	26%	31%	28%
3	14%	13%	15%	14%
4	4%	5%	10%	8%
5	5%	5%	6%	5%
6+	2%	1%	3%	2%
Avg. Variance	0.91	0.97	1.14	1.16
Sample Size	610	942	539	892

Table 11 Between Survey Variation

Panelist 2



Panelist 8



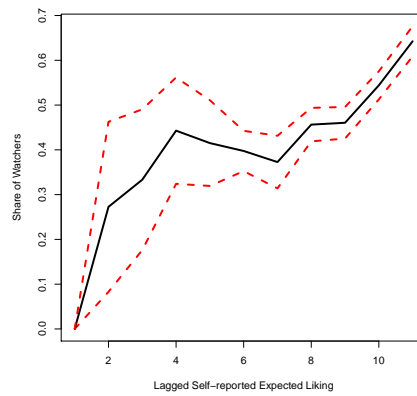
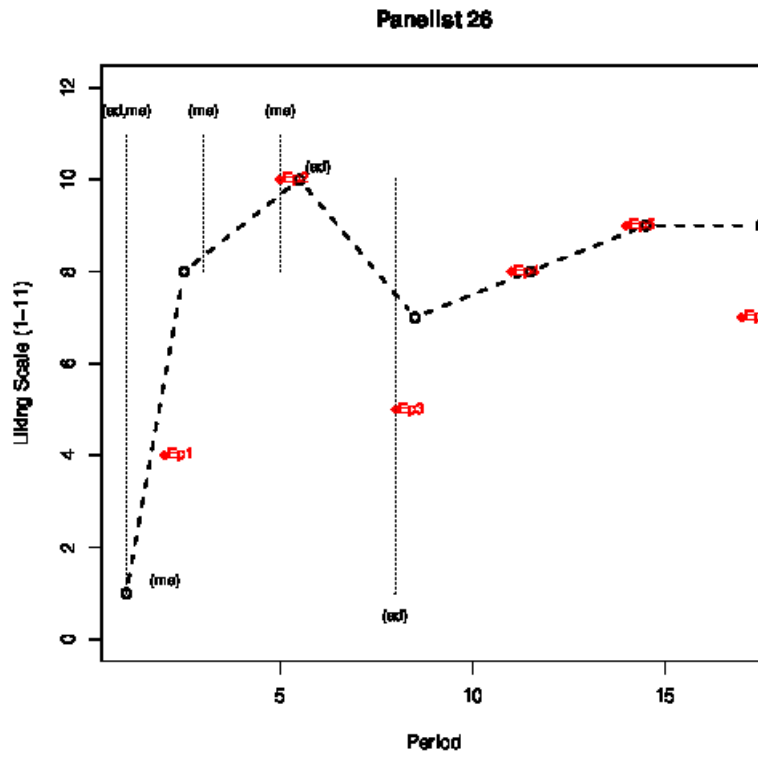


Figure 4 Watching Share by Self-reported Expected Liking