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

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Report Summary

Marketing campaigns now routinely incorporate paid media (advertising), earned media (word-of-mouth and online social media), and owned media (brand websites and other owned content), but the benefits of these strategies are unclear. In this study, Mitchell Lovett and Richard Staelin provide new empirical evidence on the relative effectiveness of these media in the context of building an entertainment brand.

They develop a structural model of viewing decisions and apply the model to a new TV show setting. This model measures the relative impact of paid, earned, and owned media and distinguishes between the roles that each media can play—reminding (increasing salience of the program in an individual's memory), informing (providing information about how well the program matches an individual's tastes), and enhancing enjoyment (enhancing anticipation of future experiences like socializing about the program).

The authors use a unique individual-level dataset about a new television show launch that contains reported viewing, communications, expectations, and experiences. The data was collected over seven weeks via a survey and has strong external validity with Nielsen ratings, Twitter posts, and advertising expenditures. The authors develop a model of program viewing choices that allows delayed viewing and leverages this dataset.

Findings

Descriptive analyses and results from the structural model indicate that earned media are more impactful than paid and owned media *per exposure*. However, paid media has far more exposures, so that *for a given percentage increase,* paid media's influence dominates earned and owned.

Informing. All three media play a modest role in informing individuals about how well the show matches their tastes. Although these informing effects can be large for some individuals, the aggregate informing effect is small because learning increases expected liking of the show for some individuals and decreases it for others.

Reminding. Paid and owned media play a meaningful role in reminding individuals to watch the program. However, the statistical evidence for owned media's reminding effect is weaker.

Enhancing enjoyment. Earned media enhance future enjoyment through individuals wanting to watch earlier in order to benefit from future socializing (or avoid spoilers). This enhancing-enjoyment role is by far the strongest for earned media and offers a new explanation for why live viewing is so prominent.

Overall, this study finds both earned and paid media play important roles in building and maintaining entertainment brands. Despite the focus on social media, this study suggests that managers should not turn away from paid media for supporting entertainment brands. Because the levels of earned media are not sufficient for most modestly successful brands, in order to build and maintain the brand, paid media must remain a central part of the marketing mix.

However, efforts to increase earned media exposures could be quite valuable because of the high impact each of those exposures provides.

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1. Introduction

Firms are increasingly using tactics involving social media marketing, brand communities, and buzz agents to help build their brands (Iezzi 2010, Keller and Fay 2012). Such campaigns now incorporate “paid” (advertising), “earned” (word-of-mouth, social media buzz, or publicity), and “owned” (seller-generated content, websites, etc.) media, but the benefits of these new media strategies are still unclear (Keller and Fay 2012, Bollinger et al. 2013). This study provides new empirical evidence on the relative effectiveness of paid, earned, and owned media in the context of television viewing audiences.

We distinguish between three different roles these media can play—reminding, informing, and enhancing future enjoyment. In the context of this study, reminding occurs when a media exposure (e.g., show promo on TV) increases the salience of the program in a person’s memory (i.e., top-of-mind awareness), making the person more likely to consider viewing the program. Informing occurs when the exposure provides information about how well the brand matches the individual’s tastes. Enhancing enjoyment involves anticipating future experiences–beyond watching episodes (e.g., socializing)–that watching will enhance. Untangling these roles is important both to understand the correct effect of media campaigns and because each of these roles can have different implications for consumers’ choices, firm strategies (e.g., whether to pulse or blast at launch), and equilibrium market structures (Dubé et al. 2005, Narayanan et al. 2005, Bagwell 2008).

We incorporate these three fundamental roles into a structural model of consumers’ viewing choices and then apply the model to data on consumers’ reported viewing, word-of-mouth, media and advertising exposures, expectations, and experiences. To obtain these data, we follow a panel of 1,127 individuals for seven weeks as they make viewing decisions about a new TV series. We obtain initial beliefs about the program as well as weekly reports of beliefs, communications received (e.g., advertising, socializing), and viewing.

This unique data set allows us to distinguish between the roles that paid, earned, and owned media play. We use stated expectations of future experiences to distinguish between the reminding and informing effects. We use the correlation between media exposures and changes in stated expectations to identify the informing effects and identify the reminding effects as the remaining relationship between media exposures and subsequent viewing that does not operate through these stated expectations. We identify the enhancing-enjoyment role by evaluating whether those that on average have more non-viewing encounters (e.g., socializing) also on average watch earlier. Watching earlier gives these frequent socializers more opportunities to benefit from social encounters about the most recent episode.

We provide descriptive evidence, structural model estimates, and counterfactual analyses that present a multi-faceted view on the role of paid, earned, and owned media. We find that because paid media have more exposures, they increase viewing the most for a given percent increase in exposures. However, for equivalent exposure levels, earned media are more impactful. All three media play a modest role in informing individuals about how well the show matches with their tastes. Although the informing effects can be large for some individuals, the aggregate informing effect is small because learning increases expected liking of the show for some and decreases it for others. Paid and owned media play a meaningful role in reminding individuals to watch the program, but the statistical evidence for owned media's effect is weaker. Earned media enhance future enjoyment through wanting to watch earlier in order to benefit from future socializing (or avoid spoilers), whereas those who use owned media tend to watch later. For earned media, this enhancing-enjoyment role is by far the strongest and offers a new explanation for why live viewing is so prominent. We also find that media are more influential for live viewing than for delayed viewing, suggesting new media practices may be needed for the delayed viewers. Finally, although we don't account for costs and consider organic (rather than firm-sponsored) earned media campaigns, we find that earned media effects can be larger than paid media effects when exposure levels are equal. Hence, paid media dominates because exposure levels are higher rather than because the effects are higher. These results suggest paid media still play the central role in shaping viewing, but that earned media can be a fundamental means of developing entertainment brands.

2. Relationship to Literature

Our study builds on several related literatures. Our study adds to the literature on TV viewing choices (Goettler and Shachar 2001) by providing new insight into the drivers of viewing decisions, including paid, earned, and owned media effects, as well as their influence on live versus delayed viewing, an understudied, important aspect of viewing. We add a new explanation (enhancing enjoyment) for why some people prefer live viewing (Vosgerau et al. 2006). Beyond TV viewing choices, we contribute to the literature that partitions advertising effects and examines social or earned media effects.

2.1. Partitioning advertising effects and the enhancing-enjoyment role

The quantitative literature on advertising has taken two different approaches to partitioning effects. The first distinguishes between informative and persuasive (a.k.a. image or prestige) advertising effects. Conceptually, informative advertising effects operate through expanding the information consumers have, and are largest for consumers with relatively little brand experience. By contrast, persuasive advertising effects can influence any individual regardless of experience. 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).

Importantly, both persuasive and informative effects would operate through the expectations consumers have about the brand, because both influence the match value.

A second distinction is between the direct effect of advertising on preferences and the indirect effect on choice by influencing the consideration set. Both Terui et al. (2011), using scanner panel data, and Draganska and Klapper (2011), using aggregate purchase and brand consideration data, find both direct and indirect effects. Mitra and Lynch (1995) use experiments and find that advertising both directly influences preferences and increases the chances an individual will include a brand in her consideration set when she must recall the options. By 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. Honka et al. (2014) use individual-level data on awareness, consideration, and choices in the setting of banks and find that advertising primarily influences awareness rather than choice. Thus, the evidence is mixed for a direct effect, but stronger for the memory/consideration effect.

Before discussing how we add to these literatures, we clarify how we are using the terms that we find used ambiguously in the literature. For example, the literature uses informative effects to describe both information that leads to awareness or consideration (Clark et al. 2009) and information that shapes the perceived quality or match-value (Narayanan and Manchanda 2009). However, the theoretical foundations for these two ideas are distinct, with the awareness approach placing an alternative in the possible set of options, and the match-value approach changing the expected value from purchasing a known, but uncertain alternative. Throughout, we use "informative" to refer only to learning about the match-value, and not awareness or consideration. We use the term "reminding effects" to refer to effects not operating through expectations, which, following Sahni (2011), we model as operating instead through consideration.[1] We acknowledge that although we model these effects as related to memory, empirically they could be confounded with other influences that do not affect expectations.

With these distinctions in mind, we present our contribution to this literature. First, we use our unique data on stated expectations to calibrate the informative effects, and then identify the indirect (reminding) effects as the remaining relationship between the media encounters and viewing behaviors after controlling for stated expectations. Second, we measure these two types of effects not only for advertising (paid media), but also for earned and owned media. Third, we introduce a new effect via anticipated direct utility from future communications (enhancing-enjoyment role). Viewing may allow the individual to express something about herself, create esteem, or avoid spoilers during later conversations (Lovett et al. 2013), or to gain more enjoyment from watching trailers (Tuchman et al. 2014) or interviews with the show's talent. This enhancing-enjoyment role is loosely related to treating advertising as a complementary good (Becker and Murphy 1993) and reflects much of the discussion in the popular literature on why engagement is so important, that is, that people become more involved in the brand as a result of these interactions (Iezzi 2010).

2.2. Earned and owned media

Our study is also related to the literature on earned (e.g., word-of-mouth and social media) and owned media (e.g., TV network website). Our research question and approach differ both from studies that associate aggregate data on choices with aggregate data on paid and/or earned media (Bruce et al. 2012, Godes and Mayzlin 2004, Pauwels et al. 2014,

[1] We also note that our memory model is different from that of Mehta et al. (2004), because 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.

Onishi and Manchanda 2012, Sonnier et al. 2011, Stephen and Galak 2012, Trusov et al. 2009) and from studies that consider individual-level decisions as influenced by geographic proximity (Manchanda et al. 2008), opinion leaders (Nair et al. 2010), particular network ties (Iyengar et al. 2011), and coordination benefits (Hartmann 2010, Yang et al. 2010). We are perhaps most similar to Bollinger et al. (2013) in that we include paid, earned, and owned media as influences on choice, but we study TV viewing, estimate relative effects, and distinguish between multiple theoretical roles the media could play.

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 or DVR) prior to the next episode airing.[2] We index the period by t. The original airing period of episode c is denoted $t_{c,A}$. An episode c can be viewed live in the airing period $t = t_{c,A}$ or in time-delay in any of the following $J-1$ non-airing periods. The next episode, $c+1$, is aired in period $t_{c,A} + J = t_{c+1,A}$. In our setting $J = 3$. Note that, for reference Table 4 contains the parameters, variables, and their definitions.

Consumer i's information set at time t is denoted $I_{i,t}$. The consumer receives cues and signals in the form of paid (ad), earned (so), and owned (ow) media exposures or viewing experiences (ex). We denote the vector of cues, $C_{i,t}$, and the cue types by $k \in ad, so, ow, ex$. If consumer 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 cues and signals received in period t are added to the prior information set, $I_{i,t-1}$, to update the information set at t.

The consumer uses this information set to make decisions. In airing periods, the choice, $w_{i,t}$, is among (1) watching c, (2) an option in P_t (the set of available competing programs

[2] 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.

which we model as a single "other" TV program option), or (3) a non-TV activity. For non-airing periods, an individual may watch episode c in time delay (or not), if she did not already watch episode c.[3] 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 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.

Our primary interest concerns the joint probability of consideration and watching, $\mathsf{P}(w_{i,t}, r_{i,t}|I_{i,t}) = \mathsf{P}(w_{i,t}|r_{i,t}, I_{i,t})\mathsf{P}(r_{i,t}|I_{i,t})$. In the following sections, we discuss $\mathsf{P}(r_{i,t}|I_{i,t})$ and the components of $\mathsf{P}(w_{i,t}|r_{i,t}, I_{i,t})$. These components include the entertainment utility, the anticipated non-viewing utility, and the benefits or costs of watching in time delay.

3.1. Consideration and reminder effects

The probability that an individual considers a program, modeled similar to Sahni (2011), is adapted from the ACT-R model of Anderson et al. (2004). The model assumes that the probability individual i considers the focal program at time t is increasing in the memory-activation level, which is given by

$$\tilde{A}_{i,t} = A_{i,t} + \varepsilon^r_{i,t} = \psi X_{A,i,t} + B_{i,t} + \varepsilon^r_{i,t}, \tag{1}$$

where $A_{i,t}$ is the deterministic component of the memory-activation level for the episode available at t, which 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 $\varepsilon^r_{i,t}$, an idiosyncratic, temporary memory shock. The contextual cues we include are "audience flow" effects (Rust and Alpert 1984, Shachar and Emerson 2000), which in

[3] We do not model competitive options in non-airing periods because we only observe watching (or not) in these periods and directly modeling competition in delayed periods would be very complex.

our case are whether in the half-hour prior to the airing of the focal program the person was watching the same channel as the focal program, $1(\text{FOX}_{i,t})$.[4] The baseline memory-activation level decreases over time because of memory loss, but increases with new cues. Formally, $B_{i,t} = \delta B_{i,t-1} + \sum_{k=1}^{K} \phi_k 1(C_{i,t,k} = 1)$, 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 non-airing periods, we do not depreciate the baseline memory-activation level during airing periods (i.e., $\delta = 1$). We assume $\varepsilon^r_{i,t}$ is distributed with the usual standardized logistic distribution. The resulting probability of consideration is $\mathsf{P}(r_{i,t}|A_{i,t}) = \frac{1}{1+e^{-A_{i,t}}}$.

3.2. Entertainment utility and learning

Assuming the person considers the focal program, the individual decides her entertainment option based on her expected utility for each available option. These utilities contain a number of additively separable elements. First, because of lower transaction costs, individuals who are already watching television may be more likely to continue watching than to switch to other activities. To capture this effect, we include an indicator, $1(\text{TV})$, in all viewing options and β_1 as its linear parameter.

Second, the utility obtained from watching the focal program is a match-value between the individual's tastes and the program, which naturally differs across people. The (average) true match-value between individual i and the focal program is denoted by μ_i.

Individuals have uncertainty about their true match value for the focal program. We model this uncertainty as a belief distribution. Upon receiving new information, the individual optimally updates her belief according to Bayes' rule, learning over time how well the TV series matches her tastes. Viewing decisions are based on the expectation of this belief.

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

We assume 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 $\hat{\sigma}^2_{0,\mu_i}$. Paid, earned, and owned media as well as viewing experiences provide informative, unbiased signals, $v_{i,t,k}$, about the true match value, namely, $v_{i,t,k} = \mu_i + \epsilon_{i,t,k}$. Following the literature, we assume the $\epsilon_{i,t,k}$ are distributed normally with mean 0 and variance $\sigma^2_{v,k}$ and that the individual knows these distributions and signal variances. As a result, following standard formulas (DeGroot 1970), the updated (posterior) belief about the person's true match-value after receiving the signals prior to time t is normally distributed with moments

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

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

These updating equations imply that individuals become more certain with each new signal, decreasing the effect of new signals, that is, diminishing returns to informative effects, and that updated expectations always fall between the prior expectation and the signals.

3.3. Enhancing-enjoyment role

Individuals may choose to watch because of the additional expected utility from future communications. For example, individuals can socialize with others about the most recent episode and gain additional utility from having already watched at the time of the socializing (or avoid a negative utility from spoilers). We assume that these encounters, $C_{i,t,k}$, are passive (i.e., exogenous and stochastic) and follow a Bernoulli process. Individuals have heterogeneous propensities, $\bar{q}^k_i \in [0,1]$, to encounter per half-week these communications related to the program.[5] Our utility formulation is agnostic about the presence of a constant utility (i.e., regardless of the viewing behavior), but because such constant utility does not affect viewing choices, we ignore it. Instead, we focus on the incremental net expected utility gained from watching the most recent episode, c, and receiving a future communication of type $k \in \{ad, so, ow\}$. If the individual watches the current episode, she gains incremental utility, ω_k, in each period she receives such a communication of type k until the next episode airs.

Because future communications are uncertain, the individual bases the viewing decision on the expected number of such communications per period, $\bar{q}_i^k$, and the number of remaining periods $(J - t - t_{c,A})$, implying the enhancing-enjoyment effect decreases the later the episode is viewed.[6] Hence, the anticipated utility from watching in period t is

$$u_{antic,i,t}^k = \omega_k \bar{q}_i^k (J - t - t_{c,A}). \tag{4}$$

3.4. Time-shifting

Finally, we allow consumers to watch after the original airing period, if they didn't already watch the current episode. Watching in time-delay may impose additional costs (monetary, psychological, or time) or generate some benefit from flexibility in scheduling or in skipping commercial breaks. We denote this cost/benefit by $\beta_{NAR,i}$, and use $1(\mathrm{NAR}_{i,t})$ as an indicator variable set to 1 in non-airing periods for the focal show (when the non-airing period's related costs/benefits would be relevant), and 0 otherwise. We note that in our model, time-shifting is endogenous, but the time-shifting decision is not forward-looking.

[5] Social connections, for example, 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 5.5.

[6] We assume $\bar{q}_i^k$ is known to the individual. We have also estimated models in which the expected frequency of earned media was updated (i.e., Bayesian learning about $\bar{q}_i^{so}$) based on observed encounters, but the estimated parameters indicated no meaningful learning. For simplicity, we dropped this learning from the model.

3.5. Viewing decisions and choice likelihoods

Putting these elements together, the expected utility of watching the focal program is[7]

$$u_{c,i,t} = \bar{\mu}_{i,t} + \sum_{k \in \{ad,so,ow\}} u^k_{antic,i,t} + \beta_1 1(TV_{i,t}) + \beta_{NAR,i} 1(NAR_{i,t}) + \alpha_{c,t} + \varepsilon^1_{i,t} \tag{5}$$

where $\alpha_{c,t}$ is an episode-specific effect as described in section 4, $\varepsilon^1_{i,t}$ is an idiosyncratic demand shock, 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

$$u_{P,it} = \alpha_{P,t} + \beta_1 1(TV_{i,t}) + \varepsilon^2_{i,t} \tag{6}$$

where the $\alpha_{P,t}$ is a time effect to control for competition at airtime and $\varepsilon^2_{i,t}$ is an idiosyncratic demand shock for the set P_t. The outside option has the deterministic component normalized to zero so that, $u_{0,i,t} = \varepsilon^0_{i,t}$, where $\varepsilon^0_{i,t}$ is an idiosyncratic demand shock to the outside option. We use the same normalization in time-shifted viewing decisions.

We assume the idiosyncratic errors $\varepsilon^0_{i,t}$, $\varepsilon^1_{i,t}$, and $\varepsilon^2_{i,t}$ are i.i.d. extreme value. In an airing period, if $r_{i,t} = 1$, the choice set is $\{c, P, 0\}$. The corresponding probabilities are

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

where $r_{i,t}$ means $r_{i,t} = 1$. If not considering c, the choice set is $\{P, 0\}$ with probabilities

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

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

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

[7] Notice that to reduce the computational burden, we do not model the decision as fully forward looking. In practice, this assumption means individuals are myopic learners; that is, they do not anticipate future learning about the show.

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

$$\begin{aligned} \mathsf{P}\left(w_{i,t+k} = c | r_{i,t+k}, I_{i,t+k}, w_{i,t+k-1} \neq c, \ldots, w_{i,t} \neq c\right) &= \tfrac{e^{u_{c,i,t+k}}}{1+e^{u_{c,i,t+k}}} \\ \mathsf{P}\left(w_{i,t+k} = 0 | r_{i,t+k}, I_{i,t+k}, w_{i,t+k-1} \neq c \ldots, w_{i,t} \neq c\right) &= 1 - \tfrac{e^{u_{c,i,t+k}}}{1+e^{u_{c,i,t+k}}}, \end{aligned} \tag{10}$$

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. The premier episode was launched on January 17, 2010. During the first six weeks, the program had last-minute schedule changes, aired in four different time slots, and faced different competing programs including the Winter Olympics. As a result, we incorporate into equation 5 episode effects, $\alpha_{c,t}$, for weeks 2-6 (week 1 is not identified). Nonetheless, 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.

As indicated above, our research goals and empirical strategy require information on offline word-of-mouth activity and stated expectations about future experiences. These data needs lead us to collect self-reported information via surveys.

4.1. Sample and data collection

The survey respondents are from P&G's VocalPoint Online Community. We enrolled individuals prior to the premier episode using 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, 1,720 individuals participated in the initial survey, a non-representative sample (see Web Appendix A for sample description). Participation and payment did not require watching the program.

Each week for the next six weeks, the panel was sent a survey via email in the mid-point between episode airings and was typically completed within two days. The surveys were largely the same with minor changes to adjust for the week (see Web Appendix B).

Not surprisingly, a large portion of the panel expressed a low likelihood of watching the initial show. Of the 1,720 initial survey participants 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 1,066 completed first surveys (after episode 1), and total drop-off to the last survey was an additional 31%. In addition to dropout, a small proportion of respondents do not complete a survey in a given week, but return to complete later surveys, amounting to 4% of potential surveys (228 surveys). However, if a panelist responds to the survey, by design the response is complete. In total, we have 1,127 respondents who completed at least one weekly survey for a total of 5,026 surveys.

In the full sample ($n = 1,720$), dropout is associated with the expressed likelihood of watching the premier ($\chi^2 = 82.9$, df $= 60$, p-value $< .05$) obtained from the initial survey. Our analysis focuses on the final sample of 1,127 individuals for whom we observe at least one weekly survey. For this sample, dropout is not correlated with the initial likelihood of watching ($\chi^2 = 59.6$, df $= 50$, p-value $= .17$). Nonetheless, we include a model of dropout to correct for any remaining censoring. In section 5.3 and Web Appendix D, we discuss in detail how we handle dropout and missing data.

4.2. Survey measures

The initial survey provided individual-level measures 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, and 0 otherwise). We also obtain a rich set of self-reported variables from the weekly surveys as described below (see Web Appendix B for details):

- **Viewing behaviors.** Through multiple questions, respondents indicated what they watched during airing periods, or, if they later watched in time delay, which non-airing period they watched, that is, $w_{i,t}$. In addition, they indicated what program, if any, they watched in the half-hour prior to the focal airing, providing the measures $1(TV_{i,t})$ and $1(FOX_{i,t})$ for airing periods (these measures are set to 0 in non-airing periods).

- **Liking and expected liking.** Respondents indicated how much they like episodes they viewed, $Lik_{i,t}$, where t is the corresponding viewing period. We assume this response is an errorful measure of $v_{i,t,ex}$, the unobserved experience signal. In addition, regardless of viewing, respondents indicated their expected liking for the upcoming episode, $EL_{i,t}$, where t refers to the period in which the question was asked. We assume this response is an errorful measure of the mean of the match-value belief, $\bar{\mu}_{i,t}$. Both questions used essentially the same interval scale that ranged between 1 and 11 with 11 being the greatest (expected) liking. We describe how we use these measures in more detail in section 5.2.

- **Media encounters/exposures.** Respondents were asked retrospectively whether they were exposed to any advertisements (paid media), had heard from any social contacts (online and offline earned media), or had engaged in related content such as on the network website (owned media) about the program.[8] 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 for the period between the airing and 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 cues, $C_{i,t}$.

[8] More than 85% of earned media encounters in our data are offline, confirming the need for surveys in this setting.

- **Change in expected liking due to cues.** We asked anyone who indicated receiving any media exposures how these exposures *in total* affected the expected liking of the upcoming episode, $cEL_{i,t}$, 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. We discuss how we use this measure in our estimation in section 5.2.

- **Viewer Segments.** To analyze the enhancing-enjoyment role, we create two segments for each media based on the propensity to encounter that media. We calculate the observed average frequency of encounters during the study, $\bar{q}_i^k$, as a rational expectation for the probability of encounters of type k about the program, q_i^k (i.e., $\bar{q}_i^k = E[1(C_{i,t,k} = 1)]$). We then use this measure to segment individuals into a high-propensity group, who are exposed on average at least one time per two weeks, and a low-propensity group, who are exposed less than one time in two weeks.[9] For the final data sample ($n = 1,127$), the segment sizes for paid media are 38% and 62%, respectively, for the low and high frequency groups with average frequencies of 0.08 and 0.71 per half-week. For earned media, the segment sizes are 83% and 17%, respectively, with average frequencies of 0.03 and 0.60 per half-week. For owned media, the sizes are 86% and 14%, respectively, with average frequencies of 0.04 and 0.56 per half-week. We use these categories in both our descriptive and structural analyses.

4.3. Basic description of survey measures

We present aggregate patterns to better understand how our sample compares to a nationally representative one and to identify key phenomena and relationships. In Panel 1 of Figure 1, we present the Nielsen viewing measure (ratings) and the percent of our sample that reported viewing the show at airtime. Both series have a similar declining trend that

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

flattens towards the end. Though the scales differ and our sample watches more on a percentage basis, we find it encouraging that the self-reported measures from our full sample, which is not designed to be representative, demonstrates a declining/flattening pattern similar to the Nielsen ratings. Similarly, we find our paid and earned media measures are consistent with aggregate observational data.[10]

In Panel 2, we present by the half-week periods the percent of our sample that is exposed to each of the three media. Paid media have the broadest reach. While exposures for paid and owned media exposures decline meaningfully over the six weeks, exposures for earned media decline only slightly and are relatively flat. These findings suggest the decline in paid and owned media might be more likely to explain the decline in viewing observed in Panel 1.

Time shifting is common in our sample. Approximately 40% of episodes are watched in time delay, a portion that is consistent across both episodes and with previous reports (Carter 2011). These time-shifting behaviors for *Human Target* are highly correlated with individuals' stated tendencies to time shift (WTD_i). For example, 92% of those who always watch *Human Target* at airtime also indicate they mostly watch TV at broadcast.

In Web Appendix C, we describe the variation in the self-reported measures of actual and expected experiences. The detailed patterns of variation are consistent with updating match-value beliefs in response to new information. For example, across individuals, we find that the variation in $Lik_{i,t}$ is approximately constant over time, the variation in $EL_{i,t}$ increases, and the difference between $EL_{i,t}$ and $Lik_{i,t}$ decreases over time, suggesting people learned about their true match values, which were heterogeneous and more extreme than

[10] In unreported analyses (available from authors), we find our self-reported paid media are reasonably related to advertising as measured by Kantar Media's Ad$pender product and are internally consistent with self-reported hours of watching TV. Our (online) earned media measure is reasonably related to aggregate counts of social media posts including on Twitter, blogs, and forums.

their initial beliefs. Note, however, that even if the media are informative, some people may learn they like the program more, while others may learn they like it less, so that the average audience effect could be close to zero.

4.4. Descriptive evidence on the multiple roles

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

4.4.1. Informative effects. We examine the self-reported changes in the expected liking ($cEL_{i,t}$) due to the three media types to evaluate the potential for informative effects. If the media exposures provide information then the portion of respondents reporting changes should decrease over time because of diminishing returns (see equations 2 and 3). Figure 2 Panel 1 plots the percent that indicate changing their expected liking of the next episode ($cEL_{i,t} \neq 0$) out of those who received only the indicated media exposure. Although the pattern in the first few half-week periods is decreasing, increases follow, and we cannot statistically reject that the observations for any given media type follow a horizontal line. Hence, the evidence does not statistically support diminishing returns consistent with informative media effects. We note, however, that we do find statistical evidence that experiences inform expectations (see Web Appendix C.4).

4.4.2. Reminding effects. To isolate the reminder effect for the three types of media, 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 in which cues were received but did not have a positive effect on expected liking (i.e., $cEL_{i,t} \leq 0$) against viewing occasions in which the individual did not receive any cues. We split the sample at approximately the average expected liking to control for preferences. The results reported in Figure 2 Panel 2 are very supportive of a reminder effect both directionally and statistically (the bars with ** indicate the percent watching is statistically different from that of the corresponding no-cues case). For all three cases, the receivers of uninformative or negative cues are more likely to watch than those who do not receive the cues. This finding is consistent with the cues serving as a reminder to watch the program. We note that the presence of reminder effects is not too surprising given the large number of TV viewing options (Mitra and Lynch 1995).

4.4.3. Enhancing-enjoyment effects. 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, Figure 3 presents bars for the percent of watching that occurs at airtime, segmented by the time-delay tendency ($X_{WTD,i}$ from the initial survey) and frequency of exposure group ($\bar{q}_i^k$). For those that indicate watching programs mostly live, both the high and low $\bar{q}_i^k$ groups prefer viewing at the original airing time. However, the high $\bar{q}_i^k$ groups for paid and earned media are more likely to watch at the original airing than the low $\bar{q}_i^k$ group, whereas the opposite pattern holds for owned media. Similarly, those that indicate watching programs mostly delayed are most likely to view in time-delay regardless of $\bar{q}_i^k$, but here all of the high $\bar{q}_i^k$ groups are more likely than the low $\bar{q}_i^k$ groups to watch earlier. These findings are consistent with our enhancing-enjoyment role for earned and paid media, but are equivocal for owned media.

4.5. Descriptive regressions

We now use linear probability models to further evaluate the media effects. The dependent variable is the choice to watch the program at airtime (1) or not (0). Our focal explanatory variables are recent exposures (last half week) to paid, earned, and owned media. 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), whether the individual states preferring live viewing, and week effects. In some specifications, we add indicators for frequent encounters with paid, earned, and owned media (i.e., $\bar{q}_i^k$=high), a polynomial function of expected liking, and individual-level fixed effects. These analyses use cases for individuals that are complete until dropout, less the first week because of lags (n=3,601). Table 1 presents the results.

The model presented in column 1 includes controls for live viewing preference, previous watching, and half hour prior TV and FOX viewing. Recent paid and earned media have significant positive effects on viewing at airtime of 0.05 and 0.06, respectively, whereas recent owned media has a smaller (0.02), insignificant effect that is also significantly smaller than paid or earned media. We find significant effects for all the control variables in the expected direction and, as compared to watching last week, paid and earned media are around one-fifth to one-sixth as effective. column 2 incorporates a cubic function of expected liking (i.e., three terms). Although the inclusions don't significantly affect any of the coefficients, the model fit improves significantly (F-stat=17.1 and p-value<.01). Because the informative effect of media should operate through expected liking, this finding suggests the average informative effects for media are not too large and that the recent media effects on viewing are likely to arise from the other roles. In column 3, we introduce the time-effect controls, which control for advertising budgeting endogeneity, competitive environment effects, time-slot changes, and the survey as reminder. We find that not only do the estimates not change significantly, but also that the model improvement is not significant (F-stat=0.93,p-value>.44). This finding suggests these sources of endogeneity are not very severe.[11] In column 4, we add the indicators for frequent encounters with paid,

[11] We also estimated an unreported version of our structural model with the survey (su) included as a variable in $C_{i,t,k}$, $k = su$. We find a very weak signal strength and a negligible reminder effect after including all other controls. This finding again suggests the survey itself did not overly influence our results.

earned, and owned media. If individuals anticipate the utility from future media encounters that enhance enjoyment, we should see positive effects for these variables. We find that frequent paid exposures are slightly negative and not significant, whereas frequent earned encounters are positive (.09) and significant, and frequent owned encounters are negative (-.04) and significant. After introducing these variables, we find the recent earned media effect decreases to become statistically insignificant, suggesting the observed effect only holds for frequent socializers. In addition, the recent owned media effect increases but is still not significant. This finding suggests accounting for the enhancing-enjoyment role is important to understanding the informative and reminding effects. In particular, earned media appear to enhance enjoyment meaningfully, paid appear to largely remind, and owned media actually encourage delayed viewing. We note that the R-squared for these linear probability models are reasonable (around 0.26), but not large. In column 5, we introduce individual-level fixed effects, which absorb any individual-level effects. We find the results for the recent media effects are robust and consistent with Model 4.[12]

4.5.1. Summary of descriptive evidence. This section provides descriptive evidence supporting the informing, reminding, and enhancing-enjoyment roles of the three types of media. However, these analyses do not model the process or control for the time-varying nature of influences on viewing decisions. Accounting for these additional influences is important in order to evaluate the relative magnitude of the various effects. Therefore, we turn to estimating our structural model.

5. Likelihood and Estimation

We next discuss the structural model estimation including heterogeneity and initial beliefs, the measurement model, the missing data and dropout model, the full model likelihood, and qualitative arguments for what variation in the data informs our parameter estimates.

[12] The qualitative findings are also robust to the use of a logistic regression, to including observations for both airing and non-airing periods, and to imputing missing data under alternative assumptions.

5.1. Heterogeneity and initial beliefs

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

$$\pi(\cdot) = f_{N,2}\left(X_{\mu,i}\left(\gamma_\mu, \gamma_{\bar{\mu}}\right)', \Sigma_\mu\right) f_{LN}\left(X_{\sigma,i}\gamma_\sigma, \sigma^2_{\sigma,\gamma}\right) f_N(X_{NAR,i}\gamma_{NAR}, \sigma^2_{NAR,\gamma}) \tag{11}$$

where f_N and f_{LN} are the normal and lognormal distributions and where the lognormal is parameterized in terms of the (underlying) normal. The parameters of these distributions 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 $X_{NAR,i}$ includes an intercept ($\gamma_{NAR,0}$), the indicator for mostly watching in time delay, WTD_i ($\gamma_{NAR,WTD}$), in time-shifted periods, and an indicator for mostly watching live in live-viewing periods ($\gamma_{NAR,LVW}$). In addition, we allow observable heterogeneity in the initial memory, $B_{i,1}$, which includes an intercept ($\gamma_{mem,0}$) and awareness for *Human Target*, $Aware_i$ ($\gamma_{mem,Aware}$). Finally, as described in section 4.2, using observed data we construct segments of high-frequency and low-frequency groups for each of the media.

5.2. Measurement model

Our data contain fallible measures of expectations and experiences, which we incorporate via a measurement model. We assume the ordered categorical variable, $cEL_{i,t}$ (stated change in expected liking) follows an ordered logit model that has two cutpoint parameters, a_{ME} and b_{ME}, 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 for $cEL_{i,t}$ is

$$
\begin{array}{ll}
\text{if } \Delta\bar{\mu}_{i,t} < a_{ME} & cEL_{i,t} = -1 \\
\text{if } b_{ME} \geq \Delta\bar{\mu}_{i,t} \geq a_{ME} & cEL_{i,t} = 0 \\
\text{if } b_{ME} < \Delta\bar{\mu}_{i,t} & cEL_{i,t} = 1.
\end{array} \tag{12}
$$

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 current match-value belief, $\bar{\mu}_{i,t}$, to the $EL_{i,t}$. Specifically, we assume

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

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

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

where $\varepsilon_{ME,Lik,i,t} \sim f_N(0, \sigma^2_{ME})$ and the parameters are common because $Lik_{i,t}$ shares essentially the same scale as $EL_{i,t}$. To allow for scale differences between the stated preferences and viewing, we introduce a scalar, d_{ME}, as a multiplicative term on $\bar{\mu}_{i,t}$ in equation 5.[13]

5.3. Missing data and dropout model

We impute missing media encounters, C^M_{it}, for the 4% of cases that miss a survey and later return to the panel. We draw C^M_{it} using the observed probabilities of media encounters conditional on $w_{i,t}$ and t. Because so little data are missing, we use five imputations of the missing data. To account for dropout, z_{it}, we incorporate the probability of dropping out for each survey period until after dropout, as a logistic function of a constant (g_0) and the true match-value (g_1). This approach is similar to a Tobit type-2 model. More details of these aspects of the model are described in Web Appendix D.

[13] We scale $EL_{i,t}$ and $Lik_{i,t}$ by .1 (min=0.1 and max=1.1) for estimation. Note also the difference in distributions between the $EL_{i,t}$ or $Lik_{i,t}$ measures and $cEL_{i,t}$ measures reflect measurement errors and not structural errors. We discuss potential mis-specification bias that these simplifying assumptions in the measurement model may create as well as robustness against alternative assumptions in Web Appendix F.

5.4. Simulated likelihood

We estimate the parameters via simulated maximum likelihood. We denote the total number of periods, $TP = 18$, in which we observe six airing periods, an inter-airing period before the first episode, 10 inter-airing periods between airings prior to the sixth episode, and one inter-airing period after the sixth episode. We refer to the full set of parameters and unobservables in the joint likelihood as $\Theta_i = \{\theta, \theta_i, \{I_{i,t}\}_{t \in 1:TP}\}$, which includes the structural, dropout, and measurement model parameters, θ, the random parameters, θ_i, and the information sets, $I_{i,t}$ (which contain the unobserved signals). The joint individual likelihood, dropping the conditioning on X variables is (see Web Appendix section E for details)

$$L_i(\theta, \theta_i, \{I_{i,t}\}_{t \in 1:TP}) = \prod_{t=1}^{TP} L_{w_{i,t}}(\Theta_i) L_{EL,i,t}(\Theta_i) L_{Lik,i,t}(\Theta_i) L_{cEL,i,t}(\Theta_i) L_{z_{i,t}}(\Theta_i). \tag{13}$$

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 with NP=5000 simulations and maximize the approximate likelihood

$$L(\theta) \approx \prod_{i=1}^{N} \frac{1}{NP} \sum_{m=1}^{NP} L_i(\theta, \theta_i^m, \{I_{i,t}^m\}_{t \in 1:TP}).$$

5.5. Identification

We focus our discussion on identifying the parameters related to the informing, reminding, and enhancing-enjoyment roles and on the exogeneity of the cues. First, the utility parameters for the enhancing-enjoyment effects are identified by the difference in the likelihood of viewing at airtime between those with a high propensity to encounter the media type and those with a low propensity.[14] This identification assumes that program behaviors or interest do not affect the frequency of media encounters.[15]

[14] 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.

[15] We argue that this assumption is reasonable given the program's genre and modest success, and we test this assumption in an unreported analysis available from the authors. In this analysis, we demonstrate that neither changes in $EL_{i,t}$ nor watching significantly affects later media exposures.

Second, our self-reported data provide the information needed to identify all of the learning model parameters. Based on standard arguments (e.g., Shin et al. 2012), a learning model can be identified up to a single signal variance parameter using choice data (i.e., $w_{i,t}$). 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 $cEL_{i,t}$. 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^2_{ex}. This information identifies the scale of this signal variance, allowing us to separate the initial belief variance from the other signal variances.[16] Our stated expectation and experience data also provide information similar to revealed preferences, increasing the precision of estimates and providing information on initial conditions and heterogeneity.[17]

Third, the stated expectations data provide information to separate the informative and reminding effects. Past studies that have separated informative and persuasive effects (e.g., Narayanan et al. 2005) do so based on either the diminishing returns to informative effects or observable variables that suggest learning has already occurred, such as through extensive experience with a product. The remaining effect of ads after obtaining extensive product experience is attributed to persuasive effects. Netting these effects out for those without extensive experience provides an estimate of the informative effects. By contrast, we estimate informative effects as the media influence on stated expectations that also affects viewing, and we attribute the remaining media effects on viewing to the reminding

[16] We can identify both σ^2_{ex} and σ^2_{ME} because we assume $EL_{i,t}$ and $Lik_{i,t}$ are on the same (homogeneous) interval measurement scale. We note these assumptions could lead to mis-specification bias, which we discuss in Web Appendix F.

[17] Similar to choices after an experience, $Lik_{i,t}$ and $EL_{i,t}$ provide information on the location of $v_{i,t,ex}$. The individual averages of $Lik_{i,t}$ also provides direct information on the distribution of μ_i. Similar to changes in shares after a media exposure, we have changes from $EL_{i,t-1}$ to $EL_{i,t}$ and the direct measures of change due to media exposures, $cEL_{i,t}$. These additional information sources indicate we can obtain more precise estimates of media informative effects. In addition, like prior research (Shin et al. 2012), we use stated data, LW_i and $nDrama_i$, to solve the initial-conditions problem, better separate prior preferences from learning, and estimate the distributions of initial match-value belief, initial uncertainty, and true match values.

process. Hence, we use our stated expectations data to separate informative effects on expectations from other effects, which we model and label as reminding effects.

Finally, we argue that media encounters can be treated as exogenous given the observed variables. First, we include time effects for each week that control for aggregate demand shocks to viewing. This approach controls for the reverse-causality concern that aggregate advertising may decline in response to declining viewing. We also saw in section 4.5 that time controls have little influence on the media effects. Second, we include observed initial heterogeneity and time-varying, individual-level observed measures of preference (e.g., $EL_{i,t}$ and $Lik_{i,t}$), which control for heterogeneity. These controls reduce the concern that unobserved heterogeneity is biasing our media effects. In section 4.5, we found no meaningful change when introducing individual fixed effects or the $EL_{i,t}$ measures.[18]

6. Results from the Structural Model

Table 2 presents the structural parameter estimates with the media effects in the first block. The informative effects for all three media types are significant. The order of signal variances is earned (0.26), owned (0.32), and paid (0.34), with earned being the most precise. However, these differences are not significant. These signal precisions are significantly different and 1/12 to 1/16 weaker than an experience (0.02). This finding suggests moderate informativeness, which we explore further below.

The reminding effect sizes are similar for paid and owned media (0.31) and smaller for earned media (0.16), but only the effect for paid media is statistically significant. These reminding effects are 1/25 to 1/50 as big as the instantaneous experience reminding effect (8.8). However, experiences typically occur two periods before the next viewing, reducing the memory effect. Relative to an experience after two periods of memory depreciation, the media reminder effects increase to be 1/8 to 1/16 that of an experience.

[18] We also examined whether watching leads to more media exposures. We find no evidence of such reverse causality.

The enhancing enjoyment estimates are 0.09 for paid, 0.37 for earned, and -0.25 for owned media. Only earned and owned media are statistically different from zero. The earned estimate is as expected–the high-frequency socializers prefer to watch earlier. This finding is consistent with our theory that individuals anticipate future social encounters that will be better because they watched, and thus, they watch earlier to have more opportunities for such encounters. The negative sign for owned media suggests individuals would rather have owned media encounters prior to watching. The small and insignificant effect for paid media exposures suggests they have a relatively small enhancing-enjoyment role.

Looking at the three media types, we find that reminding effects are strongest for paid media, and enhancing enjoyment effects are strongest for earned media. Owned media shift viewing to later, and all three media have similar informing effects that are small in comparison to the experience effect. We will evaluate the relative size of these effects in the counterfactual analysis, but first we briefly discuss the rest of the parameters.

Of the other memory model parameters, we find that initial memory is relatively high ($\gamma_{mem,0} = 5.98$ and significant) and that it is higher for those with an initial stated awareness of the show ($\gamma_{mem,Aware} = 1.65$ and significant). Memory deteriorates by almost 80% per week ($\delta = 0.473$). The constant in the memory context effects is significant and negative (-1.93), and, as expected, watching FOX in the half hour prior to *Human Target*'s airing is significant and positive (2.30). Hence, after one week without further cues, the initial memory deteriorates so that *Human Target* is considered with less than 50% probability.

The other learning model parameters are consistent with expectations. The initial uncertainty about the match-value belief (σ^2_{0,μ_i}) is moderate with a value of 0.03 (-3.48 in log scale), and we are unable to estimate significant observed or unobserved heterogeneity. With this level of initial uncertainty, as the first signal, an experience decreases the average uncertainty by 60%, whereas a media exposure decreases it by around 10%. The initial belief about the match-value has a significant constant ($\gamma_{\bar{\mu},0} = -1.21$), observed heterogeneity ($\gamma_{\bar{\mu},LW_i} = 0.02$), and unobserved heterogeneity ($\sigma_{\bar{\mu},\gamma} = 0.10$). Similarly, the true match-value has a significant constant ($\gamma_{\mu,0} = -1.31$), observed heterogeneity ($\gamma_{\mu,LW_i} = 0.04$), and unobserved heterogeneity ($\sigma_{\mu,\gamma} = 0.02$).[19] The correlation coefficient between the unobserved μ_i and $\bar{\mu}_{i,0}$ components is high (0.93). Together these initial mean belief and true match-value estimates suggest, on average, individuals who initially believe they dislike the show ($LW_i < 5$) have match values that are even lower, whereas individuals who initially like the show ($LW_i > 5$) have match values that are higher. The high correlation between the unobservables indicates this basic pattern holds for most individuals. Consistent with the descriptive analyses, these results suggest that learning is occurring, but that those for whom information is positive may cancel with those for whom it is negative.

We find the effect for prior TV viewing (0.84) is significant and consistent with expectations. The time-shifting parameters indicate that those who report watching television mostly live are more likely to watch at broadcast ($\gamma_{1,Live} = 2.14$), whereas those who report watching television mostly in time-delay are more likely to watch in time-delay ($\gamma_{1,Delay} = 18.4$). This observed heterogeneity based on the stated time-shifting preferences is so strong that individuals who prefer to watch in time delay nearly always watch in time-delay if they consider the program. Given not having already watched the episode, those who do not prefer to watch in time delay are also on average likely to watch in time delay given consideration ($\gamma_{NAR,0} = 9.09$), but unobserved heterogeneity in time-shifting preferences is large ($\sigma_{NAR,\gamma} = 6.58$), so that a meaningful proportion of those who prefer live viewing are quite unlikely to watch in time-delay. The focal program week fixed effects show no clear

[19] Recall $LW_i \in \{0, 1, \ldots, 11\}$, whereas $EL_{i,t}$ and $Lik_{i,t}$ are scaled down to be in $\{.1, .2, \ldots, 1.1\}$.

pattern and none of the effects are significant. This finding suggests the model adequately captures the average viewing trend. We also note that the competitor-programming fixed effects decrease after the first week, but otherwise don't differ much from one another. For the dropout model, dropout is relatively unlikely given that one hasn't dropped out already ($g_0 = -2.42$), but does not vary significantly with the unobserved true match-value ($g_1 = 0.01$). The measurement model parameters are all significant with the expected signs.

7. Counterfactuals

Using the estimates from the structural model, we run counterfactual experiments to evaluate the relative impact of paid, earned, and owned media as well as the relative size of each of the roles for these media. We manipulate media exposures over the first six weeks of the program. In each scenario, we simulate 40,000 individuals, resampling from the empirical distribution for all observed variables except media exposures (which we manipulate). We calculate audience effects for live viewing only (LV) and live viewing plus seven days of delayed viewing (LV+7D or total viewing).

First, we use the point estimates to calculate elasticities via a two point method (incrementing observed exposures by 10%). The live-audience elasticities are 0.055, 0.044, and -0.018 for paid, earned, and owned media, respectively. These live-audience elasticities suggest paid media are most effective, earned media are 20% weaker, and owned media actually reduce live viewership. The LV+7D elasticities are 0.028, 0.010, and 0.000, respectively. Owned media on average have no effect, and paid media are nearly 3 times more effective than earned media. Hence, given current exposure levels, paid media dominate.

Second, we construct scenarios that hold constant the exposure levels across media types and allow disentangling the relative size of the three roles. For each media type, we vary media exposures between 0 and 600 randomly assigned GRPs (an average of 6 exposures per person) and calculate the change in viewing percentages. To account for parameter uncertainty, we simulate 200 draws from the asymptotic parameter distribution. We report the median, 10th, and 90th percentiles of the outcome distribution, interpreting covering zero as insignificant. Table 3 presents the results of these counterfactual experiments for the effects on live viewing (panel A) and LV+7D (panel B). We present scenarios with the Total Effect, the effect with only reminding exposures incremented (Reminding Only), the effect with only informative exposures incremented (Informative Only), and the effect with only the $\bar{q}_i^k$ incremented (Enhancing Enjoyment Only).

The total effect for the LV scenarios indicate that earned media have the largest (and significant) median effect (0.09), which is nearly twice as large as that of paid (0.05). Owned media have a negative median effect on LV (-0.06), but neither the owned nor paid media effects are significant. The LV+7D total effects for earned media are also the largest (0.04), but paid media are much closer in magnitude (0.03). Both paid and earned media have significant LV+7D total effects, whereas owned media have a smaller, significant median effect (0.02). Contrasting against the elasticities, the total effects suggest paid media's dominant elasticities are due to higher exposure levels rather than response per se, and likewise, owned media's negligible LV+7D elasticity is due to low exposure levels.

Turning to the three roles, for reminding, paid media have the largest median effects for LV (0.014) and LV+7D (0.026). Paid media median effects are approximately double those of earned (0.007 and 0.012 for LV and LV+7D effects). Owned media reminding median effects (0.012 for LV and 0.022 for LV+7D) are similar to those of paid media.

The informative effects all are insignificant. Although individuals are learning and media are informative, the average effects are close to zero, consistent with the canceling predicted by the descriptive analysis and the structural parameters. This finding is consistent with information being potentially negative for viewership (Anand and Shachar 2011).

The enhancing-enjoyment effects for earned media are significant and large (0.09 and 0.03, respectively, for LV and the LV+7D). Paid media have a smaller positive median effect (0.03 and 0.01, respectively) and owned media have a relatively large negative median effect for LV (-0.08) and a smaller negative LV+7D effect (-0.01), but neither the paid nor owned media effects are significant. These large enhancing-enjoyment effects for earned media suggest that earned's primary influence is through this role.

8. Discussion

We find that earned media increase viewing the most per exposure, but because paid media have more exposures, they increase viewing the most for a given increase in exposures. Hence, paid media are important because exposure levels can be higher. Interestingly, paid and earned media increase live viewing more than delayed, suggesting that as viewing shifts to non-broadcast formats, new media approaches may be needed.

Paid media have a meaningful reminding effect, and this effect represents the majority of paid media's LV+7D total effect. However, paid media's average informative effect is negligible in our setting. These results are consistent with Clark et al. (2009), who find a significant effect of advertising to inform about the existence of the brand, but not an effect on perceived quality. Our results clarify that advertising's average effect of "information" is in the form of memory triggers that keep the brand in consideration, rather than informative signals that change expectations as captured in Bayesian learning models. Such a distinction is important because it suggests larger benefits to ongoing paid media support than informative effects usually suggest and more frequent pulsing as optimal (Bollinger et al. 2013). Also, our finding of reminding effects for paid media is similar to the finding of Honka et al. (2014) that bank advertising influences awareness.

For our data, earned media have a small reminding effect, a negligible average informative effect, and a large enhancing-enjoyment effect. Therefore, socializing about the TV program after watching increases viewer interest in watching live, providing a new explanation for live viewing (Vosgerau et al. 2006). Interestingly, earned media plays a role in increasing both the broadcast audience (consistent with Godes and Mayzlin (2004)) and the delayed-viewing audience through this role.

In our context, owned media average effects are only significant for total viewing (LV+7D). Although owned media have a positive reminding effect, this effect is not strong enough to overcome the negative direct effects (due to destroying enjoyment). This finding suggests that particular kinds of media may discourage live viewing (and viewing in general), and understanding these distinctions is important. However, we caution overly generalizing this owned media finding, because our earned media measure could include some owned media (e.g., Twitter posts by the show) that have a positive effect, and the owned media effect has the strongest alternative explanations (e.g., intentional delayed viewing in order to search for information about the program on the website).

9. Conclusion

In this paper, we develop a structural model of consumers viewing a new TV program. The model incorporates paid (i.e., advertising), earned (i.e., word-of-mouth and online social networks), and owned (e.g., website and other content) media effects and distinguishes between reminding, informing, and enhancing enjoyment roles for these media. The model also allows viewing to be at original broadcast and in time-delay.

We use a unique data set on television viewing that contains reported viewing, media exposures, word-of-mouth, expectations, and experiences. We find that paid media plays primarily a reminding role, whereas earned media plays primarily an enhancing-enjoyment role. In terms of elasticities, paid media dominate for total viewing and are more impactful for live viewing. However, we find that for equivalent exposure levels, earned media dominate on live viewing and are slightly more effective on total viewing.

These results indicate "engagement" strategies can be effective as a complement to paid media strategies that keep the brand in memory and consideration. Our results suggest managers of entertainment brands should look to ads that draw attention and are memorable rather than provide information, and to focus engagement strategies on earned rather than owned media.

Like all studies, we caution against over generalizing. Our analysis does not go as far as establishing the costs of achieving media exposures, and we measure organic media exposures rather than manipulated ones. Further, *Human Target* attracted a small audience of frequent socializers and a modest total audience, and these results can be more confidently applied to settings with similar levels of success. Finally, as discussed in detail in Web Appendix F, though we provide robustness tests and support for our assumptions, some simplifying assumptions (e.g., normality of measurement errors) could lead to mis-specification bias.

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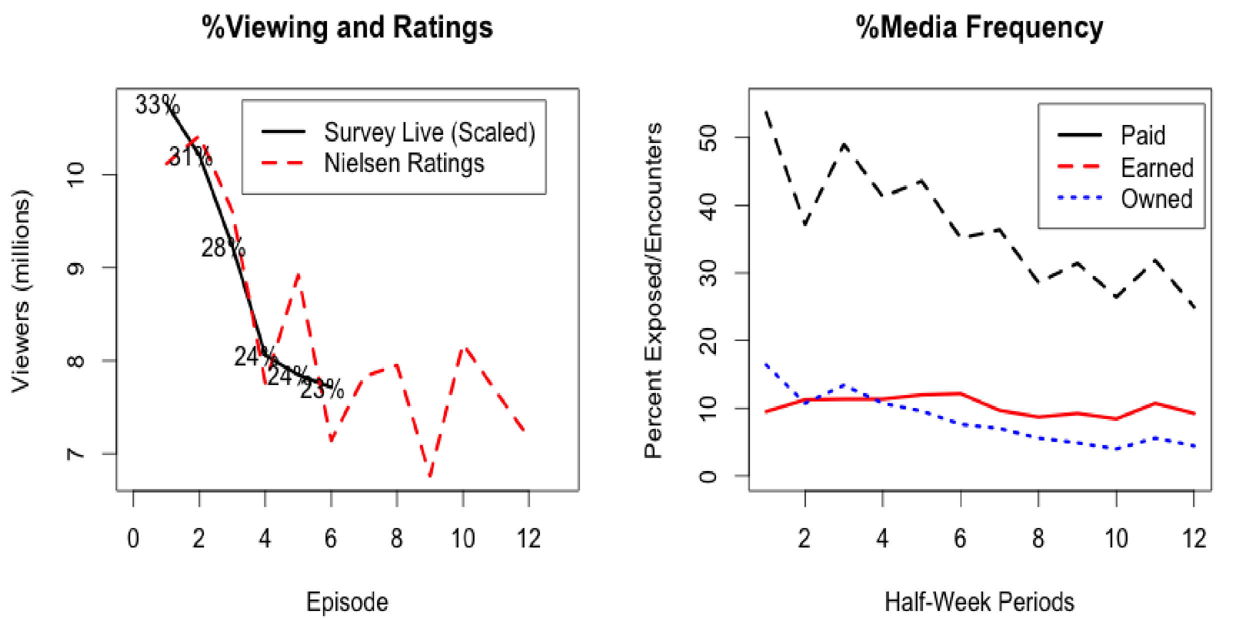

Figure 1 Panel 1: Stated viewing % for full sample vs. Nielsen ratings for the show, with stated viewing scaled by 33 million viewers to match scale with the total viewers. Panel 2: Percent of respondents having media encounters over time ($n = 1,127$).

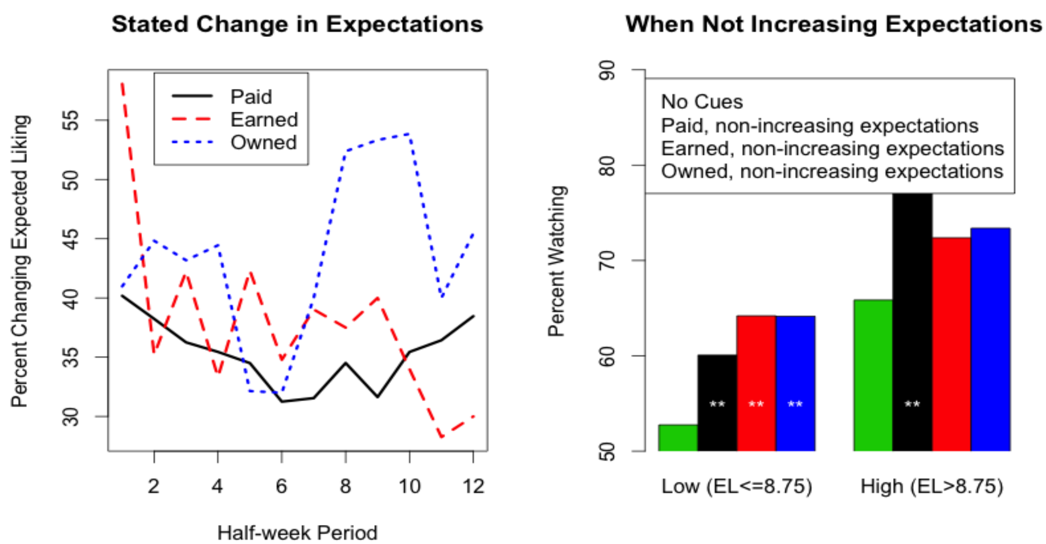

Figure 2 Media Effects. Panel 1: Percent reporting changing their expectation ($cEL_{i,t} \neq 0$) after a period in which they encountered only the indicated media ($C_{i,t,k} = 1$). Panel 2: Percent of those who encounter only the indicated media and report not increasing the expected liking ($cEL_{i,t}$ ≤0) compared to percent of those watching who receive no cues ($\sum_k C_{i,,kt} = 0$) decomposed by low and high average expected liking (split at 8.75).

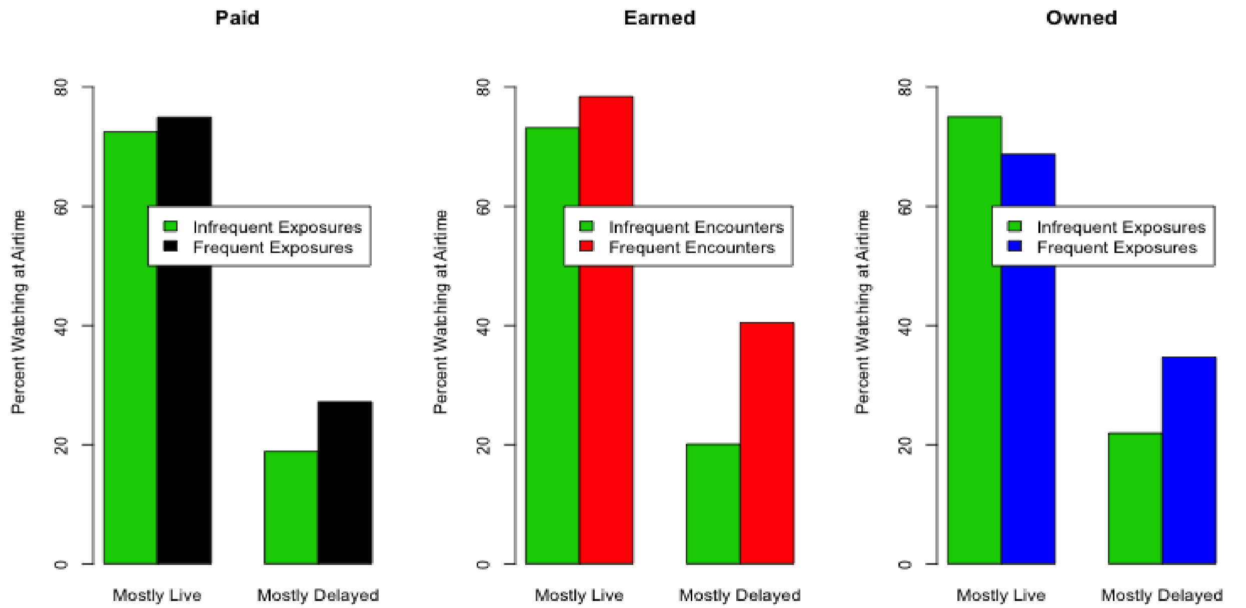

Figure 3 **Enhancing-enjoyment Role. Each panel presents a separate media type. The bars are the Percent Watching at Airtime of all those that watch and completed the survey. Each bar represents a group consisting of either those indicating Mostly Live or Mostly Delayed viewing and either frequent ($>$ 1 encounter per two weeks on average) or infrequent (≤ 1 encounter per two weeks on average) encounters with the respective media.**

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Recent Paid Media	0.048 (0.01)**	0.041 (0.01)**	0.042 (0.01)**	0.055 (0.02)**	0.057 (0.02)**
Recent Earned Media	0.060 (0.02)**	0.041 (0.02)**	0.041 (0.02)**	-0.014 (0.03)	0.011 (0.02)
Recent Owned Media	0.022 (0.02)	0.015 (0.02)	0.017 (0.02)	0.039 (0.03)	0.021 (0.02)
Frequent Paid Media	-	-	-	-0.020 (0.02)	
Frequent Earned Media	-	-	-	0.091 (0.02)**	
Frequent Owned Media	-	-	-	-0.046 (0.03)*	
Watch Last Week	0.324 (0.04)**	0.280 (0.04)**	0.280 (0.04)**	0.278 (0.04)**	-0.063 (0.04)
TV On 1/2 Hr Previous	0.140 (0.02)**	0.143 (0.02)**	0.145 (0.02)**	0.145 (0.02)**	0.103 (0.02)**
FOX On 1/2 Hr Previous	0.087 (0.02)**	0.083 (0.02)**	0.086 (0.02)**	0.087 (0.02)**	0.059 (0.02)**
Live Viewing Pref	0.443 (0.02)**	0.431 (0.02)**	0.431 (0.02)**	0.432 (0.02)**	
Time Effects	No	No	Yes	Yes	Yes
Fixed Effects	No	No	No	No	Yes
f(Expected Liking)	No	Yes	Yes	Yes	Yes
R-squared	0.253	0.263	0.264	0.267	0.725

Table 1 **Regression Analysis on Viewing at Broadcast: Entries are coefficients (standard errors) and significance indicators. ** = p-value $<.01$, * = p-value $<.05$**

Media and Experience Effects

	Informative: $\sigma^2_{v,k}$	Reminding: ϕ_k	Enhancing Enjoyment: ω_k
Paid	0.34 (0.08)*	0.31 (0.09)*	0.09 (0.05)
Earned	0.26 (0.07)*	0.16 (0.17)	0.37 (0.09)*
Owned	0.32 (0.1)*	0.31 (0.17)	-0.25 (0.09)*
Experience	0.02 (0.01)*	8.77 (0.98)*	-

Memory/Consideration Model Parameters

Initial Mem: $\gamma_{mem,0}$	5.98 (0.42)*	Context: ψ_0	-1.93 (0.30)*
Initial Mem: $\gamma_{mem,Aware}$	1.65 (0.83)*	Context: ψ_{FOX}	2.3 (0.79)*
Depreciation: δ	0.47 (0.04)*		

Learning Match Value Model Parameters

	Constant: γ_0	Observed Heterog.: γ_1	Unobserved Heterog.: σ_γ
Var(Initial Belief): $log\left(\sigma^2_{0,\mu_i}\right)$	-3.48 (0.39)*	-0.03 (0.06)	0.000 (0.000)
Mean(Initial Belief): $\bar{\mu}_{0,i}$	-1.21 (0.16)*	0.022 (0.003)*	0.10 (0.01)*
True Match-value: μ_i	-1.31 (0.16)*	0.044 (0.002)*	0.02 (0.01)*
Correlation: ρ	0.93 (0.07)*		

Utility Parameters: β

Live-viewing Preference: $\gamma_{1,Live}$	2.14 (0.07)*	Time-shifting: γ_0	9.09 (2.34)*
Time-shifting Preference: $\gamma_{1,Delay}$	18.4 (7.21)*	Time-shifting: σ_γ	6.58 (1.94)*
TV	0.84 (0.07)*	Compet. Period 1	-3.99 (0.16)*
Human Target Period 2	0.09 (0.11)	Compet. Period 2	-4.86 (0.22)*
Human Target Period 3	0.01 (0.11)	Compet. Period 3	-4.77 (0.22)*
Human Target Period 4	0.05 (0.12)	Compet. Period 4	-4.99 (0.26)*
Human Target Period 5	0.15 (0.12)	Compet. Period 5	-4.89 (0.27)*
Human Target Period 6	0.23 (0.12)	Compet. Period 6	-4.77 (0.27)*

Measurement and Dropout Model Parameters (Note EL and Lik scaled down by 10)

Dropout Intercept: g_0	-2.42 (0.41)*	Dropout Scale on μ_i: g_1	0.01 (0.40)
cEL lower cutpoint: a_{ME}	-4.19 (0.11)*	EL, Lik Intercept: c_{ME}	1.84 (0.16)*
cEL upper cutpoint: b_{ME}	0.58 (0.03)*	EL, Lik Scale: d_{ME}	1.91 (0.27)*
		EL, Lik std dev: σ_{ME}	0.15 (0.001)*

Table 2 Structural Parameter Estimates (Rubin's standard errors using 5 imputations on 4% for missing data). * indicates Rubin's t-stat>1.99.

A. Live Viewing (LV) Effect

	Total Effect	Reminding Only	Informative Only	Enhancing Enjoyment Only
Paid	0.049 (-0.078,0.094)	0.014 (0.006,0.029)	0.004 (-0.059,0.027)	0.030 (-0.042,0.06)
Earned	0.094 (0.011,0.146)	0.007 (0.000,0.021)	0.006 (-0.063,0.027)	0.092 (0.043,0.145)
Owned	-0.062 (-0.210,0.060)	0.012 (0.001,0.026)	0.006 (-0.057,0.032)	-0.08 (-0.175,0.027)

B. Total Viewing (LV+7D) Effect

	Total Effect	Reminding Only	Informative Only	Enhancing Enjoyment Only
Paid	0.033 (0.011,0.063)	0.026 (0.012,0.05)	0.003 (-0.020,0.016)	0.011 (-0.003,0.026)
Earned	0.040 (0.004,0.070)	0.012 (0.000,0.035)	0.004 (-0.019,0.016)	0.029 (0.008,0.048)
Owned	0.016 (-0.021,0.045)	0.022 (0.002,0.047)	0.004 (-0.019,0.019)	-0.013 (-0.037,0.013)

Table 3 Counterfactual Scenarios - Baseline is calculated using the existing empirical distribution to simulate 40,000 individuals, and estimates are differences from a no-media-exposure counterfactual to a 600 GRP campaign over the 6-week period. The median, 10%, and 90% quantiles of the parameter distribution are presented.

Variable	Definition	Related Parameters
i	Individual index $i = 1, \ldots, n = 1,127$	
t	Period index $t = 1, \ldots, TP = 18$	
$t_{c,A}$	Period in which episode c airs	
J	Max periods c can be viewed, $J = 3$	
$w_{i,t}$	Indicates c if watching episode c, P if competing program, or 0 if not watching	$u_{j,it}$ underlying deterministic utility for option j
$r_{i,t}$	Unoberved recall or consideration indicating 1 if $Human\ Target$ is considered, else 0	$A_{i,t}$, underlying deterministic component for recall/consideration event
$I_{i,t}$	Information set contains cues $I_{i,0}$ and $\{C_{i,h,k}\}_{\forall h<t}$ and their corresponding signals, $v_{i,h,k}$	
$C_{i,t,k}$	Indicates 1 if any media/experience was encountered of type $k \in \{ad, so, ow, ex\}$, else 0	$\sigma^2_{v,k}$ is signal variance for media type k; ϕ_k is memory-activation strength for media type k
$B_{i,t}$	Deterministic unobserved persistent component of memory-activation level	δ is the depreciation rate of $B_{i,t}$
$X_{A_{i,t}}$	Memory variables including a constant and $1(\text{FOX}_{i,t})$, whether already watching FOX	ψ the vector of effects on $A_{i,t}$ (i.e., not persistent)
$1(\text{TV}_{i,t})$	Indicator for whether already watching TV in 1/2 hour before HT airs	β_1, the effect on utility for episodes of HT and competing programs at air time.
	True match value for HT, and signal of type k; Mean and variance of belief about match value	μ_i, $v_{i,t,k}$; $\bar{\mu}_{i,t}$, $\hat{\sigma}^2_{t,\mu_i}$
$\bar{q}^k_i$	Average frequency of media exposure of type k	ω_k, expected utility per anticipated media exposure
$1(NAR_{i,t})$	Indicator for whether period is time delayed.	$\beta_{NAR,i}$, individual level effect for time delay/live viewing; $\gamma_{NAR,0}, \sigma^2_{NAR,\gamma}$, parameters of NAR mixing distribution
	Time effects for competitor options and HT	$\alpha_{P,t}$, α_c
$X_{\mu,i}$	Variables including constant and $LW_{i,t}$, a measure of likelihood of watching HT premier	$\gamma_{\mu,0}, \gamma_{\mu,LW}, \sigma^2_{\mu,\gamma}$, effects on true match-value,μ_i; $\gamma_{\bar{\mu},0}, \gamma_{\bar{\mu},LW}, \sigma^2_{\bar{\mu},\gamma}$, effects on initial match-value belief, $\bar{\mu}_{i,0}$
$X_{\sigma,i}$	Variables including constant and $nDrama_i$, the number of action dramas viewed per week	$\gamma_{\sigma,0}, \gamma_{\sigma,nDrama}, \sigma^2_{\sigma,\gamma}$, effects on initial match-value belief, $\hat{\sigma}^2_{0,\mu_i}$
$X_{mem,0}$	Initial memory variables including a constant and $Aware_{i,t}$, an awareness indicator for HT	$\gamma_{mem,0}$ and $\gamma_{mem,Aware}$, the effects on initial memory, $B_{i,0}$
WTD_i / LVW_i	General tendency to watch in time delay (live)	$\gamma_{1,Live}$,$\gamma_{1,Delay}$, effects of time delay/live-viewing tendency on utility in time-delayed/airing periods
$EL_{i,t}$, $Lik_{i,t}$	Expected liking for next episode and Liking for last episode if watched, ranging from 1 to 11.	a_{me}, d_{me}, constant and linear scaling parameters; σ^2_{me}, variance of measurement errors for these measures
$cEL_{i,t}$	Self-reported change in expected liking after receiving media exposures taking values {-1, 0, 1}	b_{cEL}, c_{cEL}, cutpoint parameters for the upper (lower) boundaries of the middle category in the $cEL_{i,t}$ measures; $\Delta\bar{\mu}_{i,t}$ the underlying change due to media exposures in the expected value of match-value
$z_{i,t}$	Whether Dropout in period t (for survey periods)	g_0, parameter for constant; g_1, parameter for true-match value

Table 4 Table of Parameter and Variable Definitions.

Appendix A: Sample Description

Table 5 presents summary statistics for the full sample ($n = 1,720$). These data come from a combination of the initial survey and information previously provided by the panelists to VocalPoint. As apparent in Table 5, 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 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, at least within this sample, the series was not building on a large base of knowledgeable and excited followers of an existing brand, allowing for potential widespread learning and memory, and as a result informative and reminding 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," and "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 17 multiselect options and a "None of the above" option. We take their selection of *Human Target* (one of the 17 options) as $Aware_i = 1$; otherwise $Aware_i = 0$.
- 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)

Respondents were also sent weekly surveys that were completed between episode airings. In these surveys, we asked a set of questions that differed only according to the different programming during the week and the different episode names. The survey used branching and conditional logic to obtain information with the fewest questions. Each weekly survey was translated into three periods–one period for the media exposures and viewing in the half-week before the airing, the airing period (1 hour), and one period for the media exposures and viewing in the half-week after the airing. The questions that relate 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 coded the "watched TV but don't remember" as $1(TV_{i,t}) = 1$ and $1(FOX_{i,t}) = 0$, whereas the "don't remember" case we coded as zeros.
- $w_{i,t}$ and $1(NAR_{i,t})$: "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]?" (referenced as Q1). 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 and 2 as in time delay in the first inter-airing period (recall the surveys were generally completed half-way into the time between airings). We assume the remaining cases did not watch *Human Target* at airing or in the first half-week. We asked two additional questions for these cases.

The first (Q2) asked what show(s) they watched during the *Human Target* airtime. Hence, although we have the exact alternative show for those who did not watch *Human Target* at air time or in the first half of the week, we did not ask this question to those who replied with a 1 or 2 (delayed viewing) to Q1 because of the length limitations in the survey (these respondents had additional questions). We asked the second, follow-up question 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)” (referenced as Q3). The answer type for Q3 had as a row the second most recent episode (along with rows for 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 Q3 to fill in the second half of the period between airings, coding options 1 and 3 as watching in this second half of the week, and the remaining cases as not watching the episode. We note that options 2 and 3 consisted of a negligible proportion of observations.

Putting these responses together, we tabulate the possible responses in Table 6 and the values for $w_{i,t}$ and $1(NAR_{i,t})$. Notice that $1(NAR_{i,t})$ takes a value of 1 when $w_{i,t}$ is c or 0 during non-airing periods, and always takes a 0 in airing periods.

- $EL_{i,t}$: “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

- $Lik_{i,t}$: Those who indicated they have watched the program also answered the question, "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

- $C_{i,t,ad}$, $C_{i,t,so}$, and $C_{i,t,ow}$: "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 paid]
2. Show or network website [coded as owned]
3. General websites (e.g., Yahoo, MSN, AOL, IMDB) [coded as owned]
4. Media coverage (e.g., TV Guide, Entertainment) [coded as owned]
5. Online social networks (e.g., Facebook, Myspace, Twitter) [coded as earned]
6. Friends [coded as earned]
7. Family [coded as earned]
8. Co-workers/colleagues [coded as earned]
9. Other (blank to fill in) (please specify)

10. Did not hear from any sources prior to watching

The translation from the survey items to the paid, earned, and owned media are provided in brackets, which were not shown to respondents. We manually translated the "Other" category into one of the three categories whenever possible. We determined the categorization of the items with the input from a committee of research executives in the TV industry. Note that in that discussion, it became clear that the typical paid, earned, and owned distinctions are somewhat different in the TV world. Advertisements on the own channel are technically not paid but are conceptually most akin to paid advertising and thus coded as such.[20] Likewise, media coverage tends to involve owned assets such as actors and talk shows on the same network. In addition, note that in consumer panel surveys like this one, distinguishing owned social media presence from earned social media presence is difficult. We did not attempt to distinguish between them and both are coded as earned. Finally, we note that the online social media exposures are only a small part of the total earned media, so the owned part of that is likely quite small.

- $cEL_{i,t}$: For those who indicated receiving a cue, we asked, "Sometimes other sources affect how much people expect to like an episode. Overall, how did [Insert all marked 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: Variation in Survey Measures

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.

C.1. Within-survey variation and correlation

Table 7 presents information related to within-survey (across individuals) variation and correlation for the two measures of interest. We find that 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, indicating substantial heterogeneity among our respondents. More interesting is the time pattern

[20] In fact, not airing a paid advertisement in place of the show promo leads to an opportunity cost, so show promos are in a sense "paid." Of course, our paid category also includes ads placed on other channels and other media, including print and internet display ads.

of these variances. Consistent with our expectations, the variance of liking does not have a clear pattern. By contrast, the variance of $EL_{i,t}$ increases over time, which is consistent with heterogeneity in the true match values and learning over time that leads to more extreme beliefs.

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 scales had 11 points rather than a more typical 5 or 7 points.[21] Further, the two questions were separated within the survey by a number of other questions including open-ended questions. This design led to Pearson correlations (see Table 7) 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 7). Specifically, we calculate 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 gave different answers to the two different measures. This finding suggests distinct variation exists for the two measures. More interestingly, the pattern of these differences is exactly what one would expect if the individuals are learning from these signals–the expectations match experiences better towards the end of the study period than at the beginning.

C.2. Between-surveys variation and correlation

Table 8 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

[21] Note also that we pretested these scales by rotating the type of scale between a 5-point fully labeled, an 11-point fully labeled, and an 11-point scale with end points and midpoint in order to evaluate whether scale usage 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.

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 their expectations fairly closely, whereas 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 8 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 two observations. This distribution suggests that although some individuals' responses do not change or change very little, over half of the individuals change their responses by two or more levels over the course of the study. Further, this variation is higher for Liking than for Expected Liking, which is what we would expect if expectations are not too far from true tastes and experiences are reasonably variable.

We next report the correlation between the lagged and the current-period 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.

C.3. Example patterns in individual-level data

Below, we present individual-level data patterns for three individuals in order to illustrate 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, where X is the episode number), and the cues from paid advertising (ad), earned media (so), and owned media (me). The vertical dotted lines indicate whether the cues in total were reported as leading to increases (dotted lines from the cue text to the top of graph), decreases (dotted lines moving from the cue text to the bottom of graph), or no change (no vertical dotted line) in the expected liking, $cEL_{i,t}$.

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 coincide with experienced liking or cues, others do not. Assuming these variables are reflective of the match value beliefs, it is easy to see how these data provide 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 the individual-level data are 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 could be helpful in this regard. In each of these patterns, one might see such diminishing response, though perhaps to varying degrees. Similarly, the data have coincidence of recent cues and watching, suggestive of reminding effects. For instance, Panelist 8 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 these observations are merely suggestive, and the descriptive and structural analyses provide the econometric evaluation of these effects.

C.4. Evaluating whether experiences are informative

In the main paper, we present analyses on whether the three media types are informative. Here, we use the self-reported actual and expected experience measures to test 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 with more experience. We estimate the linear regression equation, $EL_{i,c} = \beta_{1,c}EL_{i,c-1} + \beta_{2,c}Lik_{i,c-1} + \epsilon^d_{i,c}$, which is directly analogous to equation 2, where we have not forced the βs to equal the weights from the Bayesian learning model and where the other signals are ignored (i.e., relegated to the $\epsilon^d_{i,c}$).[22] We separately estimate these coefficients for each of episodes 2-6 , because we require lags. We note that the sample size decreases for later episodes because the regression requires observed liking data. The results are presented in Table 9 with the standard errors in parentheses. Compatible with Bayesian learning and an informative effect of experiences, all variables are positive and significant with p-values less than 0.001, and the average effect of the stated experience decreases in the first few episodes. This analysis suggests experiences are informative.[23]

Appendix D: Missing Data Model Details

As noted in section 4.1, our data contain missing cases due largely to dropout, and this missingness is weakly related to previously observed variables. In this section, we detail how we handle the missing data issue.

[22] Notice that we are using subscript c instead of t because we are using the episode ordering and not the exact timing in this regression.

[23] We note that to the extent that the signals are correlated (and received), the coefficient on $Lik_{i,c}$ may pick up the other signal effects.

D.1. Drawing missing data imputations

We begin by presenting the basis on which we impute the missing data, focusing on the distributions we use to draw the watching and cues data. First, consider individuals who return after missing a survey. Because we ask retrospectively whether they watched the program, we know they watched, but not when they watched. For each case in which the individual indicates watching (i.e., $w^M_{i,c} = 1$), we draw the period when the episode was watched. To draw this period, we use the complete data sample's distribution of when they watched, given watching. We construct these distributions specific to the episode.

Once the watching data are imputed, we impute the cues for the missing data, $C^M_{i,t,k}$, using the complete data probabilities conditional on watching (or not watching). That is, $p(C^M_{i,t,k}|w_{i,t} = h) = \frac{\sum_{i:w_{i,t}=h} C_{i,t,k}}{\sum_{i:w_{i,t}=h} 1}$, where we only include complete data in the summation. Hence, we preserve the frequency of media encounters for watchers and non-watchers that is observed in the data.

D.2. The multiple imputation estimator

Because one imputation would lead to inefficiency, we impute the missing data multiple times and estimate the effects and standard errors using a standard technique that approximates the standard error by incorporating the error across and within imputations (Rubin 1987). The technique uses "Rubin's formula," which is described at sites.stat.psu.edu/ jls/mifaq.html in detail. We reproduce the approach below and use it to obtain the results in our structural analysis and our (unreported) robustness tests for the descriptive analysis.

We find the OLS estimate for each data set $j = 1, \ldots, m$. $\hat{Q}_j$ is the point estimate for data set j and U_j is the variance of that estimate. The final estimate is the average of the estimates,

$$\bar{Q} = \frac{1}{m}\sum_{j=1}^{m}\hat{Q}_j. \tag{14}$$

The final standard error is a function of the within-imputation variance,

$$\bar{U} = \frac{1}{m}\sum_{j=1}^{m}U_j, \tag{15}$$

and the between-imputation variance,

$$\bar{B} = \frac{1}{m-1}\sum_{j=1}^{m}\left(\hat{Q}_j - \bar{Q}\right)^2, \tag{16}$$

with the total variance of the estimator being

$$\bar{T} = \bar{U} + \left(1 + \frac{1}{m}\right)\bar{B}. \tag{17}$$

The literature on multiple imputation makes clear that when the missing data represents a small portion of cases (in our case, 4% of a large sample) few imputations are needed to obtain theoretically efficient estimates (Graham et al. 2007). As a result, following these guidelines, we use only five imputations. We note that in a robustness test for our descriptive analyses, we have used more imputations and confirmed this small number of imputations does not influence the results.

D.3. Dropout in the structural analysis

To begin, we note that we model dropout as a precaution, because our descriptive analyses suggest selection is not a major concern. These analyses include the insignificant relationship between dropout and initial likelihood of watching the premier ($\chi^2 = 59.6$,df=50, p-value=0.17) and Heckman two-step models (Heckman 1979) applied to the descriptive regressions of section 4.5. In these Heckman two-step analyses, we find that the inverse mills ratio term for correcting for selection are not significant and that the point estimates do not shift meaningfully from what is presented in Table 1. Thus, including the dropout model is conservative.

Our specific approach to correct for potential selection is to incorporate the probability that the individual dropped out of the study ($z_{i,t}$) conditioned on not having already dropped out (i.e., $\mathsf{P}(z_{i,t}|z_{i,t-1} = 0)$). Each survey period has a probability of dropping out in the next period as long as the individual has not already dropped out. The observed choice and measurement model likelihoods then are conditional on not having dropped out.

The dropout likelihood for an individual i and survey period t is

$$L_{z_{i,t}}(\theta, \theta_i, I_{i,t}) = \Lambda(g_0 + g_1\mu_i)^{1(z_{i,t}=0)} \left(1 - \Lambda(g_0 + g_1\mu_i)\right)^{1(z_{i,t}=1)}, \tag{18}$$

where $\Lambda(x) = e^x/(1 + e^x)$, and we assume dropout is a function of implicit interest in the program. This function allows the unobserved true interest to be correlated with dropout. Because we do not observe the signals or cues when dropout actually occurs, this approach allows correlation in what we can measure with the observed data as well as with unobserved characteristics. Since this approach is a full-likelihood specification and could lead to bias, we note that the estimates without this dropout component are qualitatively consistent with what we present in the manuscript.

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

$$L_{EL,i,t}(\theta, \theta_i, I_{i,t}) = f_N(a_{ME} + \bar{\mu}_{i,t}, \sigma^2_{ME}) \tag{19}$$

$$L_{Lik,i,t}(\theta,\theta_i,I_{i,t}) = f_N(a_{ME} + v_{i,t,ex}, \sigma^2_{ME}) \tag{20}$$

$$\begin{aligned} L_{cEL,i,t}(\theta,\theta_i,I_{i,t}) = &(\Lambda(b_{ME} - \Delta\bar{\mu}_{i,t}))^{1(cEL_{i,t}=-1)} (1 - \Lambda(c_{ME} - \Delta\bar{\mu}_{i,t}))^{1(cEL_{i,t}=1)} \\ &\cdot (\Lambda(c_{ME} - \Delta\bar{\mu}_{i,t}) - \Lambda(b_{ME} - \Delta\bar{\mu}_{i,t}))^{1(cEL_{i,t}=0)}, \end{aligned} \tag{21}$$

where $\Lambda(x) = e^x/(1+e^x)$. The likelihood for the dropout model is as described in equation 18.

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

$$L_{w_{i,t=t_{c,A}}}(\theta,\theta_i,I_{i,t},M_{i,t}) = \prod_{j\in\{c,P,0\}} \mathsf{P}\left(w_{i,t} = j | I_{i,t}\right)^{w_{i,t}=j} \tag{22}$$

$$L_{w_{i,t\neq t_{c,A}}}(\theta,\theta_i,I_{i,t},M_{i,t}) = \prod_{j\in\{c,0\}} \mathsf{P}\left(w_{i,t} = j | I_{i,t}, w_{i,t-1} \neq c, \ldots, w_{i,t_{c,A}} \neq c\right)^{w_{i,t}=j}, \tag{23}$$

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

$$L_{w_{i,t}}(\theta,\theta_i,I_{i,t},M_{i,t}) = \left(L_{w_{i,t=t_{c,A}}}(\theta,\theta_i,I_{i,t},M_{i,t})\right)^{1(t=t_{c,A})} \left(L_{w_{i,t\neq t_{c,A}}}(\theta,\theta_i,I_{i,t},M_{i,t})\right)^{1(t\neq t_{c,A})}, \tag{24}$$

Combining all of these component likelihoods leads to the notation used in the joint likelihood of equation 13.

We do not observe all viewing behaviors for some panel members, including cases in which the survey was missing (which we discuss in Web Appendix D) and in which they indicate watching in time-delay in the first half of the week between airings. In this latter case, we do not observe whether during the airing period, the respondent watched a different program or did not have the television on. Hence, we analytically sum over these unobserved 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:

$$\mathsf{P}\left(w_{i,t} = 0 | r_{i,t} = 1, I_{i,t}\right) = \frac{1 + e^{u_{P,it}}}{1 + e^{u_{c,i,t}} + e^{u_{P,it}}} \tag{25}$$

$$\mathsf{P}\left(w_{i,t} = 0 | r_{i,t} = 0, I_{i,t}\right) = 1. \tag{26}$$

Appendix F: Potential Measurement Model Mis-specification Bias

The measurement model we discuss in section 5.2 imposes three main assumptions that could lead to mis-specification bias. These assumptions are (a) the independence assumption between measurement errors, (b) the homogeneity of scale shifters, and (c) the normality assumption imposed on the measurement errors for $Lik_{i,t}$ and $EL_{i,t}$. We briefly mention some tests we conduct to evaluate these assumptions and then discuss potential mis-specification biases that could arise from imposing these assumptions.

We examine the independence assumption using a variant of the marker variable technique used in the common methods variance literature (Lindell and Whitney 2001). We find that the variation due to common variance is at most 20% of the within-survey correlation, suggesting relatively low measurement error correlation. However, if large common methods variance did exist, it would reduce the structural part of the relationships between $Lik_{i,t}$ and $EL_{i,t}$ and between $cEL_{i,t}$ and $EL_{i,t}$. Because these relationships support a stronger informative effect in our model, common methods variance would imply a weaker informative effect. Therefore, our modest informative effect could be over-estimated if the errors are positively correlated.

We examine the homogeneity of scale shifters in two ways. First, we examine whether the cross-sectional variation in the $EL_{i,t}$ measures predict viewing, and indeed they do. Second, we insert fixed effects into the regression of section C.4 and find doing so does not influence our finding of diminishing returns to information from experiences. Although these findings suggest the data are consistent with our approach and that some of our tests are robust to such scale usage heterogeneity, these analyses do not rule out the potential for some scale usage heterogeneity. If scale usage heterogeneity exists, predicting the direction of bias from our assumption of homogeneity is difficult. However, clearly, we would have less information to estimate the learning model parameters, and we would have to fix one of the variance terms for identification.

Finally, we examine the robustness to normality by adjusting the analysis in C.4 to use an ordered logit model. We find the results are still consistent with diminishing returns to information from experiences. Again, although consistent with our assumption, this finding does not ensure our assumption is true. Unfortunately, the direction of bias if such a mis-specification bias exists is also unclear.

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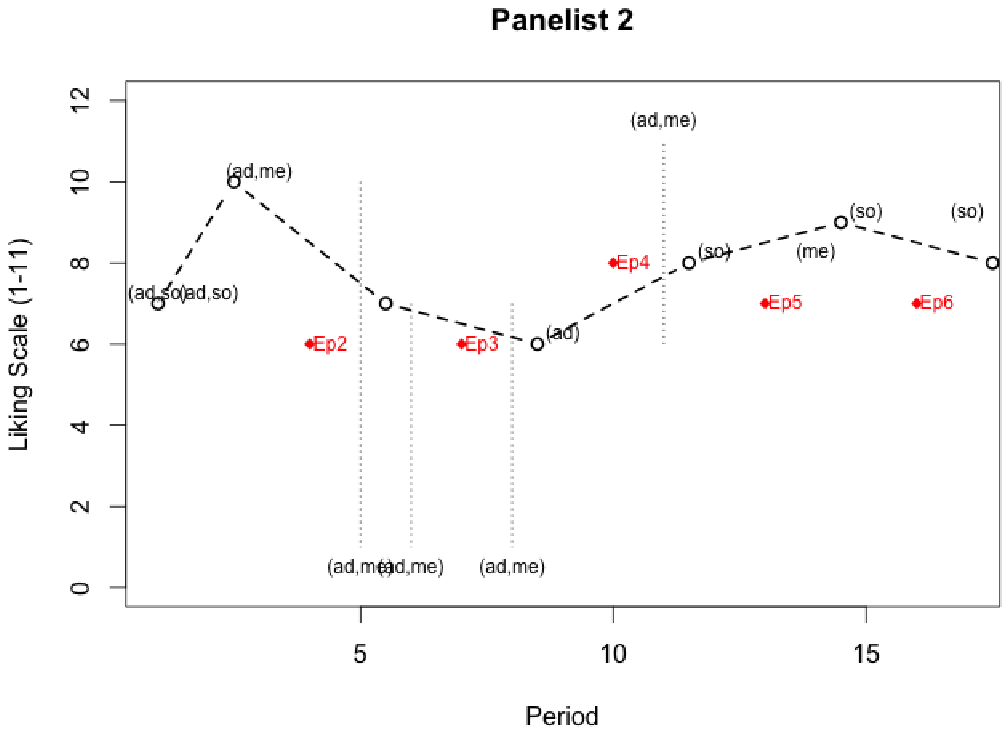
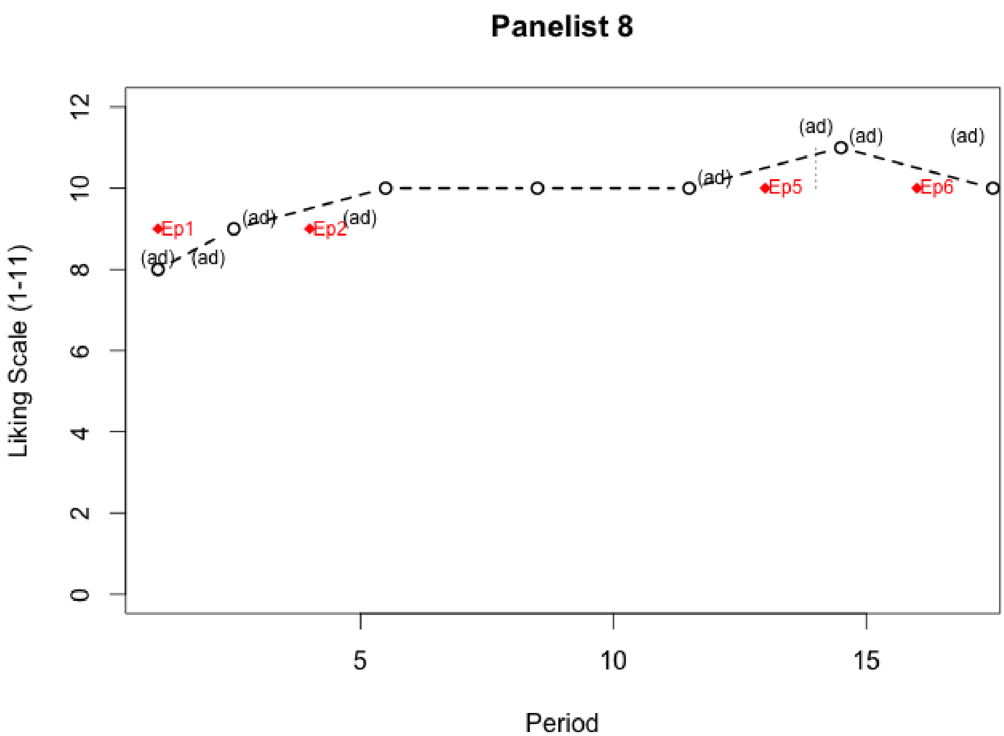
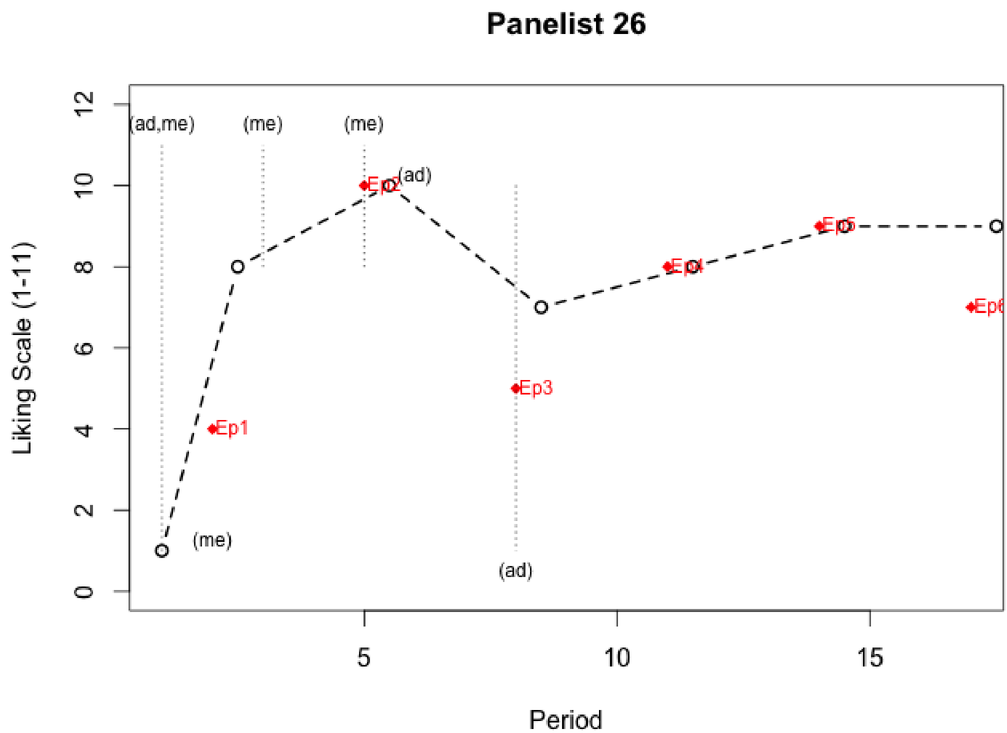


Panelist 2
Liking Scale (1-11)
Period
0
2
4
6
8
10
12
5
10
15
(ad,so)
(ad,so)
(ad,me)
Ep2
Ep3
(ad)
Ep4
(so)
(ad,me)
(me)
Ep5
(so)
(so)
Ep6
(ad,me)
(ad,me)
(ad,me)



Panelist 8
Liking Scale (1-11)
Period
0
2
4
6
8
10
12
5
10
15
Ep1
(ad)
(ad)
(ad)
Ep2
(ad)
(ad)
Ep5
(ad)
(ad)
(ad)
Ep6



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 5 Survey Sample Characteristics (for full sample)

Watching Question Options	$1(NAR_{i,\tau})$			$w_{i,\tau}$		
	airing = t	t+1	t+2	airing = t	t+1	t+2
A: Q1=1	0			c		
B: Q1 = 2	0	1		{0,P}	c	
C: Q1$\in 3,4,5$ and Q3 $\in 1,3$	0	1	1	{0,P}*	0	c
D: Q1$\in 3,4,5$ and Q3 $\notin 1,3$	0	1	1	{0,P}*	0	0

Table 6 Construction of the $w_{i,t}$ and $1(NAR_{i,t})$ variables. *Note that Q2 resolves the 0/P distinction for cases C and D.

	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 7 **Within-survey (across Respondents) Variation and Correlations (for complete data).**

	Expected Liking		Liking	
Range is	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 8 **Between-survey Variation (for respondents with at least 2 or exactly 6 completed surveys)**

Expectation after Episode	Expected Liking (c)	Liking (c)
2 (n=827)	0.296 (0.02)	0.732 (0.02)
3 (n=752)	0.308 (0.02)	0.712 (0.02)
4 (n=695)	0.409 (0.02)	0.606 (0.02)
5 (n=649)	0.449 (0.02)	0.572 (0.02)
6 (n=648)	0.390 (0.02)	0.614 (0.02)

Table 9 **Regression of Expected Liking on Current Liking and Prior Expected Liking. Regression run each period separately. Note the sample includes only those with complete Liking and Expected Liking data in the relevant periods.**