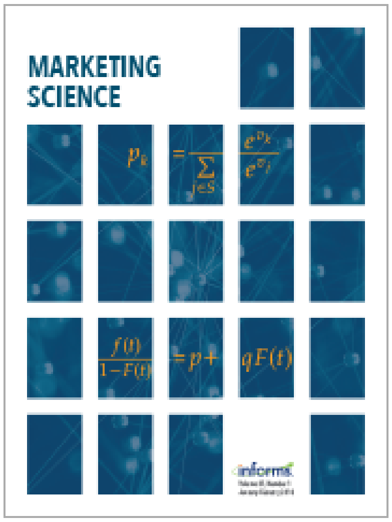

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The Role of Paid, Earned, and Owned Media in Building Entertainment Brands: Reminding, Informing, and Enhancing Enjoyment

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We study three ways firms can communicate about their brands—paid media (advertising), earned media (word of mouth and online social media), and owned media (brand websites and other owned content)—and the roles these media types play in reminding (i.e., activating memory), informing (i.e., learning their tastes for the brand), or enhancing enjoyment (e.g., gaining additional utility from socializing about the brand). We do this for a new TV show setting using a data set that contains reported viewing, exposures, expectations, and experiences. We present descriptive analyses and results from a new structural model, which indicate that earned media is more impactful than paid and owned media per exposure. However, paid media has far more exposures, so for a given percentage increase, paid media's influence dominates earned and owned media. Earned media operate primarily through enhancing enjoyment, whereas paid media operate through reminding and owned media through reminding, but discourage live viewing. We find that media exposures help consumers learn about how well they will like the program. However, this learning can either increase or decrease the expected liking, and in our data the average audience effects are negligible. Overall, we find that earned and paid media play a central role in developing and maintaining entertainment brands.

Keywords: social engagement; informative effects; reminding effects; entertainment brands; word of mouth; Bayesian learning; earned media; owned media
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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 individuals who on average have more nonviewing exposures (e.g., via socializing) also on average watch earlier. Watching earlier gives these frequent socializers more opportunities to benefit from socializing about the most recent episode.

We provide descriptive evidence, structural model estimates, and counterfactual analyses that present a multifaceted view on the role of paid, earned, and owned media. We find that 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 to benefit from future socializing (or avoid spoilers), whereas those who use owned media tend to watch later. For earned media, the enhancing-enjoyment role is by far the strongest and offers a new explanation for why live viewing is so prominent. We also find that paid and earned media increase live viewing more than delayed viewing, suggesting new media practices may be needed for the delayed viewers.

We find that paid media increase viewing the most for a given percentage increase in exposures because they have more total exposures. However, for equivalent exposure levels, earned media are more impactful. Although we do not account for costs and only consider organic (not firm-sponsored) earned media, these results suggest that paid media dominate because exposure levels can be set higher than earned media. Hence, paid media play the central role in building the brand by providing reminders, while earned media's scale limitations leave its more influential enhancing enjoyment effects in a supporting role.

2. Relationship to Literature

Our study builds on the literature on TV viewing choices (Goettler and Shachar 2001) by considering multiple media types and effects as well as live versus delayed viewing decisions. We also add a new explanation, the enhancing enjoyment role, 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 (also referred to as image or prestige) advertising effects (Ackerberg 2001, 2003; Narayanan et al. 2005). 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. Importantly, both persuasive and informative effects would operate through the expectations consumers have about the brand, because both influence the perceived value (match value). The second distinction is between the direct effect of advertising on preferences and the indirect effect on choice by influencing the consideration set (Mitra and Lynch 1995). Importantly, the indirect effect need not operate through expectations (Clark et al. 2009).

These literatures use the term "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. Awareness refers to placing an alternative in the possible set of options, and match-value refers to changing the expected value from choosing 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 (2015), we model as operating instead through consideration.[1] We acknowledge that although we model these reminding effects as related to memory, empirically they could be confounded with other influences that do not affect expectations.

In relation to these literatures, we contribute in three ways. 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 exposures and viewing behaviors after controlling for stated expectations. Second, we measure these two types of effects not only for advertising (paid media) but also

[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.

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 subsequent ads (Tuchman et al. 2014) or interviews with the show's talent. This enhancing-enjoyment role reflects why engagement can be so important to branding, that is, that these interactions lead people to become more involved in the brand (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 from both studies that associate aggregate data on choices with aggregate data on paid and/or earned media (Bruce et al. 2012, Srinivasan et al. 2015, Sonnier et al. 2011, Stephen and Galak 2012) and studies that consider individual-level decisions (Nair et al. 2010, Iyengar et al. 2011, Hartmann 2010), since none of these studies considers all three types of media. Consequently, we are more 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 episode's airing period or in time delay in any of the following $J-1$ nonairing periods. The next episode, $c+1$, is aired in period $t_{c,A}+J=t_{c+1,A}$. In our setting $J=3$.[3] Note that, for reference Table 1 contains the parameters, variables, and their definitions, and Figure 1 presents the timing of periods and data collection.

[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.

[3] For our weekly show, $J=3$ implies one airing period and then two nonairing periods, one between the airing and the survey and the other between the survey and the next airing. This time breakdown is to match the way the data were collected, but the model can, in principle, be used on, for example, daily data with minor modifications.

Consumer i's information set at time t is denoted $I_{i,t}$. The consumer receives cues and signals in the form of viewing experiences (ex) or paid (ad), earned (so), or owned (ow) media exposures (referred to also as communications). We denote the vector of experiences and exposures (we also refer jointly to these as cues) by $C_{i,t}$, and the 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 c (watching an episode), P (an option in P_t, the set of available competing programs, which we model as a single "other" TV program option), or 0 (the outside option). For nonairing periods, if the individual did not already watch episode c, she can watch it (c) or not (0).[4]

We 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, $P(w_{i,t}, r_{i,t} \mid I_{i,t}) = P(w_{i,t} \mid r_{i,t}, I_{i,t})P(r_{i,t} \mid I_{i,t})$. In §§3.1–3.4, we discuss $P(r_{i,t} \mid I_{i,t})$ and the components of $P(w_{i,t} \mid r_{i,t}, I_{i,t})$. These components include the entertainment utility, the anticipated utility from communications, and the benefits or costs of watching in time delay.

3.1. Consideration and Reminding Effects

Similar to Sahni (2015), the probability that an individual considers a program is adapted from Anderson et al.'s (2004) cognitive model of thought. Our model assumes that the probability that individual i considers the focal program at time t is increasing in the memory-activation level

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

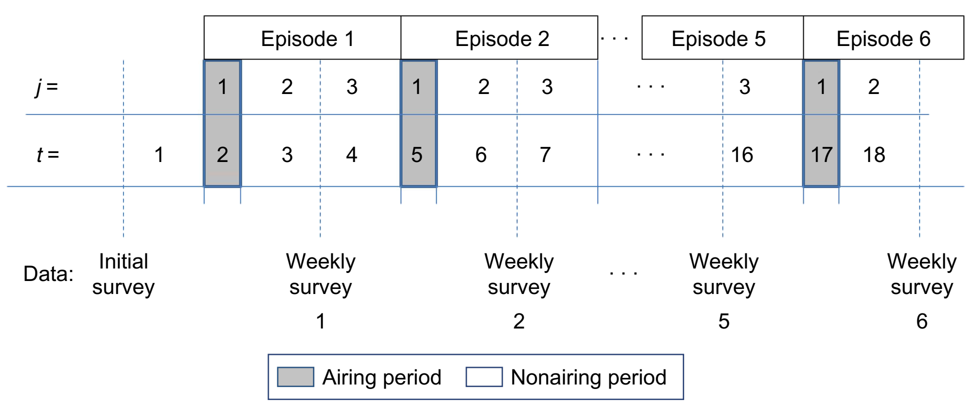
where $A_{i,t}$ is the deterministic component of the memory-activation level for the episode available at t. This $A_{i,t}$ is a function of $B_{i,t}$, the baseline memory-activation level; $\varepsilon^r_{i,t}$, an idiosyncratic, temporary memory shock; and $X_{A,i,t}$, the contextual cues related to whether and what was viewed in the half hour prior to the airing of the focal program (Rust and Alpert 1984, Shachar and Emerson 2000). We note these contextual cues are available only during airing periods and do not directly affect long-term memory.

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

Table 1 **Table of Parameter and Variable Definitions**

Variable	Definition	Related parameters
i	Individual index $i = 1, \ldots, n = 1{,}127$	
t	Period index $t = 1, \ldots, T = 18$	
$t_{c,A}$	Period in which episode c airs (A)	
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	$u_{j,i,t}$, underlying deterministic utility for option j
$r_{i,t}$	Unobserved 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 $\{C_{i,h,k}\}_{\forall h \leq t}$ and their corresponding signals, $v_{i,h,k}$	
$C_{i,t,k}$	Indicates 1 if received any cue of type $k \in \{ad, so, ow, ex\}$, else 0	$\sigma^2_{v,k}$ is the signal variance for media type k; ϕ_k is the 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)
$SW_{i,t}$	Switching costs, includes $1(\text{TV}_{i,t})$, an indicator for whether watching TV in 1/2 hour before *Human Target* airs	β_1, the effect on utility for episodes of *Human Target* and competing programs at air time.
	True match value for *Human Target*, and signal of type k	μ_i, $v_{i,t,k}$
	Mean and variance of belief about match value	$\bar{\mu}_{i,t}$, $\hat{\sigma}^2_{t,\mu_i}$
$\bar{q}^k_i$	Average frequency of media exposure of type k	ω_k, expected utility per anticipated media exposure
$q^k_i = high$ $q^k_i = low$	High (low) propensity groups for media exposures of type k, split at $\bar{q}^k_i \geq 0.25$	
$1(NAR_{i,t})$	Indicator for whether period is an airing period (0) or not (1)	$\beta_{NAR,i}$, individual-level effect for nonairing period viewing; $\gamma_{NAR,0}$, $\sigma^2_{NAR,\gamma}$, parameters of NAR mixing distribution
	Time effects for competitor options and *Human Target*	$\alpha_{P,t}$, $\alpha_{c,t}$
$X_{\mu,i}$	Variables including constant and $LW_{i,t}$, a measure of likelihood of watching *Human Target* 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 *Human Target*	$\gamma_{mem,0}$ and $\gamma_{mem,Aware}$, the effects on initial memory, $B_{i,0}$
WTD_i, LVW_i	General tendency to watch in time delay (live)	$\gamma_{NAR,WTD}$ ($\gamma_{NAR,LVW}$), effects of time delay (live-viewing) tendency on utility in nonairing (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.	c_{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 $\{-1, 0, 1\}$	a_{ME}, b_{ME}, cut-point 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, g_1, corresponding parameters for constant and true match value, μ_i

Figure 1 **Timeline and Data**



Note. The figure presents the timing of periods and episodes in the model and the timing of the surveys for data collection.

The baseline memory-activation level decreases over time because of memory loss, but increases with new cues. Hence, the expected utility of viewing does not directly affect memory (but does indirectly through experience cues). Formally, $B_{i,t} = \delta B_{i,t-1} + \sum_{k=1}^{K} \phi_k 1(C_{i,t,k} = 1)$,[5] where δ is the rate of memory decay, which we set to 1 (no depreciation) in airing periods because the airing periods are so short compared to the nonairing periods. The cue strengths, ϕ_k, represent the focal parameters for the reminding effects.

We assume $\varepsilon^r_{i,t}$ is distributed with the usual standardized logistic distribution. The resulting probability of consideration is $P(r_{i,t} \mid I_{i,t}) = 1/(1 + e^{-A_{i,t}})$.

3.2. Entertainment Utility and Learning

Assuming the person considers the focal program, she decides her entertainment option based on her expected utility for each available option. These utilities contain a number of additively separable elements. First, switching costs can cause the viewing from the previous half hour to persist. To capture this effect, we include a vector of variables, $SW_{i,t}$, in all live-viewing options and β_1 as the corresponding parameter vector.

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, modeled 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.

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

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

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

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

Ceteris paribus, as the signal variances $\sigma^2_{v,k}$ decrease, $\hat{\sigma}^2_{t,\mu_i}$ increases, or the distance between μ_i, and $\bar{\mu}_{i,t}$ increases, the informative effects increase for individuals. The average informative effects depend on the distribution of $\hat{\sigma}^2_{t,\mu_i}$, μ_i, and $\bar{\mu}_{i,t}$.

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 exposures, $C_{i,t,k}$, are passive (i.e., exogenous and stochastic) and follow a Bernoulli process. Individuals have heterogeneous propensities, $\bar{q}^k_i \in [0, 1]$, to receive such communications related to the program per half week.[6] We focus on the incremental net expected utility gained from watching the most recent episode, c, and later receiving a communication of type $k \in \{ad, so, ow\}$. If the individual watches the current episode, she will gain incremental utility ω_k in each period she receives such a communication of type k until the next episode airs. This ω_k is the parameter associated with the enhancing enjoyment effect.

Because future communications are uncertain, the individual bases the viewing decision on the expected number of such communications per period, $\bar{q}^k_i$, and the number of remaining periods, $(J - t - t_{c,A})$, implying that the enhancing-enjoyment effect decreases the later the episode is viewed.[7] Hence, the anticipated utility from watching in period t is

$$u^k_{antic,i,t} = \omega_k \bar{q}^k_i (J - t - t_{c,A}). \quad (4)$$

3.4. Time-Shifting

We allow consumers to watch in nonairing periods if they did not 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 $1(NAR_{i,t})$ as an indicator variable set to 1 in nonairing periods for the focal show (when

[6] Socializing, for example, also has 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 socializing occasions (how often and with whom they speak) in response to this television program. We discuss possible issues with this assumption in §5.5.

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

the nonairing 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.

3.5. Viewing Decisions and Choice Likelihoods

Putting these elements together, the expected utility of watching the focal program is[8]

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

where $\alpha_{c,t}$ is an episode-specific effect as will be described in §4, $\varepsilon^c_{i,t}$ 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

$$u_{P,i,t} = \alpha_{P,t} + \beta_1 SW_{i,t} + \varepsilon^P_{i,t}, \quad (6)$$

where the $\alpha_{P,t}$ is a time effect to control for competition at airtime, and $\varepsilon^P_{i,t}$ 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 $\varepsilon^0_{i,t}$, $\varepsilon^c_{i,t}$, and $\varepsilon^P_{i,t}$ are independent and identically distributed extreme value. In an airing period, if $r_{i,t} = 1$, the choice set is $\{c, P, 0\}$. The corresponding probabilities are

$$P(w_{i,t} = j \mid r^1_{i,t}, I_{i,t}) = \frac{e^{u_{j,i,t}}}{\sum_{j'\in\{c,P,0\}} e^{u_{j',i,t}}}, \quad (7)$$

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

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

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

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

[8] Note 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.

For nonairing periods, conditional on considering episode c, but not yet having watched c, we calculate the probability of watching and not watching c at time $\tau + m$, for $\tau = t_{c,A}$ and $1 \le m < J$. Because we do not model competitive options in nonairing periods (see Footnote 4), the choice set is $\{c, 0\}$, and the probability is

$$\begin{aligned} &P(w_{i,\tau+m} = c \mid r^1_{i,\tau+m}, I_{i,\tau+m},\\ &\quad w_{i,\tau+m-1} \neq c, \ldots, w_{i,\tau} \neq c) = \frac{e^{u_{c,i,\tau+m}}}{1 + e^{u_{c,i,\tau+m}}},\\ &P(w_{i,\tau+m} = 0 \mid r^1_{i,\tau+m}, I_{i,\tau+m},\\ &\quad w_{i,\tau+m-1} \neq c, \ldots, w_{i,\tau} \neq c) = 1 - \frac{e^{u_{c,i,\tau+m}}}{1 + e^{u_{c,i,\tau+m}}}. \end{aligned} \quad (10)$$

4. Data

Our application focuses on the first six episodes of *Human Target*, a new FOX action drama based on a comic book series that premiered 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 seven 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 lineup on FOX.

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

4.1. Sample and Data Collection

The survey respondents are from Proctor and Gamble's VocalPoint online community. We enrolled individuals prior to the premier episode using an initial survey on predispositions for TV viewing and the *Human Target* show. The initial survey was available to approximately 50,000 panelists, and 1,720 completed it, a nonrepresentative sample (see Web Appendix A (available as supplemental material at http://dx.doi.org/10.1287/mksc.2015.0961 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 halfway between episode airings, and it was typically completed within two days (see Figure 1). The surveys were largely the same, adjusted only for the episode 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 the total dropoff to the last survey was an additional 31%. In addition to dropout, a small proportion of respondents did not complete a survey in a given week, but returned to complete later surveys, amounting to 4% of potential surveys (228 surveys). However, if a panelist responded 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 < 0.05), as reported in 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 $= 0.17$). Nonetheless, we include a model of dropout to correct for any remaining censoring (see §5.3 and Web Appendix D).

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 obtained 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 nonairing period they watched; that is, $w_{i,t}$. In addition, for airing periods, they indicated what program, if any, they watched in the half hour prior to the focal airing, providing the measures $1(TV_{i,t})$ for whether watching TV (1) or not (0), and $1(FOX_{i,t})$ for whether watching the FOX channel (1) or not (0) (these measures are set to 0 in nonairing periods). We use these indicators in Equation (1) for the contextual cues, $X_{A,i,t}$, which contains $1(FOX_{i,t})$, and in Equations (5) and (6) for the switching costs, $SW_{i,t}$, which contains $1(TV_{i,t})$.[9]
- *Liking and expected liking.* Respondents indicated how much they liked episodes they viewed, $Lik_{i,t}$, where t is the corresponding viewing period. We assume this response is a fallible 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 a fallible 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 §5.2.
- *Media exposures.* Respondents were asked retrospectively whether they were exposed to any advertisements (paid media), had heard from any social contacts (online and off-line earned media), or had engaged in related content such as on the network website (owned media) about the program.[10] 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 intersurvey period. We use these responses and viewing to form the indicators, $C_{i,t,k}$, and the vector of these cues, $C_{i,t}$.
- *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 §5.2.
- *Viewer segments.* To parsimoniously analyze the enhancing-enjoyment role, we create two segments for each media type based on the exposure frequency. We use the observed average exposure frequency during the study, $\bar{q}_i^k$, as a rational expectation for the probability of type k exposure about the program, q_i^k (i.e., $\bar{q}_i^k = E[1(C_{i,t,k} = 1)]$). We segment individuals into a low-propensity group ($q_i^k = low$), who are exposed less than one time in two weeks, and a high-propensity group ($q_i^k = high$), who are exposed on average at least one time per two weeks.[11] 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 groups in both our descriptive and structural analyses.

4.3. Basic Description of Survey Measures

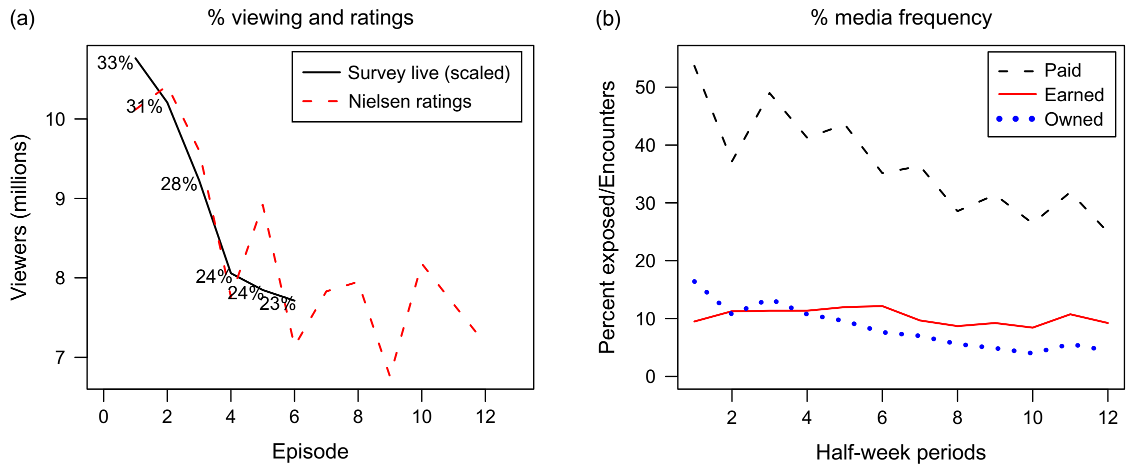
We present aggregate patterns to better understand how our sample compares to a nationally representative one

[9] We also ran models with both variables in $X_{A,i,t}$ and $SW_{i,t}$, and no qualitative differences arose.

[10] More than 85% of earned media exposures in our data are off-line, confirming the need for surveys in this setting.

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

Figure 2 **(a) Stated Viewing Percentage for Full Sample vs. Nielsen Ratings for the Show, with Stated Percentage Viewing Scaled by 33 Million Viewers to Match Scale with the Total Viewers, and (b) Percentage of Respondents Having Media Exposures Over Time** ($n = 1{,}127$)



and to identify key phenomena and relationships. In Panel (a) of Figure 2, we present the Nielsen viewing measure (ratings) and the percentage of our sample that reported viewing the show at airtime. Both series have a similar declining trend that flattens toward 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.[12]

In Figure 2, panel (b), we present by half-week periods the percentage of our sample exposed to each of the three media. Paid media have the broadest reach. Whereas 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 Figure 2, panel (a).

Time shifting is common in our sample. Approximately 40% of episodes are watched in time delay, a portion consistent across 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). 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.

4.4. Using Data to Isolate the Reminding Effects

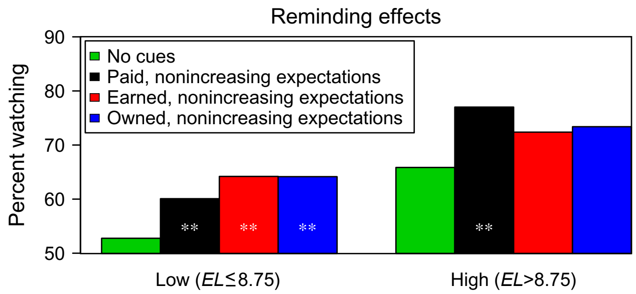
Our model proposes reminding effects, but we do not observe consideration or memory directly. We use our unique data to isolate the reminding effects indirectly. Here we present descriptive evidence using the essential logic of how this isolation works. Specifically, we contrast the percent viewing when communications were received but did not have a positive effect on stated expected liking (i.e., $cEL_{i,t} \leq 0$) against the percent viewing when no communications were received. We split the sample at approximately the average expected liking to control for preferences. The results reported in Figure 3 are very supportive of a reminding effect both directionally and statistically, where the bars with two asterisks indicate that the percent watching is statistically different (p-value ≤ 0.05) from that of the corresponding no-cues case. For all three media, 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 given the large number of TV viewing options such indirect effects are not too surprising (Mitra and Lynch 1995).

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 switching costs ($1(TV_{i,t})$ and $1(FOX_{i,t})$), whether the individual watched the program in the previous week, whether the individual states preferring live viewing, and time effects. In some specifications, we add indicators for frequent

[12] In unreported analyses (available from the authors on request), we find our self-reported paid media exposures are reasonably related to advertising expenditures 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 Twitter, blogs, and forums.

Figure 3 **Reminding Effects: Percent Watching of Those Exposed Only to the Indicated Media and Report Not Increasing the Expected Liking ($cEL_{i,t} \le 0$) Compared to Percent Watching of Those Receiving No Cues ($\sum_k C_{i,kt} = 0$) Decomposed by Low and High Average Expected Liking (Split at 8.75)**



**Significant difference (p-value < 0.05) between this bar and the no-cues case.

exposures to paid, earned, and owned media (i.e., $q_i^k = \text{high}$), 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 2 presents the results.

Model 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 the effects of paid or earned media. We find significant effects for all of the control variables in the expected direction and, compared to watching last week, paid and earned media are around one-fifth to one-sixth as effective. Model 2 incorporates a cubic function of expected liking (i.e., three terms). Although the inclusions do not significantly affect any of the coefficients, the model fit improves significantly (F-stat. = 17.1 and p-value < 0.01). 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 Model 3, we introduce the time dummies, which control for advertising budgeting endogeneity, competitive environment effects, time-slot changes, and the survey as a 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 > 0.44). This finding suggests these sources of endogeneity are not very severe.[13] In Model 4, we add the indicators for frequent exposures to paid, earned, and owned media. If individuals anticipate the utility from future media exposures 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 exposures are positive (0.09) and significant, and frequent owned exposures are negative (−0.04) 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 media 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 Model 5, we introduce individual-level fixed effects and find the results for the recent media effects are robust and consistent with Model 4.[14]

These analyses, though supportive of our model, do not capture the process or control for the time-varying nature of influences on viewing decisions. Accounting for these additional influences is important 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.

5.1. Heterogeneity and Initial Beliefs

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

$$\begin{aligned}\pi(\cdot) = {} & f_{N,2}((\mu_i, \bar{\mu}_{i,0}); X_{\mu,i}(\eta_\mu, \eta_{\bar{\mu}}), \Sigma_\mu) \\ & \cdot f_{LN}(\hat{\sigma}^2_{0,\mu_i}; X_{\sigma,i}\eta_\sigma, \sigma^2_{\sigma,\eta}) \\ & \cdot f_N(\beta_{NAR,i}; X_{NAR,i}\gamma_{NAR}, \sigma^2_{NAR,\gamma}),\end{aligned} \quad (11)$$

where f_N, $f_{N,2}$, and f_{LN} are the normal, bivariate normal, and lognormal distributions, the parameters of which are estimated. The X variables (and corresponding

[13] 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 reminding effect after including all other controls. This finding again suggests the survey itself did not overly influence our results.

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

Table 2 Regression Analysis on Viewing at Broadcast

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)*	
Watched 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

Note. Entries are coefficients (standard errors) and significance indicators.
$^{*}p < 0.05$; $^{**}p < 0.01$.

parameters) are as follows: $X_{\mu,i}$ includes an intercept ($\eta_{\mu,0}$ and $\eta_{\bar{\mu},0}$) and the stated likelihood of viewing the pilot episode, LW_i ($\eta_{\mu,LW}$ and $\eta_{\bar{\mu},LW}$); $X_{\sigma,i}$ includes an intercept ($\eta_{\sigma,0}$) and the number of action dramas viewed in a typical week, $nDrama_i$ ($\eta_{\sigma,nDrama}$); 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 previously in §4.2, using observed data, we construct segments of high-frequency and low-frequency groups for each of the media.

5.2. Measurement Model and Scaling

We incorporate the measures of expectations and experiences 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 cut-point 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

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

We set the scale of the current match-value belief, $\bar{\mu}_{i,t}$, to the stated expected liking scale of $EL_{i,t}$. As a result, in Equation (5), we scale (multiply) $\bar{\mu}_{i,t}$ by d_{ME} to match the utility scale during estimation. Our measurement model for the (stated) expected liking of the next episode, $EL_{i,t}$, also allows the survey question to have a constant scalar adjustment. Specifically, we assume

$$EL_{i,t} = c_{ME} + \bar{\mu}_{i,t} + \varepsilon_{ME,EL,i,t}, \tag{13}$$

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. The stated liking measure, $Lik_{i,t}$, follows a similar survey scale to $EL_{i,t}$, so

$$Lik_{i,t} = c_{ME} + v_{i,t,ex} + \varepsilon_{ME,Lik,i,t}, \tag{14}$$

where $\varepsilon_{ME,Lik,i,t} \sim f_N(0, \sigma^2_{ME})$, and $v_{i,t,ex}$ is the (unobserved) experienced liking for the episode viewed at t. We note the main difference between measurement model Equations (13) and (14) is the underlying measured quantity (i.e., $v_{i,t,ex}$ or $\bar{\mu}_{i,t}$).[15]

5.3. Missing Data and Dropout Model

We impute missing media exposures, 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 exposures conditional on $w_{i,t}$ and t. Because so few 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.

[15] We scale $EL_{i,t}$ and $Lik_{i,t}$ by 0.1 (min = 0.1 and max = 1.1) during estimation. Note also that the differences in distributions between the $EL_{i,t}$ and $Lik_{i,t}$ measures and $cEL_{i,t}$ measures reflect measurement errors and not structural errors. We discuss potential misspecification 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 as $T = 18$, including six airing periods, one nonairing period before the first episode, 10 nonairing periods between airings prior to the sixth episode, and one nonairing period after the sixth episode (see Figure 1). We refer to the full set of parameters and unobservables as $\Theta_i = \{\theta, \theta_i, \{I_{i,t}\}_{t\in 1:T}\}$, 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 E for details)

$$L_i(\theta, \theta_i, \{I_{i,t}\}_{t\in 1:T}) = \prod_{t=1}^{T} L_{w_{i,t}}(\Theta_i) L_{EL,i,t}(\Theta_i) L_{Lik,i,t}(\Theta_i) \cdot L_{cEL,i,t}(\Theta_i) L_{z_{i,t}}(\Theta_i). \quad (15)$$

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 $NP = 5{,}000$ simulations and maximize the approximate likelihood

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

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.[16] This identification assumes that program behaviors or interest do not affect the frequency of media exposures.[17]

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.[18] 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.[19]

Third, the stated expectations data provide information to separate the informative and reminding effects. Past studies that separated informative and persuasive effects (e.g., Narayanan et al. 2005) did 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 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 exposures 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 §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 §4.5, we found no meaningful change to the media effects when introducing individual fixed effects or the $EL_{i,t}$ measures.[20]

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

[17] We 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 on request). In that analysis, we demonstrate that neither changes in $EL_{i,t}$ nor watching significantly affects later media exposures.

[18] 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 misspecification bias, which we discuss in Web Appendix F.

[19] 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 provide 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 the initial match-value belief, initial uncertainty, and true match values.

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

Table 3 Structural Parameter Estimates (Rubin's Standard Errors Using Five Imputations of the 4% Missing Data)

Variable	Informative: $\sigma^2_{v,k}$	Reminding: ϕ_k	Enhancing enjoyment: ω_k
	Media and experience effects		
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)*	—
Parameter	**Constant: η_0**	**Observed heterog.: η_1^a**	**Unobserved heterog.: σ_η**
	Learning match value model parameters		
Var(initial belief): $\log(\hat{\sigma}^2_{0,\mu_i})$	−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)*

Parameter	Estimate	Parameter	Estimate
	Memory/Consideration model parameters		
Initial memory: $\gamma_{mem,0}$	5.98 (0.42)*	Context: ψ_0	−1.93 (0.30)*
Initial memory: $\gamma_{mem,Aware}$	1.65 (0.83)*	Context: ψ_{FOX}	2.3 (0.79)*
Depreciation: δ	0.47 (0.04)*		
	Utility parameters: β		
Live-viewing pref.: $\gamma_{NAR,LVW}$	2.14 (0.07)*	Nonairing pref.: $\gamma_{NAR,0}$	9.09 (2.34)*
Time-shifting pref.: $\gamma_{NAR,WTD}$	18.4 (7.21)*	Nonairing pref.: $\sigma_{NAR,\gamma}$	6.58 (1.94)*
TV: β_1	0.84 (0.07)*	Competition period 1	−3.99 (0.16)*
Human Target period 2	0.09 (0.11)	Competition period 2	−4.86 (0.22)*
Human Target period 3	0.01 (0.11)	Competition period 3	−4.77 (0.22)*
Human Target period 4	0.05 (0.12)	Competition period 4	−4.99 (0.26)*
Human Target period 5	0.15 (0.12)	Competition period 5	−4.89 (0.27)*
Human Target period 6	0.23 (0.12)	Competition period 6	−4.77 (0.27)*
	Measurement and dropout model parameters (note $EL_{i,t}$ and $Lik_{i,t}$ are 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 cut point: a_{ME}	−4.19 (0.11)*	*EL*, *Lik* intercept: c_{ME}	1.84 (0.16)*
cEL upper cut point: 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)*

[a]The unobserved heterogeneity variable for μ_i and $\bar{\mu}_{i,0}$ is LW_i, the stated likelihood of watching the premier, and for $\log(\hat{\sigma}^2_{0,\mu_i})$ is $nDrama_i$, the number of action dramas typically watched in a week.
*Rubin's t-stat. > 1.99.

6. Results from the Structural Model

Table 3 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 between the media types are not significant. These signal precisions are significantly different from, and 1/12 to 1/16 weaker than, that of an experience signal (0.02). This finding suggests moderate informativeness, which we explore further below.

The reminding effect parameter estimates are similar for paid and owned media (0.31) and smaller for earned media (0.16), but only paid media's is statistically significant. These magnitudes are 1/25 to 1/50 as big as that of an experience (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 parameters' relative magnitudes increase to be 1/8 to 1/16 that of an experience (see also below).

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 exposures. The negative sign for owned media implies individuals who tend to have more owned media exposures would rather have them prior to watching, which is somewhat puzzling and could suggest unplanned viewing, search, or selection in who is exposed to owned media. The small and insignificant effect for paid media exposures suggests they have a relatively small enhancing-enjoyment role, if at all.

Together the above imply 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 compared to the experience effect. We will further evaluate the relative size of these effects in §7, but first we discuss the rest of the parameters.

The other learning model parameters are consistent with expectations. The initial uncertainty about the match-value belief ($\hat{\sigma}^2_{0,\mu_i}$) 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%.

Contrasting the parameters related to the initial mean belief and the true match-value is instructive. The constants ($\eta_{\bar{\mu},0} = -1.21$ and $\eta_{\mu,0} = -1.31$) and observed heterogeneity ($\eta_{\bar{\mu},LW_i} = 0.02$ and $\eta_{\mu,LW_i} = 0.04$) are significant.[21] Together these estimates of the initial mean belief and true match-value suggests, on average, individuals who initially believe they dislike the show ($LW_i < 5$) have true match values that are even lower, whereas individuals who initially like the show ($LW_i > 5$) have true match values that are higher. The corresponding unobserved heterogeneity standard deviations are modest ($\sigma_{\bar{\mu},\eta} = 0.10$ and $\sigma_{\mu,\eta} = 0.02$), and the correlation coefficient between the unobserved μ_i and $\bar{\mu}_{i,0}$ components is high (0.93). This high correlation indicates that most individuals become more extreme in their beliefs as new information arrives. These results suggest that learning is occurring, but that those for whom information is positive may cancel with those for whom it is negative.

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.

Delayed-viewing preferences are relatively strong. Unobserved heterogeneity in preferences for watching in nonairing periods is significant and very large ($\sigma_{NAR,\gamma} = 6.58$). Observable heterogeneity is also large and significant. Given not having already watched the episode, those who report watching television mostly in time delay are much more likely to watch *Human Target* (than not) in nonairing periods ($\gamma_{NAR,WTD} = 18.4$), and those who prefer live viewing have a similar but smaller tendency ($\gamma_{NAR,0} = 9.09$). Given the observed and unobserved heterogeneity in time-shifting preferences, individuals who prefer to watch in time delay nearly always watch in a nonairing period, if they consider the program. The time-shifting parameters also indicate that those who report watching television mostly live are more likely to watch at broadcast ($\gamma_{NAR,LVW} = 2.14$).[22]

We find the effect for prior TV viewing ($\beta_1 = 0.84$) is significant and consistent with expectations. The focal program week fixed effects show no clear 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 do not differ much from one another. For the dropout model, dropout is relatively unlikely given that one has not dropped out already ($g_0 = -2.42$), but does not vary significantly with the unobserved true match-value ($g_1 = 0.01$). Thus, in our sample, dropout is not related to how much the person likes the show. 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 three 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 by randomly setting the indicator $C_{i,t,k}$ to be 1 where it was 0. We calculate audience effects for live viewing only (denoted LV) and live viewing plus seven days of delayed viewing (denoted $LV + 7D$ or *total viewing*).

First, not all media exposures have equal costs to obtain or can be purchased. To partly address the issue, we examine elasticities, which link the increase in exposures to the current prevalence of the media exposures. 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 three times more effective than earned media. Hence, given current

[21] Recall $LW_i \in \{0, 1, \ldots, 11\}$, whereas $EL_{i,t}$ and $Lik_{i,t}$ are scaled down to be in $\{0.1, 0.2, \ldots, 1.1\}$.

[22] These observed heterogeneity findings are also apparent in the raw data. For example, 92% of those who always watch *Human Target* at airtime also indicate they mostly watch TV at broadcast.

Table 4 Counterfactual Scenarios

	Total effect	Reminding only	Informative only	Enhancing enjoyment only
		A. Live-viewing (LV) effect		
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		
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)

Note. 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 gross rating point campaign over the six-week period. The median and 10% and 90% quantiles of the parameter distribution are presented.

exposure levels, paid media dominate for a percentage increase.

Second, we construct scenarios that hold constant the exposure levels across media types and allow disentangling the relative size per exposure of the three roles. For each media type, we vary media exposures between 0 and 600 randomly assigned gross rating points (an average of six 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 and 10th and 90th percentiles of the outcome distribution, interpreting covering zero as insignificant. Table 4 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 indicates that earned media have the largest (and significant) median effect (0.09), which is nearly twice as large as that of paid media (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, insignificant 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.

Turning to the three roles, for reminding, all three media have significant effects. Paid media have the largest median effects for LV (0.014) and $LV+7D$ (0.026), double those of earned (0.007 and 0.012 for LV and $LV+7D$ effects). Owned media median reminding effects (0.012 for LV and 0.022 for $LV+7D$) are smaller than paid media's.

The aggregate informative effects are insignificant. Although individuals are learning and media are informative at the individual level, the average effects are close to zero, consistent with canceling and 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 $LV+7D$). 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 media'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 percentage 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 nonbroadcast 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. By contrast, 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. As a result, paid media exposures generate larger ongoing benefits than would be implied by Bayesian informative effects alone, 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. (2015) 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. 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, through this role, earned media increases both the broadcast (consistent with Godes and Mayzlin 2004) and delayed-viewing audience.

In our context, owned media total effects are not significant. Although owned media have a positive and significant 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 to search for information about the program on the website).

9. Conclusion

We use a unique data set on television viewing that contains reported viewing, media exposures, word of mouth, expectations, and experiences. We develop and estimate a structural model of consumers viewing a new TV program that 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. We model learning and consideration and incorporate live and delayed viewing.

We find that paid media plays primarily a reminding role, whereas earned media plays primarily an enhancing-enjoyment role. Paid media effects dominate total and live viewing because of their prevalence. 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 that "engagement" strategies can be an effective complement to paid media strategies that keep the brand in memory and consideration. Our results suggest managers should create ads that draw attention and are memorable rather than provide information, and to focus engagement strategies on earned rather than owned media.

We caution against overgeneralizing. 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. Furthermore, *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 misspecification bias.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mksc.2015.0961.

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