

# Web Appendix for ‘The Role of Paid, Earned, and Owned Media in Building Entertainment Brands: Reminding, Informing, and Enhancing Enjoyment’

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## Appendix A: Sample Description

Table 1 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 1, 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)

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- 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 2 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.<sup>1</sup> 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 3 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 of these variances. Consistent with our expectations, the variance of liking does not have a clear pattern. By

<sup>1</sup> 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.

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.<sup>2</sup> 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 3) 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 3). Specifically, we calculate  $\text{abs}(EL_{i,t} - Lik_{i,t})$  and tabulate the portion of cases in each of four categories of these differences—0, 1, 2, and 3+. For this analysis (and the correlations mentioned above), we also include only the cases in which individuals provided both measures in any given week. We find that between 35% and 25% of the sample 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 4 presents the information related to between-survey variation. The main concern between surveys is that the variables don't have much variation (i.e., are too consistent). Again, the difficulty is that the liking for a show is likely to be relatively consistent over time given a person's true match-value. Our goal then is to illustrate the degree of variation in the data series  $EL_{i,t}$  and  $Lik_{i,t}$  over time. We present first the average variance within individual. For  $EL_{i,t}$  the average is 0.91 for those individuals with all cases observed and 0.97 for those with at least two cases observed. For  $Lik_{i,t}$  the average is 1.14 for those with all cases observed

<sup>2</sup> 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.

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 4 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  $\mu_i$  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  $\mu_i$ . Panelist 2 appears less unidirectional and

doesn't appear to have started too far from the ending belief, suggesting both the  $\mu_i$  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 structural analyses on whether the three media types and experiences 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,  $EL_{i,c} = \beta_{1,c}EL_{i,c-1} + \beta_{2,c}Lik_{i,c-1} + \epsilon_{i,c}^d$ , which is directly analogous to equation 2 in the main paper, where we have not forced the  $\beta$ s to equal the weights from the Bayesian learning model and where the other signals are ignored (i.e., relegated to the  $\epsilon_{i,c}^d$ ). 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. 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 5 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. 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.

## Appendix D: Missing Data Model Details

As noted in section 4.1 of the main paper, 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.

### 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.,  $w_{i,c}^M = 1$ ), 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,  $C_{i,t,k}^M$ , using the complete data probabilities conditional on watching (or not watching). That is,  $p(C_{i,t,k}^M | w_{i,t} = h) = \frac{\sum_{i:w_{i,t}=h} C_{i,t,k}}{\sum_{i:w_{i,t}=h} 1}$ , where we only include complete data in the summation. Hence, we preserve the frequency of media exposures 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 (?). The technique uses “Rubin’s formula,” which is described at [sites.stat.psu.edu/~jls/mifaq.html](http://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  $j = 1, \dots, m$ .  $\hat{Q}_j$  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,

$$\bar{Q} = \frac{1}{m} \sum_{j=1}^m \hat{Q}_j. \quad (1)$$

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

$$\bar{U} = \frac{1}{m} \sum_{j=1}^m U_j, \quad (2)$$

and the between-imputation variance,

$$\bar{B} = \frac{1}{m-1} \sum_{j=1}^m (\hat{Q}_j - \bar{Q})^2, \quad (3)$$

with the total variance of the estimator being

$$\bar{T} = \bar{U} + \left(1 + \frac{1}{m}\right) \bar{B}. \quad (4)$$

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 (?). 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 ( $\chi^2 = 59.6, df=50, p\text{-value}=0.17$ ) and Heckman two-step models (?) 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 of the main document. 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.,  $P(z_{i,t}|z_{i,t-1}=0)$ ). 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

$$L_{z_{i,t}}(\theta, \theta_i, I_{i,t}) = \Lambda(g_0 + g_1\mu_i)^{1(z_{i,t}=0)} (1 - \Lambda(g_0 + g_1\mu_i))^{1(z_{i,t}=1)}, \quad (5)$$

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

$$L_{EL,i,t}(\theta, \theta_i, I_{i,t}) = f_N(a_{ME} + \bar{\mu}_{i,t}, \sigma_{ME}^2) \quad (6)$$

$$L_{Lik,i,t}(\theta, \theta_i, I_{i,t}) = f_N(a_{ME} + v_{i,t,ex}, \sigma_{ME}^2) \quad (7)$$

$$L_{cEL,i,t}(\theta, \theta_i, I_{i,t}) = (\Lambda(b_{ME} - \Delta\bar{\mu}_{i,t}))^{1(cEL_{i,t}=-1)} (1 - \Lambda(c_{ME} - \Delta\bar{\mu}_{i,t}))^{1(cEL_{i,t}=1)} \cdot (\Lambda(c_{ME} - \Delta\bar{\mu}_{i,t}) - \Lambda(b_{ME} - \Delta\bar{\mu}_{i,t}))^{1(cEL_{i,t}=0)}, \quad (8)$$

where  $\Lambda(x) = e^x / (1 + e^x)$ . The likelihood for the dropout model is as described in equation 5.

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,  $\theta$  and  $\theta_i$ , information set,  $I_{i,t}$ , and imputed missing data,  $M_{i,t}$  are

$$L_{w_{i,t}=t_{c,A}}(\theta, \theta_i, I_{i,t}, M_{i,t}) = \prod_{j \in \{c, P, 0\}} \mathbb{P}(w_{i,t} = j | I_{i,t})^{w_{i,t}=j} \quad (9)$$

$$L_{w_{i,t} \neq t_{c,A}}(\theta, \theta_i, I_{i,t}, M_{i,t}) = \prod_{j \in \{c, 0\}} \mathbb{P}(w_{i,t} = j | I_{i,t}, w_{i,t-1} \neq c, \dots, w_{i,t_{c,A}} \neq c)^{w_{i,t}=j}, \quad (10)$$

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

$$L_{w_{i,t}}(\theta, \theta_i, I_{i,t}, M_{i,t}) = \left( L_{w_{i,t}=t_{c,A}}(\theta, \theta_i, I_{i,t}, M_{i,t}) \right)^{1(t=t_{c,A})} \left( L_{w_{i,t} \neq t_{c,A}}(\theta, \theta_i, I_{i,t}, M_{i,t}) \right)^{1(t \neq t_{c,A})}, \quad (11)$$

Combining all of these component likelihoods leads to the notation used in the joint likelihood of equation 15 in the main document.

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:

$$P(w_{i,t} = 0 | r_{i,t} = 1, I_{i,t}) = \frac{1 + e^{u_{P,it}}}{1 + e^{u_{c,i,t}} + e^{u_{P,it}}} \quad (12)$$

$$P(w_{i,t} = 0 | r_{i,t} = 0, I_{i,t}) = 1. \quad (13)$$

## 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 (?). 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.

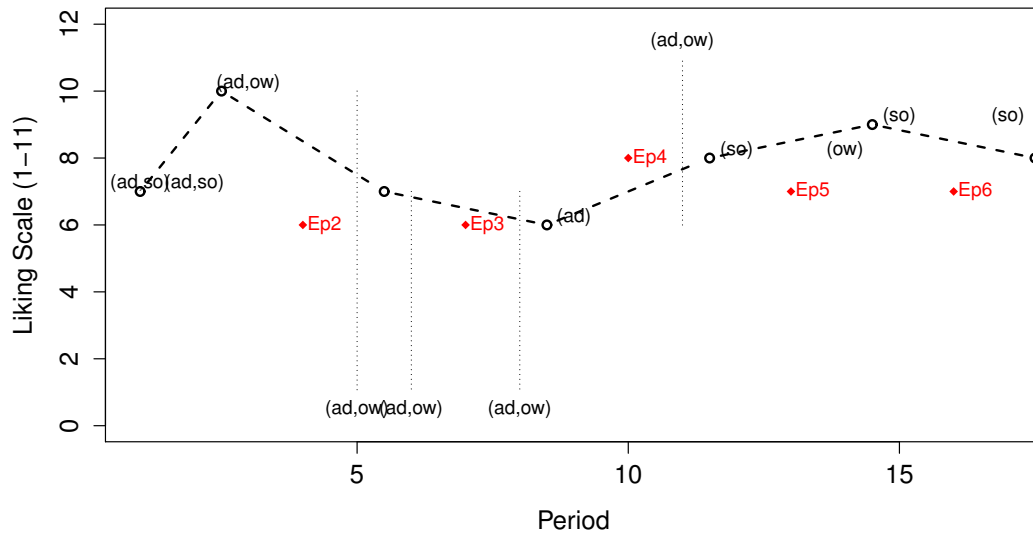
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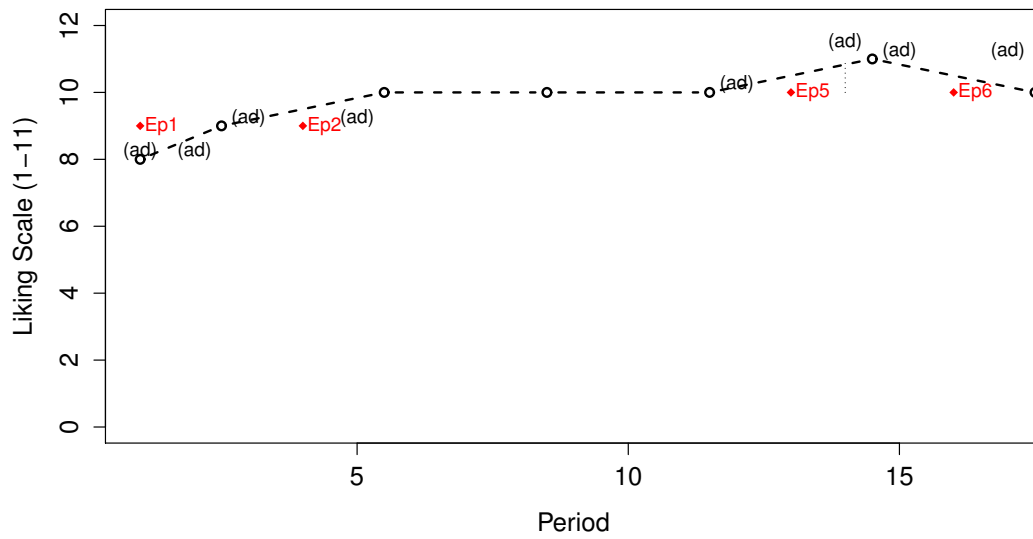
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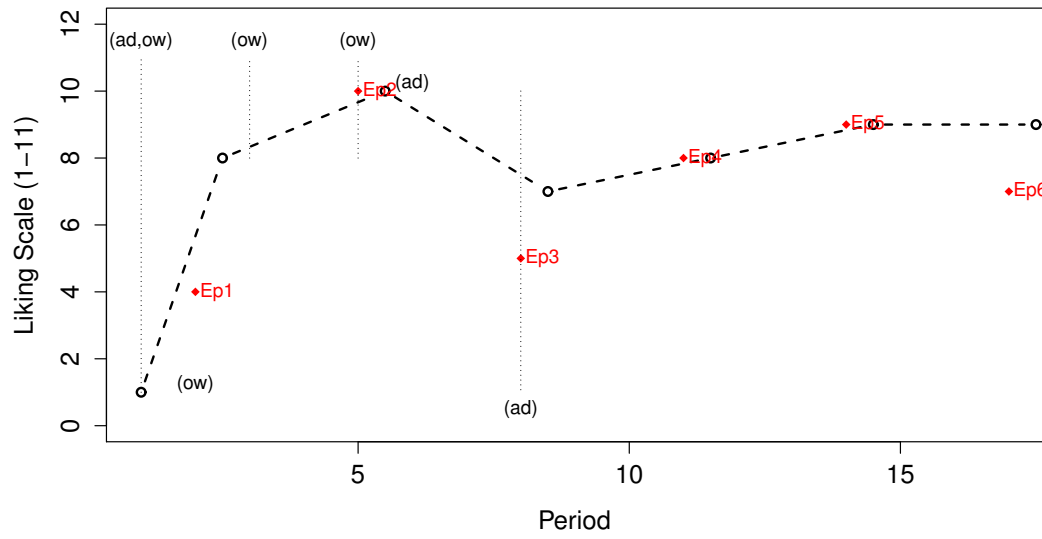
Panelist 2



Panelist 8



## Panelist 26



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

Table 1 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 ∈ 3, 4, 5 and Q3 ∈ 1, 3	0	1	1	{0,P}*	0	c
D: Q1 ∈ 3, 4, 5 and Q3 ∉ 1, 3	0	1	1	{0,P}*	0	0

Table 2 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 3 Within-survey (across Respondents) Variation and Correlations (for complete data).

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

Table 4 Between-survey Variation (for respondents with at least 2 or exactly 6 completed surveys)

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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 5** 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.