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Online Product Opinions: Incidence, Evaluation and Evolution

ABSTRACT

While recent research has demonstrated the impact of online product ratings and reviews on product sales, we still have a limited understanding of the individual’s decision to contribute these opinions. In this research, we empirically model the individual’s decision to provide a product rating and investigate factors that influence this decision. Specifically, we consider how previously posted opinions in a ratings environment may affect a subsequent individual’s posting behavior, both in terms of whether to contribute (incidence) and what to contribute (evaluation), and identify selection effects that influence the incidence decision and adjustment effects that influence the evaluation decision.

Our results indicate that individuals vary in their underlying behavior and in their reactions to previously posted product ratings. While less frequent posters exhibit bandwagon behavior, more active customers reveal differentiation behavior when posting online opinions. Systematic patterns in these behaviors have important implications for the evolution of online product opinions, which we illustrate through the use of simulations. Our simulations also show that posted product opinions can be affected substantially by the composition of the underlying customer base. Specifically, when a product’s customers are polarized, posted opinions are more negative and exhibit a stronger downward trend when compared to a homogeneous, neutral customer base with the same median opinion. This is a result of a core group of “activist” customers posting increasingly negative opinions in an effort to differentiate themselves from others in the community.
INTRODUCTION

The post-Internet marketplace is no longer limited to the one-way communications from sellers to buyers. Instead, consumers have become much more active in influencing and altering the nature of conversations around brands and products. Facilitated by developments in online technologies, consumers can easily contribute their thoughts and opinions to the marketplace through discussion groups, product ratings and reviews, and blogs. As a result, consumers have begun to talk with each other on a scale larger than marketers have previously experienced. However, this new environment is not without risks for marketers. In particular, marketers are increasingly losing control over the dialogue taking place around their products and brands. While this can be a positive development as consumers become more engaged and generate an increased level of “buzz” in the market, it can also have adverse consequences if the tone and content turn negative.

Of even more concern is that extant research has shown the existence of systematic biases in online consumer product ratings. Several researchers have shown empirically that posted product ratings and reviews become increasingly negative as ratings environments mature (Li and Hitt 2008; Godes and Silva 2009; Moe and Trusov 2011). Schlosser (2005) also showed in a lab environment that posters adjust their product evaluations depending on the opinions expressed by others. As these studies demonstrate, a ratings environment can take on a life of its own, sometimes to the detriment of the product or brand to which it is dedicated. In some cases, the posted content provides a fair evaluation of the product/brand. However, as illustrated in the aforementioned studies, posted content can also reflect the influence of others.

The objective of this research is to empirically examine the behavior of individuals providing product ratings in an effort to better understand how expressed opinions (as reflected
in posted product ratings) systematically evolve over time\(^1\). Specifically, we investigate the role that others’ ratings can have in influencing posting behavior. We consider two separate effects that may influence the subsequent evolution of product opinion. First, previously posted ratings may affect the incidence with which individuals choose to contribute their own opinions, which we refer to as a selection effect. Second, while some customers may prefer to provide their comments such that they will stand out from the crowd, others may prefer to be consistent with the majority. Thus, in addition to selection effects, there may also be adjustment effects where those individuals who ultimately decide to post revise their evaluations upward or downward based on previously posted comments.

In contrast to much of the existing research on online ratings which has examined posted ratings at the product level, we model posted ratings at the level of the individual consumer. Many individuals actively contribute their ratings for a variety of different products. Examining an individual’s behavior across products allows us to identify and measure the influence that previously posted ratings (which vary across products) have on these two aspects of posting behavior.

We model an individual’s posting incidence decision (i.e., whether to post) as a probit process subject to the fact that he/she has had experience with the product. Since we do not observe whether or not an individual has purchased and/or experienced the product, we incorporate a latent experience component in the incidence model. We simultaneously estimate the individual’s evaluation decision (i.e., what to post) as an ordered probit process governing the number of stars provided on a 5-star scale. In both the incidence and the evaluation models,

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\(^1\) We use the term rating to refer to the quantitative product evaluation provided by the consumer and the term review to refer to the textual content of their posted evaluation. We use the term opinion to refer to the more general construct that encompasses both ratings and reviews. In this paper, we use a consumer’s posted product rating as a quantitative metric of that individual’s product opinion.
we explicitly examine (1) the role of a consumer’s post-purchase product evaluation, (2) the effect of previously contributed opinions and (3) heterogeneity across individuals.

Our results show that there is substantial heterogeneity in underlying incidence and evaluation behaviors across individuals. Moreover, we find differences in how individuals respond to previously expressed opinions in a ratings environment. Individuals who post infrequently are more positive and likelier to contribute to environments that exhibit a consensus of opinions (i.e., lower opinion variance). When these individuals post, they adjust their ratings upward in more positive ratings environment, thereby exhibiting “bandwagon” behavior. In contrast, we find that highly active posters are more negative in their evaluations and more prone to post in dissentious environments (i.e., environments with higher opinion variance). When they post, they adjust their ratings downward in the presence of more positive ratings, thereby differentiating themselves. These differences across individuals lead to a systematic shift in both posted ratings and the composition of the posting population over time – a dynamic which has not been posited previously as a potential explanation for the documented downward trends in online ratings.

To illustrate this dynamic, we simulate ratings environments arising from different customer bases, each defined by their underlying distribution of product evaluations. From these simulations, we show that posted opinions evolve over time as a core group of active individuals become more prevalent among the posting population. The behavior of this core group can significantly shape the direction of expressed opinions. This dynamic is most pronounced when the customer base is highly polarized. When customers are polarized, posted opinions are more negative and exhibit a stronger downward trend when compared to a neutral customer base with the same median opinion. Posted ratings from polarized customer bases tend to be dominated by
individuals with extremely negative opinions while under-representing individuals with more positive opinions. As a result, the opinions expressed online are not representative of the entire customer base, highlighting the caution that must be exercised in drawing conclusions from a cursory view of posted product opinions.

In the next section, we discuss factors that influence an individual’s posting behavior, both in terms of their posting incidence decision and their posted evaluation. We subsequently present a joint modeling framework for the incidence and evaluation decisions and examine the robustness of the results to variations in model specification. Using the empirical results of this model, we conduct a series of simulations to demonstrate how product opinions evolve and the effect of customer base composition on this evolution.

WHY DO PEOPLE POST?

In this section, we discuss the process in which a consumer formulates, modifies and ultimately expresses his/her opinion about a product (see Figure 1). These product opinions can be expressed either in the form of a verbal/textual review or as a numerical rating. While publically posted opinions (in our case, product ratings) are typically provided after the consumer purchases and experiences the product, the process in which an opinion is formulated can start well before. Berinsky (2004) proposes a framework that separates an individual’s response to political polling into two separate stages: opinion formation and opinion expression. In the context of product opinion, we similarly distinguish between a consumer’s underlying product evaluation and his/her posted product rating.

Figure 1. Conceptual Model of the Consumer Ratings Process
With respect to a consumer’s underlying product evaluation, past researchers have differentiated between pre-purchase and post-purchase product evaluations, two constructs separated in time by the consumer’s purchase of and direct experience with the product (Kuksov and Xie 2008, Anderson and Sullivan 1993)\(^2\). Pre-purchase evaluations are often formulated on the basis of publically available information such as observable product attributes, marketing mix activities, word-of-mouth, etc. and drive the consumer’s purchase decision. These pre-purchase evaluations reflect the consumer’s expected utility for the product, \(E[u_{ij}]\), and as a result, provide a benchmark against which the actual product experience will be compared (Anderson and Sullivan 1993). In the post-purchase stage, the consumer has access to new private information obtained from his/her own experience with the product. This new information contributes to customer satisfaction and the formulation of a post-purchase evaluation. Specifically, Anderson and Sullivan (1993) have shown that customer satisfaction is a function of both the individual’s experienced utility, \(u_{ij}\), and how this experienced utility compares the expected utility, \(E[u_{ij}]\). Together, these constructs contribute to the individual’s post-purchase evaluation of the product, \(V_{ij}\).

In this paper, our focus is not directly on the antecedents of a consumer’s post-purchase evaluation. Instead, our objective is to develop a model that estimates \(V_{ij}\), accounting for the fact that not all individuals in the consumer population have necessarily purchased/experienced the product. Our particular interest in this research is the processes that follow once a consumer purchases/experiences the product and develops a post-purchase evaluation, namely his/her

\(^2\) While some consumers may experience the product without purchasing it (e.g., if the product were received as a gift), this constitutes a small proportion of consumer experiences. Our modeling methodology is not dependent on observing purchasing behavior. We use “post-purchase” simply for ease of exposition and to be consistent with existing literature.
decision of whether to post a product rating (incidence decision) and what rating to post (evaluation decision).

The Incidence Decision: What Influences Participation?

Across a variety of online contexts, an overwhelming majority of individuals engaged with a site tend to be “lurkers” (i.e., those who read the comments of a small population of posters but do not provide posts themselves). While some studies have examined the behavioral differences between posters and lurkers (Schlosser 2005), few have looked at the factors that encourage (or discourage) a given individual to post (or be silent).

In the offline word-of-mouth literature, Anderson (1998) showed that individuals who are extremely dissatisfied are more likely to engage in word-of-mouth activities. As a consequence, offline word-of-mouth tends to be disproportionately negative. However, for reasons still unknown, a very different dynamic exists in the online environment. Across several studies, researchers have observed overwhelmingly positive product ratings being posted online (see Chevalier and Mayzlin 2006 for an example). For this reason, Dellarocas and Narayan (2006) propose that individuals with extreme opinions, both positive and negative, will be more likely to post an opinion online than those with more moderate opinions. While different effects have been shown across contexts, it is clear that an individual’s post-purchase product evaluation impacts his/her decision to engage in word-of-mouth activities, be it offline or online. Therefore, we will explicitly examine the effect post-purchase evaluations have on posting incidence.

In addition, the posting incidence decision may also be subject to environmental factors. Political scientists have long known that the results from opinion polls can affect election turnout (see McAllister and Studlar 1991 for a review). The direction of these effects have been the
subject of extensive discussion, and researchers have debated the presence of a “bandwagon” effect, where opinion polls influence voter behavior in favor of the candidate leading in the polls (McAllister and Studlar 1991, Marsh 1984), versus an “underdog” effect, where the candidate trailing in the polls is favored (Gartner 1976, Straffin 1977). Other have shown that the declaration of a clear winner in opinion polls can depress overall voter turnout as voters perceive their votes to be inconsequential (e.g. Epstein and Strom 1981; Dubois 1983; Jackson 1983; Delli Carpini 1984; Sudman 1986). Taken together, these studies show that the opinion of others can influence an individual’s decision of whether or not to voice his/her own opinion. In this research, we also examine how the ratings environment, as characterized by previously posted opinions, can affect an individual’s posting incidence decision and refer to these covariates as having a selection effect.

The Evaluation Decision: What Influences Posted Ratings?

Should an individual choose to post an opinion, the decision of what to post can also be subject to a number of factors. In theory, an individual posts a rating that is reflective of his/her post-purchase evaluation of the product. However, a number of recent studies have emerged documenting the presence of noticeable opinion dynamics in online product ratings (Godes and Silva 2009, Li and Hitt 2008, Moe and Trusov 2011). These studies contribute to a larger body of work (including the political science literature mentioned previously) suggesting that an individual’s publically expressed opinion can be influenced by the opinions of others and does not necessarily mirror the individual’s socially unbiased and independent product evaluation.

In a controlled experimental setting, Schlosser (2005) shows that an individual poster has a tendency to adjust his/her posted product evaluation after viewing what others have posted.
She demonstrates a differentiation effect where some posters, particularly those who consider themselves “experts,” try to differentiate themselves from others by posting more negative opinions. This is in contrast to studies that have shown that individuals can be subject to bandwagon effects and adopt the opinion of the majority (McAllister and Studlar 1991, Marsh 1984). The conclusion we take from these results is that individuals are heterogeneous and may be subject to either differentiation or bandwagon effects. Studies have also shown that individuals moderate their expressed opinions in the presence of an audience with high opinion variance (Fleming et al 1990). Overall, these studies highlight the fact that previously posted opinions can influence the individual’s decision of what to post. Therefore, we consider a number of covariates that characterize the ratings environment in terms of the previously expressed opinions of others and examine their effects on the individual’s evaluation decision. We refer to these covariates as having an adjustment effect on posting behavior, allowing for differentiation effects, bandwagon effects and the effect of consensus (or dissention).

*The Composition of the Posting Population*

While observed ratings dynamics have been attributed to the aforementioned adjustment effect (Schlosser 2005), few researchers have considered the additional impact that selection effects have on posted product ratings. Specifically, factors affecting the incidence decision have the potential to systematically alter the composition of the posting population. Overall, the composition of the posting population is determined by (1) the composition of the larger customer base from which it is drawn and (2) the selection effect of covariates. In this paper, we explicitly consider both factors and examine the impact of each on the ratings environment.
Understanding the factors that influence the composition of the posting population can have significant implications for managers and consumers. If the posting population were randomly drawn from the full customer base (i.e., there is no selection bias), the posted opinions would resemble the opinions held by the customer base as a whole. As a result, online product ratings could provide an informative source of product feedback for both managers and potential buyers. However, differences across both consumers and ratings environments may influence the incidence decision, consequently skewing the composition of the posting population such that it no longer resembles the overall customer base.

**DATA**

Our data, provided by BazaarVoice, consist of product ratings that were contributed by customers of an online retailer of bath, fragrance and home products. For each product, consumers can provide an overall product rating on a discrete 5-star scale along with review text, a ratings format that is very common in the online environment. The average overall rating is displayed prominently in the middle of the product page immediately below the manufacturer’s description of the product. Individual ratings and reviews are presented (by default) in reverse chronological order as one scrolls down the page, making it easy for consumer to ascertain the number of reviews that have been posted. For the purposes of this research, we consider each consumer’s posted star-rating as a metric of his/her product opinion.

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3 This retailer primarily sells products under its own brand name. No national brands are represented in this data set. The products carrying this retailer’s name are sold only through its stores. Marketing is limited to activities that promote the retailer’s overall brand; the retailer does not engage in product-specific marketing efforts.

4 This particular retail site also allows consumers to rate specific product attributes as defined by the retailer. These attributes vary across products depending on the nature of the product. While the attribute-specific evaluations and textual content are interesting to consider, they raise methodological complications without contributing directly to our research objective. Furthermore, product pages prominently feature the average overall product rating. Our focus on the overall product rating as the key metric of consumer opinion is consistent with this emphasis.
The data span a six month time period in 2007 when the ratings functionality was first introduced to the site. All ratings provided in this initial six month period are included in our data. During this time, 4,974 unique individuals posted product ratings, resulting in a total of 10,460 ratings across 1,811 products. Approximately 18% of the raters posted ratings for multiple products. The data also indicate the time at which ratings were posted, facilitating identification of the set of products for which an individual provides evaluations in each of his/her rating sessions.

Our objective is to model the behavior of each individual across a variety of products. With this data set, this would necessitate the construction of a 4,974 x 1,811 matrix of ratings. Because of the computational constraints associated with a matrix of such size, we sample 200 products from this data set. However, to maintain a sufficient number of observations for each individual rater in the sample, we draw a systematic sample as follows. We include the 100 most rated products at the site, which provide a large base of individual raters, many of whom post ratings for multiple products. To ensure variation across products and hence ratings environments, our sample also includes 100 additional products that were chosen at random. Our sampling results in a dataset that includes 2,436 individual raters who provide a total of 3,681 product ratings.

We supplement our ratings data with data pertaining to search trends of our product categories obtained from Google Trends. These data reflect the weekly volume with which terms are searched on Google. The data have been linked to short-term economic trends (Varian and Choi 2009) and disease outbreaks (Carneiro and Mylonakis 2009). We use these data as a proxy for consumer interest levels in the different product categories we study and, in the next section, discuss how it is incorporated into our model to serve as a control variable.
**MODEL DEVELOPMENT**

Consistent with the conceptual framework presented above, we model ratings incidence and evaluation behavior as two separate but related processes. Central to our modeling framework is the role that individual $i$’s post-purchase evaluation for product $j$, denoted as $V_{ij}$, has on both components of posting behavior. In our model, the post-purchase evaluation $V_{ij}$ is the primary driver of the individual’s posted rating (evaluation decision) and simultaneously affects the decision of whether or not to post (incidence decision) in a non-linear manner.

Methodologically, our approach is similar to prior models that have employed parsimonious latent constructs to model multiple outcomes, and hence allow for relationships among the outcomes (e.g., Kamakura et al 2003; Park and Bradlow 2005; Li, Sun and Wilcox 2005). Our specification builds upon previous models of product ratings (e.g., Ansari, Essegaier and Kohli 2000; Ying, Feinberg and Wedel 2006) by flexibly linking the incidence and evaluation decisions, a desirable feature given the variety of relationships that have been documented between word-of-mouth activity and customer satisfaction (Anderson and Sullivan 1993, Dellarocas and Narayan 2006).

To capture selection and adjustment effects, we include a set of covariates that characterize the ratings environment in terms of the previously posted ratings of others. We allow these covariates to differentially influence both the incidence and evaluation decisions. These covariates take advantage of the longitudinal nature of our data, as the ratings environment varies both across products and over time during the six-month period.

Finally, we consider two methodological assumptions. First, we condition the incidence decision on the occurrence of a rating session defined as any day in which an individual posts at
least one rating. This assumption provides model tractability given our longitudinal data. Our second assumption is that individuals will only consider rating a product if he/she has had experience with the product. Since product experience or purchase is not observable to us at the individual level, we incorporate a latent measure of experience in our incidence model.

We begin our model development by presenting first the evaluation model, which is comprised of a latent post-purchase evaluation \( V_{ij} \) and adjustment effects from the ratings environment. We then describe the incidence model which includes a latent experience component, an effect from one’s post-purchase evaluation and selection effects resulting from the ratings environment.

**Evaluation Model: What to Rate a Product**

Assuming that an individual decides to post a product rating, the expressed opinion is dependent on both the underlying post-purchase evaluation of the product, \( V_{ij} \), and the ratings environment. Therefore, conditional on a rating being contributed, we model the posted product rating using an ordered probit model (Ying, Feinberg and Wedel 2006).

First, we assume that the rating contributed by \( i \) is driven in large part by his/her post-purchase evaluation \( V_{ij} \).

\[
V_{ij} = \gamma_{i0} + \kappa_j
\]

where \( \gamma_{i0} \) allows for different levels of baseline positivity (or negativity) across customers and \( \kappa_j \) allows for variation across products (perhaps as a result of differences in product quality) such that \( \kappa_j \sim N(0,\sigma_k^2) \). The respondent, however, may demonstrate adjustment effects due to the

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5 The alternative is to model incidence and evaluation decisions for each moment in time. If we aggregated time to the daily level, this would result in 445,788 (2,436 individuals x 183 days) observations per product compared to the 2,960 observations per product when we condition on a rating session.
nature of the ratings environment. As such, we denote the net of the post-purchase evaluation and the adjustment effect as $V_{ijk}^*$:

$$V_{ijk}^* = V_{ij} + \gamma_{i,1:N}X_{j,k(i)}$$

where $X_j$ is a $N \times 1$ vector of covariates that describe the ratings environment for product $j$ at the time of rating session $k$ by individual $i$. The $1 \times N$ vector $\gamma_{i,1:N}$ captures the impact that the ratings environment may have on an individual’s posted rating, which may result in the posted evaluation differing from individual’s post-purchase evaluation.

As ratings are submitted on a 5-point scale, we model posted product ratings as follows:

$$P(y_{ijk} = r | z_{ijk} = 1) = \Pr(V_{ijk}^* > \mu_r, V_{ijk}^* < \mu_{r+1})$$

where $y_{ijk}$ is the rating contributed by $i$ for product $j$ in ratings session $k$, $z_{ijk}=1$ indicates that a rating is contributed (and $z_{ijk}=0$ otherwise), and $\varepsilon_{ijk}$ is the idiosyncratic error with mean zero.

Under the assumption that $\varepsilon_{ijk}$ follows a standard normal distribution, the probability with which an $r$-star rating is contributed is represented by the following ordered probit specification:

$$P(y_{ijk} = r | z_{ijk} = 1) = \begin{cases} \Phi(-V_{ijk}^*), r = 1 \\ \Phi(\mu_{r+1} - V_{ijk}^*) - \Phi(-V_{ijk}^*), r = 2 \\ \Phi(\mu_{r+2} - V_{ijk}^*) - \Phi(\mu_{r+1} - V_{ijk}^*), r = 3 \\ \Phi(\mu_{r+3} - V_{ijk}^*) - \Phi(\mu_{r+2} - V_{ijk}^*), r = 4 \\ 1 - \Phi(\mu_{r+3} - V_{ijk}^*), r = 5 \end{cases}$$

where $\mu_i$ are individual-specific cutpoints for the ordered probit model and $\Phi(\cdot)$ denotes the standard normal c.d.f. Though our empirical context examines a 5-star rating scale, our evaluation model can be generalized with ease to other rating formats. In the case of ordinal scales with a different number of response options, this would simply require modifying equation (4) to accommodate the number of options available. For a continuous rating scale, the reported
rating can be assumed to follow a normal distribution, in which case the reported rating $y_{ijk}$ can be modeled directly using a linear model (Ansari, Essegaier and Kohli 2000) with mean $V^*_ijk$.

**Incidence Model: Whether or Not to Rate a Product**

We model an individual’s decision to submit a product rating based on four components. First, the decision to contribute a product rating is contingent on an individual having experience with the product. Second, individuals may vary in their baseline tendencies to submit ratings for those products for which they have experience. Third and central to this research, the incidence decision may depend on the current state of the ratings environment at the time of the ratings session. Last, we consider the impact of an individual’s post-purchase evaluation for a particular product on his/her incidence decision.

We begin by discussing the importance of conditioning the incidence decision on a latent experience measure:

\[
P(z_{ijk} = 1) = P(\text{experience}_j = 1) \cdot P(z_{ijk} = 1 | \text{experience}_j = 1)
\]

where $P(z_{ijk} = 1)$ represents the probability that $i$ contributes a rating for product $j$ on rating session $k$. The inclusion of a latent experience term serves an important conceptual role. On a given rating session, we may observe products for which an individual does not post ratings. This may be a deliberate decision, perhaps due to the selection effects of the ratings environment, or it may arise from an individual not having experienced the product and hence not having the requisite knowledge to contribute a rating. The latent experience component allows for the likelihood of the latter. In equation (5), we conceptualize experience as a product-specific construct. As a result, our estimate of this latent construct would represent the average consumer’s experience with the product and is analogous to market penetration parameters in
models of product sales (Fourt and Woodlock 1960; Eskin 1973; Hardie, Fader and Wisnewski 1998; Moe and Fader 2001). While we cannot identify the latent experience model at the individual level, future researchers with observable measures of experience can easily incorporate such data as covariates in this model component.

Our main interest lies in the way in which incidence behavior may vary across individuals as a function of post-purchase evaluation and the ratings environment. Conditional on having experienced product $j$, individual $i$ submits a rating for the product if:

$$
(6) \quad \beta_{i0} + \beta_{i,1:N} X_{j,k(i)} + \beta_{i,N+1} GT_{j,k(i)} + \delta_1 V_{ij} + \delta_2 V_{ij}^2 + \omega_{ijk} > 0.
$$

where $\omega_{ijk}$ is idiosyncratic error with mean zero. Assuming that $\omega_{ijk}$ follows a standard normal distribution, this results in the following probit model with conditional probability given by:

$$
(7) \quad P (z_{ijk} = 1 | experience_j = 1) = \Phi (\beta_{i0} + \beta_{i,1:N} X_{j,k(i)} + \beta_{i,N+1} GT_{j,k(i)} + \delta_1 V_{ij} + \delta_2 V_{ij}^2)
$$

where $\Phi (\cdot)$ denotes the standard normal c.d.f.

The first term ($\beta_{i0}$) allows for variation across individuals in their baseline propensities to submit product ratings. The vector $\beta_{i,1:N}$ captures the effect of covariates characterizing the ratings environment on the incidence decision (i.e., the selection effects). As public opinion and political science research has demonstrated, we expect the current ratings environment to affect an individual’s decision to contribute product ratings. However, the nature and direction of these effects is an empirical question to be answered with the above specified model. The term $\beta_{i,N+1}$ is a coefficient for the Google Trends control variable $GT$ that serves as a proxy for general category level interest which can vary over time. This model component allows for differences in posting propensity across product categories related to the level of interest, as some types of products may generate more discussion than others (Berger and Schwartz 2011).
The coefficients $\delta_1$ and $\delta_2$ allow for variation in incidence behavior based on $i$’s post-purchase evaluation of product $j$. Research has suggested that individuals holding extreme opinions (either positive or negative) will be more likely to contribute online opinions than individuals with moderate opinions (Dellarocas and Narayan 2006). We therefore expect that the post-purchase evaluation $V_{ij}$ will affect the decision to post a rating in a non-linear manner, allowing us to link the incidence and evaluation decisions in a flexible fashion.

The probability that $i$ contributes a rating for product $j$ on rating session $k$ ($z_{ijk}=1$) is given by the following unconditioned probability statement,

$$
P(z_{ijk} = 1) = \Phi(\nu_j) \cdot \Phi(\beta_0 + \beta_{i,1:N} X_{j,k(i)} + \beta_{i,N+1} GT_{j,k(i)} + \delta_1 V_{ij} + \delta_2 V_{ij}^2)
$$

where $\Phi(\nu_j)$ is a function representing the probability that an average individual has experience with product $j$, $\nu_j = \theta + \tau_j$, $\theta$ is a parameter to be estimated and $\tau_j \sim N(0, \sigma_{\tau}^2)$.\(^6\) Note that by simultaneously estimating the incidence and evaluation models, along with the inclusion of the $GT$ covariate, we can distinguish among the effects of post-purchase evaluation $V_{ij}$ (with coefficient vector $\delta$), baseline incidence behavior ($\beta_0$) and response to the ratings environment ($\beta_{i,1:N}$) in the posting incidence model.

### Linking the Incidence and Evaluation Models

Post-purchase evaluation, $V_{ij}$, is a key component in both the incidence and evaluation models. While $V_{ij}$ directly affects the evaluation model, its impact on posting incidence is governed by the parameters $\delta_1$ and $\delta_2$. Thus, if $\delta_1 \neq 0$ or $\delta_2 \neq 0$, the incidence and evaluation models are not independent of each other. Our model allows for a flexible relationship to exist between

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\(^6\) The model specified in equation (8) assumes that latent experience and posting incidence are governed by two separate probit processes. As an alternative, we considered a single probit process that incorporates the components in equation (8). This results in a more restrictive specification of the model that had a lower log marginal density, but yields the same substantive findings as our proposed model.
the incidence and evaluation models. Consider first a linear relationship between post-purchase product evaluation and ratings incidence such that individuals with higher post-purchase evaluations for a given product will be more likely to contribute a product rating. This would emerge from parameter values such that $\delta_1>0$ and $\delta_2=0$. However, the relationship between ratings incidence and post-purchase evaluation may not be monotonic. In fact, as noted previously, we anticipate that individuals with extreme post-purchase evaluations (either positive or negative) will be more likely to contribute product ratings ($\delta_2>0$).

To illustrate the associations between the incidence and evaluation components of our modeling framework, we assume a common distribution of post-purchase evaluations ($V_{ij}$) and consider three sets of values for the parameters $\delta_1$ and $\delta_2$, yielding the three distinct distributions of posted ratings presented in Figure 2. While the scenarios presented in the first two panels are accommodated by a model specification in which the idiosyncratic error terms for the evaluation and incidence models ($\varepsilon_{ijk}$ and $\omega_{ijk}$, respectively) are correlated (e.g., Heckman 1979; Ying, Feinberg and Wedel 2006), such a model does not permit the non-monotonic relationship presented in the third panel\(^7\).

\textit{Figure 2. Illustrative Distributions of Posted Ratings}

\textit{Model Estimation}

The incidence model developed thus far has been conditional on a rating session occurring. However, in order to observe a rating session, at least one product rating must be posted; that is, it is not possible for $z_{ijk}=0$ for all $j$. As a consequence, the joint likelihood of

\(^7\) We also estimated a correlated error model like the one proposed by Ying, Feinberg and Wedel (2006) for comparison purposes. Like Ying, Feinberg and Wedel (2006), we find a small positive correlation between the two decision stages. Furthermore, the parameter estimates were not substantively different.
observing the vector of posting decisions $z_{i,k}$ and the set of ratings observed on $i$’s $k^{th}$ rating session $y_{i,k}$ is given by:

$$L^i(z_{i,k}, y_{i,k} \mid X_{k(i)}, \beta_i, \gamma_i, \delta, \theta, \kappa, \tau) = \frac{\prod\text{Pr}(y_{ijk} \mid z_{ijk} = 1) \text{Pr}(z_{ijk} = 1) \prod\left(1 - \text{Pr}(z_{ijk} = 1)\right)}{1 - \prod\left(1 - \text{Pr}(z_{ijk} = 1)\right)}.$$  

where $\text{Pr}(y_{ijk} \mid z_{ijk} = 1)$ is given by equation (4) and $P(z_{ijk}=1)$ is given by equation (8). For those products for which ratings are posted ($z_{ijk}=1$), the likelihood is comprised of both the likelihood that a rating is posted (incidence) and the likelihood associated with the particular rating posted (evaluation). For those products for which ratings are not posted ($z_{ijk}=0$), the likelihood is comprised only of the likelihood associated with the incidence model. The denominator accounts for the fact that at least one rating must be contributed during a rating session.

The joint likelihood for individual $i$ who has $K_i$ rating sessions is then given by:

$$L((z_{i1}, y_{i1}),(z_{i2}, y_{i2}), \ldots, (z_{iK_i}, y_{iK_i}) \mid X_i, \beta_i, \gamma_i, \delta, \theta, \kappa, \tau) = \prod_{k=1}^{K_i} L^i(z_{ijk}, y_{ijk} \mid X_{i(k)}, \beta_i, \gamma_i, \delta, \theta, \kappa, \tau).$$

To fit the proposed model, we use a hierarchical Bayes procedure. To allow for heterogeneity across individuals, as well as consider the correlation that may exist among the individual-level response parameters for the evaluation ($\gamma$) and incidence models ($\beta$), we assume that:

$$\begin{bmatrix} \beta_i \\ \gamma_i \end{bmatrix} \sim MVN\left( \begin{bmatrix} \bar{\beta} \\ \bar{\gamma} \end{bmatrix}, \Sigma \right)$$

Allowing for correlation between the parameters governing the incidence ($\beta$) and evaluation models ($\gamma$) generalizes the assumptions of heterogeneity made in prior analysis of online ratings. Ying, Feinberg and Wedel (2006) assume that the individual-level parameters governing the incidence decision are correlated with each other and that those governing the evaluation
decision are correlated with each other, but they do not consider the relationship that may exist across these two sets of parameters.

To complete our hierarchical model specification, we assume diffuse normal priors for the mean effects of the individual-level parameters in the incidence and evaluation models (\(\bar{\beta}\) and \(\bar{\gamma}\), respectively), the mean latent experience measure (\(\theta\)), and the influence of post-purchase evaluation on the incidence decision (\(\delta_1\) and \(\delta_2\)). For \(\Sigma\), we employ an Inverse-Wishart prior. For the cutpoints of the ordered probit evaluation model, we take the logs of the difference of adjacent cutpoints (Ying, Feinberg and Wedel 2006) and assume that the vector \([\log(\mu_{i1}), \log(\mu_{i2}-\mu_{i1}), \log(\mu_{i3}-\mu_{i2})]\) \(\sim\) MVN(\(\eta, T\)). We assume a diffuse normal prior for the elements of \(\eta\) and an Inverse-Wishart prior for \(T\). To make inferences under the proposed model, an MCMC sampler was run for 20,000 iterations which served as a burn-in period. We then obtained inferences from posterior samples from the next 20,000 iterations. Details of the estimation procedure are presented in an online technical appendix.

To assess model robustness, we also considered a number of alternative model specifications. These allowed for (1) differences across product categories and (2) changes over time. In both cases, the results were not meaningfully different from the proposed model.\(^8\)

**Covariate Specification**

Extant research in the ratings literature has converged on a set of metrics that best describe previously posted ratings (see Dellarocas and Narayan 2006). These metrics have focused on the valence, variance and volume of posted product ratings. Valence is typically represented by average rating; variance has been measured using statistical variance measures as

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\(^8\) Details and results of these alternative models are available from the authors upon request.
well as other dispersion measures such as entropy; and volume is simply captured as the number of posted product ratings. However, the interpretation of these metrics can be problematic when each metric is considered separately. Consider a ratings environment with a single 5-star rating compared to another with multiple 5-star ratings. The valence and variance of ratings in both cases are the same. The effect of valence, however, may depend on the volume of ratings that have been contributed. For instance, a ratings environment with multiple 5-star ratings may be perceived as more positive than one with a single 5-star rating while a ratings environment with multiple 1-star ratings may be seen as more negative than one with just a single 1-star rating. In a similar fashion, the impact of the ratings variance on the incidence and evaluation decisions may also depend on the volume of postings.

In addition to the main effects of valence, variance and volume of previously posted ratings, we also consider the two-way interactions among these metrics. However, for the sake of parsimony and to eliminate potential collinearity in our modeled covariates, we performed a factor analysis on the set of 36,600 daily ratings environments (200 products x 183 days) as described by the main effects and interactions (see Mason and Perreault 1991 and Lehmann, Gupta and Steckel 1998 for discussions of using factor scores as independent variables). The factor analysis results in two underlying constructs that explain 92% (61% by the first factor and 31% by the second factor) of the observed variation in daily ratings environments (see Table 1).

<table>
<thead>
<tr>
<th>Rotated component matrix resulting from factor analysis</th>
</tr>
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</table>

Though interpretation of the resulting factors is a concern when using factor analysis (Mason and Perreault 1991), our resulting factors scores offer a straightforward interpretation. The first factor (F1) is strongly related to the variance of posted ratings and variance’s interaction

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9 Measures of valence, variance, volume and their interaction terms are highly correlated. A complete correlation matrix is available from the authors upon request.
with volume, while the second factor (F₂) is influenced by valence, volume, and their interaction. In other words, F₁ reflects the degree of consensus or dissention in the ratings environment with higher values associated with increased dissention, while higher values of F₂ reflect the overall positivity of posted product ratings, accounting for the number of ratings that have contributed to this positivity.¹⁰ To assess the sensitivity of our analysis and the robustness of our findings, we considered an analysis in which we directly employed the valence and variance measures (omitting volume as a variable due to its collinearity with valence) and found that the model performed worse in terms of the log marginal density while yielding the same substantive results.

RESULTS

Parameter Estimates

Table 2 provides estimates of the mean effects and random effects from our model estimation. To demonstrate the extent of heterogeneity across individuals and products, we present the square root of the diagonal element from the corresponding covariance matrix.

We observe considerable heterogeneity across individuals in their incidence decisions. In addition to variation in the baseline propensity to post, we find variation in the nature and direction of selection effects (see Figure 3). We see that individuals vary in terms of their preference for posting in environments that exhibit consensus. While some may be more prone to provide a product rating when previous posters were in agreement (β₁₁<0), others may abstain from posting in such environments and instead exhibit a preference for contributing product ratings when there is increased dissention (β₁₁>0). In contrast to the variation in how individuals

---

¹⁰ An examination of the scatterplots comparing the relationships between the raw metrics and the factor scores supports this interpretation of the factors. The scatterplots are available from the authors upon request.
respond to consensus (or the lack thereof), virtually all individuals exhibited a preference for posting in more positive ratings environments ($\beta_{i2}>0$).

**Table 2. Model estimation results**

**Figure 3. Posterior means from incidence model**

**Figure 4. Posterior means from evaluation model**

To examine adjustment effects, we turn our attention next to the results of the evaluation model (see Figure 4). In comparison to the variation seen across individuals’ responses to opinion variance on the incidence model (as shown in Figure 3), we find less heterogeneity in the same effect in the evaluation model. In contrast, our results indicate a wider range of adjustment effects in the evaluation decision associated with the positivity of the ratings environment. While some adjust their ratings upward in more positive ratings environments ($\gamma_{i2}>0$), others adjust their ratings downward ($\gamma_{i2}<0$) by lowering their reported product evaluations. In other words, we observe substantial heterogeneity in individuals’ propensities to exhibit bandwagon versus differentiation effects in the evaluation stage.

An individual’s posting decisions are also influenced by his/her post-purchase evaluation for product $j$, $V_{ij}$. While it is tautological that an individual’s post-purchase evaluation for a product will affect his/her posted evaluation of it, $V_{ij}$ also affects the incidence decision. Figure 5 shows the relationship between the post-purchase evaluation ($V_{ij}$) and the argument of the probit incidence model in equation (7), as governed by the parameters $\delta_1$ and $\delta_2$. We see that individuals are more likely to submit ratings when their post-purchase evaluation is high, consistent with empirical findings in the literature that show a strong positivity bias in online product ratings (Dellarocas and Narayan 2006). We also observe an increased likelihood of posting incidence when post-purchase evaluation is low, consistent with research showing that
consumers are more likely to engage in word-of-mouth activities when they are dissatisfied (Anderson 1998). This empirical finding illustrates the potentially non-linear relationship between the incidence and evaluation decisions and is in contrast with the monotonic relationship that has been assumed in previous research (e.g., Ying, Feinberg and Wedel 2006).

**Figure 5. Role of post-experience evaluation in rating incidence**

*Relationships Among Incidence and Evaluation Behavior*

To further examine the interdependencies between the incidence and evaluation decisions, we present the correlation matrix between the incidence model parameters ($\beta$) and the evaluation model parameters ($\gamma$) resulting from posterior estimates of the covariance matrix $\Sigma$ in Table 3. The correlation coefficients indicate a number of interesting relationships, particularly with respect to the incidence model intercept, which reflects the frequency with which an individual posts a rating. The correlation coefficients indicate that frequent raters are more likely to post in dissentsious environments ($r = .37$) and more positive environments ($r = .45$). In terms of their evaluation behavior, these frequent raters also tend to be more negative in their ratings ($r = -.68$) and tend to differentiate their posted ratings from others ($r = -.34$).

**Table 3. Correlation Matrix**

To further highlight the differences across posters, Table 4 categorizes individuals into low, moderate and high frequency posters based on posterior estimates of their incidence baseline ($\beta_0$). Our results indicate noticeably different posting behavior between frequent and infrequent posters. While all individuals are more prone to post in more positive environments, the impact of consensus varies. Less active posters are more prone to post in consensus.
environments \((\beta_1=-.0932)\) while the most active posters are more likely to contribute when there is higher opinion variance \((\beta_1=.116)\).

**Table 4. Low-Involvement vs. Activist Comparison**

A closer examination of evaluation behaviors further distinguishes active posters from less active posters. The least active posters tend to be more positive \((\gamma_0=3.496)\) than more active posters. Furthermore, they exhibit bandwagon effects \((\gamma_2=.0749)\) by adjusting their posted evaluations upward when previous ratings have been more positive. They are also more positive when previously posted opinions vary \((\gamma_1=.0497)\). To some extent, these individuals can be characterized as “low-involvement.” Not only are they less engaged in terms of their level of posting activity, but they are also easily influenced by others through bandwagon effects.

The most active posters stand in stark contrast to the “low-involvement” posters. In general, they are more negative \((\gamma_0=2.591)\) and exhibit differentiation behavior (as opposed to bandwagon behavior) by adjusting their evaluations downward in more positive ratings environments \((\gamma_2=-.298)\). Their posted opinions are even more negative when there is increased opinion variance \((\gamma_1=-.0965)\). These behaviors are consistent with previous research showing that individuals who want to be perceived as “experts” often try to differentiate themselves by contributing more negative opinions (Schlosser 2005, Amabile 1983). Overall, these individuals appear to be “activists” who are highly engaged (as indicated by their high posting frequency) and may try to establish themselves in the community by offering opinions designed to attract the attention of others that are both differentiated and more negative.
Discussion of Empirical Results

Our results show that both the incidence and evaluation decisions are affected by an individual’s post-purchase evaluation in a non-monotonic fashion. Individuals with either high or low post-purchase evaluations are more likely to contribute ratings, whereas individuals with moderate post-purchase evaluations are less likely to contribute ratings. By decomposing ratings behavior into distinct but related incidence and evaluation stages, we see that the effects of the ratings environment differ across stages. Though prior research has documented the role of the ratings environment on the evaluation decision (Schlosser 2005), the literature has not discussed the effect that the ratings environment can have on incidence. We find that the ratings environment significantly impacts an individual’s decision of whether or not to contribute a rating, resulting in a selection effect that affects the composition of the posting population. Our analysis further reveals that incidence and evaluation behaviors are linked and that the opinions of those who frequently contribute ratings differ from those who do not. These dynamics result in the distribution of posted ratings not necessarily resembling the underlying sentiment of the full customer base – an important caveat for marketers who turn to such online forums to gauge customer opinion and for consumers looking for unbiased product evaluations.

THE EVOLUTION OF PRODUCT OPINION

In this section, we simulate ratings environments based on the results obtained from our model in an effort to more closely examine the drivers of observed evolutionary patterns. Our simulation procedure is as follows:

1. Based on the model parameters, we simulate a population of 10,000 individuals
2. From the population of 10,000 individuals, we draw a sample of 1,000 individuals to represent the product’s customer base.
3. We categorize each individual according to their baseline posting incidence.
4. We simulate the post-purchase evaluation $V_{ij}$.
5. Based on $V_{ij}$, we simulate the incidence decision according to equation (7) and the posted rating conditional on a rating being posted according to equation (4).
6. We repeat steps 4 and 5 until 50 ratings are posted.
7. We repeat steps 1-6 for 5,000 iterations and average the results across iterations.

**Simulation 1: Overall Evolutionary Patterns**

We begin by randomly drawing a customer base from the total population and examining their posted ratings over time. Figure 6a plots the average rating and ratings variance while Figure 6b illustrates the composition of the poster population. As more ratings arrive, the average rating decreases and the variance across ratings increases, a dynamic driven by a shift in the composition of the posting population. As more ratings are posted, the ratings environment is likely to exhibit more variation in opinions, thereby attracting activists who are more negative in their evaluations and further contributing to a gradual decline in average ratings. Though this trend has been observed in prior research (Li and Hitt 2008; Godes and Silva 2009), our analysis and simulation suggest that this trend can (at least partially) be explained by a shift in the composition of the posting population. As such, the selection effect is central to the way in which expressed opinions evolve.

*Figure 6. Simulated ratings evolution resulting from a representative customer base*

**Simulation 2: Diversity of Customer Opinions**

We next compare a ratings environment resulting from a highly polarized customer base to one that is relatively homogeneous and representative of the median opinion. To construct the highly polarized customer base, we sample the 500 individuals with the lowest evaluation model intercept ($\gamma_0$) and the 500 individuals with the highest evaluation model intercept. To construct the median customer base, we sample the 1,000 individuals in the middle of the distribution.
While the variance differs substantially between these two hypothetical customer bases, the average evaluation is the same.

Figure 7 describes the simulated ratings resulting from the median customer base and the polarized customer base. As expected, the posted ratings resulting from the homogeneous, median customer base are relatively uniform and exhibit a slight downward trend. In contrast, the posted ratings from the polarized customer base are more negative and exhibit a stronger downward trend over time. This dynamic is driven by the more negative baseline evaluation and the differentiation behavior of the activists who represent half of the customer population in the polarized customer base but are absent from the median customer base. The contributions of this core group of posters eventually results in posted ratings that are dominated by extreme negative opinions and do not reflect the distribution of opinions from the overall customer base.

**Figure 7. Simulated ratings evolution resulting from a median vs. polarized customer base**

**DISCUSSION AND CONCLUSIONS**

While previous work has studied the effects of online product ratings on consumers’ purchase decisions at the product level, research to date has not explored dynamics affecting the individual-level decisions of whether to post an opinion or what to post. We present a modeling framework to examine the effects of previously posted content on both posting incidence and evaluation decisions. While the evaluation decision is subject to adjustment effects that alter the content of future postings, the incidence decision is subject to selection effects that can shape the composition of the posting population. This latter dynamic has been largely ignored in the extant research on online product opinions.
Our analysis reveals that previously posted ratings can affect the tone that subsequent postings will take through both selection effects and adjustment effects. While both the variance and overall positivity in a ratings environment impact the incidence decision, only the positivity of opinions appears to influence the extent to which individuals revise their product evaluations when they post an online product rating. Our results further show that the incidence and evaluation decisions are related.

Differentiating between low-involvement posters and activists reveals systematic differences in their incidence and evaluation behaviors. Overall, we find that online opinions are dominated by activists who offer opinions that are more negative and differentiated from previously expressed opinions. Moreover, participation by these activists increases over time while participation by low-involvement individuals decreases. This shift in the composition of the posting population can substantially affect the overall tone of posted opinions.

Additionally, the composition of the customer base can exert a substantial influence on the manner in which posted online opinions evolve. Due to selection and adjustment effects, the content posted may not necessarily reflect the customer base’s overall opinion of the product. Rather, a vocal subset of the customer base may dominate the ratings environment, consequently steering the subsequently posted evaluations and deterring some customers from contributing to the environments. Marketers and consumers alike must consequently exercise caution in drawing inferences from posted product ratings and reviews, as the opinions they observe may not provide an accurate gauge of the overall customer base’s perceptions.

While we considered a number of extensions to our general modeling framework, a number of directions remain open for future research. For example, with additional information our framework can be generalized to investigate the pre-purchase and post-purchase processes
simultaneously. Browsing behavior or past purchases, for instance, could provide additional information as to the set of products for which an individual has the requisite experience to post ratings, as well as distinguish between the pre-purchase expectation and post-purchase evaluation. This would allow for the development of an individual-level experience model, which may be related to subsequent incidence and evaluation decisions. We believe such an integrated model of the pre- and post-purchase processes can offer additional insight into individuals’ rating decisions and offer further guidance to marketers who must decide how to react to online evaluations of their products or brands.

Though our empirical application considers product ratings, it is worthwhile to examine the way in which other types of online forums are shaped by such opinion dynamics. In addition to the generalizations for ordinal and continuous scales noted in our discussion of the model, future research may consider extending our framework to contexts that use multi-item scales or textual comments. Research may also explore more flexible discussion forums to further our understanding of user-generated content and how this increasingly important factor in the consumer decision process is created. Whatever opinion format is being studied, both selection and adjustments effects must be taken into account in examining the dynamics of the forum.

As our research suggests, future work must recognize that the direction of the conversation may discourage the participation of some individuals and consequently no longer represent the general customer base. As the online marketplace becomes increasingly interactive, consumers play a larger role in the creation of content that can influence the success or failure of a product. Because of this, it is critical that marketers understand who is contributing their opinions to forums, their motives for doing so, and what influences their behavior. This paper contributes to this larger effort.
REFERENCES


Online Technical Appendix: Estimation Details

Following Netzer, Lattin and Srinivasan (2005), the model parameters to be estimated can be divided into three parts: (1) the fixed effects governing the evaluation, incidence, and latent experience components of the model which do not vary across individuals or products, (2) individual-specific deviations from the fixed effects governing evaluation and incidence behavior, and (3) product-specific deviations from the fixed effects in the evaluation model and latent experience component.

We denote by $\psi$ the set of fixed effects from the evaluation model ($\gamma$ and $\eta$), the incidence model ($\beta$, $\delta_1$ and $\delta_2$), and latent experience model ($\theta$). We let $\zeta_i$ be a vector of the individual-specific deviations from the fixed effects $\gamma$ and $\beta$. As noted in equation (11), $\zeta_i \sim \text{MVN}(0, \Sigma)$. We let $\xi_i$ denote the individual-specific deviations from $\eta$, where $\xi_i \sim \text{MVN}(0, T)$.

The MCMC procedure draws parameters from the conditional distribution of the model parameters:

$$
\begin{align*}
\zeta_i | Y_i, X_i, \xi_i, \psi, \{\kappa\}, \{\tau\}, \Sigma \\
\xi_i | Y_i, X_i, \zeta_i, \psi, \{\kappa\}, \{\tau\}, T \\
\{\kappa\} | Y, X, \{\zeta_i\}, \{\xi_i\}, \psi, \{\tau\}, \sigma_\kappa \\
\{\tau\} | Y, X, \{\zeta_i\}, \{\xi_i\}, \psi, \{\kappa\}, \sigma_\tau \\
\Sigma | \{\zeta_i\} \\
T | \{\xi_i\} \\
\sigma_\kappa^2 | \{\kappa\} \\
\sigma_\tau^2 | \{\tau\} \\
\psi | Y, X, \{\zeta_i\}, \{\xi_i\}, \{\kappa\}, \{\tau\}
\end{align*}
$$

where $Y_i$ the set of observations from $i$ (incidence decisions $z_i$ and evaluation decisions $y_i$) and $X_i$ denotes the state of the ratings environment at the time of the observations.
We next describe how we sample the individual-specific random effects ($\zeta_i$ and $\xi_i$), product-specific random effects ($\{\kappa\}$ and $\{\tau\}$), covariance matrices governing the random effects ($\Sigma$, $T$, $\sigma_\kappa$, and $\sigma_\tau$), and fixed effects ($\psi$).

(1) Generating individual-specific random effects for individual $i$

$$f(\zeta_i|Y_i, X_i, \xi_i, \psi, \{\kappa\}, \{\tau\}, \Sigma) \propto \pi(\zeta_i|\Sigma) L(Y_i|\zeta_i)$$

$$\propto |\Sigma|^{-\frac{1}{2}} \exp\left[-\frac{1}{2}(\zeta_i - \zeta_i^{(t)}) \Sigma^{-1} (\zeta_i - \zeta_i^{(t)})\right] L(Y_i|\zeta_i) \tag{A1}$$

where $\pi(\zeta_i|\Sigma)$ is the prior distribution of $\zeta_i$ and $L(Y_i|\zeta_i)$ is the individual-specific likelihood given by equation (10). Since (A1) does not have a closed form, we use a random walk Metropolis-Hastings algorithm with a Gaussian jumping distribution to draw from the conditional distribution of $\zeta_i$. Letting $\zeta_i^{(t)}$ denote the value of the vector on draw $t$, the probability that of accepting draw $t+1$ is given by:

$$\Pr(\text{accept}) = \min\left\{\frac{\exp[-.5(\zeta_i^{(t+1)} - \zeta_i^{(t)}) \Sigma^{-1} (\zeta_i^{(t+1)} - \zeta_i^{(t)})]}{\exp[-.5(\zeta_i^{(t)} - \zeta_i^{(t)}) \Sigma^{-1} (\zeta_i^{(t)} - \zeta_i^{(t)})]} \frac{L(Y_i|\zeta_i^{(t+1)})}{L(Y_i|\zeta_i^{(t)})}, 1\right\} \tag{A2}$$

The procedure to draw $\xi_i$ is similar:

$$f(\xi_i|Y_i, X_i, \xi_i, \psi, \{\kappa\}, \{\tau\}, T) \propto \pi(\xi_i|T) L(Y_i|\xi_i)$$

$$\propto |T|^{-\frac{1}{2}} \exp\left[-\frac{1}{2}(\xi_i^{(t+1)} - \xi_i^{(t)}) T^{-1} (\xi_i^{(t+1)} - \xi_i^{(t)})\right] L(Y_i|\xi_i) \tag{A3}$$

A random walk Metropolis-Hastings algorithm is used to draw from the conditional distribution of $\xi_i$, where the probability of accepting a new draw is:
\[
\Pr(\text{accept}) = \min \left\{ \frac{\exp\left[ -5 \left( \xi_i^{(t+1)} - \xi_i^{(t+1)} \right) \right] T^{-1} \xi_i^{(t+1)} L(Y_i \mid \xi_i^{(t+1)})}{\exp\left[ -5 \left( \xi_i^{(t)} - \xi_i^{(t)} \right) \right] T^{-1} \xi_i^{(t)} L(Y_i \mid \xi_i^{(t)})}, 1 \right\}
\]

\[ (A4) \]

(2) **Generating product-specific random effect for product** \( j \)

\[
f(\{\kappa\} \mid Y, X, \{\zeta_i\}, \{\xi_i\}, \psi, \{\tau\}, \sigma) \\
\propto \pi(\{\kappa\} \mid \sigma) L(Y \mid \{\kappa\}) \\
\propto \prod (\sigma^{-1} \exp[-\kappa_j^2/2\sigma_j^2]) L(Y \mid \{\kappa\}) \quad (A5)
\]

where \( L(Y \mid \{\kappa\}) \) denotes the likelihood of the data, derived by taking the product of the individual-specific likelihood in equation (10) across individuals. We use a random walk Metropolis-Hastings algorithm to draw from the conditional distribution of \( \{\kappa\} \). The probability of accepting \( \{\kappa\}^{(t+1)} \) is:

\[
\Pr(\text{accept}) = \min \left\{ \frac{\exp\left[ -1 \sum_j \left( \frac{\kappa_j^{(t+1)}}{\sigma_j} \right)^2 \right] L(Y \mid \{\kappa_j^{(t+1)}\})}{\exp\left[ -1 \sum_j \left( \frac{\kappa_j^{(t)}}{\sigma_j} \right)^2 \right] L(Y \mid \{\kappa_j^{(t)}\})}, 1 \right\}
\]

\[ (A6) \]

Drawing from the conditional distribution of \( \{\tau\} \) follows a similar procedure:

\[
f(\{\tau\} \mid Y, X, \{\zeta_i\}, \{\xi_i\}, \psi, \{\kappa\}, \sigma) \\
\propto \pi(\{\tau\} \mid \sigma) L(Y \mid \{\tau\}) \\
\propto \prod (\sigma^{-1} \exp[-\tau_j^2/2\sigma_j^2]) L(Y \mid \{\tau\}) \quad (A7)
\]

Using the random walk Metropolis-Hastings algorithm, the probability of accepting draw \( t+1 \) is:
Pr(accept) = \min \left( \frac{\exp\left(-\frac{1}{2} \sum_j \left( \frac{\tau_j^{(t+1)}}{\sigma_{\tau}} \right)^2 \right) L(Y | \{\tau_j^{(t+1)}\})}{\exp\left(-\frac{1}{2} \sum_j \left( \frac{\tau_j^{(t)}}{\sigma_{\tau}} \right)^2 \right) L(Y | \{\tau_j^{(t)}\})}, 1 \right) \tag{A8}

For efficiency, we update the parameters \{\kappa\} and \{\tau\} in blocks of multiple products (Chib and Greenberg 1995).

(3) Updating Covariance Matrices

Conditional on the values of the individual-specific random effects (\{\zeta_i\} and \{\xi_i\}) and the product-specific random effects (\{\kappa\} and \{\tau\}), the corresponding covariance matrices can be sampled directly. We begin by drawing values of \Sigma conditional on the individual-specific random effects \{\zeta_i\}. Following Netzer, Lattin and Srinivasan (2005), the conditional distribution of \Sigma is given by:

\[ \Sigma | \{\zeta_i\} \sim IW_p \left( f_0 + N, G_0^{-1} + \sum_{i=1}^{N} \zeta_i' \zeta_i \right) \tag{A9} \]

where \(IW_p\) denotes an inverse-Wishart distribution, \(p\) is the length of the vector \(\zeta_i\) (in our case, \(p=6\)), and \(N\) is the number of observations. To assume a diffuse prior, we assume that \(f_0=p+5\) and \(G_0^{-1}\) is an identity matrix of size \(p\).

In the same fashion, the covariance matrix \(T\) is drawn from the conditional distribution \(T | \{\xi_i\}\), the variance \(\sigma_\kappa^2\) is drawn from the distribution \(\sigma_\kappa^2 | \{\kappa\}\), and \(\sigma_\tau^2\) is drawn from \(\sigma_\tau^2 | \{\tau\}\).

(4) Updating Fixed Effects
The vector of fixed effects $\psi$ is drawn in a similar fashion to the individual-specific and product-specific random effects. The conditional distribution of $\psi$ is given by:

$$f(\psi|Y,X,\zeta_i,\xi_i,\kappa,\tau)$$

$$\propto \pi(\psi) L(Y|\psi)$$

$$\propto |V|^{-\frac{1}{2}} \exp[-0.5\psi'V^{-1}\psi]L(Y|\psi)$$

(A10)

where $\pi(\psi)$ is the prior distribution of $\psi$. We assume a diffuse normal prior by setting the mean equal to a vector of zeros of length $q$, where $q$ is the length of $\psi$, and covariance matrix $V=5I_q$.

As the conditional distribution given in (A10) does not have a closed form, we use a random walk Metropolis-Hastings algorithm to draw from the conditional distribution. The probability of accepting draw $t+1$ is given by:

$$\Pr(\text{accept}) = \min\left(\frac{\exp[-0.5\psi^{(t+1)}'V^{-1}\psi^{(t+1)}]L(Y|\psi^{(t+1)})}{\exp[-0.5\psi^{(t)}'V^{-1}\psi^{(t)}]L(Y|\psi^{(t)})},1\right)$$

(A11)

Additional References


### Table 1. Rotated component matrix resulting from factor analysis

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<th>Component</th>
<th>F₁</th>
<th>F₂</th>
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<tbody>
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### Table 2. Model estimation results

<table>
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<tr>
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<th>Diag(Σ)₁/₂ (s.e.)</th>
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<td>-.11 (.06)</td>
<td>.50 (.06)</td>
</tr>
<tr>
<td></td>
<td>log(μ₁₁)</td>
<td>Difference in cutoff for Rating=2</td>
<td>-1.13 (.17)</td>
<td>.60 (.10)</td>
</tr>
<tr>
<td></td>
<td>log(μ₂₁-μ₁₁)</td>
<td>Difference in cutoff for Rating=3</td>
<td>-.81 (.10)</td>
<td>.40 (.08)</td>
</tr>
<tr>
<td></td>
<td>log(μ₃₁-μ₂₁)</td>
<td>Difference in cutoff for Rating=4</td>
<td>-.68 (.11)</td>
<td>.53 (.10)</td>
</tr>
</tbody>
</table>
Table 3. Correlation Matrix

<table>
<thead>
<tr>
<th></th>
<th>Incidence Model</th>
<th>Evaluation Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \beta_0 )</td>
<td>( \beta_1 )</td>
</tr>
<tr>
<td>Intercept (( \beta_0 ))</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Variance (( \beta_1 ))</td>
<td>(.37^*)</td>
<td>1</td>
</tr>
<tr>
<td>Valence-Volume (( \beta_2 ))</td>
<td>(.45^*)</td>
<td>(.45^*)</td>
</tr>
<tr>
<td>Intercept (( \gamma_0 ))</td>
<td>(-.68^*)</td>
<td>(-.25^*)</td>
</tr>
<tr>
<td>Variance (( \gamma_1 ))</td>
<td>(-.17)</td>
<td>(.10)</td>
</tr>
<tr>
<td>Valence-Volume (( \gamma_2 ))</td>
<td>(-.34^*)</td>
<td>(-.21^*)</td>
</tr>
<tr>
<td>Google Trends (( \beta_3 ))</td>
<td>(-.12^*)</td>
<td>(-.01)</td>
</tr>
</tbody>
</table>

* indicates 0 is not contained in the 95% HPD interval

Table 4. Comparing Low-Involvement Contributors to Activists

<table>
<thead>
<tr>
<th></th>
<th>Low-Involvement</th>
<th>Moderates</th>
<th>Activists</th>
</tr>
</thead>
<tbody>
<tr>
<td>Incidence Model</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept (( \beta_0 ))</td>
<td>(-4.426)</td>
<td>(-2.490)</td>
<td>(-.566)</td>
</tr>
<tr>
<td>Variance (( \beta_1 ))</td>
<td>(-.0932)</td>
<td>(.00251)</td>
<td>(.116)</td>
</tr>
<tr>
<td>Valence-Volume (( \beta_2 ))</td>
<td>(.379)</td>
<td>(.534)</td>
<td>(.685)</td>
</tr>
<tr>
<td>Evaluation Model</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept (( \gamma_0 ))</td>
<td>3.496</td>
<td>3.043</td>
<td>2.591</td>
</tr>
<tr>
<td>Variance (( \gamma_1 ))</td>
<td>(.0497)</td>
<td>(-.0284)</td>
<td>(-.0965)</td>
</tr>
<tr>
<td>Valence-Volume (( \gamma_2 ))</td>
<td>(.0749)</td>
<td>(-.109)</td>
<td>(-.298)</td>
</tr>
</tbody>
</table>
Figure 1. Conceptual Model of the Consumer Ratings Process

Pre-Purchase Evaluation $E[u_i]$

Purchase Decision and Product Experience

Post-Purchase Evaluation $v_j = E[u_j | u_i]$

Incidence Decision

Evaluation Decision

SELECTION EFFECT

ADJUSTMENT EFFECT

Posted Product Ratings

Figure 2. Illustrative Distributions of Posted Ratings

$\delta_1 = \delta_2 = 0$

$\delta_1 > 0, \delta_2 = 0$

$\delta_1 = 0, \delta_2 > 0$
**Figure 3.** Posterior means from incidence model

- **Incidence Model:**
  - Variance Effect ($\beta_1$)
  - Valence/Volume Effect ($\beta_2$)

**Figure 4.** Posterior means from evaluation model

- **Evaluation Model:**
  - Variance Effect ($\gamma_1$)
  - Valence/Volume Effect ($\gamma_2$)
Figure 5. Role of post-experience evaluation in rating incidence
Figure 6. *Simulated ratings evolution resulting from a representative customer base*
(a) Ratings environment
(b) Poster composition

Figure 7. *Simulated ratings evolution resulting from a median vs. polarized customer base*
(a) Median customer base
(b) Polarized customer base