Identifying the Actual Impact of Online Social Interactions on Demand

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Abstract

Firms often engage in manipulating online reviews as a promotional activity to influence consumers' evaluation on their products. With the prevalence of the promotional activities, consumers may notice and discount the reviews generated by the promotional activities. Discounting the firm-generating reviews may cause systematic measurement errors in the valence variable and lead to a negative bias when estimating the effect of consumers' organic reviews on demand. To correct the bias, this study proposes including product-specific bias-correction terms representing the proportion of extreme reviews in analysis. For illustration, the proposed method is applied to a demand model for data of movies released in South Korea. The results confirm a negative bias in the estimate of the valence sensitivity of demand. The negative bias potentially leads to an underestimation of the magnitude of the contagion effect through social interactions, a key component of evaluating the value of a satisfied consumer.

Keywords: Bias correction, Word-of-Mouth (WOM), Promotional activities, Skepticism, Movie industry

1. Introduction

Social interaction, often called word-of-mouth (WOM), is one of the key factors that influence consumer demand (Godes et al. 2005).[1] The advance in digital technologies for the past decades has enabled consumers to interact with each other through online channels where researchers can collect data to analyze the impact of the interactions on demand (Donthu et al. 2021). Using the data collected from online review platforms, prior studies have found that online social interactions have a significant impact on sales (Babić Rosario et al. 2016).

A key metric investigated in the literature is the average valence of online reviews (Babić Rosario et al. 2016; You, Vadakkepatt, and Joshi 2015). Despite its long history, conclusions on the effect of the average valence on demand is somewhat mixed. For example, a significant (e.g., Dellarocas, Zhang, and Awad 2007), insignificant (e.g., Duan, Gu, and Whinston 2008), and mixed (e.g., Chintagunta, Gopinath, and Venkataraman 2010) results have been found in the movie industry. A possible explanation for the mixed conclusions is the prevalence of firms' promotional activities (Mayzlin 2006), which is our focus in this paper.

The anonymity afforded by online communities makes it easy for interested agents to participate in online conversations, so marketers have incentives to strategically intervene, manipulate, invent, and purchase online reviews to influence the consumers' evaluation (Dellarocas 2006; He, Hollenbeck, and Proserpio 2022; Luca and Zervas 2016; Mayzlin 2006). Such promotional activities lead the observed average valence to, at least partially, deviate from the overall valence of real consumers' reviews. In addition, consumers' awareness of the presence of such promotional activities may lead them to discount online recommendations (Mayzlin 2006).

The distortion made by firms' promotional activities may result in a biased estimate of the sensitivity

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[1] We use "social interactions" instead of WOM or electronic WOM (eWOM) in this paper for clarity. Although WOM and eWOM have been widely used in the literature, boundaries around the definition of WOM/eWOM are ambiguous as pointed out by Godes et al. (2005) and Babić Rosario, De Valck, and Sotgiu (2020). Social interactions, as defined by Godes et al. (2005), include all of the actions that are taken by an individual not actively engaged in selling the product or service and that impact others' expected utility for that product or service. Such actions range from "traditional" face-to-face recommendations from a friend to "trendy" interactions through social media such as Instagram and TikTok.

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of demand to the valence of consumers' organic reviews. Conventional econometric models of online reviews typically regress demand on a valence variable as well as other covariates (Babić Rosario et al. 2016; You, Vadakkepatt, and Joshi 2015), and the valence variable is a summary statistic that covers both consumers' organic reviews and the reviews generated by the promotional activities. Discounting firm-generating reviews implies that the valence variable includes systematic noises, which hinder unbiasedly estimating the effect of consumers' organic reviews on demand.

To correct such a bias, we propose a method that includes product-specific bias-correction terms representing the proportion of extreme reviews in analysis. Our method is "efficient" in that it requires neither outside instruments nor advanced econometric techniques beyond regression analysis to correct the bias. For illustration, the proposed method is applied to a demand model for the box-office and online review data of movies released in South Korea, where we find that (*i*) the proposed method improves the fitting performance of the demand model, (*ii*) the valence sensitivity of demand is underestimated in the model without the bias-correction terms, and (*iii*) the bias-correction terms are estimated to be significant and offset the effect of the valence for various movies. Our findings confirm a negative bias in the estimate of the valence sensitivity of demand. The negative bias in the sensitivity estimate potentially leads to an underestimation of the magnitude of the contagion effect through social interactions, a key component of evaluating the value of a satisfied consumer.

The remainder of the paper is organized as follows. Section 2 discusses the prior literature and the conceptual background related to firms' promotional activities. The proposed method is introduced in Section 3 and applied to the data of movies released in South Korea in Section 4. Section 5 provides general discussions and managerial implications.

2. Promotional activities

Firms often engage in strategic activities to observe and collect social interaction information, foster and manage consumers' social interactions, and generate social interactions by themselves (Godes et al. 2005), called promotional activities in the literature (Mayzlin 2006). Such activities include monitoring and managing the online buzz (Chen and Xie 2005), intentionally posting good/bad fake reviews (Godes and Mayzlin 2009; Luca and Zervas 2016; Mayzlin, Dover, and Chevalier 2014), and purchasing a bunch of fake reviews (He, Hollenbeck, and Proserpio 2022). Under several boundary conditions, marketers have incentives to promote and manipulate social interactions in such legal/illegal ways to influence consumers' evaluation of their products, and the anonymity of the Internet facilitates the promotional activities, as analytically shown by Dellarocas (2006) and Mayzlin (2006).

However, firms' promotional activities in online channels may distort the distribution of social interactions generated and transmitted solely by consumers. Firms have no incentives to spend their budget for neutral reviews instead of positive (for their product) or negative ones (for their competitors' products), i.e., most manipulated reviews are extremes, or near-extremes, as in the prior studies above. Some of the manipulated reviews for a product may deceive consumers into spreading words about the product, but not all of them can do so. Thus, the average valence of online reviews becomes deviated from the overall valence of the "true" reviews believed to be generated by real consumers and used as information for decision making by other consumers.

In addition, if consumers notice firms' such efforts, the promotional activities may lead to skepticism in minds of the consumers related to online reviews and may harm credibility of the firms and review platforms (Mayzlin 2006). Skepticism refers to the tendency toward disbelief in marketing claims (Darke and Ritchie 2007; Obermiller and Spangenberg 1998) and mistrust in marketers' motives (Boush, Friestad, and Rose 1994; Schindler, Morrin, and Bechwati 2005; Thakor and Goneau-Lessard 2009). Consumers tend to be skeptical of marketers' persuasive efforts (Buell and Norton 2011) such as advertising (Calfee and Ringold 1994; Dahlén 2005), and may disbelieve advertising messages and online reviews (Sher and Lee 2009). The opposite of skepticism is often referred to as credibility (Isaac and Grayson 2017; Tsfati 2010; Tsfati and Cappella 2003), which is conceptualized in terms of trust and belief (Flanagin and Metzger 2000; Hovland and Weiss 1951; Petty and Cacioppo 2012). Online reviews come from unknown sources and may have low credibility as compared to traditional social interactions (Park, Lee, and Han 2007) although there may be altruistic online reviews to share true information with others (Phelps et al. 2004).

A widely accepted theory to explain consumers' skepticism is the persuasion knowledge model proposed by Friestad and Wright (1994). According to their model, persuasion knowledge refers to personal knowledge that consumers develop about persuasion attempts made by marketers, such as advertising, and their reactions to the attempts. Persuasion knowledge fosters skepticism when consumers realize that they are the target of a persuasion attempt. The persuasion knowledge model suggests that consumers may

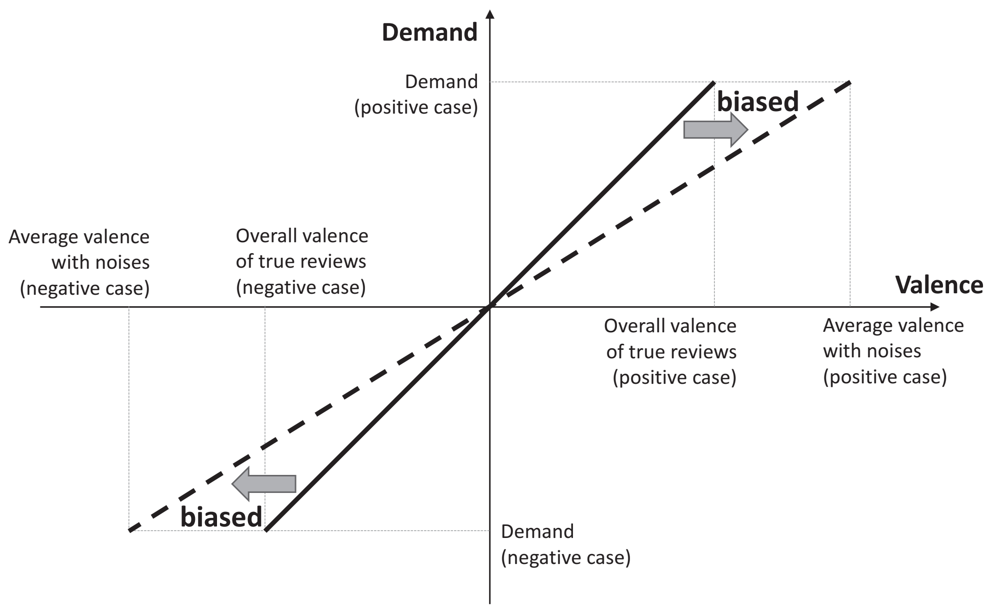

Fig. 1. A negatively biased estimate of the demand sensitivity to the valence of reviews.

be skeptical of a firm's promotional activities for its products in an online review platform, the firm and the platform may lose their credibility, and consumers may discount extreme online reviews, as pointed out by Mayzlin (2006).

The prior studies above suggest that the prevalence of firms' promotional activities adds some positively or negatively skewed noises that are counted in the average valence variable but do not influence other consumers. Because researchers cannot observe whether a review in data is such a systematic noise or a "true" review, conventional econometric models of online reviews regress demand on a valence variable including the noises. The noises become systematic measurement errors that generate a bias in the estimate of the effect of consumers' organic reviews on demand. As illustrated in Fig. 1, the bias is expected to be negative. The solid line in the figure is the true demand curve with respect to the overall valence of the true reviews (the noises excluded) and the dashed line is the estimated demand curve with respect to the average valence observed in data (the noises included). Due to the skewed noises, the observed average valence is larger in absolute value than the overall valence of the true reviews. Thus, the slope of the demand curve is estimated to be smaller than its true value.

3. The bias-correction method

This section presents the proposed method to correct the bias. For clarity, we define "trusted" reviews as reviews that are believed to be generated by real consumers and used as information for decision making by other consumers, and "untrusted" reviews as reviews that are neither regarded to be generated by real consumers nor used for decision making. Trusted reviews include all organic reviews generated and transmitted by real consumers and some promotional activities that successfully lead to consumers' good or bad evaluation on the target product. Untrusted reviews are the other promotional activities that fail to do so. For simplicity, we assume that there are only three levels – negative (N), positive (P), and neutral (O) – of the valence and that untrusted reviews are always negative or positive, not neutral, i.e., all neutral reviews are trusted.

Letting r_{ij} be the valence (N, P, or O) of review j on product i, we have the following demand model with respect to r_{ij}:

$$
\begin{aligned}
D_i = {} & \alpha_i + \boldsymbol{\gamma}'\mathbf{x}_i \\
& + \beta \frac{1}{M_i} \sum_{j=1}^{M_i} \{ w_{\mathrm{N}} \mathbb{I}(r_{ij} = \mathrm{N},\ j \text{ is trusted}) \\
& \qquad + w_{\mathrm{P}} \mathbb{I}(r_{ij} = \mathrm{P},\ j \text{ is trusted}) + w_{\mathrm{O}} \mathbb{I}(r_{ij} = \mathrm{O}) \} \\
& + \epsilon_i, \qquad (1)
\end{aligned}
$$

where D_i is the demand of product i, α_i is a product-specific intercept, $\boldsymbol{\gamma}'\mathbf{x}_i$ is a term that captures the effects ($\boldsymbol{\gamma}$) of all the other factors of the product ($\mathbf{x}_i$), such as price, promotions, seasonality, and the volume of reviews, β is the valence sensitivity of demand, M_i is the number of reviews on the product, w_{N}, w_{P}, and w_{O} denote the scores assigned to negative (N), positive (P), and neutral valence (O), respectively,

$\mathbb{I}(x)$ is an indicator function that has 1 if x is true and 0 otherwise, and ϵ_i is an idiosyncratic error.

We assume that w_N is negative ($w_\text{N} < 0$), w_P is positive ($w_\text{P} > 0$), and w_O is greater than w_N and less than w_P ($w_\text{N} < w_\text{O} < w_\text{P}$), implying that negative reviews lower the demand, whereas positive ones raise the demand, and neutral reviews can neither lower the demand more than negative ones nor raise the demand more than positive ones. The terms within the braces in Equation (1) collectively serve as an assignment function that returns w_N for trusted negative reviews, w_P for trusted positive reviews, and w_O for neutral reviews. Thus, the sum indicates the total score from trusted reviews. Rescaling the total score by the number of reviews ($\frac{1}{M_i}$), we have the effect of the valence separated from the effect of the volume.

Equation (1) is the model for unbiased estimation of the effect of the trusted reviews on demand. The problem is that researchers cannot observe which reviews are trusted/untrusted reviews. To solve the problem, we introduce probabilities of being trusted for negative reviews and positive reviews. Assume that a negative review for product i is trusted with probability $\phi_{\text{N},i}$ and untrusted with probability $1 - \phi_{\text{N},i}$ and that a positive review for the product is trusted with probability $\phi_{\text{P},i}$ and untrusted with probability $1 - \phi_{\text{P},i}$. Then, Equation (1) can be written as follows:

$$D_i = \alpha_i + \boldsymbol{\gamma}'\mathbf{x}_i + \beta\frac{1}{M_i}\sum_{j=1}^{M_i}\{\phi_{\text{N},i}w_\text{N}\mathbb{I}(r_{ij}=\text{N}) + \phi_{\text{P},i}w_\text{P}\mathbb{I}(r_{ij}=\text{P}) + w_\text{O}\mathbb{I}(r_{ij}=\text{O})\} + \epsilon_i. \quad (2)$$

Although the probabilities ($\phi_{\text{N},i}$ and $\phi_{\text{P},i}$) are still unknown in Equation (2), they can be estimated from panel data. Adding time indicator t and rearranging the terms in Equation (2), we have:

$$D_{it} = \alpha_i + \boldsymbol{\gamma}'\mathbf{x}_{it} + \beta\bar{r}_{it} + \beta_{\text{N},i}s_{\text{N},it} + \beta_{\text{P},i}s_{\text{P},it} + \epsilon_{it}, \quad (3)$$

where

$$\bar{r}_{it} = \frac{1}{M_{it}}\sum_{j=1}^{M_{it}}\{w_\text{N}\mathbb{I}(r_{ijt}=\text{N}) + w_\text{P}\mathbb{I}(r_{ijt}=\text{P}) + w_\text{O}\mathbb{I}(r_{ijt}=\text{O})\},$$

$$s_{\text{N},it} = \frac{\sum_{j=1}^{M_{it}}\mathbb{I}(r_{ijt}=\text{N})}{M_{it}} \text{ and } s_{\text{P},it} = \frac{\sum_{j=1}^{M_{it}}\mathbb{I}(r_{ijt}=\text{P})}{M_{it}},$$

$$\beta_{\text{N},i} = -\beta(1-\phi_{\text{N},i})w_\text{N} \text{ and } \beta_{\text{P},i} = -\beta(1-\phi_{\text{P},i})w_\text{P},$$

which is the model proposed to be estimated. The right-hand side of the equation is a linear combination of "observables" in typical online review data (e.g., Liu 2006), including the average valence of all reviews ($\bar{r}_{it}$) and two additional terms representing the proportion of negative reviews ($s_{\text{N},it}$) and positive reviews ($s_{\text{P},it}$). Equation (3), therefore, can be directly estimated via linear regression for panel data. The coefficients of the additional terms ($\beta_{\text{N},i}$ and $\beta_{\text{P},i}$) that reparameterize the probabilities $\phi_{\text{N},i}$ and $\phi_{\text{P},i}$ are called the *bias-correction coefficients* for product i.

Adding the terms of $s_{\text{N},it}$ and $s_{\text{P},it}$ to the demand model allows for correcting the bias in the estimate of the sensitivity of demand to the valence of the trusted reviews (β). Because w_N is negative and w_P is positive, $\bar{r}_{it}$ and $s_{\text{N},it}$ are negatively correlated, $\beta_{\text{N},i}$ is positive, $\bar{r}_{it}$ and $s_{\text{P},it}$ are positively correlated, and $\beta_{\text{P},i}$ is negative. Therefore, if those terms are omitted as in the prior studies, the estimate of β is negatively biased as expected in Fig. 1.

4. Empirical illustration

For illustration, we apply the proposed method to a demand model for the daily box-office and online review data of 553 movies released in South Korea from July 2006 to June 2009.

4.1. Details of the data

We collect the box-office data from Korea Film Council (KOFIC) and the online review data from Naver. Reviewers' ratings were originally measured in a 1-to-10 scale (1 means "extremely negative" and 10 means "extremely positive"), but we transform them into a 1-to-5 scale (1 means "extremely negative" and 5 means "extremely positive") by aggregating 1s and 2s, 3s and 4s, 5s and 6s, 7s and 8s, and 9s and 10s, for simplicity. All 553 movies received each of 1-, 2-, 3-, 4-, and 5-point ratings at least once in Naver. The total number of day-movie pairs in the data is 22,131, and the average number of observations per movie is 40 days. The total number of reviews in the data is 366,604, and the average number of reviews per movie is about 663. The mean (standard deviation) of the ratings is 3.83 (1.45), and the mean (standard deviation), maximum, and minimum of the per-movie averages are 3.62 (0.66), 4.66, and 1.49.

4.2. Empirical models

Equation (3) is modified in this analysis as follows. First, we use the log of relative market shares, a widely used form in the marketing and economics literature (e.g., Einav 2007), as the demand variable (D_{it}). Second, we use the scores of the ratings (1 through 5) "as is" when computing the average valence because any linear transformation of the scores does not affect estimation of the equation. Third, only 1s and 5s are regarded as the extremes where untrusted reviews exist. Thus, $s_{\text{N},it}$ is the proportion of 1s and $s_{\text{P},it}$ is that of 5s. Fourth, considering the data frequency (daily), we use the cumulative average and cumulative proportion for $\bar{r}_{it}$, $s_{\mathrm{N},it}$, and $s_{\mathrm{P},it}$, i.e., $\bar{r}_{it}$ is given by averaging all of the ratings posted from the release of the movie to time t, and $s_{\mathrm{N},it}$ and $s_{\mathrm{P},it}$ are given by computing the proportion of 1s and that of 5s posted from the release of the movie to time t. Fifth, considering the time lag, we use the lagged variables, $\bar{r}_{i,t-1}$, $s_{\mathrm{N},i,t-1}$, and $s_{\mathrm{P},i,t-1}$, instead of $\bar{r}_{it}$, $s_{\mathrm{N},it}$, and $s_{\mathrm{P},it}$, in the equation. Sixth, we assume that there is a systematic decaying pattern of the effect of the average valence over time. This assumption is empirically pre-tested: we fit the demand model to the data with (i.e., the effect is decaying over time) and without the assumption (i.e., the effect is constant over time), and it is found that assuming a systematic decaying pattern yields better fitting performance.

With the modification above, we fit the following models to the data:

Proposed model:

$$\begin{aligned}\log y_{it} - \log y_{0t} = {} & \alpha_i + \boldsymbol{\gamma}'\mathbf{x}_{it} \\ & + e^{-\lambda(t-z_i)}(\beta\bar{r}_{it} + \beta_{\mathrm{N},i}s_{\mathrm{N},it} + \beta_{\mathrm{P},i}s_{\mathrm{P},it}) \\ & + \epsilon_{it}, \end{aligned} \tag{4}$$

Benchmark model:

$$\log y_{it} - \log y_{0t} = \alpha_i + \boldsymbol{\gamma}'\mathbf{x}_{it} + e^{-\lambda(t-z_i)}\beta\bar{r}_{it} + \epsilon_{it}, \tag{5}$$

where y_{it} is the market share of movie i at time t, y_{0t} is the aggregated market share of all outside movies (movies released during the same period but not included in the data) at time t, and z_i is the release date of movie i. The dependent variable, $\log y_{it} - \log y_{0t}$, is the log of the relative market share of the movie. A linear time trend after the release of the movie, the number of competing movies, and several dummy variables indicating weekends, Fridays, and holidays are included as the other factors ($\mathbf{x}_{it}$). We note that the number of screens and the volume of the reviews are excluded because their effects are not significant and cause a multi-collinearity problem in a pre-test with the benchmark model. $e^{-\lambda(t-z_i)}$ captures the systematic decaying pattern of the effect of the average valence over time from the release of the movie. The error ϵ_{it} is assumed to be normally distributed, i.e., $\epsilon_{it} \sim N(0, \sigma^2)$, in both models. Thus, the model parameters to be estimated are α_i, $\boldsymbol{\gamma}$, β, $\beta_{\mathrm{N},i}$, $\beta_{\mathrm{P},i}$, λ, and σ^2.

4.3. Estimation results

The parameters of the proposed and benchmark models in Equations (4) and (5) are estimated via a Bayesian MCMC method. The model parameters are partitioned into three groups: the movie-specific parameters, α_i, $\beta_{\mathrm{N},i}$, and $\beta_{\mathrm{P},i}$, the linear-regression parameters, $\boldsymbol{\gamma}$, β, and σ^2, and the non-linear decaying parameter λ. We generate posterior draws of the parameters through the following steps:

1) Draw $\alpha_i, \beta_{\mathrm{N},i}, \beta_{\mathrm{P},i} \mid \boldsymbol{\gamma}, \beta, \sigma^2, \lambda$ via a multiple regression for each movie.
2) Draw $\boldsymbol{\gamma}, \beta, \sigma^2 \mid \alpha_i, \beta_{\mathrm{N},i}, \beta_{\mathrm{P},i}, \lambda$ via a multiple regression.
3) Draw $\lambda \mid \alpha_i, \beta_{\mathrm{N},i}, \beta_{\mathrm{P},i}, \boldsymbol{\gamma}, \beta, \sigma^2$ via a Random-Walk Metropolis-Hastings algorithm.
4) Repeat 1) through 3) R times.

A standard algorithm introduced in Rossi, Allenby, and McCulloch (2005) is used for each step. For estimation, we generate 5,000 draws, discard the first 2,000 draws as burn-in, and compute the posterior mean and standard deviation of each parameter. The log-marginal density (LMD) proposed by Newton and Raftery (1994) is used for model comparison.

Table 1 reports the estimation result. We find that the LMD of the proposed model (−40131.15)

Table 1. The posterior mean (standard deviation) of the model parameters

Parameters	Benchmark model	Proposed model
Movie-specific intercept (α_i)$^+$	−1.6374 (0.1327)**	−1.5536 (0.1797)**
Valence (β)	0.6987 (0.0168)**	0.6291 (0.0571)**
Decaying parameter (λ)	0.0798 (0.0024)**	0.0433 (0.0014)**
Bias-correction coefficient, negative ($\beta_{\mathrm{N},i}$)$^+$		3.8770 (0.4686)**
Bias-correction coefficient, positive ($\beta_{\mathrm{P},i}$)$^+$		−0.8343 (0.4476)*
The other factors ($\boldsymbol{\gamma}$)		
– Linear time trend	−0.0948 (0.0011)**	−0.1251 (0.0016)**
– # of competing movies	0.0186 (0.0045)**	0.0199 (0.0050)**
– Weekend	0.2952 (0.0272)**	0.2956 (0.0225)**
– Friday	−0.0146 (0.0370)	−0.0274 (0.0287)
– Holiday	0.7312 (0.0810)**	0.5820 (0.0755)**
Variance (σ^2)	3.0759 (0.0284)**	2.1858 (0.0215)**
LMD	−43885.23	−40131.15

$^+$For those movie-specific parameters, the posterior mean (standard deviation) of the average across the movies are reported.
*The 90% credible interval does not contain zero (significant at the 90% level).
**The 95% credible interval does not contain zero (significant at the 95% level).

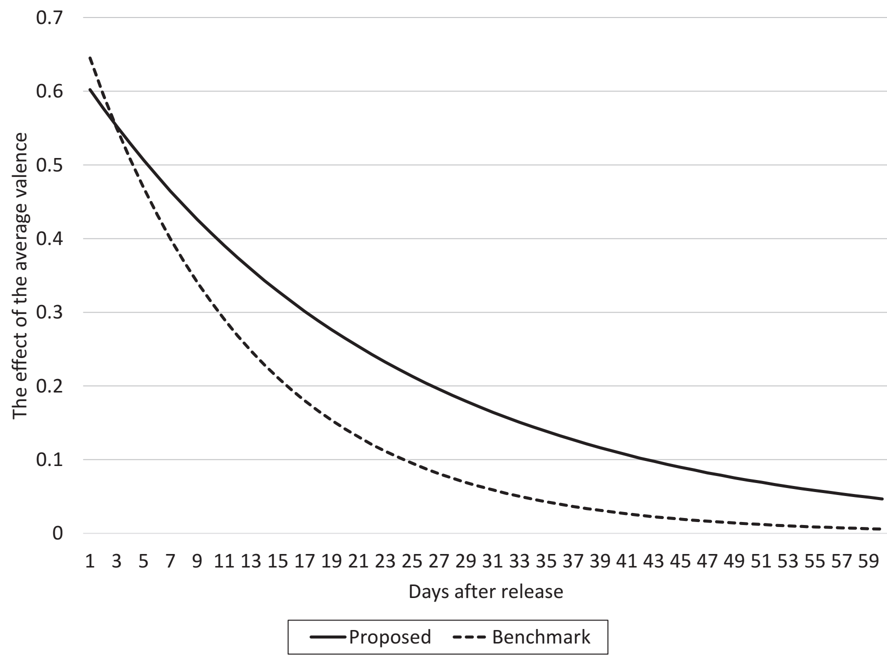

Fig. 2. The effect of the average valence ($e^{-\lambda(t-z_i)}\beta$) over time.

is significantly greater than that of the benchmark model (−43885.23), implying that the additional terms for the bias-correction improve the fitting performance. The estimate of the variance parameter (σ^2; 2.1858 for the proposed vs. 3.0759 for the benchmark) conforms to the LMD values. We also find that most parameters are significant in both models and the signs of them are estimated as expected. The positive estimate of the valence parameter (β; 0.6291 for the proposed and 0.6987 for the benchmark) implies that higher ratings of the online reviews led to larger box-office sales. The positive estimate of the decaying parameter (λ; 0.0433 for the proposed and 0.0798 for the benchmark) indicates that the effect of the valence was systematically decaying over time. On average, the bias-correction coefficients are estimated as expected ($3.8770 > 0$ for $\beta_{\mathrm{N},i}$ and $-0.8343 < 0$ for $\beta_{\mathrm{P},i}$), implying that they offset the inflated effect of the valence for some movies.

We note that the valence parameter (β) indicates the sensitivity at the release date ($t = z_i$), and the sensitivity exponentially decays over time with rate λ in both the proposed model and the benchmark model. The valence sensitivity, therefore, should be evaluated through the entire term including the decaying pattern ($e^{-\lambda(t-z_i)}$). Fig. 2 displays the estimated valency sensitivity over time based on the estimates of β and λ for the proposed model (solid curve) and the benchmark model (dashed curve). Except for the first three days after the release of a movie, the estimated valence sensitivity in the benchmark model is lower than that in the proposed model, implying underestimation, i.e., a negative bias, in the estimate of the valence sensitivity when the bias-correction terms are omitted as analytically expected in Section 3. The exceptions for the very first days may come from “opening” noises in demand, which are typically observed for movies (Kim 2023).

Table 1 also shows that most of the other factors ($\boldsymbol{\gamma}$) are estimated as expected. The negatively estimated linear time trend (−0.1251 for the proposed and −0.0948 for the benchmark) captures a systematic decrease in sales over time. The positively estimated coefficients of weekend (0.2956 for the proposed and 0.2952 for the benchmark) and holiday dummies (0.5820 for the proposed and 0.7312 for the benchmark) indicate large demand on weekends and holidays for 553 movies in the data. The positively estimated coefficient of the number of competing movies (0.0199 for the proposed and 0.0186 for the benchmark) indicates a market expansion effect. The insignificant estimate of the Friday effect (−0.0274 for the proposed and -0.0146 for the benchmark) is the only exception. People did not spend more time on Fridays than the other weekdays for watching the movies in the data.

5. Conclusion

We, in this paper, propose a method to correct a potential negative bias in the estimate of the valence sensitivity of demand due to firms’ promotional activities on online reviews. With the prevalence of the promotional activities, consumers may notice and discount the reviews generated by the promotional activities. Discounting the firm-generating reviews may cause systematic measurement errors in the valence variable and lead to a negative bias when estimating the effect of consumers' organic reviews on demand through conventional econometric models of online reviews. The proposed method adds two terms representing the proportion of extreme reviews, typically observable in online review data, to a demand model to correct the bias. The additional terms are product-specific and can be directly estimated via linear regression for panel data, implying that neither other instruments nor advanced econometric techniques are necessary. In an illustrative application to the box-office and online rating data of movies, the negative bias in the estimate of the valence sensitivity is found, and the bias-correction terms improve the fitting performance of the demand model by offsetting the inflated effect of the valence.

One may argue that the sensitivity estimate from the conventional models reflects what consumers actually do – discounting the firm-generating reviews – in the market, and it thus is an unbiased estimate of the demand response. We note that the proposed method is a complement, not a substitute, for conventional models, and researchers' choice of a model depends on the research objective. For example, the sensitivity estimate from the conventional models should be used to predict demand responses to a summary statistic displayed in online stores (e.g., the average rating), whereas the estimate from the proposed method should be applied for causal inference on the effect of consumers' organic social interactions.

In practice, the proposed method is also useful for economic valuations of customer acquisition and retention. The social interactions have become a key component of customer lifetime value (CLV), or customer lifetime social value (CLSV), by creating a contagion effect with low costs (Haenlein and Libai 2017; Kumar and Mirchandani 2012; Ofek, Libai, and Muller 2021). The negative bias in the estimate of the valence sensitivity leads to an underestimation of the magnitude of the social contagion. Because the valence sensitivity exponentially affects the size of the contagion effect, even a small bias may result in losing a chance of a long-run profit.

A challenge of applying our method is data frequency. The method relies on the variation in the proportion of extreme reviews to identify the product-specific bias-correction coefficients. In the empirical illustration, we use daily data instead of less frequent ones (e.g., weekly data) to ensure a sufficient number of observations to identify the bias-correction coefficients per movie. If such a high-frequency dataset is not available, external instruments, econometric techniques, and/or additional assumptions may still be required. We leave this challenge and other issues for future research.

Recent advances in machine learning techniques allows for much richer information on online social interactions (e.g., Ghose, Ipeirotis, and Li 2019), and the review platforms have updated their systems to enable users to filter out firms' promotional activities (e.g., "helpfulness" scores of Amazon reviews). Some firms, however, still deploy their financial and human resources in black markets for promotional activities through social media (He, Hollenbeck, and Proserpio 2022). In the realm of such complexity, identifying the actual impact of social interactions becomes much harder in practice. We believe our study sheds light on which variation in data is useful for such an identification task.

Conflict of interest

The author declares that there is no conflict of interest.

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