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# Too good to be true: the role of online reviews' features in probability to buy

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Online consumer reviews are broadly believed to be a necessary and powerful marketing tool, and as such they have attracted considerable attention from both marketers and academics. However, previous research has not sufficiently focused on the effects of various review features on sales but rather used proxy measures such as consumers' purchase intention or perceived helpfulness of reviews. Hence, the aim of this study was to investigate the effect of review valence and volume on actual sales. We use data from three different e-commerce websites and study light bulbs, women's athletic shoes, natural hair care products, and herbal vitamins. The results show that, contrary to popular belief, more positive ratings do not simply result in higher sales. We find that the effect can be nonlinear, where the probability of purchase increases with rating to about 4.2−4.5 stars, but then decreases. Also, although the majority of extant research suggests that larger numbers of reviews bring more positive outcomes, we show that it is not always the case.

**Keywords:** online reviews; probability of purchase; online ratings; review valence; review volume

## Introduction

Online consumer reviews have changed the marketing reality in which advertising has traditionally operated as one-way communication from companies to consumers via mass communication channels (Campbell et al. 2011). Although brands still advertise in these traditional 'paid' media such as television, radio, and print, new advertising channels are now available to them (Edelman and Salsberg 2011). Companies can utilize 'owned' media to contact customers directly to, for example, compel them to share their experiences or visit the company's website, or their 'earned' media by providing customers with space where they can promote the company to other consumers. These new communication channels have become especially important for companies, especially in the context of consumer endorsements being an important advertising strategy (Bernritter, Verlegh, and Smit, 2016; Lee, Park, and Han 2011).

Consumers do not rely solely on advertising messages anymore, but direct their attention to other sources of information, especially online reviews. Surveys show that more than half of consumers consults online reviews (CMA 2015; Mintel 2015). That is because the majority of consumers trust recommendations from others more than traditional forms of advertising (Nielsen, 2012). Online reviews help consumers make

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decisions such as purchasing products, watching movies, or joining a sports club. They have become a major driving force in marketing (Cui, Lui, and Guo 2012) and are a common feature on many websites. Information from other consumers, such as online reviews, is thought to be more persuasive and trustworthy, and is especially important in the online environment (Ba and Pavlou 2002; Willemsen, et al. 2011). Consumers buying products online have to rely on the information provided on the website and do not have the ability to try out the product (Lee 1998). Due to their alleged persuasiveness and prevalence, online reviews have attracted substantial attention from both researchers and practitioners.

However, while online product reviews may affect consumers' purchase decisions (Zhu and Zhang 2010), even overshadowing other relevant product information such as price (de Langhe, Fernbach, and Lichtenstein 2016), past research has mostly neglected the effect of review features on actual sales and rather focused on other outcomes such as review helpfulness, credibility, attitude, and intention (e.g., Jiménez and Mendoza 2013; Purnawirawan, Dens, and De Pelsmacker 2014; Wang, Cunningham, and Eastin 2015), or used proxy measures of sales (Wang et al. 2015) such as sales rank (e.g., Amblee and Bui 2011; Chevalier and Mayzlin 2003) or the number of reviews (e.g., Öğüt and Onur Taş 2012; Ye, Law, and Gu 2009). Also, a large body of consumer review research is built on experimental- or survey-based work (e.g., Purnawirawan, de Pelsmacker, and Dens 2012), and assumes that effects of online reviews are linear. One exception is a recent meta-analysis conducted by Purnawirawan et al. (2015), in which the authors demonstrate that valence has a curvilinear effect on usefulness and a ceiling effect on attitudes. They do not look at actual sales though. Previous research has also looked into different review features such as valence, length, variation, and volume, but as we will show in the remainder of this paper, the results are mixed (King, Racherla, and, Bush 2014; Zhang et al. 2010; Zhu and Zhang 2010). We aim to address these shortcomings by studying the effect of two main features of online reviews, namely the average star rating of a product (i.e., valence) and the number of reviews (i.e., volume) on actual sales in three different online shops. We are able to do this using purchase data from three companies.

These inconsistencies and gaps in the literature emphasize that there is still much to be known about the workings and limits of consumers' online reviews (Kimmel and Kitchen 2014). In addressing these shortcomings, we are contributing to the literature in at least three important ways. First, by investigating the nonlinear nature of the effects of review valence and volume on sales, we are providing an explanation for the often-mixed results of studies that treated these effects as linear. Second, by examining the effects of online product reviews on actual sales, we are able to show whether often-mixed findings that are based on proxy measures of sales also hold for actual purchases. Finally, by testing the effects of online review features among a diverse set of product categories, we acknowledge the need for the comparison of the effects of review features among a broad spectrum of products (Zhu and Zhang 2010). This is essential since previous research has primarily focused on one product category (e.g., entertainment products such as movies or books) (Cui, Lui, and Guo 2012) or compared two categories of products (Zhu and Zhang 2010).

## The role of reviews' features

The valence of online product reviews is usually summarized by the average number of stars rated on a five-point scale. Most online retailers also display the number of reviews next to the valence. The amount of information that can influence customers' decisions is limited. Reviews can be seen as the most reliable and accessible indicators of product quality and customer experiences (Simonson 2015), and hence, affect customers simplifying decision-making process. Because consumers are cognitive misers with limited cognitive resources, and as such they often use heuristics instead of elaboration, they may rely on heuristic cues in the shopping environment. Product reviews have been shown to influence consumers via heuristic processing (Forman, Ghose, and Wiesenfeld 2008) during which consumers use peripheral cues – rather than the content of reviews – to form opinions. This is especially the case when consumers face an information overload (Forman, Ghose, and Wiesenfeld 2008) or in low-risk situations when consumers apply simple search and evaluation techniques. Thus, cues such as the average number of stars (valence hereafter) and the number of reviews (volume hereafter) are perfectly suited as a summary for consumers processing product information based on heuristics. The advantage of these kinds of summaries is that they cannot be misinterpreted, in contrast to information provided in the text of a review. We also focus on volume and valence because they are commonly shown next to the product price and thus all customers are exposed to them, even those who do not navigate to the 'review tab.' This makes them two key (Wang et al. 2015, 73) and broadly studied (e.g., Mahajan, Muller, and Kerin 1984; Liu 2006) metrics.

### *Review valence*

Valence is widely believed to positively influence attitudes toward the brand and purchase behaviors. Many companies even want to remove negative reviews because they fear that they will discourage potential customers. However, as Table 1 shows, the results of past studies are equivocal (King, Racherla, and Bush 2014; Zhang et al. 2010). A positive effect of valence has been shown for book sales rank and box office performance of movies (Chevalier and Mayzlin 2006; Chintagunta, Gopinath, and Venkataraman 2010; Zhang and Dellarocas 2006). Also, Gopinath, Thomas, and Krishnamurthi (2014) find that valence has a direct effect on sales of cell phones. Chevalier and Mayzlin (2006) show that 1-star reviews can negatively affect sales rank on Amazon.com and Clemons, Gao, and Hitt (2006) find that while high ratings can predict sales, bad ratings do not predict poor sales. Finally, Kim et al. (2015) demonstrate that negative reviews are associated with a decrease in readers' spending levels. Valence has been also shown to affect other variables such as consumers' attitude, perceived source credibility, and purchase intention (Wang, Cunningham, and Eastin 2015).

Others demonstrate that valence does not matter. In their study of the online movie reviews on Yahoo.com, Duan, Gu, and Whinston (2008a) show that valence has no significant effect on box office sales, which is in line with the findings of Liu (2006) for box office revenue. Similarly, Chen, Wu, and Yoon (2004) show that online reviews do not affect book sales rank on Amazon. Finally, Amblee and Bui (2011) find that the valence does not predict purchases of digital microproducts. Still, the majority of studies demonstrate valence effects.

Some studies suggest that a disproportional number of positive online reviews may cause consumers to discount positive reviews as not reliable (Chevalier and Mayzlin 2006) and therefore may negatively affect sales. In accordance with this reasoning, Bosman, Boshoff, and van Rooyen (2013) show that valence significantly affects review credibility and that for every additional star, credibility decreases on average by 2.39% (if all other factors remain unchanged). This suggests that a review with a poor rating is

Table 1. Overview of some relevant literature on the effects of valence and volume of reviews.

| Study | Findings of valence | Findings on volume | Context |
|---|---|---|---|
| Amblee and Bui (2011) | No effect | + | Sales rank<br>Short stories |
| Basuroy, Chatterjee, and Ravid (2003) | +<br>The effect of negative reviews diminishes over time<br>Negative reviews hurt more than positive ones help | | Box office revenue |
| Bosman, Boshoff, and van Rooyen (2013) | −<br>For every additional star, the review credibility decreases by 2.39% | | Credibility of book reviews on Amazon.com and Barnesandnoble.com |
| Chen, Wu, and Yoon (2004) | No effect | + | Amazon.com books |
| Chevalier and Mayzlin (2006) | + For Amazon<br>No effect for BN | + for Amazon | Books sales Amazon and Barnes and Noble |
| Chintagunta, Gopinath, and Venkataraman (2010) | + | No effect | Box office sales (movies) |
| Chiou and Cheng (2003) | + Negative messages hurt low-image brands | + Message repetition helps high-image brands | Brand evaluation and attitude toward the Web owner |
| Clemons, Gao, and Hitt (2006) | + | No effect | Beer sales |
| Cui, Lui, and Guo (2012) | +<br>Stronger effect than volume for search products<br>Stronger effect of negative reviews than positive ones | +<br>More important for experience products<br>The effect decreases over time | Sales rank data Amazon<br>New products (electronics and video games)<br>Differences between search and experience products |
| Dellarocas, Zhang, and Awad (2007) | + | + | Box office sales (movies) |
| Dhar and Chang (2009) | + | | Sales of music albums |
| Duan, Gu, and Whinston (2008a) | No effect | + | Box office sales (movies) |
| Duan, Gu, and Whinston (2008b) | + On volume | + | Box office performance |

(*continued*)

Table 1. (*Continued*)

| Study | Findings of valence | Findings on volume | Context |
|---|---|---|---|
| Floyd et al. (2014) | + Sales elasticities based on valence are significantly higher than those based on review volume | + | Sales Elasticities Meta-analysis |
| Ghose and Ipeirotis (2011) | + For audio video only | + For DVDs and digital cameras, but not for audio video | Sales rank |
| Gopinath, Thomas, and Krishnamurthi (2014) | + | No effect | Cell phones |
| Gu, Park, and Konana (2012) | No effect for retailer-hosted reviews + For external reviews | + For both retailer-hosted and external reviews | Cameras Amazon sales rank |
| Ho-Dac, Carson, and Moore (2013) | + For weak brands No effect for strong brands | | Blue-Ray and DVD players sales Differences between strong and weak brands |
| Jang, Prasad, and Ratchford (2012) | + A unit increase in the mean of product reviews is worth $45 on average | + Less important | Experiment on hotel choice |
| Kostyra et al. (2016) | + | Doesn't have a direct effect, but moderates the effect of valence | A choice-based conjoint experiment Effect on willingness-to-pay |
| Kusumasondjaja, Shanka, and Marchegiani (2012) | − When the reviewer's identity is not disclosed, there is no significant difference between positive and negative reviews | | Credibility |
| Lee and Youn (2009) | + Moderated by review platform | | Willingness to recommend |
| Liu (2006) | Valence does not offer explanatory power | + | Box office revenue |
| Öğüt and Onur Taş (2012) | + | | Number of reviews as a proxy for hotel rooms sales on Booking.com |

(*continued*)

Table 1. (*Continued*)

| Study | Findings of valence | Findings on volume | Context |
|---|---|---|---|
| Park and Lee (2009) | Greater effect of negative reviews than positive reviews, established websites than unestablished websites, experience goods than search goods | | eWOM effectiveness |
| Purnawirawan et al. (2015) | Curvilinear effect on usefulness, stronger for experience than search products+ belongs to the ceiling effect on attitudes | | Perceived usefulness, attitude |
| Wang et al. (2015) | moderated by volume | | Hotel rooms |
| Yang et al. (2012) | + Only for niche movies No effect for niche movies with greater box office revenue | + Greater for mass movies | Box office revenues |
| Ye, Law, and Gu (2009) | + A 10% improvement in reviewers' rating can increase sales by 4.4% | | Number of reviews as a proxy of the number of hotel room bookings |
| Zhang et al. (2010) | + | + | Restaurants popularity |
| Zhu and Zhang (2010) | + For less popular online games | + For both popular and less popular online games | Sales of console games Popularity of games Online and offline games |

perceived as more trustworthy. In line with this notion, O'Reilly and Marx (2011) show that consumers are skeptical of reviews that are too positive. In other words, consumers who see only 5-star reviews become suspicious (Dholakiya 2014). The theory that excessively positive reviews can have negative effects is also supported by the research of Mudambi and Schuff (2010) who find that moderate reviews are better than extreme reviews for experience goods.

There are several reasons why moderate reviews may be more appreciated and excessively positive reviews may be perceived as unreliable. First, when consumers rate a product on a five-point scale, a mean rating of three may indicate variance in reviewers suggesting that both positive and negative product attributes are discussed, which builds credibility and reduces reporting bias. Previous research has shown that two-sided messages can enhance source credibility and brand evaluation. For example, in advertising, Kamins and Assael (1987) show that one-sided versus two-sided messages increase derogation of the advertiser. Similarly, Eisend (2006) finds that two-sided advertising can enhance persuasion by indicating that it is trustworthy. Second, positive product characteristics may be perceived as less diagnostic of product quality (Herr, Kardes, and Kim 1991; Mizerski 1982). Reviews are often posted by either extremely satisfied or extremely disappointed customers (Hennig-Thurau et al. 2004), which may diminish their usefulness. In addition, positive reviews are more prominent (Melián-González, Bulchand-Gidumal, and González López-Valcárcel 2013), which (1) causes a contrast effect with negative reviews, enhancing consumers attention to negative reviews, and (2) may be responsible for the fact that consumers seek out negative reviews to get assurance the company is not hiding anything (O'Neil 2015). Third, very positive reviews may be seen as not reliable because of consumers' naive theories about the sources of positive information (Chen and Lurie 2013). For instance, consumers may write positive reviews to signal competence or for self-presentation reasons (Chen 2014). Finally, consumers also know that firms can alter or remove reviews, or stimulate positive reviews with financial rewards to create high ratings (Li and Hitt 2008). Hence, having some extremely positive reviews (i.e., 5-star reviews) is not problematic as long as there are some moderate ones (or even fewer negative ones) to average things out. Such reasoning is in line with the findings of Doh and Hwang (2009) showing that a few negative messages can enhance attitudes toward website and review credibility.

To disentangle extant findings, we build on Mudambi and Schuff (2010) who show that extreme reviews of experience goods are less helpful than moderate ones, producing an inverted U-shape effect, and Schindler and Bickart (2012) who find that the proportion of positive evaluative statements in a review has an inverted U-shape effect on review value. Also, Purnawirawan et al (2015) in their meta-analysis find that the effects of review valence are nonlinear: Valence has a curvilinear effect on usefulness and a ceiling effect on attitudes.

The phenomenon that too much of a good thing can have negative consequences has been acknowledged by a stream of research in various disciplines. For instance, it has been demonstrated that an overabundance of users' connections with friends on Facebook harms how others rate these users' attractiveness and extraversion, compared to a rather intermediate amount of connections (Tong, van der Heide, Langwell, and Walther 2008). Another study found that consumers' trust in brands could decrease if they have experienced too many satisfying transactions with the brand previously (Vlachos, Vrechopoulos, and Pramatari 2011). In the same vein, it has been shown that too much positive affect can decrease proactive behavior (Lam, Spreitzer, and Fritz 2014). Therefore, we propose that the relationship between valence and sales is nonlinear. We expect that higher valence will lead to more positive effects (i.e., higher purchase probability), but extremely good average star ratings will lead to less positive outcomes, because they imply a lack of variation and induce suspicion. Hence, we hypothesize that:

**H1:** The relationship between valence and purchase probability is nonlinear, where higher valence leads to higher purchase probability, but extremely high valence leads to lower purchase probability.

***Review volume***

The presence of reviews is expected to bring positive outcomes. For example, Amblee and Bui (2011) demonstrate that digital microproducts with reviews sell significantly better than products without reviews. However, extant research does not agree on the effect of the number of reviews (Table 1).

For example, Bazaar (2015) and Matfield (2011) show that volume is generally positively correlated with sales volume and revenues, regardless of valence. Also, other past studies have shown that volume affects market outcomes, such as box office sales (Duan, Gu, and Whinston 2008b; Liu 2006), sales rank of electronic products (Cui, Lui, and Guo 2012; Gu, Park, and Konana 2012), but also other measures such as consumer attention (Godes and Mayzlin 2004; Liu 2006). Chiou and Cheng (2003) find that consumers exposed to 12 posts (vs. 6) about cell phones evaluate the product more positively, have a higher overall attitude, and show stronger overall liking. Although the majority of studies confirms the positive belief about the effect of volume (King, Racherla, and Bush 2014), there are also studies suggesting that volume on its own is not enough.

For example, Gopinath, Thomas and Krishnamurthi (2014) show that the volume of online word of mouth (WOM) does not impact sales of cell phones in a significant way. Similarly, Chintagunta, Gopinath, and Venkataraman (2010) find that volume does not have a significant impact on box office performance. One study even shows that, for attribute-focused reviews, a large number of reviews create information overload for consumers (Park and Lee 2008), which might result in negative effects on consumers' purchase behavior. This suggests an important distinction between the displayed number of reviews, which is a peripheral cue signaling popularity and credibility, and the actual reviews. We are looking at the displayed number of reviews and hence do not expect such an effect. For consumers to experience overload, they would need to read all the reviews. In addition, as discussed by Simonson (2015), too much information does not have to lead to cognitive overload, because consumers are usually offered a way to choose information they want to process. Summarizing, although the results of previous research seem mixed, most of the extant research suggests a positive effect of volume.

As stated earlier in the introduction, the number of reviews constitutes a heuristic cue. Such a cue can trigger more positive responses (Chiou and Cheng 2003). According to the elaboration likelihood model (Cacioppo et al. 1986), consumers use a shortcut and follow the peripheral route of processing, which means they focus on heuristics when they are not motivated to process a message. Hence, they look for cues that could signal the value of a message, such as volume.

The idea behind the alleged positive effect is that volume, as a peripheral cue, can signal the popularity of a product and intensity of WOM (Duan, Gu, and Whinston 2008a; Cui, Lui, and Guo 2012; Liu 2006; Park and Lee 2008). More reviews can elicit consumers' interest and increase product awareness (Chen, Wu, and Yoon 2004), that is, make it more salient in the consumer's mind. The number of online product reviews may indicate the product's popularity because consumers can assume that the number of reviews is related to the number of consumers who have bought the product, and hence, purchase intention increases with the number of reviews (Park, Lee, and Han 2007). Also, higher volume suggests more information and hence can reduce consumers' uncertainty and strengthen their confidence in a product, leading to a greater willingness to pay for it (Brynjolfsson and Smith 2000). More reviews may be perceived as more objective and thus more trustworthy (Wang et al. 2015). Finally, higher volume can suggest that consumers care about the brand or product, because they take their time to write a review about it (Chiou and Cheng 2003). Thus, volume can also be indicative of consumers' enthusiasm about the product (Duan, Gu, and Whinston 2008a).

We thus hypothesize that:

**H2:** The relationship between volume and purchase probability is positive with higher volume leading to higher purchase probability.

## Method

To test our hypotheses, we use data from three different Internet-only retailers selling products from different categories. Since none have physical stores, all purchases can be recorded and linked to the reviews that were shown at the time of ordering. We are thus able to link online reviews to real purchase behavior. Our focus is on whether or not an item was purchased rather than predicting the quantity or purchase amount. Retailer 1 sells different types of light bulbs, retailer 2 sells health and beauty care products, and retailer 3 is an Internet retailer in apparel, jewelry, electronics, home, toy, health, and beauty.

We have six weeks of sales data from 31 August 2014 through 11 October 2014 for retailer 1, and 15 weeks of sales data from 29 Jun 2014 to 11 October 2014 for retailers 2 and 3. We include four product categories: light bulbs, women's athletic shoes, natural hair care products, and herbal vitamins. We restrict our attention in this study to the six largest brands or brands that were bought at least 1.000,00 times. For retailer 1, we also focus on the five largest categories of light bulbs, that is, LED, halogen, incandescent, linear, and compact fluorescent. We included dummy variables indicating the category as control variables, but do not report results for these variables since they are not part of our hypotheses. Table 2 gives summary statistics for the categories. For each exposure we know the following about the reviews to which the customer was exposed: (1) the average number of stars across the reviews for the stock keeping units (SKU) (stars), (2) the number of reviews for the SKU (num), and (3) the price.

Purchases are complicated decision processes that depend on factors beyond review traits. Previous research suggests that information on prices should be included when discussing purchase decisions. In addition, brand awareness, which is a result of marketing

Table 2. Descriptive statistics.

| Product category | Number of SKUs | Number of orders | Number of displays | Buy rate |
|---|---|---|---|---|
| Light bulbs | 919 | 2608 | 118,891 | 2.19% |
| Women's athletic shoes | 107 | 438 | 49,958 | 0.88% |
| Natural hair care | 26 | 915 | 14,838 | 6.2% |
| Herbal vitamins | 81 | 1701 | 21,512 | 7.9% |

communication efforts, should also be included. Some previous studies have shown that the effect of reviews may differ for different brand familiarity and price (e.g., Ba and Pavlou 2002; Berger, Sorensen, and Rasmussen 2010; Chiou and Cheng 2003). We include the brand and the price in our model to control for such effects. Notice that brand is a proxy for ad spend. We create a dummy variable indicating brands in order to control for the effect of brands' advertising. Our data are summarized at the SKU level, which corresponds to a web page used to display the SKU. For each SKU (web page) we know the volume, valance and price for the item, the number of times the page was viewed (exposures), and the number of times the item was included in an order. Thus, a simple estimate of purchase probability is the number of orders divided by the number of exposures. Our model attempts to explain these probabilities with volume and valence, after controlling for price and brand. Volume and price are logged because they are right skewed with outliers.

We estimate the following logistic regression using generalized additive models (GAMs) (Hastie and Tibshirani 1990):

$$\log\left(\frac{\pi}{1-\pi}\right) = \text{brand} + \log\text{ price} + s(\text{valence}) + s(\log\text{ volume})$$

where $\pi$ is the probability of purchase, $s$ is a univariate smoothing spline with three degrees of freedom representing the nonlinear effect of valence and volume on log odds of purchase. GAMs extend standard linear models by permitting nonlinear functions of each of the independent variables. In such models each linear component is replaced with a nonlinear function. They are called *additive*, because they estimate a separate function for each variable and then add their contributions together (James et al. 2013). SAS PROC GAM uses smoothing splines, which are flexible, nonparametric functions that can approximate any continuous univariate function. The flexibility of each function is controlled by a penalty term. GAM software compares the fit from the nonlinear spline model with the fit from a linear model to determine whether nonlinearity is necessary. When the effect of the spline is significant, the nonlinear function explains significantly more variance than the linear term.

## Results

Table 3 provides the analysis of deviance results for the different terms in the model, which indicates whether there are significant nonlinear contributions from the variables. Each smoothing effect in the model has a chi-square test comparing the deviance between the full model and the model without this variable. Table 4 gives parameter estimates of the linear terms.

Concerning the first hypothesis, the nonlinear effect of valence (i.e., average stars) is significant ($p < .05$) for all four product categories (Table 3, Spline (avgstar)), indicating that the spline explains significantly more variance than a linear term. Figure 1 shows the effect of the number of stars on the log odds ratio, where the shaded bands indicate 95% confidence intervals for the mean prediction. As discussed in the Methods section, with additive models each term affects the logit of buying in an additive way. Consider, for example, Figure 1(a) and the average star rating. The spline has an 'effect' of about 0 for a product with 2.5 stars, and the effect is about 0.4 for 4.2 stars. Thus, the logit of buying is about 0.4 higher for a 4.2 star bulb compared with a 2.5 star bulb. Likewise the logit of buying Brand D is 0.56 higher than base-category brand (Table 4). A logit of 0

Table 3. Analysis of deviance.

| Source | df | Sum of squares | Chi-square | $p$ |
|---|---|---|---|---|
| Light bulbs | | | | |
| Spline (avgstar) | 2 | 28.058908 | 28.0589 | <.0001 |
| Spline (logreview) | 2 | 3.904887 | 3.9049 | 0.1419 |
| Women's athletic shoes | | | | |
| Spline (avgstar) | 2 | 7.952682 | 7.9527 | 0.0188 |
| Spline (logreview) | 2 | 92.309074 | 92.3091 | <.0001 |
| Natural hair care | | | | |
| Spline (avgstar) | 2 | 14.322789 | 14.3228 | 0.0008 |
| Spline (logreview) | 2 | 6.055067 | 6.0551 | 0.0484 |
| Herbal vitamins | | | | |
| Spline (avgstar) | 2 | 6.390388 | 6.3904 | 0.0410 |
| Spline (logreview) | 2 | 25.969568 | 25.9696 | <.0001 |

corresponds to a purchase probability of 50% = $1/(1 + \exp(-0))$. Likewise a logit of $-1$ gives a probability of $1/(1 + \exp(--1))$ = 27%, a logit of $-2$ gives a probability of 12%, a logit of $-3$ gives a probability of 4.7%, and a logit of $-4$ gives a probability of 1.8%.

For light bulbs and hair care products (Figure 1(a) and 1(c)), the number of stars seems to have no effect between 1 and 3, but the function increases after 3 stars, indicating that, for example, products with 4-star reviews are more likely to be purchased than those with an average of 3 stars. The function achieves a maximum around 4.2, and decreases somewhat thereafter. For athletic shoes and herbal vitamins (Figure 1 (b) and 1(d)), the number of stars has an increasingly positive effect up to about 3.8 and 4 stars, respectively. Then the effect flattens and later decreases. This suggests that a SKU with an average of 3.8–4.2 stars is more likely to be purchased than one with 5 stars, confirming H1.

With regard to the second hypothesis, Table 3 (Spline (logreview)) shows that the nonlinear effect of volume (i.e., number of reviews) is significant ($p < .05$) for all product categories except light bulbs ($p = .14$). This means that adding nonlinear term to our models significantly reduces deviance for the three product categories, but not for light bulbs. Also, the linear effect of volume on purchase probability of bulbs (Table 4, linear logreview) is not significant ($p = .45$), which means that volume does not matter for bulbs. Figure 1 demonstrates that the function of volume increases for light bulbs, but it is quite flat and slightly decreasing for natural hair care products and herbal vitamins, suggesting that a larger number of reviews are associated with a lower probability to buy these products. For women's athletic shoes, the function of volume increases slightly and then flattens as well. Such results are in line with H2 for women's athletic shoes, but not for other categories. Hence, we cannot support H2.

Price and brand also play roles in predicting consumers' probability to buy products. Not surprisingly, price has a negative effect on purchase probability of bulbs. However, its effect on purchase probability of athletic shoes and vitamins is nonsignificant ($p$ = .92, $p$ = .19, respectively). Interestingly, price has a positive effect on purchase probability of hair care products. We will discuss the reasons for and implications of our findings in the next section.

Table 4. Parameter estimates.

| | Light bulbs | | | | | Natural hair care | | | |
|---|---|---|---|---|---|---|---|---|---|
| Parameter | Estimate | SE | *t* | *p* | Parameter | Estimate | SE | t | *p* |
| Intercept | −3.59619 | 0.15914 | −22.60 | <.0001 | Intercept | −4.22661 | 0.50173 | −8.42 | <.0001 |
| Brand A | −0.24638 | 0.10744 | −2.29 | 0.0218 | Brand A | 0.38659 | 0.22914 | 1.69 | 0.0916 |
| Brand B | −0.27761 | 0.12946 | −2.14 | 0.0320 | Brand B | 0.53540 | 0.23519 | 2.28 | 0.0228 |
| Brand C | −0.15320 | 0.09970 | −1.54 | 0.1244 | Brand C | 0.23020 | 0.19495 | 1.18 | 0.2377 |
| Brand D | 0.56069 | 0.15348 | 3.65 | 0.0003 | Brand D | 0.50228 | 0.19139 | 2.62 | 0.0087 |
| Brand E | −0.3736 | 0.13838 | −2.72 | 0.0065 | Brand E | 0.24193 | 0.13334 | 1.81 | 0.0696 |
| Linear log price | −0.14578 | 0.03237 | −4.50 | <.0001 | Linear log price | 0.49267 | 0.17257 | 2.85 | 0.0043 |
| Linear avg. stars | 0.08213 | 0.02664 | 3.08 | 0.0020 | Linear avg. stars | 0.09737 | 0.09764 | 1.00 | 0.3187 |
| Linear log review | 0.01991 | 0.02619 | 0.76 | 0.4471 | Linear log review | −0.11643 | 0.03501 | −3.33 | 0.0009 |
| | Women's athletic shoes | | | | | Herbal vitamins | | | |
| Intercept | −5.15012 | 0.83974 | − 6.13 | <.0001 | Intercept | −2.41724 | 0.31787 | −7.60 | <.0001 |
| Brand A | −0.61653 | 0.10067 | −6.12 | <.0001 | Brand A | −0.13324 | 0.11701 | −1.14 | 0.2548 |
| Linear log price | 0.01553 | 0.15626 | 0.10 | 0.9208 | Brand B | −0.51356 | 0.10543 | −4.87 | <.0001 |
| Linear avg. stars | 0.11419 | 0.11744 | 0.97 | 0.3309 | Brand C | −0.33159 | 0.14221 | −2.33 | 0.0197 |
| Linear log review | 0.31602 | 0.02659 | 11.88 | <.0001 | Brand D | −0.64769 | 0.19225 | −3.37 | 0.0008 |
| | | | | | Linear log price | −0.08559 | 0.06545 | −1.31 | 0.1910 |
| | | | | | Linear avg. stars | 0.15663 | 0.05730 | 2.73 | 0.0063 |
| | | | | | Linear log review | −0.08713 | 0.02303 | −3.78 | 0.0002 |

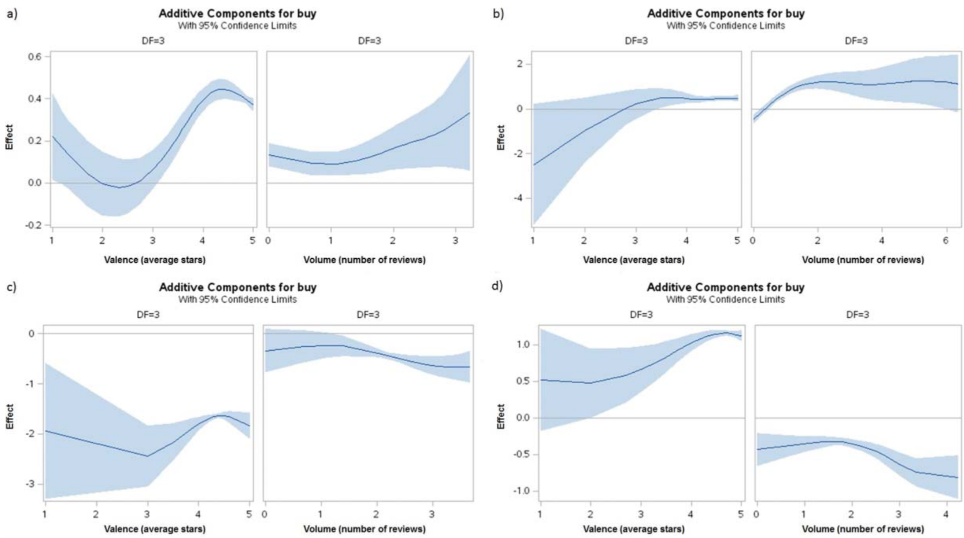


Figure 1. The effect of valence and volume on purchase probability.
Note: Clockwise from top left: (a) light bulbs, (b) women's athletic shoes, (c) natural hair care products, (d) herbal vitamins.
Source: Author

## Discussion

Despite the substantial interest in the workings and limits of online reviews, there are still gaps in the literature. The aim of this study was to address some of them by investigating the effect of review valence and volume on actual sales across different product categories. For the categories studied, we found that products with the average star rating of 4.5 through 5 are less likely to be purchased than those between 4 and 4.5 stars. The reason for that may be that consumers perceive such reviews as too good to be true. They may also think that such reviews were possibly generated by representatives from the company or their public relations agency. This suggests that it is important to have some fraction of nonperfect reviews, which supports the findings of Doh and Hwang (2009), who suggest that a few negative messages can increase attitudes and perceived credibility. Hence, we agree with Zhang, Craciun, and Shin (2010) and Zhang, Li, and Chen (2012) that companies should not censor negative reviews. Moreover, if consumers learned that negative reviews were being censored, then reviews would lose credibility. It is not in the interest of the retailer to censor negative reviews.

With regard to the volume of reviews, the results are more complicated and show that a higher volume is not always good. Volume seems to have a small positive effect for athletic shoes, but the effect is quite flat. We also find that for some product categories volume does not matter (i.e., light bulbs), while for others (i.e., natural hair care products and herbal vitamins) an increase in volume may lead to slightly lower probability of purchase. Such results are in line with some of the extant research finding no effects of volume, but in contrast to previous research showing that volume has a positive effect. An explanation for our findings may be found in the work of Park and Lee (2008) who argue that being exposed to too many reviews may make consumers experience cognitive overload, '[…] the phenomenon of too much information overwhelming a consumer, causing adverse judgmental decision making' (Park and Lee 2008, p. 388).

The negative effect of volume could also be due to an omitted variable bias – whether or not the consumer reads the reviews. Perhaps in some categories consumers are more likely to read reviews, and so the effect is negative. In categories where consumers rely on the heuristic (volume), the effect should be positive. Such reasoning would be in accordance with the cognitive overload theory. It is important to notice that even though we find an effect for reviews, the detected effect is almost flat. That would suggest that the number of reviews does not have such a strong effect, which would be more in line with previous studies finding no effects of volume (e.g., Chintagunta, Gopinath, and Venkataraman 2010).

In addition, the positive effects of volume demonstrated by some previous studies are mainly grounded in the view that volume increases product awareness (cf., Dellarocas, Awad, and Zhang 2004). However, this idea may only hold true for reviews posted on external review websites or blogs, but not on retailer websites (Duan, Gu, and Whinston 2008a; Kostyra et al. 2016). In line with such a theory, online reviews posted on a retailer's internal website have been shown to have a limited influence on sales rank of high-involvement goods (Gu, Park, and Konana 2012). In our study, we are dealing with retailer websites, which suggests that consumers are aware of products offered there and thus volume does not play a big role in their decision process.

Due to the complicated nature of purchase decisions, we included in our analysis price and brand. These two product characteristics can serve as cues signifying product quality and hence they can decrease uncertainty and simplify decision process (Kostyra et al. 2016). The analysis shows that the effect of price differs per product category. Price has a negative effect for light bulbs, which means that more expensive products have a lower probability of purchase. Such a result is in line with some previous studies, which have also demonstrated a negative effect of price in the context of online reviews (e.g., Gu, Park, and Konana 2012; Ye, Law, and Gu 2009). Price also has a negative but nonsignificant effect on the purchase of vitamins. On the other hand, price has a positive effect on purchase of natural hair care products and athletic shoes (although the effect is nonsignificant). Hence, customers choose more expensive products. It is plausible that customers buying natural products are looking for quality and treat price as an indicator of it. These results suggest that price – as a heuristic cue – has a different meaning for high- versus low-involvement products.

### *Limitations, alternative explanations, future research, and implications*

Our findings bring significant implications, but it is important to notice that we used real-life data, which have limitations in terms of internal and external validities. Our sample comes from three different retailers in different categories, but we could not include all the possible categories. In addition, our data may not represent other populations or situations, such as with higher priced products. Consumers differ in their attention to, and reliance on, reviews and their previous experience. Also, some consumers are more likely to write online reviews (Zhu and Zhang 2010). Consumers also have pre-existing product knowledge, attitudes toward brands and stores. However, we did not have a chance to control for such variables. As Chiou and Cheng (2003) argue, the effect of valence may depend on pre-existing brand image. The effect of reviews is also contingent on customers' previous loyalty and intensity of information search (Vázquez-Casielles, Suárez-Álvarez, and del Río-Lanza 2013). Although we did control for the effect of brand, we did not know consumers' individual characteristics, such as brand preferences. Therefore, these personal factors could be included in the future studies.

Furthermore, consumers are aware that companies can moderate or censor reviews, as well as motivate positive reviews with rewards (Li and Hitt 2008). This may diminish the trustworthiness of reviews. Although we did not observe such patterns in our data (e.g., only 0.10% of reviews of light bulbs and cosmetics were rejected), such an assumption may motivate customers to also look for external information about the product. In order to address this problem, some retailers syndicate reviews, believing it can make them more credible. Although we did not examine such practices in our data, future studies could include customers' knowledge about such practices, perceived review trustworthiness, and the effect of external reviews.

Correspondingly, based on research into advertising message processing, we assumed that customers may perceive negative reviews as more diagnostic and informative and hence useful. However, customers may also consider positive product reviews to be ambiguous, which may lead them to look for information elsewhere (Lee and Youn, 2009). Research is needed to gain a more qualitative insight into how customers perceive reviews and how they combine them with other sources of information.

In our study we looked at four product categories. These products were all used offline and were rather commonly purchased goods, yet we found some mixed results with regard to volume and price. That may be because even though similar, the categories may have differed with respect to involvement and motivations driving their purchase. Light bulbs are a highly utilitarian product category, while natural hair care may be perceived as both utilitarian and emotional choice. We can expect that the results may differ also for other categories, for example, for goods that are used online (Zhu and Zhang 2010) or depend on product lifetime (Chen, Wang, and Xie 2011). As discussed by Allsop, Bassett, and Hoskins (2007), customers turn to different sources for different information, and the effect of WOM depends on the specific situation. For some product categories, reviews are more prevalent and useful. For example, reviews may be more likely to affect customers interested in higher price and highly coveted products (Riegner, 2007). Also, the effect of valence seems to be conditional upon the type of product: search versus experience (Willemsen et al. 2011). Future studies should look at the effects of reviews across different categories of products, as also suggested by Purnawirawan et al. (2015). The role of such product characteristics as utilitarian versus hedonic nature of the purchase or product involvement should be included.

Our results concerning valence also bring important implications for future research. For example, as Bazaar's report (2015) shows, reviews with different star ratings contain different features, with 1–3 star reviews containing product shortcomings and 3–4 star reviews suggesting product improvements. Investigating the effect of these differences in content might be worthwhile for future research. Correspondingly, content of the reviews can influence customers and the way they process heuristic cues. As mentioned above, whether customers read or not reviews can explain the negative effect of volume. It can also moderate the effect of valence. Nevertheless, it was not the focus of our study for several reasons. We saw in our data that the overwhelming majority of customers did not consider the content (e.g., for natural hair products only between 0.28% and 16% of customers looked at the content of reviews). This may be explained by the low-involvement character of the product category studied. In addition, when customers did consult the reviews, we do not know which specific reviews and to what degree they read them. Therefore, future studies should investigate the role of review content in relation heuristic cues.

Moreover, different characteristics of reviews, such as review length, valence, and volume, can affect each other. For example, volume may be a moderator of valence (cf., Kostyra et al. 2016). According to the selective attention theory (Treisman 1969), people are not able to process and respond to all the stimuli, because their processing capacity is limited. In order to simplify the processing, individuals rely on heuristic cues and filter out information that is less relevant. We can expect this process to be especially at play when involvement with the decision process is low. Hence, in our case, we expected customers to rely on heuristic cues (i.e., volume and valence), which was supported by our data showing that the majority of customers did not read the reviews. These cues may interact with each other, especially when providing ambiguous information. Only a few studies have looked at the interaction of different review characteristics, and we do not know whether it is better to have, for example, 10 moderate reviews (i.e., with an average of 3) or 2 negative ones. Because we were interested in nonlinear effects, we applied GAMs, which are not suitable for testing interaction effects. Including interactions would require splitting the data and running several additional models for different values of volume, which would make the results complicated. In addition, some previous studies have shown that volume has an effect regardless of valence (e.g., Bazaar 2015), which supported our approach. However, we do acknowledge that various interaction effects between review characteristics require further investigation.

The effectiveness of influence efforts depends on environmental and contextual factors and interactions between them (Hansen 1976). Hence, other information sources may affect consumers' decisions. Purchase decisions may be influenced by person-related factors, but also factors such as price, brand, product information, product quality and value, advertising, promotion, or the reference price (e.g., Chang and Wildt 1994). For example, increased marketing efforts can diminish the effect of valence (Yang et al. 2012). To control for some of those variables we included price in our analysis, but future studies should investigate how price influences the effects of online reviews. For example, the role of price has been shown to decrease when online reviews are present (Kostyra et al. 2016), but it is also plausible that the importance of online reviews differs depending on the product price.

We also controlled for the effect of brand. Although brands are extremely important in marketing communication, the relationship between brands and online reviews has received little attention (Lovett, Peres, and Shachar 2013). Past research has shown that the effect of brand diminishes when reviews are included (Kostyra et al. 2016). In addition, the effect of online reviews has been shown to differ for different brands. For example, Berger, Sorensen, and Rasmussen (2010) suggest that negative reviews can increase sales of unestablished brands by increasing their awareness, Chiou and Cheng (2003) show that the effect of reviews differs for low-image vs. high-image brands, and Ho-Dac, Carson, and Moore (2013) show that online reviews matter less for strong brands. Therefore, future research should not only control for the effect of brand, but should examine how different brands are affected by online reviews, and marketers should measure what the effects of reviews for their brand are.

To conclude, this study demonstrates how the valence and volume of online consumer reviews affect purchases. It is important to stress that – contrary to popular belief – better reviews do not always have a more positive effect. Since products that are rated on average higher than 4.5 out of 5 stars can be less likely to be purchased than those with an average around 4– 4.5 stars, retailers should not delete too negative reviews in order to only display perfect reviews of their products.

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## Disclosure statement

No potential conflict of interest was reported by the authors.

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