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The Effects of Online Incentivized Reviews on Organic Review Ratings

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THE EFFECTS OF ONLINE INCENTIVIZED REVIEWS

ON ORGANIC REVIEW RATINGS

by

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ABSTRACT

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As online reviews become a major factor in the consumer decision-making process, firms have started seeking ways to create and leverage reviews to help achieve their marketing objectives. One productive strategy to generate reviews is to incentivize or reward customers to write reviews. While such a strategy certainly augments the number of reviews, it naturally raises questions of how unbiased such reviews are, and how such a "bias," if it exists, affects potential customers. Complicating the issue further, such incentives can be provided by either the vendor or the platform, which may affect the nature of "bias."

To understand the marketing value of such reviews, this research examines the effects of online incentivized reviews on subsequent organic reviews. First, we investigate whether incentivized reviews are biased compared to organic reviews. Specifically, we find that vendor–initiated incentivized reviews are more favorable whereas platform–initiated incentivized reviews are more critical. Second, we study how incentivized reviews affect future organic review ratings. The findings suggest that vendor (platform) –initiated incentivized reviews reduce (increase) the subsequent organic review ratings. Moderating effects of helpfulness of

incentivized reviews and product type are significant. These findings offer important insights about the effectiveness of incentivized reviews.

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CHAPTER 1

INTRODUCTION

In a continuously changing world where marketers are racing to find newer and newer methods of communicating with their customers (e.g., podcast, video on demand, webisodes, and streaming media), the one constant is consumers continued trust in the opinion of another consumer. The fear that the impersonal electronic world would replace the traditional word of mouth has been laid to rest by the online persona of traditional word of mouth – online reviews. Not surprisingly, there is preponderance of statistics to show the continued relevance of user-generated content (e.g., customer reviews) in the consumer decision process (TurnTo 2017). As per an industry study (Nielsen 2015), 70% of global consumers trust online reviews and 90% of those who read online reviews state that their buying decisions are influenced by online reviews. Most shoppers begin their online journey by searching for product reviews and place increasing reliance upon such reviews when making final purchasing decisions (Dimensional Research 2013).

Given the widely recognized importance of product reviews for consumer decision making, firms have been actively seeking ways to encourage customers to post reviews and share their experiences with other potential customers. Firms such as Amazon.com, Macy’s, and Walmart are known to regularly incentivize their customers to write a review by offering free or discounted products. Reviews written by customers who avail themselves of these incentives are called incentivized reviews, and they are seamlessly interspersed between regular organic reviews in the review profile of products. Both organic and incentivized reviews are used in determining the overall product rating that is presented to all site visitors. The proliferation of incentivized reviews has led to calls for a careful study of their effectiveness in consumer decision making (Dost et al. 2019; Rosario, Valck, and Sotgiu 2020; You, Vadakkepatt, and Joshi 2015). A recent meta-analysis of electronic word of mouth (eWOM) and a review paper on eWOM identify the lack of knowledge regarding incentivized reviews as a research gap (Rosario, Valck, and Sotgiu 2020; You, Vadakkepatt, and Joshi 2015). Unlike organic reviewers, who are intrinsically motivated to share information with others, incentivized reviewers are motivated and encouraged to post reviews by rewards offered by firms. The financial motivations to write an incentivized review may affect how the content is perceived by potential customers and thus may have an impact on its effectiveness.

The incentivized reviewers could potentially write their true opinions about the product – positive or negative; however, in practice incentivized reviews tend to be overwhelmingly biased in favor of the product being rated (Petrescu et al. 2018). Using a sample of 151,904 reviews across seven categories posted on Amazon.com, we find that incentivized reviews are on an average .415 points higher than organic reviews on a 5-point scale.

The growing number of incentivized reviews can artificially inflate the product rankings, leading to ethical issues since one can convincingly argue that consumers are being “bribed” to write positive reviews. To instill confidence in their customers, some retailers impose the condition that incentivized reviewers disclose their affiliation with the vendor in question in the text of their review. It is easy to see something like “I received this product for free or at a discount in exchange for my honest and unbiased review” while browsing reviews at online retailers’ websites. Figures 1 and 2 show examples of incentivized reviews at Amazon.com.

Figure 1
An Example of a Vendor-Initiated Incentivized Review
for a Beauty Product on Amazon.com

Amazing lightweight moisturizer with anti-aging benefits

April 15, 2015

With so many anti-aging treatments, serums, and potions out on the market, it's getting harder and harder to find anything reasonably priced that does the anti-aging thing AND moisturizes your skin without gimmicks. InstaNatural has come up with exactly such a moisturizer. It's lightweight, not heavy like you're slathering vaseline on your skin. It's really surprising, since it's loaded with retinol, hyaluronic acid, shea butter and jojoba oil that it feels so light on the skin.

I used this after washing my face and using an anti-aging serum. My skin has been absolutely glowing from the combination - and that's something of a miracle. What's more of a miracle is the large size of this product and the reasonable price. I'm hoping other manufacturers will start noticing that you can get quality ingredients in skincare products without charging a fortune for them.

(I received this product at a discount in exchange for my impartial and unbiased review.)

Helpful | Comment | Report abuse | Permalink

Figure 2
An Example of a Platform-Initiated Incentivized Review
for a Beauty Product on Amazon.com

It's As Simple As A Pimple

February 16, 2009

Vine Customer Review of Free Product (What's this?)

Growing up, I dealt with what most would consider normal teenage acne. As I have matured, the acne has slowly gone away, with only a blemish or two popping up here or there. My wife also tackled the average teen's acne, but after the birth of our second child, her breakouts increased. Granted, she doesn't suffer from severe acne, but she does have a higher degree of breakouts than before she had our second child. With that in mind, I decided to pick up Nature's Gate Organics Acne Treatment System for her.

The system is very simple to use. So simple, in fact, that the bottles are numbered one, two, and three. The first bottle, the Corrective Cleanser, attacks acne with good ol' fashioned salicylic acid. Fans of Oxy and other cleansers will recognize this stuff. Coupled with it is encapsulated tea tree oil, which helps unclog pores. The second step in the process involves the Calming Toner, which contains Oligopeptide-10, more of the aforementioned tree oil and "botanical extracts" which together supposedly control the amount of oil on the skin and further clean out those pores. The last bottle is the Controlling Lotion, which uses the Oligopeptide-10 and our old friend salicylic acid to maintain a clear complexion.

When my wife tried this product, she did mention a slight burning sensation. However, this was expected thanks to the salicylic acid and the tree oil. I can see where those with sensitive skin could experience an adverse reaction to this, so use this product at your own risk if your skin is sensitive.

After using the product a few days, she did notice a slight reduction in acne, but nothing more or less than the results when using Oxy products. While she liked the Nature's Gate Organics system, she saw no reason to abandon her other cleanser.

The product is certified organic, which is a plus, but in this day and age the almighty dollar is what speaks the loudest. In my opinion, if you get similar or better results using a cheaper product, use it instead of Nature's Gate Organics Acne Treatment System. The system works fairly well, but nothing makes it stand out from any of the other systems on the market other than its eco-friendliness.

Recommended to anyone with moderate acne problems who prefers to use organic brands.

Helpful | Comment | Report abuse

In fact, incentivized reviews without this disclosure could be subject to sanction by the Federal Trade Commission (FTC) (Fair 2019). Unfortunately, such a disclosure does not address the problem completely. While astute consumers can ignore incentivized reviews, the harsh reality is that the majority of consumers cannot distinguish between organic and incentivized reviews (Sterling 2018). Furthermore, it is impossible for anyone to ascertain the true overall product rating without the contribution of incentivized reviews. For consumers looking for accurate, unbiased product ratings before making a purchase, this can be a significant challenge.

To address the ethical questions surrounding incentivized reviews, some retailers have responded by prohibiting incentivized reviews. In a much-publicized move, Amazon.com banned all incentivized reviews from its platform on September 19, 2016 (Weise 2016). Several other firms, such as Google, Yelp, and Better Business Bureau, followed suit by banning all kinds of incentivized reviews. However, due to the enormous number of reviews posted daily (e.g., Amazon.com sells about 600 million products, each with hundreds of reviews), catching all the incentivized reviews is nearly impossible. A recent Wall Street Journal study found more than a third of online reviews on major websites, such as Amazon.com, Walmart, and Sephora, to be fake, a category which includes incentivized reviews (Kapner, 2019). Last year, a Washington Post investigation of Amazon.com 18 months after the ban found that many reviews were paid for (Dwoskin and Timberg 2018). The consequence of the Internet been so permeated with 5-star praise is that consumers are losing trust in online reviews (Dolan 2019).

The more intriguing aspect in the development of incentivized reviews is that Amazon.com did not ban all kinds of incentivized reviews. While Amazon.com discontinued online reviews that were incentivized by the vendors selling products on its platform, it retained online reviews where the incentive is provided by Amazon.com itself. Amazon.com calls these reviews “Vine reviews.” To differentiate between these two kinds of reviews, we term reviews where the incentive is provided by the vendor as vendor-initiated incentivized reviews and the other as platform-initiated incentivized reviews. While Amazon.com has banned the former, it continues to support the latter. For our data, we interestingly find that the ratings of the platform-initiated incentivized reviews are lower than those of the organic reviews. This is the opposite of what is found for vendor-initiated incentivized reviews.

It appears that incentivized reviews will continue to exist since some businesses obviously believe in their effectiveness despite the constant threat of reputational and/or financial penalties. However, is it a good long-term business strategy to incentivize reviewers? This is the central question that this research aims to answer. We tap into the expectation-confirmation theory to hypothesize that the answer will depend on who provides the incentive: vendor or platform. We also develop additional hypotheses about the role of product type and helpfulness of the incentivized review in determining the effectiveness of incentivized reviews.

We test our hypotheses on 180,267 reviews for 2,817 products across seven product categories obtained from Amazon.com. We find that vendor (platform) – initiated incentivized reviews have a higher (lower) rating than the average rating of the previously posted organic reviews for the product. This in turn lowers (increases) the subsequent organic review ratings. Further, we show that the effect is more pronounced for experience products than for search products. We also find that the effect is less pronounced if the incentivized review is viewed as more helpful.

In the following sections, we first discuss related studies on online WOM and product sampling to develop the theoretical foundation of this research. We then examine the nature of biases in incentivized reviews and provide empirical evidence. After presenting the corresponding hypotheses, we sequentially describe the data, the model, and the empirical results. We conclude with a discussion of the findings, managerial implications, and directions for future research.

CHAPTER 2

LITERATURE REVIEW

Most research into online product reviews has investigated relationships between customer reviews and different marketing outcomes (Chen, Wu, and Yoon 2004; Chevalier and Mayzlin 2006; Duan, Gu, and Whinston, 2008; Moe and Trusov 2011; Resnick and Zeckhauser 2002; Sun 2012). Some important research from this area is highlighted first in this section. A few recent studies have focused specifically on the impact of previous reviews on subsequent ones from a social dynamics standpoint (Godes and Silva 2012; Li and Hitt 2008). Our empirical analysis also involves studying how incentivized reviews affect subsequent organic review ratings, and therefore empirical studies that relate online reviews to subsequent reviews are reviewed next. There is a stream of literature on product sampling that has parallels to incentivized reviews, and therefore, some relevant papers from the product sampling field are also reviewed.

2.1 Online Review Rating

Prior research on consumer online reviews has concentrated on establishing the causal relationship between the average rating and sales and reported mixed results (Chen, Wu, and Yoon 2004; Chevalier and Mayzlin 2006; Duan, Gu, and Whinston, 2008; Moe and Trusov 2011; Resnick and Zeckhauser 2002; Sun 2012). For example, Resnick and Zeckhauser (2002) examine a large data set from eBay and find that sellers with better reputations are more likely to succeed in selling their products. Chevalier and Mayzlin (2006) find that an improvement in a book’s reviews leads to an increase in its sales, with one-star reviews having a greater impact on sales than five-star reviews. Sun (2012) demonstrates that a higher standard deviation in review ratings increases sales rank when the average rating is lower than 4.1. Chintagunta, Gopinath, and Venkataraman (2010) find the valence to be an important predictor of box office performance

In contrast, Liu (2006) studies movie reviews and finds that the valence of reviews is not correlated with the weekly movie sales. Duan, Gu, and Whinston (2008) also show that online consumer review ratings do not affect movie sales after accounting for endogeneity of user reviews and product heterogeneity. Interestingly, both studies find that the number of consumer reviews has a positive impact on sales. These results suggest that online reviews have little persuasive effect on consumer purchase decisions but strong awareness effect.

Previous studies have examined the factors that drive consumers to voluntarily share their experiences with others by contributing online reviews. Wu and Huberman (2008) argue that customers are less likely to post positive reviews for highly-rated products since posting a review is costly. Reviewers are motivated to post reviews by the expected impact their reviews will have on the average rating. This implies that reviewers are more likely to post reviews if they have opinions that differ greatly from the average rating and/or when there are fewer reviews available. Therefore, a new review tends to be substantially different from the existing reviews in order to have an impact. Moe and Schweidel (2012) show how previously posted ratings affect an individual's posting behavior in terms of (a) whether to write a review and (b) what rating to assign. They find that a positive rating environment increases posting incidence, whereas a negative rating environment discourages posting. These studies provide strong evidence that reviewers are influenced by previous reviewers, strengthening our conviction that incentivized reviews will influence subsequent reviews.

2.2 Impact of Reviews on Subsequent Reviews

In theory, it is assumed that posted reviews reflect individuals' post-purchase evaluation of the product and are supposed to be independent of the experience of other reviewers. However, a few studies show that an individual's publicly expressed opinion can be influenced by the opinions of others and does not necessarily reflect the individual's true unbiased, independent product evaluation (Godes and Silva 2012; Li and Hitt 2008; Moe and Trusov 2011). Schlosser (2005) finds evidence that reviewers tend to negatively adjust their opinions after reading a negative review. This is because reviewers likely view the person posting a negative review as intelligent, which triggers concerns about the quality and social outcomes of their review. As a result, even when consumers have positive experiences with a product, they adjust their ratings downward in order to avoid giving the impression that they have low standards or are indiscriminate. Further, Schlosser (2005) discusses a multiple-audience effect, that is, people adjust their message to offer a more balanced opinion (Fleming et al. 1990) when facing a heterogeneous audience.

A few recent studies have examined the dynamic processes of online ratings and found that ratings exhibit systematic patterns over time. Specifically, the valence of ratings on average tends to decrease over time (Godes and Silva 2012; Li and Hitt 2008). Li and Hitt (2008) argue that customers who purchase a product early in the product life cycle have significantly different tastes and preferences than those who purchase later in the cycle. Most of the initial product ratings are provided by the early customers but consumed by later customers. This in turn increases the level of dissatisfaction since later customers purchase based on the reviews provided by early customers who have different tastes. In contrast, Godes and Silva (2012) demonstrate that the valence of ratings decreases with the ordinality of the rating rather than time. This is because more reviews lead to more purchase errors, leading to greater dissimilarity between past reviewers and potential customers, which then lowers future ratings. Due to the importance of time and ordinality, our empirical model controls for both while measuring the impact of previous reviews on subsequent ones.

2.3 Product Sampling

Marketers are increasingly adopting product sampling (seeded marketing) as a strategy to drive brand awareness, increase sales, and build customer loyalty. Seeded marketing campaigns involve firms sending products to selected customers and encouraging them to generate WOM in return. This form of marketing communications strategy is also known as “buzz,” or a viral marketing campaign.

Research on online seeded marketing tends to focus on the impact of product sampling on future sales (Hu et al. 2010; Yao et al. 2017; Zhang, Goh, and Lin 2017). For example, Yao et al. (2017) show that offering samples of physical products online increases sales of the products, with the impact being greater for popular brands. In the context of digital products, Hu et al. (2010) examine the effect of offering free samples of music and find that product sampling reduces product uncertainty, leading to better sales. They also find that the impact of online reviews on sales is lower for products with a sampling option than those without.

Zhang, Goh, and Lin (2017) examine the impact of product sampling on the sales of other products in the same store and the sales of the same product in other stores. They find that sampling of a search (experience) product increases (decreases) the sales of other products in the same store, whereas sampling of experience products increases the sales of the same product in another store. Chae et al. (2016) also study the spillover effects of seeded marketing in online contexts. They find that seeding increases conversations about the product among non-selected consumers and decreases WOM about other products from the same brand and about competitors' products in the same category as the focal product. While this literature has explored the effect of product sampling on online reviews, there are no studies that have examined the impact of incentivized reviews (a consequence of product sampling) on organic reviews.

CHAPTER 3

BIASES IN INCENTIVIZED REVIEWS

Marketing communication is a major source for influencing consumer attitudes and behavior. This has been true in the non-digital age and continues to be true in today's digital environment. An important classification in marketing communication is the distinction between media (or marketer) generated content (MGC) and consumer generated content (CGC).

In the non-digital age, advertising by companies over mass media (e.g., TV, Print) made up much of MGC while word of mouth (e.g., by friends, family, and others) was the common manifestation (Day 1971; Sheth 1971) of CGC. Past research has shown that word of mouth is more effective than mass media advertising in terms of influencing potential consumers. Day (1971) mentions that word of mouth is more impactful because the source is viewed as more reliable. *Trust* in the source of communication is of vital importance in the non-digital age. Word of mouth also influences consumer *expectations* (Zeithaml et. al. 1993).

In today's increasingly digital environment, both MGC and CGC permeate the market, each offering information about products and services to individuals who browse the web. MGC takes various forms such as banner advertising, or Google's Adwords type advertising that is related directly to usage of search engines by individuals. CGC takes many forms including blogs, forums, specific applications like Facebook or Twitter, and also *online reviews*.

Marketer generated content in company websites provides information about product specifications and uses. CGC in the form of online reviews provides feedback about the actual experiences of consumers with brand items in almost innumerable number of product categories and subcategories. The growth in the quantum of online reviews has truly been quite phenomenal.

The rise of user-generated content (e.g., customer reviews) in e-commerce is fast outranking all other forms of marketing when it comes to influencing the consumer decision process (TurnTo 2017). In recent years, the number of consumers who read online reviews and contribute their opinions to review forums has dramatically increased (PowerReviews 2019). Most shoppers will begin their online journey by searching for product reviews. Consumers are increasingly reliant upon online reviews when making purchasing decisions (Dimensional Research 2013). According to Kee (2008), 64% of the respondents in Forrester Research's online survey want to read reviews and check ratings on the e-commerce websites they visit and 68% of online shoppers read at least four reviews before making a purchase. In fact, 70 percent of global consumers trust online reviews (Nielson 2015) and 90% of those who read online reviews state that their buying decisions are influenced by online reviews (Dimensional Research 2013).

Just as traditional CGC in the form of word of mouth is considered trustworthy and thus shapes consumer expectations, we believe that this should also be the case with for today's most pervasive CGC source — *online reviews*. Hoeffler (2018) mentions that consumers value opinions from one another more than they value communication that emanates from marketers. Hoeffler (2018) also states that shoppers who interact with CGC such as online reviews, are more than twice as likely to convert compared to those who do not interact. Gesenhues (2013) says that in a survey, a large proportion of surveyed consumers indicate that online reviews influence their buying decisions. It seems obvious to conclude then that online reviews strongly affect consumer *expectations* and *behavior*. How online customer reviews are helpful for the consumer purchasing decision has been studied by Mudambi and Schuff (2010). A meta-analysis of how online reviews affect retail sales also throws light on this important aspect of such reviews (Floyd et al. 2014).

The vast majority of online reviews are written by “organic” consumers who provide feedback about their actual experiences with brands in a variety of product categories and subcategories. It is therefore reasonable to assume that the content of organic reviews provides accurate information about the *true quality* of the products purchased and reviewed.

Like other forms of CGCs, online organic reviews of the digital age are also considered to provide reliable and trustworthy information. Online organic reviews are thus helpful while making consumer purchase decisions. Feedback from the trade (Hoeffler 2018; Gesenhaus 2013) and academic studies (Mudambi and Schuff 2010; Floyd et al. 2014) confirm the existence of this trend. Hoeffler (2018) also describes a study where a majority of their 3,000 respondents find organic reviews and incentivized reviews to be equally credible. Assuming this pattern generalizes to the greater general population, we propose that given the trust in incentivized online reviews, the review contents will have considerable impact on shaping the *expectations* of potential consumers.

Hence, we would expect that readers would typically find incentivized reviews to be worthy of trust. If incentivized reviews happen to be biased or inaccurate, individuals who buy and experience the product after reading the incentivized reviews, will be disillusioned. This will happen because consumer *expectations* (as built up by the incentivized reviews) about the supposedly true product quality will not match the actual product quality experienced by the product buyers. In this chapter, we describe the nature of biases in incentivized reviews and provide empirical evidence.

3.1 The Nature of Biases in Incentivized Reviews

Although online reviews written by "organic" consumers form the vast majority of online reviews, there is a form of such reviews called "incentivized reviews" that are different in nature from organic or non-incentivized reviews. Incentivized reviews are posted by individuals who are usually incentivized by manufacturers or retailers who offer them free samples or products free of charge in exchange for their online reviews (Petrescu et al. 2018). There are two types of incentivized reviews—(1) vendor-initiated incentivized reviews and (2) platform-initiated incentivized reviews.

Vendor-initiated incentivized reviewers are believed to highly praise the product even though they claim that their reviews are unbiased and honest (Petrescu et al. 2018). There are three possible explanations for the higher ratings of vendor-initiated incentivized reviews. First, the norm of reciprocity is a social convention that requires people to return a favor when the favor is given by others (Falk and Fischbacher 2006; Gouldner 1960). This suggests that incentivized reviewers may feel obligated to provide positive reviews in return for free products. Second, vendors prefer choosing reviewers who tend to write positive reviews since they will be more likely to provide favorable reviews. Third, many incentivized reviewers gain reputations for consistently posting positive reviews and ratings in order to make sure that they will receive more free products in the future. Therefore, we expect that vendor-initiated reviews are more positively biased when compared to organic reviews.

Unlike vendor-initiated incentivized reviews, platform-initiated incentivized reviews are initiated by the platform that provides a platform for the vendors. In this case, the firm operating the platform (e.g., Amazon.com, Google) selects participants to receive free products in exchange for posting reviews, and the reviewers typically have no contact with the vendor. This allows the platform to avoid reviewers posting upward biased reviews.

The platform-initiated incentivized reviews are generated by experts who are selected by the platform. Prior studies have found that expert reviewers are more likely to express negative opinions (Goes, Lin, and Yeung 2014; Moe and Schweidel 2012; Schlosser 2005). According to Moe and Schweidel (2012), highly active reviewers are more negative in their evaluations. In an experimental setting, Schlosser (2005) demonstrates that reviewers strive to differentiate their reviews, and negative reviews are more differentiated because negative reviewers are perceived as more intelligent (Amabile 1983; Amabile and Glazebrook 1982). Goes, Lin, and Yeung (2014) suggest that reviewers are more likely to post a negative rating when they receive higher social recognition. They argue that as reviewers become more popular and gain higher social recognition from other customers, they are more likely to provide a negative rating because posting negative reviews makes them look like experts. Expert reviewers or highly active reviewers are more likely to post negative opinions about products. Thus, we expect that platform-initiated incentivized reviews have lower ratings than organic reviews.

In the following section, we test whether such biases exist in incentivized reviews and provide empirical evidence.

3.2 Empirical Evidence

3.2.1 Data

We collect data from Amazon.com's Web Service (AWS). Amazon.com was one of the first online stores to allow consumers to post product reviews in 1995, and it remains one of the most important resources for consumers looking to make informed purchase decisions. For each product, consumers can rate the product on a discrete five-star rating scale, write a review, and vote on the helpfulness of other reviews. On each product's page, Amazon.com displays the overall product rating (on a scale of 5), with the percentage of reviews per star and stacks them sequentially next to customer reviews. The customer reviews can be sorted by helpfulness or recency.

We use product reviews posted from October 1, 2004 to August 31, 2015. We collect reviews from three categories: (a) beauty, (b) grocery, and (c) health and personal care. For each product, we obtain all the posted review texts, dates, ratings, and votes on helpfulness.

On Amazon.com, vendor-initiated incentivized reviews are required to include a disclosure indicating that the reviewer was provided the product for free or at a discounted price in exchange for a review. Therefore, vendor-initiated incentivized reviews explicitly include some variants of the following disclosure statement: "I received this product for free or at a discount in exchange for my honest and unbiased review." To detect all the variants of such statements, we first select any review that includes the following variants of disclosure statements in a single sentence of the review text:

[*given* | *provided* | *received* | *sent*] &

[*discount* | *free*] &

[*in exchange* | *in trade*] &

[*authentic* | *fair* | *genuine* | *honest* | *impartial* | *unbiased*] &

[*experience* | *feedback* | *opinion* | *review* | *trial*].

A human coder then manually inspects each review and excludes any non-incentivized reviews that happen to match the above disclosure expression. For platform-initiated incentivized reviews, we select reviews that include a label, "Amazon Vine Review," which indicates that the review was written for the Vine program. These considerations result in a data set of 664,183 reviews, with 180,501 reviews from 2,319 vendor-initiated incentivized products, and 483,682 reviews from 3,052 platform-initiated incentivized products.

3.2.2 Results

Tables 1 and 2 present the faction of star ratings for vendor-initiated incentivized reviews and platform-initiated incentivized reviews, respectively. We find that vendor-initiated incentivized reviews have more five-star rating reviews (80.35% versus 68.67%) and fewer one-star rating reviews than organic reviews for the same products (.75% versus 6.66%). Contrary to the distributions of the vendor-initiated incentivized review ratings, platform-initiated incentivized reviews include far less extreme positive (five-star) ratings (80.35% versus 38.09%). Overall, we find that vendor (platform) – initiated incentivized reviews have much higher (lower) ratings than organic reviews.

Table 1
Fraction of Star Ratings of Vendor-Initiated Incentivized Reviews

	Beauty		Grocery		Health and Personal Care		Overall	
Star Rating	Organic	Incentivized	Organic	Incentivized	Organic	Incentivized	Organic	Incentivized
1 star (%)	6.03	.91	3.61	1.80	8.34	.51	6.66	.75
2 stars (%)	3.72	.66	3.08	.60	4.39	.70	3.91	.68
3 stars (%)	6.30	2.89	5.52	2.99	6.38	3.17	6.24	3.04
4 stars (%)	14.29	16.65	14.10	13.17	14.92	14.27	14.52	15.18
5 stars (%)	69.66	78.90	73.69	81.44	65.96	81.36	68.67	80.35

Table 2
Fraction of Star Ratings of Platform-Initiated Incentivized Reviews

	Beauty		Grocery		Health and Personal Care		Overall	
Star Rating	Organic	Incentivized	Organic	Incentivized	Organic	Incentivized	Organic	Incentivized
1 star (%)	8.07	2.01	6.56	2.66	9.05	2.83	8.17	2.46
2 stars (%)	5.32	6.00	4.53	7.36	5.29	6.24	5.17	6.37
3 stars (%)	7.97	17.16	7.20	20.01	7.03	16.23	7.50	17.37
4 stars (%)	18.60	37.52	13.72	35.91	15.12	33.72	16.52	35.71
5 stars (%)	60.05	37.31	67.99	34.05	63.52	40.99	62.64	38.09

We analyze the difference between the average ratings of organic reviews and that of incentivized reviews by conducting t-tests. The results are presented in Tables 3 and 4. On average, vendor-initiated incentivized reviews have a rating of 4.74/5.00 and organic reviews have a rating of 4.35/5.00. The results show that the ratings of vendor-initiated incentivized reviews are significantly higher than those for organic reviews (difference = .391, $p < .001$). In contrast, platform-initiated incentivized reviews receive lower ratings than organic reviews. Specifically, platform-initiated incentivized reviews have an average rating of 4.01/5.00, while organic reviews receive that of 4.20/5.00 (difference = -.197, $p < .001$). The results are consistent across the three categories. Overall, we confirm that vendor (platform) – initiated incentivized reviewers post more positive (negative) reviews than organic reviewers.

Table 3
Comparison of Means by Review Type
Vendor-Initiated Incentivized Reviews

Product Category	**Number of Products**	**Review Type**	**Number of Observations**	**Average Rating**	**Standard Deviation**	**Difference**	**t-Value**
Beauty	921	Organic Incentivized	83,005 1,213	4.378 4.720	1.144 .639	.341***	10.373
Grocery	129	Organic Incentivized	22,438 167	4.512 4.719	.989 .719	.207***	2.698
Health and Personal Care	1,269	Organic Incentivized	72,101 1,577	4.258 4.753	1.258 .594	.495***	15.583
Overall	2,319	Organic Incentivized	177,544 2,957	4.346 4.737	1.177 .620	.391***	18.025

Notes: *** represents the significance level at the 1%.

Table 4
Comparison of Means by Review Type
Platform-Initiated Incentivized Reviews

Product Category	Number of Products	Review Type	Number of Observations	Average Rating	Standard Deviation	Difference	t-Value
Beauty	1,162	Organic	188,384	4.172	1.260	-.151***	20.772
		Incentivized	33,309	4.021	.982		
Grocery	625	Organic	67,224	4.321	1.192	-.407***	40.437
		Incentivized	16,612	3.913	1.033		
Health and Personal Care	1,265	Organic	146,100	4.188	1.302	-.150***	19.296
		Incentivized	32,026	4.038	1.037		
Overall	3,052	Organic	401,708	4.203	1.266	-.197***	41.8445
		Incentivized	81,947	4.006	1.015		

Notes: *** represents the significance level at the 1%.

3.3 Discussion

In this chapter, we examine the nature of biases in incentivized reviews. We find that vendor-initiated incentivized reviews have higher ratings than organic reviews. Therefore, they have the potential of misleading customers and putting businesses that do not incentivize their reviewers at a disadvantage. Realizing these pitfalls, most platforms, such as Amazon.com, Google, and Yelp, have banned incentivized reviews by imposing financial and/or reputational penalties on violators. It is, however, difficult for platforms to police vendors due to the sheer volume of online reviews. Amazon.com, for example, carries 600 million products, with each product having hundreds of reviews.

Industry studies have found that even after the ban, many vendors at Amazon.com continue to incentivize their reviewers (Dwoskin and Timberg 2018). The fact that despite platforms like Amazon.com, Google, etc., banning such practices, many vendors continue to incentivize their reviewers would suggest that some businesses think it is a profitable strategy. But is it? This is what we seek to answer with this research.

Interestingly, while Amazon.com discontinued most incentivized online reviews, they retained incentivized online reviews from "expert" reviewers called Vine reviews. These reviewers are selected based on their reviewer rank, which is a reflection of the quality and helpfulness of their reviews as judged by other customers on the platform (Amazon.com 2019). According to Amazon.com (2019), such reviews offer the independent opinions of the Vine reviewers as the vendors cannot influence, modify or edit the reviews. The purpose of the program is to provide customers with honest and unbiased feedback from some of the most trusted reviewers. However, we find that platform-initiated incentivized reviews are negatively biased when compared to organic reviews.

In the following chapter, we develop a set of hypotheses to test how such biases in incentivized reviews affect the nature of subsequent organic (i.e., non-incentivized) reviews.

CHAPTER 4

THEORY AND HYPOTHESES

Although the number of incentivized reviews has dramatically increased over recent years, none of the previous studies of online reviews has examined how incentivized reviews affect subsequent customers. We draw on expectation-confirmation theory (Oliver 1980) to develop a conceptual understanding of incentivized reviews on subsequent organic review ratings. We next briefly describe the expectation-confirmation theory and then develop our hypotheses.

4.1 Expectation-Confirmation Theory

The process of a consumer's product evaluation involves pre-purchase and post-purchase evaluations separated in time by the consumer's purchase of and direct experience with the product (Anderson and Sullivan 1993; Kuksov and Xie 2010). Consumers form pre-purchase evaluations based on publicly available information, such as marketing mix activities and WOM. These pre-purchase evaluations reflect consumer's expectations of the product, and as a result, they provide a benchmark against which the actual product experience is compared (Anderson and Sullivan 1993). In the post-purchase stage, a consumer forms post-purchase evaluation based on the new information that he or she gains from the actual performance of the product. The expectation-confirmation theory (Oliver 1980) states that if the actual performance meets one's expectations, confirmation is formed and the consumer is satisfied, whereas if the perceived performance falls short of expectation, disconfirmation results and the consumer is dissatisfied.

Online organic reviews provide feedback about the actual experiences of consumers with brands in a variety of product categories and subcategories. Online organic reviews are like a pure-form exemplification of consumer generated content (CGC). In the nondigital age, CGCs in the form of WOM have traditionally been more impactful because the source is viewed as more credible (Day 1971). WOM-type CGCs also influences consumer *expectations* (Zeithaml, Berry, and Parasuraman 1993). Like other forms of CGCs, online organic reviews of the digital age are also considered to provide reliable and trustworthy information. Online organic reviews are thus helpful while making consumer purchase decisions. Feedback from the trade (Hoeffler 2018) and academic studies (Floyd et al. 2014; Mudambi and Schuff 2010) indicate the existence of this trend. It is therefore reasonable to conclude that the content of organic reviews provides accurate information about the *true quality* of the products purchased and reviewed. One would therefore expect the organic online reviews to lead to the formation of *true consumer expectations*. Normally, this should match the product performance that a consumer would witness after purchase and consumption.

Hoeffler (2018) describes a study in which a majority of their 3,000 respondents find organic reviews and incentivized reviews to be equally credible. Hence, due to consumers' inability to discern between organic and incentivized reviews, we would expect potential consumers to find incentivized reviews as worthy of trust as organic reviews. If incentivized reviews happen to be biased or inaccurate, their insertion into a product's reviews would bias the product ratings and reviews, leading to the formation of *biased consumer expectations*.

A positive bias would lead to artificially raising consumer expectations, setting consumers for future disillusionment. This will happen because consumer *expectations* (as built up by the incentivized reviews) about the supposedly true product quality will not match the actual product quality experienced by the product buyers. On the contrary, a negative bias would lower consumer expectations and subsequently improve satisfaction among consumers because the product performance would exceed consumer expectations (weighed down by negative incentivized reviews). The size of bias would be the difference between the rating of an incentivized review and the average rating of organic reviews posted before the incentivized review.

4.2 Vendor-Initiated Incentivized Review

Since vendor-initiated incentivized reviews tend to praise products being reviewed and have overwhelmingly higher ratings than organic reviews, subsequent consumers are more likely to form higher expectations about the product. These higher expectations may lower the consumer's post-purchase evaluation if the product falls short of expectations. Therefore, subsequent reviewers are more likely to engage in disconfirmation behavior by posting negative reviews. This will lead to dissatisfaction and, we suggest, to a lower level of evaluation of organic reviews posted after the vendor-initiated incentivized review. This leads us to our first hypothesis $H1_a$ .We express the hypothesis as:

$H1_a$: *A vendor-initiated incentivized review will lower subsequent organic review ratings if it has a higher rating than the prevailing rating of the previous organic reviews.*

4.3 Platform-Initiated Incentivized Reviews

Platforms select incentivized reviewers based on several criteria but mainly on their review rank which is a reflection of the quality and helpfulness of their reviews judged by other customers. Therefore, the chosen reviewers are more active and highly involved in the online community. Prior studies have found that expert reviewers are more likely to post negative opinions (Goes, Lin, and Yeung 2014; Moe and Schweidel 2012; Schlosser 2005). According to Moe and Schweidel (2012), highly active reviewers are more negative in their evaluations. In an experimental setting, Schlosser (2005) demonstrates that reviewers strive to differentiate their reviews, and negative reviews are more differentiated because negative evaluations are perceived as more intelligent (Amabile and Glazebrook 1982; Amabile 1983). Goes, Lin, and Yeung (2014) suggest that reviewers are more likely to post a negative rating when they receive higher social recognition. They also propose that as reviewers become more popular and gain higher social recognition by other customers, they are more likely to provide a negative rating because posting negative reviews makes them look like experts.

Hence, the expected quality of the product as perceived by the potential consumer would be low after he or she reads a platform-initiated incentivized review. The actual product quality of the purchased product as experienced by potential customers is likely to be higher than this expected quality level, which will lead to customer satisfaction. Therefore, subsequent reviewers are more likely to post positive organic reviews. This leads us to hypothesis $H1_b$.

$H1_b$: A platform-initiated incentivized review will raise the subsequent organic review ratings if it has a lower rating than the prevailing rating of the previous organic reviews.

4.4 Review Helpfulness

To provide reliable recommendations, major online retailers, including Amazon.com, incorporate mechanisms designed to control the quality of product reviews. For example, they allow users to vote on the helpfulness of other users' reviews. If a potential customer reads a review and finds it helpful, he or she can vote for it. If someone else reads the review and finds it unhelpful, he or she can vote against it. Overall helpfulness of the review then determines the rank of the review to be displayed on each product's page. Most online retailers display each product's reviews in the order of helpfulness. Therefore, a review with more helpful votes carries more weight in the minds of potential customers.

Review helpfulness refers to a customer's attitude towards the information conveyed in a review by another customer (Baek, Ahn, and Choi. 2012; Mudambi and Schuff 2010; Pan and Zhang 2011; Yin, Zhang, and Li 2014). It reflects customers' perceived value of the information that helps reduce their uncertainties and risks when considering a potential purchase and assists them in their decision-making processes. Previous research finds that reviews viewed as helpful by other customers have a stronger influence on the purchase decisions than unhelpful reviews (Tormala and Rucker 2007). If a review is viewed as helpful, it increases the ability of potential customers to assess the quality of the product and reduce purchase errors.

Reviews that are more in-depth or that contain more arguments are perceived as more helpful (Mudambi and Schuff 2010; Willemsen et al. 2011) and thus allow potential customers to predict how much they will like the reviewed product with greater certainty. Thus, we expect that the negative (positive) effect of a vendor (platform) –initiated incentivized review on the subsequent organic review ratings would be less pronounced if the content of the incentivized review is viewed as more helpful. This leads to hypotheses $H2_{a(b)}$.

> $H2_{a(b)}$:*The negative (positive) effect of the vendor (platform) –initiated incentivized review on the subsequent organic review ratings would be less pronounced if the incentivized review is viewed as more helpful.*

4.5 Product Types

Nelson (1970; 1974) proposes the classification of products into search and experience goods based on consumers' ability to discover product quality before purchase. Search products are those for which consumers can obtain information on product quality prior to purchase, while experience products are those that require actual purchase in order to evaluate product quality (Nelson 1970). Examples of search products include cameras, cell phones, and printers; examples of experience products are video games, movies, and music.

The main reason for consumers to read online reviews from other customers prior to purchase is to reduce purchase uncertainty. Perceived quality of a search product can be objectively compared and evaluated, while that of an experience product is subjectively compared and evaluated with more difficulty (Huang, Lurie, and Mitra 2009). In general, information about search attributes is typically presented in a straightforward manner and should require less time to obtain, whereas obtaining information about experience attributes may involve reading consumer reviews and ratings. Therefore, the difference between search and experience products should influence consumer's reliance on other consumers' reviews.

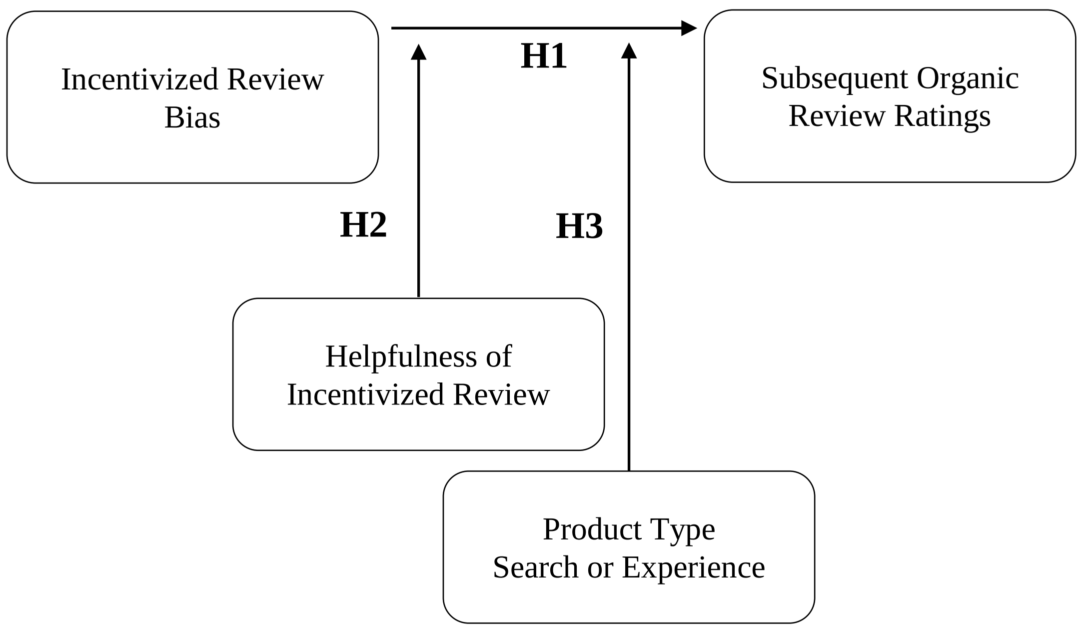
Nelson (1970) predicts that the recommendations of others will be used more and have greater impact for purchases of experience products than search products. Huang, Lurie, and Mitra (2009) find that the presence of product reviews from other consumers have a greater impact on consumer search and purchase behavior for experience products than for search products. Further, they find that experience products involve greater depth (time per page) and lower breadth (total number of pages) of search than search products. Thus, online reviews could be more useful in reducing the risk of purchasing experience goods than search goods. The conclusion we take from these results is that the negative (positive) effect of a vendor (platform)

– initiated incentivized reviews on subsequent organic review ratings would be more pronounced for experience products than for search products. This leads to hypotheses $H3_{a(b)}$.

> *$H3_{a(b)}$:The negative (positive) effect of the vendor (platform) – initiated incentivized review on the subsequent organic review ratings would be more pronounced for experience products than for search products.*

Figure 3 illustrates the conceptual model of this research.

Figure 3
Conceptual Model



CHAPTER 5

EMPIRICAL ANALYSIS

5.1 Data

We collect data from Amazon.com's Web Service (AWS). For vendor-initiated incentivized reviews, we use product reviews posted from January 1, 2012 to August 31, 2015. For platform-initiated incentivized reviews, we collect product reviews posted after the Vine program was launched. Specifically, we use reviews posted from August 1, 2007 to August 31, 2015. We collect reviews for some search and experience products that are classified based on Nelson's categorization (1970; 1974). For search products, we collect reviews from four categories: (a) clothing, shoes, and jewelry; (b) sport and patio, (c) lawn and garden, and (d) toys. For experience products, we gather reviews from another three categories: (a) beauty, (b) health and personal care, and (c) grocery and gourmet food.

For each product, we obtain all the posted review texts, dates, ratings, and votes on helpfulness. Using computer-aided text analysis (CATA) and manual coding of the online review text as described in Chapter 3, we then identify vendor-initiated incentivized reviews as ones that have a disclosure indicating that the reviewer was provided the product for free or at a discounted price in exchange for a review. For platform-initiated incentivized reviews, we select reviews that include a label, "Amazon Vine Review," which indicates that the review was written for the Vine program.

Since it is difficult to ascertain the impact of each incentivized review in cases where there are more than one, we limit our sample to products that have only one incentivized review. We remove items that do not have any reviews posted before or after the incentivized review.

These considerations result in a data set of 180,267 reviews, with 132,933 reviews from 1,710 experience products, and 47,334 reviews from 1,107 search products.

5.2 Dependent and Independent Variables

Our dependent measure is RATING_{ij}, the rating assigned by reviewer i to product j. The best rating is a five-star rating, and the worst is a one-star rating. We next describe the independent variables.

Incentivized review bias (INCENT BIAS). We used the difference between the rating of an incentivized review and the average rating of previously posted organic reviews to measure the potential degree of bias in the incentivized review relative to organic reviews. The larger the difference, the more favorable (unfavorable) the vendor (platform) – initiated incentivized review is.

Incentivized review helpfulness (INCENT REV HELP). The helpfulness of an incentivized review is measured by the percentage of customers who find the review helpful. This is derived by dividing the number of customers who voted that the incentivized review was helpful by the total votes in response to the "was this reviews helpful to you" question. Figure 4 shows an example of the question on Amazon.com.

Figure 4
Review Helpfulness on Amazon.com

Product type (PROD TYPE). Product type is coded as a binary variable, with the value of 0 for search products and 1 for experience products.

5.3 Control Variables

Previous research suggests that review ratings change systematically over both order and time (Godes and Silva 2012; Li and Hitt 2008; Wu and Huberman 2008). Specifically, Godes and Silva (2012) find that ratings become increasingly negative as more reviews arrive when controlling for time. Since our focus is on measuring the impact of previously posted incentivized review on subsequent ratings, we must account for both processes. To control for the impact of sequential and temporal dynamics (Godes and Silva 2012), we include the variable ORDER_{ij}, which captures the position of a review from reviewer i in the sequence of reviews for a given product j, and the variable TIME, which captures how much time has elapsed since the first review.

Reviewer average (REV AVG). Some reviewers tend to be more positive or negative than others when assigning ratings to products (Godes and Silva 2012; Peng et al. 2019). We control for observed reviewer-level heterogeneity via $\mathrm{REV\ AVG}_{ij}$, which captures the average rating of all the reviewer i's reviews on products in the same category other than j.

Review length (REV LEN). Godes and Silva (2012) find that long reviews are likely to be more negative than short reviews. Thus, we control for the length of the written review by REV LEN, which measures the number of words in the incentivized review.

Total helpfulness votes received by the incentivized review (*INCENT HELP VOTE*). We also include the total number of votes on each incentivized review's helpfulness as a control variable. Since we measure helpfulness of an incentivized review as a percentage, this could hide some potentially important information. For example, "8 out of 10 people found the review helpful" may have a different impact on the subsequent ratings than "80 out of 100 people found the review helpful" (Mudambi and Schuff 2010). Table 5 summarizes the variables and the measures.

Table 5
Variables and Measures

Variable	Measure
1. Rating	Online product rating for a product by a reviewer
2. Incent Bias	The difference between the rating of an incentivized review and the average rating of previously posted organic reviews
3. Order	The position of a review in the sequence of reviews for a given product
4. Time	The time that has elapsed since the first review
5. Rev Len	The length of the written review, in number of words.
6. Rev Avg	The average rating of all of a reviewer's reviews on products other than a given product
7. Incent Help Vote	The number of total helpfulness votes received by an incentivized review
8. Incent Rev Help	The number of helpfulness votes divided by the total number of votes received by an incentivized review
9. Prod Type	0 for search products; 1 for experience products

5.4 Model Specification

Since our dependent variable is a discrete ordinal response, we employ the ordered-logit model to measure consumer evaluation. Let U_{ij} be the underlying latent variable that captures the reviewer i's evaluation of product j. The ordered logit model is as follows:

$$
\begin{aligned}
(1)\ U_{ij} = {} & \beta_1 \mathrm{INCENT\ BIAS}_{ij} + \beta_2 \mathrm{INCENT\ BIAS}_{ij} \times \mathrm{INCENT\ REV\ HELP}_{ij} \\
& + \beta_3 \mathrm{INCENT\ BIAS}_{ij} \times \mathrm{PROD\ TYPE}_{ij} + \beta_4 \mathrm{ORDER}_{ij} + \beta_5 \mathrm{TIME}_{ij} + \beta_6 \mathrm{REV\ LEN}_{ij} \\
& + \beta_7 \mathrm{REV\ AVG}_{ij} + \beta_8 \mathrm{INCENT\ HELP\ VOTE}_{ij} + \beta_9 \mathrm{INCENT\ REV\ HELP}_{ij} \\
& + \beta_{10} \mathrm{PROD\ TYPE}_{ij} + \beta_{11} \mathrm{YEAR}_{ij} + \delta_w \mathrm{MONTH}_{ij} + \varepsilon_{ij}
\end{aligned}
$$

In Equation 1, β_1 is the main effect of $\mathrm{INCENT\ BIAS}_{ij}$ on reviewer i's online rating of product j. The hypothesized moderation effects of $\mathrm{INCENT\ REV\ HELP}_{ij}$ and $\mathrm{PROD\ TYPE}_{ij}$ are given by the coefficients β_2 and β_3, respectively. The effects of the control variables are given by the coefficients β_4 to β_{10}. δ_w is the fixed effect of different months in a year. The effect of the calendar year when a review was posted is captured by the coefficient β_{11}.

The model is estimated via maximum likelihood where a set of four cutoff values $\mu_k, k \in \{1, 2, 3, 4\}$ is estimated, and the discrete ordered response $RATING_{ij}$ is generated based on where the latent evaluation U_{ij} falls within the cutoffs:

$$RATING_{ij} = 1 \Leftrightarrow U_{ij} < \mu_1,$$

$$RATING_{ij} = k \in \{2,3,4\} \Leftrightarrow U_{ij} \in [\mu_{k-1}, \mu_k],$$

$$RATING_{ij} = 5 \Leftrightarrow U_{ij} \geq \mu_4$$

5.5 Results

5.5.1 Summary Statistics and Correlations

Table 6
Descriptive Statistics
Vendor-Initiated Incentivized Products

	M	**SD**	**Min**	**Max**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1. Rating	4.363	1.144	1	5	1								
2. Incent Bias	.214	.668	-4	4	-.092*	1							
3. Order	262.860	411.794	3	2967	-.021*	.039*	1						
4. Time	266.965	244.572	2	1308	-.071*	.180*	.554*	1					
5. Rev Len	53.339	73.888	0	2217	.065*	-.032*	-.118*	-.132*	1				
6. Rev Avg	4.388	.780	1	5	.340*	-.038*	-.071*	-.090*	.083*	1			
7. Incent Help Vote	8.027	26.712	0	836	-.004	.047*	-.016*	-.072*	-.002	.005	1		
8. Incent Rev Help	.596	.451	0	1	.011*	.002	-.111*	-.116*	.043*	.010*	.183*	1	
9. Prod Type	.744	.436	0	1	-.021*	.026*	.181*	.083*	-.025*	.002	.113*	.059*	1

Notes: Correlations above are significant at *p* < .10 and above.
$\text{Incent Bias}_{\text{vendor-initiated}} = (\text{Incentivized Rating}) - (\text{Average of Previous Ratings})$

Table 7
Descriptive Statistics
Platform- Initiated Incentivized Products

	M	SD	Min	Max	1	2	3	4	5	6	7	8	9
1. Rating	4.202	.986	1	5	1								
2. Incent Bias	.027	1.093	-4	3.429	.137*	1							
3. Order	79.434	105.054	3	1542	.131*	-.011	1						
4. Time	450.889	638.359	2	3145	.112*	.111*	.561*	1					
5. Rev Len	119.950	112.368	0	2325	-.106*	-.032*	-.209*	-.230*	1				
6. Rev Avg	4.175	.479	1	5	.314*	.041*	.142*	.162*	-.106*	1			
7. Incent Help Vote	1.751	6.589	0	100	.025*	.075*	-.063*	.018*	.006	.028*	1		
8. Incent Rev Help	.316	.415	0	1	-.002	.155*	-.108*	.130*	.035*	.024*	.341*	1	
9. Prod Type	.783	.412	0	1	-.109*	.023*	-.262*	-.283*	.030*	-.136*	-.106*	-.026*	1

Notes: Correlations above are significant at p < .10 and above.
$\text{Incent Bias}_{\text{platform-initiated}} = \text{(Average of Previous Ratings)} - \text{(Vine Rating)}$

Tables 6 and 7 report the summary statistics and the correlation matrix of the major variables in the full data set by incentivized review type. Note that for an intuitive interpretation purpose, we subtract the average rating of the previous organic reviews from an incentivized review rating for each product when we construct INCENT BIAS for each of the vendor–initiated incentivized products. For platform–initiated incentivized products, we subtract the average rating of the previous organic reviews from the rating of a platform–initiated incentivized review.

For vendor–initiated incentivized reviews, INCENT BIAS has an average value of .214. This means that vendor-initiated incentivized reviews have higher ratings than the average rating of organic reviews posted before the vendor-initiated incentivized review. For the platform-initiated incentivized reviews, INCENT BIAS has an average value of .027. This finding suggests that platform-initiated incentivized reviewers in general post more negative ratings than the previous organic reviewers. The difference between the average rating of the previous organic reviews and the rating of a vendor (platform) –initiated incentivized review is significantly negatively (positively) correlated with the average rating of subsequent organic review ratings ($r_{\text{vendor-initiated}}$= -.092, $p < .001$; $r_{\text{platform-initiated}}$ = .137, $p < .001$).

Table 8
Fraction of Star Ratings of Vendor-Initiated Incentivized Reviews

	Organic			Incentivized		
Star Rating	**Search**	**Experience**	**Overall**	**Search**	**Experience**	**Overall**
1 star (%)	5.14	7.31	6.77	.22	.56	.43
2 stars (%)	3.62	4.02	3.92	.44	.56	.52
3 stars (%)	5.83	6.24	6.13	2.77	3.18	3.02
4 stars (%)	14.61	14.29	14.37	12.97	15.67	14.62
5 stars (%)	70.81	68.13	68.81	83.59	80.03	81.41
Average Stars	4.423	4.319	4.345	4.793	4.740	4.761
	(1.093)	(1.210)	(1.182)	(.523)	(.598)	(.570)

Notes: Numbers in parentheses are standard deviations.

Table 9
Fraction of Star Ratings of Platform- Initiated Incentivized Reviews

	Organic			Incentivized		
Star Rating	**Search**	**Experience**	**Overall**	**Search**	**Experience**	**Overall**
1 star (%)	3.79	2.52	2.89	3.41	3.41	3.41
2 stars (%)	4.29	5.25	4.97	3.90	1.37	2.41
3 stars (%)	9.51	14.28	12.87	13.17	10.92	11.85
4 stars (%)	23.59	32.36	29.77	33.17	49.49	42.77
5 stars (%)	58.82	45.6	49.49	46.34	34.81	39.56
Average Stars	4.294	4.133	4.242	4.151	4.109	4.127
	(1.053)	(1.001)	(.810)	(1.020)	(.900)	(.951)

Notes: Numbers in parentheses are standard deviations.

Tables 8 and 9 show the fraction of star ratings for both incentivized reviews and organic reviews by incentivized review type. For both experience and search products, we find that vendor-initiated incentivized reviews have fewer one-star rating reviews (.43% versus 6.77%) and more five-star rating reviews (81.41% versus 68.81%) than organic reviews for the same products. Vendor-initiated incentivized reviews have an average rating of 4.761 and organic reviews have an average rating of 4.345. Contrary to the distributions of the vendor-initiated incentivized review ratings, platform-initiated incentivized reviews include far less extreme positive (five-star) ratings (81.41% versus 39.56%). Overall, we find evidence that vendor (platform) - initiated incentivized reviews have much higher (lower) ratings than organic reviews.

5.5.2 Preliminary Results

Table 10
Comparison of Means by Review Type
Vendor- Initiated Incentivized Reviews

Review Type	Number of Observations	Average Rating	Standard Deviation	Difference	t-Value
Organic	149,585	4.345	1.182	.415***	16.897
Incentivized	2,319	4.761	.570		

Notes: *** represents the significance level at the 1%.

Table 11
Comparison of Means by Review Type
Platform- Initiated Incentivized Reviews

Review Type	Number of Observations	Average Rating	Standard Deviation	Difference	t-Value
Organic	27,865	4.242	.810	-.116***	3.143
Vine	498	4.127	.951		

Notes: *** represents the significance level at the 1%.

We analyze the difference between the average ratings of organic reviews and that of incentivized reviews by conducting a t-test. The results are presented in Tables 10 and 11. On average, vendor-initiated incentivized reviews have a rating of 4.76/5.00 and organic reviews have a rating of 4.35/5.00. A t-test indicates that the ratings of vendor-initiated incentivized reviews are significantly higher than those of organic reviews (difference = .415, $p < .001$). In contrast, platform-initiated incentivized reviews have lower ratings than organic reviews (difference = -.116, p < .001). Specifically, platform-initiated incentivized reviews have an average rating of 4.13, while organic reviews receive that of 4.24. The results indicate that vendor (platform) -initiated incentivized reviewers post more positive (negative) reviews than organic reviewers.

Table 12
Comparison of Means by Product Category
Vendor- Initiated Incentivized Reviews

Product Category	Number of Products	Number of Observations (Pre/Post)	Ave. Rating of Previous Reviews	Average rating of Incentivized Reviews	Average Rating of Post Reviews	Difference between Pre and Post Reviews	t-value
Search	902	23,622/14,349	4.582 (.555)	4.793 (.523)	4.425 (.705)	-.157***	6.121
Experience	1,417	72,172/39,442	4.496 (.567)	4.740 (.598)	4.316 (.710)	-.181***	9.292
Overall	2,319	95,794/53,791	4.530 (.564)	4.761 (.570)	4.358 (.710)	-.172***	11.051

Notes: 1) *** represents the significance level at the 1%.
2) Numbers in parentheses are standard deviations.

Table 13
Comparison of Means by Product Category
Platform- Initiated Incentivized Reviews

Product Category	Number of Products	Number of Observations (Pre/Post)	Ave. Rating of Previous Reviews	Average rating of Vine Reviews	Average Rating of Post Reviews	Difference between Pre and Post Reviews	t-value
Search	205	4,858/3,398	4.216 (1.122)	4.151 (1.020)	4.402 (.945)	.187***	7.927
Experience	293	8,557/11,052	4.114 (1.030)	4.109 (.900)	4.146 (.994)	.032**	2.180
Overall	498	13,415 /14,450	4.151 (1.065)	4.127 (.950)	4.206 (.989)	.055***	4.491

Notes: 1) ***, ** represent the significance levels at the 1%, and 5%, respectively.
2) Numbers in parentheses are standard deviations.

We then compare the average rating of reviews posted prior to incentivized reviews to that of reviews posted after incentivized reviews. Tables 12 and 13 summarize the results.

Overall, we find that organic reviews posted prior to vendor-initiated incentivized reviews receive an average rating of 4.53/5.00 and reviews posted after incentivized reviews receive an average rating of 4.36/5.00 (difference = -.172, $p < .001$). Organic reviews posted prior to platform-initiated incentivized reviews receive an average rating of 4.15/5.00 and reviews posted after incentivized reviews receive an average rating of 4.21/5.00 on average (difference = .055, $p < .001$). These findings indicate that vendor (platform) –initiated incentivized reviews lower (increase) future organic review ratings.

We compare the effect of incentivized review on future ratings for both search and experience products. Tables 12 and 13 show the t-test results for both experience and search goods by incentivized review type. For vendor-initiated incentivized reviews of search products, previous reviews receive an average rating of 4.58/5.00, whereas post reviews receive an average rating of 4.43/5.00 (difference = -.157, $p < .001$). For vendor-initiated incentivized reviews of experience products, reviews posted prior to incentivized reviews receive an average rating of 4.50/5.00, whereas reviews posted after incentivized reviews receive an average rating of 4.32/5.00 (difference = -.181, $p < .001$).

For platform-initiated incentivized reviews, we find the opposite results. The prior reviews of search products have an average rating of 4.22/ 5.00, whereas the post reviews receive an average rating of 4.40/5.00 (difference = .187, $p < .001$). Similarly, the prior reviews of experience products receive an average rating of 4.11/5.00, whereas the post reviews receive an average rating of 4.15/5.00 (difference = .032, $p < .05$). Overall, we find that the subsequent reviews of a platform–initiated incentivized review have a higher average rating than that of the previously posted reviews (difference = .055, $p < .001$). We interpret these findings as evidence that vendor (platform) - initiated incentivized reviews are more likely to have a negative (positive) effect on subsequent organic review ratings (p < .001).

5.5.3 Model Selection

In our data set, 10,493 out of 68,241 of reviews posted after incentivized reviews are provided by reviewers who author only a single review. Inclusion of REV AVG causes discarding 10,493 unique observations. Given how many reviews are discarded, we assess the robustness of our results via an additional specification. In Model 1, we estimate the effects of incentivized reviews on our entire data set. This requires us to drop the REV AVG variable. Model 2 presents the full model with the inclusion of the effects of reviewer-level heterogeneity. The coefficient estimate for REV AVG suggests that a reviewer's individual rating tendency has a great deal of explanatory power. Some reviewers assign systematically higher ratings to their products than do others ($\beta_{7,\ \text{vendor-initiated}}$ = .867, p < .001; $\beta_{7,\ \text{platform-initiated}}$ = 1.355, p < .001). Model 2 shows significantly improved fit over Model 1 ($\Delta_{\text{deviance-vendor}} = 26{,}984.64$, $\text{d.f.} = 1,\ p < .01$; $\Delta_{\text{deviance-platform}} = 2{,}065.52,\ \text{d.f.} = 1,\ p < .01$). Thus, we use the results of Model 2 for hypotheses testing.

Table 14
Estimation Results

Ordered Logistic Regression of *Rating*

		Vendor- Initiated Incentivized Reviews		**Platform- Initiated Incentivized Reviews**	
	Hypotheses	**Model 1 Parameter Estimate (SE)**	**Model 2 Parameter Estimate (SE)**	**Model 1 Parameter Estimate (SE)**	**Model 2 Parameter Estimate (SE)**
Incent Bias	H_{1a} (-), H_{1b} (+)	-.357*** (.034)	-.302*** (.038)	.175*** (.046)	.200*** (.048)
Incent Bias×Incent Rev Help	H_{2a} (+), H_{2b} (-)	.228*** (.034)	.147*** (.038)	-.099** (.047)	-.121** (.048)
Incent Bias× Prod Type	H_{3a} (-), H_{3b} (+)	-.054* (.032)	-.061* (.037)	.170*** (.045)	.149*** (.047)
Order		2.010E-04*** (2.680E-05)	2.269E-04*** (3.180E-05)	.002*** (2.614E-04)	.002*** (3.034E-04)
Time		-3.818E-04*** (4.590E-05)	-2.776E-04*** (5.250E-05)	1.407E-04*** (3.530E-05)	5.230E-05 (3.650E-05)
Rev Len		.001*** (1.421E-04)	4.596E-04*** (1.483E-04)	-.001*** (1.465E-04)	-.001*** (1.487E-04)
Rev Avg			.867*** (.013)		1.355*** (.038)
Incent Help Vote		-.001** (3.367E-04)	-.001 (3.883E-04)	.008*** (.003)	.007** (.003)
Incent Rev Help		-.002 (.023)	.041 (.026)	-.080* (.045)	-.123*** (.047)
Prod Type		-.049** (.026)	-.086*** (.027)	-.357*** (.044)	-.267*** (.047)
Year dummies		Included	Included	Included	Included
Month dummies		Included	Included	Included	Included
Number of Observations		53,791	43,639	14,450	14,109
LL		-55,284.287	-41,790.98	-16,832.72	-15,798.96
AIC		110,620.6	83,635.96	33,729.44	31,663.92

Notes: 1) ***, **, * represent the significance levels at the 1%, 5%, and 10%, respectively.
2) Numbers in parentheses are standard errors.
3) $\text{Incent Bias}_{\text{vendor-initiated}} = (\text{Incentivized Rating}) - (\text{Average of Previous Ratings})$
$\text{Incent Bias}_{\text{platform-initiated}} = (\text{Average of Previous Ratings}) - (\text{Vine Rating})$

Table 15
Robustness Check

Ordered Logistic Regression of *Rating*

		Vendor- Initiated Incentivized Reviews	Platform- Initiated Incentivized Reviews
	Hypotheses	**Model 2 Parameter Estimate (SE)**	**Model 2 Parameter Estimate (SE)**
Incent Bias	H_{1a} (-), H_{1b} (+)	-.417*** (.055)	.213*** (.049)
Incent Bias×Incent Rev Help	H_{2a} (+), H_{2b} (-)	.255*** (.050)	-.124*** (.048)
Incent Bias× Prod Type	H_{3a} (-), H_{3b} (+)	-.097** (.049)	.137*** (.047)
Order		1.856E-04*** (3.450E-05)	.002*** (3.110E-04)
Time		-2.408E-04*** (6.460E-05)	4.960E-05 (3.660E-05)
Rev Len		-7.190E-05 (2.138E-04)	-.001*** (1.503E-04)
Rev Avg		.824*** (.017)	1.370*** (.038)
Incent Help Vote		-.001 (4.402E-04)	.007** (.003)
Incent Rev Help		.071** (.035)	-.120*** (.047)
Prod Type		-.044 (.038)	-.271*** (.047)
Year dummies		Included	Included
Month dummies		Included	Included
Number of Observations		25,505	14,009
LL		-24,941.962	-15,678.92
AIC		49,937.92	31,423.84

Notes: 1) ***, ** represent the significance levels at the 1% and 5%, respectively.
2) Numbers in parentheses are standard errors.
3) $\text{Incent Bias}_{\text{vendor-initiated}} = (\text{Incentivized Rating}) - (\text{Average of Previous Ratings})$
$\text{Incent Bias}_{\text{platform-initiated}} = (\text{Average of Previous Ratings}) - (\text{Vine Rating})$

5.5.4 Estimation Results

Table 14 presents the estimation results of the empirical model (Equation 1). We first discuss the vendor-initiated incentivized review results and then the platform-initiated incentivized review results, followed by similarities/differences between the two.

Hypotheses testing. To test $H1_a$, we examine the effect of the difference between the average rating of previous reviews and the rating of a vendor-initiated incentivized review. We find a significant negative effect of INCENT BIAS on subsequent organic review ratings ($\beta_{1,\ \text{vendor-initiated}}$ = -.302, $p < .001$). This suggests that a vendor-initiated incentivized review attracts more negative reviews if it has a higher rating than the prevailing rating of the previous organic reviews, lending support to $H1_a$.

In $H2_a$, we hypothesize a positive moderating effect of the helpfulness of a vendor-initiated incentivized review on subsequent organic review ratings. The interaction between INCENT BIAS and INCENT REV HELP has a positive and significant effect on RATING ($\beta_{2,\ \text{vendor-initiated}}$ = .147, $p < .001$). Hence, $H2_a$ is supported.

The results also provide strong support for $H3_a$, which hypothesizes that the product type moderates the effect of an incentivized review on subsequent organic review ratings. The negative interaction term between INCENT BIAS and PROC TYPE indicates that INCENT BIAS has a more negative effect on the subsequent review ratings for experience products than for search products ($\beta_{3,\text{vendor-initiated}}$ = -.061, $p < .10$). This supports $H3_a$.

Control variables. We find the sequential and temporal dynamic effects on subsequent organic review ratings. Specifically, we find positive sequential dynamics, suggesting that subsequent organic review ratings increase over sequence of reviews ($\beta_{4,\ \text{vendor-initiated}}$ = .0002269, $p < .001$). We also find negative temporal dynamics that subsequent organic review ratings decrease over time even after controlling for review order and calendar-time ($\beta_{5,\ \mathrm{vendor-initiated}}$ = -.0002776, p < .001).

With respect to review characteristics, the review length has a positive and significant effect on subsequent ratings ($\beta_{6,\ \mathrm{vendor-initiated}}$ = .0004596, p < .001). In regard to reviewer-level heterogeneity, we find that some reviewers have a strong tendency to assign higher ratings than do others ($\beta_{7,\ \mathrm{vendor-initiated}}$ = .867, p < .001). We also find that incentivized help votes ($\beta_{8,\ \mathrm{vendor-initiated}}$ = -.001, n.s.) and helpfulness of incentivized reviews ($\beta_{9,\ \mathrm{vendor-initiated}}$ = .041, n.s) do not affect subsequent organic review ratings. Finally, we find that overall the subsequent review ratings of experience products have lower ratings than that of search products ($\beta_{10,\ \mathrm{vendor-initiated}}$ = -.086, p < .001)

The results of the models with subsequent organic ratings of platform-initiated incentivized reviews as the dependent measure appear in columns 3 and 4 of Table 14. The effect of the difference between a platform-initiated incentivized review rating and the average rating of the previous reviews on the subsequent ratings is consistent. For each product, we subtract the rating of a platform-initiated incentivized review from the average rating of all the previous organic reviews to construct INCENT BIAS. This is to provide intuitive interpretation of the results.

We find that the lower the rating of a platform-initiated incentivized review is, the higher is the rating of subsequent organic reviews ($\beta_{1,\ \mathrm{platform-initiated}}$ = .200, p < .001). Therefore, $H1_b$ is supported. The significant negative interaction of INCENT BIAS and INCENT REV HELP suggests that the positive effect of INCENT BIAS is less pronounced when the incentivized review is viewed as more helpful ($\beta_{2,\ \mathrm{platform-initiated}}$ = -.121, p < .05). Hence, $H2_b$ is supported. The positive interaction term between INCENT BIAS and PROC TYPE indicates that

INCENT BIAS has a more positive effect on the subsequent organic review ratings for experience products than for search products ($\beta_{3,\ \mathrm{platform-initiated}}$ = 149, $p < .001$), lending support to $H3_b$. We also confirm that the findings are robust when products that have a minimum of 30 previous organic reviews are used (see Table 15). Table 16 provides a summary of our key findings.

Table 16
Summary of Key Findings

	Incentivized Review Type	
Independent Variable	Vendor-Initiated	Platform-Initiated
Incent Bias	- (H_{1a})	+ (H_{1b})
Incent Bias×Incent Rev Help	+ (H_{2a})	- (H_{2b})
Incent Bias × Prod Type	- (H_{3a})	+ (H_{3b})

CHAPTER 6

CONCLUSION

6.1 Summary of Findings and Academic Contributions

In this research, we examine the effects of two types of incentivized reviews on subsequent organic review ratings: vendor – initiated incentivized reviews and platform – initiated incentivized reviews. Using online product reviews posted on Amazon.com, we find that incentivized-reviews are systematically more biased than organic reviews. Specifically, we confirm that vendor (platform) – initiated incentivized reviews have higher (lower) ratings than organic reviews. Across seven product categories, we show that the average rating of organic reviews posted after a vendor (platform) – initiated incentivized review is lower (higher) than the prevailing rating of the previous organic reviews.

The above effects become more pronounced when the incentivized review is more biased. In other words, the larger the difference between the rating of the vendor-initiated incentivized review and the average rating of the previously posted organic reviews, the lower the subsequent organic review ratings. The findings suggest that vendor-initiated incentivized reviewers provide exaggerated positive reviews, thus misrepresenting the true quality of the product. This in turn raises the expectations of subsequent consumers and leads them to engage in disconfirmation behavior. In contrast, platform-initiated incentivized reviews increase the subsequent organic review ratings as they lower the expectations of future customers, resulting in higher post purchase evaluations.

Further, we show that the effect of an incentivized review on subsequent organic review ratings is less pronounced if the review is viewed as more helpful. A helpful review reduces customers' uncertainties and risks when buying the product and hence reduces purchase errors. We also find a moderating effect of product type. Specifically, we demonstrate that the effect of an incentivized review on subsequent ratings is greater for experience products than for search products. This finding indicates that the reviews' informational role becomes more salient in an environment where reliance on other consumers' reviews is high.

Since previous research has dedicated relatively little attention to different types of online customer reviews, this research supports previous calls for improved understanding of the effectiveness of incentivized reviews (Dost et al. 2019; You, Vadakkepatt, and Joshi 2015). Despite the significant recent growth in the number of incentivized reviews, we do not know enough about how they influence consumer decision making. The findings of our empirical research demonstrate the distinct influences of the two types of incentivized reviews on subsequent organic review ratings and shed light on how and when incentivized reviews affect subsequent customers' review-generation behavior.

This research contributes to the literature on social dynamics of product ratings. By building on the foundation of expectation-confirmation theory (Oliver 1980), we empirically show that positively (negatively) biased incentivized reviews lower (increase) subsequent organic review ratings. While prior research has demonstrated the positive effects of free samples on sales (Hu et al. 2010; Yao et al. 2017; Zhang, Goh, and Lin 2017) and the spillover effects of sampling campaigns (Chae 2016), this study extends the research on product sampling to online review generation, with respect to subsequent organic reviewers' posting behavior. Thus, this study enriches our understanding of sampling in online contexts by showing that biased incentivized reviews may incorrectly signal the quality of the product and therefore mislead potential customers.

6.2 Managerial Implications

The central question to our research is: "Is it a good long-term business strategy to incentivize reviewers?" Our analyses have provided clear answers to this important question. Inclusion of vendor-initiated incentivized reviews that typically exaggerate the quality of products should not be part of a business strategy. This is because they depress the ratings of subsequent organic reviews as a result of disconfirmation between customer expectation and the purchased product experience. These subsequent ratings will create a poor image of the product in the minds of individuals reading the reviews.

In order to build a reputable and trustworthy platform for online customers, vendors should more carefully match reviewers with free products. Our findings should motivate platforms to increase their focus on finding the right customers to offer free products so that their reviews truthfully reflect the true quality of the products. Both vendors and platforms should look for reviewers who have offered more diverse and balanced opinions about their products.

6.3 Future Research

This work could be extended in several directions. In our research, we focus on numeric values of incentivized review ratings. Future research could investigate textual content of reviews when assessing the effectiveness of incentivized reviews. Further, it would be interesting to examine the interaction of numeric values and textual content of incentivized reviews. Our research could also be extended to include products that have multiple incentivized reviews. We limit our samples to products that include a single incentivized review. It would be practical to test whether the number of incentivized reviews moderates the effect.

In addition, future research could compare the influence of incentivized reviews among multiple products. While our analysis focuses on experience and search products, the results could be applicable to multiple categories. For example, we expect online incentivized reviews to have a greater impact on high-involvement products. Finally, future research could investigate the effect of incentivized reviews on financial outcomes (e.g., sales). It would be interesting to examine if favorable incentivized reviews can boost short-term sales.

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