# First-Mover Advantage in Online Review Platform

*Research-in-Progress*

**Qianran Jin**
McGill University
Montreal, Canada
qianran.jin@mail.mcgill.ca

**Animesh Animesh**
McGill University
Montreal, Canada
animesh.animesh@mcgill.ca

**Alain Pinsonneault**
McGill University
Montreal, Canada
alain.pinsonneault@mcgill.ca

## Abstract

*While first-mover advantage has been widely studied at firm-level, our research focuses on individual-level first-mover advantage in online review platform. More specifically, we study whether early reviews receive higher proportion of helpful votes than later reviews. We try to answer three questions. (1) Does first-mover have advantage in online review platform? (2) Does the first-mover advantage differ across different types of reviewers? (3) Are reputation-seeking reviewers more likely to exploit the first-move advantage? We analyze the model using Zero-inflated Beta with the review data from Amazon.com. Our preliminary results show that early reviews are more helpful than later reviews when controlling for total time being posted, review characteristics, and reviewer characteristics. The first-mover advantage is greater for high frequency reviewer than low frequency reviewer.*

**Keywords:** first-mover advantage, social influences, online review

## Introduction

User-generated reviews have been part of our life as they are extremely important and useful for ascertaining the quality of products that a consumer has not experienced before. For example, consumers go to Amazon for daily product reviews, consult Yelp for restaurant reviews, and check TripAdvisor for hotel reviews etc. Consumers go to these websites with the hope that information from the crowd can assist them in making an informed decision.

In recent years, online review platforms have started to better guide consumers by enabling them to provide feedbacks on the reviews. Consumers can either vote a review as "helpful" or "not helpful". This "helpfulness rating system" can reduce the search cost for consumers in finding a helpful one among the abundant reviews, and can potentially reduce the uncertainty consumers faced regarding the quality of the review. It also helps the platform to analyze which reviewer is more valuable. Prior research shows that helpful reviews have a strong impact on product sales than other reviews (Dhanasobhon et al. 2007). Therefore, a better understanding of the underlying mechanism that affect the value of the "helpfulness rating system" is necessary. Though there is a large body of research in the field of online reviews, most of the research has either focused on examining the economic impact of online reviews (Chevalier and Mayzlin 2006; Dellarocas et al. 2004; Godes and Mayzlin 2004; Moe and Trusov 2009) or on examining the behavior of the users who write reviews, including the motivations for writing reviews, the popularity of the products being reviewed and the rating for the review (Burtch et al. 2013; Dellarocas and Narayan 2006; Hennig-Thurau et al. 2004; Li and Hitt 2008; Wasko and Faraj 2005). In spite of the importance of review helpfulness, there is a lack of research examining the factors that influence the helpfulness of a review with a few notable exceptions (Forman et al. 2008; Kuan et al. 2015; Mudambi and Schuff 2010; Yin et al. 2014).

Prior literature on helpful reviews has examined the impact of (1) review characteristics (2) reviewer characteristics, and (3) product type on review helpfulness. While studying review characteristics, researchers find that longer, higher argument quality, easier to understand, and indicative of anxious reviews are relatively more helpful (Chen and Lurie 2013; Forman et al. 2008; Ghose and Ipeirotis 2011; Kuan et al. 2015; Mudambi and Schuff 2010; Racherla et al. 2012; Yin et al. 2014). However, the effect of review valence on helpfulness is mixed. Some find a negative relationship exists between review valence and helpfulness, some find extreme ratings are more helpful, and the others find extreme ratings are less helpful (Chen and Lurie 2013; Kuan et al. 2015; Mudambi and Schuff 2010). The studies on reviewer characteristic find disclosing identity information, higher innovativeness, higher reputation, higher similarity with the consumer, and higher helpfulness in historical reviews results in higher trust from the reader (Forman et al. 2008; Ghose and Ipeirotis 2011; Kuan et al. 2015; Pan and Zhang 2011; Racherla et al. 2012). Experience goods and search goods moderate the effect of review characteristics and reviewer characteristics on helpfulness. While some find reviews with more extreme ratings are less helpful for experience goods (Mudambi and Schuff 2010), others find positive valence is more pronounced for experience goods (Pan and Zhang 2011).

Given the conflicting results of review valence on helpfulness, we suspect that there is some important factor that is affecting the helpfulness but has been ignored in the previous research. Drawing on the strategic principle of "first mover advantage", we argue that review's perceived helpfulness is driven by the timing of the review, which is its review chronological order. Researchers have found support for first-mover advantage at business unit level, brand level and consumer level (Kerin et al. 1992). At the consumer level, the order of entry has a significant impact on consumer's preferences and judgment. Therefore, in online review platform, where reviews are seen as "product" and potential consumers are seen as "consumer" in a market, an early entry time of a review is expected to greatly impact its helpfulness, which we refer to as first-mover advantage in online review platform. Otterbacher (2009), which is the only relevant paper at a review level, demonstrates a strong correlation between their control variable review's chronological order and helpfulness, and this effect is surprisingly much higher than all other review characteristics. However, Otterbacher (2009) does not further analyze this relationship with regression models and does not explain why this relationship might exist.

Hence, the goal of this paper is to study whether first-mover advantage exists in online review. In particular, we try to answer the following questions:

(1) Does first-mover have advantage in online review platform? More specifically, are early reviews more helpful by potential consumers?

(2) Does first-mover advantage differ across different types of reviewers? More specifically, are early reviews that are written by high frequency reviewers more helpful?

(3) Are reputation-seeking reviewers more likely to exploit the first-move advantage? More specifically, are high frequency reviewers more likely to write reviews earlier?

To answer our research questions, we utilize a data set of consumer reviews for books at Amazon.com. Our data include 4811 observations of 80 books that are published within 3 years of our data collection period. Our analysis suggests that early reviews are perceived to be more helpful than later reviews when controlling for factors that can affect the helpfulness score. We also find that review frequency moderates the relationship between review order and its helpfulness.

Our paper contributes to the literature by drawing on first-mover advantage to explain the helpfulness of reviews at individual-level. It shows that the timing of reviews is a critical reason for a review to be helpful rather than review characteristics and reviewer characteristics that have been studied. We also demonstrate the impact of reviewers' behaviors while previous studies mostly concentrate on the numerical aspect of reviews. We empirically support Li and Hitt (2008)'s argument that early reviewers are different from later reviewers by investigating who are the early reviewers. Our results imply that potential consumers do not observe that early reviews are not necessarily the best quality reviews. This suggests that the current review helpfulness system does not do a good job in accounting for the sequential effect.

The rest of the paper is organized as follows. Section 2 describes the theoretical background of the paper. Section 3 develops the hypothesis. Then we present the data and method used. We describe the preliminary results and robustness check in Section 6 and 7, and then conclude and the paper.

## Theoretical Background

First-mover advantage was proposed by Lieberman and Montgomery in 1988, which is defined as the ability of pioneering firms to earn positive economic profits. The concept of first-mover advantage has thus been studied in many fields including strategy, information systems, marketing, and supplies chain. Most of these studies are firm-level analysis, analyzing firms and markets, while the notion of first-mover advantage can be applied to individual-level studies, and is appropriate to study the reviewer behavior in online review platform.

We can think of online review platform as a marketplace with multiple sellers, who are the reviewers. The reviews they write are the products they want to sell in this market. Buyers are those potential customers who read the reviews, and their purchase decisions can be seen as whether they choose to evaluate the reviews by clicking yes or no according to the question "Was this review helpful to you". There are three sources for first-mover in marketplace to gain advantage according to Lieberman and Montgomery (1998), technological leadership, preemption of assets and buyer switching cost. By analogizing them to the online review platform, we find three sources for first-mover reviewers to gain advantage: cost of writing review, visibility of the review and consumer search cost.

The *cost of writing review* for each individual is similar to the production cost in an industry. Unlike the production cost that decreases for first-mover because of learning overtime, the cost for writing reviews increases for later reviewer (Lieberman and Montgomery 1988). Later reviews who want to catch the eyes of potential customers have to significantly differentiate themselves from the early reviews, which is a costly process, thereby giving a cost advantage to the early reviewers (Moe and Trusov 2009). The asset for online review platform is the *visibility of the review*. Reviews from first-mover have higher visibility than reviews posted by the later reviewers because visibility largely depends the accumulation of helpful votes (we will discuss this in the later section). Due to *consumer search cost*, readers will not search for all the reviews that are posted. They only read the ones that are most visible to them. Therefore, early reviews benefits from the search cost imposed to consumers.

Even though online review platform has a relatively low entrant barrier that might mitigate the advantage of early-movers, Makadok (1998) finds that first-movers still enjoy a sustainable advantage compared with later entrants in mutual fund industry, which has a low entrant barrier. Additionally, consumers generally perceive first-movers to be high-quality and perceive the followers just follow a me-too strategy (Kerin et al. 1992). These evidences all confirm our belief that first-mover advantage exist in online review platform.

## Hypotheses

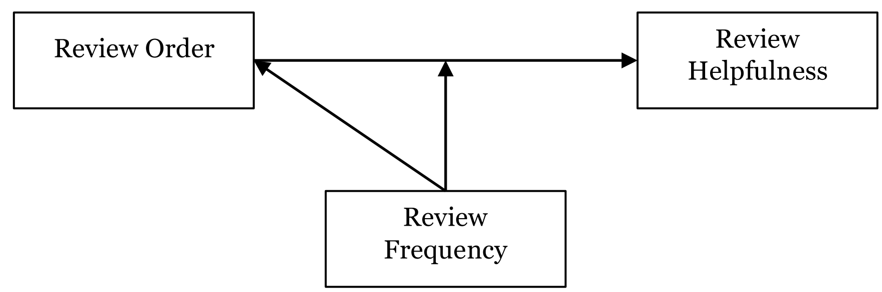


**Figure 1. Research Model and Hypotheses**

While assuming the cost for each reviewer to write a review is the same, early reviews enjoys the benefit of relatively low cost in writing the review. For a new product which does not have any reviews, early reviews are perceived to be distinct, and can influence potential consumers' knowledge of the product and therefore become the "prototype" against later reviews (Kerin et al. 1992). By reducing the uncertainty in consumer's perception of the product, early reviews gain more trust from the potential customers, which means they will be perceived more helpful (Ba and Pavlou 2002).

In general, reviews that are posted early are more visible than later reviews. The total amount of reviews in the early stage is less than later stage. Assuming consumers read same amount of reviews for each product, the probability for early reviews to be read is higher than the later reviews. Having more exposure to potential consumers makes the early reviews more likely to be perceived helpful than reviews with the same quality but posted later. Online information search literature suggests that consumers search limited information online. The decreased search cost brought by the Internet surprisingly does not lead to consumers search for more information online (Johnson et al. 2004). Sponsored search literature also indicates that consumers think it is cognitively "costlier" to visit sites at the bottom of the listing than at the top of the listing (Animesh et al. 2011). Thus, recent reviews and the most helpful reviews will be read more frequently because (1) reviews are sorted either by the date they are posted or by helpfulness (2) consumers find it natural to read from top to bottom and reviews (Nilssen 1997) (3) potential consumers will only read a small proportion of the existing reviews. Assuming the probability for potential buyers to vote a review is helpful or not is the same, early reviews will receive higher proportion of helpful votes than later reviews because of the first-mover advantage that allows early reviews to accumulate more helpful votes overtime. Suppose a helpful review (R1) posted at T1. R1 will have higher exposure at T2 period than another less helpful review (R2) written at T1, and same exposure as a new review (R3) posted at T2. Thus, in T3 and other periods onward, R1 will receive relatively more helpful votes than R2 and R3 assuming their quality is perceived to be the same. Therefore, we hypothesize:

**HYPOTHESIS 1 (H1).** *Early reviews are more likely to receive higher proportion of helpful votes (i.e., higher review helpfulness) than reviews posted later.*

High frequency reviewers, according to Moe and Schweidel (2012), are usually perceived as "activists", who are more involved in online review community and establish themselves by providing opinions that are designed to attract other's attention. These high frequency reviewers are more likely to generate reviews that are more appeal to consumers because they are seeking reputation, and the only way for online reviewers to gain reputation is through receiving more helpful votes (Hennig-Thurau et al. 2004). Other reviewers contribute to the platform for reasons such as altruism and venting feelings (Sundaram et al. 1998). While their reviews are not intended to attract attentions, these reviews have lower probability to be perceived helpful. Therefore, early reviews that come from high frequency reviewers are more likely to be perceived helpful than reviews that come from low frequency reviewers because high frequency reviewers have the intention to achieve approval from others.

Reviews that are posted in the later stage are perceived less helpful than in the early stage as discussed above. However, among these later reviews, the ones written by high frequency reviewers will still be perceived more helpful than low frequency reviewers because posting reviews in later stage is both costly and has less impact for reputation-seeking reviewers (Wu and Huberman 2008). When high frequency reviewers post reviews in the later stage, they perceive the benefits of writing reviews exceed the cost and their review is superior than the existing reviews (Hauser and Shugan 1983). Therefore, their “strategically written” reviews will be perceived more helpful than reviews from low frequency reviewers who are simply expressing their thoughts on the product.

While perceived helpfulness of reviews written by high frequency reviewers and low frequency reviewers are different in the early stage, this difference increases as time pass as the cost for writing reviews increases and the chances of high frequency reviewers writing reviews decreases. Therefore, whenever high frequency reviewer decides to write a review, its quality must be perceived much higher than other reviews otherwise the high frequency reviewers would not spend the effort to write it. Therefore, we hypothesize:

**HYPOTHESIS 2 (H2).** *Early reviews generated by high frequency reviewers are more likely to receive higher proportion of helpful votes (i.e., higher review helpfulness) than early reviews generated by low frequency reviewers, this effect is greater when review order increases.*

Wu and Huberman (2008) find that the impact of reviews decreases when there are already many reviews, and increases when the reviews deviate from the previous reviews. For high frequency reviewers, who seek reputation through writing reviews, their costs to differentiate themselves to attract higher attention from others are high in later stage than in early stage as more and more reviews are posted. The cost is high because reviewers need to read previous reviews to differentiate their opinion. High frequency reviewers will encounter all these extra costs if they want to attract more attention from early reviews (Kerin et al. 1992). Therefore, high frequency reviewers will post early so as to avoid the cost of differentiation in the later stage. Crowding-out effect suggests that when other individuals contribute more frequently, the marginal utility a contributor gains from contributing to the same project will diminish and therefore they will contribute to other projects that have fewer contributors. Hence, in the context of online review platform, high frequency reviewers will post early so that they do not need to bear for the utility lost from competing with other reviewers or finding another product to review (Burtch et al. 2013). They are more likely to write reviews for products that do not have many existing reviews. Therefore, we hypothesize:

**HYPOTHESIS 3 (H3).** *High frequency reviewers are more likely to post reviews at early stage than later stage.*

## Data

### *Data Collection*

We collected data from Amazon.com website. Amazon.com is a leading online market for books and many other products. It provides a platform where consumers can post reviews of the products sold on Amazon.com. We choose books as our study subjective because 1) books are experience good (Forman et al. 2008), which means reviews are important for consumers to make up their purchase decisions, 2) book has a publish date so that we can know how long the review has been posted. We randomly select books that are published within 1000 days and have at least 10 reviews. Our data consists of 80 books that are published within three years of the data collection period. The final sample consists of 4811 reviews written between from January 1, 2013 to March 20, 2015. For each review, we collected the following three folds of data: (1) reviewer characteristics, which include reviewers ID, previous reviews’ average rating, number of reviews they have written, reviewer’s overall helpfulness and the personal information they disclose (2) review characteristics, which include review’s rating, number of helpful votes, number of total votes, number of comments the review gets, review content and the order of reviews (3) book characteristics, which includes publish date, average rating of the book, and number of reviews.

### *Variables*

Our dependent variable is review helpfulness (Review Helpfulness). At the bottom of each review, Amazon lists the question “Was this review helpful to you?”, along with “Yes” and “No” options. A review that has received at least one vote will display “ ‘number of helpful votes’ of ‘number of total votes’ people found the following review helpful” above their review content. Therefore, review helpfulness measures the proportion of helpful votes out of the total votes a review received.

Our major independent variable is review order (Review Order). Each review has a chronological order within the reviews for the same book. In order to see the further effect on review order, we create 5 dummy variables based on the order, denoting whether the review is among the first 10 reviews, first 11-20 reviews, first21-30 reviews, first 31-40 reviews, and first 41- 50 reviews. We also measure the moderator (Review Frequency) in this study. Review frequency is calculated by the number of total reviews written by a reviewer divided by the days between reviewer's first review and last review.

We include total number of votes (Total Votes) on each review's helpfulness as a control variable because the dependent variable is a proportion, which does not take into account the difference between "2 out of 5 people found the following review helpful" and "20 out of 50 people found the review helpful". We also control for other variables that are discussed in the literature, including number of words of the review (Review Length), review rating (Review Rating), dummy variables for reviewer who has revealed real name (Real Name) and geographic location (Location), and elapsed time from the date of review written (Elapsed Review Date) (Forman et al. 2008; Mudambi and Schuff 2010; Peng et al. 2014). We have other control variables that specify reviewer characteristics (for example, number of reviews the reviewer has written in the past (Review Experience)), and book characteristics (for example, the total number of reviews each book has (Number of Book Reviews)).

Table 1 provides the summary statistics of the key variables and their description. We also checked the correlations between variables. All the independent variables are not highly correlated.

**Table 1. Descriptive Statistics for Key Variables**

| | N | Mean | S.D | Min | Max | Variable Description |
|---|---|---|---|---|---|---|
| Review Helpfulness | 4811 | 0.362 | 0.438 | 0 | 1 | Review Helpful Vote ÷ Review Total Vote |
| Reviewer Experience | 4811 | 233.3 | 1352 | 1 | 59827 | Number of past reviews the reviewer has written |
| Review Frequency | 4811 | 0.347 | 1.033 | 0.0004 | 54.938 | Reviewer Experience ÷ Duration between first review and last review |
| Total Votes | 4811 | 2.593 | 7.947 | 0 | 206 | Total votes a review receives |
| Review Length | 4811 | 114.398 | 161.887 | 1 | 1982 | Number of words in a review |
| Review Rating | 4811 | 4.305 | 1.091 | 1 | 5 | The rating reviewer gives this product (from 1 to 5) |

## Empirical Methodology

We use Zero-inflated Beta to analyze the model. Previous studies have used Tobit regression as they argue that helpfulness is bounded within 0 and 1, and a potential selection bias exists because we do not know how many people read the reviews without casting a vote (Mudambi and Schuff 2010; Yin et al. 2014; Yin et al. 2012). However, Tobit regression assumes the mechanism determining the censoring or selection is the same as the equation determining the outcome (Kennedy 2003; Wooldridge 2010), which means the reason for people to read the review without casting a vote is the same as the reasons for them to vote helpful or not helpful for the review. This is clearly not the case. In addition, Tobit regression assumes observations less than 0 are not observed because of censoring. However, helpfulness is not observationally censored but rather it is defined only over the interval [0,1], it is not the case that it has negative values but we substitute zero for it (Maddala 1991). Moreover, Tobit regression also assumes a normally distributed error term. But with abundant zeros, the error term is clearly not normally distributed.

Given the fact that our data (1) contains excessive zeros (2) is a proportion (3) has zeros that are determined by two different processes, the literature has suggested to use Zero-inflated Beta, Hurdle model or Heckman selection model (Cook et al. 2008; Cragg 1971; Lambert 1992; Maddala 1991). Compared with Zero-inflated Beta, Heckman selection model is more restrictive with the normality assumption and the required instrument variable in the second stage. In a Hurdle model, it assumes all zeros come from the same source. However, in a Zero-inflated model, it considers the zeros are from two different processes. One process generates strictly zeros, and the other process generates a non-zero probability of having positive values (however, it can still produce zeros) (Lambert 1992). For our dependent variable review helpfulness, some are zero because no one ever votes for that review, while others are zero because the reviews are perceived to be not helpful. Therefore, we choose Zero-inflated Beta to examine the data.

In H1, we hypothesize that early reviews are more helpful when controlling for everything else. We expect that Review Order (larger number means later reviews) has a negative effect on Review Helpfulness. Following previous literature on books, we expect equivocal reviews to be perceived less helpful (Forman et al. 2008). In H2, we expect Review Frequency moderates the effect of Review Order on the helpfulness of review. Therefore, we add an interaction term Review Order * Review Frequency. In H3, we hypothesize Reviewer Frequency is positively related with Review Order, meaning higher frequency reviewer will review early.

The estimation process of zero-inflated beta includes two parts: (1) a Logit regression for estimating zero inflation (2) a Beta regression with logit link function to estimate the rest. We take the following specification:

$$logit(\alpha) = \beta_1 + \beta_2 Review\ Order + \beta_3 Review\ Frequency + \beta_4 Review\ Order * Review\ Frequency + \mathrm{X} + \varepsilon_1$$

$$logit(\gamma) = \rho_1 + \rho_2 Review\ Order + \rho_3 Review\ Frequency + \beta_4 Review\ Order * Review\ Frequency + \mathrm{X} + \varepsilon_2$$

X is vector of control variables that includes total votes, review length, review rating, review rating$^2$, real name, location, log of elapsed review date, and reviewer overall helpfulness.

## Preliminary Results

The Zero-inflated models generate two sets of parameter estimates, and the signs of the coefficients in the Logit model are usually opposite to those in the Beta parts (Burger et al. 2009).We only report the Beta model's results because our interest is in the zeros that are perceived to be not helpful rather than the zeros that have no total votes. Conditional on the fact that the review has received at least one vote, Review Order is negatively related with Review Helpfulness, meaning early reviews are generally more helpful. When Review Order increases by 1%, the probability of the review being more helpful decreases by 0.002%. Thus, H1 is supported. In order to further identify how the order of review affect Review Helpfulness, we create dummy variables for the first 50 reviews of each book. We find that first 10 reviews are most helpful, while the helpfulness decreases as Review Order increases, which is consistent with what we expected.

We add the interaction term Review Order * Review Frequency in Model 2. The coefficient of Frequency is not significant, but the positive sign is what we expected. The interaction of Review Order and Frequency is negative, statistically significant. We chart the predicted values of the Review Helpfulness at 1 standard deviation above and below the mean for Review Order. It shows that the relationship between Review Order and Review Helpfulness is higher when Frequency is high. However, we do not perceive that there is a big difference between high frequency reviewer and low frequency reviewer posting early or late. These results lend partial support for H2.

We test H3 by regressing Frequency on Review Order using OLS. The results show a negative relationship between Frequency and Review Order, meaning higher frequency reviewer will review early. However, it is not significant.

The results involving the control variables are mostly consistent with prior literature. Equivocal reviews are rated less helpful than clearly positive and negative reviews (Forman et al. 2008). Review Length is statistically significant and positive: there is higher probability for longer reviews to be perceived helpful. Log of Total Number of Book Reviews are positively significant, meaning reviews of a more popular book were considered less valuable (Yin et al. 2014). Reviewer Overall Helpfulness is statically significant and positive; that is reviews written by relatively more helpful reviewer have higher chances of being perceived as helpful (Ghose and Ipeirotis 2011). We observe positive coefficients for Real Name and Location, which are consistent with the signs of Forman et al. (2008)'s finding, but are not significant. Table 2 includes part of the results.

| **Table 2. Regression Output** | | | | |
|---|---|---|---|---|
| | Model 1 | | Model 2 | |
| VARIABLES | Coefficient | Standrard Error | Coefficient | Standard Error |
| Review Order | -0.002*** | (0.001) | -0.001** | (0.001) |
| Frequency | 0.001 | (0.013) | 0.008 | (0.014) |
| Review Order*Frequency | | | -0.001** | (0.001) |
| Constant | -0.653*** | (0.236) | -0.683*** | (0.236) |
| Log- PseudoLikehood | -3291 | | -3289 | |
| Df | 10 | | 11 | |
| $Chi^2$ | 163.3 | | 168.4 | |

## Robustness Check

We conduct the following analyses to check the robustness of our results. First, it is plausible that Review Order may be correlated with some unobservable reviewer characteristics that may influence their perceived helpfulness. Such correlation would lead to inconsistent estimation of our model. To control for this potential problem, we use Tobit regression with instrumental variables. Specifically, we use review frequency of other reviewers (not including the focal reviewer) as an instrument. It is related with focal reviewer's review order, but it does not affect the focal reviewer's review helpfulness. The results show that endogeneity is not an issue in the data. Second, we use Hurdle Model to analyze the model. Review Order is still statistically significant. We obtain similar results with Tobit regression and OLS. Third, we excluded observations that has zero helpful votes, and ran the Tobit regression model. Our results remain robust.

## Conclusion

This paper examines the first-mover advantage in online review platform by analyzing the relationship between review order and review helpfulness. We contribute to the literature by showing review order is one of the key determinants for review helpfulness. We also propose to use Zero-inflated Beta to analyze the helpfulness data, which is more appropriate than Tobit regression.

The results of our regression suggest that early reviews are more helpful than later reviews, which implies that late reviews do not have equal opportunity as early reviews in terms of perceived helpfulness. This further suggests that the current calculation of helpfulness and the display of reviews are not sufficient enough in aiding potential customers making their purchase decisions. Potential consumers are more likely to read the reviews that are posted early with different individual utility compared with later reviewers. For experience goods, such as books, reviews are one of the key determinants for consumers to make purchase decision. One way for online review platform to avoid these issues is to redesign the helpfulness mechanism to reduce the advantage first-mover gets so as to better aid potential customers.

This paper also has some limitations. First, our data only consists of books. Previous research has shown that product type influence the helpfulness. Therefore, we will collect data on other experience goods and search goods so as to search analyze the first-mover advantage. Second, H3 is not supported by the data. One possible reason is that the measurement for Review Frequency does not really represent what we want to capture. Therefore, we will address the problem by collecting more data and find a better measurement for Review Frequency. Third, Review Rating is relatively high, although it is in consistence with the previous literature. We will use quantile regression in the future to address this limitation.

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