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Toward a More Populous Online Platform: The Economic Impacts of Compensated Reviews

Peng Li*
Department of Supply Chain Management, Rutgers Business School, Rutgers University, Newark, New Jersey 07102, peng.li.scm@rutgers.edu

Arim Park
Department of Marketing & Supply Chain Management, Willie A. Deese College of Business and Economics, North Carolina A&T State University, Greensboro, North Carolina 27401, apark@ncat.edu

Soohyun Cho
Department of Accounting Information System, Rutgers Business School, Rutgers University, Newark, New Jersey 07102, scho@business.rutgers.edu

Yao Zhao
Department of Supply Chain Management, Rutgers Business School, Rutgers University, Newark, New Jersey 07102, yaozhao@business.rutgers.edu

Many companies nowadays offer compensation to online reviews (called compensated reviews), expecting to increase the volume of their non-compensated reviews and overall rating. Does this strategy work? On what subjects or topics does this strategy work the best? These questions have still not been answered in the literature but draw substantial interest from the industry. In this paper, we study the effect of compensated reviews on non-compensated reviews by utilizing online reviews on 1,240 auto shipping companies over a ten-year period from a transportation website. Because some online reviews have missing information on their compensation status, we first develop a classification algorithm to differentiate compensated reviews from non-compensated reviews by leveraging a machine learning-based identification process, drawing upon the unique features of the compensated reviews. From the classification results, we empirically investigate the effects of compensated reviews on non-compensated. Our results indicate that the number of compensated reviews does indeed increase the number of non-compensated reviews. In addition, the ratings of compensated reviews positively affect the ratings of non-compensated reviews. Moreover, if the compensated reviews feature the topic/subject of a car shipping function, the positive effect of compensated reviews on non-compensated ones is the strongest. Besides methodological contributions in text classification and empirical modeling, our study provides empirical evidence on how to prove the effectiveness of compensated online reviews in terms of improving the platform’s overall online reviews and ratings. Also, it suggests a guideline for utilizing compensated reviews to their full strength, that is, with regard to featuring certain topics or subjects in these reviews to achieve the best outcome.

Key words: online reviews, compensated reviews, classification, unlabeled data, text analysis
1 Introduction and Motivation

In recent years, online review platforms have emerged as indispensable research and business tools for consumers and businesses alike. Moreover, many consumers have relied on online shopping through these platforms while staying at home, particularly during the recent pandemic.\(^1\) For instance, Amazon’s sales increased as COVID-19 shifted people’s shopping habits to online platforms once the pandemic began.\(^2\) When consumers shop online, they are exposed to other users’ experiences and opinions, which constitute user-generated content (UGC).\(^3\) Such websites can help consumers obtain and exchange information, especially for firsthand experiences. Simultaneously, from the business owner’s perspective, the exposure that products or restaurants receive through such platforms enables them to attract new consumers.

According to a Marketing Land (2018) survey, 90% of respondents read online reviews to decide whether to purchase a product or not, and positive reviews impacted 68% of consumers before deciding to buy products and/or services through online platforms such as Yelp and TripAdvisor.\(^4\) Therefore, online reviews significantly influence companies’ sales and market performance (Dhar and Chang 2009, Chevalier and Mayzlin 2006). Luca (2016) found that “a one-star increase in a Yelp rating leads to a 5-9% increase in revenue.” Moreover, online reviews serve as “word of mouth” (WOM), which is one of the marketing strategies used to promote sales (Chevalier and Mayzlin 2006).

Many online review platforms motivate online reviewers to share their experiences by posting online reviews. These online platforms (e.g., TripAdvisor, Yelp) seek to create online review communities to enhance consumer engagement (Sun et al. 2017). Moreover, such communities allow companies to understand consumers’ opinions by reading their reviews (Bapna et al. 2019, Miller et al. 2009). However, in practice, few consumers actively create online reviews. Yelp’s 1/9/90 Rule states that “only 1 percent of users will actively create content. Another 9 percent, the editors, will participate by commenting, rating, or sharing the content. The other 90 percent watch, look and read without responding” (Kuchinskas 2011). To amplify their business profiles on online review platforms, many businesses have begun compensating consumers to increase the number of online reviews (Reviewtrackers 2019, Ryu and Feick 2007).

\(^1\) See more details at https://www.forbes.com/sites/louiscolumbus/2020/04/28/how-covid-19-is-transforming-e-commerce/#e170103544f (last accessed date: January 20, 2022)

\(^2\) See more details at https://time.com/5870826/amazon-coronavirus-jeff-bezos-congress/ (last accessed date: January 20, 2022).

\(^3\) User-created content such as text and images is called ‘User-generated content (UGC)’ (Lee et al. 2018).

\(^4\) See more details at https://www.brightlocal.com/research/google-reviews-study/#number-of-reviews (last accessed date: January 20, 2022).
Online reviews with monetary incentives are increasing in many businesses. Amazon launched the ‘Early Reviewer Program’ to encourage consumers to share their experiences by offering rewards. This program helps potential consumers make purchase decisions more wisely. Not only Amazon but also other online platforms gradually initiate monetary rewards or sponsorship in their businesses. Facebook allows people to get paid by promoting posts (Gray 2012). Epinions is a shopping information website where many consumers can share their purchase experiences. Nordstrom developed a marketing strategy to advertise their store’s safety measures by sponsoring influencers in response to the spread of COVID-19. Influencers with many followers share their offline experiences on social media with ‘sponsored’ recommendations.

To establish a reliable online platform and protect consumers, the Federal Trade Commission has made it mandatory for sellers to inform consumers if their online reviews are sponsored. However, not all sponsorship or compensation toward online reviews is disclosed (Moon 2018). For example, some sellers on Taobao, who wish to increase their number of online reviews, offer consumers monetary rewards to post a review by inserting a card in a package (Duan et al. 2019). In addition, some platforms do not disclose whether reviews are compensated or not. Mathur et al. (2018) has pointed out that only 10.7% of YouTube videos disclose written sponsorship. Many online reviewers (e.g., influencers) are reluctant to reveal that they are sponsored by sellers (Moon 2018).

In this study, we collected online reviews from an auto shipping online review platform that allows online reviewers to share their service experiences with respect to auto shipping. This website follows the Federal Trade Commission (FTC)’s disclosure by providing reviewers with the option to disclose whether they received a reward from a transportation company or not. Specifically, this website displays a “compensated reviews” icon to reveal paid reviews. Also, several companies have indicated that they do not provide any compensation to online reviewers at all. However, some online reviewers do not disclose their sponsorship. Therefore, consumer reviews need to be identified in terms of whether reviews are compensated or not. Figure 1 illustrates the research framework below.

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5 This platform is a C2C platform in China.
6 In this case, sellers do not disclose that they offer monetary rewards.
7 For propriety and privacy protection, company name is not disclosed in this paper.
In this paper, we raise two research questions: (1) Can we distinguish compensated and non-compensated reviews through a classification technique using text features? There is no way to identify the exact number of compensated reviews on this platform, as no icons or disclaimers signify this. (2) Should the platform encourage compensated reviews? This paper makes two contributions. First, it contributes to the literature on online review classification by examining whether review types can be classified via machine learning using textual analysis based on a classification approach. Classification accuracy shows that our classification with the TSVM approach is validated. Second, we analyze online reviews' economic impact and provide strong evidence to show that compensated reviews can promote the overall review volume and ratings. This study also provides suggestions on which topics are most conducive to compensated reviews in terms of getting the best results.

This paper is organized as follows: Sections 2 and 3 review the literature with the hypothesis development regarding online reviews and methods. In Section 4, we classify compensated vs. non-compensated reviews based on text mining. We study the economic impact of compensated reviews in Section 5. Section 6 examines the robustness of our analysis. Section 7 provides managerial implications and concludes with the research findings.

2 Literature Review

2.1 Online Review

Today’s consumers routinely use online reviews as an important factor in their decision-making process (Kumar et al. 2018a). Accordingly, companies utilize Word-Of-Mouth (WOM) marketing strategies by encouraging consumers to share their experiences with other shoppers (Petrescu et al. 2018). Rishika et al. (2013) found that a higher number of consumers’ messages and posts can generate more transactions and can ultimately increase companies’ profits. More specifically, if companies can secure a high volume of online reviews, they can increase their sales (or financial performance) (Wang et al. 2012).
2.1.1 Impact of Online Reviews

Previous studies have focused on the way that online reviews affect consumers’ purchase decisions. These studies have also introduced the specific features of online reviews that are most likely to influence purchase decisions. Luca (2016), for example, examined the relationship between star ratings and restaurant revenues using Yelp.com restaurant reviews, concluding that higher ratings increase restaurant revenues. Chintagunta et al. (2010) found that average star ratings boost movie box office sales, demonstrating how sales can be interpreted as a consumer’s purchase decision.

In addition to star ratings, prior studies have examined the impact that textual components (e.g., review length, sentiment, and topics) can exert on online reviews, given that such components can more precisely reveal certain consumer preferences that cannot be captured by star ratings (Khern-am et al. 2018). Some studies have examined the impact of review length (Pan and Zhang 2011, Mudambi and Schuff 2010). Meanwhile, Cao et al. (2011) used textual analysis to argue that the semantic features of online reviews can determine purchase decisions. Robinson et al. (2012) also examined how the textual features of online reviews (e.g., positive or negative sentiment, keywords) can affect engagement between companies and consumers.

Companies use online reviews as a marketing strategy to attract more people to boost their sales (Petrescu et al. 2018). According to Burtch et al. (2018), companies (e.g., retailers) can also attempt to increase the online review volume, review length, and number of higher star ratings by manipulating online reviews to increase sales.

2.1.2 Online Reviews with Monetary Incentives

Compensated reviews are one notable example of review manipulation (Petrescu et al. 2018). Earlier studies exploring spam detection in the online domain have also examined companies’ financial support with regard to motivating online reviews from consumers (Luca and Zervas 2016, Mayzlin et al. 2014). A consumer who receives compensation for writing a review will post a biased review that encourages other consumers to purchase the item based on the slanted review (Kumar et al. 2018a). Zhu and Tan (2007) argued that the paid sponsorship of bloggers promotes product sales, resulting in a market strategy that can ultimately help improve the overall quality of products or services of many businesses in online platforms (Wang et al. 2012). Accordingly, to expand the volume of online reviews, many companies have begun offering monetary incentives such as gift cards and small financial benefits to online reviewers (Pu et al. 2017, Burtch et al. 2018).

In 2012, Facebook began allowing users to promote posts by paying them a small amount of compensation. Several studies have shown that monetary rewards are an effective strategy for motivating online behavior. Burtch et al. (2018), for example, found that financial incentives could
ultimately produce a larger volume of online reviews and that the expectation of even modest payment rewards could motivate people to write reviews. In a similar vein, Khern-am et al. (2018) demonstrated that offers of incentives produced more positive online reviews. With this in mind, many business owners (e.g., retailers) pursue marketing strategies to increase their review volume and higher ratings by compensating online reviewers.

2.2 Methods — Text Mining and Classification

Many researchers seek to analyze user-generated content using Latent Dirichlet Allocation (LDA) to capture constructed keyword sets (Khern-am et al. 2018, Lee et al. 2018). LDA is a useful tool for understanding the topics in online reviews that allow companies to predict consumers’ experiences, as well as for highlighting the relative importance of topics based on keywords (Bapna et al. 2019).

Previous studies have investigated the effects of online review using machine learning classification methods with unlabeled data. For example, Li et al. (2010) proposed an online review classification for unlabeled data using Transductive Support Vector Machine (TSVM) techniques to improve classification filtering. Moreover, Kumar et al. (2018b) showed how applying several supervised-learning approaches such as logistic regression, support vector machines, and k-nearest neighbors for classifiers can increase the probability of detecting online review manipulation.

In their online fake review research, Wu et al. (2020) pointed out that many prior studies have focused on detecting review spam, spammers, and spammer groups using unlabeled learning approaches such as SVM and TSVM for efficiency. While earlier research largely concentrated on abnormal online reviews (e.g., spam), our study focuses on detecting compensated reviews via text features using classification methods with partially labeled data. Therefore, our study uses a semi-supervised learning approach for classifiers, which seeks to identify which compensated review characteristics function as features from LDA.

In our study, we focus on the effectiveness of compensated reviews as a marketing strategy. We first examine how compensated reviews can be distinguished from non-compensated ones through semi-supervised classification techniques. Then we seek to demonstrate how companies can effectively boost their review volume and ratings through financially incentivized online reviews.

3 Theory and Hypotheses

In a marketing context, business owners seek to attract more consumers and minimize their marketing costs so that they can maximize their profits. To attract more consumers, they can create a marketing strategy that leverages online reviews. First, consumers are more likely to choose a business with many reviews (Burch et al. 2018, Petrescu et al. 2018, Chen et al. 2017, Hsieh et al. 2010). Moreover, consumers generally prefer more reviews featuring higher ratings (Lin and Heng
We posit that business owners are cognizant that the above review factors can attract consumers based on these two consumer behaviors. In other words, business owners might consider offering rewards (e.g., monetary incentives) to consumers who are willing to write (positive) reviews (i.e., compensated reviews). In addition, if a business owner pays for a review, the compensated review will eventually be posted on the business owner’s website or an online platform (e.g., TripAdvisor, Yelp). Hence, the number of compensated reviews is equivalent to the number of reviews paid for by a business owner. Accordingly, the business’ reviews are either the same as the number of compensated reviews or greater than the number of compensated ones.

Furthermore, business owners seek to minimize marketing costs through compensated reviews. When business owners pay for reviews, they incur marketing costs. Moreover, despite knowing that a larger number of reviews can attract more consumers, they do not want to pay for all their reviews. In other words, business owners must consider strategies that optimize marketing expenses to generate more reviews. Additionally, business owners solicit compensated reviews to generate additional reviews. More specifically, compensated reviews can draw the attention of more consumers, some of whom will then write their own reviews with no monetary incentives (i.e., non-compensated reviews).

Online reviews are an influential signal of product quality stemming from signaling theory (Kwark et al. 2021, Ho-Dac et al. 2013, Luo et al. 2013, Spense 1973). They can be translated as an indication of the consumer’s judgment of products or services. Moreover, a stimulating online review can generate new consumers for products or services based on WOM (Hu et al. 2006, Godes and Mayzlin 2004). In the online review domain, higher numbers of online reviews are considered as primary motivating factors (i.e., signals) that can assuage consumer uncertainty and enable companies to enhance their financial performance (e.g., sales) (Kwark et al. 2021). As such, signaling theory can be applied to our study context because compensated review volume is an influential signal of service for potential customers. Businesses can use relevant strategies to compile a greater number of reviews to ultimately attract more consumers (Burtch et al. 2018, Petrescu et al. 2018, Chen et al. 2017, Hsieh et al. 2010). Given these theoretical arguments and considering business owners’ budgeting strategies (i.e., minimization of marketing costs), we hypothesize the following:

**Hypothesis 1 (H1).** A larger number of compensated reviews can generate a larger number of non-compensated reviews.

Second, online reviews allow people to evaluate products or services using star ratings. Companies that consider monetary incentives expect to improve not only their review volume but also their ratings. Such rating behaviors can positively affect company sales (Pu et al. 2017, Khern-am et al.
Indeed, many studies have concluded that positive evaluations for products or services can increase sales based on the “theory of herding.” This theory considers the mechanism of a channel of behavior and patterns among individuals (Sunder et al. 2019). Huang and Chen (2006) pointed out that positive online reviews can be inferred as “good,” using them as evidence to explain herding behavior in the context of online reviews. For instance, people can evaluate the ratings of products or services based on another person’s rating information within a larger body of information (Sunder et al. 2019). In other words, consumers can consider online review ratings and follow other people’s evaluations according to herd behavior (Muchnik et al. 2013). Accordingly, we can complement this theory and apply it to our study context by considering online reviews as a trigger for herd behavior. Put differently, consumers who read online reviews with high ratings tend to submit online reviews with higher ratings. Moreover, because online reviews that are compensated with rewards or other monetary incentives can lead consumers to submit higher ratings (Lin and Heng 2015, Petrescu et al. 2018, Wang et al. 2012), these compensated reviews will potentially generate reviews with higher ratings. Given these theoretical arguments, we hypothesize the following:

**Hypothesis 2 (H2).** Highly rated compensated reviews can positively affect non-compensated review ratings.

Additionally, the textual features attached to compensated reviews are related to online review volume (Wang et al. 2012), while compensated reviews that include specific textual features can spark an increasing number of non-compensated reviews. Our study closely examines which topics using compensated reviews contribute more to increasing the volume of non-compensated reviews. James and Bolstein (1990) argued that people who are spurred to complete surveys in return for monetary incentives generally submit more positive comments to the survey sponsor. In such cases, the textual features can affect the review volume. For example, in the case of an auto shipping online platform used to share customers’ opinions on services, online compensated reviewers might mention specific topics directly related to shipping services when posting compensated reviews. Note that business owners usually request that reviewers include specific contexts and topics. Thus, we additionally test the following hypothesis:

**Hypothesis 3 (H3):** Compensated reviews generate non-uniform effects on different topics, that is, a compensated review may generate more non-compensated reviews on some topics than others.

In summary, based on the prior studies cited above, we study the impact of compensated reviews on the number of non-compensated ones while parsing the relationship between compensated and non-compensated review ratings. Additionally, we use textual analysis to assess which topics of compensated reviews can affect the non-compensated review volume. These research objectives are summarized in Figure 2.
4 Data and Methods

4.1 Data Collection and Classification

We study online reviews in the auto shipping industry, which involves vehicle transport. The customers of this industry look for reliable service providers to move their cars. However, it can be challenging to find service information regarding a specific transportation company (Sweeney 2010) because the industry consists of many independent owner-operators—an indication that transporters are generally small businesses (Armstrong 2019). Therefore, customers are highly reliant on the online reviews of prior consumers. In other words, the online reviews of auto shipping services provide a fertile area for examining how compensated reviews affect consumers’ decision-making processes, with fewer interruptions from other sources (e.g., online advertisements).

We collected 208,583 reviews of 1,240 auto shipping companies from 2009 to 2018, including the review posting dates, types of review, review contents, review ratings, and company responses to posted reviews. We then preprocessed the collected data as follows: 1) We deleted duplicate reviews based on the methodology employed by Zhu and Fang (2015). 2) We removed reviews lacking a textual description because we used textual features in our analysis. After this preprocessing, we were left with 202,332 online reviews that were categorized as follows: 1) 43,414 labeled and compensated reviews; 2) 7,185 labeled and non-compensated reviews, and 3) 151,733 unlabeled groups. We performed a descriptive analysis using only labeled data (see Table 1).

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8 This online platform was launched in 2003; however, our study excluded data from 2003 to 2008 due to the low number of observations and high occurrence of missing values from that period.

9 If a review is compensated, the information can be disclosed using a unique icon (or not). However, if a review is not compensated, the review cannot use the icon. In other words, any review featuring the icon can be categorized as a labeled and compensated review.

10 The 7,185 reviews are from four companies. The companies explicitly stated that they did not offer any compensation to their reviewers; we confirmed the information through additional phone interviews. In other words, these companies’ reviews can be labeled as non-compensated reviews.
Table 1 presents the summary statistics of the labeled data. The overall rating of the compensated reviews is 4.713, while the overall rating of the non-compensated reviews is 4.66, indicating that compensated reviews have higher ratings than non-compensated ones. However, there are no significant differences between compensated and non-compensated reviews in terms of sub-ratings for honesty, knowledge ability, promptness, and customer service;\(^\text{11}\) We use other characteristics (i.e., textual features) for classification purposes.

We use the 13 topics from the LDA textual analysis. The \(t\)-test results for the topics in Table 2 show that compensated reviews differ significantly from non-compensated ones in terms of textual characteristics.\(^\text{12}\) These results enable us to use textual features to classify compensated and non-compensated reviews.\(^\text{13}\)

### 4.2 Transductive Support Vector Machine (TSVM)

We use Transductive Support Vector Machines (TSVM) for classification purposes, as our dataset contains partially labeled data. Because this method works properly with textual features (Wang et al. 2007, Joachims et al. 1999), we use it to classify unlabeled reviews into compensated and non-compensated reviews using the textual features in Table 2.

To develop the classifier with TSVM, we use a balanced training set. Meanwhile, the test set is determined by the ratio between labeled compensated reviews and non-compensated ones among all labeled reviews (see Table 3). We find that the TSVM classifier has 73.76% accuracy.

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\(^{11}\) We consider the sub-ratings as service-related ratings (see Figure EC.1 in the e-companion).

\(^{12}\) The 13 topics are determined based on the coherence score (Altaweel et al. 2019, Stevens et al. 2012). After determining the number of topics, we applied LDA to the preprocessed reviews and conducted a survey to interpret the keywords per topic from LDA.

\(^{13}\) This result is consistent with the findings of previous studies. Because textual content conveys critical information (Petty and Cacioppo 1986), text reviews are generally assumed to represent a more accurate basis regarding the value of labeled reviews than crude positive and negative ratings (Cabral and Hortacsu 2010, Pavlou and Dimoka 2006).
Table 2: Textual Feature Differences between Compensated and Non-Compensated Reviews

| Variables                      | (1) Compensated | (2) Non-Compensated | (3) Difference |
|--------------------------------|-----------------|---------------------|----------------|
| Finance                        | 0.132           | 0.118               | −0.015***      |
|                                | (0.198)         | (0.195)             | (0.000)        |
| Operations                     | 0.025           | 0.033               | 0.007***       |
|                                | (0.054)         | (0.066)             | (0.000)        |
| Reservation Service            | 0.019           | 0.013               | −0.006***      |
|                                | (0.035)         | (0.028)             | (0.000)        |
| Delivery                       | 0.178           | 0.082               | −0.098***      |
|                                | (0.157)         | (0.142)             | (0.000)        |
| Car Shipping Function          | 0.311           | 0.383               | 0.073***       |
|                                | (0.277)         | (0.305)             | (0.000)        |
| Recommendation                 | 0.182           | 0.191               | 0.009***       |
|                                | (0.230)         | (0.248)             | (0.004)        |
| Staff Features                 | 0.010           | 0.011               | 0.002***       |
|                                | (0.020)         | (0.026)             | (0.000)        |
| Responsiveness                 | 0.026           | 0.024               | −0.002**       |
|                                | (0.052)         | (0.049)             | (0.011)        |
| Communication                  | 0.045           | 0.051               | 0.006***       |
|                                | (0.092)         | (0.098)             | (0.000)        |
| Auto Transport Company Characteristics | 0.015         | 0.017               | 0.002***       |
|                                | (0.034)         | (0.036)             | (0.000)        |
| Customer Assets                | 0.011           | 0.015               | 0.004***       |
|                                | (0.025)         | (0.031)             | (0.000)        |
| Problematic                    | 0.019           | 0.022               | 0.003***       |
|                                | (0.044)         | (0.049)             | (0.000)        |
| Time                           | 0.026           | 0.040               | 0.013***       |
|                                | (0.064)         | (0.087)             | (0.000)        |
| Observations                   | 7,185           | 43,414              | 50,599         |

Note: The standard deviation is reported in the parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 3: Data for the TSVM Classifier

| Training set | Test set |
|--------------|----------|
| (Labeled Only) | (Labeled only) |
| 11,200        | 11,600   |

5,600 labeled compensated reviews | 10,200 labeled compensated reviews
5,600 labeled non-compensated reviews | 1,400 labeled non-compensated reviews

4.3 Classification Results

Using the TSVM classifier, we categorize the unlabeled reviews as compensated and non-compensated.\textsuperscript{14} Table 4 summarizes the classification results. According to our findings, this platform has more compensated than non-compensated reviews, implying that small businesses actively offer rewards to reviewers and use compensated reviews as their marketing strategies.

\textsuperscript{14} We validate the classification results by comparing them using the Support Vector Machine (SVM) approach, which is a popular classification method in the online review domain. The results show that TSVM accuracy is higher than SVM.
Moreover, after checking for consistency between the LDA results of the labeled online reviews and those of the classified reviews, we find that the TSVM classifiers work properly with textual features (see Table EC.2 and Table EC.3 in the e-companion).

5 The Econometric Model and the Economic Impacts of Compensated Reviews

In this section, we examine the economic impacts of compensated reviews by analyzing 131,143 reviews. We employ econometric models to explore how the number of compensated reviews and average ratings can impact those of non-compensated reviews. First, we build a panel dataset at the reviewer-week (it) level, where i and t signify a reviewer and a week, respectively. We then develop fixed effect ordinary least squares (OLS) regression, considering the heterogeneity of the company and time trends (given that a company might have, for example, many online reviews in 2009 and very few reviews in 2010). The fixed effects are used for controlling the unobserved time trends and companies across models.

5.1 Effect of the Number of Compensated Reviews

We analyze whether compensated reviews significantly affect the total number of non-compensated ones. We utilize a fixed effect model to estimate the number of compensated reviews on the number of non-compensated ones for this analysis. Specifically, we use the following model (see Equation (1)):

17 After the classification, we remove the missing overall ratings and service-related ratings to examine the economic impact of the compensated reviews from the classification results. Additionally, we followed the example of Kumar et al. (2018b) and deleted companies with fewer than three reviews. Ultimately, we use a total of 131,143 reviews for our economic impact analysis.
log(total number of non-compensated reviews)\textsubscript{it} \\
\begin{align*}
&= \beta_0 + \beta_1 \times \log(\text{number of compensated reviews})\textsubscript{it} \\
&+ \beta_2 \times \log(\text{number of compensated reviews})\textsubscript{i(t-1)} \\
&+ \beta_3 \times \text{average ratings of compensated reviews}\textsubscript{it} \\
&+ \beta_4 \times \text{company response}\textsubscript{it} \\
&+ \beta_5 \times \log(\text{review length})\textsubscript{it} \\
&+ \beta_6 \times \text{average service rating honesty}\textsubscript{it} \\
&+ \beta_7 \times \text{average service rating customer}\textsubscript{it} \\
&+ \beta_8 \times \text{average service rating knowledge ability}\textsubscript{it} \\
&+ \beta_9 \times \text{average service rating promptness}\textsubscript{it} + \delta_i + \gamma_t + \epsilon_{it} \\
\end{align*} 

Where \(\log(\text{total number of non-compensated reviews})\textsubscript{it}\) is a dependent variable representing the natural log transformation for the total number of non-compensated reviews posted by online reviewers for company \(i\) during week \(t\). The independent variables, \(\log(\text{number of compensated reviews})\textsubscript{it}\) and \(\log(\text{number of compensated reviews})\textsubscript{i(t-1)}\), represent the natural log-transformed weekly total number of compensated reviews posted by customers for the current week \((t)\) and the previous week \((t - 1)\), respectively. The control variables in the model include the following factors: the \text{average rating of compensated review}\textsubscript{it} represents the average rating of compensated reviews posted by consumers. Let \(\text{company response}\textsubscript{it}\) be a dummy variable representing whether or not a company \(i\) replied to a customer’s comment at week \(t\). If company \(i\) responded to a consumer’s review at week \(t\), the action is labeled as \(\text{company response}\textsubscript{it} = 1\). If the company did not reply, the action is labeled as \(\text{company response}\textsubscript{it} = 0\); Let \(\log(\text{review length})\textsubscript{it}\) indicate the natural log-transformed word count in the review comments for the company \(i\) at week \(t\). \text{Average ratings of honesty, consumer service, knowledge ability, and promptness} are sub-ratings concerning the services. We also controlled for rating-related indicators, review length, and company response. \(\delta_i\) indicates a control variable for company-specific time-invariant heterogeneity, including any observable or unobservable time-invariant company characteristics (e.g., company size, company value, and some inherent company characteristics). We use a weekly variable, \(\gamma_t\), to account for time trends. The unobserved error term \(\epsilon_{it}\) is assumed to be orthogonal to other independent variables, and we let \(\beta_i\) be the main estimated regression coefficients.

Table 5 presents our regression results. We display the Ordinary Least Squares (OLS) regression results in column (1) to estimate the coefficient of the number of compensated reviews without considering the heterogeneity of the company or time trends. We also report the estimation results
for a fixed effects model without an instrumental variable in column (2). To check the robustness of our model, we rerun the fixed effects regression model, considering the instrumental variable as a Two-stage Least Squares (2SLS) regression to control for the endogenous number of compensated reviews (see Section 6.1). The results of our main model are presented in column (2), on which our discussion will mainly focus.

Table 5  Estimation Results for the Effect of the Number of Compensated Reviews

| Variables                                      | (1) OLS       | (2) OLS FE    |
|------------------------------------------------|---------------|---------------|
| log(Number of compensated reviews at week t)  | 0.410***      | 0.226***      |
| ($\beta_1$)                                    | (0.004)       | (0.038)       |
| log(Number of compensated reviews at week t − 1) | 0.211***      | 0.063**       |
| ($\beta_2$)                                    | (0.004)       | (0.025)       |
| Control Variables                               | YES           | YES           |
| Observations                                    | 129,591       | 129,584       |
| R-squared                                       | 0.340         | 0.713         |
| Company FE                                      | NO            | YES           |
| Time FE                                        | NO            | YES           |

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5 shows that the number of compensated reviews significantly and positively affects the total number of non-compensated reviews. Thus, H1 is supported. Table 5 reports that the number of non-compensated reviews is not only affected by the number of compensated reviews of the current week but also by the previous week. For example, in column (2) of Table 5, the coefficient regarding the number of compensated reviews in the current week is 0.226 ($p < 0.01$). This result means that a 10% increase in the number of compensated reviews results in a 2.26% average increase in the number of non-compensated reviews. It also means that a 10% increase in the number of compensated reviews last week results in a 0.63% average increase in the number of non-compensated reviews. The results show that the non-compensated review volume is affected by the number of compensated reviews of the current week $t$, while it is also influenced by the previous week ($t − 1$). The results imply that once a company offers compensation for reviewers and the compensated reviews are posted, its non-compensated review volume increases.

For comparison, we also run two alternative regressions that generate consistent results with what has been discussed in the above mentioned model. The first regression only includes the main effect of the number of non-compensated reviews and does not consider the heterogeneity of the company or time trends. The second regression runs the fixed effects OLS regression with instrumentation for the number of non-compensated reviews, a well-known regression called 2SLS. The results of these two alternative models are consistent with the prior work of column (2) on online reviews (see Section 6.1). We demonstrate that the number of compensated reviews can generate more than the
number of non-compensated reviews, which shows good robustness. Comparing the results listed in Table 5, we claim that the results are still robust despite the heterogeneity of the company and time trends.

5.2 Effect of Compensated Reviews’ Average Ratings

We also analyze whether the ratings of compensated reviews positively affect the ratings of non-compensated reviews from H2. We perform fixed effects regression to capture the relationship between the ratings of compensated and non-compensated reviews. The fixed effects regression model is given as follows (see Equation (2)):

\[
\log(\text{average rating of non-compensated reviews})_{it} = \beta_0 + \beta_1 \times \text{average rating of compensated reviews}_{it} + \beta_2 \times \text{average rating of compensated reviews}_{i(t-1)} + \beta_3 \times \text{number of compensated reviews}_{it} + \delta_i + \gamma_t + \epsilon_{it}
\]  

(2)

where \(\log(\text{average rating of non-compensated reviews})_{it}\) is the dependent variable for company \(i\) at week \(t\). The independent variable is the average ratings of paid review \(_{it}\) for company \(i\) at time \(t\). We also consider the previous period effect regarding the ratings of compensated reviews, represented by the average ratings of compensated review \(_{i(t-1)}\). We also control for the number of compensated reviews \(_{it}\) to analyze the efforts of the independent variables. \(\delta_i\) indicates the control variables. We selected the quoted price and length reviews as the control variables because it is reasonable to expect lower quoted prices and longer reviews to increase the volume of non-compensated reviews. \(\gamma_t\) shows the company and time fixed effects. We let \(\beta_i\) be the estimated regression coefficients, and \(\epsilon_{it}\) be the residual term of the regression.

Table 6 shows the regression results, where the main variable of interest is the average rating of the compensated reviews by week. The results show that the coefficient \((\beta_1 = 0.113, p < .01)\) of the average rating of compensated reviews is positive and significant across different model specifications, which supports H2. This finding indicates that the individual company and time trends cannot change the average rating of compensated or non-compensated reviews. The results have good robustness across the different models.

Column (2) in Table 6 shows that the average rating of compensated reviews is positive and significant, thus supporting H2. The coefficient of the average rating of compensated reviews is 0.113, which means that a one-unit (one-star) increase in the average rating of compensated reviews results in an 11.3% average increase in the rating of non-compensated reviews. This finding also means that a one-unit increase in the average rating of compensated reviews last week resulted
### Table 6  Estimation Results for the Effect of Compensated Reviews’ Average Ratings

| Variables                                           | (1)          | (2)          |
|-----------------------------------------------------|--------------|--------------|
| Average ratings of compensated reviews from week $t$ ($\beta_1$) | 0.119***     | 0.113***     |
|                                                     | (0.002)      | (0.006)      |
| Average ratings of compensated reviews from week $t-1$ ($\beta_2$) | 0.008***     | 0.005***     |
|                                                     | (0.001)      | (0.001)      |
| Control Variables                                   | YES          | YES          |
| Observations                                        | 47,018       | 46,937       |
| R-squared                                           | 0.614        | 0.667        |
| Company FE                                          | NO           | YES          |
| Time FE                                             | NO           | YES          |

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In a 0.5% average increase in the rating of non-compensated reviews. This result indicates that non-compensated online reviewers tend to give higher average ratings if the average ratings of the compensated reviews are also high. Moreover, they rely on the current week $t$’s average ratings of compensated reviews rather than the average of the previous week $t-1$. The results imply that the average ratings of compensated reviews immediately impact the ratings of non-compensated reviews.

### 5.3 Influence of Topics

In this section, we study the third hypothesis regarding the impact of compensated reviews on non-compensated ones. More specifically, to validate H3, we employ panel data to identify which topics of the compensated reviews contribute more to increasing the number of non-compensated reviews. To determine the contribution of each topic, we first estimate the coefficient of each topic (see Equation (3)), and then calculate the Shapley-Owen values (Huettner et al. 2012), which decompose the explained variance measured by the R-squared of those regressions into contributions over groups of regressors (see the results from Table EC.6 in the e-companion).

$$
\text{Number of non-compensated review}_{it} = \beta_0 + \beta_1 \times \text{number of compensated reviews}_{it} + \sum_{k=0}^{12} \beta_{2,k} \times \text{number of compensated reviews}_{it} \times \text{Topic}_k + \sum_{k=0}^{12} \beta_{3,k} \times \text{Topic}_k + \delta_i + \gamma_t + \epsilon_{it}
$$

(3)

The dependent variable $\text{number of non-compensated reviews}_{it}$ in the model is the number of non-compensated reviews for each company at week $t$. The independent variable $\text{number of compensated reviews}_{it}$ is for company $i$ at week $t$. For the moderating roles of the topics, we consider
an interaction term between \( \text{number of compensated reviews}_{it} \) and \( \text{Topic}_k \). \( \text{Topic}_k \) is a binary variable equal to 1 if it indicates that the review of company \( i \) at time \( t \) belongs to topic \( k \), and 0 otherwise. We also include a set of control variables (i.e., \( \delta_i \)). To further control for time-invariant, unobservable characteristics, we include the fixed effect \( \gamma_t \) to control for unobserved time trends and the unobserved error term \( \epsilon_{it} \).

Table 7 summarizes how the number of compensated reviews affects the number of non-compensated reviews based on different topics. An exciting finding is that the number of compensated reviews generates a non-uniform effect on various topics. In other words, for the topic of car shipping functions, the number of compensated reviews generates more non-compensated reviews than others. The coefficient of interest, \( \beta_{2,k} \), represents the differential effect among various topics regarding the number of compensated reviews. Table 7 shows that the coefficient of Topic 4 (\( \beta_{2,4} = 0.032, p < 0.01 \)) is positive and significant, which stands for the car shipping functions. This finding means that some compensated reviews related to the topic of car shipping functions are more associated with non-compensated reviews.

| Variables                                      | DV: Number of non-compensated reviews (Standard Error) |
|-----------------------------------------------|--------------------------------------------------------|
| Number of compensated reviews (NCR)          | 0.116*** (0.005)                                       |
| NCR × Finance                                 | 0.000 (0.000)                                          |
| NCR × Operations                              | 0.018 (0.017)                                          |
| NCR × Reservation service                     | 0.007 (0.061)                                          |
| NCR × Delivery                                | −0.008 (0.007)                                         |
| NCR × Car shipping functions                  | 0.032*** (0.005)                                       |
| NCR × Recommendation                          | 0.012** (0.005)                                        |
| NCR × Staff features                          | 0.011 (0.068)                                          |
| NCR × Responsiveness                          | 0.004 (0.023)                                          |
| NCR × Communication                           | 0.013 (0.009)                                          |
| NCR × Auto Transport company Characteristics   | 0.018 (0.041)                                          |
| NCR × Customer assets                         | 0.041 (0.057)                                          |
| NCR × Problematic                             | −0.039 (0.030)                                         |
| NCR × Time                                    | −0.008 (0.012)                                         |
| Constant                                      | −0.808 (0.569)                                         |
| R-squared                                     | 0.534                                                 |
| Company FE                                    | YES                                                   |
| Time FE                                       | YES                                                   |
| Control Variables                             | YES                                                   |
| Observations                                  | 131,140                                                |

Note: × indicates interaction effects;

We also provide suggested strategies for business owners. Compared to other topics, the car shipping function topic of compensated reviews generates more non-compensated reviews, which
helps business owners obtain additional reviews. Business owners can suggest that online reviewers post more special keywords, such as “car,” “transport,” and “driver,” (which are related to car shipping functions) to enhance the number of reviews. Therefore, the results are consistent with our research topic, given that online reviews are used to evaluate car shipping service companies.

6 Robustness Check

We validate our results by conducting a series of robustness checks.

6.1 Two-Stage Least Squares Regression

To address the potential endogeneity of our key independent variables, number of compensated reviews and average ratings of compensated reviews, and to validate our results, we employ a 2SLS estimation with the generated instrumental variable (IV) approach (Hong and Pavlou 2017, Granados et al. 2012).

Formally, we investigate 2SLS regressions for H1 and H2, respectively, as follows:

\[
\log(\text{number of compensated reviews})_{it} = \beta_0 + \beta_1 \times \log(\text{number of compensated reviews})_{i(t-3)} + \beta_2 \times \log(\text{number of compensated reviews})_{i(t-1)} + \beta_3 \times \text{average ratings of compensated reviews}_{it} + \beta_4 \times \text{company response}_{it} + \beta_5 \times \log(\text{review length})_{it} + \beta_6 \times \text{average service rating honesty}_{it} + \beta_7 \times \text{average service rating customer}_{it} + \beta_8 \times \text{average service rating knowledge ability}_{it} + \beta_9 \times \text{average service rating promptness}_{it} + \delta_t + \gamma_i + \epsilon_{it}
\]
\[
\log(\text{total number of non-compensated reviews})_{it} = \beta_0 + \beta_1 \times \log(\text{number of compensated reviews})_{it} + \beta_2 \times \log(\text{number of compensated reviews})_{i(t-1)} + \beta_3 \times \text{average ratings of compensated reviews}_{it} + \beta_4 \times \text{company response}_{it} + \beta_5 \times \log(\text{review length})_{it} + \beta_6 \times \text{average service rating honesty}_{it} + \beta_7 \times \text{average service rating customer}_{it} + \beta_8 \times \text{average service rating knowledge ability}_{it} + \beta_9 \times \text{average service rating promptness}_{it} + \delta_i + \gamma_t + \epsilon_{it}
\]

where Equation (4) reflects the first-stage regression, and Equation (5) reflects the second-stage regression for H1.

\[
\text{average rating of compensated reviews}_{it} = \beta_0 + \beta_1 \times \text{average rating of compensated reviews}_{i(t-3)} + \beta_2 \times \text{average rating of compensated reviews}_{i(t-1)} + \beta_3 \times \text{number of compensated reviews}_{it} + \delta_i + \gamma_t + \epsilon_{it}
\]

\[
\log(\text{average rating of non-compensated reviews})_{it} = \beta_0 + \beta_1 \times \text{average rating of compensated reviews}_{it} + \beta_2 \times \text{average rating of compensated reviews}_{i(t-1)} + \beta_3 \times \text{number of compensated reviews}_{it} + \delta_i + \gamma_t + \epsilon_{it}
\]

where Equation (6) reflects the first-stage regression, and Equation (7) reflects the second-stage regression for H2.

Tables 8 and 9 show that the results are qualitatively consistent with our main findings. The results in column 4 of both tables are consistent with our OLS fixed effects model (column 2 in Tables 8 and 9), thus supporting our proposed relationship.

Furthermore, to test the validity of the proposed instruments in Tables 8 and 9, we consider the first-stage F statistic in column (3) of Table 8, which shows that the first-stage F value (469.45) for both regressions is greater than 10, indicating that our IVs are not weak (Staiger and Stock 1997). In addition, the Cragg-Donald F value (4745.956) is above 13.91; this is a critical value suggested
by Stock and Yogo (2005) for relative significance bias at a level higher than 5%, which alleviates the weak instrument concern.\footnote{Note that the first-stage $F$ statistic is no longer sufficient to test the instruments in column (3) of Table 9 because we consider multiple endogenous variables, three lags of the current period, and the response of the car company (Sanderson and Windmeijer 2016).}

Similar to Table 8, we also consider the Cragg-Donald $F$ statistic and the Stock and Yogo test statistic to determine the validity of the proposed instruments. The results show that our proposed instrument variables are not weak. Lastly, we conduct the Sargan-Hansen Test to examine whether the instruments are uncorrelated with the error term because the number of IVs for H2 is larger than the number of endogenous variables for H2 (the Sargan-Hansen statistic is 0.8502). We cannot reject the over identification restriction, and our instruments satisfy the exogeneity.

### Table 8  Estimation Results of the Number of Compensated Reviews Effect

| Variables                        | OLS   | OLS FE | First Stage | Main Regression |
|----------------------------------|-------|--------|-------------|-----------------|
| log(Number of compensated)       | 0.410*** | 0.226*** | —           | 0.330*          |
| from week $t$($\beta_1$)         | (0.004) | (0.038) | —           | (0.155)         |
| log(number of compensated)       | 0.211*** | 0.063**  | 0.276***    | 0.032           |
| reviews from week $t - 1$($\beta_2$) | (0.004) | (0.025) | (0.002)     | (0.026)         |
| Average rating of compensated    | 0.413*** | 0.254*** | -0.067***   | 0.267***        |
| reviews                          | (0.017) | (0.040) | (0.009)     | (0.045)         |
| Company response                 | 0.337*** | 0.439*** | -0.018***   | 0.446**         |
| (0.012)                          | (0.192) | (0.008) | (0.192)     |                 |
| log(Length of reviews)           | -0.039*** | -0.019*** | -0.028***   | -0.016*         |
| (0.012)                          | (0.006) | (0.002) | (0.007)     |                 |
| log(number of compensated)       | —      | —      | 0.160***    | —               |
| reviews from week $t - 3$($\beta_3$) | —      | —      | (0.002)     | —               |
| Control variables               | YES    | YES    | YES         | YES             |
| Constant                         | 0.795*** | 0.747*** | 0.962***    | -0.775***       |
| (0.044)                          | (0.289) | (0.036) | (-0.047)    |                 |
| Observations                     | 129,591 | 129,584 | 126,428     | 126,428         |
| R-squared                        | 0.340  | 0.713  | 0.773       | 0.711           |
| Company FE                       | NO     | YES    | YES         | YES             |
| Time FE                          | NO     | YES    | YES         | YES             |
| First-stage $F$ statistic        | —      | —      | 469.45      |                 |
| Wald $\chi^2$(1)                | —      | —      | —           | 9.415**         |
| Cragg-Donald Wald $F$            | —      | —      | —           | 4745.956        |
| Kleibergen-Paap rk Wald $F$      | —      | —      | —           | 194.402         |

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.  

### 6.2 Additional Company Service Characteristics

We incorporate additional control variables to check the robustness of our main models based on Huang et al. (2020), Ghose et al. (2019), and Lee et al. (2018), all of whom use demographic
# Table 9  Estimation Results of Compensated Reviews’ Ratings Effect

| Variables                                | OLS 1 | OLS FE 2 | First Stage 3 | Main Regression 4 |
|------------------------------------------|-------|----------|---------------|-------------------|
| Average ratings of compensated reviews from week $t$ ($\beta_1$) | 0.119*** | 0.113*** | —             | 0.151***          |
|                                           | (0.002) | (0.006) | —             | (0.011)           |
| Average ratings of compensated reviews from week $t-1$ ($\beta_2$) | 0.008*** | 0.005*** | 0.048***      | 0.003***          |
|                                           | (0.001) | (0.001) | (0.004)      | (0.001)           |
| Number of compensated reviews            | 0.054*** | 0.052 | -1.376***     | 0.108**           |
|                                           | (0.007) | (0.045) | (0.088)      | (0.037)           |
| Requote price                            | -0.000 | -0.000 | -0.001       | 0.000             |
|                                          | (0.000) | (0.000) | (0.001)      | (0.000)           |
| log(Length of reviews)                   | -0.004** | -0.002** | 0.017*      | -0.003*           |
|                                          | (0.001) | (0.001) | (0.010)      | (0.001)           |
| log(Length of reviews)$^2$               | 0.000** | 0.000 | -0.005***     | 0.000*            |
|                                          | (0.000) | (0.000) | (0.001)      | (0.000)           |
| Average ratings of compensated reviews from week $t-3$ ($\beta_3$) | — | — | 0.068*** | — |
| Response                                 | — | — | (0.003) | — |
| Constant                                 | 1.152*** | 1.192*** | 4.369*** | 1.023*** |
|                                          | (0.012) | (0.030) | (0.037) | (0.023) |
| Observations                             | 47,018 | 46,937 | 46,792 | 46,792 |
| R-squared                                | 0.614 | 0.667 | 0.128 | 0.526 |
| Control variables                        | YES | YES | YES | YES |
| Company FE                               | NO | YES | YES | YES |
| Time FE                                  | NO | YES | YES | YES |
| First-stage $F$ statistic                 | — | — | 17.49 | — |
| Wald $\chi^2$                            | — | — | — | 5.996 |
| Cragg-Donald Wald $F$                     | — | — | — | 229.08 |
| Kleibergen-Paap rk Wald $F$               | — | — | — | 15.35 |
| Hansen $J$ Test                          | — | — | — | 0.8502 |

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Variables and location variables as control variables. Because our paper is related to online reviews concerning auto shipping companies, we re-estimate our models by controlling the auto shipping company-specific variables related to the level of company services (e.g., car condition after shipping, on-time pick-up, and delivery). The results consistently support our H1 and H2.  

## 7 Discussion

### 7.1 Key Findings

We use online reviews from auto shipping companies to study the impact of compensated reviews and identify compensated reviews’ most attractive content characteristics. First, we use an advanced machine learning technique to identify compensated reviews from unlabeled reviews.

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19 See columns (4) and (5) of Table EC.4 and Table EC.5 in the e-companion.
Second, our study regarding the economic impact of compensated reviews on non-compensated ones shows that the non-compensated review volume is affected by the number of compensated reviews of the current week, while it is also influenced by the previous week. More specifically, this finding means that a 10% increase in the number of compensated reviews results in a 2.26% average increase in the number of non-compensated reviews. It also means that a 10% increase in the number of compensated reviews last week resulted in a 0.63% average increase in the number of non-compensated reviews. The results imply that once a company offers compensation for reviewers and the compensated reviews are posted, its non-compensated review volume increases. Furthermore, higher-rated compensated reviews lead to higher-rated non-compensated reviews.

The results illustrate that non-compensated online reviewers tend to give higher average ratings if the average ratings of the compensated reviews are also high. Moreover, they rely on the current week’s average ratings of compensated reviews rather than the previous week’s average. More specifically, this finding means that a one-unit (one-star) increase in the average rating of compensated reviews results in an 11.3% average increase in the average rating of non-compensated reviews. The results imply that the average ratings of compensated reviews immediately impact the ratings of non-compensated reviews. Finally, our study shows that compensated reviews generate a non-uniform effect on various topics. In other words, regarding the topic of car shipping functions, the number of compensated reviews generates more non-compensated reviews than others. We also provide suggested strategies for business owners to get online reviewers to post more special keywords, such as “car,” “transport,” and “driver” (which are related to car shipping functions) to enhance the number of reviews. Therefore, the results are consistent with our research topics because online reviews are used to evaluate car shipping service companies.

7.2 Theoretical Implications

This study contributes to the online review classification literature by determining whether a review is compensated or not using a machine learning approach based on textual features. Our work expands the recent literature on classifying fully labeled or unlabeled reviews with supervised or unsupervised learning (Kumar et al. 2019) by performing the classification of partially labeled reviews with semi-supervised learning.

In addition, our work extends prior research on online review domains by proving the effectiveness of compensated online reviews to boost a platform’s online review volume and ratings. Previous studies have centered on parsing the impacts of compensated online reviews in regard to the number and ratings of other online reviews (which can be either compensated or non-compensated reviews) (Duan et al. 2019, Burtch et al. 2018, Khern-am et al. 2018). However, because our study examines the impact of compensated reviews on non-compensated ones, we contribute to the literature by identifying the net effects of compensated reviews and promotion costs.
7.3 Managerial Implications

Our study provides several managerial implications. First, compensated reviews have distinct features from non-compensated ones, which can be captured by machine learning-based classification algorithms, and thus, can be classified. Second, we find that compensated reviews positively impact both the volume of non-compensated reviews and the overall average rating. Third, business owners can leverage our study results to generate more non-compensated reviews by encouraging reviewers to include specific content (i.e., topics). Our results may be more helpful to small businesses that rely on promotions through online reviews rather than on other promotional methods that require large budgets (e.g., TV or news advertisements).\(^\text{20}\)

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E-Companion for Toward a More Populous Online Platform: The Economic Impacts of Compensated Reviews

**EC.1 Data Collection**

In this section, we conduct an online review analysis of the auto shipping industry. Consumers can share their experiences and opinions on this online review platform by posting online reviews to evaluate the shipping services offered by auto transport companies. The online review platform shares customers’ experiences to help new users find the best car carrier to ship their equipment. We employed a web-scraping technique and collected all available reviews of 1,240 auto shipping companies from 2009 to 2018. We collected the review posted date, review type, content, rating, response to the customer (or not), car condition, and service quality for each review. We apply a similar processing method used by Jindal and Liu (2007), drawing upon the classic definition of duplicate reviews from previous studies (e.g., Jindal and Liu (2007)). More specifically, we have removed all duplicate reviews (repetitive contents) and empty comments prior to our classification and model analysis. After the cleaning, the data set contains 202,332 reviews categorized into three groups: 1) 43,414 compensated reviews (labeled data) with a unique image icon. If the review of the website appears, the image icon indicates that the review is compensated; 2) 7,185 non-compensated online reviews from four companies (confirmed through a phone call survey); and 3) 151,733 reviews (unlabeled data) from the remaining data set. We have employed a machine learning technique to identify compensated and non-compensated reviews based on unlabeled data.

**EC.2 Textual Analysis and Classification**

To detect the classification between compensated and non-compensated reviews posted by consumers, we conduct a textual analysis using text mining to understand the characteristics of compensated reviews. We selected a topic modeling technique widely used in the Information Systems (IS) domain as a valuable way of identifying topics by constructing keyword groups for each topic (Khern-am-nuai et al. 2018). Textual analysis indicates compensated review patterns based on written online reviews that contain invisible consumer preferences (Xiang et al. 2015). This approach allows us to understand compensated online reviews (which are critical topics with different weights) by analyzing the labeled compensated review data set.

Based on textual features, we classify compensated and non-compensated reviews with a machine learning approach. We can identify compensated review characteristics based on the labeled data. In this case, semi-supervised learning is suitable for classifying reviews by combining the labeled and unlabeled data in the training process (Wu et al. 2020). Xu et al. (2019) illustrate that
the Transductive Support Vector Machine (TSVM) demonstrates significant improvement in the performance of other classifiers via training based on the labeled data. Therefore, this study can determine a better way to classify reviews using textual features with TSVM.

**EC.2.1 Latent Dirichlet Allocation (LDA)**

Based on the cleaned textual features, we begin our analysis of textual features through topic modeling, which is an approach used to extract hidden topics from large amounts of text (Blei 2012). We employ LDA to discover topics through online reviews in the auto shipping industry. LDA is a prevalent algorithm for topic modeling using Python’s Gensim package. This algorithm considers each document as a collection of topics in a particular proportion. Before estimating the topic distribution, the number of topics should be determined (Khern-am-nuai et al. 2018).

| Topic | Keywords | Label                  | Compensated Review |
|-------|----------|------------------------|--------------------|
| 0     | pay, quote, price, money, make, say, tell, pick, time, review | Finance             | 13.27%             |
|       | truck, unload, car, load, transport, mile, transportation, driver, drive, connection reservation, schedule, request, assistance, help, dial, process, call, phone, staff day, pickup, deliver, pick, issue, problem, happen, drop, date, trip, schedule | Operations         | 0.59%             |
| 1     | reservation, schedule, request, assistance, help, dial, process, call, phone, staff day, pickup, deliver, pick, issue, problem, happen, drop, date, trip, schedule | Reservation service | 0.02%             |
| 2     | car, transport, driver, deliver, condition, vehicle, ship, service, delivery, arrive thank, recommend, help, contact, experience, process, service, need, customer, assist skill, associate, hurry, highway, alpine, ship, jerry, jay, julie, matt | Delivery           | 5.92%             |
| 3     | car, transport, driver, deliver, condition, vehicle, ship, service, delivery, arrive thank, recommend, help, contact, experience, process, service, need, customer, assist skill, associate, hurry, highway, alpine, ship, jerry, jay, julie, matt | Car shipping functions | 52.68%           |
| 4     | thank, recommend, help, contact, experience, process, service, need, customer, assist skill, associate, hurry, highway, alpine, ship, jerry, jay, julie, matt | Recommendation     | 23.28%            |
| 5     | skill, associate, hurry, highway, alpine, ship, jerry, jay, julie, matt | Staff features     | 0.05%             |
| 6     | response, expectation, exceed, ensure, form, driver, vehicle, service, move, answer answer, phone, email, contact, text, update, respond, mail, time, question | Responsiveness     | 0.20%             |
| 7     | answer, phone, email, contact, text, update, respond, mail, time, question | Communication      | 1.83%             |
| 8     | destination, trucker, auto, logistics, port, broker, carrier, mover, auto-transport, job treat, car, tire, watch, trunk, track, key, item, stuff, piece damage, scratch, claim, repair, insurance, mark, report, address, cover, note morning, night, afternoon, pick, Saturday, Thursday, Monday, Friday, day | Auto transport company characteristics | 0.11% |
| 9     | destination, trucker, auto, logistics, port, broker, carrier, mover, auto-transport, job treat, car, tire, watch, trunk, track, key, item, stuff, piece damage, scratch, claim, repair, insurance, mark, report, address, cover, note morning, night, afternoon, pick, Saturday, Thursday, Monday, Friday, day | Customer assets    | 0.03%             |
| 10    | destination, trucker, auto, logistics, port, broker, carrier, mover, auto-transport, job treat, car, tire, watch, trunk, track, key, item, stuff, piece damage, scratch, claim, repair, insurance, mark, report, address, cover, note morning, night, afternoon, pick, Saturday, Thursday, Monday, Friday, day | Problematic        | 0.34%             |
| 11    | destination, trucker, auto, logistics, port, broker, carrier, mover, auto-transport, job treat, car, tire, watch, trunk, track, key, item, stuff, piece damage, scratch, claim, repair, insurance, mark, report, address, cover, note morning, night, afternoon, pick, Saturday, Thursday, Monday, Friday, day | Time              | 1.67%             |

Table EC.1 illustrates the topic modeling results. In the first ranking topic of compensated reviews, "car," "transport," and "driver" are the top three keywords. Therefore, this topic conveys the functions of car-shipping-related topics, given that online reviews evaluate shipping services
for moving cars. The second-highest compensated review keywords are "thank," "recommend," and "help." These keywords indicate recommendation-related topics. Therefore, the compensated reviews contain popular car-shipping-related, recommendation, and finance-related topics; furthermore, these features will enable us to classify whether reviews are compensated or not.

Table EC.2 shows the results of non-compensated reviews using LDA. Our findings show that there are many similar topics among the labeled and unlabeled predicted groups. Significantly, there are similar topics related to liability by combining "damage," "scratch," "repair," and "claim" by checking similarity topics based on the labeled and predicted unlabeled non-compensated data sets. Moreover, time-related topics with "morning," "afternoon," and "time" are popular in non-compensated online reviews. Therefore, many online reviews that do not receive any compensation include time and liability when posting online reviews on this platform.

### Table EC.2  Validation of Non-Compensated Reviews Using LDA

| Ranking | Keywords | Percentage | Keywords | Percentage |
|---------|----------|------------|----------|------------|
| 1       | car, service, ship, deliver | 59.29% | car, driver, transport, deliver | 51.22% |
| 2       | pay, quote, price, money | 25.56% | drop, contact, deliver, pick | 24.68% |
| 3       | damage, scratch, sue, repair process, answer, thank, recommend | 8.72% | pay, quote, price, charge pick, experience, recommend, need | 16.46% |
| 4       | morning, night, afternoon, pick | 2.12% | morning, night, afternoon, time | 5.11% |
| 5       | transport, help, need, satisfy | 1.68% | damage, scratch, sue, repair | 1.27% |
| 6       | issue, solve, resolve, complete | 0.97% | response, phone, email, contact | 0.68% |
| 7       | highway, moving, facility, space | 0.95% | help, problem, issue, handle | 0.23% |
| 8       | secure, lift, work, vehicle equipment, load, unload, drop | 0.36% | thank, trucker, trip, auto | 0.20% |
| 9       | benefit, relationship, service, share answer, phone, email, contact | 0.14% | load, transport, trip, fuel | 0.11% |
| 10      | 0.13% | | | |
| 11      | 0.04% | | | |
| 12      | 0.04% | | | |
| 13      | bid, negotiate, accept, explain | 0.00% | assurance, thank, people, support transparency, labor, kind, auto transport quality, assist, educate, provide | 0.00% |

Table EC.3 illustrates the results of compensated reviews by comparing all labeled and predicted unlabeled compensated reviews. The results demonstrate that there are many similar topics among the compensated groups for validation. Therefore, we validate our model using textual analysis.
In compensated reviews, the topic keywords are primarily positive and cite words such as "recommend," "thank," and "service." Compared to non-compensated reviews, there are many positive topics. This insightful result implies that compensated reviews are posted online with a positive tone.

Table EC.3 Validation of Compensated Reviews Using LDA

| Ranking | Keywords                          | Percentage | Keywords                          | Percentage |
|---------|----------------------------------|------------|----------------------------------|------------|
| 1       | car, ship, transport, deliver    | 30.71%     | auto, driver, pick, ship         | 46.40%     |
| 2       | process, contact, answer, question | 29.36%    | morning, night, afternoon, pick | 16.14%     |
| 3       | recommend, review, experience, know | 29.16%    | answer, phone, email, contact    | 9.72%      |
| 4       | enjoy, pleasure, expect, thank   | 5.06%      | price, match, quote, money       | 8.20%      |
| 5       | driver, drive, honesty, truck    | 3.23%      | process, explain, review, know   | 7.84%      |
| 6       | pay, money, deposit, charge      | 1.79%      | communication, experience, recommend, service | 7.69% |
| 7       | issue, relocate, transit, transfer | 0.34%    | damage, insurance, cover, claim  | 1.71%      |
| 8       | communication, prompt, service, handle, speed, logistics, transport | 0.17%    | fee, pay, price, money           | 1.43%      |
| 9       | trust, mind, care, operation     | 0.06%      | thank, pleasure, recommend, care | 0.35%      |
| 10      | deadline, incentive, option, cover | 0.04%    | response, expectation, exceed, ensure | 0.15% |
| 11      | suggest, interaction, access, company | 0.04%    | shipment, shipping, ship, automobile | 0.13% |
| 12      | loading, unloading, perform, inquiry | 0.03%    | kind, idea, review, transporter  | 0.13%      |
| 13      |                                  | 0.03%      | moving, carry, truck, item       | 0.11%      |

**EC.3 Econometric Model**

**EC.3.1 Instrumental Variables**

Unobserved variables affect the outcome, and critical explanatory variables in the estimation models often generate bias. Ho et al. (2017) suggest that the instrumental variable method can correct for efficiency to mitigate the omitted variable bias. This section considers two appropriate instrumental variables (IVs) for the independent variables: the number of compensated reviews and the ratings of compensated reviews in our H1, H2, and H3, respectively.

We employ the lagged number of compensated reviews as an instrument for the current number of compensated reviews to test our H1. In particular, we use the lagged terms as the instrumental
variable. Given that the lagged three weeks of the number of compensated reviews satisfy the underlying assumption, the lagged period of the number of compensated reviews is not systematically correlated with unexpected changes in the current period of the number of compensated reviews. Although a longer lag will potentially provide a better instrument because more distant lags are less correlated with the disturbances in the current period error term, more distant lags are more likely to be weakly correlated with troublesome explanatory variables.

**EC.4 Empirical Robustness Checks**

**EC.4.1 Additional Company Characteristics**

| Variables                      | (1)  | (2)  | (3)  | (4)  | (5)  | (6)  |
|--------------------------------|------|------|------|------|------|------|
| log(Number of compensated      | 0.363*** | 0.215*** | 0.226*** | 0.226*** | 0.226*** | 0.226*** |
| reviews from week t)           | (0.004) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| log(Number of compensated      | 0.163*** | 0.062*** | 0.061*** | 0.061*** | 0.061*** | 0.061*** |
| reviews from week t-1)         | (0.004) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Average ratings of             | 0.416*** | 0.282*** | 0.257*** | 0.257*** | 0.254*** | 0.254*** |
| compensated reviews            | (0.016) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) |
| Company response               | 0.337*** | 0.443*** | 0.441*** | 0.441*** | 0.440*** | 0.440*** |
| (0.011) | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) |
| log(Length of words)           | -0.038*** | -0.032*** | -0.019*** | -0.019*** | -0.018*** | -0.018*** |
| (0.004) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Average ratings of honesty     | 0.096*** | -0.021 | -0.016 | -0.016 | -0.019 | -0.019 |
| (0.019) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) |
| Average ratings of customer    | -0.337*** | -0.181*** | -0.141*** | -0.141*** | -0.146*** | -0.146*** |
| service                        | (0.020) | (0.014) | (0.013) | (0.013) | (0.013) | (0.013) |
| Average ratings of knowledgeable | -0.196*** | -0.060*** | -0.071*** | -0.071*** | -0.083*** | -0.083*** |
| (0.018) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) |
| Average ratings of promptness  | -0.225*** | -0.054*** | -0.054*** | -0.054*** | -0.057*** | -0.057*** |
| (0.013) | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) |
| Constant                       | 0.766*** | 0.366*** | 0.241*** | 0.243*** | 0.369*** | 0.371*** |
| (0.049) | (0.037) | (0.035) | (0.035) | (0.039) | (0.039) |
| Observations                   | 127,952 | 127,914 | 127,914 | 127,914 | 127,315 | 127,315 |
| R-squared                      | 0.343 | 0.684 | 0.713 | 0.713 | 0.714 | 0.714 |
| Company FE                     | NO    | YES   | YES   | YES   | YES   | YES   |
| Time FE                        | NO    | NO    | YES   | YES   | YES   | YES   |
| Car Condition FE               | NO    | NO    | NO    | YES   | YES   | YES   |
| Ship Pickup FE                 | NO    | NO    | NO    | NO    | YES   | YES   |
| Ship Delivery FE               | NO    | NO    | NO    | NO    | YES   | YES   |
| Top Domain FE                  | NO    | NO    | NO    | NO    | YES   | YES   |

Note: Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.
Table EC.5  Robustness Check for Compensated Reviews’ Average Ratings Effect

| Variables                                      | (1)     | (2)     | (3)     | (4)     | (5)     | (6)     |
|------------------------------------------------|---------|---------|---------|---------|---------|---------|
| DV: log(Average ratings of non-compensated reviews) | 0.113*** | 0.119*** | 0.113*** | 0.113*** | 0.111*** | 0.111*** |
| Average ratings of compensated reviews from week t | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Average ratings of compensated reviews from week t - 1 | 0.008*** | 0.005*** | 0.005*** | 0.005*** | 0.005*** | 0.005*** |
| Number of compensated reviews                   | 0.043*** | 0.045*** | 0.035*** | 0.052*** | 0.049*** | 0.049*** |
| Requote price                                    | (0.008) | (0.006) | (0.008) | (0.008) | (0.008) | (0.008) |
| Company response                                 | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| log(Length of reviews)                           | -0.002** | -0.003*** | -0.001 | -0.002** | -0.002** | -0.002** |
| log(Length of reviews)^2                         | 0.000* | 0.000* | 0.000 | 0.000* | 0.000* | 0.000* |
| Constant                                         | 1.216*** | 1.152*** | 1.193*** | 1.192*** | 1.201*** | 1.201*** |
| Observations                                     | 47,001 | 47,018 | 46,937 | 46,937 | 46,740 | 46,740 |
| R-squared                                        | 0.665 | 0.616 | 0.664 | 0.667 | 0.660 | 0.660 |
| Company FE                                       | YES | NO | YES | YES | YES | YES |
| Time FE                                          | YES | NO | NO | YES | YES | YES |
| Car condition FE                                 | NO | NO | NO | NO | YES | YES |
| Ship delivery FE                                 | NO | NO | NO | NO | YES | YES |
| Ship pick up FE                                  | NO | NO | NO | NO | YES | YES |
| Topic domain FE                                  | NO | NO | NO | NO | NO | YES |

Note: Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

EC.4.2 R-squared Decomposition

To identify the contribution of different variables to enlarge the number of non-compensated reviews, we first estimate the coefficient of each topic for H3. Next, we calculate the Shapley-Owen values to characterize the decomposition of the R-squared for the regression measures into the contributions over all variables (Huettner et al. 2012).

The Shapley-Owen decomposition of R-squared values, reported in Table EC.6, allows us to measure the relative weight of each topic in terms of the increase in the number of non-compensated reviews. The contribution of Topic 4 (named the Car shipping function) and Topic 5 (named recommendation) is 44.875% and 12.49%, respectively. The car shipping function and recommendation drive the regression results on the coefficients of Topics 4 and 5 in our Model 2. In Table EC.6, the Shapley-Owen values of the partial contribution to R-squared allow us to disentangle each topic’s importance when considering the topic model via textual analysis. From the estimation results, our finding is that Topic 4 (Car shipping function) is driving the increase in the number of non-compensated reviews. Although Topic 5 (Recommendation) has a second higher contribution
to R-squared, the p-value of Topic 5 is 0.148, meaning that the recommendation of this topic is insignificant.

We also measure the contributions of each regressor according to the Shapley-Owen values reported in Table EC.6, which allows us to measure the relative weight of each topic in terms of the increase in the number of uncompensated reviews. The contributions of Topics 4 and 5 are 44.875% and 12.49%, respectively, which means that the car shipping function and recommendation drive the regression results on the coefficients of Topics 4 and 5. In Table EC.6, the Shapley-Owen values of the partial contribution to R-squared allow us to disentangle each topic’s importance when considering the topic model via textual analysis. From the estimation results, our exciting finding is that Topic 4 (Car shipping function) is driving the increase in the number of non-compensated reviews. Although Topic 5 (Recommendation) has a second higher contribution to R-squared, the p-value of Topic 5 is 0.148, which means that the recommendation of this topic is insignificant. In other words, under Topic 4 (Car shipping function), the number of compensated reviews increases the number of non-compensated reviews.

| Variables                              | Coefficient | Standard Error | P-value | Shapley-Owen% |
|----------------------------------------|-------------|----------------|---------|---------------|
| Average ratings of compensated reviews | -1.405***   | 0.102          | 0.000   | 7.419         |
| Company response                       | 1.385***    | 0.137          | 0.000   | 3.792         |
| log(Length of reviews)                 | -2.065***   | 0.360          | 0.000   | 5.253         |
| log(Length of review)^2                | 0.185***    | 0.050          | 0.000   | 4.881         |
| Operations                             | -2.266***   | 0.431          | 0.000   | 3.232         |
| Reservation service                    | -9.048***   | 0.906          | 0.000   | 4.897         |
| Delivery                               | 1.494***    | 0.272          | 0.000   | 1.119         |
| Car shipping function                  | 4.347***    | 0.177          | 0.000   | 44.875        |
| Recommendation                         | 0.278       | 0.192          | 0.148   | 12.490        |
| Staff features                         | 0.464       | 1.010          | 0.646   | 0.110         |
| Responsiveness                         | -3.619***   | 0.537          | 0.000   | 3.355         |
| Communication                          | 3.761***    | 0.337          | 0.000   | 3.245         |
| Auto transport company characteristics  | -5.723***   | 0.718          | 0.000   | 3.681         |
| Customer assets                        | -2.120***   | 0.874          | 0.015   | 0.640         |
| Problematic                            | 3.765***    | 0.688          | 0.000   | 0.667         |
| Time                                   | 1.191***    | 0.382          | 0.002   | 0.344         |

Note: Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.
EC.4.3 Online Review Platform for Auto Shipping Service Example

Figure EC.1 shows an illustration of the auto shipping review platform. Online reviewers can evaluate the overall ratings and specify whether they are compensated or not. Since reviewers expect auto shipping companies to be honest, knowledgeable, prompt, and excellent in customer service, they can give ratings for each category. After receiving their car at the designated destination, reviewers can rate their car condition if any apparent defects such as damage or dirt. Finally, this online review platform provides specific reviews with the posted date and time, company name, shipment details, and review details.

| Car Shipping Company Name | Customer Service |
|---------------------------|------------------|
| ★★★★★ ★★★★★ ★★★★★ ★★★★★ ★★★★★ | Honesty: ★★★★★ |
| ★★★★★ ★★★★★ ★★★★★ ★★★★★ ★★★★★ | Knowledgeable: ★★★★★ |
| ★★★★★ ★★★★★ ★★★★★ ★★★★★ ★★★★★ | Promptness: ★★★★★ |
| ★★★★★ ★★★★★ ★★★★★ ★★★★★ ★★★★★ | Customer Service: ★★★★★ |

Service and communications were good after another company scammed me.

| Shipment Details | Review Details |
|------------------|----------------|
| Origin State: Florida | Quote or Order ID: 12345 |
| Pickup: On time | Quote or Order Cost: $1425 |
| Destination State: Washington | Dirty | Damaged |
| Delivery: On time | |

| Overall rating | Company Name |
|---------------|--------------|

| Overall rating | Service & Communications |
|---------------|--------------------------|

| Overall rating | Vehicle Condition |
|---------------|-------------------|

**Figure EC.1** Online Review Platform Example
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