TWO ESSAYS ON REDUCTION OF FAKE REVIEWS

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PhD

The Hong Kong Polytechnic University

This programme is jointly offered by The Hong Kong Polytechnic University and Harbin Institute of Technology

2018

The Hong Kong Polytechnic University

Department of Management and Marketing

Harbin Institute of Technology

School of Economics and Management

Two Essays on Reduction of Fake Reviews

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A thesis submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy

May, 2018

CERTIFICATE OF ORIGINALITY

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Abstract

The thesis includes two essays. In this thesis, two novel mathematical models are developed to analyze the effect of consumer behavior on the number of fake reviews. Moreover, the approaches to effectively reduce fake reviews are explored. Four areas are solved by synthetically analyzing consumer behavior. These areas are the motivation values of firms posting fake reviews, type of firms with high motivation value, characteristics of fake reviews and the efficient reduction of fake reviews by consumers, firms and online platforms.

An original agent-based model depicting the dynamic influence of prior reviews on subsequent reviews is proposed to describe consumer behavior. This model is applied to quantify the motivation values of firms posting fake reviews to determine the effective approaches to reduce fake reviews. A series of computer simulation are performed to corroborate that the average star ratings of products normally converge on actual quality, and that fake reviews significantly increase the convergent value. I quantified and compared the motivation values of firms posting fake reviews under different scenarios. The results show that motivation values generally decrease with the existing number of unscrupulous products. Firms are highly motivated to post fake reviews under three situations, namely, facing fierce competition, selling low-quality products and obtaining numerous consumers. The results also reveal that the current exhibition rule for ordering online reviews unwittingly increases fake reviews.

This thesis builds an original game-theoretical model, wherein two competing firms sell substitutable products in a platform, and successively observes equilibrium results in three different situations: two players (one firm and platform), three players (two firms and platform) in non-cooperative cases, and three players in cooperative cases. To the best of my knowledge, this study is the first to explore ways on how to reduce fake reviews through game-theoretical model, the first to consider the dynamic changing process of loyal consumers in game-theoretical model, and also the first to examine online reviews from a novel perspective of platforms. The results show that the cooperative case constantly benefits firms, but it would damage the platform and occasionally lead to additional fake reviews. By analyzing and comparing equilibrium results, we find that the platform with many fake reviews bears the following characteristics: (1) low sensitive degree of fake reviews on platform's reputation; (2) prefers to sell products with low unit misfit cost; and (3) improper degree of penalty. Firms prefer to issue fake positive reviews to themselves, instead of releasing fake negative reviews to their opponents.

Keywords: Consumer behavior, Motivation value, Online product review, Fake review, Agent-based model, Game-theoretical model

Acknowledgements

I would like to take this opportunity to express my deepest and sincere appreciation to all those people who helped me go through the PhD journey. First, I am especially grateful to my supervisors, Prof. Eric W.T. Ngai and Prof. WU Chong, for their guidance, supervision, and encouragement through my whole study process. The thesis would not have been possible without their trust right from the start.

I also thank my BOE members, Prof. Mingming Leng, Dr. Raymond Lau, and Dr. Vincent Cho, for their valuable suggestions on my PhD thesis.

Within PolyU MM Department and HIT Business School, there are many good opportunities for research collaboration. Many thanks to these talented scholars in PolyU and HIT, for their insightful suggestions for promoting my research project.

My family has provided crucial support during my pursuit of academic and research excellence. Many of my achievements, including this thesis, could not have happened without their support. A special acknowledgement to my wife, Yuanyuan, for her unconditional care and love.

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Chapter 1 Introduction

1.1 Motivation of the Study

With the rapid development of Internet and E-commerce, online shopping has been the indispensable shopping way for all people (Chiang et al. 2003; Zhao et al. 2013). Customers can purchase almost all kinds of products remotely, from home or the office, via the Internet, phone, facsimile, or from mail order catalogs (Ketzenberg and Zuidwijk 2009). However, online customers cannot physically interact with products in person, and only depend on the perceived assessments to judge whether the products are worthy to be purchased (Chen et al. 2008). As a result, products' return rate in some countries is even high at roughly 75% (Mostard et al. 2005).

Relative to offline customers, online customers are uncertainty about products, leading to an increasing loss caused by product return (Guide Jr et al. 2006; Hong and Pavlou 2014; Li et al. 2013). Product uncertainty, recently identified as a serious impediment to online markets (Dimoka et al. 2012; Ghose 2009; Kim and Krishnan 2015), is defined as the customers' difficulty in evaluating product attributes and predicting how a product will perform in the future (Hong and Pavlou 2014).

To mitigate product uncertainties, many customers even pay some extra costs to visit a brick-and-mortar retail store to first examine the product, and then switch to an e-tailer to purchase it at a cheaper price (Balakrishnan et al. 2014). There is no doubt that this kind of consumer behavior significantly reduces the profits of various parties. It is very necessary to propose some measures to help consumers directly realize products online (Avery et al. 1999; Zhao et al. 2013). As a result, online product reviews emerge in various platforms, including third-party websites, such as cnet.com, and online retail sites, such as amazon.com (Berger and Iyengar 2013; Chen and Xie 2005; Ye et al. 2009b).

Similar to other social information (Culotta and Cutler 2016), online product reviews have become an important source for customers to reduce their uncertainties about online products (Gao et al. 2015; Kwark et al. 2014; Li and Hitt 2010; Li et al. 2011). An increasing number of customers read online product reviews before purchasing products (Chevalier and Mayzlin 2006; Ghose et al. 2014; Li and Hitt 2008; Park and Kim 2009; Sparks and Browning 2011; Zhu and Zhang 2010). Online product reviews are even able to shift the demand for each product, and significantly affect revenues online (Ghose et al. 2012; Kwark et al. 2014; Luca 2016; Ye et al. 2009a).

Many studies have analyzed the effect of online product reviews on firms as well as confirmed a significant positive relationship between online product reviews and product sales (Mayzlin 2006; Tucker and Zhang 2011). The specific influence factors include the variance of product rating (Clemons et al. 2006), the valence of review ratings (Ye et al. 2011), the volume of ratings (Liu 2006), the content of text reviews (Archak et al. 2011), reviewer identities (Forman et al. 2008), and product characteristics (Zhu and Zhang 2010).

The well-documented effects of online reviews motivate firms to develop strategies in response to online reviews (Narasimhan and Turut 2013). Given the sensitivity of online reviews (Susarla et al. 2016), firms have high probability of altering online reviews in improving competitive positions (Dellarocas 2006; Mayzlin 2006), especially for firms currently ranked at low competitive position (Branco and Villas-Boas 2015). Online reviews are susceptible to unscrupulous firms that attempt to alter existing information by posting either fake positive reviews of themselves or fake negative reviews to their competitors, thereby resulting in review fraud (Mayzlin et al. 2014; Pranata and Susilo 2016). The complementary data sets from Yelp.com also prove that economic incentives factors heavily cause the decision of committing fraud (Luca and Zervas 2016).

Fake reviews deliberately mislead consumers by giving undeserving positive opinions to promote target products or by giving malicious negative opinions with the aim of discrediting other objects to damage the reputation of competitors (Jindal and Liu 2008; Mukherjee et al. 2013). Fake reviews lead consumers into making risky purchase decisions, causing undesirable influence to consumers, normal firms, and platforms (Choo et al. 2017; Jindal and Liu 2007; Jindal and Liu 2008; Lau et al. 2011). The effective way of reducing fake reviews has become a primary difficult problem in online marketing field (Luca and Zervas 2016).

Certain studies have designed algorithms to detect fake reviews and asserts that their algorithms have achieved a high percentage of accuracy (Alarifi et al. 2016; Cresci et al. 2015; Li et al. 2016; Mukherjee et al. 2013; Savage et al. 2015; Wang et al. 2012; Zhang et al. 2016a). The governments also have made some great efforts to reduce fake reviews. In 2015, the attorney general of the State of New York spearheaded "Operation Clean Turf," which is an investigation to identify and expose firms that create reviews; this initiative identified and fined such firms (Schneiderman 2013).

However, the effect of reducing fake reviews is not obvious, when only external efforts are taken. Developing computerized algorithm to identify fake reviews just treat the symptom, not the underlying problem. Many fake reviews still exist online regardless of algorithms with high detection because smart firms frequently post novel fake reviews endowed with new features that evade filter detection (Lappas et al. 2016). A considerable number of unscrupulous firms remain active and the percentage of fake reviews is estimated at around 15%–30% (Lappas et al. 2016; Luca and Zervas 2016).

We should explore ways to fundamentally reduce fake reviews from other effective perspectives, such as quantifying the motivation values of firms posting fake reviews. Proposing ways to make firms have no intention to alter online reviews is the suitable way to reduce radically fake reviews. If firms cannot obtain additional benefits from posting fake reviews, they will not alter online product reviews.

1.2 Research Objectives and Questions

The goal of this thesis is to explore the efficient ways to reduce the number of fake reviews. Given the aim of this study, we first quantify the motivation values of firms posting fake reviews and identify the characteristics or distributions of fake reviews. Then, we find the reasons why fake reviews have these specific features, and explore the ways to reduce fake reviews.

By the end of this dissertation, the following research questions will be synthetically answered.

RQ1: What are the motivation values of firms posting fake reviews?

RQ2: Which type of firms has high motivation values?

RQ3: What are the characteristics of fake reviews?

RQ4: What can consumers, firms and online platforms can do to efficiently reduce fake reviews?

To solve these four research questions, we build original agent-based model to analyze consumer behaviors in Essay one, and game-theoretical model to calculate equilibrium consumer behaviors in Essay two. Besides these four common research questions, we also solve some specific research questions by using different models.

In Essay one, we build agent-based model to describe consumer behaviors and analyze the effect of consumer behaviors on the number of fake reviews. Besides solving four common research questions, we also answer the research questions: How do the online product reviews evolve with or without fake reviews.

In Essay two, we build game-theoretical model to analyze the effect of equilibrium consumer behaviors on the number of fake reviews. Besides solving four common research questions, we also answer these four research questions: (i) Is there a significant difference about the number of fake reviews among all platforms? (ii) Which types of platforms are utilized by unscrupulous firms to post fake reviews? (iii) Will firms post less fake reviews when they cooperate? (iv) Is high degree of penalty can effectively reduce fake reviews?

Our research questions differ from prior researches on fake reviews that have not been examined previously as we focus on the underlying reasons leading to the characteristics or distributions of fake reviews. We also provide some practical suggestions to reduce fake reviews.

1.3 Structure of the Dissertation

This dissertation consists of two separate, but related, analytical essays that are titled:

1. “Agent-based model for the reduction of fake reviews”, and
2. “Reduction of fake reviews through game-theoretical model”.

These two essays focus on consumer behaviors, since the sender and the receiver of online reviews are both consumers. In the first study, we build an agent-based model to describe consumer behaviors about writing and reading online reviews and to explore their effects on the number of fake reviews. In the second study, we build a game-theoretical model to calculate the equilibrium consumer behaviors about writing and reading online reviews and to explore their effects on the number of fake reviews. Accordingly, we propose some efficient suggestions to reduce fake reviews. The essay one using agent-based model to describe consumer behaviors mainly provides some micro suggestions about reducing fake reviews, and the essay two using game-theoretical model to calculate equilibrium consumer behaviors mainly provides some macro suggestions about reducing fake reviews.

The detailed structures of these two essays are summarized below.

Chapter 2, “Agent-based model for the reduction of fake reviews”, is organized as follows. Section 2.1 provides the introduction, and Section 2.2 analyzes and summarizes prior literature. Section 2.3 proposes an original agent-based model to depict the dynamic influence process of prior reviews on subsequent reviewers. The research scenarios are designed in Section 2.4. And, Section 2.5 quantifies the motivation values of firms posting fake reviews by using a series of computer simulations and analyzes the motivation values under different scenarios. Section 2.6 concludes the study and discusses its implications and limitations, and directions for future work.

Chapter 3, “Reduction of fake reviews through game-theoretical model”, is organized as follows. We provide the introduction in the Section 3.1, and analyze prior literature in the Section 3.2. In Section 3.3, we outline the game-theoretical model with three players. In Section 3.4, we successively obtain and compare equilibrium results in three different situations: two players (one firm and platform), three players (two firms and platform) in non-cooperative cases, and three players in cooperative cases. In Section 3.5, we analyze and compare the effect of different parameters on the number of fake reviews to solve the three research questions. In Section 3.6, we discuss the robustness checks conducted on the main assumptions of our model and discuss their effect on our results. Finally, we conclude this study and discuss implications, limitations, and directions for future work in Section 3.7.

At the beginning of this dissertation, we provide the whole introduction in Section 1. After introducing these two essays, we summary the general conclusions in Section 4.

Chapter 2 Agent-based Model for the Reduction of Fake Reviews

2.1 Introduction

Marketers and sociologists have recognized the importance of word-of-mouth and proposed related theories (Feick and Price 1987; Holt 2002; King and Summers 1970; Kozinets et al. 2010). These theories focused on the importance of conversations among consumers and posited that consumers can obtain product information from prior online reviews (Arndt 1967; Engel et al. 1969; Gatignon and Robertson 1986). Considering the influence process of prior reviews on subsequent reviewers can yield useful conclusions, such as an accurate estimation of firms' motivation value for posting fake reviews.

Agent-based model (ABM) is appropriate and flexible (Harrison et al. 2007; Mason et al. 2007; Smith and Conrey 2007), and is suitable to be used to depict opinion diffusion (Macy and Willer 2002). ABM can effectively describe how a simple rule leads to complex marketing phenomena (LeBaron 2000; Rand and Rust 2011). A series of ABMs have been proposed in the fields of open communities and social networks (Baldassarri and Bearman 2007; Carletti et al. 2008; Ding et al. 2010; Flache and Macy 2011; Fu and Zhang 2016; La Rocca et al. 2014; Mark 2003; Mas and Flache 2013; Mas et al. 2013; Proskurnikov et al. 2016; Salzarulo 2006; Sichani and Jalili 2017; Song and Boomgaarden 2017; Watts and Dodds 2007;

Xiong et al. 2011). However, unlike open communities and social networks, online reviews have two unique features: a one-way influence pathway and the special rule of accessibility. The existing ABMs cannot be used in our research to analyze the evolution of online reviews. Thus, we proposed a novel original ABM to depict the dynamic influence process of prior reviews on subsequent reviewers and explore ways to reduce the number of fake reviews.

2.2 Literature Review

2.2.1 Evolution of Online Reviews

In the past decades, E-commerce sites have grown rapidly, and millions of products have been sold online (Avery et al. 1999; Zhao et al. 2013). Along with the advent of opinion-rich review forums, the number of reviews has grown massively (Berger and Iyengar 2013; Chen and Xie 2005).

These abundant consumer reviews guide consumers in selecting suitable products from a large number of choices (Gregan-Paxton and John 1997; Iyengar et al. 2007; Khandani et al. 2010; Villas-Boas 2004; Wang and Yu 2017; Zhao et al. 2013; Zhao et al. 2011), but consumers have limited time and patience to read online reviews (Hanni et al. 2016). To help consumers efficiently use online reviews, some studies used natural language processing to analyze and summarize online reviews (Hanni et al. 2016), and platforms designed the exhibition rule for ordering online reviews to guarantee that the selected online reviews would be located at the top. However, the credibility of the selected online reviews has yet to be verified (Pranata and Susilo 2016). Some studies have revealed a link between social network site cues and various aspects of the reviewer's credibility (D'Angelo and Van der Heide 2016; Flanagin and Metzger 2007; Van Der Heide and Lim 2016; Westerman et al. 2012; Westerman et al. 2014). Notably, under the current exhibition rules for ordering online reviews, some fake reviews have been located at the top of the sites.

Besides developing computer technologies to analyze online reviews, understanding the evolution of online reviews is important for all to use e-commerce and for consumers to better select products (Wang et al. 2017; Zhang et al. 2016b). The evolution of online reviews is a particular type of opinion diffusion, and to model it, researchers have developed various probabilistic models (Dermouche et al. 2014) and collaborative filtering methods (Koren 2010; Su et al. 2015) as well as ABMs (Baldassarri and Bearman 2007; Fu and Zhang 2016; La Rocca et al. 2014; Macy and Willer 2002; Mas and Flache 2013; Mas et al. 2013; Proskurnikov et al. 2016; Sichani and Jalili 2017; Song and Boomgaarden 2017; Watts and Dodds 2007). Although the methods concerning mathematical derivations can arrive at some general conclusions, they lack the flexibility to analyze personal behavior and cannot provide detailed suggestions for consumers to utilize online reviews. The complex online marketing industry consists of countless agents (e.g., consumers, sellers, and platforms) who behave in different ways (Rand and Rust 2011).

ABM is appropriate and flexible (Harrison et al. 2007; Mason et al. 2007; Smith and Conrey 2007), and is suitable to be used to depict opinion diffusion (Macy and Willer 2002). ABM can effectively describe how simple agent behaviors lead to complex online marketing (LeBaron 2000; Lorenz 2009; Rand and Rust 2011).

2.2.2 Agent-based Model

The idea behind ABMs is that researchers first describe agents' behaviors and then aggregate individual agent behavior to model complex phenomenon. An agent in an ABM is any autonomous entity with its own properties and behaviors (Rand and Rust 2011). To model the evolution of opinions, researchers have proposed ABMs. Table 2.1 summarizes the representative ABMs for such modeling.

Table 2-1 Summary about the representative ABMs about opinion evolution

Study	Selection rule of actors	Influence	Methods	Final distribution
Mark, 2003	Opinion similarity	Mutual	Simulation	N.A.
Salzarulo, 2006	Opinion similarity	Mutual	Simulation	Polarization or consensus
Baldassarri and Bearman, 2007	Opinion similarity	Mutual	Simulation	Polarization or consensus
Watts and Dodds, 2007	Linked neighbors	Mutual	Simulation	N.A.
Carletti, 2008	Opinion similarity	Mutual	Simulation	Consensus
Ding et al., 2010	Linked neighbors	Mutual	Simulation	Polarization or consensus
Flache and Macy, 2011	Opinion similarity	Mutual	Simulation	Polarization or consensus
Xiong et al., 2011	Linked neighbors	Mutual	Simulation	Polarization or consensus
Mas and Flache, 2013	Opinion similarity	Mutual	Simulation and experiment	Bi-polarization
Mas et al., 2013	Demographic attributes and opinion similarity	Mutual	Simulation	Short term: polarization Long term: consensus
La Rocca et al. 2014	All the population	Mutual	Simulation	Persuasion: polarization Compromise: consensus
Fu and Zhang, 2016	Opinion similarity	Mutual	Simulation	Bi-polarization or consensus
Proskurnikov, 2016	Linked neighbors	Mutual	Mathematical Proof	Polarization or consensus
Sichani and Jalili, 2017	Linked neighbors	Mutual	Simulation	N.A.
Song and Boomgaarden, 2017	Opinion similarity	Mutual	Simulation	Polarization or consensus

When modeling the evolution of opinions, the agents in the ABM first select actors to exchange opinions. In these representative ABMs, actors are selected mainly in two ways: opinion similarity in open community and linked neighbors in social networks (Baldassarri and Bearman 2007; Carletti et al. 2008; Ding et al. 2010; Flache and Macy 2011; Fu and Zhang 2016; La Rocca et al. 2014; Mark 2003; Mas and Flache 2013; Mas et al. 2013; Proskurnikov et al. 2016; Salzarulo 2006; Sichani and Jalili 2017; Song and Boomgaarden 2017; Watts and Dodds 2007; Xiong et al. 2011).

Based on the position bias theory in click model (Granka et al. 2004; Joachims et al. 2017), the content in higher positions always receive significantly more clicks than those in lower positions (Jansen et al. 2013). Similarity, the reviews in higher positions are easily selected and studied by consumers. However, the ranking of online reviews is decided not by the consumers themselves but by the platforms, who design the exhibition rule to organize online reviews. These two selection rules of actors, opinion similarity, and linked neighbors cannot be used in studying the evolution of online reviews. Accordingly, we built the original ABM by treating the objective exhibition rule of online reviews as the selection rule of actors.

In existing ABM research, agents exchange their information with actors and revise their opinions. The influence is mutual. However, in the field of online reviews, subsequent reviewers obtain information from prior reviews, but existing reviews cannot be modified. In the ABM depicting the evolution of online reviews, the influence is one-way.

Unlike open communities and social networks, online reviews have two unique characteristics: one-way influence and the passive selection rule of actors. These existing ABMs about opinion diffusion cannot be used to depict the evolution of online reviews. The present study is the first attempt to propose a novel ABM to depict the dynamic influence process of prior reviews on subsequent reviewers.

2.3 The Model

To help readers better understand this chapter, we exhibit the definitions of all notations used in this chapter in Table 2.2.

Table 2-2 Definitions of the notations used in Chapter 2

Notations	Definition
m	Total number of consumer agents in the model
n	Total number of products in the model
i	Index for products, $i \in n$
j	Index for agents, $j \in m$
k	Index for factors used to rank online reviews
l	Index for existing number of unscrupulous products
o	Index for online review
	Purchase stage
u_i	Number of existing online reviews for product i during research
s_i	Average star rating of product i, $0 \le s_i \le 5$
q_i	Actual value of product i, $0 \le q_i \le 5$
t_{io}	Star rating of reviewer located at o th place for product i, $0 \le t_{io} \le 5$
f_{ij}	Perceived value about product i before purchase from agent j, $0 \le f_{ij} \le 5$
f_j	Perceived value about a selected product purchased by agent j, $0 \le f_j \le 5$
θ_1	Percentage of fake positive reviews, $0 \le \theta_1 \le 1$

θ_2	Percentage of fake negative reviews, $0 \le \theta_2 \le 1$
α	Degree of evaluation score of fake negative reviews on product value, $0 \le \alpha \le 1$
b_{io}	Order score of o th review of product i, $0 \le b_{io} \le 1$
b_{jk}	Order score of review posted by agent j in the k th factor, $0 \le b_{jk} \le 1$
β_k	Weight of factor k when calculating order score, $0 \le \beta_k \le 1, k = 1,2,3$
b_j	Synthetic score of a review posted by agent j, $0 \le b_j \le 1$
δ	Average number of reviews considered by consumers
r_{ij}	Number of reviews about product i selected by agent j, $r_{ij} \sim N(\delta,1), 0 \le r_{ij} \le u_i$
	Evaluation stage
g_j	Perceived value about a selected product after use from agent j, $0 \le g_j \le 5$
d_j	Evaluation score posted by normal agent j after use, $0 \le d_j \le 5$
$d^{'}$	Evaluation score of fake positive reviews, $d^{'} \equiv 5$
$d^{''}$	Evaluation score of fake negative reviews, $d^{''} \sim N(\alpha q,1), 0 \le d^{''} \le 5$
p_j	Probability of posting reviews of agent j, $0 \le p_j \le 1$
σ	Weight of f_j in the calculation of d_j, $0 \le \sigma \le 1$
χ_j	Mean of the probability of posting online reviews of agent j, $0.5 \le \chi_j \le 1$
	Measure variables (when there are l unscrupulous firms)
wf_l	Mean number of consumers of unscrupulous products
wn_l	Mean number of consumers of normal products
zf_l	Mean final average star rating of unscrupulous products
zn_l	Mean final average star rating of normal products
$y1_l$	Motivation value in a factor of final average star rating
$y2_l$	Motivation value in a factor of the number of consumers
	Extension
c_j	Reliability of a review posted by agent j, $0 \le c_j \le 1$
γ	Threshold value of accepted c_j
B_j	New synthetic score of a review posted by agent j, $0 \le B_j \le 1$

2.3.1 Model Overview

In our study, we focus on the fierce market, in which the products have same actual product value and product prices. Although some studies reveal that positive online reviews increase firm reputations and product prices (Diekmann et al. 2014; Diekmann et al. 2008), we ignore considering the role of product prices for two reasons. First, when firms have more positive reviews and higher reputations, they attract more consumers. After realizing their consumer number increase, firms perhaps increase product prices to obtain higher profits. In this study, we cannot describe the dynamics of firms' behaviors, and thus can only consider the first influence of more positive reviews, i.e. positive reviews attract more consumers. Second, even though firms with more positive reviews design higher product prices, the difference of the product prices is so small that we can ignore it in the specific research environment.

The reason why we focus on the specific competitive research environment is that, almost all of fake reviews emerge in fierce competitive markets. The firms facing low-income consumers will not post any fake reviews to those facing high-income consumers, and vice versa. Only when the firms need to win consumers, they post fake reviews. For example, in one city there are four hotels: A, B, C, and D. Hotel A face high-income consumers, so it provides high-quality services and sell high price. Hotels B and C face middle-income consumers, so they provide medium-quality services and sell medium prices. Hotel D face low-income consumers, so it provides low-quality services and sell low price. We can expect that Hotels A and D do not need to post any fake reviews since they have no direct competitors. Hotels B and C have high probability to post fake reviews to the opponent, but have low motivations to post fake reviews to Hotels A and D. Although the services provided by Hotels B and C are similar, fake reviews can induce consumers to think one hotel provides significantly better services than the other hotel. Compared with the possible perceived service differences, the price differences between Hotels B and C are so small that we ignore the product price in our ABM.

To reflect the highly competitive circle, we set that the firms selling the products with same actual product value and product price have similar abilities to adopt strategies, like posting fake reviews. Although the products sold by these firms have same actual product values, consumers cannot realize the actual product value and rely on online reviews to perceive product values. To induce the consumers to purchase their products, some firms hire consumers to post fake reviews.

All consumer agents in the proposed ABM are divided into three parts: normal consumer agents, consumer agents posting fake positive reviews, and consumer agents posting fake negative reviews. The normal agents are not manipulated by others, and aims to purchase the perceived best product and then express their evaluations on the purchased products. The consumer agents posting fake reviews are hired by unscrupulous firms, and aims to post fake reviews to maximum their employers' profits. According to the law of large numbers (Feller 1971; Hsu and Robbins 1947), when the number of customer agents is very large, the proportion of consumer agents posting fake reviews is similar with that of fake reviews. All consumer agents appear randomly. Thus, we decide the type of each agent through a random number (RD) from 0 to 1. According to the generated RD, we judge whether agent j posts fake reviews.

Then, all consumer agents experience two stages: purchase stage and evaluation stage. Figure 2.1 depicts the overview of the proposed ABM and provides the mechanism for all agents purchasing products and evaluating the purchased products.

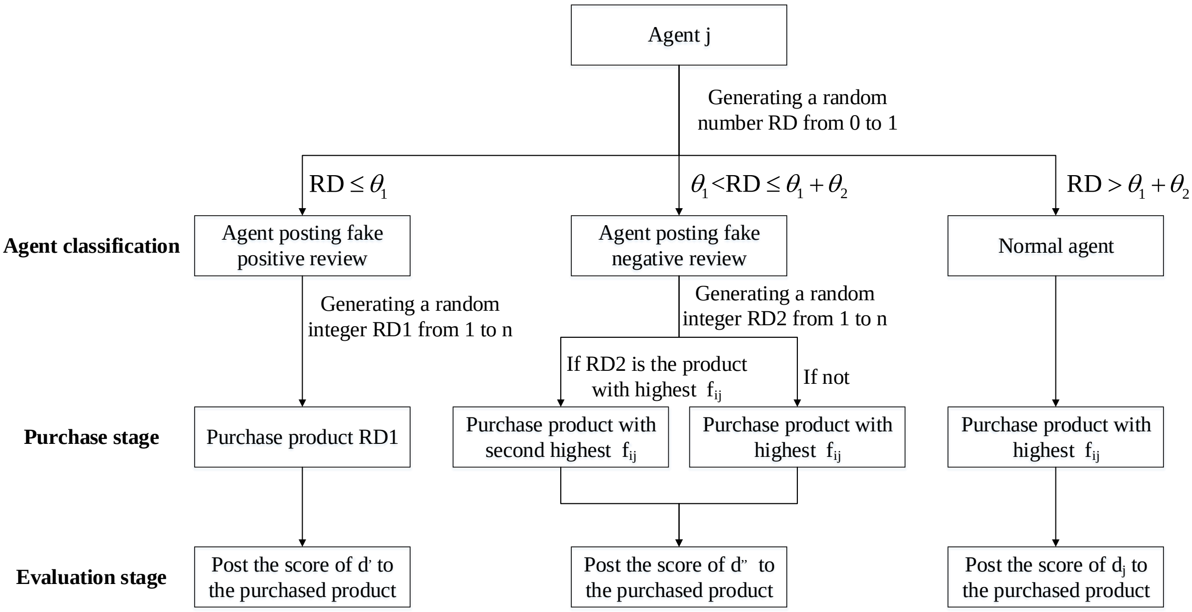


Figure 2-1 Overview of the proposed ABM

There are seven decisions to be made when designing an ABM (Rand and Rust 2011). Table 2.3 summarizes the seven decisions of our proposed ABM.

Table 2-3 Seven key design choices of the proposed ABM

Design choices	Our proposed ABM
1. Model scope	Evolution of online reviews.
2. Agents	Only consumer agents.
3. Properties	Agent j purchase one product from n substitutable products with same actual product value q_i and product price. For each product i, agent has initial impression s_i from the average star rating and updates the perceived value from selected online reviews to get perceived value f_{ij}. After using the purchased product, agent j has a new perceived value g_j. f_j and g_j co-determine p_j and d_j.
4. Behavior	The type of each agent is decided by a RD from 0 to 1. If the RD is lower than θ_1, the agent posts fake positive review with $d^{'}$. If the RD is larger than θ_1 but lower than $\theta_1+\theta_2$, the agent posts fake negative review with $d^{''}$. Otherwise, agent j is normal consumer agent and posts online review with d_j with probability p_j.
5. Environment	In the online market, the proportions of fake positive reviews and fake negative reviews are $\theta_1=15\%$ and $\theta_2=5\%$, respectively. And, the degree of evaluation score of fake negative reviews on actual product value is $\alpha=0.5$. (The detailed reasons for these settings are provided in the Section 2.5.3)
6. Input and output	Inputs: u_i, s_i, q_i, and g_j; outputs: $y1_l$ and $y2_l$.
7. Time step	The initialization step creates agents and describes the environment. Then, in each iteration step, each agent experiences the purchase stage and the evaluation stage. If the agent decides to post review, the average star rating of the purchased product is updated. The process is repeated until all consumer agents have been adopted.

2.3.2 Purchase Stage

From a series of products, consumer agents choose the perceived best one. Discrete choice models are widely used to predict the consumer choices from multiple discrete alternative products (Berry 1994; Talluri and Ryzin 2004). Discrete choice models take various forms, and have these common features: decision marketers, choice set, attributes of alternatives, and the decision rules (Train 2003).

In this study, the decision marketers are the consumer agents, and the choice set is the n products. In the fierce competitive market, all these products have same product properties, including the same actual product quality and product price. The only differences among these products are reflected by their online reviews. Thus, the attribute of alternatives is the available online reviews. Consumer evaluate all products through the star rating of available online reviews, and have their perceived values for these products. The decision rule is that normal consumer agents choose the product with highest perceived value; consumer agents posting fake positive reviews choose the product sold by their employers; and consumer agents posting fake negative reviews choose the product sold by the largest competitor of their employers.

Thus in the purchase stage, we first analyze the process how consumer agents perceive product value before purchase from the existing online reviews, and then use the decision rule to make consumer purchase decision.

2.3.2.1 Selection of Interaction Partners

When evaluating product i, consumer agents have their first impressions from the average star rating s_i. Then, consumer agents select some online reviews to study and update their perceived product values.

Unlike people located in open communities or social networks, all consumers cannot subjectively select valuable online reviews. Based on the foundation theory, position bias theory in click model (Granka et al. 2004; Joachims et al. 2017), the contents in higher positions always receive significantly more clicks than those in lower positions (Jansen et al. 2013). Similarly, the reviews in higher positions are easily selected and studied by consumers. But, the ranking order of online reviews are decided by not themselves, but the platforms, who design exhibition rule to organize online reviews.

Although different platforms have different exhibition rules to organize existing online reviews, they have similar key features used to organize online reviews. Specific review content, reviewer reputation, and evaluation time are three important features used in the mainstream platforms, such as taobao.com (Taobao 2017), yelp.com (Yelp 2017), and amazon.com (Amazon 2017). All reviews in taobao.com are organized by a synthesis score, which considered three key features: review content, review reputation, and evaluation time (Taobao 2017). These three characteristics guarantee that the selected online reviews can provide abundant, authoritative, and latest information.

For the sake of comparing and analyzing, we set review content as the first fact, reviewer reputation as the second factor, and evaluation time as the third factor.

When only the k th factor is considered, we define the score of a review posted by agent j as $b_{jk}, 0 \le b_{jk} \le 1, k = 1,2,3$.

Review contents provide specific information to subsequent consumers. A well-detailed review is considerably valuable for consumers. Normal reviewers do not focus on the abundance of the reviews, so the content abundance of their reviews is considered stochastic and follows truncated normal distribution. However, unscrupulous firms have sufficient ability and motivations to take action to make their reviews richness. The abundant of the reviews from unscrupulous firms is defined as 1. Therefore, for each agent j, the order score of normal reviewers and unscrupulous reviewers are $b_{j1} \in N\left(0.5,1\right), 0 \le b_{j1} \le 1$ and $b_{j1} \equiv 1$, respectively.

Reviewer reputation is also an important factor since consumers would like to trust the reviews posted by authorities. Even if reviewer reputation is difficult to be manipulated, some influential are still manipulated by unscrupulous firms. Many popular users are not always trustworthy with their reviews, and the distribution of normal reviewers and unscrupulous reviewers are similar (Pranata and Susilo 2016). Thus, all agents randomly become influential or common reviewers. On the basis of the second factor, we define the order score of all reviewers posted by agent j as $b_{j2} \in N\left(0.5,1\right), 0 \le b_{j2} \le 1$.

Unlike prior two factors, evaluation time is an unalterable objective factor. The review written by the newest agent should rank first until the next review emerges. Thus, if agent j is the newest agent, the order score of the review posted by agent

j is $b_{j3} \equiv 1$. Otherwise, when the number of existing review is defined as u_i, the order score of all reviews posted by existing agents who also purchase product i is updated be $b_{j3} = b_{j3} \times u_i / (u_i + 1)$. Table 2.4 summarizes the order scores of reviews for agent j based on these three different factors.

Table 2-4 Order score of reviews for agent j

	Fake review	Normal review
Review content ($k = 1$)	$b_{j1} \equiv 1$	$b_{j1} \in N(0.5,1), 0 \le b_{j1} \le 1$
Reviewer reputation ($k = 2$)	$b_{j2} \in N(0.5,1), 0 \le b_{j2} \le 1$	
Evaluation time ($k = 3$)	$b_{j3} = \begin{cases} 1 \\ b_{j3} \times u_i / (u_i + 1) \end{cases}$	

The synthetic order score of a review posted by agent j is b_j, which is the weighted value of b_{jk}. When we define the weight of factor k as β_k, the calculation of b_j is shown in Eq. (2-1):

$$b_j = \sum_k \beta_k b_{jk} . \tag{2-1}$$

Through calculating the order scores of all reviews, we place all reviews into suitable locations. Based on the foundation theory, position bias theory in click model (Granka et al. 2004; Joachims et al. 2017), the reviews in higher positions are easily selected and studied by consumers. The number of reviews selected by different agents is discriminate and follows truncated normal distribution in the range from 0 to u_i. When we define the average number of reviews considered by consumers as δ, the number of reviews selected by agent j about product i is $r_{ij} \sim N(\delta,1), 0 \le r_{ij} \le u_i$.

2.3.2.2 Influence Mechanism of Selected Reviews

Each agent first has an initial perceived value from average star rating s_i and then learn selected online reviews to update this score. Based on the aforementioned analyses, the number of online reviews selected by agent j about product i is r_{ij}. When the star rating of the online review located at the o th place for product i is defined as t_{io}, agent j updates the perceived value about product i through Eq. (2-2):

$$f_{ij} = \frac{u_i \times s_i + \sum_{o \in r_{ij}} t_{io}}{u_i + r_{ij}}. \tag{2-2}$$

In this function, f_{ij} is computed as the total star rating values of studied online reviews divide the total number of studied online reviews. In reality, consumer agents initially perceive the product values from the average star rating s_i, which reflects the star rating values of all u_i existing online reviews. Then, consumer agents update the perceived product values from the selected r_{ij} online reviews. These selected reviews are more important than other unselected reviews, so they are double counted.

Normally, consumer agents choose the product with highest perceived value. But there also exist some unscrupulous firms in the real world. The agents posting fake positive reviews undoubtedly choose their own product, and the agents posting fake negative reviews choose the product with highest perceived value except their own products.

2.3.3 Evaluation Stage

After purchasing the product, agent j posts evaluation score d_j with probability p_j. d_j and p_j are decided by both perceived value before purchase f_j and perceived value after use g_j.

2.3.3.1 Evaluation Score

When the actual value of the product i purchased by agent j is q_i, the perceived value after use g_j follows truncated normal distribution with mean q_i in the range from 0 to 5, i.e., $g_i \sim N(q_i, 1), 0 \le g_i \le 5$. Perceived value before purchase f_j and perceived value after use g_j co-determine evaluation score d_j. When the weight of f_j in the calculation of d_j is defined as σ, d_j can be calculated through Eq. (2-3):

$$d_j = \sigma \times f_j + (1 - \sigma) \times g_j. \tag{2-3}$$

Unlike normal consumer agents, unscrupulous consumer agents have unique mechanisms to calculate evaluation scores and post online reviews. The agents who post fake positive reviews undoubtedly choose the products sold by their employers and provide extremely high evaluation scores. And, the agents who post fake negative reviews choose the product with highest f_{ij} except the products sold by their employers, and post a low evaluation score to the purchased product.

Through analyzing the distribution of star ratings of online reviews, we find that the score of 5 is a common star rating value (Anderson and Simester 2014; Chevalier and Mayzlin 2006), so we assume that $d^{'} \equiv 5$.

When posting low evaluation scores to reduce opponents' reputations, the consumer agents posting fake negative reviews also consider how other agents evaluate this product. Normally, the average star rating of online reviews can reflect the actual product value. The average star rating of fake negative reviews is associated with the actual product value. Thus, we assume that the average star rating of fake negative reviews is αq_i. The existing literature only discover that extremely low scores are easily perceived as fake (Luca and Zervas 2016), but still have not provided any specific proportion of average star rating of fake negative reviews on the actual product value. We can only realize that α should be a moderately low value, but cannot realize its accurate value. Thus, in the benchmark scenario, we assume that $\alpha = 50\%$ (The reason for this assumption is provided in the Section 2.5.3, in which we conduct the detailed sensitive analyses about the parameter α).

Therefore, the agents posting fake reviews are hired by unscrupulous firms. Some unscrupulous agents purchase the products sold by their employers, and post fake positive reviews with $d^{'} \equiv 5$. Other unscrupulous agents purchase the products with highest f_{ij} except the products sold by their employers, and post fake negative reviews with $d^{''} \sim N(\alpha q, 1), 0 \le d^{''} \le 5$.

2.3.3.2 Probability of posting online reviews

Although advanced technology enables consumers to conveniently post online reviews, consumers are not forced to write online reviews. For each agent j, the probability of posting online reviews obeys truncated normal distribution with the mean value of χ_j, i.e., $p_j \sim N\left(\chi_j, 1\right)$, $0 \le p_j \le 1$.

Based on the expectation confirmation theory (Bhattacherjee 2001; Kuksov and Xie 2010), the value of χ_j is decided by the difference between f_j and g_j. When f_j is equal to g_j, χ_j is 0.5. When the difference between f_j and g_j is larger than 5, χ_j is 1. For normal agent j, χ_j can be calculated through Eq. (2-4):

$$\chi_j = \frac{5 + \left| f_j - g_j \right|}{10}. \tag{2-4}$$

The unscrupulous consumer agents spare no effect to post fake reviews. Therefore, for the agents posting fake reviews, the probability of posting online reviews is $\chi_j \equiv 1$.

When p_j is greater than or equal to 0.5, agent j posts an evaluation score to the purchased product, whose average star rating s_i should be updated. Otherwise, agent j does not post any evaluation scores, and s_i keeps unchanged. The updated process of s_i is described in Eq. (2-5):

$$s_i = \begin{cases} \dfrac{s_i \times u_i + h_j}{u_i + 1} & , p_j \geq 0.5 \\ s_i & , p_j < 0.5 \end{cases} . \tag{2-5}$$

After the process of updating s_i, agent j finishes its iteration step. The process is repeated until all agents have been adopted.

2.3.4 Measurement of Motivation Values

This study measures the motivation values of unscrupulous firms for posting fake reviews through observing the changing trend of two important indicators: final average star rating and number of consumers. Specifically, we divide all firm into two parts: normal firms and unscrupulous firms posting fake reviews. The motivation values are measured through comparing the performance difference between these two parts.

In this study, each firm sells one product. When there are l unscrupulous products, the mean value of final average star rating of normal products and that of unscrupulous products are zn_l and zf_l, and the mean value of number of consumers of normal products and that of unscrupulous products are wn_l and wf_l. The motivation values under these two factors ($y1_l$ and $y2_l$) are measured through calculating the changing trend when firm $l+1$ joins into the unscrupulous group. The specific measure equation is shown in Eq. (2-6):

$$\begin{cases} y1_l = \dfrac{zf_{l+1} - zn_l}{q} \\ y2_l = \dfrac{n\left[wf_{l+1} - wn_l\right]}{m} \end{cases} . \tag{2-6}$$

2.4 Scenarios Design

In this section, we use the proposed ABM to quantify motivation values of firms posting fake reviews and explore ways to reduce fake reviews. We first design the research scenarios, and then simulate and analyze the results under different scenarios to propose six propositions to answer our research questions.

All parameters are divided into three groups. In the first group, the values of parameters can be any possible values in different situations and need to be further analyzed. In this study, the parameters in the first group include the total number of consumer agents (m), the total number of products (n), actual quality value of product i (q_i), average number of reviews considered by consumers (δ), weight of f_j in the calculation of d_j (σ), and weight of k th factor when calculating order score (β_k). We cannot obtain the specific values for these parameters, since they vary from case to case. For these parameters in the first group, we first set the basic value and then conduct further discussions in the scenario 2.

In the second group, the values of parameters are decided by the macro social environment. But according to the known information, we cannot accurately acquire their values. So for these parameters in the second group, we first set the rough approximations and then conduct detailed robustness in the scenario 3. In this study, the parameters in the second group include percentage of fake positive reviews (θ_1), percentage of fake negative reviews (θ_2), and degree of evaluation score of fake negative reviews on actual product value (α). On the basis of prior studies (Lappas et al. 2016; Luca and Zervas 2016), we can only realize that the proportion of fake reviews is 15%-30%, and that fake positive reviews are much more common than fake negative reviews. Thus, we assume that the percentages of fake positive reviews and fake negative reviews are 15% and 5%, respectively. The existing literature only discover that extremely low scores are easily perceived as fake (Luca and Zervas 2016), but still have not provide any specific proportion of average star rating of negative reviews on the actual quality value. We can only realize that α should be a moderately low value in the range from 0 to 1, but cannot realize its accurate value. Thus in the benchmark scenario, we assume that $\alpha = 0.5$.

In the third group, the values of parameters are also decided by the macro social environment, but can be accurately determined based on the known information, so that they need not to be further analyzed. In this study, the parameter in the third group only includes evaluation score posted by agents posting fake positive reviews ($d^{'}$). Through analyzing the distribution of star ratings of online reviews, we find that the score of 5 is very common (Anderson and Simester 2014; Chevalier and Mayzlin 2006), so it is easily determined that $d^{'} \equiv 5$.

Thus, it is necessary to further discuss the values of parameters in the first and second group. Initially in the benchmark scenario, we set the basic values for the parameters in the first and second group. Subsequently, we change the values for these parameters in the first group to form scenario 2 to explore appropriate ways to reduce fake reviews from three parties: consumers, firms, and platforms. Then in scenario 3, we discuss the parameters in the second group to conduct the robustness about the main assumptions.

2.4.1 Scenario 1: Benchmark Scenario

At the baseline situation, there are fifty consumer agents ($m = 50000$) and ten products ($n = 10$). All these ten products have same actual product value ($q_i = 4$) and product price. The average number of reviews considered by consumers is $\delta = 20$. f_j and g_j are equally important for calculating d_j , e.g. $\sigma = 0.5$. And, the three selected factors are equally importance for ranking online reviews, e.g. $\beta_k = 1/3, k = 1, 2, 3$. These parameters in the first group vary from case to case. For example, the number of products in the fiercely competitive market is larger than that in the less competitive market.

Unlike the parameters in the first group, the parameters in the second group are decided by macro social environment. On the basis of prior studies (Lappas et al. 2016; Luca and Zervas 2016), we assumed that the percentages of fake positive reviews and fake negative reviews are 15% and 5%, respectively. Since the value of α should be a relatively small value (Luca and Zervas 2016), we assume that $\alpha = 0.5$.

Sensitive analyses about these parameters are done in Scenarios 2-3 to better understand and apply the proposed ABM in the real world. The scenario 2 helps us explore the effect of the behaviors of consumers, firms and platforms. And, the scenario 3 helps us understand the effect of current macro social environment, and verify our main assumption in this study.

2.4.2 Scenario 2: Parameters in the First Group

In scenario 2, experiments conducted in scenario 1 are repeated by changing the values of the parameters in the first group, including total number of agents (m), average number of reviews considered by consumers (δ), the weight of f_j in the calculation of d_j (σ), total number of products (n), actual quality of product i (q_i), and the weight of factor k in the calculation of synthetic ordering scores (β_k). All these parameters are divided into three parts related to three different parties: consumers, firms, and platforms.

For each parameter, we set two different values (one high value and one low value) to analyze the effect on the motivation values of firms posting fake reviews. Specifically, for most of parameters, we use the fourfold value to represent the high level and use the quarter value to represent the low level. Table 2.5 exhibits the specific research designs in scenario 2.

Table 2-5 Research designs in scenario 2

Parameters			Consumers			Firms		Platforms[1]		
			m	δ	σ	n	q_i	β_1	β_2	β_3
Benchmark			50000	20	0.5	10	4	1/3	1/3	1/3
Parameters about consumers	High	m	200000	20	0.5	10	4	1/3	1/3	1/3
	Low		12500							
	High	δ	50000	80	0.5	10	4	1/3	1/3	1/3
	Low			5						
	High	σ	50000	20	1[2]	10	4	1/3	1/3	1/3
	Low				0.125					
Parameters about firms	High	n	50000	20	0.5	40	4	1/3	1/3	1/3
	Low					3[3]				
	High	q_i	50000	20	0.5	10	5[4]	1/3	1/3	1/3
	Low						1			
Parameters about platforms	High	β_1	50000	20	0.5	10	4	1	0	0
	Low							0	1/2	1/2
	High	β_2	50000	20	0.5	10	4	0	1	0
	Low							1/2	0	1/2
	High	β_3	50000	20	0.5	10	4	0	0	1
	Low							1/2	1/2	0

---

[1]We analyze different combinations of three key characteristics: review content, reviewer reputation, and evaluation time through allocating different weights. For each characteristic's weight, we use 1 and 0 to represent its high and low importance, respectively.

[2]Although the fourfold of 0.5 is 2, we set this parameter in a high case as 1, which is the maximum value of this parameter.

[3]Although one quarter of 10 is 2.5, we set this parameter in a low case as 3 given that this parameter must be an integer.

[4]Although the fourfold of a product quality is 16, we set this parameter in a high case as 5 since the upper boundary of product quality is 5.

2.4.3 Scenario 3: Parameters in the Second Group

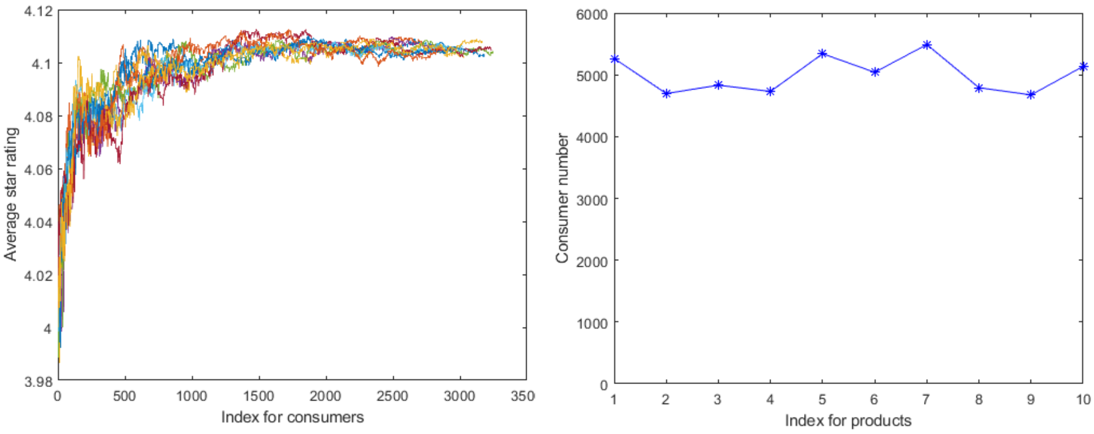
By referring to prior studies' conclusions (Lappas et al. 2016; Luca and Zervas 2016) , we assume that the percentages of fake positive reviews and negative reviews are 15% and 5%, respectively, and that the degree of evaluation score of fake negative reviews on actual product value is $\alpha = 0.5$.

In scenario 3, we discuss the important robustness check about these main assumptions. Specifically, we set the value of θ_1 from 0 to 0.3 with an interval of 0.1 and the value of θ_2 from 0 to θ_1 with the interval of 0.1. And to discuss the effect of the value of α, we set the value of α from 0.2 to 0.7 with an internal of 0.1.

2.5 Simulation Results

2.5.1 Simulation Results of Scenario 1

We first simulate the evolution of online reviews and quantify the motivation values of firms posting fake reviews in the basic scenario. Figure 2.2 depicts the main simulation results under the benchmark scenario.



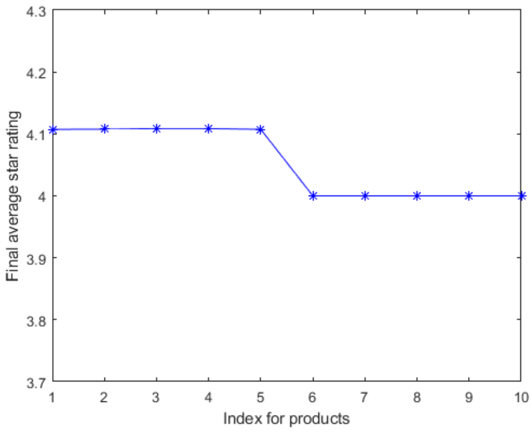
(a) Evolution of online reviews (b) Consumer number

Figure 2-2 Simulation results under the benchmark scenario

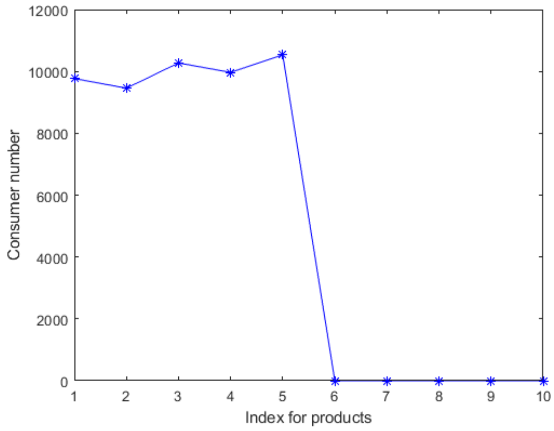
Figure 2.2a exhibits the convergence procedures of average star rating of online reviews. Although some drastic fluctuations arise during the process, the average star rating of online reviews are convergent to roughly 4.1 for all products. The finding that fake reviews can significantly increase the final average star rating is proofed in the Appendix. The additional part of the final average star rating with fake reviews compared to the actual quality value is shown in Eq. (A-5). The factors causing that fake reviews significantly increase the final average star rating are discussed in the later scenarios.

Figure 2.2b shows that numbers of consumers for all products are quite close under the benchmark scenario.

To analyze the effect of fake reviews, we set a specific research situation, in which the first five products belong to the unscrupulous group and the later five ones belong to the well-behaved group. When these ten products are averagely divided into two groups, the numerical values of these two important indicators for all these ten products are shown in Figure 2.3.



(a) Final average star rating



(b) Consumer number

Figure 2-3 Results of the case in which only first five products are unscrupulous

Compared with the well-behaved products, the products with fake reviews obtain higher final average star ratings and have tremendous power to attract consumers. The mean average star ratings of the first five products and the later five products are 4.10794 and 4, respectively. Although the difference of the final average star ratings between these two groups is small, the difference is enough to affect consumers' purchase decision. All consumers are rarely divided by these unscrupulous products. Therefore, we obtain the proposition 1, related to the research question 1.

Proposition 1: Without fake reviews, the average star rating of products converges on their actual product values. Fake reviews significantly increase the final average star rating with a slight amplitude, and have tremendous power to attract consumers.

Proof: See the appendix A.

Proposition 1 reveals a general fact that the final average star rating of online reviews reflects the actual product values, when there are not fake reviews. Normally, consumers can realize the actual product values through observing the evolution of online reviews. This is intuitive for that the final average star rating can reflect the recognized product information, based on the law of large numbers (Feller 1971; Hsu and Robbins 1947).

Proposition 1 also discovered the tremendous capacities of fake reviews in affecting the evolution of online reviews and attracting consumers. As fake reviews have a significant capacity to improve product profits, firms have high motivations to manipulate online reviews.

We further explore the specific variation tendency of motivation values with the changing number of unscrupulous products. Table 2.6 calculates and presents the specific numerical values of measure variables under different numbers of unscrupulous products.

Table 2-6 Motivation values under different numbers of unscrupulous products

Number of unscrupulous products	0	1	2	3	4	5	6	7	8	9	10
zf	/	4.447	4.140	4.116	4.112	4.108	4.105	4.103	4.106	4.092	4.104
zn	3.992	2.531	3.998	3.987	3.999	4	3.994	4	4	4	/
$y1$	0.091	0.322	0.024	0.025	0.022	0.021	0.022	0.021	0.018	0.021	/
wf	/	47510	24997	16666	12497	10000	8332	7143	6250	5556	5000
wn	5000	277	1	0	2	0	2	0	0	0	/
$y2$	8.502	4.944	3.333	2.499	2.000	1.666	1.428	1.250	1.111	1.000	/

If there only exists one unscrupulous product, the unscrupulous product never receives fake negative reviews, leading to that the final star rating of the unscrupulous product is high to 4.482. But, other normal products receive a series of fake negative reviews from the only one unscrupulous product, resulting in that the average final star rating of normal products is low to 2.534. When considering the final average star rating, the motivation value y_1 has the maximum value (0.319) when there exists only one unscrupulous product. When more than two unscrupulous products exist, the final average star ratings of unscrupulous products and normal products are convergent to roughly 4.10 and 4, respectively. Motivation value y_1 becomes stable, since all firms experience fake negative reviews.

Motivation value y_2 increases with the decrease of the number of unscrupulous products. If fake reviews exist, almost all consumers are divided by these unscrupulous products. Along with the increase in the number of unscrupulous products, the number of consumers per unscrupulous product decreases sharply, so the motivation values of firms for posting fake reviews decrease.

Therefore, we obtain the proposition 2, related to the research question 1.

Proposition 2: The motivation values of firms posting fake reviews generally decrease along with the existing number of unscrupulous products. When only considering the final average star rating, the motivation value has maximum value when there only exists one unscrupulous product and becomes stable when there are more than two unscrupulous products.

Proof: See the appendix A.

Proposition 2 reveals the changing trend of motivation values of firms posting fake reviews. When fake reviews do not exist, all firms have high motivation values to manipulate online reviews. The motivation values usually decrease with the number of unscrupulous products, because of the negative relationship between abnormal profits assigned to unscrupulous products and the number of unscrupulous products. But when only the average star rating is considered, the motivation value is maximized when only one unscrupulous product exists, because the only one scrupulous product gets much fake positive reviews from itself and does not receive any fake negative reviews.

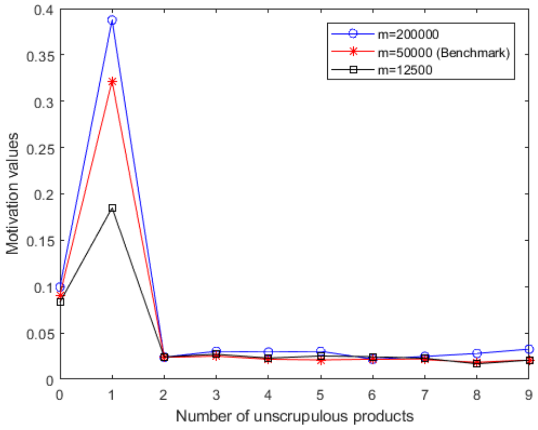
In short, the proposition 2 reflects a worthy in-depth conclusion that there exists an equilibrium percentage of fake reviews, in which the motivation value is equal to the negative influence of firms posting fake reviews.

2.5.2 Simulation Results of Scenario 2

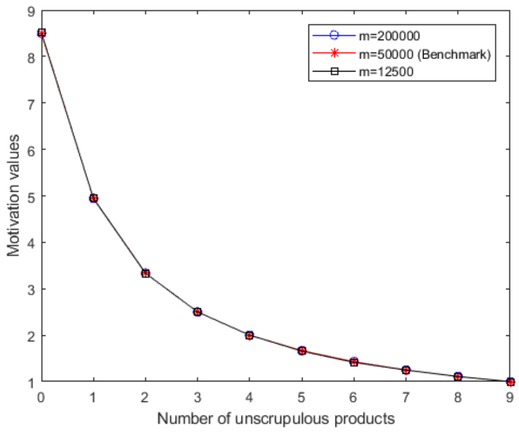
To better understand and utilize the ABM, we compare the results of benchmark scenario with the cases with different values for the parameters in the first group. All these relevant parameters are divided into three parts: consumers, firms, and platforms. One of the purposes of the scenario 2 is to consider how the results would change and how robust the proposed ABM would be if the parameter changes. Through comparing and analyzing the different results, we propose proposition 3-5 to solve our research questions.

2.5.2.1 Parameters about Consumers

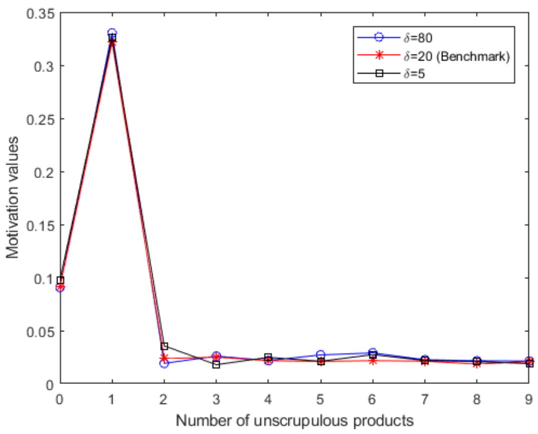
The parameters related to consumers include number of consumer (m), average number of reviews considered by consumers (δ), and the weight of f_j in the calculation of h_j (σ). In the benchmark scenario, these parameters are set as $m = 50000$, $\delta = 20$, and $\sigma = 0.5$. For each parameter, we use the given values shown in Table 2.5 to represent its high and low levels. We calculate the motivation values under the different levels of these three parameters and present them in Figure 2.4.



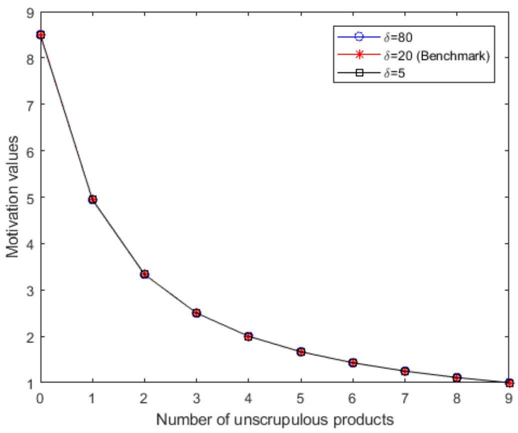
(a) Value of y_1 under different m



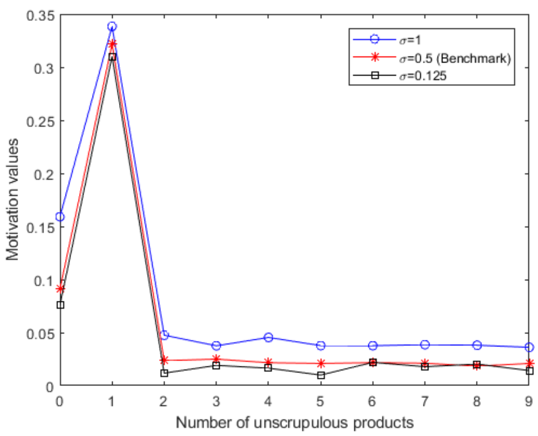
(b) Value of y_2 under different m



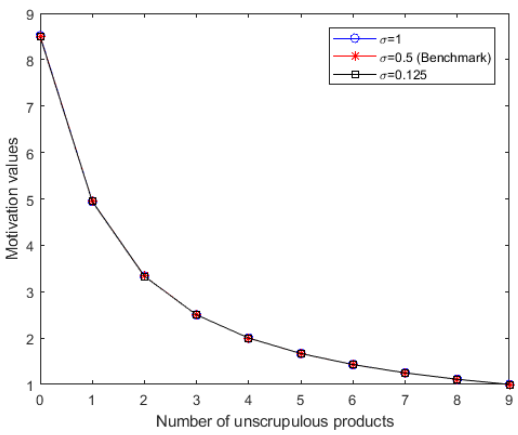
(c) Value of y_1 under different δ



(d) Value of y_2 under different δ



(e) Value of y_1 under different σ



(f) Value of y_2 under different σ

Figure 2-4 Motivation values under different parameters about consumers

Figure 2.4a shows that the total consumer number positively affect the motivation value $y1$, only when there exists one unscrupulous firm. If only one unscrupulous firm posts fake reviews, the firm never receive fake negative reviews but other firms receive many fake negative reviews, so the difference of average star rating between unscrupulous firms and normal firms increase along with the total consumer number (e.g. total number of online reviews). But when there are more than 2 firms posting fake reviews, all firms receive fake negative reviews, so the difference of average star rating between unscrupulous firms and normal firms can keep balance, and firms' motivation values $y1$ do not change. In summary, when the total consumer number increases, firms have higher motivations to begin to post fake reviews, but the equilibrium percentage of fake reviews keep unchanged.

Figure 2.4b shows that the number of consumers has no effect on the motivation value $y2$. The absolute difference of consumer number between unscrupulous firms and normal firms is positively related with the total consumer number, but the relative difference is not associated with the consumer number, since the increased average star rating caused by fake reviews has tremendous ability to attract all consumers no matter consumers the markets have.

Figures 2.4(c-d) show that $y1$ and $y2$ keep unchanged under different average number of reviews considered by consumers δ, stating that the effect of δ values on firms' motivation values is small. Under the current exhibition rule of presenting online reviews, consumers are easily affected by fake reviews regardless of the number of their selected online reviews. Fake reviews easily induce consumers, because of the unreasonable of the current exhibition rule. To eliminate the effect of fake reviews, we extend our study in the later section through considering how to reasonably present the online reviews.

Figure 2.4e reveals a positive relationship between weight σ and firms' motivation values $y1$. The weight σ measures the importance degree of the perceived value before purchase f_j on deciding the evaluation score d_j. If consumers rely more on f_j when writing online reviews d_j, the effect of prior online reviews on subsequent online reviews become larger, so fake reviews have higher opportunities to affect the evolution of online reviews. Thus, we appeal that consumers should rely more on their actual perceived value after use g_j, when posting the evaluation value d_j.

But no matter how low the effect of f_j on d_j is, we must acknowledge that fake reviews increase the average star rating of unscrupulous products. The increased average star rating invariably induces consumers to purchase the unscrupulous products. Thus, Figure 2.4f shows that the firms' motivation values $y2$ keep unchanged when the weight σ changes.

Thus, we obtain the proposition 3 related to the research question 1 and 4.

Proposition 3: Motivation values are not affected by consumer behaviors about learning online reviews, but affected by consumer behaviors about writing online reviews. Firms have low motivations to post fake reviews if consumers highly rely on the perceived value after use to decide the evaluation score.

Proof: See the appendix A.

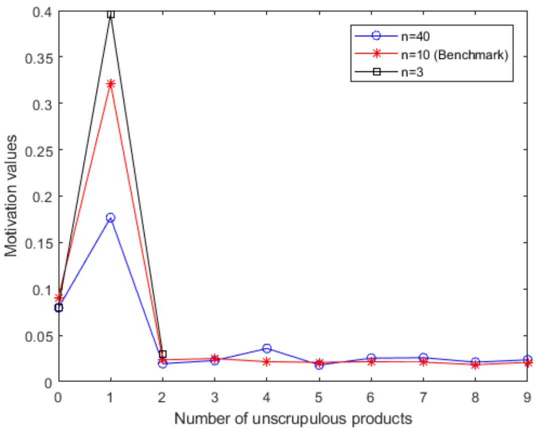
Proposition 3 studies consumer behaviors from two different perspectives: learning online reviews and writing online reviews. The consumer learning behavior is mainly reflected by the number of online reviews selected to help consumer agents realize the products. No matter how many online reviews are selected, the motivation values of firms posting fake reviews keep unchanged. This is intuitive, since the exhibition rule for presenting online reviews are decided by platforms, not consumer agents themselves. Owing to the particular exhibition rule for ordering online reviews, consumer reading behaviors cannot virtually affect the evolution of online reviews. Thus, in the following sections, we take further analyses on the exhibition rules to explore whether and how an effective exhibition rule for presenting online reviews can reduce fake reviews.

Proposition 3 also analyzes the effect of consumer behaviors about writing online reviews on firms' motivation values. If consumers can highly rely on the perceived product value after use and rarely consider prior reviews when writing online reviews, the firms' motivation values significantly decrease.

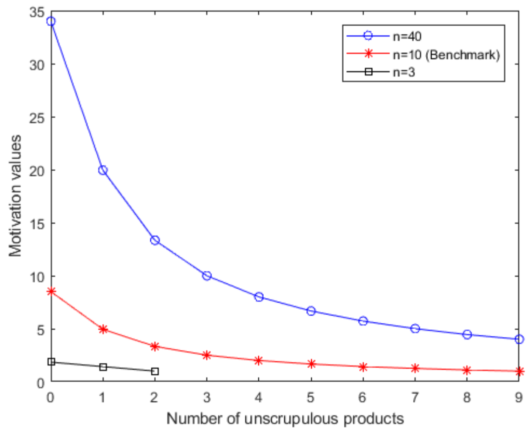
Thus, we put forward the suggestion to reduce fake reviews from the perspective of consumers: consumers had better ignore prior reviews and highly consider their actual user experience when writing online reviews.

2.5.2.2 Parameters about Firms

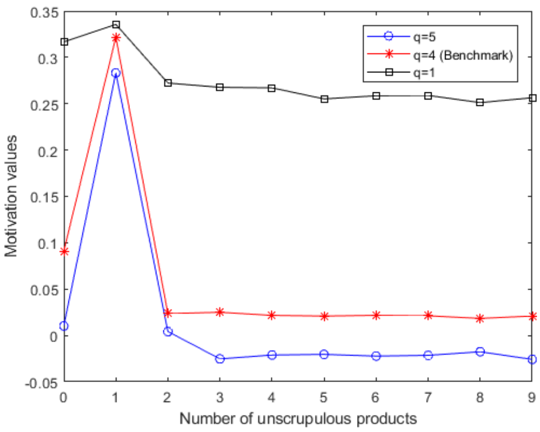
The parameters related to firms include number of products (n), and actual quality (q_i). In the benchmark scenario, these two parameters are set as $n = 10$, and $q_i = 4$, respectively. For each parameter, we use the given values in Table 5 to represent its high and low levels. We calculate the motivation values under the different levels of these two parameters and present them in Figure 2.5.



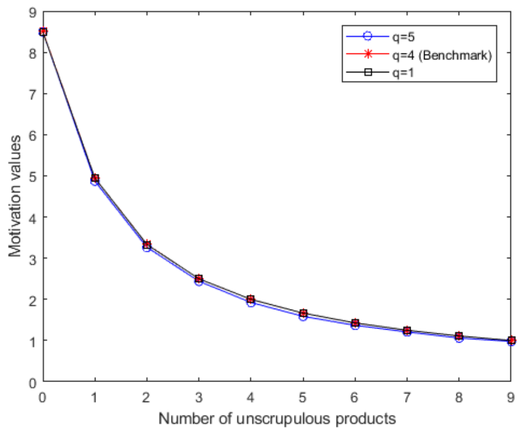
(a) Value of y_1 under different n



(b) Value of y_2 under different n



(c) Value of y_1 under different q



(d) Value of y_2 under different q

Figure 2-5 Motivation values under different parameters about firms

Figure 2.5a shows that the number of product (n) negatively affect the motivation value $y1$, only when there exists one unscrupulous firm. When the number of products increases, the negative influence per normal product attacked by unscrupulous products decreases, so firms have lower motivations to begin to post fake reviews. But when there are more than 2 firms posting fake reviews, all firms receive fake negative reviews, so the difference of average star rating between unscrupulous firms and normal firms can keep balance, and firms' motivation values $y1$ do not change. In summary, when the total product number increases, firms have lower motivations to begin to post fake reviews, but the equilibrium percentage of fake reviews keep unchanged.

But from Figure 2.5b, we find that the number of products (n) has a significantly positive effect on motivation value $y2$. When the number of products increases, the number of consumers per normal product decreases, while unscrupulous products still have a high capacity to attract consumers, so the motivation value of $y2$ increases significantly. In the benchmark scenario where the number of products is 10, firms' motivation values are 8.502, 4.943967, and 3.333025, when there are 1 (e.g. 10%), 2 (e.g. 20%), and 3 (e.g. 30%) unscrupulous products, respectively. In the scenario where the number of products is 40, firms' motivation values are 9.9924 and 5, when there are 4 (e.g. 10%) and 8 (e.g. 20%) unscrupulous products, respectively. In the scenario where the number of products is 3, firms' motivation value is 1.84574, when there is 1 (e.g. 33%) unscrupulous products. Through observing 9.9924>8.502, 5>4.943967, and 3.333025>1.84574, we conclude that the equilibrium percentage of fake reviews is positively related with the number of products. Thus, in a fiercely competitive market, firms have high motivations to post more fake reviews.

Figure 2.5c shows that shows that the product value negatively affects firms' motivation values. For the firms selling high-quality product, the motivation values $y1$ is even lower than 0 when more than two unscrupulous products exist, revealing a counterintuitive fact that the negative influence of fake reviews perhaps exceeds their positive influence. This is also intuitive, since for the high-quality product, the positive influence from fake positive reviews (5-q_i) is limited but the negative influence from fake negative reviews ($q_i - \alpha q_i$) is huge.

Figure 2.5d also shows that the motivation values $y2$ of firms selling high-quality products is lower than that of firms selling low-quality products. But, the difference of $y2$ among these three kinds of firms is very small, illustrating that consumers are easily affected by fake reviews. It is of high importance to design effective exhibition rule ordering online reviews to help consumers filter fake reviews and learn online reviews.

Therefore, we obtain the Proposition 4 related to the research question 2.

Proposition 4: The motivation values of firms posting fake reviews are significantly affected by firms themselves. Firms facing fierce competition and selling low-quality products have high motivations to post fake reviews.

Proof: See the appendix A.

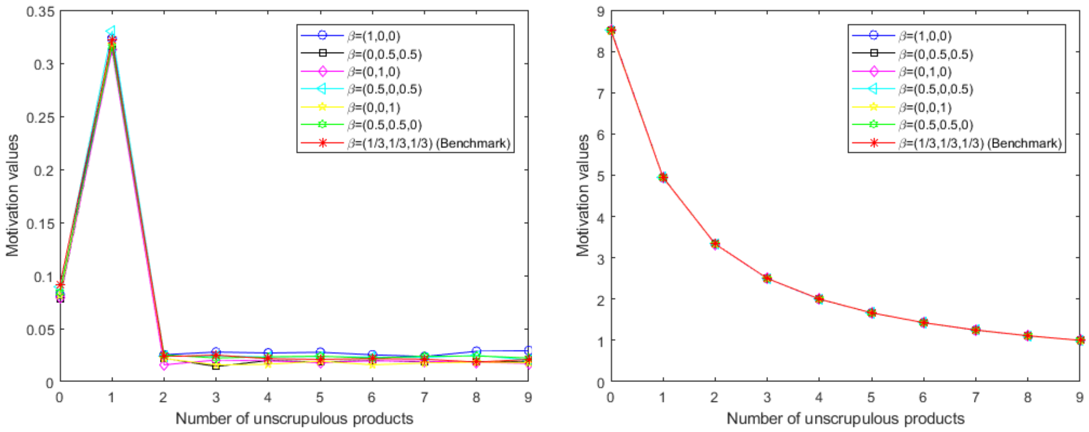
Proposition 4 analyzes the effect of firms themselves on the motivation values of firms posting fake reviews. When facing fierce competition, firms have great urgencies and high motivations to promote their products. Prior studies elucidated that product value significantly affects the motivation values of firms posting fake reviews (Dellarocas 2006; Mayzlin 2006) and that firms located at low competing positions are highly motivated to alter fake reviews (Branco and Villas-Boas 2015). Our findings are consistent with their conclusions that firms selling low-quality products have higher motivations to alter online reviews than firms selling high-quality products.

Thus, we put forward the suggestion to reduce fake reviews from the perspective of firms: consumers should pay more attention to the online reviews of the firms locating in the fierce competitive market or selling low-quality products. To insist on out posting fake reviews, firms should continuously improve their product values to occupy the favorable position in the fierce competitive market.

2.5.2.3 Parameters about Platforms

Unlike agents in open communities or social networks, all consumers cannot subjectively select valuable online reviews. Based on the foundation theory, position bias theory in click model (Granka et al. 2004; Joachims et al. 2017), the reviews in higher positions are easily selected and studied by consumers. The ranking order of online reviews are decided not by the consumers themselves but by the platforms who design the exhibition rule to present online reviews. Thus, platforms also significantly affect the evolution of online reviews and firms' motivation values, through designing the exhibition rule to present online reviews.

In this section, we analyze the effect of exhibition rule for ordering online reviews on motivation values of firms posting fake reviews. The commonly used features to order online reviews include specific review content, reviewer reputation, and evaluation time. In the benchmark scenario, we set the weights of three key characteristics as 1/3. For the weight of each parameter, we use the given values shown in Table 2.5 to represent its high and low levels. We calculate the motivation values under these different weight combinations and present them in Figure 2.6.



(a) Value of y_1 (b) Value of y_2

Figure 2-6 Motivation values under different weight combinations

Figure 2.6 shows that some weight combinations significantly change firms' motivation values, but the difference is so small that we conclude that these six weight combinations cannot effectively optimize the motivation values. Firms have highest motivation values when only the first indicator, review content, is considered, e.g. the weight combination is (1,0,0). Then, firms have relatively higher motivation values under two weight combinations: (0.5,0,0.5) and (0.5,0.5,0). Under other three weight combinations: (0,0.5,0.5), (0,1,0), and (0,0,1), firms have lower motivation firms. This is intuitive for that only the first indicator is easily manipulated by firms, and the second and third indicators are random.

But, the difference of firms' motivation values among these difference weight combinations are very small, so we cannot consider that changing the weight combinations can significantly reduce firms' motivation values. And, all these three characteristics have their unique roles in helping consumers realize products. If we only use to first indicator to rank online reviews, consumers perhaps can realize abundant product information but cannot guarantee that the received information are authoritative and latest. Thus, we cannot and also do not need to change the weight for these indicators.

Actually, fake reviews can affect the evolution of online reviews and induce consumers, since they always provide extreme information, which tremendously differ from the true product values. No matter how we change the weight combinations, the fake reviews can still have their effects. Thus, we consider that the key imperfection of the current exhibition rule is that the rules do not consider the characteristics of fake reviews.

It is very hard to guarantee that there are no fake reviews in the selected online reviews, since detecting fake reviews is very difficult. Many studies have focused on the identification of fake reviews and stated that their algorithms have extremely perfect performance (Alarifi et al. 2016; Cresci et al. 2015; Savage et al. 2015;

Zhang et al. 2016a). However, no matter how accurate the existing detection algorithms are, the percentage of fake reviews remains high (Luca and Zervas 2016). It seems that the only way to reduce the motivation values is to impose punitive measures on firms whose fake reviews have been detected. However, platforms have difficulties finding strong evidence to prove that the reviews are fake.

To avoid wrong penalties, developing an effective exhibition rule for presenting online reviews is a suitable new paradigm to reduce fake reviews with low cost and high efficiency. When designing the exhibition rules for presenting online reviews, we do not need to consider how to filter out fake reviews, and only need to reduce the effects of fake reviews. For example, fake reviews usually take effects through induce consumers to believe some opinions that are extremely different with the actual product values. In view of the phenomenon, we consider the exhibition rules excluding the online reviews whose opinions are extremely different with the actual product values can significantly reduce firms' motivation values, and thus to effectively reduce fake reviews.

However, because of the lack of consideration of the characteristics of fake reviews, the existing exhibition rule for presenting online reviews unintentionally facilitates the emergence of fake reviews. Designing an effective exhibition rule for ordering online reviews to reduce fake reviews by considering the distribution characteristics of fake reviews is highly important. Thus, we then conduct the exploratory work.

Since it is very difficult to accurately rank normal online reviews at the top, we consider how to use to exhibition rules to reduce the effects of fake reviews, through analyzing the characteristics of fake reviews. For example, the prior studies have confirmed that fake reviewers always post extreme star ratings (Luca and Zervas 2016), while the distribution of normal reviews should follow truncated normal distribution with the mean of actual quality (q_i). In this study, we also find that fake reviews always mislead consumers through their extreme fake reviews, which significantly differ from the actual product values. Thus, we consider if the online reviews that are extremely different with the actual product values are filtered, the effects of fake reviews can be significantly restricted.

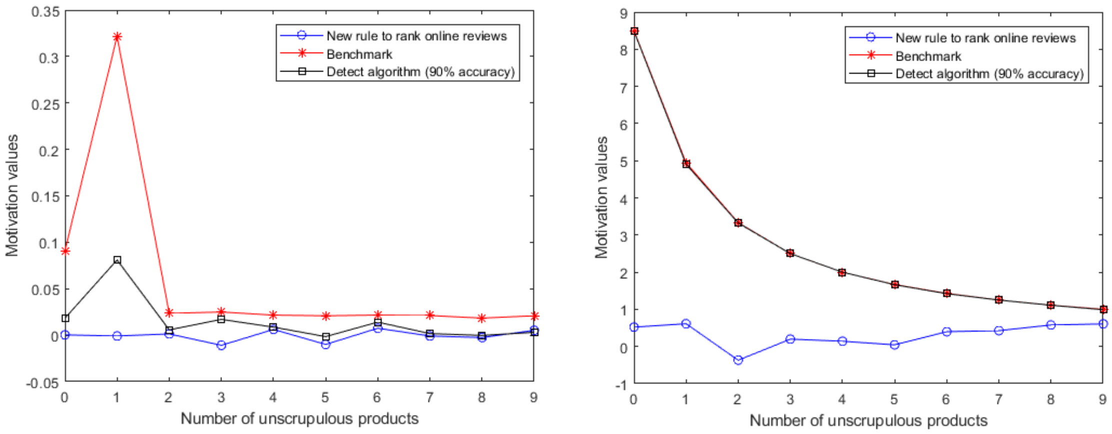
Therefore, we propose the indicator called reliability (c_j), which is set in Eq. (2-7).

$$c_j = \frac{1}{\sqrt{2\pi}} e^{-\frac{(h_j - q)^2}{2}}. \tag{2-7}$$

We define the Heaviside function as $H(x) = \begin{cases} 0 & ,if\ x < 0 \\ 1 & ,if\ x \geq 0 \end{cases}$ and the accepted threshold value for c_j as γ. The new synthetic score of the review posted by agent j is calculated through Eq. (2-8).

$$B_j = \left(\sum_k \beta_k b_{jk}\right) H\left(c_j - \gamma\right). \tag{2-8}$$

Under the new exhibition rule for presenting online reviews, we use computer simulations to calculate the final average star rating and number of consumers, and to quantify motivation values of firms posting fake reviews. Most of the algorithms are stated to successfully filter 90% of fake reviews (Alarifi et al. 2016; Cresci et al. 2015; Savage et al. 2015; Zhang et al. 2016a), so we define that parameter γ can filter out 90% of fake reviews. Figure 2.7 exhibits the motivation values ($y1$ and $y2$) under our exhibition rule for ordering reviews and the traditional detection algorithm.



(a) Value of y_1 (b) Value of y_2

Figure 2-7 Results under the proposed rule and traditional detection algorithms

Figure 2.7 shows that both our new exhibition rule and traditional detection algorithm can effectively reduce motivation values $y1$, which even remains approximately zero under our exhibition rule. When considering the effect on number of consumers, our new exhibition rule significantly reduce firms' motivation value $y2$, while traditional detection algorithms cannot.

Therefore, we obtain the Proposition 5 related to the research question 4.

Proposition 5: Platforms can effectively restrain fake reviews through adopting strict regulatory policies, such as imposing serious punitive measures and designing exhibition rule for presenting online reviews. Although the current exhibition rules for presenting online reviews can guarantee that they provide abundant, authoritative, and latest product information, they have been criticized for their weakness in considering the characteristics of fake reviews. It is of high importance to explore an effective exhibition rule for presenting online reviews, which can reduce the effects of fake reviews.

Proof: See the appendix A.

Proposition 5 proposes that tradition detection algorithms are costly and cannot reduce motivation values of firms posting fake reviews. Our proposed simple exhibition rule for ordering online reviews shown in Eq. (7-8) can effectively prevent the emergence of fake reviews, and even reduce the motivation value reduces to approximately zero and even negative.

Besides proving the new exhibition rule's relative advantage over traditional detection algorithms, our findings show that this new exhibition rule reduces fake reviews with low cost and significant efficiency. Thus, we believe that when we cannot accurately detect fake reviews, we can also reduce fake reviews through restricting the effects of fake reviews.

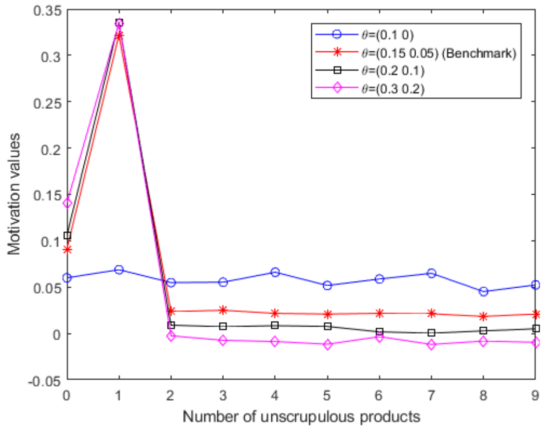
Thus, we also suggest that platforms invest more on designing an effective exhibition rule for ordering online reviews, not only on developing detection algorithms.

2.5.3 Simulation Results of Scenario 3

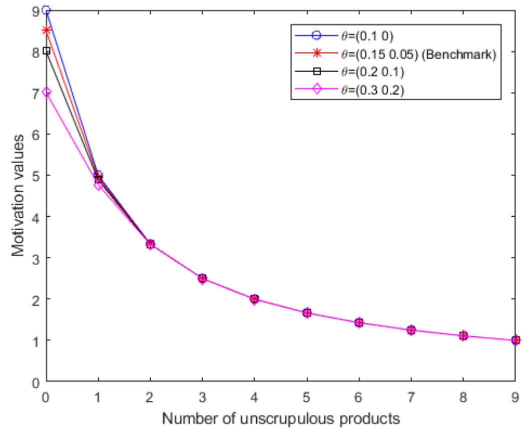
In this section, we discuss the influence of the main assumption on our results. By referring to the conclusions of prior studies (Lappas et al. 2016; Luca and Zervas 2016), we assume the percentages of fake positive reviews and fake negative reviews are 15% and 5%, respectively, and the degree of evaluation score of fake negative reviews on actual product value is $\alpha = 0.5$.

Our results are consistent with the main findings of prior researches, but we still discuss the important robustness check about the main assumptions. In scenario 3, we set the value of θ_1 from 0 to 0.3 with the interval of 0.1 and the value of θ_2 from 0 to θ_1 with the interval of 0.1. And to discuss the effect of the value of α, we set the value of α from 0.2 to 0.7 with an internal of 0.1.

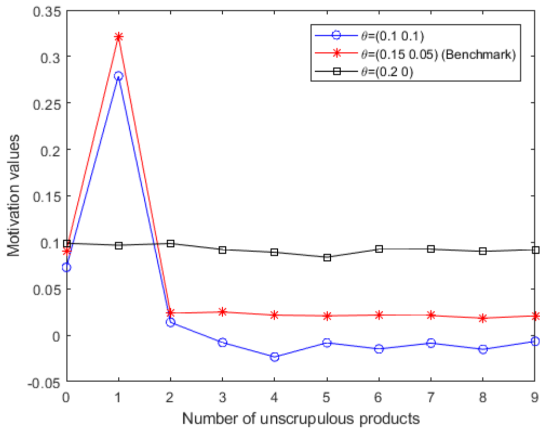
Figure 2.8 exhibits the calculated motivation values ($y1$ and $y2$) under different combinations of θ_1 and θ_2 and different α values. The percentage of fake positive reviews (θ_1) is 10% more than that of fake negative reviews (θ_2) in other three scenes, in which the percentages of fake positive reviews (θ_1) and negative reviews (θ_2) are (0.1,0), (0.2,0.1), and (0.3,0.2). And the total percentage of fake positive reviews and fake negative reviews is 20% in other two scenes, in which the percentages of fake positive reviews (θ_1) and negative reviews (θ_2) are (0.2,0), and (0.1,0.1).



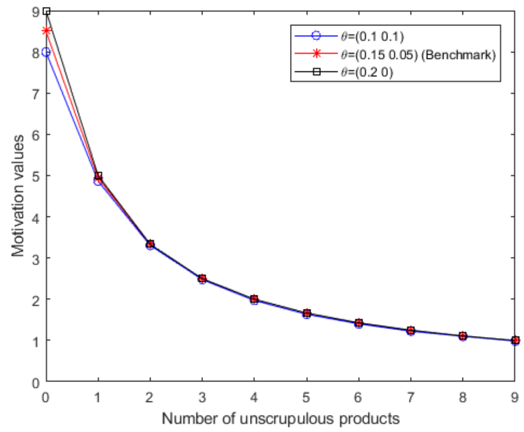
(a) Value of y_1 when θ_1-θ_2≡0.1



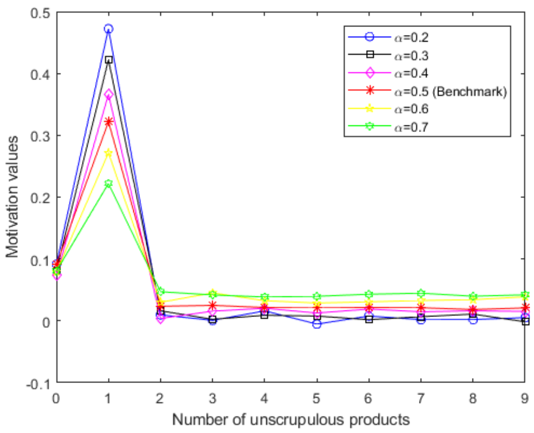
(b) Value of y_2 when θ_1-θ_2≡0.1



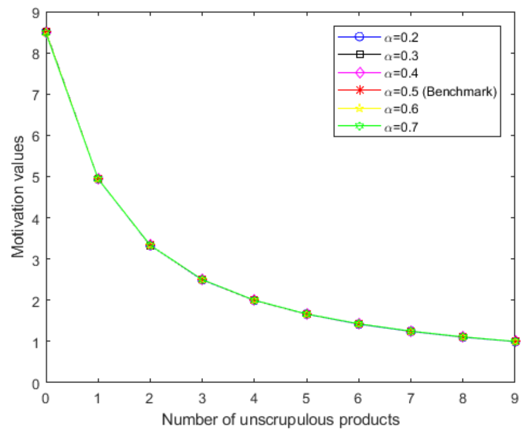
(c) Value of y_1 when θ_1+θ_2≡0.2



(d) Value of y_2 when θ_1+θ_2≡0.2



(e) Value of y_1 under different α



(f) Value of y_2 under different α

Figure 2-8 Motivation values under different parameters in the second group

When there is no fake negative reviews (e.g. $\theta_2 = 0$), all normal firms never receive any fake negative reviews, so their final average star ratings are not reduced. Thus when there is only one unscrupulous firm, firms' motivation values $y1$ in these two scenarios (0.1,0) and (0.2,0) are significantly lower than those in other scenarios. But, the values of $y1$ in these two points are still relatively high, meaning that firms still have sufficient motivations to post fake reviews.

Figures 2.8(a-b) reveal an obvious negative relationship between $\theta_1 + \theta_2$ and firms' motivation values, when $\theta_1 - \theta_2 \equiv 0.1$. Firms' motivation values decrease along with the increase of $\theta_1 + \theta_2$, until that the firms' motivation value is equal to the cost of firms posting fake reviews.

Figures 2.8(c-d) reveal an obvious relationship between $\theta_1 - \theta_2$ and firms' motivation values, when $\theta_1 + \theta_2 \equiv 0.2$. Firms' motivation values increase along with the increase of $\theta_1 - \theta_2$, illustrating that firms have high motivation values to increase the difference between θ_1 and θ_2.

Figure 2.8e shows that the α value negatively affect the motivation value $y1$, only when there exists one unscrupulous firm. If only one unscrupulous firm posts fake reviews, the firm never receive fake negative reviews but other firms receive many fake negative reviews. When α value decreases, the damage degree of fake negative reviews increase and normal firms suffer heavy loss, so firms have high motivations to begin to post fake reviews.

But when there are more than 2 firms posting fake reviews, all firms receive fake negative reviews. So, the difference of average star rating between unscrupulous firms and normal firms can keep balance, and firms' motivation values $y1$ become stable. When there are more than 2 unscrupulous firms, there exists a counterintuitive finding about the positive relationship between α value and firms' motivation values $y1$. When the damage degree of fake negative reviews increases, firms' motivation values decreases, meaning that fake negative reviews are also not welcomed by unscrupulous firms. Through analyzing the simulation results, we find the reason for the finding is that unscrupulous firms cannot obtain ideal average star rating when serious fake negative reviews can offset the positive influence of fake positive reviews.

Figure 2.8f shows that α value has no effect on the motivation value $y2$. The relative difference of consumer number between unscrupulous firms and normal firms is not associated with the α value, since fake positive reviews always have tremendous ability to attract all consumers.

Thus, even without the fake detection, the unscrupulous firms do not allow α value be very small. The median value 0.5 perhaps is suitable since it can well reflect the existing of fake negative reviews and is not a small value. Moreover, the finding that fake positive reviews are much more common than fake negative reviews is validated again from analyzing α value.

Therefore, we obtain the Proposition 6 related to the research question 4.

Proposition 6: Fake positive reviews are much more common than fake negative reviews in the real world. Motivation values of firms posting fake reviews increase, when the total percentage of fake reviews ($\theta_1 + \theta_2$) decreases or the difference of percentage between fake positive reviews and fake negative reviews ($\theta_1 - \theta_2$) increases.

Proof: See the appendix A.

Proposition 6 analyzes the characteristics of fake reviews and explores the effect of percentage of fake reviews on the motivation values of firms posting fake reviews. From a totally new pathway, proposition 6 verifies the known conclusions that fake positive reviews are much more common than fake negative reviews in the real world. The motivation values of firms posting fake reviews increase, when the difference of percentage between fake positive reviews and fake negative reviews ($\theta_1 - \theta_2$) increases. Thus, we analyze that the firms have higher motivations to increase the difference ($\theta_1 - \theta_2$), indirectly proving the sentence. Through realizing the distribution characteristics of fake reviews, we can better design mechanisms to avoid or reduce fake reviews.

Proposition 6 also discovers that firms' motivation values are directly affected by the existing percentage of fake reviews. Finding the equilibrium percentages of fake positive reviews and fake negative reviews is also important and useful to explore ways to reduce fake reviews.

2.6. Conclusions and Discussions

Online product reviews significantly affect consumer purchase decisions. Therefore, firms have sufficient motivations to post fake positive reviews on themselves or fake negative reviews on their opponents. A primary difficult problem in marketing research is how to effectively reduce the number of fake reviews. Prior studies have mainly focused on developing algorithms to detect fake reviews and have stated that they achieved high percentages of accuracy. However, plenty of fake reviews remain in online marketing. This study is among the first to explore the ways to reduce fake reviews by quantifying the motivation values of firms that post fake reviews.

2.6.1 Conclusions

This study proposes an original ABM to depict the dynamic influence process of prior reviews on subsequent reviewers and explore ways to reduce the number of fake reviews. To achieve our research goal, we proposed an original ABM to solve four research questions.

2.6.1.1 A Novel ABM

ABM is appropriate and flexible (Harrison et al. 2007; Mason et al. 2007; Smith and Conrey 2007), and is suitable to be used to depict opinion diffusion (Macy and Willer 2002). ABM can effectively describe how a simple rule leads to a complex marketing phenomena (LeBaron 2000; Rand and Rust 2011). In traditional ABMs, agents are located in open communities or social networks and exchange their opinions about a certain topic with people selected through the rule of opinion similarity or linked neighbors (Xiong et al. 2011).

However, unlike open communities and social networks, online reviews have two unique features: the one way of influence pathway and the special rule of accessibility. Existing ABMs cannot be applied to depict the dynamic process of online reviews. Accordingly, we take the first step toward proposing anovel ABM to depict the dynamic influence process of prior reviews on subsequent reviewers. The proposed ABM can be applied to all related fields in which the influence pathway is one-way.

The entire process of our proposed ABM is divided into two parts: purchase stage and evaluation stage. Extensive computer simulations and sensitive analyses of the parameters are conducted to verify the proposed ABM and enhance our understanding of the application of the proposed ABM in the real world. Under the proposed ABM, we present six propositions to answer our four research questions.

2.6.1.2 Quantization of motivation values

Propositions 1–3 are proposed to answer research question 1. Proposition 1 is about the final average star rating. The star rating of online reviews follows truncated normal distribution with one peak. Under the health market environment, the average star rating of a product converges on its actual quality. If fake reviews exist, they slightly increase the peak value of unscrupulous products. Although the increase amplitude of final average star rating is limited, fake reviews have a huge capacity to attract consumers. The tremendous capacity to attract consumers provided by fake reviews can be used to measure the motivation value of firms for posting fake reviews.

Proposition 2 is about the changing tendency of the motivation values of firms posting fake reviews. As the number of existing unscrupulous products increases, the attractive capacity of fake reviews on consumers significantly decreases, so the motivation values of firms for posting fake reviews decreases.

Proposition 3 explores the effect of consumer behaviors on the motivation values of firms for posting fake reviews and states that the motivation values are usually not influenced by consumer behaviors. Some characteristics of consumers, such as average number of reviews considered by consumers, do not change the motivation values of firms for posting fake reviews.

Proposition 4 is proposed to answer research question 2. The motivation values of firms that post fake reviews are significantly affected by products. Firms that sell low-quality products have more motivation to alter online reviews than firms that sell high-quality products. The motivation values of firms that face fierce competition are significantly higher than those of firms selling uncompetitive products. Results verify that firms have high motivations to alter online reviews under three situations: facing fierce competition, selling low-quality products, and having a large number of consumers.

2.6.1.3 Ways to reduce fake reviews

We quantify and compare the motivation values under different scenarios to explore suitable ways to reduce fake reviews from three parties: consumers, products, and platforms. Specifically, proposition 6 is provided to solve research question 3, and propositions 3 and 5 are provided to solve research question 4.

Proposition 6 is about the characteristics of fake reviews. The sensitive analyses about the percentages of fake reviews adopt a new channel to prove that the percentage of fake positive reviews is much more than that of fake negative reviews.

Proposition 3 illustrates the relationship between consumer behavior and motivation value. Although consumer behavior on learning online reviews usually has no effect on motivation values, the consumer behavior on writing online reviews has a significant influence on the motivation values. When writing online reviews, consumers had better reduce the external effects from existing online reviews and only consider their actual use experience.

Proposition 5 is about the exhibition rule for ordering online reviews. This study confirms a counterintuitive factor that some products with low star ratings can attract many consumers by placing their fake reviews at the top. The current exhibition rule for ordering reviews is unscientific. After considering the distribution characteristics of fake reviews, we innovatively propose a new exhibition rule for ordering online reviews to prevent the emergence of fake reviews. By combining data mining and machine learning to filter out extreme reviews, an effective exhibition rule for ordering online reviews is proposed as a new paradigm to reduce fake reviews. Our results do not deny that detection algorithms can reduce fake reviews but suggest that a new exhibition rule for ordering reviews can reduce fake reviews with low cost and high efficiency. We recommend that platforms highly invest in designing an effective rule for ordering reviews and in developing detection algorithms. We also recommend further research and testing on the exhibition order of existing reviews.

2.6.2 Implications

2.6.2.1 Theoretical implications

A novel ABM is proposed to depict the dynamic influence process of prior reviews on subsequent reviewers, describing the evolution of average star rating of online reviews. The proposed ABM contributes to the existing ABMs as the first attempt to consider one-way influence, and can be applied to all related fields with the characteristics of one-way influence. Influence in most open communities and social networks is a two-way path because agents exchange their opinions with others and easily revise their opinions. In some fields, however, the influence is a one-way path because prior opinions cannot be changed even if the prior opinions are wrong or unsuitable. For example, in the marketing field, the influence is a one-way path because consumers do not usually change their purchase decisions due to a strict refund policy.

2.6.2.2 Practical implications

This study quantifies the motivation values of firms posting fake reviews and provides useful suggestions to reduce fake reviews from three parties: consumers, firms, and platforms. Our suggestions to reduce fake reviews restrict the number of fake reviews intrinsically, and our suggestions can effectively reduce fake reviews more than a detection algorithm can.

Our results can help consumers understand the underlying reason for the emergence of fake reviews. This study reveals that the motivation of firms posting fake reviews is deduced because even though fake reviews have a slight effect on the evolution of online reviews, the slight increase of star ratings has a significant capacity to attract consumers. To reduce the influence of fake reviews on the evolution of online reviews, results suggest that consumers ignore the perceived value before purchase when writing online reviews.

Our findings help identify the characteristics of fake reviews and discover that the number of fake reviews is high for the low-quality products in a fiercely competitive field. We also verify the known characteristics of fake reviews through a completely new pathway. For example, we show that fake positive reviews are much more common than fake negative reviews.

On the basis of results, some suggestions are proposed to reduce fake reviews. Other than paying attention to the consumer behaviors, this study elucidates that the current exhibition rule for ordering online reviews is unscientific. Thus, we design a simple but effective exhibition rule to prevent the emergence of fake reviews. Designing the rule for ordering online reviews is a new paradigm to reduce the number of fake reviews. We suggest that platforms invest substantially in developing detection algorithms and designing an effective exhibition rule for ordering reviews. Finally, we recommend further research and testing on the exhibition rule.

2.6.3 Limitations and future research

This study has certain limitations. Although our study explores the dynamic evolution of online reviews, we must acknowledge that the measured motivation values are static. Through analyzing how online reviews and consumer number develop with fake reviews or without fake reviews, we measure firms' motivation values. Then, through comparing the firms' motivation values in different specific research scenarios, we solve our research questions. But, we are unable to consider the dynamic changing trends of motivation values in different periods. In the further studies, we hope to analyze the dynamic firms' motivation values at different period to get further conclusions about firms' motivation values.

The proposed ABM considers only consumer agent. In the complex online markets, however, various types of agents, such as firms and platforms, are involved. We must analyze the influence of other types of agents in online markets on the firms' motivation values in the future studies.

In the ABM, we analyze the evolution of average star rating of online reviews but do not consider the specific review contents. Although the exploration of star rating can solve our research question, we must acknowledge that analyzing the specific review contents of fake reviews can get more interesting findings. In the future studies, we can consider specific review contents and include them in our analyses.

We use computer simulations to demonstrate our proposed ABM but do not place actual data into our model for two reasons: completely appropriate and accurate data for the model are difficult to obtain, and research questions can be addressed by comparing the equilibrium results under various parameters.

Our study is among the first to explore the effect of exhibition rule for presenting online reviews on firms' motivation values, and to design an effective exhibition rule to prevent the emergence of fake reviews. However, designing an effective exhibition rule for ordering online reviews is complex. We need to fully consider various consumer behaviors. For example, consumers may choose to see only the positive or negative online reviews. These various consumer behaviors about reading online reviews need to be considered when designing effective exhibition rules for presenting online reviews.

Chapter 3 Reduction of Fake Reviews Through Game-theoretical Model

3.1 Introduction

The goal of this study is to reduce the number of fake reviews. Given the aim of this study, which is to reduce fake reviews, we first realize some basic characteristics about fake reviews, including the sites these unscrupulous firms prefer to post fake reviews and their characteristics. When firms decide to alter online product reviews, where will they post fake reviews? If there are other different platforms, such as Yelp, eBay, TripAdvisor, Expedia, and Amazon, which platform firms will use to post fake reviews? Thus, we propose the first research question.

RQ1: Is there a significant difference about the number of fake reviews among all platforms? Which types of platforms are utilized by unscrupulous firms to post fake reviews?

After finding the characteristics of fake reviews, we should realize the underlying reasons leading to these characteristics. However, some important characteristics of fake reviews have not been explained before. For example, existing research found that detective firms prefer to post fake positive review to themselves rather than fabricate fake negative reviews of their competitors. But existing research did not explain the underlying reason for this phenomenon (Lappas et al. 2016). Some studies demonstrated that only small firms prefer to post fake reviews, whereas successful firms want to maintain their reputation (Luca 2016; Luca and Zervas 2016; Mayzlin et al. 2014). However, the Taiwan Fair Trade Commission fined Samsung $340,000 for hiring two companies to post fake negative reviews about their main competitor HTC (Lappas et al. 2016). The reason some firms prefer to post fake reviews should be examined. To address this gap, we propose the second research question.

RQ2: What are the underlying reasons that lead to these characteristics or distributions of fake reviews? For example, what kind of firms prefer to post fake reviews? Why are fake positive reviews more common than fake negative reviews in some platforms? Will firms post less fake reviews when they cooperate?

After making clear the specific characteristics of fake reviews and the underlying reasons leading to these characteristics, we propose the third research question to identify an efficient mechanism to reduce fake reviews.

RQ3: What the relative stakeholders, including online platform designers, firms and consumers, can do to efficiently reduce fake reviews? Is high degree of penalty can effectively reduce fake reviews?

Our research questions differ from prior researches on fake reviews that have not been examined previously as we focus on the underlying reasons leading to the characteristics or distributions of fake reviews. We also provide some practical suggestions to reduce fake reviews.

In our studies, we should simultaneously consider complex relationships among online platforms, firms, and consumers. Thus, we put online platforms, firms, and consumers into a big system and study their interaction effects. One of the best ways to achieve our research goal is to employ the game-theoretical model because this game model can effectively describe the relationship among multiple players, including firms, consumers, and platforms. For each player, the decision-making process is very complicated. Each player selects the appropriate strategy after considering the strategy that can maximize its payoff and how other players will respond to its behavior (Chen and Xie 2008). The dynamic process is regarded as a game.

3.2 Literature Review

Through considering the complex relationships among online platforms, firms, and consumers during the review process, many studies employ game-theoretical model to analyze online reviews (Chen and Xie 2005; Johnson and Myatt 2006; Kocas and Akkan 2016; Kuksov and Xie 2010; Mayzlin 2006; Narasimhan and Turut 2013). The recent game-theoretical models about online product reviews are summarized in Table 3.1. However, these recent game-theoretical models did not consider the effect of online product reviews, especially fake reviews, on reputable, influential, and susceptive platforms (Dellarocas 2006; Kwark et al. 2014). The reputation of these platforms and that of the commentators are important (Chen et al. 2011; Ma et al. 2013; Tang et al. 2012). If one platform is covered by fake reviews, users will abandon it and select other platforms (Woo et al. 2016). An analytical framework wherein multiplayers, including consumers, firms, and platforms, are considered, must provide realistic and accurate results. Thus, we construct a game-theoretical model involving three players: two firms and a platform to solve these research questions from a novel perspective.

Table 3-1 Summary about recent game-theoretical models about online reviews

Studies	Players	Whether considering fake reviews	Whether considering impact of platform	Whether considering dynamics of loyal consumers
Kuksov and Xie (2010)	Consumer and Firm	×	×	×
Li and Hitt (2010)	Consumer and Firm	×	×	×
Li et al. (2011)	Two Firms	×	×	×
Sun (2012)	Two Firms	×	×	×
Narasimhan and Turut (2013)	Two Firms	×	×	×
Gu and Xie (2013)	Two Firms	×	×	×
Kwark et al. (2014)	Firm and Manufacture	×	×	×
Wei and Li (2015)	Firm and Manufacture	×	×	√
Adner et al. (2016)	Two Firms	×	×	×
This study	Consumers, Firms, and Platforms	√	√	√

Many game-theoretical models for analyzing online reviews assume that firms have the same numbers of loyal customers and that the numbers are fixed (Kocas and Akkan 2016; Kwark et al. 2014). Actually, these numbers vary with firms and time (Reczek et al. 2014; Wei and Li 2015; Zhao and Zhong 2015). The number of loyal consumers could vary with cultural context and industry (Veghova 2012). In our game-theoretical model, we consider two different types of consumers, namely, loyal customers and switcher shoppers. Loyal customers purchase products from the firm that they are loyal to and know its quality and fit, but they may or may not purchase because of its price. Switcher shoppers purchase products that can provide high consumer value. Each consumer has his or her own initial assessment about the quality of the products and its suitability to his or her need. Online product reviews provide additional information about the quality and fit dimensions of the products to consumers. After obtaining information from online reviews, consumers change their preferences, which in turn lead to the difference in the number of loyal customers to each firm and can be changed, thereby making our model realistic.

To address these questions, we design a novel game-theoretical model based on a new perspective of platforms, which has been ignored before. In our game-theoretical model, two competing firms sell two different products in one platform. The products differ in quality and fit to consumer needs. The objective of maximum profit is the goal of the two firms and the platform. Our approach differs from the aforementioned studies using game-theoretical model, as we consider the effect of fake reviews on platforms and the dynamic number of customers, which has not been proposed in previous game-theoretical models.

3.3 Analytical Model

In this section, we introduce our game-theoretical model with two competing firms selling substitutable products a and b at zero marginal cost in the platform. We assume that all players (consumers, firms, and platforms) are rational and the market is fully competitive. The definition of all notations used in our model is shown in Table 3.2.

Table 3-2 Definitions of notations used throughout Chapter 3

Notation	Definition
i, j	Index for products, $i \in (a,b)$, $j \in (a,b)$
	Descriptive variables
u_i	A consumer's net utility of product i
v_i	Perceived value of product i
λ	Degree of misfit between a consumer and product a
p_i	Price of product i
θ_i	The market size of loyal consumer for product i
$1-\theta_a-\theta_b$	Total market size of switcher shoppers
D_i^l	Demand for product i from loyal customer
D_i^s	Demand for product i from switcher shoppers
D_i	Total demand for product i
η_i	Reputation of product i
η	Reputation of the investigated platform

γ	Total number of consumer in investigated platform
	Environment parameters
γ_0	Ideal number of consumer in investigated platform
t	Unit misfit cost
h	Sensitive degree of fake reviews on platform's reputation
δ	Commission rate in the investigated platform
w	The advertising revenue providing by per consumers
χ	Unit punishment for firms posting fake reviews
φ	Average probability of being detected for fake reviews
θ_i^0	Ideal market size of loyal consumers of firm i
v_i^0	Initial assessment about the value of product i
ζ_i	Star rating of product i
	Manipulative variables
m_j^i	Degree of fake review posting by firm i on firm j
φ_i	Probability of being detected for fake reviews posting by firm i
z_i	Unit cost of posting fake reviews of firm i
z	Cost of detecting fake reviews of this platform
	Output variables
π_i	Profit for product i
π_p	Profit for the investigated platform

3.3.1 Model Description

With the aim of acquiring many consumers, each firm shows no effect in promoting its competitive position, as well as posting fake reviews to itself or its opponent. All firms want to add the perspective values of their products by posting fake positive reviews of themselves and reducing the perspective values of their opponents by posting fake negative reviews of their opponents. By contrast, firms are frightened that they will incur penalty from the platforms, and the total consumers in these platforms will be reduced to some extent, which is related to the number of fake reviews.

Aside from considering the effect of fake reviews, each firm monitors positive responses from other firms. For example, when they make a choice, these firms believe that other firms will post fake reviews. The strategies of firms differ in every case. They employ different strategies for the two situations: other firms do not post any fake reviews, and other firms also alter online reviews. Game-theoretical model is one of the best ways to describe these dynamic processes.

In reality, the most common case is that all firms employ optimal strategies to maximize their profits. For example, Apple and Samsung does not affect each other in capturing consumers and maximizing profits. We call this situation as non-cooperative case. In another case, we found that some firms cooperate as one group and employ some strategies together to maximize the entire group’s profit. For example, Samsung and LG constitute as one group as they all implement Android system, and they challenge Apple to increase the market shares of Android. We call this situation as cooperative case. The two cases can represent all the situations about electronic commerce competition.

3.3.2 Profit Function of Firms

Similar to mainstream studies (Adner et al. 2016; Chen and Xie 2008; Gu and Xie 2013; Shaffer and Zettelmeyer 2002; Sun 2012; Sun and Tyagi 2012; Villas-

Boas 2004), we use horizontal differentiation models to deduce the equilibrium firm profit functions.

Two products are characterized by two attributes: quality and fit. Product quality can be largely assessed with product description, such as food ingredient, engine horsepower, and clothing materials. Customers generally value high over low quality, so product quality is an inherent attribute. Product fit is a sensory attribute and relates to experiential product attributes, such as the design of cell phone, the taste of food, and the fit of shoes.

3.3.2.1 Consumer Utilities

By considering the existence of loyal consumers, we expand the classic Hotelling Model (Hotelling 1929) to make this model realistic. The two products are assumed to be situated at location 0 and 1 on a line of length 1, and consumers are uniformly distributed along the line. The distances between consumers and products measure the degree of misfit of the product to consumers. When the degree of misfit between consumers and product a is λ, the degree of misfit between consumers and product b is $1\text{-}\lambda$ (Adner et al. 2016; Chen and Xie 2008; Gu and Xie 2013; Shaffer and Zettelmeyer 2002; Sun 2012; Sun and Tyagi 2012; Villas-Boas 2004). The misfit cost is the degree of misfit times the unit misfit cost t.

In the Hotelling model (Adner et al. 2016; Kwark et al. 2014; Kwark et al. 2017; Sun 2012), consumer net utility for each product is the quality value that the consumer derives from the product minus the corresponding price and misfit cost caused by mismatch between the product and consumer's taste. For product i, $i \in (a,b)$, consumer net utility u_i can be formulated as:

$$\begin{cases} u_a = v_a - t\lambda - p_a \\ u_b = v_b - t(1-\lambda) - p_b \end{cases}. \tag{3-1}$$

in which v_i represents the perceived value of product i, and p_i represents the price of product i.

3.3.2.2 Consumer Segments and Demand Functions

The two types of consumers are loyal customers and switcher shoppers. Loyal customers purchase products from the firm that they are loyal to and know its quality and fit, but they may or may not purchase depending on its price. We assume the proportion of loyal customers for firm i is θ_i, and the total market size of consumer in this platform f is γ. Thus, the market size of loyal consumers for firm i is $\gamma\theta_i$. The misfit degree of the marginal consumer for product a, who derives zero net utility from consuming product a, is $\lambda_a^* = (v_a - p_a)/t$ (i.e., $u_a = v_a - t\lambda_a^* - p_a = 0$), thus the demand for product a from loyal consumers is $\gamma\theta_a\lambda_a^*$. Similarity, the misfit degree of the marginal consumer for product b, who derives zero net utility from consuming product b, is $1-\lambda_b^* = (v_b - p_b)/t$ (i.e., $u_b = v_b - t(1-\lambda_b^*) - p_b = 0$), thus the demand for product b from loyal consumers is $\gamma\theta_b(1-\lambda_b^*)$. Thus, the demand function for product i from its loyal customer can be formulated as:

$$D_i^l = \frac{\gamma\theta_i\left(v_i - p_i\right)}{t} = \frac{\gamma\theta_i v_i}{t} - \frac{\gamma\theta_i}{t} p_i, \tag{3-2}$$

in which $\gamma\theta_i / t$ measures the price sensitivity to product i from its loyal customer.

In contrast to loyal customers, switcher shoppers compare products from both firms and select the product that offers high net utility. The net utility difference between product a and b is

$$u_a - u_b = v_a - v_b + \left(1-2\lambda\right)t - \left(p_a - p_b\right). \tag{3-3}$$

The degree of misfit of the marginal consumer for product a, which derives equal utility from consuming product a or b, is $\lambda^* = \left[t + \left(v_a - v_b\right) - \left(p_a - p_b\right)\right] / 2t$. The demand function for product i from switcher shoppers is

$$\begin{cases} D_a^s = \dfrac{\gamma\left(1-\theta_a-\theta_b\right)\left[t + v_a - v_b - \left(p_a - p_b\right)\right]}{2t} \\ D_b^s = \dfrac{\gamma\left(1-\theta_a-\theta_b\right)\left[t - v_a + v_b + \left(p_a - p_b\right)\right]}{2t} \end{cases}. \tag{3-4}$$

After deriving the demand function for loyal customers and switcher shoppers, we can formulate the total demand for product i as:

$$\begin{cases} D_a = D_a^l + D_a^s = \dfrac{2\gamma\theta_a\left(v_a - p_a\right) + \gamma\left(1-\theta_a-\theta_b\right)\left[t + v_a - v_b - \left(p_a - p_b\right)\right]}{2t} \\ D_b = D_b^l + D_b^s = \dfrac{2\gamma\theta_b\left(v_b - p_b\right) + \gamma\left(1-\theta_a-\theta_b\right)\left[t - v_a + v_b + \left(p_a - p_b\right)\right]}{2t} \end{cases}. \tag{3-5}$$

3.3.2.3 Equilibrium Analysis of Firm Profit Functions

The marginal cost in competing situations is assumed to be zero. Thus, the profits of two firms can be formulated as:

$$\begin{cases} \pi_a = p_a D_a = p_a \dfrac{2\gamma\theta_a\left(v_a - p_a\right) + \gamma\left(1-\theta_a-\theta_b\right)\left[t + v_a - v_b - \left(p_a - p_b\right)\right]}{2t} \\ \pi_b = p_b D_b = p_b \dfrac{2\gamma\theta_b\left(v_b - p_b\right) + \gamma\left(1-\theta_a-\theta_b\right)\left[t - v_a + v_b + \left(p_a - p_b\right)\right]}{2t} \end{cases}. \tag{3-6}$$

Solving the first-order conditions for Eq. (3-6) yields the equilibrium prices, profits, and indifferent consumers, as summarized by the following lemma.

Lemma 1. During this baseline game-theoretical model, the equilibrium prices are:

$$\begin{cases} p_a = \dfrac{\left(3-3\theta_a+\theta_b\right)t + (1+3\theta_a+3\theta_b)v_a + (-1+\theta_a-\theta_b)v_b}{3+5\theta_a+5\theta_b} \\ p_b = \dfrac{\left(3+\theta_a-3\theta_b\right)t + (-1-\theta_a+\theta_b)v_a + (1+3\theta_a+3\theta_b)v_b}{3+5\theta_a+5\theta_b} \end{cases}. \tag{3-7}$$

For loyal consumers, the degrees of misfit of the marginal consumer for products are:

$$\begin{cases} \lambda_a^* = \dfrac{\left(-3+3\theta_a-\theta_b\right)t + (2+2\theta_a+2\theta_b)v_a + (1-\theta_a+\theta_b)v_b}{t\left(3+5\theta_a+5\theta_b\right)} \\ 1-\lambda_b^* = \dfrac{\left(-3-\theta_a+3\theta_b\right)t + (1+\theta_a-\theta_b)v_a + (2+2\theta_a+2\theta_b)v_b}{t\left(3+5\theta_a+5\theta_b\right)} \end{cases}. \tag{3-8}$$

Among the switcher shoppers, the indifferent consumer is located at:

$$\begin{cases} \lambda^* = \dfrac{(3+9\theta_a+\theta_b)t+(1+\theta_a+3\theta_b)v_a+(-1-3\theta_a-\theta_b)v_b}{2t(3+5\theta_a+5\theta_b)} \\ 1-\lambda^* = \dfrac{(3+\theta_a+9\theta_b)t+(-1-\theta_a-3\theta_b)v_a+(1+3\theta_a+\theta_b)v_b}{2t(3+5\theta_a+5\theta_b)} \end{cases}. \quad (3\text{-}9)$$

Thus, the equilibrium profits are:

$$\begin{cases} \pi_a = \dfrac{\gamma(3t+v_a-v_b)\left[(3-3\theta_a-\theta_b)t+(1+7\theta_a+5\theta_b)v_a+(-1+\theta_a-\theta_b)v_b\right]}{2t(9+30\theta_a+30\theta_b)} \\ \pi_b = \dfrac{\gamma(3t-v_a+v_b)\left[(3-\theta_a-3\theta_b)t+(-1-\theta_a+\theta_b)v_a+(1+5\theta_a+7\theta_b)v_b\right]}{2t(9+30\theta_a+30\theta_b)} \end{cases}. \quad (3\text{-}10)$$

All proofs are included in the appendix B.

3.3.3 Profit Function of Online Platforms

In contrast to ordinary businesses, wherein profits are mainly dictated by prices, demands, and costs of their products (Berger and Iyengar 2013; Levin et al. 2008), platforms, such as Yelp, Amazon, TripAdvisor, and eBay provide a place for firms to sell their goods and allow people to write public reviews. Their profits primarily come from two sources: commission revenues from the firms selling products in the platform and advertising revenues from the firms advertisements in the platform (Mayzlin et al. 2014).

The calculation equation of commission revenues differs with the online platforms. Different online platforms set different rule to collect the commission revenues. But for all online platforms, there exist one common rule that there exists a significant positive relationship between commission revenue and the total revenues of all firms in this platforms. For simply calculation, we define the commission rate as δ here.

Normally, the advertiser could pay a fixed amount for every click in the website or every consumer in the online platform (Chickering and Heckerman 2003; Interactive Advertising Bureau 2012). Thus, the advertising revenue is the linear function of the total number of consumers. The advertising revenue is defined as $w\gamma$. The profit function of this platform is:

$$\pi_p = \delta\left(\sum_i \pi_i\right) + w\gamma \,. \tag{3-11}$$

3.3.4 Effect of Online Reviews

The profits of firms and platforms are significantly affected by their reputation, whereas consumer satisfaction significantly affect reputation through reviews (Chatterjee et al. 2012). Under normal circumstance, each product reputation can be measured through its star rating. The reputation of firm is the weighted average value of the reputation of all products sold by this firm, and the reputation of one platform is the weighted average value of the reputation of all firms presented in this platform. The size of one firm can be suitably used to be its corresponding weight. In this game-theoretical model, these two firms only sell one product, the price of the product is roughly to be used to replace the size of the firm.

To enhance their level of competitiveness, many firms prefer to alter online reviews (Dellarocas 2006; Mayzlin 2006) by posting fake reviews (Mayzlin et al. 2014; Pranata and Susilo 2016). The large numerical values of fake reviews considerably influence star ratings and reputation.

To penalize fake reviews, most platforms, such as yelp.com and dianping.com, post warnings in the homepage of these unscrupulous firms and alert consumers that these firms posted fake reviews. However, these platforms does not impose fines (Chinese News 2017; Technology 2012). Thus, if fake reviews are detected, the reputation of these unscrupulous firms will be reduced, which is equivalent to the calculation of star ratings. We denote the reputation of product i as η_i, the reputation of this platform as η, the star rating of product i as ζ_i (range from 0 to 5), the degree of impact of fake review posting by firm j on the star rating of firm i as m_j^i (range from 0 to 5), and unit penalty and the probability of being detected for firms posting fake reviews as χ (range from 0 to 5, and φ_i (range from 0 to 1), respectively.

We define Heaviside function as $H(x)=\begin{cases}0, & if\ x<0\\ 1, & if\ x\geq 0\end{cases}$ and sensitivity degree of proportion of fake reviews on platform's reputation as h, expressions about reputation of firms and platforms are:

$$\begin{aligned}&\eta_i=\left[\zeta_i+\sum_j m_i^j-\varphi_i\chi\left|\sum_j m_j^i\right|\right]H\left[\zeta_i+\sum_j m_i^j-\varphi_i\chi\left|\sum_j m_j^i\right|\right]\\&\eta=\frac{\sum_i p_i\eta_i}{5\sum_i p_i}\left(1-\frac{h\sum_i\sum_j m_i^j}{\sum_i\left(\zeta_i+\sum_j m_i^j\right)}\right)\end{aligned}\qquad (3\text{-}12)$$

Since ζ_i ranges from 0 to 5, the ideal value of η_i and η would be 5.

Shoppers are uncertain about product quality and misfit. Thus, they are not aware of the true quality difference and true degrees of misfit. Each consumer has his or her own initial assessment of the quality of product i based on product description and other information sources. We denote that the initial assessment about the value of product i as v_i^0. By reading product reviews, a consumer obtains an extra indicator of product value, which helps him or her to find reasonable products (Li et al. 2011). With respect to this model, the total number of consumers in the platform will decrease if this platform's reputation reduces, and vice versa. If the reputation of one firm increases, the value of its product and the number of its loyal customer will subsequently increase[5]. We denote the ideal number of consumers as γ_0, and the ideal number of loyal consumers of firm i as θ_i^0. Since the ideal value of η_i and η is 5, these relationships can be described as:

$$\gamma = \gamma_0 \frac{\eta}{5}, v_i = v_i^0 \frac{\eta_i}{5}, \theta_i = \theta_i^0 \frac{\eta_i}{5}. \tag{3-13}$$

In contrast, the firm posting fake reviews should pay a fine when posting fake reviews. In terms of this phenomenon, platforms also have the right to impose

[5] Normally, the number of loyal consumer is directly related to the reputation of all products (a, b). If the reputation of the opposite product b decreases, the number of loyal consumer of product a will increase. This type of consumer who is loyal to product b will select product a through another pathway, in which they become switcher shoppers, thereby selecting the product providing high consumer utility. Thus, the expression $\theta_i = \theta_i^0 \eta_i / 5$ is sufficient to describe the change in preference of loyal consumers.

additional fines to detect fake reviews. The probability for firm i of being detected for posting fake reviews (φ_i) is affected by the two costs about fake reviews of platform and firm i. If the online platforms invest much money in developing advanced algorithms to detect fake reviews, the probability of fake reviews being detected should be high. If one firm invest much money in packaging its fake revises, the probability of detecting the fake reviews posted by this firm should be low. Thus, the probability of detecting fake reviews is positively related with the cost of detecting fake reviews of online platform, and negatively related to the cost of packaging fake reviews of firms. We denote the average probability of being detected for fake reviews as φ, cost of posting fake reviews of firm i as z_i, and cost of detecting fake reviews of this platform as z. The calculation formula for φ_i is:

$$\varphi_i = \begin{cases} 1 \quad , if\ \varphi \dfrac{z}{z_i} > 1 \\ \varphi \dfrac{z}{z_i},\ if\ \varphi \dfrac{z}{z_i} \le 1 \end{cases} . \tag{3-14}$$

If the probability of being detected for firm i for posting fake reviews is 1, the maximum profit for firm i can only be achieved when $z_i = 0$. Thus, this firm will not prefer to post fake reviews. We realize that the costs for escaping detection from the platform increase with the alteration on fake reviews from Eq. (3-14). The situation $\eta_i = \zeta_i + \sum_j m_i^j - \varphi_i \chi \left| \sum_j m_j^i \right| < 0$ will not reduce the pointless expenses due to fines. Eq. (3-12) and Eq. (3-14) can be simplified as follows:

$$
\begin{cases}
\eta_i = \zeta_i + \sum_j m_i^j - \varphi_i \chi \left| \sum_j m_j^i \right| \\
\varphi_i = \varphi \dfrac{z}{z_i}
\end{cases}
. \tag{3-15}
$$

3.3.5 Game-theoretical Model

Through the above analysis, we obtained the game-theoretical model, wherein three players (two firms and one platform) are involved. The payoffs of the three players are deduced in Eq. (3-16).

In this model, three players are involved in the situation in which the platform has seven parameters: γ_0, δ, w, h, t, χ, and φ, whereas firm i has three parameters: θ_i^0, ζ_i, and v_i^0. The strategy for the three players is that firm i has the right to manipulate two parameters: m_j^i and z_i (i.e., φ_i); and the platform has the right to decide parameter z.

$$\pi_a = \frac{\gamma\left(3t + v_a - v_b\right)\left[\left(3 - 3\theta_a - \theta_b\right)t + (1 + 7\theta_a + 5\theta_b)v_a + (-1 + \theta_a - \theta_b)v_b\right]}{2t\left(9 + 30\theta_a + 30\theta_b\right)} - z_a\left|\sum\nolimits_j m_j^a\right|$$

$$\pi_b = \frac{\gamma\left(3t - v_a + v_b\right)\left[\left(3 - \theta_a - 3\theta_b\right)t + (-1 - \theta_a + \theta_b)v_a + (1 + 5\theta_a + 7\theta_b)v_b\right]}{2t\left(9 + 30\theta_a + 30\theta_b\right)} - z_b\left|\sum\nolimits_j m_j^b\right|$$

$$\pi_p = \delta\left(\pi_a + \pi_b\right) + w\gamma - z$$

$$\begin{cases}
p_a = \dfrac{\left(3 - 3\theta_a + \theta_b\right)t + (1 + 3\theta_a + 3\theta_b)v_a + (-1 + \theta_a - \theta_b)v_b}{3 + 5\theta_a + 5\theta_b} \\[2ex]
p_b = \dfrac{\left(3 + \theta_a - 3\theta_b\right)t + (-1 - \theta_a + \theta_b)v_a + (1 + 3\theta_a + 3\theta_b)v_b}{3 + 5\theta_a + 5\theta_b} \\[2ex]
\eta_i = \zeta_i + \sum\nolimits_j m_i^j - \varphi_i \chi \left|\sum\nolimits_j m_j^i\right| \\[2ex]
\gamma = \gamma_0 \left(\dfrac{\sum\nolimits_i p_i \eta_i}{5\sum\nolimits_i p_i}\right)\left(1 - \dfrac{h\sum\nolimits_i \sum\nolimits_j m_i^j}{\sum\nolimits_i \left(\zeta_i + \sum\nolimits_j m_i^j\right)}\right) \\[2ex]
\varphi_i = \varphi \dfrac{z}{z_i} \\[2ex]
v_i = v_i^0 \dfrac{\eta_i}{5} \\[2ex]
\theta_i = \theta_i^0 \dfrac{\eta_i}{5} \\[2ex]
0 \le m_i^i \le 5 \\
-5 \le m_b^a, m_a^b \le 0 \\
0 \le \varphi_i \le 1
\end{cases}$$

(3-16)

3.4 Equilibrium Results

We obtain the equilibrium results through programming in Matlab. With the aim of obtaining comprehensive equilibrium results, we distinguish three different cases: two players (one firm and platform), three players (two firms and platform) in non-cooperative cases, and three players in cooperative cases.

3.4.1 Game Order

In the game-theoretical model, three players do not simultaneously employ strategies. The platform observes the possible rational behaviors of firms, and then decides the number of investment (z) to detect fake reviews to maximize payoff. After realizing the platform's investment in detecting fake reviews, firm i selects rational strategies, including m_a^i, m_b^i, and φ_i (e.g., z_i), to maximize its payoff. The integrated order of this game-theoretical model is shown in Figure 3.1.

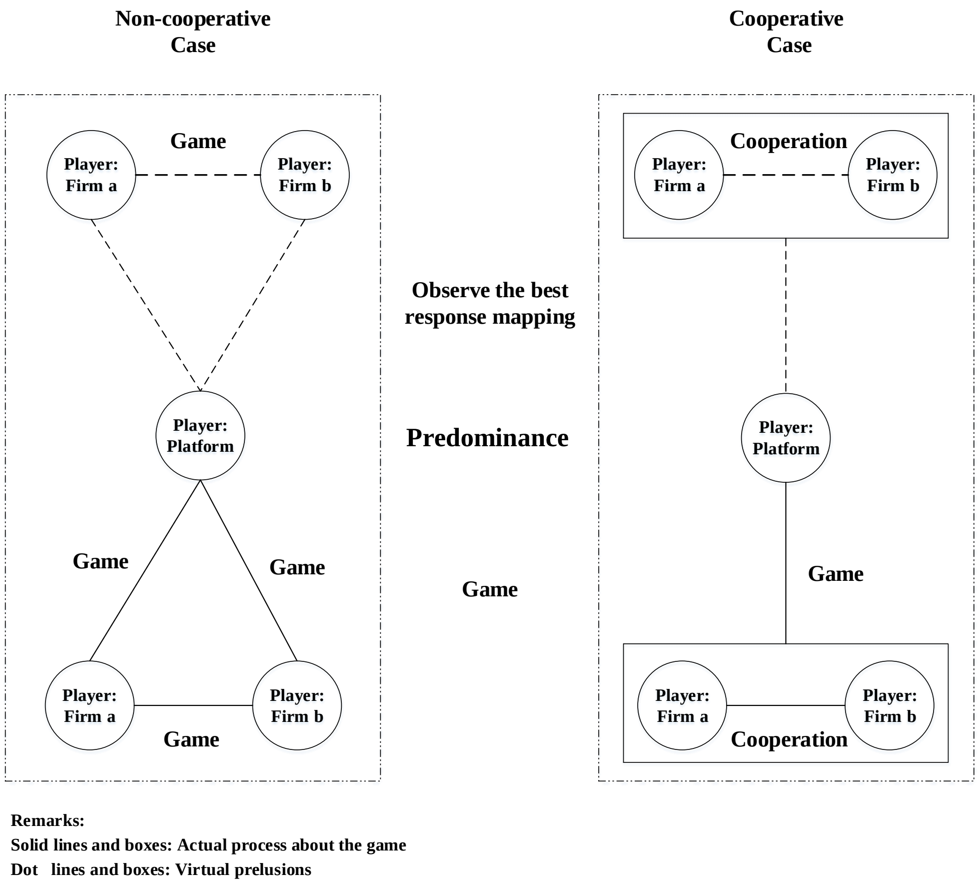


Figure 3-1 Integrated action order of this game-theoretical model

For this model, the platform first observes the best response mapping from two firms and then optimal z to maximize its payoff. The corresponding values for m_j^i and φ_i corresponding to the selected z are the best strategy for the two other players.

3.4.2 Benchmark Scenario

Actually in our model, these are some parameters that need to be further analyzed. The values of these parameters vary from case to case. Thus, we first set the basic level of these parameters in the benchmark scenario, and design different sceneries to explore the specific research questions.

At the baseline situation, two competing firms sell their products to consumers in the platform. To describe the fully competitive situation, these two products have same initial properties. For each firm i, the ideal market size of loyal consumer is $\theta_i = 0.1$, average star rating is $\zeta_i = 4$, the initial perceived value is $v_i^0 = 1$, and unit misfit cost is $t = 1$.

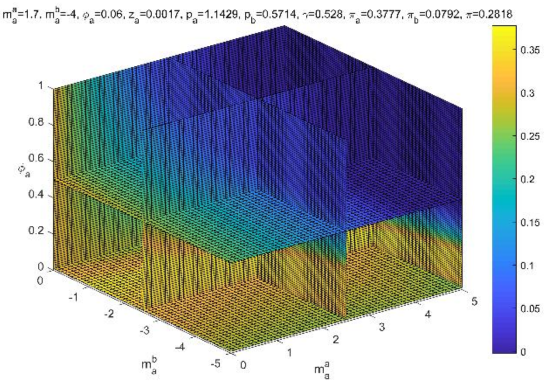
In terms of the parameters about the platforms, we define the initial market size as $\gamma_0 = 1$, the commission rate as $\delta = 0.04$, advertising revenue per consumer as $w = 0.5$, sensitive degree of proportion of fake reviews on platform's reputation as $h = 0.5$, unit penalty for unscrupulous firms as $\chi = 2$, and average probability of being detected for fake reviews as $\varphi_i = 0.2$.

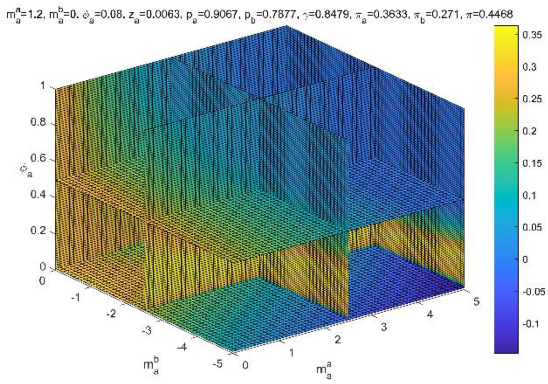
3.4.3 Single Firm Analysis

Three players employ suitable strategies to maximize payoffs. Specifically, each firm selects to alter the number of fake reviews, including fake positive reviews to themselves and fake negative reviews to their opponents; the platform can decide the amount of money to invest in detecting fake reviews.

Before exploring the equilibrium results of this game-theoretical model, we first analyze the behavior of the single player. Specifically, we add conditions that firm b does not alter any online product reviews in the benchmark scenario (e.g., $m_a^b = m_b^b = 0$, and $\varphi_b = 1$), and then observe the best responses of firm a to different values of z. As the value of π_p will be roughly 0.5, we set z as 0.0005($0.001\pi_p$), 0.0025($0.005\pi_p$), 0.005($0.01\pi_p$), 0.025($0.05\pi_p$), 0.05($0.1\pi_p$), and 0.25($0.5\pi_p$). The best responses from firm a and corresponding results are shown in Figure 3.2 under these values of z.

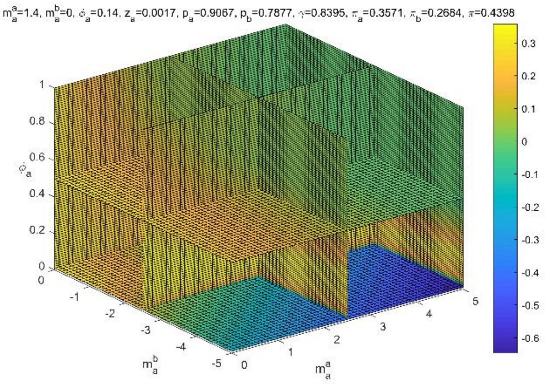
When z varies, firm a changes its behavior toward m_a^a, m_b^a, and φ_a. In the prior three subgraphs, high profit can be achieved on the lower regions (e.g., $\varphi_a \le 0.2$) when z is small. In the latter three subgraphs, high profit can be achieved on the upper regions (e.g., $\varphi_a \ge 0.2$) when z is large.

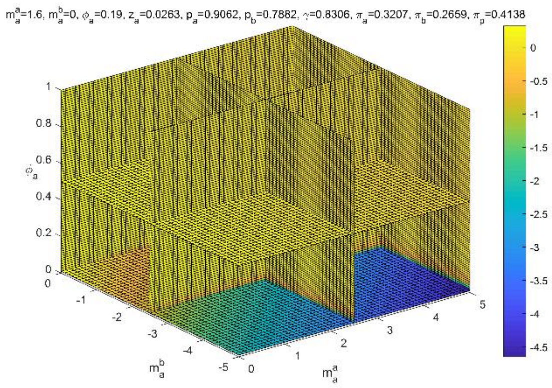




(a). z=0.0005

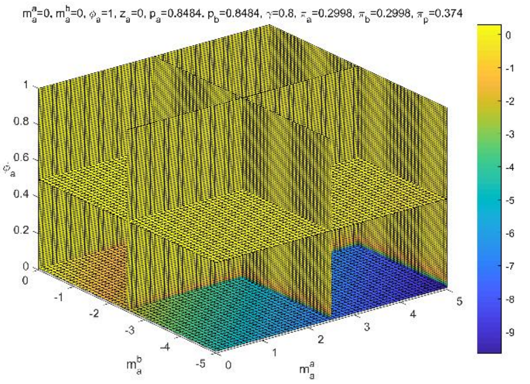
(b). z=0.0025

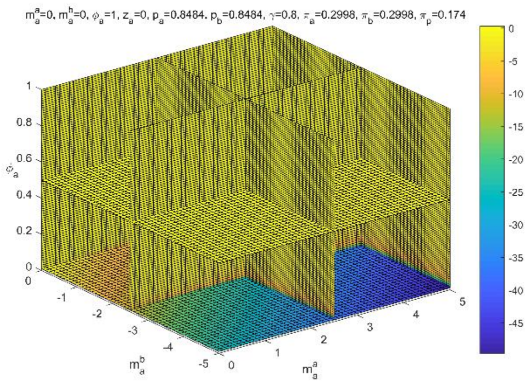




(c). z=0.005

(d). z=0.025





(e). z=0.05

(f). z=0.25

Figure 3-2 Behaviors of firm i under different z values in the benchmark scenario

Remarks: The color in all subgraphs represents the values of firm i 's profit; the specific values are shown in the boxes to the right of each subgraph;

Under $z = 0.0005$ (roughly $0.001\pi_p$), firm a posts fake positive reviews with the degree of 1.7 to itself, fake negative reviews with the degree of -4 to its opponent, and its unit cost posting fake reviews is 0.0017, which is 3.4 times of z. The probability that the fake reviews of firm a can be detected is 0.06. The price of a and b will be 1.1429 and 0.5714, respectively, and the total number of consumers will be reduced to 0.528 because of fake reviews posted by firm a. Thus, the profits of firms a, b and this platform are 0.3777, 0.0792, and 0.2818.

When $z = 0.0025$ (roughly $0.005\pi_p$), firm a posts only fake positive reviews with the degree of 1.2 to itself, and the unit cost of posting fake reviews is 0.0063, which is 2.52 times that of z. The prices of a and b are 0.9067 and 0.7877, respectively, and total number of consumers decreases to 0.8479. Thus, the profits of firms a, b, and this platform are 0.3633, 0.271, and 0.4468, respectively.

When $z = 0.005$ (roughly $0.01\pi_p$), firm a posts only fake positive reviews with the degree of 1.4 to itself, and the unit cost of posting fake reviews is 0.0071, which is 1.42 times that of z. The probability that the fake reviews can be detected is 0.14. The prices of a and b remain 0.9067 and 0.7877, respectively, but the total number of consumers decreases to 0.8395. Thus, the profits of firm a, firm b, and this platform are 0.3571, 0.2684, and 0.4398, respectively.

When $z = 0.025$ (roughly $0.05\pi_p$), firm a posts only fake positive reviews with the degree of 1.6 to itself, and the unit cost of posting fake reviews is 0.0263, which is 1.052 times that of z. The prices of a and b are still 0.9062 and 0.7882, respectively, but the total number of consumers decreases to 0.8306. Thus, the profits of firm a, firm b, and this platform are 0.3207, 0.2659, and 0.4138, respectively.

When $z = 0.05$ (roughly $0.1\pi_p$) and $z = 0.25$ (roughly $0.25\pi_p$), firm a does not post any fake positive reviews or fake negative reviews. Both products cost 0.848, and the total number of consumers is 0.8. The profit of both firms is equal to 0.2998, and the profits of the platform under the two cases are 0.374 and 0.174. When z is larger than 0.05 ($0.1\pi_p$), firm a does not post any fake reviews because the cost of escaping detection is too high or is lesser than the profit, given that for each firm to have fake reviews that are undetectable is impossible.

If we fix the behaviors of firm b, the game theoretical model only includes two players: firm a and the platform. The profits of firms a, b, and platform under the six values of z are shown in Figure 3.3.

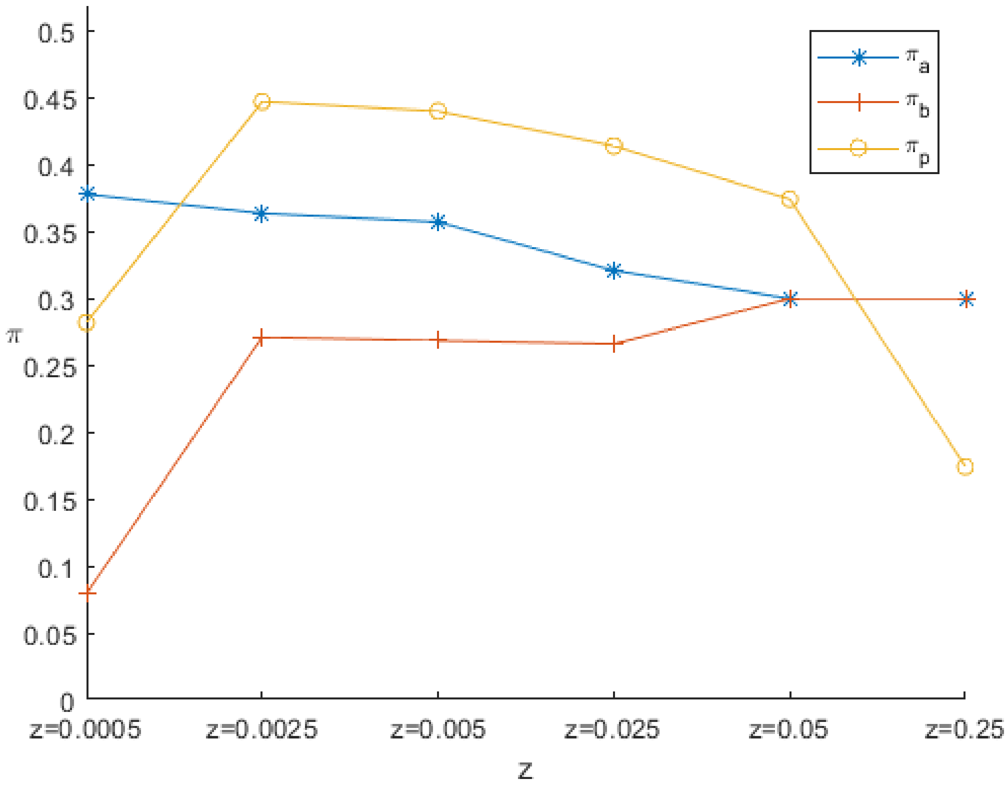


Figure 3-3 Profits of two firms and the platform in a two-player game

After observing the best response mapping from firm a, the platform chooses $z = 0.0025$ to obtain its maximum profit π_p=0.4468. The equilibrium result for the two-player game is as follows: firm a ($m_a^a = 1.2$, $m_b^a = 0$, $\varphi_a = 0.08$, $z_a = 0.0063$), platform ($z = 0.0025$). The profits of firms a and b are 0.3633 and 0.271, respectively. Only when z is too small will firm a post fake negative reviews against its opponents.

The difference between the profits of firm a and those of firm b is so large that firm b must initiate a response to maintain its profit. In the next part, we will explore the game among these three players.

3.4.4 Equilibrium Results in Non-Cooperative Case

We define a non-cooperative case as the one wherein two firms take actions on their own and try to maximize their own payoffs. As a result of the complexities of their payoffs, calculating the best response mappings from two firms using traditional ways, such as first-order partial derivatives, is impossible. In our Matlab program, we ensure that the value of z to fall into the range of 0–0.025 with the step size of 0.0005 because of the above analyses. The solving algorithm is presented below.

```
set the basic parameters for this game-theoretical model
for any possible value of z (0:0.0005:0.05)
    for any possible strategy of firm a (m_a^a --0:0.1:5, m_b^a --0:-0.1:-5, φ_a --1:-0.1:0.1)
        for any possible strategy of firm b (m_b^b --0:0.1:5, m_a^b --0:-0.1:-5, φ_b --1:-0.1:0.1)
            observe profits of two firms π_a, π_b and set compare objections as π1, π2
            if π_a > π1 && π_b > π2
                update π1=π_a, π2=π_b
                save this best strategy: m_j^i and φ_i (z_i), and corresponding results
            end
        end
    end
    output these best response mapping under different z
end
compare and choose z to maximize π_p
get the equilibrium result in cooperative case
```

The best response mapping is obtained by observing the equilibrium results in the platform of Matlab. The result is presented in Table 3.3.

Table 3-3 The best response mappings from two firms in non-cooperative case

z	m_a^a	m_b^a	φ_a	m_a^b	m_b^b	φ_b	z_i	η_i	θ_i	v_i	γ	p_i	π_i	π_p
0	1.3	0	0.1	0	1.3	0.1	0	5	0.1	1	0.8774	0.85	0.3334	0.4654
0.002	1.2	0	0.1	0	1.2	0.1	0.004	4.96	0.0992	0.9920	0.8775	0.8497	0.3283	0.4630
0.004	1.2	0	0.1	0	1.2	0.1	0.008	4.96	0.0992	0.9920	0.8775	0.8497	0.3235	0.4607
0.006	1.2	0	0.1	0	1.2	0.1	0.012	4.96	0.0992	0.9920	0.8775	0.8497	0.3187	0.4583
0.008	1.2	0	0.1	0	1.2	0.1	0.016	4.96	0.0992	0.9920	0.8775	0.8497	0.3139	0.4559
0.010	1.2	0	0.1	0	1.2	0.1	0.020	4.96	0.0992	0.9920	0.8775	0.8497	0.3091	0.4535
0.012	1.2	0	0.1	0	1.2	0.1	0.024	4.96	0.0992	0.9920	0.8775	0.8497	0.3043	0.4511
0.014	1.6	0	0.2	0	1.6	0.2	0.014	4.96	0.0992	0.9920	0.8503	0.8497	0.3004	0.4352
0.016	0	0	1	0	0	1	0	4	0.08	0.8	0.8	0.8484	0.2998	0.4080
0.018	0	0	1	0	0	1	0	4	0.08	0.8	0.8	0.8484	0.2998	0.4060
0.020	0	0	1	0	0	1	0	4	0.08	0.8	0.8	0.8484	0.2998	0.4040
0.022	0	0	1	0	0	1	0	4	0.08	0.8	0.8	0.8484	0.2998	0.4020
0.024	0	0	1	0	0	1	0	4	0.08	0.8	0.8	0.8484	0.2998	0.4000

Remarks: p_a and p_b have same values because these two firms take same strategy in the equilibrium. So are η_a and η_b, z_a and z_b, θ_a and θ_b, v_a and v_b, and π_a and π_b.

For ease of exposition, we describe the best response mapping under the values of z from 0 to 0.025 with the step of 0.002. For all the values of z, the profits of firm a, firm b, and the platform under the best response mappings from two firms are shown in Figure 3.4.

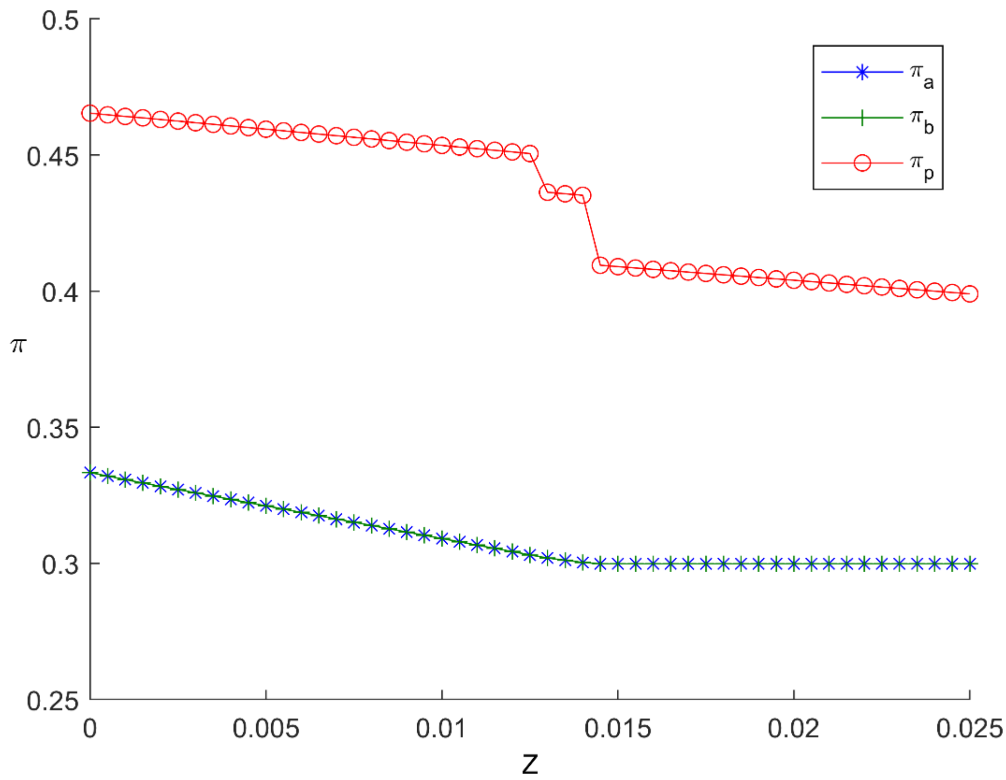


Figure 3-4 Profits of three players in a non-cooperative case

After observing the best response mapping from firms a and b, the platform chooses the optimal z to maximize π_p. By comparing the values of

π_p, we find that the platform chooses $z=0$ in the non-cooperative case. The equilibrium strategies of these three players are $m_a^a=m_b^b=1.3$, $m_b^a=m_a^b=0$, $\varphi_a=\varphi_b=0.1$, and $z=0$. The corresponding results are presented in the first row of Table 3.4.

In the non-cooperative case, we can realize that (i) the platform does not invest in the detection of fake reviews because the investment cannot exceed the increased profit; (ii) the two firms choose to post fake positive reviews with the degree of 1.3 to themselves, and they do not post any fake negative reviews to their opponents; and (iii) the two firms need not invest any money on escaping detection of fake reviews because the platform does not detect fake reviews. Thus, the star ratings, loyal consumers, perceptive values, prices, and profits of the two firms are high. Although the number of consumers declines due to these fake reviews, the impact of such reviews on the profits of the three players is minimal.

3.4.5 Equilibrium Results in Cooperative Case

In a cooperative case, these two firms become a community and take actions together to maximize their total payoffs. Since the decision is jointly made by these two cooperative firms in the cooperative case, the total profit of these two firms can be redistributed to each firm. If there is no external incentives, the cooperative case can be founded, only when both firms can obtain higher profits in cooperative case than in non-cooperative case. In this study, the total profits of these two firms are uniformly redistributed to each firm.

We also set that the value of z to fall into the range of 0–0.025 with the step size of 0.0005. The solving algorithm is presented below.

```
set the basic parameters for this game-theoretical model
for any possible value of z (0:0.0005:0.05)
    for any possible strategy of firm a (m_a^a --0:0.1:5, m_b^a --0:-0.1:-5, φ_a --1:-0.1:0.1)
        for any possible strategy of firm b (m_b^b --0:0.1:5, m_a^b --0:-0.1:-5, φ_b --1:-0.1:0.1)
            observe the total profit of two firms π_{a+b} and set compare objection as π1
            if π_{a+b} > π1
                update π1=π_{a+b}
                save this best strategy: m_j^i and φ_i (z_i), and corresponding results
            end
        end
    end
    output these best response mapping under different z
end
compare and choose z to maximize π_p
get the equilibrium result in cooperative case
```

For all the values of z, the profits of firm a, firm b, and the platform under the best response mappings from two firms are shown in Figure 3.5. The platform also chooses $z=0$ to maximize π_p in the cooperative case. Three players take the same strategies: $m_a^a = m_b^b = 1.3$, $m_b^a = m_a^b = 0$, $\varphi_a = \varphi_b = 0.1$, and $z = 0$. The equilibrium results in the cooperative case are that same as those in the non-cooperative case.

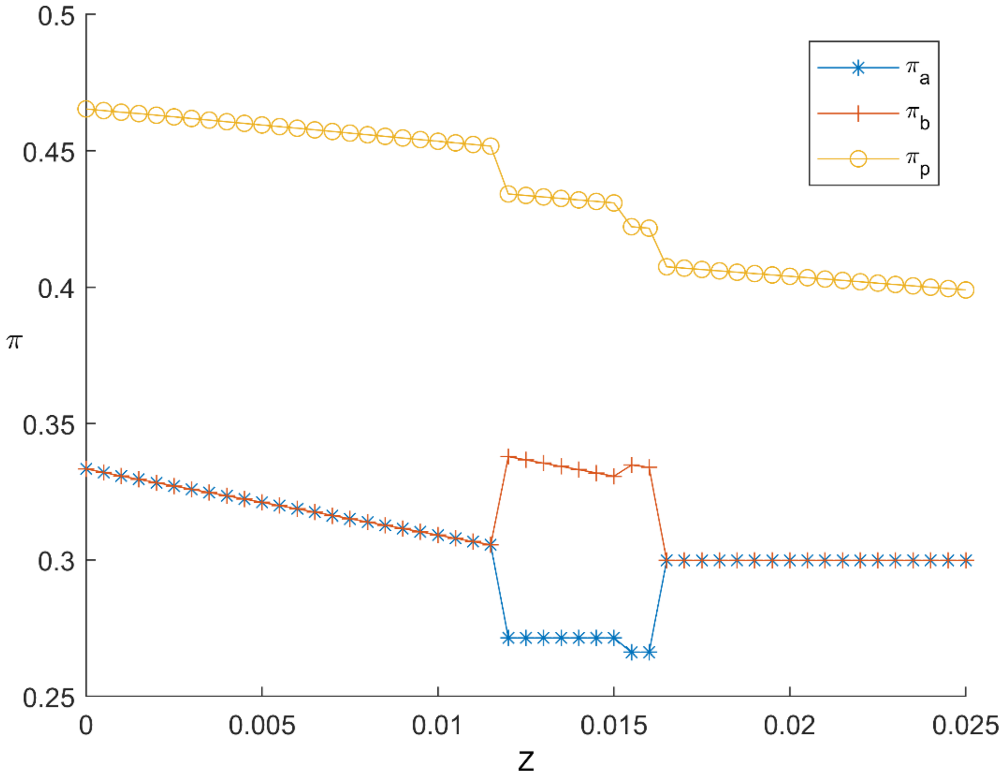


Figure 3-5 Profits of three players in a cooperative case

But through comparing Figure 3.4 and Figure 3.5, we obtain an interesting finding. Between z=0.012 and z=0.016, the equilibrium results under these two cases are different, and firms can obtain higher profits in cooperative cases than in non-cooperative case. Under other z values, firms adopt same strategy under these two cases. The specific equilibrium results under two different cases between z=0.012 and z=0.016 are shown in Table 3.4.

Table 3-4 Equilibrium results under two different cases from *z=0.012* to *z=0.016*

	z	m_a^a	m_b^b	φ_a	φ_b	m_b^a / m_a^b	π_a	π_b	$\pi_a+\pi_b$	π_p
Non-cooperative case	0.012	1.2	1.2	0.1	0.1	0	0.3043	0.3043	0.6087	0.4511
Cooperative case		0	1.2	1	0.1	0	0.2714	0.3379	0.6093	0.4342
Non-cooperative case	0.0125	1.2	1.2	0.1	0.1	0	0.3031	0.3031	0.6063	0.4505
Cooperative case		0	1.2	1	0.1	0	0.2714	0.3367	0.6081	0.4336
Non-cooperative case	0.013	1.6	1.6	0.2	0.2	0	0.3020	0.3020	0.6040	0.4363
Cooperative case		0	1.2	1	0.1	0	0.2714	0.3355	0.6069	0.4331
Non-cooperative case	0.0135	1.6	1.6	0.2	0.2	0	0.3012	0.3012	0.6024	0.4357
Cooperative case		0	1.2	1	0.1	0	0.2714	0.3343	0.6057	0.4325
Non-cooperative case	0.014	1.6	1.6	0.2	0.2	0	0.3004	0.3004	0.6008	0.4352
Cooperative case		0	1.2	1	0.1	0	0.2714	0.3331	0.6045	0.4320
Non-cooperative case	0.0145	0	0	1	1	0	0.2998	0.2998	0.5997	0.4095
Cooperative case		0	1.2	1	0.1	0	0.2714	0.3319	0.6033	0.4314
Non-cooperative case	0.015	0	0	1	1	0	0.2998	0.2998	0.5997	0.4090
Cooperative case		0	1.2	1	0.1	0	0.2714	0.3307	0.6021	0.4309
Non-cooperative case	0.0155	0	0	1	1	0	0.2998	0.2998	0.5997	0.4085
Cooperative case		0	1.6	1	0.2	0	0.2714	0.3348	0.6062	0.4216
Non-cooperative case	0.016	0	0	1	1	0	0.2998	0.2998	0.5997	0.4080
Cooperative case		0	1.6	1	0.2	0	0.2714	0.3340	0.6054	0.4222

The total profits of these two firms in cooperative case should be as large as those in non-cooperative case and should probably higher than those in some situations. Without special protocols, the total profits of these two firms are uniformly redistributed to each firm. So in cooperative case, the profit of each firm is better off for both firms via some relocation of profits.

This is intuitive for that these two firms can adopt some strategies to increase the reputation of one firm and thus to increase corresponding product price. In a fixed market, although the total demand function cannot be increased, the firms can increase their total profits through significantly inducing the consumers to purchase the product with higher product price.

Unlike these two firms, platforms cannot always obtain higher profits in cooperative case. From z=0.014 to z=0.016, the profit of the platform are higher in the cooperative case than in the non-cooperative case. But from z=0.012 to z=0.014, the profit of the platform are lower in the cooperative case than in the non-cooperative case.

These results indicate the following: (i) in this benchmark scenario, the platform does not invest in the detection of fake reviews even with the collaboration of two firms; (ii) two firms always obtain more profit in the cooperative case than in the non-cooperative case; (iii) when the platform invests heavily in the detection of fake reviews, the number of fake reviews is higher in the cooperative case than in the non-cooperative case. The number of fake reviews in the cooperative case could only decline when the platform invests little money in the detection of fake reviews.

3.5 Parameter Analyses

We design different scenarios to observe the impacts of certain parameters on firm behaviors toward posting fake reviews. We calculate the equilibrium results under different parameters and compare them to realize the impact of the parameters on firm strategies about posting fake reviews.

3.5.1 Research Designs

We set two different values (one high value and one low value) for each parameter to form the control group. For each parameter, we use the fourfold value in the benchmark scenario to represent the high level of the parameter and use the quarter of the value to represent the low level of this parameter. We divide these parameters into two parts, namely, one part about the platform and the other part about the firm. The specific research designs are shown in Table 3.5.

Table 3-5 Research designs about the parameters

Parameters			Platforms							Firms		
			γ_0	δ	w	h	t	χ	φ	θ_i^0	ζ_i	v_i^0
Benchmark			1	0.04	0.5	0.5	1	2	0.2	0.1	4	1
Parameters about platforms	High	γ_0	4	0.04	0.5	0.5	1	2	0.2	0.1	4	1
	Low		0.25									
	High	δ	1	0.16	0.5	0.5	1	2	0.2	0.1	4	1
	Low			0.01								
	High	w	1	0.04	2	0.5	1	2	0.2	0.1	4	1
	Low				0.125							
	High	h	1	0.04	0.5	2	1	2	0.2	0.1	4	1
	Low					0.125						
	High	t	1	0.04	0.5	0.5	4	2	0.2	0.1	4	1
	Low						0.25					
	High	χ	1	0.04	0.5	0.5	1	8	0.2	0.1	4	1
	Low							0.5				
	High	φ	1	0.04	0.5	0.5	1	2	0.8	0.1	4	1
	Low								0.05			
Parameters about firms	High	θ_i^0	1	0.04	0.5	0.5	1	2	0.2	0.4	4	1
	Low									0.025		
	High	ζ_i	1	0.04	0.5	0.5	1	2	0.2	0.2	5[6]	1
	Low										1	
	High	v_i^0	1	0.04	0.5	0.5	1	2	0.2	0.2	4	4
	Low											0.25

[6] Although the fourfold of average star rating is 16, we still set this parameter in higher case as 5 since the upper boundary of star rating is 5.

3.5.2 Parameters about Platforms

Through using the algorithm described above, we obtain equilibrium results under different situations and present them in Figure 3.6.

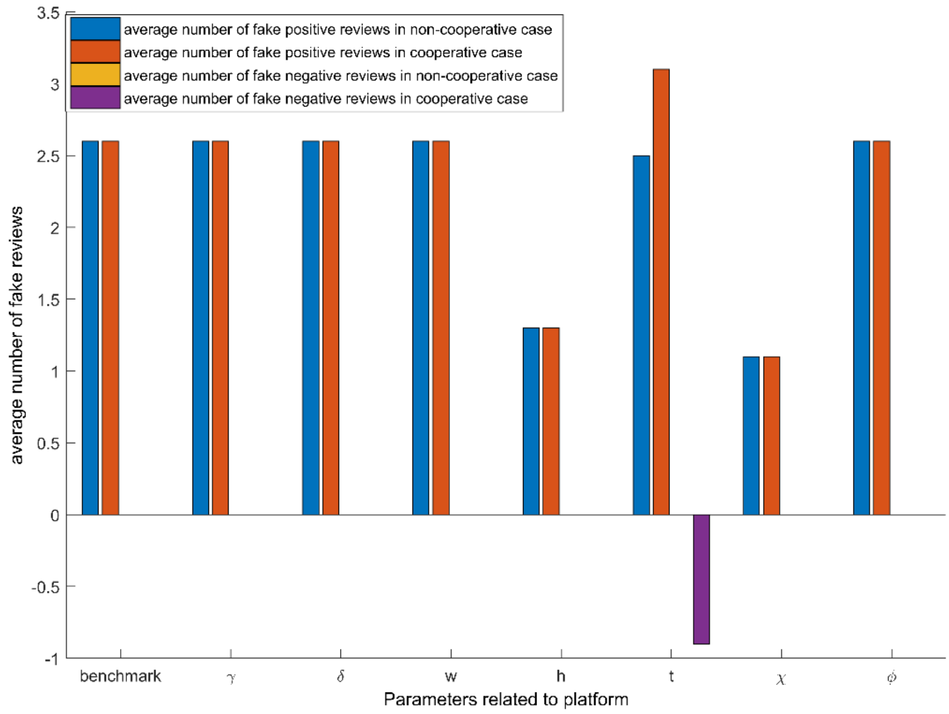


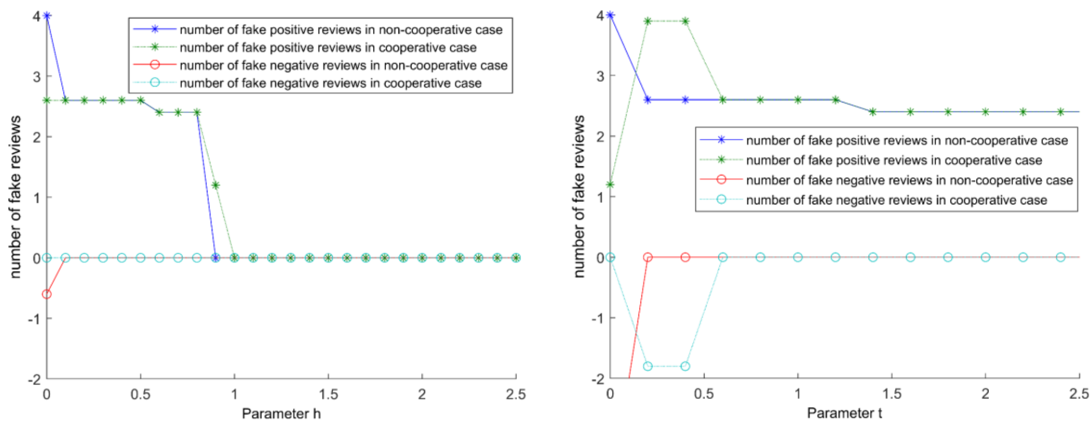
Figure 3-6 Number of fake reviews under different parameters related to platform

Remarks: 1. The eudipleural relationships between the alphabets and parameters are r-γ_0, a-δ, w-w, h-h, t-t, x-χ, and f-φ. 2. *nc* represents the non-cooperative case, and *c* represents the cooperative case (the same below).

By comparing the equilibrium results between the benchmark and the control group, we find three parameters, h, t, and χ, which exhibit certain effects on the number of fake reviews. In most cases, χ and φ are directly related. Thus, we further analyze the impact of these selected parameters on the number of fake reviews in the non-cooperative case. Based on the equilibrium results above, we set $\left|m_j^i\right|$ in the interval $[0,2]$ to reduce algorithm complexity without damaging the accuracy of the results.

3.5.2.1 Parameters h and t

We set h from 0 to 2.5 with the step of 0.1 because η in Eq. (3-12) approaches 0 when $h \approx 2$ under the condition that the equilibrium number of fake reviews is 2.6 in the benchmark scenario. Given that $v_i^0 = 1$, we set t from 0 to 5 with the step of 0.2. Figure 3.7 depicts the variation trends related to the number of fake reviews under different h and t.



(a). Research on parameter *h* (b). Research on parameter *t*

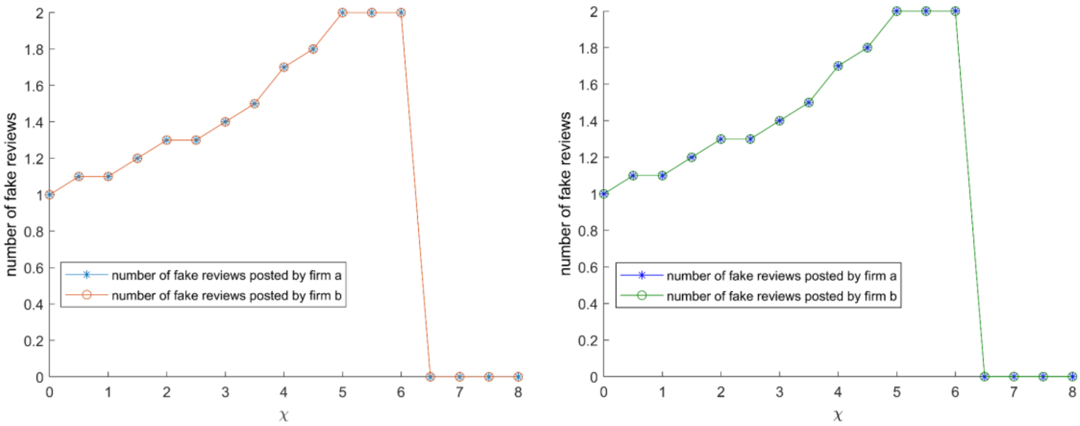
Figure 3-7 Changing trend of the number of fake reviews under parameters *h* and *t*

The number of fake reviews in the non-cooperative case is the same as that in the cooperative case if parameters h and t are large. However, these two cases show certain differences. For parameter h, we can find that the number of fake negative reviews becomes zero unless $h = 0$. The number of fake positive reviews declines gradually with the increase of parameter h and until it reaches 0. Low h means that the impact of fake reviews on the platform's reputation is small that firms are confident enough to post fake reviews. When h is low, the number of fake positive reviews is roughly 2.5.

Parameter t is the unit misfit cost. This value reflects the importance degree of taste compared with quality. When t is low, consumers make decision depending on product quality. Therefore, firms are motivated to manipulate fake reviews. Thus, the number of fake reviews is larger when t is low than when t is high. Firms even post some fake negative reviews to cooperators that are designed to enlarge the distance about their perspective qualities so that one firm can obtain more profits.

3.5.2.2 Punishment Intensity

Most platforms punish unscrupulous firms by penalizing their mistakes and warning all firms not to issue fake reviews. Many propose that high punishment undoubtedly reduces the number of fake reviews. However, from the above analyses, we find that the positive relationship between the number of fake reviews and punishments is not always true. Specifically, the total number of fake reviews is 2.6 when $\chi=2$. However, when the unit punishment decreases to 0.5, the total number of fake reviews decreases to 2.2. To realize whether high punishment can effectively reduce the number of fake reviews, we set χ from 0 to 8 with the step of 0.5. The numbers of fake reviews under these values are presented in Figure 3.8.



(a). In non-cooperative case (b). In cooperative case

Figure 3-8 The number of fake reviews under punishment intensity changes

As shown in Figure 3.8, firms stop to issue fake reviews if $\chi \geq 6.5$ in the benchmark scenario. Otherwise, the number of fake reviews increases along with χ. The changing trend of the number of fake reviews remains the same regardless of whether two firms cooperate. The potential of high punishment to reduce the number of fake reviews cannot be ascertained. In some cases, it could even lead to an increase in fake reviews. This finding shows the existence of a demarcation point in which firms stop issuing any fake reviews to escape punishment. If punishment intensity is lower than this point, firms continue to post fake reviews to ensure the most significant effect. Future research should explore how each platform should find this demarcation point about punishment intensity.

The intuitive reason causing this interesting phenomenon is that increasing the punishment intensity reduce the effect of fake reviews but cannot seriously reduce the reputations of these firms. For example, without punishment intensity, the optimal effective number of fake reviews is 2 units; when the punishment intensity is 1 unit, the optimal effective number of fake reviews is reduced to 1.5 units. But since the existing of 1 unit punishment intensity, the firms need to post 2.5 units fake reviews. But if the punishment intensity is extremely high, the huge costs posting fake reviews lead to that the optimal effective number of fake reviews is reduced to 0. The scientific explanations for this phenomenon are still need to be further explored in the further studies.

3.5.3 Parameters about Firms

Equilibrium results under different parameters about firms are got and presented in Figure 3.9. By comparing the equilibrium results between the benchmark and the control group, we find that all these three parameters exert a significant impact on the number of fake reviews. We further explore the influencing mechanism of these parameters in a non-cooperative case.

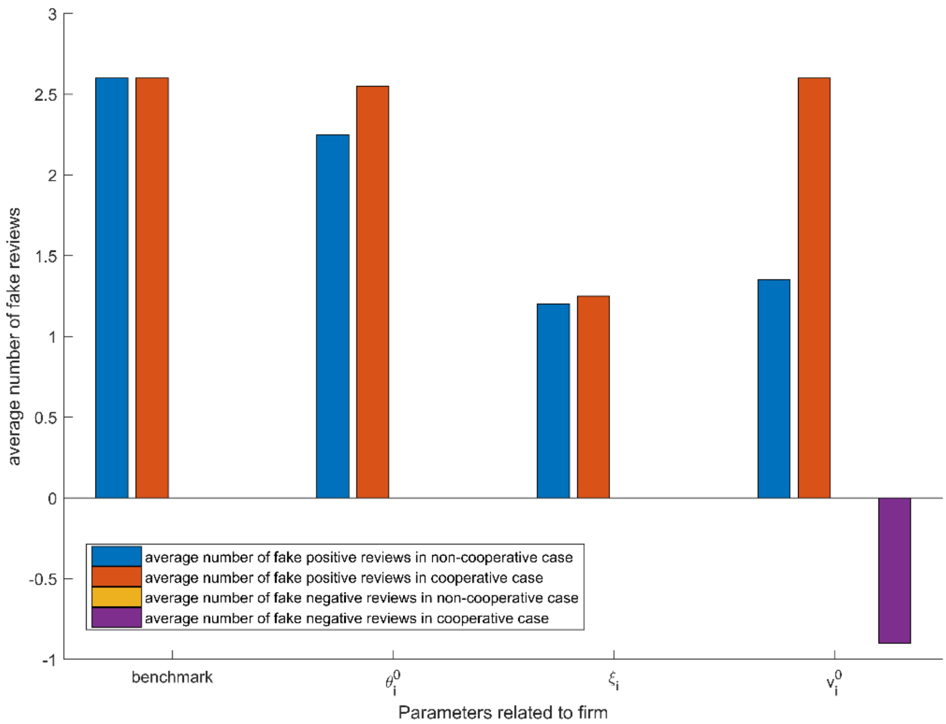


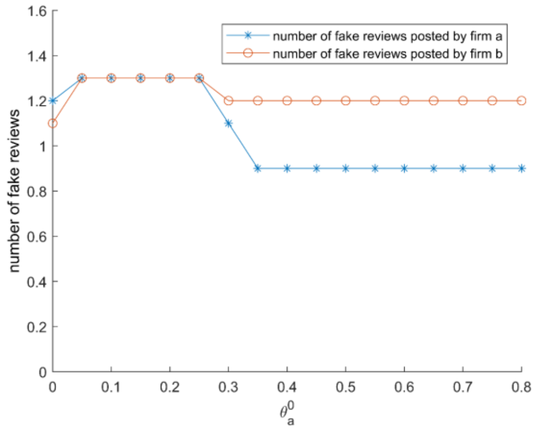
Figure 3-9 Number of fake reviews under different parameters about firms

Loyal consumers bring more profits to firms than switcher shoppers do, but the relationship between the number of fake reviews and the proportion of loyal consumers is unknown. To realize this relationship, we set $\theta_b^0 = 0.1$ and change θ_a^0 from 0 to 0.8 with the step of 0.05. From Figure 3.9, we realize that the degree of change in the number of fake reviews under parameter ζ_i is significantly greater than those under the other two parameters and that firms perhaps post fake negative reviews to their opponents when v_a^0 changes. To realize the specific impact of parameters ζ_i and v_a^0 on the number of fake reviews, we set

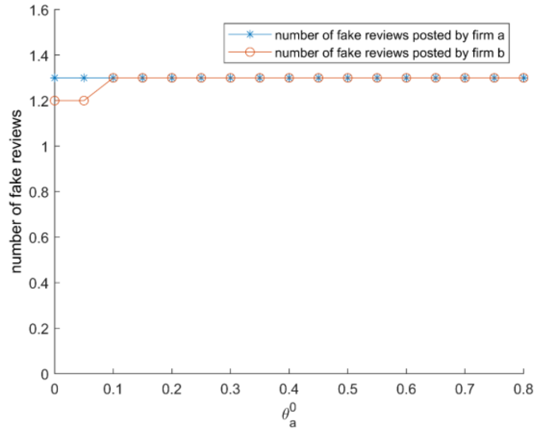
$\zeta_b = 4, v_b^0 = 4$ and change ζ_a, v_a^0 from 0 to 5 with the step of 0.5. The numbers of fake reviews posted by firms a and b under different parameters (θ_a^0, ζ_a, and v_a^0) are presented in Figure 3.10.

In our benchmark scenario, two firms possess the same proportion of loyal consumers. This proportion is 0.1. Each firm posts 1.3 units of fake positive reviews to themselves with equilibrium results. Even if the proportion of loyal consumers of firm a increases, two firms still basically post 1.3 units of fake reviews in a cooperative case. By contrast, the number of fake reviews posted by firm i undergoes considerable fluctuation in a non-cooperative case. When $\theta_a^0 > 0.2$, the number of fake reviews posted by firm a drops from 1.3 to 0.9. Thus, the total number of fake reviews declines slightly as θ_a^0 increases.

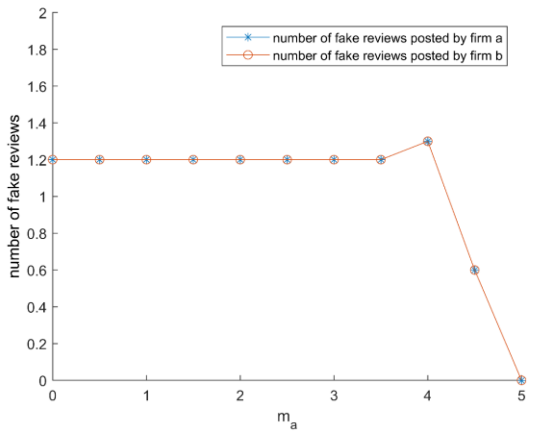
If $m_b = 4$, the total number of fake reviews can be maximized only when m_a is also equal to 4. When $m_a < 4$, the number of fake reviews posted by a and b decreases from 1.3 to 1.2. When $m_a > 4$, the number of fake reviews decreases with a high slope and even drops to 0 when $m_a = 5$. However, if two firms cooperate, the number of fake reviews dramatically fluctuates along with m_a. When m_a is large or extremely small, firm a does not post any fake positive reviews of itself because it aims to help itself and firm b in earning more profits. Therefore, the total number of fake reviews decreases. When m_a is moderately low, firm a posts many fake reviews to itself to increase its profit to increase the total number of fake reviews in a cooperative case.



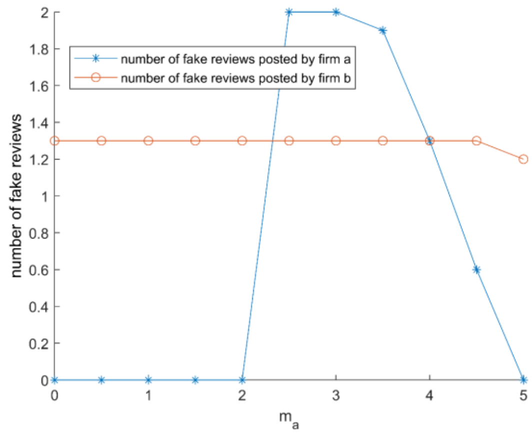
(a). Research on $\theta_a{}^0$ in non-cooperative case



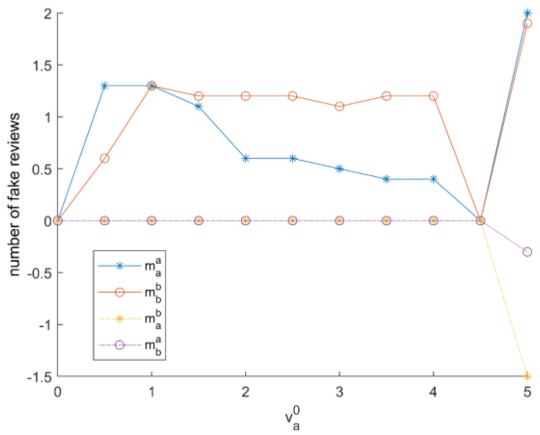
(b). Research on $\theta_a{}^0$ in cooperative case



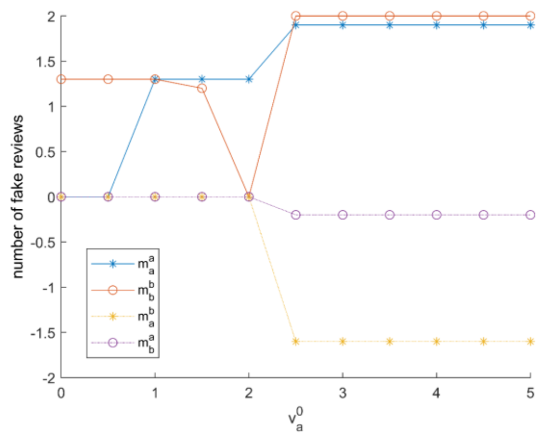
(c). Research on m_a in non-cooperative case



(d). Research on m_a in cooperative case



(e). Research on $v_a{}^0$ in non-cooperative case



(f). Research on $v_a{}^0$ in cooperative case

Figure 3-10 Number of fake reviews under different parameters about firms

The firm with high v_i^0 normally posts numerous fake reviews to increase its profit in a non-cooperative case. When v_b^0 is fixed, there exists a demarcation point about v_a^0 in which the number of fake reviews is the lowest. For example, when $0 < v_a^0 < v_b^0 = 1$, the number of fake reviews posted by firm a is greater than that posted by firm b; when $1 = v_b^0 < v_a^0 < 4.5$, the number of fake reviews posted by firm a is lesser than that posted by firm b. However, if v_a^0 reaches 4.5, these two firms post numerous fake positive reviews to themselves, and they even post some fake negative reviews to their opponents. The demarcation point in the cooperative case is 2, which is lesser than that in the non-cooperative case. In the cooperative case, these firms choose to post many fake positive reviews to the firm with a high v_i^0. If v_a^0 is higher than v_b^0, firm a even chooses to post many fake negative reviews to its opponents to boost its profit.

In summary, the impact of these parameters about firms on the number of fake reviews in the cooperative case is more significant than that in the non-cooperative case. A reverse relationship exists between θ_a^0 and the number of fake reviews posted by firm a. When θ_a^0 increases to a certain degree, firm a chooses to post few fake reviews to maintain its loyal consumers. In the cooperative case, firm a does not post any fake positive reviews because it wants to help itself and firm b in boost their profits when m_a is large or extremely small. Moreover, firm a chooses to post many fake reviews only when m_a is moderately low. A reverse relationship exists between v_a^0 and the number of fake reviews posted by firm a.

3.6 Robustness Checks

In the benchmark scenario, two firms post 2.6 units of fake reviews in the equilibrium results. As the total number of online reviews is 10.6 (8+2.6), the proportion of fake reviews in this platform is 24.5%, which is consistent with the prior finding that the percentage of fake reviews is estimated to be around 15%–30% (Lappas et al. 2016; Luca and Zervas 2016). Although our results are consistent with the main findings of prior research, we still discuss the important robustness checks we conducted on our assumptions to testify our game theoretical model.

3.6.1 Game Order

By referring to the predominance of platforms in real life, we consider that the platform first chooses its strategy before firms make strategies. However, these players can dynamically make strategies. We calculate the equilibrium results when these three players respond simultaneously.

In the benchmark scenario, the equilibrium strategies of the three players are $m_a^a = m_b^b = 1.3$, $m_b^a = m_a^b = 0$, $\varphi_a = \varphi_b = 0.1$, and $z = 0$ in the non-cooperative case. When we revise the game order as three players who make decisions with no communication, the new equilibrium strategies of these three players are $m_a^a = m_b^b = 1.2$, $m_b^a = m_a^b = 0$, $\varphi_a = \varphi_b = 0.1$, and $z = 0$. The differences between these two equilibrium results are so small that we believe our assumption about game order not only conforms to reality but also shows strong robustness.

3.6.2 Financial Punishment

Yelp.com and Dianping.com post warnings in the homepages of unscrupulous firms and alert consumers that these firms post fake reviews, but they do not impose monetary penalty (Chinese News 2017; Technology 2012). Thus, we assume that the platform does not issue any financial punishments. However, many financial punishments are implemented in practice. One wonders whether the results hold when financial punishments are also used to punish these unscrupulous firms. Thus, to investigate this issue, we define the standard of financial punishment as f and revise the profits of firms as

$$\pi_a = \frac{\gamma\left(3t + v_a - v_b\right)\left[\left(3 - 3\theta_a - \theta_b\right)t + (1 + 7\theta_a + 5\theta_b)v_a + (-1 + \theta_a - \theta_b)v_b\right]}{2t\left(9 + 30\theta_a + 30\theta_b\right)} - \left(z_a + \varphi_a f\right)\left|\sum_j m_j^a\right|$$
$$\pi_b = \frac{\gamma\left(3t - v_a + v_b\right)\left[\left(3 - \theta_a - 3\theta_b\right)t + (-1 - \theta_a + \theta_b)v_a + (1 + 5\theta_a + 7\theta_b)v_b\right]}{2t\left(9 + 30\theta_a + 30\theta_b\right)} - \left(z_b + \varphi_b f\right)\left|\sum_j m_j^b\right|$$

(3-17)

According to prior analysis, the equilibrium profits of these firms are roughly 0.3. Thus, we set f as 0.0003 ($0.001\pi_p$), 0.0015 ($0.005\pi_p$), 0.003 ($0.01\pi_p$), 0.015 ($0.05\pi_p$), 0.03 ($0.1\pi_p$), and 0.15 ($0.5\pi_p$). The equilibrium results under these values of f are presented in Table 3.6.

The data in Table 3.6 show that the equilibrium results stay the same regardless of whether financial punishments are taken to punish unscrupulous firms. The effect of financial punishments on reducing the number of fake reviews is inconspicuous. When financial punishments increase, the number of fake reviews slightly decreases. Although it does not effectively consider financial punishments, our game theoretical model can effectively find equilibrium results among consumers, firms, and platforms.

Table 3-6 Equilibrium results under different financial punishments

	Benchmark	f =0.0003	f =0.0015	f =0.003	f =0.015	f =0.03	f =0.15
m_a^a	1.3	1.3	1.3	1.3	1.3	1.2	1.2
m_b^a	0	0	0	0	0	0	0
m_a^b	0	0	0	0	0	0	0
m_b^b	1.3	1.3	1.3	1.3	1.3	1.2	1.2
φ_a	0.1	0.1	0.1	0.1	0.1	0.1	0.1
φ_b	0.1	0.1	0.1	0.1	0.1	0.1	0.1
z	0	0	0	0	0	0	0
π_a	0.3334	0.3334	0.3332	0.3330	0.3314	0.3295	0.3151
π_b	0.3334	0.3334	0.3332	0.3330	0.3314	0.3295	0.3151
π_p	0.4654	0.4653	0.4653	0.4653	0.4652	0.4651	0.4640

3.7 Conclusions and Discussions

As online product reviews significantly affect consumers' purchase decisions, firms have sufficient motivation to issue fake reviews of themselves or their opponents. Thus, the impact of fake reviews when researching online reviews should be considered. Many prior studies employ a game theoretical model to study the rational behaviors of firms and consumers, but they do not consider the existence of fake reviews. To the best of our knowledge, this study is among the first to introduce fake reviews into the game theoretical model to explore why fake reviews are popular and how to reduce their number. Aside from considering consumers and firms, this study is also the first to explore fake reviews from the novel perspective of platforms. Although the dynamics of loyal consumers has not been considered in prior game theoretical models, we set the proportion of loyal consumers to each firm to change along with its reputation. We also set the total number of consumers purchasing in this platform to change along with the platform's reputation.

We use a game theoretical model to explore three research questions and derive conclusions, which are described in three parts.

3.7.1 Conclusions

3.7.1.1 Where to Post Fake Reviews

The numbers of fake reviews among platforms varies with different h, t, and χ. The platform with low h has much more fake reviews than the platform with high h. Low h means that the impact of fake reviews on the platform's reputation is small so that firms have enough courage to post fake reviews. When h is low, the number of positive fake reviews is roughly 2.5. When $h = 0$, two firms post about 5 units of fake reviews, including fake positive reviews to themselves and fake negative reviews to their opponents.

When t is low, consumers make decisions depending on the products' quality. Thus, firms are strongly motivated to manipulate fake reviews. The number of fake reviews is larger in the platform with low t than in the platform with high t.

The platform with high punishment intensity has more fake reviews than that with low punishment intensity for many cases, unless the punishment intensity is extremely high. A demarcation point exists wherein firms stop to issue any fake reviews to escape punishment. If punishment intensity is lower than this point, firms post many fake reviews to ensure a maximum effect.

With respect to the first research question, we find a significant difference in the numbers of fake reviews among platforms. Unscrupulous firms tend to issue fake reviews in platforms with low sensitivity to fake reviews, and they prefer to sell products with low unit misfit cost and improper punishment intensity. If the punishment intensity cannot reach the proper demarcation point, high punishment intensity would lead to numerous fake reviews.

3.7.1.2 Why Post Fake Reviews

When only firm a can choose to manipulate fake reviews under the condition that the behaviors of firm b are fixed, the platform chooses $z = 0.0025$ to detect fake reviews, and firm a intends to issue 1.2 units of fake reviews to itself. When two firms are able to manipulate fake reviews, they post a total of 2.6 units of fake reviews, and the platform does not invest in the detection of fake reviews regardless of the collaboration of the firms.

By comparing the equilibrium results under different parameters (θ_i^0, ζ_i, and v_i^0), we find that all three parameters affect the number of fake reviews considerably. A reverse relationship exists between θ_a^0 and the number of fake reviews posted by firm a. When θ_a^0 increases to a certain degree, firm a chooses to post few fake reviews to maintain its loyal consumers. In the cooperative case, firm a does not post any fake positive reviews because it wants to help itself and firm b in boosting their profits when m_a is large or extremely small. Furthermore, firm a chooses to post many fake reviews only when m_a is moderately low. A reverse relationship exists between v_a^0 and the number of fake reviews posted by firm a.

By analyzing these factors, we show that the platform does not want to detect fake reviews for many cases as its profits are connected closely to firm profits. However, in an improper mode, such as one in which only one firm, has the ability to manipulate online reviews. The platform invests heavily in detecting fake reviews as it realizes the only one unscrupulous firm damage other firms' profits and reduce its profit. The number of fake reviews declines to a certain degree once the platform invests heavily in detecting fake reviews.

Thus, we think that one of the most important underlying motivations leading to fake reviews is that platforms do not want to spend much money to detect fake reviews. Firms located at the lower competing position have high incentives to manipulate online reviews. Specifically, fake reviews are mostly posted by firms with only a few loyal consumers, low initial assessment about their values, and moderately low star rating. They also prefer to issue fake positive reviews to themselves to boost their profits instead of posting fake negative reviews to their opponents. Cooperative cases always benefit firms, but they would hurt platforms and lead to extra fake reviews.

3.7.1.3 How to Reduce Fake Reviews

The first order of importance for platform designers is to develop mechanisms to reduce fraud (Luca and Zervas 2016). Through the results of our game theoretical model, we propose some actions that the three players can do to reduce the number of fake reviews.

We hope the profits of platforms mainly come from advertising revenues rather than commission revenues. Platforms with revenues that highly depend on its consumers tend to invest in the detection of fake reviews and in turn reduce fake reviews. If the platform mainly sells products with high unit misfit cost and enacts proper punishment intensity, the number of fake reviews also declines markedly.

To reduce fake reviews, we suggest that firms promote their competitiveness. For example, they could take action to capture more loyal consumers, promote consumers' initial assessment about their values, and improve their actual star ratings.

Severe punishment cannot always reduce the number of fake reviews, and it could even lead to more fake reviews in some cases. A demarcation point exists in punishment intensity, wherein which firms stop issuing fake reviews to escape punishment. If punishment intensity is lower than this point, firms post more fake reviews to ensure the maximum effect.

3.7.2 Implications

This study has five potential implications. (i) This study is among the first to examine fake reviews from a novel perspective of platforms. Based on our findings, we offer some suggestions to reduce fake reviews. (ii) Our game theoretical model is realistic because it has three players (i.e., two firms and one platform) instead of two. (iii) By considering the existence of loyal consumers, we expand the classic hoteling model and deduce new equilibrium prices and profits for products and firms. (iv) Some new findings are obtained in our research work. These important findings include the existence of a demarcation point about punishment intensity in which firms stop issuing any fake reviews to escape punishment. In addition, this study reveals that a cooperative case among firms always benefits them, but it would hurt platforms and lead to extra fake reviews. (v) Our suggestions to reduce fake reviews restrict the number of fake reviews intrinsically. Thus, we are confident that our suggestion can effectively reduce fake reviews more than a detection algorithm could.

3.7.3 Limitations and Future Research

This study has some limitations. (i) All platforms, firms, and consumers learn to take rational strategies in a dynamic process. Although our static game theoretical model can yield equilibrium results, it cannot describe the underlying dynamic learning process. An intertemporal game theoretical model may be built to realize the dynamic process of these players' responses and in turn yield effective suggestions to reduce fake reviews.

(ii) Referring to the punishment from Yelp.com and Dianping.com, we think that the punishment from platforms will only weaken unscrupulous firms' reputations. Although this assumption is consistent with reality, the lack of consideration for financial penalties is a limitation. In our work, we propose the existence of a demarcation point in punishment intensity in which firms stop issuing any fake reviews to escape punishment. Financial and reputational punishment should be simultaneously considered to explore the function calculating this demarcation point, which is determined by many complex parameters.

(iii) Some interesting findings still need scientific explanations. For example, in the game-theoretical model, we cannot clearly describe the underlying mechanisms for the phenomenon that the potential of high punishment intensity to reduce the number of fake reviews cannot be ascertained.

(iv) Similar to most research adopting game theoretical models, we do not put actual data into our model for two reasons: completely appropriate and accurate data about this model are difficult to obtain, and research questions can all be solved by analyzing these equilibrium results under different parameters. In the next step, we continue to utilize suitable data into our model to obtain comprehensive results.

Chapter 4 General Conclusions

Due to the well-documents effect of fake reviews on firm profits, many scrupulous firms post some fake reviews to improve their competitive positions and add their profits. To reduce the fake reviews, plenty of computation algorithms and government regulation measures are proposed. These measures only add the cost of firm posting fake reviews, but cannot reduce these firms' motivation values. A considerable number of unscrupulous firms remain active and the percentage of fake reviews is estimated at around 15%–30% (Lappas et al. 2016; Luca and Zervas 2016).

Aims to quantify the motivation values of firms posting fake reviews and explore the ways to reduce the number of fake reviews, this dissertation develops two models: agent-based model and game-theoretical model. Related to the proposed research questions, this dissertation gets some useful research findings, shown in Table 4.1.

Table 4-1 Summary of findings

Studies / Research questions	Agent-based Model To describe consumer behaviors and analyze its effect on the number of fake reviews	Game-theoretical Model To calculate equilibrium consumer behaviors and analyze its effect on the number of fake reviews
RQ1: What are the motivation values of firms posting fake reviews?	**Proposition 1**: Without fake reviews, the average star rating of products converges on their actual product values. Fake reviews significantly increase the final average star rating with a slight amplitude, and have tremendous power to attract consumers. **Proposition 2**: The motivation values of firms posting fake reviews generally decrease along with the existing number of unscrupulous products. When only considering the final average star rating, the motivation value has maximum value when there only exists one unscrupulous product and becomes stable when there are more than two unscrupulous products.	One of the most important underlying motivations leading to fake reviews is that platforms do not want to spend much money to detect fake reviews.
RQ2: Which type of firms has high motivation values?	**Proposition 4**: The motivation values of firms posting fake reviews are significantly affected by products themselves. Firms facing fierce competition and selling low-quality products have high motivations to post fake reviews.	Firms located at the lower competing position have high incentives to manipulate online reviews. Specifically, fake reviews are mostly posted by firms with only a few loyal consumers, low initial assessment about their values, and moderately low star rating.
RQ3: What are the characteristics of fake reviews?	**Proposition 6**: Fake positive reviews are much more common than fake negative reviews in the real world. Motivation values of firms posting fake reviews increase, when the total percentage of fake reviews decreases or the difference of percentage between fake positive reviews and fake negative reviews increases.	Unscrupulous firms always prefer to issue fake positive reviews to themselves to boost their profits instead of posting fake negative reviews to their opponents.
RQ4: What can consumers, firms and online platforms can do to efficiently reduce fake reviews?	**Proposition 3**: Motivation values are not affected by consumer behaviors about learning online reviews, but influenced by consumer behaviors about writing online reviews. Firms have low motivations to post fake reviews if consumers highly rely on the perceived value after use to decide the evaluation score.	We hope the profits of platforms mainly come from advertising revenues rather than commission revenues. Platforms with revenues that highly depend on its consumers tend to invest in the detection of fake reviews and in turn reduce fake reviews. If the platform mainly sells products with high unit misfit cost and enacts

	Proposition 5: Platforms can effectively restrain fake reviews through adopting strict regulatory policies, such as imposing serious punitive measures and designing exhibition rule for presenting online reviews. Although the current exhibition rules for presenting online reviews can guarantee that they provide abundant, authoritative, and latest product information, they have been criticized for their weakness in considering the characteristics of fake reviews. It is of high importance to explore an effective exhibition rule for presenting online reviews, which can reduce the effects of fake reviews.	proper punishment intensity, the number of fake reviews also declines markedly. To reduce fake reviews, we also suggest that firms promote their competitiveness. For example, they could take action to capture more loyal consumers, promote consumers' initial assessment about their values, and improve their actual star ratings.
How do the online product reviews evolve with or without fake reviews.	**Proposition 1**: Without fake reviews, the average star rating of products converges on their actual product values. Fake reviews significantly increase the final average star rating with a slight amplitude, and have tremendous power to attract consumers.	
(i) Is there a significant difference about the number of fake reviews among all platforms? (ii) Which types of platforms are utilized by unscrupulous firms to post fake reviews?		There is a significant difference in the numbers of fake reviews among platforms. Unscrupulous firms tend to issue fake reviews in platforms with low sensitivity to fake reviews, and they prefer to sell products with low unit misfit cost and improper punishment intensity. If the punishment intensity cannot reach the proper demarcation point, high punishment intensity would lead to numerous fake reviews.
(iii) Will firms post less fake reviews when they cooperate?		Cooperative cases always benefit firms, but they would hurt platforms and lead to extra fake reviews. Sometimes, the number of fake reviews increase in the cooperative cases.
(iv) Is high degree of penalty can effectively reduce fake reviews?		Severe punishment cannot always reduce the number of fake reviews, and it could even lead to more fake reviews in some cases. A demarcation point exists in punishment intensity, wherein which firms stop issuing fake reviews to escape punishment. If punishment intensity is lower than this point, firms post more fake reviews to ensure the maximum effect.

Appendices

Appendix A: Proof of Propositions 1-6 in Essay One

In this section, we bring mathematical proofs illustrating the proposed propositions.

Proof of Proposition 1

The update process of average star rating for each product is described in Eq. (4-5) , in which the average star rating is s_{j-1} and s_j before and after agent j posts the evaluation score d_j.

To simple Eq. (4-2), we use ξ to represent the manipulation degree by unscrupulous firms. Since the fake positive reviews aim to increase ξ but the fake negative reviews aim to decrease ξ, the initial fundamental formula of ξ is set as $\theta_1/(\theta_1+\theta_2)$. The total manipulation degrees come from the total n firms, but are divided by the l unscrupulous firms. ξ is also negatively affected by the regulation force of platforms, defined as ϖ. ξ should be low on the platform that highly invests to prevent the emergence of fake reviews. Thus, we set the expression of ξ, in which φ is a constant, shown in Eq. (A-1).

$$\xi = \frac{\varphi\theta_1 n}{\varpi(\theta_1+\theta_2)l}. \tag{A-1}$$

When choosing the products, the agent j is not only directly influenced by the average star rating s_{j-1}, but also unconsciously affected by the unscrupulous firms with the degree of ξ. We combine the Eqs. (4-2), (4-3), and (4-5) to obtain Eq. (A-2).

$$\begin{aligned} s_j &= \frac{\sum_j d_j}{j} = \frac{\sum_j \left(\sigma f_j + (1-\sigma) g_j\right)}{j} = \frac{\sum_j \left(\sigma\left(s_{j-1}+\xi\right)+(1-\sigma)q\right)}{j} \\ &= \frac{\sigma \sum_j s_{j-1} + j\left(\sigma\xi + (1-\sigma)q\right)}{j} \end{aligned} . \tag{A-2}$$

The process of s_j is deduced as follows:

$$\begin{aligned} & js_j = \sigma\sum_j s_{j-1} + j\left(\sigma\xi+(1-\sigma)q\right) \\ & (j-1)s_{j-1} = \sigma\sum_{j-1} s_{j-2} + (j-1)\left(\sigma\xi+(1-\sigma)q\right) \\ & \qquad\qquad\qquad \Downarrow \\ & js_j = (j+\sigma-1)s_{j-1} + \sigma\xi + (1-\sigma)q \\ & \qquad\qquad\qquad \Downarrow \\ & j\left(s_j + \frac{\sigma\xi+(1-\sigma)q}{\sigma-1}\right) = (j+\sigma-1)\left(s_{j-1} + \frac{\sigma\xi+(1-\sigma)q}{\sigma-1}\right) \\ & \qquad\qquad\qquad \Downarrow \\ & s_j + \frac{\sigma\xi+(1-\sigma)q}{\sigma-1} = \frac{j+\sigma-1}{j}\left(s_{j-1} + \frac{\sigma\xi+(1-\sigma)q}{\sigma-1}\right) \end{aligned} . \tag{A-3}$$

When $j \to \infty$, we obtain $(j+\sigma-1)/j \to 1$, and $s_j = s_{j-1}$. Therefore, the average star rating of the product is convergent.

When $j=1$, the first agent cannot refer to prior reviews, so $\sigma = 0$ and $s_1 = d_1 = q$. Thus, we obtain the expression of the final s_j by the following:

$$s_j = q + \frac{\sigma\xi}{\sigma - 1}\left(\prod_j \frac{j+\sigma-1}{j} - 1\right). \tag{A-4}$$

Without fake reviews, $\xi = 0$ and $s_j = q$. However, there are many fake reviews in the real world. Unscrupulous firms always want to obtain extra profits through posting fake reviews. Accordingly, $\xi > 0$ when fake reviews exist. We always have $\sigma - 1 \le 0$ and $(j+\sigma-1)/j \le 1$. We further, thus, deduce the expression of the final s_j to obtain Eq. (A-5).

$$\begin{aligned} & s_j = q + A\xi \\ & A = \frac{\sigma}{\sigma-1}\left(\prod_j \frac{j+\sigma-1}{j} - 1\right) > 0 \\ & \xi = \frac{\varphi\theta_1 n}{\varpi(\theta_1+\theta_2)l} > 0 \end{aligned} \tag{A-5}$$

We verify Proposition 1 through the above mathematical derivation. The average star rating of the product is convergent. The convergent value is its actual quality if no fake reviews exist. Fake reviews significantly increase the convergent value of the average star rating and, thus, attract consumers.

Proof of Proposition 2

Proof of proposition 1 describes the convergent values of s_j with and without fake reviews are $q + A \times \xi$ and q, respectively. Therefore, we define firms' motivation value as y and obtain the expression of y in Eq. (A-6).

$$
\begin{aligned}
& y=\frac{A\xi}{q} \\
& A=\frac{\sigma}{\sigma-1}\left(\prod_j \frac{j+\sigma-1}{j}-1\right)>0 . \\
& \xi=\frac{\varphi\theta_1 n}{\varpi\left(\theta_1+\theta_2\right) l}>0
\end{aligned}
\tag{A-6}
$$

We deduce the first-order condition $\partial y / \partial l$, shown in Eq. (A-7) to explore the relationship between motivation value y and the existing number of unscrupulous products l.

$$
\begin{aligned}
& \frac{\partial y}{\partial l}=-A\frac{\varphi\theta_1 n}{q\varpi\left(\theta_1+\theta_2\right)}\frac{1}{l^2} \\
& A=\frac{\sigma}{\sigma-1}\left(\prod_j \frac{j+\sigma-1}{j}-1\right)>0
\end{aligned}
\tag{A-7}
$$

The first-order condition $\partial y / \partial l$ is always negative. Therefore, firms' motivation value decreases with the existing number of unscrupulous firms. Proposition 2 is confirmed.

Proof of Proposition 3

We analyze the expression of y and confirm that most of the parameters cannot be influenced by consumers. Only parameter σ is decided by consumers. σ becomes larger if consumers highly rely on perceived value f_j when writing online reviews.

We deduce first-order condition $\partial y / \partial \sigma$ to explore the relationship between motivation value y and parameter σ. We define functions $A(\sigma)$ and $B(\sigma)$ in Eq. (A-8).

$$
\begin{aligned}
A(\sigma) &= \frac{\sigma}{(\sigma-1)\, j!} B(\sigma) \\
B(\sigma) &= \prod_j (j+\sigma-1) - j! = \sigma(\sigma+1)\cdots(\sigma+j-1) - j!
\end{aligned}
. \qquad \text{(A-8)}
$$

We first deduce first-order condition $\partial A(\sigma)/\partial\sigma$ in Eq. (A-9).

$$
\frac{\partial A(\sigma)}{\partial\sigma} = \frac{\left(B(\sigma)+\sigma B'(\sigma)\right)(\sigma-1)-\sigma B(\sigma)}{(\sigma-1)^2\, j!} = \frac{\sigma^2 B'(\sigma)-B(\sigma)-\sigma B'(\sigma)}{(\sigma-1)^2\, j!}. \qquad \text{(A-9)}
$$

The denominator of Eq. (A-9) is always larger than 0. We judge the sign of the numerator of Eq. (A-9), define $C(\sigma) = \sigma^2 \times B'(\sigma) - B(\sigma) - \sigma \times B'(\sigma)$, and deduce condition $\partial C(\sigma)/\partial\sigma$ in Eq. (A-10).

$$
\begin{aligned}
&\frac{\partial C(\sigma)}{\partial\sigma} = 2\sigma B'(\sigma)+\sigma^2 B''(\sigma)-B'(\sigma)-B'(\sigma)-\sigma B''(\sigma) = 2(\sigma-1)B'(\sigma)+\sigma(\sigma-1)B''(\sigma) < 0 \\
&B'(\sigma) = (\sigma+1)(\sigma+2)\cdots(\sigma+j-1)+\sigma(\sigma+2)\cdots(\sigma+j-1)+\cdots+\sigma(\sigma+2)\cdots(\sigma+j-2) > 0 \\
&B''(\sigma) = (\sigma+2)\cdots(\sigma+j-1)+(\sigma+1)\cdots(\sigma+j-1)+\cdots+\sigma(\sigma+2)\cdots(\sigma+j-3) > 0
\end{aligned}
$$

$$. \qquad \text{(A-10)}$$

$C(\sigma) = \sigma^2 \times B'(\sigma) - B(\sigma) - \sigma \times B'(\sigma)$ is minimum when $\sigma = 1$ since $\partial C(\sigma)/\partial\sigma < 0$ and $0 \le \sigma \le 1$. Therefore, we obtain Eq. (A-11).

$$
C(\sigma) \ge B'(1) - B(1) - B'(1) = -B(1) = -(j! - j!) = 0\,. \qquad \text{(A-11)}
$$

The denominator and numerator of Eq.(A-9) are always larger than 0. Therefore, we obtain Eq. (A-12).

$$\begin{aligned}
&\frac{\partial y}{\partial \sigma}=\frac{\xi}{q}\frac{\partial A(\sigma)}{\partial \sigma}>0\\
&A(\sigma)=\frac{\sigma}{\sigma-1}\left(\prod_j \frac{j+\sigma-1}{j}-1\right).\\
&\xi=\frac{\varphi\theta_1 n}{\varpi(\theta_1+\theta_2)l}>0
\end{aligned} \tag{A-12}$$

First-order condition $\partial y/\partial\sigma$ is always positive. Therefore, the motivation values are not influenced by consumer behaviors, and firms have lower motivation to post fake reviews if consumers highly rely on the perceived value after use to decide the evaluation score. Proposition 3 is confirmed.

Proof of Proposition 4

We deduce first-order conditions $\partial y/\partial n$ and $\partial y/\partial q$ shown in Eq. (A-13) to explore the relationship between motivation value y and the total number of products n and product quality q.

$$\begin{aligned}
&\frac{\partial y}{\partial n}=A\frac{\varphi\theta_1}{\varpi q(\theta_1+\theta_2)l}\\
&\frac{\partial y}{\partial q}=-A\frac{\varphi\theta_1 n}{\varpi(\theta_1+\theta_2)l}\frac{1}{q^2}\\
&A=\frac{\sigma}{\sigma-1}\left(\prod_j \frac{j+\sigma-1}{j}-1\right)>0
\end{aligned}\quad. \tag{A-13}$$

$\partial y/\partial n$ is always positive, and $\partial y/\partial q$ is always negative. Therefore, firms have highly motivated to post fake reviews when they face fierce competition and sell low-quality products. Proposition 4 is confirmed.

Proof of Proposition 5

We deduce first-order condition $\partial y / \partial \varpi$ shown in Eq. (A-14) to explore the relationship between motivation value y and the regulation force of platforms ϖ.

$$\begin{aligned} \frac{\partial y}{\partial \varpi} &= -A \frac{\varphi \theta_1 n}{q\left(\theta_1 + \theta_2\right) l} \frac{1}{\varpi^2} \\ A &= \frac{\sigma}{\sigma - 1}\left(\prod_j \frac{j + \sigma - 1}{j} - 1\right) > 0 \end{aligned} \quad . \tag{A-14}$$

$\partial y / \partial \varpi$ is always negative. Therefore, firms in the platform with strict regulation have low motivation to post fake reviews. The present study proposes a new exhibition rule for ordering online reviews to enhance the regulation of platforms and, thus, increase ϖ. We combine Eq. (A-14) and conclude that our proposed exhibition rule for ordering online reviews given that the features of fake reviews is a suitable new paradigm to reduce fake reviews because the new exhibition rule increases ϖ and reduces y. Proposition 5 is confirmed.

Proof of Proposition 6

We explore the relationship between motivation value y and the percentage of fake reviews (θ_1 and θ_2). We first deduce first-order conditions $\partial y / \partial \theta_1$ and $\partial y / \partial \theta_2$ shown in Eq.(A-15).

$$\begin{aligned} \frac{\partial y}{\partial \theta_1} &= A \frac{\varphi n}{q \varpi l} \frac{\theta_2}{\left(\theta_1 + \theta_2\right)^2} \\ \frac{\partial y}{\partial \theta_2} &= -A \frac{\varphi n}{q \varpi l} \frac{\theta_1}{\left(\theta_1 + \theta_2\right)^2} \\ A &= \frac{\sigma}{\sigma - 1}\left(\prod_j \frac{j + \sigma - 1}{j} - 1\right) > 0 \end{aligned} \quad . \tag{A-15}$$

$\partial y / \partial \theta_1$ is always positive, and $\partial y / \partial \theta_2$ is always negative. Therefore, firms prefer to post fake positive reviews on themselves rather than post fake negative reviews on their opponents. Therefore, the percentage of fake positive reviews is more than that of fake negative reviews.

We consider that fake positive reviews and negative reviews exist simultaneously in the online market. When the difference between the percentage of fake positive reviews and that of fake negative reviews $\eta = \theta_1 - \theta_2$ is fixed, we use $\theta_2 + \eta$ to represent θ_1 and deduce first-order condition $\partial y / \partial \theta_2$ in Eq. (A-16).

$$\begin{gathered} \frac{\partial y}{\partial \theta_2} = -A \frac{\varphi n}{q \varpi l} \frac{\theta_2 + \eta}{\left(2\theta_2 + \eta\right)^2} \\ A = \frac{\sigma}{\sigma - 1}\left(\prod_j \frac{j + \sigma - 1}{j} - 1\right) > 0 \end{gathered} . \tag{A-16}$$

The new $\partial y / \partial \theta_2$ is always negative. Therefore, when the difference between the percentage of fake positive reviews and that of fake negative reviews is fixed, a negative relationship exists between the total proportion of fake reviews and firms' motivation value.

Appendix B: Proof of Lemma 1 in Essay Two

For ease of exposition, we tentatively define the total market size of switcher shoppers as $\theta = 1 - \theta_a - \theta_b$. Then, we can write the two profit functions in Eq.(B-1).

$$\begin{cases} \pi_a = p_a D_a = \gamma p_a \dfrac{2\theta_a\left(v_a - p_a\right) + \theta\left[t + v_a - v_b - \left(p_a - p_b\right)\right]}{2t} \\ \pi_b = p_b D_b = \gamma p_b \dfrac{2\theta_b\left(v_b - p_b\right) + \theta\left[t - v_a + v_b + \left(p_a - p_b\right)\right]}{2t} \end{cases}. \tag{B-1}$$

Since the second order conditions are negative, e.g. $\partial^2 \pi_a(p_a, p_b) / \partial p_a{}^2 = -4\theta_a - 2\theta < 0$ and $\partial^2 \pi_b(p_a, p_b) / \partial p_b{}^2 = -4\theta_b - 2\theta < 0$, the profit functions are strictly concave functions. Thus, we then deduce the first order derivatives to calculate the equilibrium product prices.

Through deducing the first order conditions: $\partial \pi_a(p_a, p_b) / \partial p_a = 0$ and $\partial \pi_b(p_a, p_b) / \partial p_b = 0$, we have:

$$\begin{cases} \left(4\theta_a + 2\theta\right) p_a - \theta p_b = 2\theta_a v_a + \theta t + \theta v_a - \theta v_b \\ -\theta p_a + \left(4\theta_b + 2\theta\right) p_b = 2\theta_b v_b + \theta t - \theta v_a + \theta v_b \end{cases}. \tag{B-2}$$

Through solving Eq.(B-1) and Eq.(B-2), we yield the equilibrium prices (p_a and p_b) in Eq.(B-3). Because the market size of loyal consumers is relatively small, so their products, including $\theta_a\theta_b$, $\theta_a{}^2$, and $\theta_b{}^2$, are all ignored during the process of simplification (similarly hereinafter).

$$\begin{cases} p_a = \dfrac{(3\theta+4\theta_b)t+(\theta+4\theta_a+4\theta_b)v_a+(-\theta-2\theta_b)v_b}{3\theta+8\theta_a+8\theta_b} \\ p_b = \dfrac{(3\theta+4\theta_a)t+(-\theta-2\theta_a)v_a+(\theta+4\theta_a+4\theta_b)v_b}{3\theta+8\theta_a+8\theta_b} \end{cases}. \tag{B-3}$$

Then, we use $1-\theta_a-\theta_b$ to replace θ, the equilibrium prices are deduced and presented in Eq.(6-7). After putting Eq.(6-7) into the corresponding expression, we can get the equilibrium degrees of misfit of the marginal consumer for product i (λ_a^* and $1-\lambda_b^*$), and the location of indifferent consumer for switcher shoppers (λ^* and $1-\lambda^*$), shown in Eq.(6-8) and Eq.(6-9).

The other expression for profit function are shown in Eq.(B-4):

$$\begin{cases} \pi_a = p_a D_a = p_a\left[\gamma\left(\theta_a\lambda_a^*+\theta\lambda^*\right)\right] \\ \pi_b = p_b D_b = p_b\left[\gamma\theta_b\left(1-\lambda_b^*\right)+\gamma\theta\left(1-\lambda^*\right)\right] \end{cases}. \tag{B-4}$$

The expression of $\theta_a\lambda_a^*+c\theta\lambda^*$ and p_a can be changes as follows:

$$\begin{aligned} &\theta_a\lambda_a^*+\theta\lambda^* = \frac{(3-2\theta_b)t+(1+4\theta_a+2\theta_b)v_a+(-1)v_b}{2t(3+5\theta_a+5\theta_b)} = \frac{(3t+v_a-v_b)+(4v_a)\theta_a+(-2t+2v_a)\theta_b}{2t(3+5\theta_a+5\theta_b)} \\ &p_a = \frac{(3t+v_a-v_b)+(-3t+3v_a+v_b)\theta_a+(t+3v_a-v_b)\theta_b}{3+5\theta_a+5\theta_b} \end{aligned} \tag{B-5}$$

Since $\theta_a\theta_b$, $\theta_a^{\ 2}$, and $\theta_b^{\ 2}$ are all ignored due to its minimum value, the profit function of firm a is deduced and presented in Eq.(6-10). The same procedure is used to get the profit function of firm b.

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