Essays on Network Effects on Online Reviews

by

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As members of the Dissertation Committee, we certify that we have read the dissertation prepared by Yang Wang, titled Essays on Online Reviews and Network Effects and recommend that it be accepted as fulfilling the dissertation requirement for the Degree of Doctor of Philosophy.

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Statement by Author

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To my parents

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Abstract

This dissertation studies online reviews and focuses on the network effects on individuals' incentives to contribute to an important form of online word of mouth—online reviews. Provided by either consumers or third-party professionals, online reviews are closely correlated with consumer purchasing decisions and hence sales. Individuals have incentives of free riding and maximizing social capital when providing feedbacks online. The first essay, "Free Riders versus Social Capital: An Empirical Analysis of an Exogenous Shock on Online Reviews," examines the average peer effects. We leverage a "natural experiment," which led to an exogenous expansion in the user population of a major online review platform to better understand the trade-off between the two conflicting incentives. We find that a larger population of audience and peer review writers, an immediate consequence of the exogenous shock, causally led to more reviews posted, higher and more diverse ratings assigned, and reviews of higher quality by the users.

We continue our exploration of the peer impacts on individuals' contributions to online reviews in the second essay, "Impact of Network Size on Contributions: The Moderating Roles of User Characteristics," by studying the moderating roles of several user characteristics. We find that, first of all, the increases in an individual's contribution volume, valence (the review ratings), and helpfulness of reviews are all smaller for a more active user. Also interesting enough, we find that a user who

focuses more on book reviews responded more positively to the exogenous shock, while in sharp contrast a user with preferences in writing other reviews was less affected. Last but not least, although not statistically significant, the popularity plays a negative role in moderating the group size effects.

The third essay, “Heterogeneity in Peer Effects: An Application of Finite Mixture Models,” further extends our study of peer influence to consider the impacts of unobserved heterogeneity. An example of latent variables under investigation is individuals’ intrinsic motivation. We use a Finite Mixture Model to identify the segments of users. Our statistical process recommends that a three-segment model performs the best. We interpret the three groups as users of low motivation, mediocre motivation, and high motivation. Interestingly, we find that the increases in contribution volume, valence, and quality of reviews are all bigger for users of high motivations than the other two segments. We also examine how the moderating roles of user characteristics vary across segments. Our findings have important theoretical as well as managerial implications.

1. Introduction

Online reviews, as an important form of word of mouth, has attracted attention from both practitioners and researchers. A consensus among researchers is that online reviews are closely related to product sales (Dellarocas 2003, 2006, Chevalier and Mayzlin 2006). In particular, an extensive strand of literature establishes that the volume of reviews posted by either third-party professionals or consumers is positively correlated with sales and revenue (Liu 2006, Dellarocas, Zhang, and Awad 2007, Chen and Xie 2008, Duan, Gu, and Whinston 2008, Forman, Ghose, and Wiesenfeld 2008, Zhu and Zhang 2010). Although the consequences have been well established in the literature, very few papers have explored individuals' incentives to contribute in the first place (Goes, Lin, and Au Yeung 2014, Wang, Zhang, and Hann 2015). This dissertation is dedicated to study individuals' motivations to add to online reviews.

It is not hard to see that there might be several motivations under which individuals contribute to online reviews. First, a few recent papers argue that individuals generate online content, online reviews per se, out of motivations to contribute to public goods (Goes, Lin, and Au Yeung 2014, Zhang and Zhu 2011). People will also contribute because of social image or reputation concerns (Andreoni and Bernheim 2009, Lacetera and Macis 2010). Other incentives include receiving symbolic awards and monetary motivations (Khern-am-nuai and Kannan 2016). These various motivations all boil down to a fundamental factor—the peer effects. More specifically, review writers' behaviors are shaped by their audience, followers, or friends online.

In this dissertation, we try to establish whether and how an individual's reference groups (e.g., audience, followers, or friends) causally change his or her behavior of posting online reviews. A departure from the literature is that instead of focusing on product- or review-level analysis, we study individual review writers, which is governed by the essence of our research questions. This dissertation is also among the first few studies exploring these questions in a systematic manner. We study not only the contribution volume, but also the valence and the quality of reviews.

Our theoretical foundation is a tradeoff between the incentives to free ride others' contributions and social benefit considerations. It is not hard to see that individuals have incentives to free ride others' contributions on the one hand, which predicts a negative effects of the population size of an individual's reference groups (Olson 1965, Chamberlin 1974). On the other hand, one can produce more social benefits by contributing more product reviews in a larger network (Harsanyi 1980, Andreoni 1989, 2007). Therefore, it is not clear a priori about the directions of the network size effects. Chapter 2 develops these theoretical foundations in a systematic manner and generates our key hypotheses.

The main challenge in identifying the network size effects is the endogenous network formations on these platforms (Manski 1993, Goldsmith-Pinkham and Imbens 2013). Specifically, choosing whom to follow is a selection by a user, which introduces a natural selection bias. In addition, there exist unobserved individual characteristics governing both network formation processes and review posting decisions. The former determines the size of an individual's reference groups and the latter the outcomes. This challenge of identification is prevalent in the literature on social networks.

We address the challenge of endogeneity by studying a "natural experiment" on a major third-party platform of online reviews. We start with Chapter 3 studying the average impacts of peer group sizes on our variables of interests including volume, valence, and helpfulness. We continue in Chapter 4 by exploring the moderating roles of several user characteristics. This chapter motivates our exploration of individual heterogeneity and its role in understanding individuals' incentives to contribute. Therefore, in the last chapter I close this dissertation by studying unobserved heterogeneity in review posting behaviors. This is the path taken in this dissertation. We summarize our main findings in these three chapters below.

Free Riders versus Social Capital: An Empirical Analysis of an Exogenous Shock on Online Reviews

This chapter studies the average treatment effects of an enlarged network on an individual's review posting behavior. We address the endogeneity of network sizes by using a "natural experiment" on Douban.com, a major third-party platform of online reviews in China. The special structure of the exogenous shock provides us a unique opportunity to study individuals' incentives to contribute. Using the exogenous shock, we borrow a differences-in-differences method to uncover the causal impacts.

We find that, interestingly, an exogenously enlarged network, with more audience and peer review contributors, will causally change a user's behavior to posting online reviews. Specifically, an individual will post more and longer reviews, assign higher and more dispersed ratings in their reviews, and post more helpful reviews. These findings suggest that social benefit considerations are dominant in an individual's incentives to contribute to online content, online reviews being an example.These findings also suggest that platforms that target at promoting more active contributions should adopt strategies to enlarge the user base or more followers for individual users. For example, our results demonstrate that user recommendations will be effective in promoting more active contributions.

Impact of Network Size on Contributions: The Moderating Roles of User Characteristics

A natural question following our findings in the last chapter is whether the average impacts of network sizes are necessarily the same across different types of users (Zhu and Zhang 2010). We begin our exploration of heterogeneity by studying the moderating roles of several user characteristics that are observed. Specifically, we study the moderation of a user's activeness or engagement with the platform, expertise, and popularity. The identification of these moderating effects come from the same "natural experiment."

We find that, first of all, individuals who are more active in contribution or more engaged with platforms are less affected by a larger network. We construct two measures of a user's activeness, the number of reviews and the number of followees whom a user follows. We find that a user with more historical reviews or more followees increases their contribution volume, valence, and quality of reviews in a smaller degree. Also interesting enough, the results suggest that a user who is an expert and affected by the exogenous shock will increase his or her contributions more, assign even higher ratings, and post even more helpful reviews. In sharp contrast, an expert who is not affected by the shock will be less attenuated by the event. Third, the popularity plays a negative role in moderating the average treatment effects (although not statistically significant).

Findings in this essay have further implications both theoretically and managerially. First, the moderating effects of user characteristics suggest that although pro-social considerations dominate an individual's incentives to contribute, there exists individual heterogeneity by some observed characteristics. In other words, individuals differ in their motivations, which is governed by some of their characteristics such as activeness and expertise. Second, managerially, our results suggest that a targeted promotion strategy might be more effective than a strategy that influences all users. For example, we can draw an implication from one of our main findings that user recommendations to follow less active or less popular users must be more effective.

Heterogeneity in Peer Effects: An Application of Finite Mixture Models

The last chapter is devoted to studying the unobserved heterogeneity in an individual's incentives to contribute. We use a finite mixture model (Bapna et al. 2011, Tan, Lu, and Tan 2016) to help identify the segments of users. We establish a three-segment model and interpret these subgroups as users of low motivation, mediocre motivation, and high motivation. Also interesting enough, we find that highly motivated individuals tend to be more affected by an enlarged network, in the sense that the increases in volume, valence, and quality are all bigger in the high-motivation segment. Conversely, the low motivation group is the subset of users who were affected by the event the least. Another interesting finding is that the low motivation segment comprises of the largest group among the three segments.

Apparently, the findings in this chapter suggest that individuals differ by not only the characteristics observed to researchers but also unobserved types. Theoretically, this implies that it is not necessarily the case that maximizing social capital dominates all individuals incentives to contribute to online content. This has more important managerially implications. It suggest that firms or platforms should try to identify users' latent types based on their historical activities and observed characteristics. Our approach, the finite mixture models, provides a framework that platforms can use to identify the latent user segments.

2. Theoretical Foundations and Research Context

2.1. Introduction

The management of online customer response is increasingly important for companies because of the advancement of the Internet and related technologies (Gu and Ye 2014, Sun and Xu 2016). Online product or service reviews are a major form of customer response (or word of mouth), and grabbing attention from any type of business supplying tangible and intangible products (Abrahams et al. 2015, Chen, Zheng, and Ceran 2016). Provided by either consumers or third-party professionals, online reviews are shown to be closely correlated with consumer purchasing decisions and hence sales (Dellarocas 2003, Chevalier and Mayzlin 2006, Liu 2006, Forman, Ghose, and Wiesenfeld 2008, Zhu and Zhang 2010). The majority of online retailing platforms, such as Amazon.com and eBay.com (Li and Hitt 2008, Mudambi and Schuff 2010), allow consumers to post feedback and opinions. Platforms specialized in facilitating third-party online reviews, such as Yelp.com and Douban.com, have also emerged in recent years (Chen and Xie 2005). According to an online survey in 2014, only 10% consumers do not take any form of online reviews. Among those who pay attention to reviews, 88% trust them as much as personal recommendations.[1]

[1] The Local Consumer Review Survey conduct consumer studies on a yearly basis. The 2014 briefing can be found at http://searchengineland.com/88-consumers-trust-online-reviews-much-personal-recommendations-195803.

Although the consequences are well understood, an individual's incentive to post online reviews in the first place is not equally treated. We are among the first few studies investigating the antecedents of online product reviews (Goes, Lin, and Au Yeung 2014, Huang, Hong, and Burtch 2016, Khern-am-nuai and Kannan 2016). Regardless of the various motivations, a fundamental factor governing an individual's contributions is peer effects. Similar to other forms of user-generated content, an individual's reference groups, online friends/followers/audience have significant influence on his or her review posting behavior (Zhang and Zhu 2011, Peng et al. 2016, Parker, Van Alstyne, and Jiang 2017). In sharp contrast, we draw on theories predicting an individual's contributions to online public goods in a network setting and utilize a "natural experiment" on a major third-party platform to identify the size effects of audience and peer groups.

Online reviews are public goods on the Internet (Duan, Gu, and Whinston 2008). No one can be effectively excluded from "consuming" online reviews, and an individual's "consumption" does not crowd out the access of others. With this in mind, our theoretical foundations are three-fold. First, regarding the *volume* of contributions, it is not hard to see that there are conflicting incentives for individuals to contribute to this public good. With a larger size of reference group, an individual has the incentive to free ride others' contributions and post fewer reviews. On the other side, individuals may be encouraged to post more because they want to add to their social capital and maximize social benefits. Second, social image considerations dictate that individuals exhibit more prosocial behavior in a larger network, and, therefore, tend to assign higher *ratings* for products under review. Last but not least, with similar prosocial considerations, an individual will pay more attention to the *quality* of reviews facing a larger audience or more peer review writers.

We test these predictions empirically in this study. In particular, we ask which incentive—free riding or prosocial considerations—dictates the private provision of the public good—product reviews, and how activities are affected by the size of the reference groups. Specifically, do more peer review writers or a larger population of audience necessarily cause a review writer to devote more effort and post more product reviews? In addition to the volume effects, does an increase in the network size make review writers assign higher ratings in their product reviews? Is the helpfulness or the quality of reviews, evaluated by review readers, attenuated by an enlarged population of audience and peer reviewers?

We seek answers to these questions by studying Douban.com, the largest platform of third-party reviews in China. Launched on March 6, 2005, Douban.com specializes in providing a platform for consumers and professionals to write reviews for books, movies, TV shows, and music. The platform witnessed a sudden expansion in the number of registered users starting from August 1, 2009, because of the introduction of a web application, "Douban Reading," on the largest social networking platform in China, the QZone of Tencent.com.[2] The application granted Tencent users Douban

[2]QZone can be found at http://qzone.qq.com/. The Wikipedia page for QZone is http://en.wikipedia.org/wiki/Qzone. According to "We Are Social" reports, the number of active

accounts and direct access to all Douban book reviews. This exogenous shock, the unexpected merge of two large-scale and influential networks, provides us a unique opportunity to study an individual's incentive to contribute to online reviews in an exogenously enlarged network.

We collected our data using Douban's API service in November 2014. We start with a random sample of 119 Douban groups and focus on a subset of 24,374 users who joined the platform before the exogenous shock. We obtain all relevant information from their webpages using a web data crawler. The main study period is between July 4, 2009 and August 28, 2009, which is four weeks before and four weeks after the exogenous shock. No policy changes were noted other than the introduction of Douban Reading during this period. The identification of peer effects (Manski 1993, Goldsmith-Pinkham and Imbens 2013) comes from a unique feature of the exogenous shock. Specifically, Douban Reading users gained direct access to only the book reviews within the app, while it did not allow access to other sections unless the users went to the corresponding pages on Douban.com. This particular arrangement divides Douban reviews into two groups, book reviews being the treatment group and all other reviews the control group. With this "natural experiment," we conduct a quasi-experimental study, the differences-in-differences analysis (Card and Krueger 1994, Athey and Imbens 2006), to identify the effects of the policy change—a sudden increase in the population of registered users—on an individual user's contributions

users on QZone had reached over 644 million as of May 2014, making it the second largest online social network worldwide, second only to Facebook.com.

to product reviews.

Our empirical findings are mainly two-fold. We first establish the average effects of an enlarged user population in the sense that we do not explore the differential effects by user characteristics in this set of results. We find that the exogenous merge between Douban and Tencent caused a user to post more and longer reviews, assign higher and more diverse ratings in their reviews, and post reviews of higher quality. Quantitatively, an average user increased the number of reviews by more than 0.6% and the total textual length by over 4.2%. The rating assigned per review rose by about 0.03 in absolute values with the range of rating being 1 to 5. As a measure of a review's quality, the percentage of helpfulness votes (%) increased by about 0.27.

More interestingly, the second set of findings concerns the moderating role of user characteristics in peer effects. We first find that a user who was more engaged with Douban.com, measured by a larger number of early reviews (prior to our study period) or the number of followees, was less affected by the merging event in the volume, valence, and quality of reviews. A user who focused on writing reviews in other categories, movies, TV shows, or music, was also less affected, but, in sharp contrast, a book review enthusiast was encouraged to contribute even more reviews, assign even higher ratings, and post reviews of even higher quality. However, the moderating effects of an individual's popularity, measured by the number of followers, were negative but not statistically significant.

These findings speak to the fundamental question for whom the users review. Our results suggest that they review for their online friends and audience. An immediate implication is that peer effects contribute to the reporting bias identified in Chen, Zheng, and Ceran (2016). First, the asymmetry in the popularity of review writers apparently aggravates the asymmetry in contributions. Second, the positive peer effect on ratings also adds to the bias in opinions expressed in social media. Third, the moderating effects by user characteristics imply that users are indeed heterogeneous in willingness to speak up in social media. Managerially, these observations imply that companies can take advantage of social media in managing online customer response. There are also implications for online platforms that rely on users' contributions. Only if we have better understanding of individuals' incentives to post online reviews, can we design more efficient platforms to facilitate online reviews and better utilize this important form of word of mouth.

The study first contributes to the literature on the integration of user-generated content (UGC). Recent studies explore the usage of the enormous amount of UGC, online reviews in particular, in product defect discovery and service management (Abrahams et al. 2015, Sun and Xu 2016). From the perspective of managing customer response, Gu and Ye (2014) empirically show that managing customers' response on social media influence their future satisfaction, and Chen, Zheng, and Ceran (2016) develop a framework to uncover the real UGC generating process. We add to this literature in two dimensions. First, we take a step back and explore an individual's motivations to provide response online. As a complement, we empirically show that customers provide product or service response for other customers—peer effects. Second, given the significance of UGC in social media, our results have implications for companies in their efforts to manage customers in such platforms.

We also contribute to the literature on online reviews and product ratings across disciplines (Dellarocas 2003, Chevalier and Mayzlin 2006, Goes, Lin, and Au Yeung 2014, Lee, Hosanagar, and Tan 2015, Wang, Zhang, and Hann 2015, Huang, Hong, and Burtch 2016, Khern-am-nuai and Kannan 2016). In particular, Goes, Lin, and Au Yeung (2014) study the temporal relationships between reviewing activities and a user's popularity in a network. Huang, Hong, and Burtch (2016) use a similar identification strategy to uncover the audience effects on the linguistic features of product reviews. Our departures from the previous studies are at least the following. First, given our motivations to study individuals' incentives, our empirical analysis is conducted at the review writer level instead of at the aggregate product or firm level.[3] In addition, not limited to the volume of contributions, our research context allows us to explore other important features about online reviews, including the valence and an objective measure of the review quality.

Theoretically, we add to the long-standing literature on the private provision of public goods (Chamberlin 1974, Andreoni 1989). Our results provide another piece of evidence that supports the social benefit conjecture—social effects are a generic

[3] Another reason for focusing on a more granular reviewer level is to circumvent the well-known Simpson Paradox first coined by Blyth (1972). The paradox formalizes the idea that an effect at the individual level can be reversed at the aggregate level. It is encountered particularly in studies with causal interpretation.

part of the incentives for an economic agent (Zhang and Zhu 2011). Last but not least, the paper contributes to the broader literature on users' contributions in online communities (Gu et al. 2007, Ransbotham, Kane, and Lurie 2012) by illustrating how community members respond to the growth of the community.

In the next section we develop our research hypotheses for this dissertation. We introduce the research context, Douban.com and the exogenous shock, in Section 2.3.

2.2. Related Literature and Research Hypotheses

2.2.1. Related Literature

We draw on several strands of literature: online WOM in the form of product reviews, public goods, online communities, and exogenous shocks to complex systems. Our goal is not to exhaust related papers but to highlight those that are most relevant, and present the gaps we seek to fill.

Consequences of online product reviews have been studied extensively (see Wang, Zhang, and Hann (2015) for a recent survey). The majority of the literature focuses on how product reviews inform of either online or offline sales (Dellarocas 2003, Chen and Xie 2005, Chevalier and Mayzlin 2006, Liu 2006, Dellarocas, Zhang, and Awad 2007, Duan, Gu, and Whinston 2008, Forman, Ghose, and Wiesenfeld 2008, Li and Hitt 2008, Mudambi and Schuff 2010, Sun 2012). More recent studies on online reviews start exploring the antecedents, in particular the role of user interactions in the form of peer effects or social influence in shaping users' contributions. Goes, Lin, and Au Yeung (2014) and Wang, Zhang, and Hann (2015) are two closest papers. Goes, Lin, and Au Yeung (2014) study the intertemporal dynamics of a user's popularity, measured by his or her quantity of followers in the previous period, and review-posting behaviors. In contrast, Wang, Zhang, and Hann (2015) show that online friendship aggravates the similarity of review ratings. There is still no credible evidence of causal effects of a user's online networks on review posting behaviors. We start filling this gap in the literature by studying users' incentives to post online reviews, and how an exogenously larger population of audience leads to changes in their review posting behaviors.

We draw on a long-standing literature on the private provision of public goods (Olson 1965, Chamberlin 1974, Bergstrom, Blume, and Varian 1986, Andreoni 1988, 1989, Duncan 2004, Bramoullé and Kranton 2007, Zhang and Zhu 2011) as our theoretical backgrounds. Online reviews can be considered as a public good on the Internet (Duan, Gu, and Whinston 2008). The tension we deal with in this study (*i.e.*, free-riding incentives versus social influence) is directly informed by the theoretical development in the literature. A recent investigation of Wikipedia.org by Zhang and Zhu (2011) reports how article editors respond to exogenous blocks in China. They find that individuals significantly reduce contributions after some of their cohorts being blocked. Including the study by Zhang and Zhu, a series of recent empirical or experimental studies (Andreoni 2007, Andreoni and Bernheim 2009) lend support to the dominance of social influence and predict positive effects of group sizes on the level of private contributions to public goods. The current study adds to the literature by presenting evidence supporting the social effects hypothesis, and documenting individuals' responses to an exogenous increase in reference group sizes. We obtain causal relations by the unique structure of the exogenous shock.

Another related literature concerns individuals' contributions to online communities in general (Gu et al. 2007, Bateman, Gary, and Butler 2011, Ransbotham and Kane 2011, Ransbotham, Kane, and Lurie 2012). Platforms for third-party reviews can be considered as online communities. The success of online communities relies on users' private contributions in the absence of monetary payoffs, the majority of the literature therefore deals with individuals' incentives of voluntary contributions (Ma and Agarwal 2007, Bateman, Gary, and Butler 2011). We add to the literature by presenting empirical evidence how community members respond to the growth of the community. The results suggest that the success of online communities hinges on its popularity that leads to more contributions from users. The last literature we contribute to explore the effects of exogenous shocks on complex systems (Barabási 2005, Crane and Sornette 2008, Beaman 2012). The current study provides empirical evidence how a complex system, an online social network *per se*, responds to an exogenous shock.

2.2.2. Hypotheses

Online reviews can be considered as public goods (Duan, Gu, and Whinston 2008). Specifically, product reviews are *non-excludable*, as the review pages are generally public on the Internet and accessible to any users. In addition, a user's access to reviews does not preclude others' ability to access (*non-rivalry*). In the private provision of public goods, contributors gain utilities not only from contributions by the whole group but also from personal contributions (Andreoni 1989).

Early literature on public goods provision hinges on the assumption that individuals gain utilities from only the volume of contributions by the whole group (Chamberlin 1974). They predict that an individual's contribution level decreases with the group size—the "free riding" phenomenon. However, as pointed out by more recent studies (Andreoni 2007), these models fail to explain the extensive giving behavior observed in field and laboratory studies. Therefore, recent behavioral research extends the assumption and formulates the idea that individuals also gain utilities from personal contributions (Andreoni 1989, Duncan 2004, Andreoni 2007). A fundamental conjecture of the new theories is that when the group size is sufficiently large, the relative importance of social benefits dictates individuals' incentives to contribute. Thus with sufficiently large groups, individual contribution levels increase with the group size. In contrast to early public goods theory, empirical findings generally support the social benefit hypothesis (Andreoni 2007, Zhang and Zhu 2011).

In our specific context, theory suggests that review writers gain utilities from not only the total stock of reviews on the platform but also from their personal contributions. As the theory predicts, users will find it more beneficial to contribute more reviews with a larger audience population. Thus our first set of hypotheses reflects the conjecture that social effects dominate a user's incentive to produce online reviews.

Hypothesis 1a. *(Volume I)* A larger number of reference group members causes individuals to write and post a larger number of product reviews.

Hypothesis 1b. *(Volume II)* A larger number of reference group members causes individuals to write and post on average longer product reviews.

In addition to the *volume* effects, the size of audience population can affect the *valence* of reviews—review ratings. On third-party platforms including Douban.com, the review writers can choose an integer or a number of stars as their overall ratings of the products. Goes, Lin, and Au Yeung (2014) find a negative correlation between the average rating and the number of followers up to the previous period. They attribute the finding mainly to the fact that readers or consumers find negative evaluations more informative and professional (Ofir and Simonson 2001, Bateman, Gary, and Butler 2011). However, the effects of peer-group size can be biased because of the endogeneity of the followers count. For example, users gain expertise and followers simultaneously on the platform as they write more reviews, which may attenuate the true network size effects.

We draw on the social image theory that usually concludes that social image concerns are a primary motivator of prosocial behavior, such as the private provision of public goods (Andreoni and Bernheim 2009, Lacetera and Macis 2010, Lee, Hosanagar, and Tan 2015). The argument is that people care about fairness and how they are perceived by the public (Andreoni and Bernheim 2009). As an example, Lacetera and Macis (2010) find that, in a series of field experiments, blood donors significantly increase the frequency of their donations only if the events are publicly announced in local newspapers and if they are honored in public ceremonies. By analogy, review writers also care about how they are perceived by their audience when they produce reviews and assign ratings to products. The theory suggests that, with a larger population of review readers—the audience, review writers are more likely to assign higher ratings out of altruism (Andreoni and Bernheim 2009) and social image considerations (Lacetera and Macis 2010, Lee, Hosanagar, and Tan 2015).

Hypothesis 2. *(Valence)* A larger number of reference group members causes individuals to assign higher ratings in their reviews.

The dispersion of product ratings also influences product sales. A product with more diversified but lower average rating has subsequently higher demand (Sun 2012). Goes, Lin, and Au Yeung (2014) hypothesize that because of the special structure of the rating system—with lower and upper bounds—the change in average rating leads to higher variance of ratings. Following the same logic, we also hypothesize that a larger audience population causes users to assign more diverse ratings.

Hypothesis 3. *(Valence Dispersion)* The variance of review ratings assigned by individuals is higher with a larger population of reference group members.

The "quality" of online reviews helps consumers better evaluate the quality of products. This feature has been studied in the literature and shown to be critical for consumer information distraction and final product sales (Mudambi and Schuff 2010, Cao, Duan, and Gan 2011). Factors that influence the quality or helpfulness of reviews include reviewer expertise, textual characteristics, and timing of posting online reviews in terms of the product lifecycle (Mudambi and Schuff 2010, Cao, Duan, and Gan 2011). That being said, the quality of product reviews may also be influenced by the population size of an individual's audience.

Previous studies have established that larger communities are likely to maintain postings of lower quality (Gu et al. 2007). Gu et al. (2007) theorize that as a community becomes larger, it has more incentive to provide bundled information because of economies of scale, rather than the quality of postings. Essentially, the community faces a tradeoff between fixed costs (bundled information that does not change with the community size) and marginal costs (the quality of each posting). In contrast, users of third-party review communities do not face a similar tradeoff. Instead, they are weighing the benefits and costs from posting reviews of high quality. On one hand, by providing more helpful reviews, review writers contribute more benefits to the community. The aforementioned theories of prosocial behavior and social image both imply that users will improve the quality of reviews with more audience and peer reviewers. On the flip side, the costs of posting reviews clearly increase with the quality or helpfulness. With a larger population of audience, users spend more time and effort in composing more reviews and thus will pay much less attention to the quality of their reviews. Therefore, it is not clear *a priori* in which direction a larger group of review readers and cohort review writers will change the quality or helpfulness of reviews. We therefore propose the following competing hypotheses:

Hypothesis 4a. *(Quality I)* A larger number of reference group members causes individuals to post reviews of higher quality—more helpful for review readers.

Hypothesis 4b. *(Quality II)* A larger number of reference group members causes individuals to post reviews of lower quality—less helpful for review readers.

In addition, we also consider the moderating roles of several user characteristics. The activeness, expertise, and popularity of a user have been shown as important factors affecting an individual's contributions. First, the activeness of a user may play a negative role in moderating the effects of the exogenous shock for several reasons. The reasons are mainly three-fold. First, compared to a less active user on Douban.com, a more engaged user is mostly motivated by intrinsic incentives

(Andreoni 1989). Unlike extrinsic motivations that are more likely to be affected by outside environment changes, higher levels of intrinsic motivations are immune to exogenous shocks like the one we consider in the current thesis (Khern-am-nuai and Kannan 2016). Second, a higher level of activeness implies a higher level of engagement. if a user is more engaged with a platform or the service provided by the platform, he or she will be less likely to be affected by some exogenous shocks (Bateman, Gary, and Butler 2011). Last but not least, a more active user has typically made more contributions and spends much more time on the platform. Therefore, the marginal cost of producing more reviews will be higher than a less active user. In other words, the constraints in time and energy precludes a more active user to contribute even more in a larger population of peer reviewers. Due to these reasons, we hypothesize that the activeness of a user plays a negative role in moderating the exogenous shock effects on all outcome variables—volume, valence, and helpfulness.

Hypothesis 5. *(Activeness)* An increase in a user's activeness in participation reduces the incremental increase in his or her contribution volume, the valence assigned in the reviews, and the quality of reviews.

Expertise measures the level of knowledge a consumer or a third-party professional has about a certain type of products. It is not hard to see that an expert in a certain category of products receives significantly more utility from making more contributions to that particular category. This is a recognition process during which a larger audience can make an expert more salient, therefore, generating higher benefits for him or her (Bergstrom, Blume, and Varian 1986). Going further, more contributions from experts will certainly attract more audience, which creates a feedback loop that boost up the experts' contributions even more. In sharp contrast, the feedback loop will undoubtedly discourage an amateur of a particular category due to the same reason. Therefore, we are expecting a positive role in moderating the effects of the merge between Douban and QZone.

Hypothesis 6. *(Expertise)* An increase in a user's expertise in a certain category of product reviews boosts up the incremental increase in his or her contribution volume, the valence assigned in the reviews, and the quality of reviews.

The last user characteristic we consider in this chapter is the popularity of a user. A more popular user has typically a larger audience than others. He or she is usually more engaged with the platform by actively writing reviews and potentially interacting with his or her audience. Because of the exact same reasoning as for Hypothesis 5, a more popular user should be less impacted by the exogenous shock that leads to a sudden expansion in the user population, which most likely translates into a large base of audience. On the other hand, the marginal benefit of gaining one more audience is clearly decreasing, which suggests that the same amount of increase in one's followers or audience will have a smaller effect on a more popular user. This second reason is consistent with the argument of marginal cost in Hypothesis 6. Based on these reasoning, we argue that the popularity of a user will play a negative role in moderating the effects of a sudden expansion in the population of users.

Hypothesis 7. *(Popularity)* An increase in a user's popularity decreases the incremental increase in his or her contribution volume, the valence assigned in the reviews, and the quality of reviews.

Note that all hypotheses reflect causal effects of reference group sizes on individual behaviors. Our empirical strategy is a quasi-experimental design of differences-in-differences (DID) analyses (Imbens and Wooldridge 2009) utilizing a unique feature of the exogenous shock on Douban book reviews. Hypothesis 1a to 4b are the focus of Chapter 3, and the rest will be tested in Chapter 4.

2.3. Douban.com and Douban Reading

Launched on March 6, 2005, Douban.com was originally advertised as a platform providing social networking service. In contrast to the generic networking sites such as Facebook.com and Twitter.com, friendships on Douban.com are mainly based on users' common interests in books, movies, TV shows, or music. The network formation process on Douban.com is identical to that on Twitter.com. Specifically, a user can send a request to follow another user. Upon approved, a following relationship is established with the request sender being the follower and the receiver the followee.

The follower will be able to observe all activities by the followee, including his or her reviews ever posted. The followee's all subsequent updates will show up in the follower's news feed.

More important, in addition to forming networks on the platform, all Douban users are allowed to rate and write reviews of all products collected by the website. The platform creates and maintains webpages for all its collections.[4] Douban users can read and write product reviews, make comments on the reviews, and chat with other users on the product pages. These are in sharp contrast to main activities in other social networking platforms, where sharing life events, news, or articles with friends are among the top activities. By the end of 2014, the number of registered Douban users had passed 100 million, with over 200 million monthly unique visitors and average daily page views (PV) beyond 210 million. On the other side of the market, Douban.com has over 17 million books, 320 million movies, and 1 million songs in storage.[5] Douban.com is now the largest platform of third-party reviews in China.

In this study we consider the introduction of "Douban Reading" on Tencent.com being an exogenous shock to Douban network. Tencent.com, the largest online social network in China, started testing customizable installations of third-party applica-

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[4]Take book pages as an example, Douban provides detailed information such as the ISBN number, and brief introduction. All user reviews with preview sentences are listed underneath the information section. Douban also makes the links to purchase the corresponding products available on product pages.

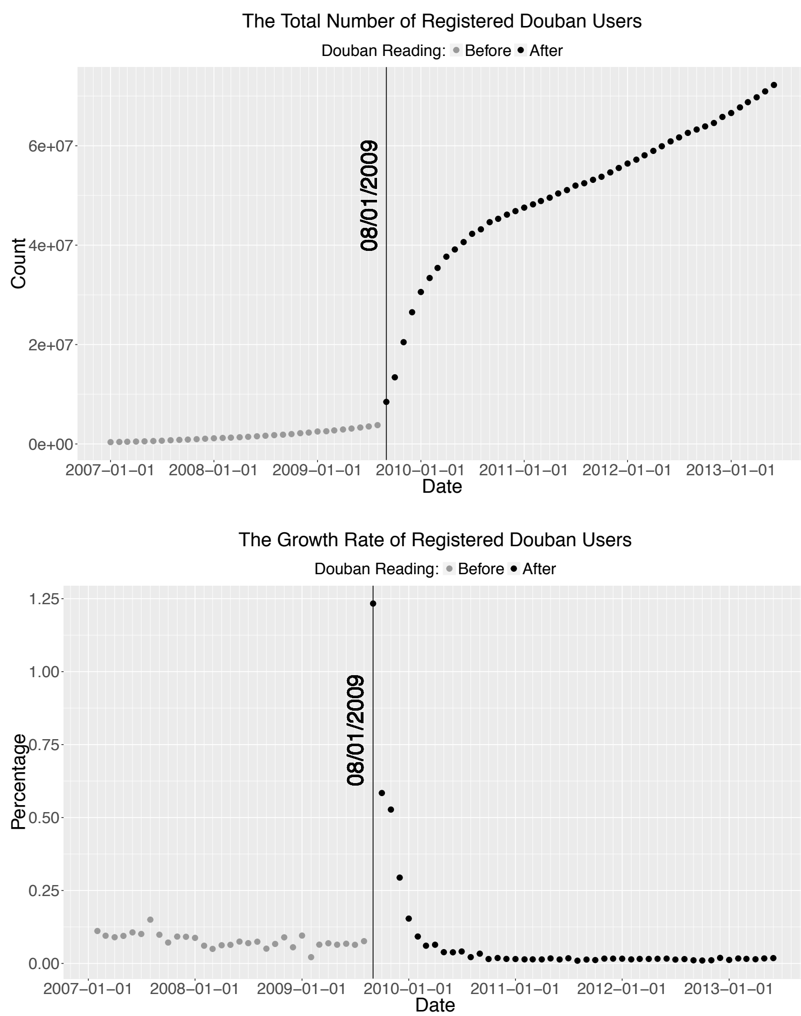
[5]Statistics on the size of Douban.com can be found in the annual surveys prepared by the program "We Are Social" at http://www.wearesocial.com/.

Figure 2.1: An Illustration of "Douban Reading" Installed on a Tencent User's QZone

tions on their users' profile pages (called "QZone") on August 1, 2009. The first such application was Douban Reading. Figure 2.1 is a screenshot of Douban Reading taken from a Tencent user's QZone. This application essentially granted a Tencent user a registered Douban account or a connection to his or her existing Douban account, and direct access to all Douban books and book reviews. However, as its name suggests, the application did not provide direct entry into other product pages on Douban.com. More specifically, Tencent users, who chose to install the application on their QZone, were able to read and search all Douban books together with all the reviews. Furthermore, this application also made the links to online bookstores available to Tencent users. Douban discontinued this service on October 31, 2011, after which the Tencent users were able to maintain their Douban accounts.

A straightforward impact of this exogenous shock is on the number of registered Douban users. In Figure 2.2 we depict the total number and growth rate of registered users on Douban.com. Note that the platform experienced a sudden outburst of its users population. Particularly, the total number of registered users was $3,790,891$ before the start of August 1, 2009, and skyrocketed to $8,466,660$ by the end of the same month.[6] The population was more than doubled within a month.

Figure 2.2: The Total Number and Growth Rate of Registered Users on Douban.com



[6]Douban.com used to publishing and updating the total number of registered users on its homepage on a daily basis, and removed it after June 2013.We obtain the statistic from the historical data maintained by the Internet Archive, http://www.archive.org.

The merge between Douban.com and QZone of Tencent.com, through the web application Douban Reading, provides us a unique opportunity to evaluate its impacts on individuals' incentives and behavior of posting online product reviews.

3. Free Riders versus Social Capital: An Empirical Analysis of an Exogenous Shock on Online Reviews

We conduct our empirical analysis of the network effects on contributions to online reviews in the following three chapters. We begin with the average network effects in this chapter. The effects are average in the sense that we do not control for the differential impacts by either observed or unobserved factors. This chapter is organized as follows. Section 3.1 describes our datasets and presents summary statistics. We provide detailed discussions of our empirical strategies in Section 3.2.1. We report findings in Section 3.2.2. Section 3.3 discusses and concludes.

3.1. Data and Sample

This section provides a detailed description of the data and samples used in our empirical analysis. We start with our sampling process and a brief overview of the original sample. The main sample used in our empirical analysis is introduced in Section 3.1.2.

3.1.1. The Original Sample

To evaluate the effect of the exogenous shock on Douban users' contributions, we crawled all relevant information from the webpages of 24,374 users. The specific sampling process is as follows. We start with a random sample of 119 Douban groups with all their members, originally $552,827$ users. We select $24,374$ users in this sample, because only these users joined Douban.com before the exogenous shock. We crawled all user demographics on their profile pages, all reviews, and all related product information. We focus on this specific subgroup because, by design, we study the network size effects on an individual user's reviewing behavior. Only this subsample allows us to compare the changes in onsite activities before and after the exogenous shock.

From the user profile pages, we obtain user demographic information including age, gender, location, and registration date. We dumped all reviews of books, movies, TV shows, and music for each sampled user. For each product review, we collected the timestamp, title, full content, and all comments attached. We also obtained the review ratings, ranging from 1 being the worst to 5 indicating the best in integers, the number of helpfulness votes, and the number of non-helpfulness votes for each review.[1] In addition, we crawled all other activities such as the number of photo albums, personal notes, product collections,[2] and public messages. For a user's network information, we obtained the identities of all his or her followers and followees by the data collection date, November 1, 2014.

[1] The readers of a product review have the option to characterize the review being either "helpful" or "not helpful." The platform displays the total number for each option.

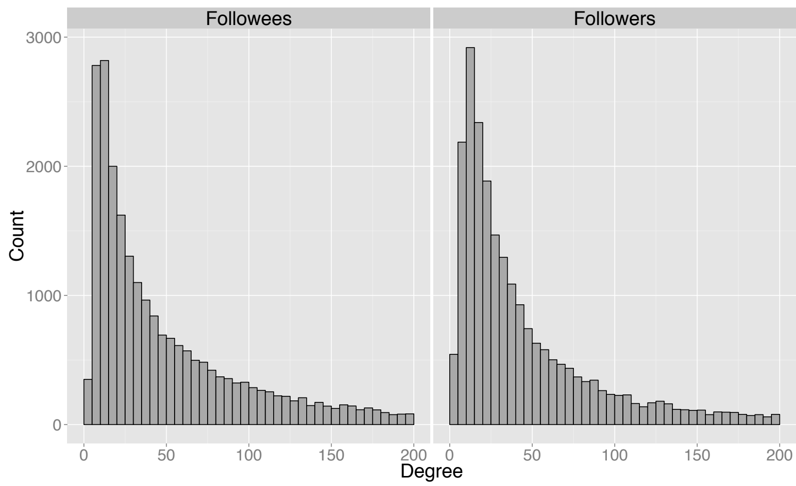
[2] Douban users can choose to display their own collections of books, movies, TV shows, or music on their profile pages. Products in collections are usually personal favorites including those reviewed by themselves. The collections are divided into three categories. Collections of books, as examples, are categorized into those read, those being reading, and those on a wish list. Similar categorization applies to other types of products.

For each review, we downloaded all product information from the product pages. For instance, if the product is a book, we crawl the authors, the publisher, the ISBN number, the publishing date, the total number of pages, a brief outline of the book content, and the author introduction. We also obtained the product rating, ranging from 1 (the worst) to 10 (the best). Note that this rating is assigned by any Douban user that selects an integer within the range, not necessarily those who have reviewed the product. Therefore, it differs from the rating assigned in the reviews. As mentioned above, the review rating is chosen by the review writer, within a range of 1 to 5. While the product rating is the average among ratings assigned by the users that have visited the product page. These users are not necessarily review writers for the particular product.

By our data collection date, among all sampled users, the median number of followees and followers are 36 and 33 respectively. Figure 3.1 shows the distributions of the followee count and follower count. Both distributions abide by the power law or "fat-tail" phenomenon that is well documented in the literature.[3] Indeed, in our sample, we notice that the maximum number in the followee count is $2,144$ and for the follower count more than $88,000$.

[3] Jackson (2010) provides a thorough review and theoretical treatments on the distributions of network sizes.

Figure 3.1: Distributions of the Followee and Follower Count for the Main Sample



3.1.2. The Sample in Regressions

In our main empirical analysis in Section 3.2, we focus on the reviews posted by the sampled users between July 4, 2009 and August 28, 2009, which is 4 weeks before and 4 weeks after the exogenous shock. We choose this specific time window mainly because the exogenous shock was the only policy change on Douban.com within this period. Another reason for focusing on a relatively small time window is to control for the "spill over" effect of the exogenous shock. Tencent users who installed the Douban Reading app may gradually start reading nonbook reviews, i.e., movie or music reviews. We argue that in our sampling period, a short period of time before and after the merge, this spill-over effect does not significantly affect our comparisons.

We first take a closer look at these sampled reviews categorized by type, i.e., either book or other reviews, in Table 3.1. We notice that more than half of the sampled

Table 3.1: Summary Statistics of the Sampled Reviews by Product Type

	Summary Statistics					
	Book reviews		Other reviews			
			All other reviews[a]		Movie reviews	
Variables:	Mean	s.d.	Mean	s.d.	Mean	s.d.
Length of review	884.490	1,483.970	845.141	2,190.490	824.766	2,239.410
# Helpful votes[b]	6.023	30.385	8.698	92.331	9.530	103.241
# Non-helpful votes	0.747	3.606	1.156	7.202	1.261	7.982
Helpfulness votes (%)[c]	48.753	46.264	41.090	45.378	38.438	44.789
Rating (1 - 5)	3.929	1.132	4.000	1.046	3.934	1.057
1 (Missing rating)	0.030	0.169	0.012	0.110	0.011	0.103
1 (Douban Reading)	0.554	0.497	0.451	0.498	0.47	0.499
Num. obs.	14,969		26,806		21,150	

[a] All reviews than those in book section, including movie, TV show, and music reviews.
[b] The number of "helpful" clicks by review readers, likewise for "# Non-helpful votes."
[c] The score equals #helpful votes / (#helpful votes + #non-helpful votes).

book reviews were posted during the four weeks after the exogenous shock, while less than 50% of other reviews (including all movie, TV show, and music reviews) were made in the same period. This suggests that Douban users indeed became more "active" in writing book reviews after the exogenous shock, relative to their activeness in composing other reviews.

In the original sample, 23,548 users registered on Douban.com before July 4, 2009. Notice the slight difference from the original sample of 24,374 users who joined before August 1, 2009. It turns out that these two samples are not significantly different in terms of review activities or demographic information. However, there is a non-negligible fraction of "silent" users in the sample. Specifically, about 16.5% (3,878 of 23,548) of the sampled users posted at least one review, regardless of the

Table 3.2: Sample Comparisons

	Sample in regressions			Original sample		
Variables:	Median	Mean	s.d.	Median	Mean	s.d.
# All reviews	4	9.416	26.023	0	2.570	12.603
# Groups	52	75.865	71.113	43	66.536	68.274
# Followees	51	100.862	161.432	36	78.926	142.174
# Followers	52	229.683	1,840.202	33	158.171	1,517.22
1 (Missing followers)	0	0.003	0.056	0	0.002	0.044
Length on site[a]	648	688.208	382.911	424	498.221	365.539
Users		3,878			24,374	

[a]The number of days since a user's registration till Aug. 1, 2009, the date of the exogenous shock.

product section, during the study period. The workhorse or the main sample used in the empirical analysis in Section 3.2 contains these 3,878 active users. We provide a sample comparison in Table 3.2. Not surprisingly, these users were indeed more active in posting reviews and more engaged with the platform.[4]

3.2. Average Network Effects

3.2.1. Differences-In-Differences Design

Our purpose is to establish the causal effect of larger group sizes on Douban users' behavior of posting online reviews. With the exogenous shock, a simple and naïve method is to compare some measures of individual contribution behaviors, e.g., the

[4]This may lead to a concern about sample selection. We conduct a robustness check in Section 3.2.2 by including all 23,548 users, and the results are qualitatively the same as our main findings. In fact, we are able to reproduce all findings using the larger sample. This is expected since the rest of the users contributed no reviews either before or after the event.

weekly number or the average textual length of reviews posted within a short time interval, before and after the introduction of Douban Reading on QZone. A serious concern undermining this simple method is that the revealed effects confound with the overall trend on Douban.com. Specifically, this method hypothetically treats reviews after the exogenous shock as the treatment group, while those prior to the shock the control group. Then a potential problem is that the difference between the groups before and after captures not only the treatment effect , but also the intrinsic difference between these two groups, such as the overall trend in review posting on Douban.com. Thus this before-and-after comparison masks the true effect of group size on review contributions.

A quasi-experimental design, differences-in-differences,[5] provides a solution to the endogeneity problem (Ashenfelter 1978, Card and Krueger 1994, Athey and Imbens 2006, Chevalier and Mayzlin 2006). The exogenous shock to Douban.com provides us a unique opportunity to apply this method to explore our research questions. Suppose Y_i is some measure of individual i's contributions to Douban reviews, e.g., the weekly number of reviews posted. Let Y_i^T denote the user's contributions to Douban book reviews, and Y_i^C his or her contributions to other reviews including those for movies, TV shows, and music.[6] As the superscripts suggest, we divide

[5]The technique of diffs-in-diffs is widely adopted in economics literature. In the literature of marketing and management, this research design is receiving rising attentions. Particularly in the literature of online reviews, Chevalier and Mayzlin (2006) study the effects of online reviews on book sales using a diffs-in-diffs design.

[6]Traditional DID method leaves the choice of control groups to the researchers, prompting critics about the arbitrariness of the selection and the degree to which the control units can credibly proxy for the treated group's counterfactual outcomes. A recent strand of literature (Abadie, Diamond, and

all Douban reviews into two groups—book reviews as the treated group and other reviews as the untreated/control group.[7] A DID estimator of the treatment effect uses an assumption—usually called the assumption of common trend) that in the absence of treatment the average difference in the outcome variable, Y_i, between the treated and untreated would have stayed roughly constant, in our case, before and after the exogenous shock (Abadie 2005).

Based on the setup and common trend assumption above, let $\bar{Y}_s^T$ and $\bar{Y}_s^C$ be the average contributions in period s with $s = 1, 2$ to Douban book reviews and other reviews, respectively, for our sampled users. Period $s = 1$ indicates the period before the exogenous shock, while period $s = 2$ takes place after the exogenous shock. A simple DID estimator would be to calculate $\hat{\beta} = \left(\bar{Y}_2^T - \bar{Y}_2^C\right) - \left(\bar{Y}_1^T - \bar{Y}_1^C\right)$. That is, an *unconditional* version of the DID estimator can be defined as the difference between the difference in average contribution levels between book and other reviews after the exogenous shock, and the same difference for the pre-treated period.

In some instances, the common trend assumption adopted for DID estimator may not be plausible because the treated and untreated differ according to some variables, X_{it}. An example is the user demographics. The rationale is that the treatment effect may differ for different types of users. In this situation, a regression formulation of

Hainmueller 2010) propose the synthetic control method to "optimally" select the control units based on pre-treatment characteristics. Our setup can circumvent this issue because we are comparing the same user in the treated group (book reviews) and in the control group (other reviews).

[7] One might have a concern that movie reviews are essentially distinct from music reviews, and more than half of Douban reviews fall into the movie section. Thus we conduct a robustness check comparing book reviews with movie reviews only later in our empirical results.

the DID estimator is useful to compute a *conditional* version that corrects for the effect of X_{it}. Specifically, our main empirical specification is

$$Y_{it}^{j} = \beta_0 + \beta_1 \cdot D^j \cdot D_t + \beta_2^{'} \mathbf{X}_{it} + \beta_3 \cdot D^j + \mu_i + \nu_t + \epsilon_{it}^{j}, \tag{3.1}$$

where the superscript j ($j = T, C$) indicates corresponding variables for book reviews and other reviews respectively, e.g., Y_{it}^{T} is a certain measure of individual i's contributions to book reviews in the period t; the dummy $D^T = 1$ indicates book reviews; the event dummy $D_t = 1$ ($t = 1, 2, 3, ...$) stands for the period after the exogenous shock on August 1, 2009. In addition, $\mathbf{X}_{it}$ include user demographics such as the length of time on site and user location dummies.

In this equation, β_1 is the coefficient for the interaction term between the dummy for book reviews and the event dummy. It is the coefficient of interests capturing the treatment effect of the introducing Douban Reading on some outcome variable, Y_{it}^{j}. We include user fixed effects, μ_i, and time fixed effects, ν_t, to control for unobserved characteristics at the individual user level and those affecting all users but differing in time. Note that a separate term for D_t is omitted because of the time dummies ν_t.

3.2.2. Empirical Results

The DID design helps uncover the causal effect of the exogenous shock, which leads to changes in reference group sizes, on Douban users' behavior of contributing to online reviews. Before presenting the evidence of group size effects, we first show that the exogenous shock indeed led to larger population of audience for sampled reviews. We continue with evidence from summary statistics showing distinct behaviors in posting book reviews and other reviews before and after the shock. We then report estimation results from the regression-adjusted model, Equation (3.1) in the last section. We conduct several robustness checks in addition to our main empirical specifications and samples. In the last subsection, we discuss the implications, both theoretically and managerially, of our results.

Larger Reference Groups Before presenting the evidence of the group size effects, we first show that the exogenous shock indeed led to a larger audience for the sampled reviews. A prerequisite of our analysis is whether the introduction of Douban Reading indeed led to a larger population of audience and peer review writers on Douban.com. Unfortunately, we are unable to observe the number of actual review readers. However, a proxy for the audience population is the quantity of comments made to the reviews. Unambiguously positive correlations exist between the population of audience and the number of comments they post. Thus, controlling for all observed characteristics, we hypothesize that the exogenous shock led to more comments for reviews.

We focus on the comments made to the reviews posted before July 4, 2009. We keep track of all comments between July 4, 2009 and August 28, 2009, which is our main study period. During this period, $1,110$ reviews of $20,539$ total reviews received

Table 3.3: Exogenous Shock Effects on the Number of Comments

Dep var.: log (# Comments)	OLS estimates
$1\,(\textbf{Tencent}) * 1\,(\textbf{Book})$	$\mathbf{0.001}^{**}$
	(0.408e-03)[a]
Control variables[b]	Yes
Review fixed effects	Yes
Week fixed effects	Yes
1 (Book)	Yes
Adj. R^2	0.020
Num. obs.	328,624

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

[a] We report the robust standard errors in all estimation results. It may be argued that the precision of estimates can be overestimated with the robust standard errors. Therefore, we also check the results with standard errors clustered at an individual user level for all estimations. The significance results are, not surprisingly, similar.

[b] We control for the length of time the review has been posted and the squared of the length.

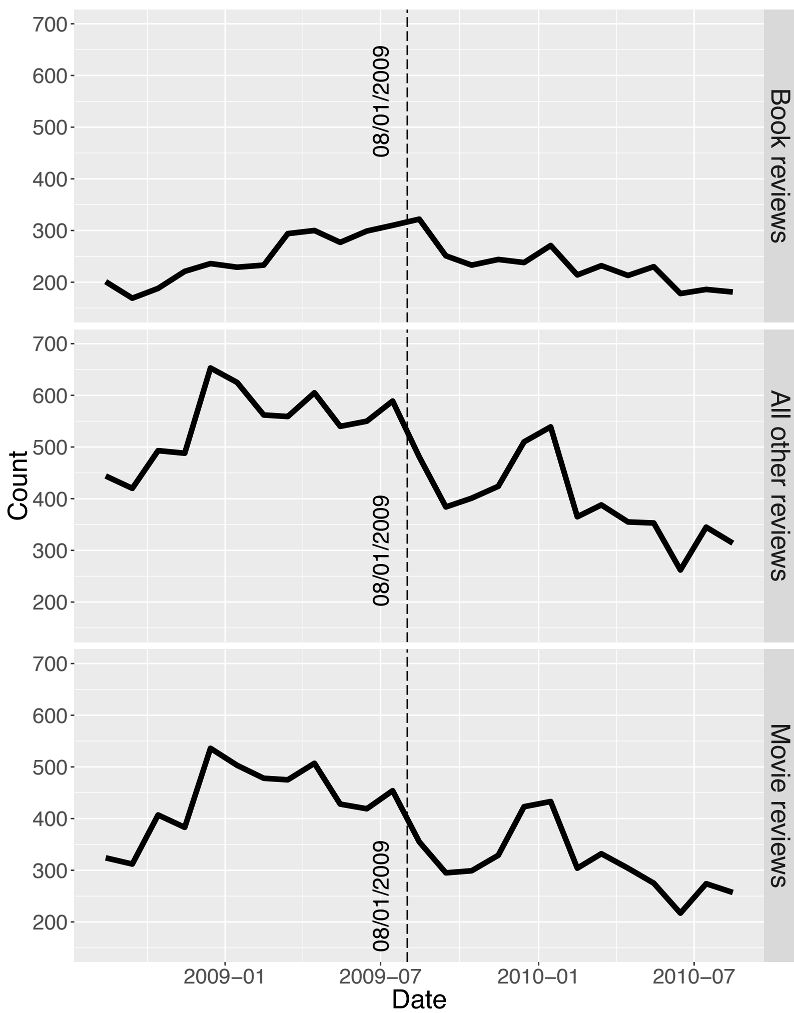
2, 123 comments from readers. The average number of comments a review received during the period was 1.39 per week. We conduct a similar DID analysis to that Section 3.2.1 to explore the effect of the exogenous shock on the number of comments made to an individual review. The dependent variable, Y_{it}^{j} in Equation (3.1) is the log of the number of comments per review per week in this set of analysis.

The estimates are reported in Table 3.3. The estimates of the main effect support our hypothesis. Specifically, the estimate of β_1, reported in the first row of Table 3.3, suggests that the exogenous shock led to on average about 1% more comments per review per week. The finding implies that the group size of review readers who posted the comments was indeed enlarged because of the exogenous shock. This fills the gap between the exogenous shock—the introduction of Douban Reading on Tencent QZone—and the group size effects on review posting behaviors. It is safe to use the event indicator as a proxy for the increase in the size of peer groups.

Evidence from Summary Statistics In our research design, we divide Douban reviews into two groups: the book reviews as the treatment group and all other reviews as the untreated group. We first compare the total reviews posted by our sampled users in the two groups. Figure 3.2 displays the monthly total number of reviews by categories between August 2008 and August 2010, which is one year before and one year after the exogenous shock. It clearly shows the difference between the monthly volume of book reviews and other (or movie) reviews around the shock. The monthly number of book reviews rose from 310 in July 2009 to 322 in August 2009 by our sampled users; in contrast the total number of all other reviews dropped from 589 in July 2009 to 481 in August 2009 by more than 18%. Similarly, we observe that movie reviews also decreased by more than 20% from 454 in July to 355 in August 2009 over the exogenous shock.

The main sample used in our estimations is constructed from the original $24,374$ users, who registered before the exogenous shock. Since we focus on a period between July 4 and August 28, 2009, we examine the users that registered before July 4, 2009. We keep track of their weekly contributions to all types of reviews over the study

Figure 3.2: Monthly Total Numbers of Reviews by Review Categories



period. There are 23,548 individuals in this subsample. They posted 1,553 reviews with 1,226,204 characters during the 8-week time window. Among these reviews, 585 were posted in book sections while there were 736 movie reviews. The rest were music reviews. Accordingly, each observation in the sample corresponds to an individual user's contributions to either book reviews or non-book (or movie) reviews per week during our study period.

Table 3.4: A Summary of Dependent Variables

Hypothesis	Dependent variable (weekly)
H1A	Log of the number of reviews
H1B	Log of the total textual lengths of reviews
H2	Average review ratings
H3	Standard deviation of review ratings
H4	Percent of helpfulness votes (%)[a]

[a]The measure is constructed from the votes by review readers, not assigned by the review writers. Specifically, all readers can vote a review being "helpful" or "not helpful." This variable is equal to the percentage of the "helpful" votes among all votes.

To test each of our hypotheses, we construct the dependent variables accordingly as in Table 3.4. Table 3.6 presents the detailed summary statistics of all dependent variables by category. For each individual user and each type of reviews, we cluster the weeks before and the weeks after the exogenous shock separately, and compare them using the paired one-sided T-tests. The results, reported in the last two columns, suggest that without any control variables, on average, these users posted more and longer book reviews after August 1, 2009; while their non-book reviews or movie reviews were less and shorter. The average and standard deviation of ratings were both higher after the shock for book reviews only. In contrast, the average helpfulness scores were not significantly different before and after for either book or other reviews.

We further compare differences in individuals' reviewing behaviors before and after August 1, 2009. As an example, we first calculate, for each individual in each week, the difference between the total number of book reviews and that of non-book (or movie) reviews before the exogenous shock. Then we compute the same difference for the cohorts after the exogenous shock. Ultimately, we compare these two sets of difference using paired one-sided T-tests. We replicate similar comparisons for the other dependent variables. The first two comparisons, as shown in the panel of "Difference in # reviews" and "Difference in total lengths of reviews" in Table 3.6, suggest that compared to the difference prior to the shock, the difference afterwards was significantly bigger implying that the individuals contributed more to book reviews relative to other reviews after the exogenous shock. Similarly, we find that both the difference in the average ratings and the difference in the standard deviation of ratings were bigger significantly after the shock, illustrated in the panel of "Difference in the avg. review rating" and "Difference in the s.d. of the review ratings" of Table 3.6. In contrast, the differences in the average score of helpfulness were not significantly different before and after the shock, as shown in the last panel of Table 3.6.

Table 3.5: Comparing Individuals' Review Activities Before and After – Summary Statistics

	Before Aug. 1, 2009			After Aug. 1, 2009				
Variables: (weekly[a])	Median	Mean	s.d.	Median	Mean	s.d.	t-stats[b]	p-values
Book reviews								
Avg. # reviews	0	0.017	0.147	0	0.019	0.109	-0.438	0.331
Avg. textual length	0	14.924	190.950	0	17.109	279.944	-0.402	0.344
Avg. rating	0	0.048	0.265	0	0.060	0.299	-1.949	0.026
Avg. s.d. of rating	0	0.001	0.019	0	0.002	0.026	-0.655	0.256
Avg. helpfulness votes (%)[c]	0	0.643	4.775	0	0.800	5.156	-1.395	0.082
Non-book reviews								
Avg. # reviews	0	0.034	0.184	0	0.027	0.168	1.758	0.961
Avg. textual length	0	24.609	213.531	0	20.516	214.079	0.843	0.800
Avg. rating	0	0.099	0.386	0	0.082	0.346	2.092	0.982
Avg. s.d. of rating	0	0.003	0.033	0	0.002	0.026	1.293	0.902
Avg. helpfulness votes (%)	0	0.967	5.435	0	0.858	4.961	0.921	0.822
Users				3,878				
Weeks				8				
Num. obs.				62,048				

[a]We evaluate all variables on a weekly basis. Our sampling period is between July 4 and August 28, 2009, spanning an 8-week window before and after the shock.

[b]In the paired one-sided T-tests our null hypotheses are that the mean value of the variable before the exogenous shock is greater than that after the shock.

[c]The measure is constructed from the votes by review readers, not assigned by the review writers. Specifically, all readers can vote a review being "helpful" or "not helpful." This variable is equal to the percentage of the "helpful" votes among all votes.

Table 3.6: Comparing Differences in Individuals' Review Activities

	Before Aug. 1, 2009			After Aug. 1, 2009				
Variables:	Median	Mean	s.d.	Median	Mean	s.d.	t-stats	p-values
Difference in avg. # reviews								
Book – non-book[a]	0	-0.016	0.208	0	-0.008	0.180	-1.880	0.030
Difference in avg. lengths of reviews								
Book – non-book	0	-9.685	283.25	0	-3.407	349.026	-0.870	0.192
Difference in avg. review rating								
Book – non-book	0	-0.051	0.427	0	-0.021	0.414	-3.132	<0.001
Difference in the avg. s.d. of review rating								
Book – non-book	0	-0.001	0.037	0	-0.0002	0.036	-1.478	0.070
Difference in avg. helpfulness votes (%)								
Book – non-book	0	-0.324	6.683	0	-0.058	6.703	-1.752	0.040
Users					3,878			
Weeks					8			
Num. obs.					62,048			

[a]This variable calculates, for each user, the difference between the average value of the variable (across four weeks) before the exogenous shock and that after the shock.

Regression-Adjusted Analyses Summary statistics show the patterns of distinct individual behaviors in posting book reviews versus other reviews before and after the exogenous shock. However, the T-tests provide rough comparisons of mean values without any controls. Arguably, the introduction of Douban Reading on QZone may have heterogeneous treatment effects on different groups of users. For example, the individuals with Tencent account prior to the shock may exhibit very different reactions than those without such an account. In order to control for these concerns as well as others such as users' experience with the setting of Douban.com, we conduct regression-adjusted analyses by adding controls including individuals' length of time on site and user fixed effects. Table 3.7 reports the main estimation results from Equation (3.1).[8] Each table corresponds to one hypothesis in Section 2.2.

[8]For all estimations, there exist concerns of serial correlations since the observations are weekly records in a continuous period. In the tables we report the robust standard errors as suggested by Wooldridge (2002). We obtain similar results by calculating either bootstrapped standard errors or standard errors clustering at user level.

Table 3.7: Main Results – Estimates of the Exogenous Shock Effects

	OLS estimates				
Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
1 (**Tencent**) ∗ 1 (**Book**)	**0.006*****	**0.042*****	**0.030*****	**0.001***	**0.003*****
	(0.002)[a]	(0.013)	(0.008)	(0.001)	(0.001)
Control variables[b]	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.138	0.109	0.091	0.052	0.079
Num. obs.	62,048	62,048	62,048	62,048	62,048

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

[a] We report the robust standard errors in all estimation results. One may argue that it is likely to overestimate the precision of estimates with the robust standard errors. Therefore in all estimations, we also check the results with standard errors clustered at individual user level. The significance results are not surprisingly similar.

[b] We control for a user's experience with Douban platform by including the length of time on site, and the squared term of the length. This applies to all subsequent estimations.

"Volume" of Reviews: We first report the estimates from regressions using the weekly number of reviews posted as a measure of contribution levels. The results are presented in Table 3.7. From the semi-log specifications, the coefficient estimates of the key dummy variable for book reviews after the exogenous shock indicate that compared to the conditional difference between the number of book reviews and that of other reviews before the exogenous shock, the same difference afterwards rose by about 0.094% supporting the hypothesis H1a.[9] The value suggests that suppose there is a representative individual posting 10 book reviews and 20 non-book reviews each week before the shock. If he or she were to post 21 non-book reviews after the exogenous shock, our estimates suggest that he or she would mostly likely post 11.001 book reviews after the shock.

It is noted that the estimates for the coefficient of the interaction dummy are the exactly the same across specifications. The reasons are that, first of all, the effect of the number of weeks on site is picked up by the dummy for the exogenous shock, since they are perfectly multicolinear. In addition, the individual fixed effects do not vary across time. The estimates of β_3 in Equation (3.1) may potentially change if we include controls that vary across users and weeks. In addition, the estimate seems to suggest that although the effect is statistically significant at all common significance levels, the magnitude is too small to have real impacts on Douban review

[9]The marginal effect of the key dummy variable, $1\,(\text{Tencent}) \times 1\,(\text{Book})$, can be easily shown to be equal to $\exp\left(\hat{\beta}_3\right) - 1$ from our semi-log specification. Therefore, in this case, the marginal effect is $\exp\left(0.941e-03\right) - 1 \approx 0.941e-03$.

outcomes overall. However, first notice that in our sample of $23,548$ users, only less than $6,000$ individuals have posted reviews ever. The small absolute value of estimates picks up the fact that there are a non-trivial fraction of 0 observations in the regressions. In addition, considering the population of more than 100 million Douban users, an increase by about 10 basis points in activeness seems to be non-trivial. Similar arguments apply for other estimation results.

As an alternative evaluation of individuals' contributions to product reviews, the number of characters in a review also reflects the effort the contributor devotes into the provision of the public good. We thus consider an alternative specification using the log of textual lengths as the dependent variable. Estimation results are presented in Table 3.7. The coefficient estimate for the variable of interests shows that compared to the difference between the weekly total lengths of book reviews and those of other reviews before the shock, the same difference after the exogenous shock increased by around 0.691% supporting the hypothesis H1b. Similar interpretation as that in the last paragraph applies. We also note that the estimates of β_3 are the same across specifications.

"Valence" of Reviews: In addition to the volume effects, we also estimate the causal effects on the valence of reviews. Column 2 and 3 of Table 3.7 present the estimation results with the dependent variable the average ratings assigned by an individual reviewer in a week. Consistent with our hypothesis H2, the estimate suggest that the sampled Douban users assigned, on average, higher ratings for book reviews than other reviews conditional on all observed characteristics. The precise marginal effect is around 0.005, and statistically significant. It is interpreted that the exogenous shock causes individuals to assign, on average, 0.005 point of ratings conditional on all control variables.

Our findings of positive effect on the valence of review ratings are in sharp contrast to those in Goes, Lin, and Au Yeung (2014). We attribute the disagreement to the potential endogeneity of followers count in social networks. Goes, Lin, and Au Yeung (2014) explore the intertemporal correlations between a user's quantity of followers in the previous period and his or her rating assignments this period. The endogeneity of one's follower count does not vanish using a dynamic panel data method. In fact, our findings of positive effects on review ratings lend support to our argument that the results could be biased by the potential endogeneity problem.

We report the estimation results for the test of hypothesis H3 in Table 3.7. The findings support the hypothesis that the variance, or the standard deviation, of weekly review ratings assigned by an individual is indeed higher for the book section than in other sections. Similarly, the calculated causal effect of the exogenous shock is about 0.0002. In other words, the exogenous shock increases the average variation of review ratings by about 0.0002 standard deviation, which is statistically significant.

"Quality" of Reviews: The last set of estimation results are presented in the last column of Table 3.7 and are used to test the hypotheses H4a and H4b. The positive estimate of β_1 lends support to H4a, suggesting that a representative Douban user tends to post more helpful reviews in a larger network. Quantitatively, the exogenous shock led to about a 0.13% increase in the percentage of helpful votes.

The findings above support all our hypotheses. Various concerns may hurt the reliability of these findings, including concerns about our samples and empirical specifications. In the following section, we conduct robustness checks and placebo tests according to each of those concerns.

Robustness Checks In our main specification, we stack all other (than book) reviews together and treat them as the control group. In fact, this group is composed of reviews of movies, music, and locations. The behavior of posting reviews is arguably different in different segments. As seen in our summary statistics, more than half of Douban reviews were posted in the movie section. One might have a concern that combining all other reviews altogether may mask the true difference, between individual behaviors devoted to book reviews and those to other reviews. In the first set of specification tests, we investigate whether our main findings will be attenuated suppose we compare book reviews with other reviews separately.[10] Specifically, we perform two separate comparisons, *i.e.*, book reviews versus movie reviews and book reviews versus music reviews. Estimation results are reported in Table 3.8 and 3.9. We find qualitatively consistent estimates of the exogenous shock effects with our main findings in Table 3.7.

[10]We are unable to compare other combinations, book reviews versus location reviews, due to small number of observations in the location section. There are only 81 location reviews in our sample.

The second concern about our main specification is that one may worry about the sampling period we focus on. In our main estimations, we focus on a period between July 4, 2009 and August 28, 2009. One might have concerns about the validity of our results from this special period. Correspondingly we conduct robustness checks based on alternative samples that cover different periods of time.

Specifically, we construct two additional samples that include reviews between June 6, 2009 and September 25, 2009 (8 weeks before and 8 weeks after the exogenous shock), and between May 9, 2009 and November 22, 2009 or 12 weeks before and after the shock respectively. We report estimation results in Table 3.10 and 3.11. We find the estimates qualitatively consistent with our main findings again. We also notice that the magnitudes of the coefficient estimates for the contribution levels, the log of reviews quantity and textual lengths, are decreasing with the length of time covered in studying periods, *i.e.*, the effect is more significant with tighter period around the exogenous shock.

The original sample comprises of users that registered before July 4, 2009. One may worry that individuals joining the platform earlier are qualitatively different from those joining late. For instance, the early users, who are still active in our study period, tend to be more loyal to use the platform than those that enter late. So their behavior of writing reviews might be significantly different from the newcomers. To make sure that our findings are consistent across different groups of users in terms of their maturity with the platform, we conduct a third set of robustness checks.

In particular, we divide our original sample to two subsamples and conduct subsample analysis. More specifically, the first subsample contains all users that joined before July 4, 2008, which is one year before July 4, 2009; the second subsample includes all other users. In the first subsample, $12,996$ users posted $30,911$ reviews altogether during our study period between July 4, 2009 and August 28, 2009. While in the second one, $10,552$ individuals wrote $10,043$ reviews during the same period. We repeat our main estimations using these two subsamples separately, and report the results in Table 3.10 and 3.11. We find consistent results as our main findings again. We also notice that the exogenous shock has greater effects on the individuals that entered later than those joining earlier.

As mentioned in Section 3.1, a non-negligible fraction of users contribute no reviews during our study period. There are even “zombie” users who had never posted any reviews by the data collection date in 2014. As a last robustness check, we ask whether including these inactive users can change our results qualitatively. We report the same set of estimations in Table 3.14. Although all estimates are much smaller in absolute values, the directions and significance levels are highly comparable with our main results as in Table 3.7. This is not unexpected since by our empirical strategy, the DID design, we are essentially comparing a user’s activities before and after the shock. No difference at all was found in inactive user activities before and after. Therefore, the estimated causal effects are smaller in magnitude, but the directions should follow.

We conduct a placebo test to make sure that it is indeed the exogenous shock that is driving our results, not coincidence. Specifically, if the exogenous shock had no effects at all on individual user behavior, we would expect similar results—positive effects on volume/valence/helpfulness—by treating a random date, other than August 1, 2009, as the date of the exogenous shock. We look at two such dates, one before the exogenous shock and the other afterwards. We choose July 4, 2009 and August 29, 2009 as the two dates. For each date, we repeat our estimations by focusing on the same length of time as in our main specification, four weeks before and four weeks after the "fake" event date. For example, for July 4, 2009, we compare the changes from June 6, 2009 to July 31, 2009. We report the results in Table 3.15 and 3.16. Clearly, both "fake" exogenous shock dates had no effects at all on review volume/valence/helpfulness. These findings provide strong evidence that it is indeed the exogenous shock that causes the behavioral changes.

3.3. Summaries

The management of online consumer response is increasingly important for companies to using social media (Gu and Ye 2014, Sun and Xu 2016). As a major form of consumer response, online reviews, provided by either consumers or third-party professionals, are closely related to customer satisfaction and product sales. We study an individual's incentives to post online reviews in the first place and focus on the fundamental factor governing their contributions—the peer effects. We complement the recent literature on the antecedents of online reviews by establishing the causal effects of peer groups. Instead of the aggregate product or firm level, our analysis is at a more granular review writer level, which is governed by our theoretical motivations of studying an individual user's incentives. In addition to the volume, we manage to conduct a more comprehensive investigation by studying the effects on the valence and quality of reviews.

Table 3.8: Robustness – Comparing Book Reviews with Movie Reviews

	OLS estimates				
Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
1 (**Tencent**) * 1 (**Book**)	**0.005*****	**0.039*****	**0.029*****	**0.001***	**0.003****
	(0.002)	(0.012)	(0.005)	(0.001)	(0.001)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.128	0.103	0.085	0.056	0.076
Num. obs.	62,048	185,760	62,048	62,048	62,048

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3.9: Robustness – Comparing Book Reviews with Music Reviews

	OLS estimates				
Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
1 (**Tencent**) * 1 (**Book**)	**0.003****	**0.021****	**0.015****	**0.001**	**0.001**
	(0.001)	(0.009)	(0.006)	(0.001)	(0.001)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.114	0.089	0.075	0.042	0.067
Num. obs.	62,048	185,760	62,048	62,048	62,048

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3.10: Robustness – An Alternative Sample: Jun 6, 2009 – Sep. 25, 2009

	OLS estimates				
Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
1 (**Tencent**) ∗ 1 (**Book**)	**0.004*****	**0.024*****	**0.019*****	**0.001***	**0.001**
	(0.001)	(0.009)	(0.006)	(0.001)	(0.001)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.112	0.090	0.074	0.038	0.064
Num. obs.	123,968	123,968	123,968	123,968	123,968

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3.11: Robustness – An Alternative Sample: May 9, 2009 – Oct. 23, 2009

	OLS estimates				
Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
1 (**Tencent**) ∗ 1 (**Book**)	**0.003*****	**0.019*****	**0.019*****	**0.001****	**0.001**
	(0.001)	(0.007)	(0.005)	(0.416e-03)	(0.001)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.092	0.075	0.062	0.024	0.055
Num. obs.	185,760	185,760	185,760	185,760	185,760

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3.12: Robustness – Users Joining before July 4, 2008

	OLS estimates				
Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
1 (**Tencent**) ∗ 1 (**Book**)	**0.003***	**0.026***	**0.017***	**0.001**	**0.003***
	(0.002)	(0.014)	(0.009)	(0.001)	(0.001)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.123	0.094	0.081	0.061	0.073
Num. obs.	46,080	46,080	46,080	46,080	46,080

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3.13: Robustness – Users Joining after July 4, 2008

	OLS estimates				
Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
1 (**Tencent**) ∗ 1 (**Book**)	**0.012*****	**0.088*****	**0.067*****	**0.002**	**0.003**
	(0.004)	(0.030)	(0.020)	(0.002)	(0.003)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.158	0.132	0.103	0.043	0.090
Num. obs.	15,968	15,968	15,968	15,968	15,968

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3.14: Robustness – With “Inactive” Users

	OLS estimates				
Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
1 (**Tencent**) ∗ 1 (**Book**)	**0.941e-03*****	**0.688e-04*****	**0.493e-04*****	**0.201e-03***	**0.044****
	(0.298e-03)	(0.002)	(0.001)	(0.121e-03)	(0.022)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.149	0.120	0.102	0.053	0.085
Num. obs.	376,768	376,768	376,768	376,768	376,768

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3.15: Placebo Tests – A "Fake" Shock on July 4, 2009

	OLS estimates				
Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
1 (**Tencent**) * 1 (**Book**)	**-0.002**	**-0.019**	**-0.011**	**-0.001**	**-0.137**
	(0.002)	(0.013)	(0.008)	(0.001)	(0.131)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.114	0.098	0.080	0.046	0.069
Num. obs.	61,984	61,984	61,984	61,984	61,984

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3.16: Placebo Tests – A "Fake" Shock on August 29, 2009

	OLS estimates				
Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
1 (**Tencent**) * 1 (**Book**)	**-0.001**	**-0.010**	**-0.006**	**0.000**	**-0.188**
	(0.002)	(0.012)	(0.008)	(0.001)	(0.126)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.127	0.098	0.082	0.037	0.070
Num. obs.	61,984	61,984	61,984	61,984	61,984

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

To answer our research questions, we examine a large-scale online networking platform, Douban.com, which allows its users to publish product reviews. The identification of the causal effect of peer groups hinges on a sudden and unexpected merge with a large-scale and influential online social network—an exogenous shock to the Douban network. Using this "natural experiment," we conduct DID analysis and find that, first of all, the exogenous shock caused Douban users to write more and longer reviews. Not limited to the effects on the volume of contributions, we also find statistically significant effects on the ratings. Specifically, the exogenous shock caused individual users to assign higher and more extensive ratings. Also, consistent with our hypothesis, we find that users posted reviews of higher quality (more helpful for review readers) after the merge event. Even more interestingly, we document the moderating roles of user characteristics. In particular, a user who was more active on the platform, more popular, and less knowledgeable was less affected by the exogenous shock. In other words, these characteristics all have negative moderating effects.

Our results have important managerial implications for any type of business including online platforms that rely on user contributions. The ultimate goal of these platforms is to encourage their users to speak up. Therefore, our findings suggest that they should target extending their user base. Integration with the popular social media and social networks, such as Facebook.com and Twitter.com, will be an efficient way to encourage more onsite activities. Furthermore, our results on the moderating effects suggest that platforms can pay more attention to “small” users who are less active or less popular. The larger effects on these users indicate that this can be a more efficient way of promoting active contributions.

From the operations perspective, understanding consumer incentives to post online reviews and how their behaviors are affected by online friends/audience/followers lies at the core of any company’s management of online customer responses. Our empirical findings suggest that firms can improve the ratings of their product or service and encourage consumers to post more helpful responses by using strategies to enlarge the population of the review audience and peer review writers. Furthermore, our findings of the moderating effects suggest that companies should focus on targeted groups of consumers. For example, companies should encourage less active review writers to speak up and pay more attention to those reviewers who are more knowledgeable about their own products or service.

Our study can be extended in several ways. First, in the current study, we focus on the network size effects. Future studies can explore more from the perspective of network positions. It will be interesting to study the dynamics between a user’s online contributions and his or her positions in a network. Along this line of research, future studies can explore the interrelationships between a user’s contributions and his or her neighbors’ contributions. Second, we notice that less than 25% of the sampled users ($5,823$ of $24,374$) have ever posted any reviews in our data. More on the skewness of contributions in online communities and how to remedy this problem to encourage even more contributions from the whole community may be a future direction of research. Last but not least, beyond the specific context in the current study, future research can apply similar identification strategies, the quasi-experimental analysis of similar "natural experiments," to address the endogeneity issue in social network studies.

4. Impact of Network Size on Contributions: The Moderating Roles of Contributor Characteristics

4.1. Introduction

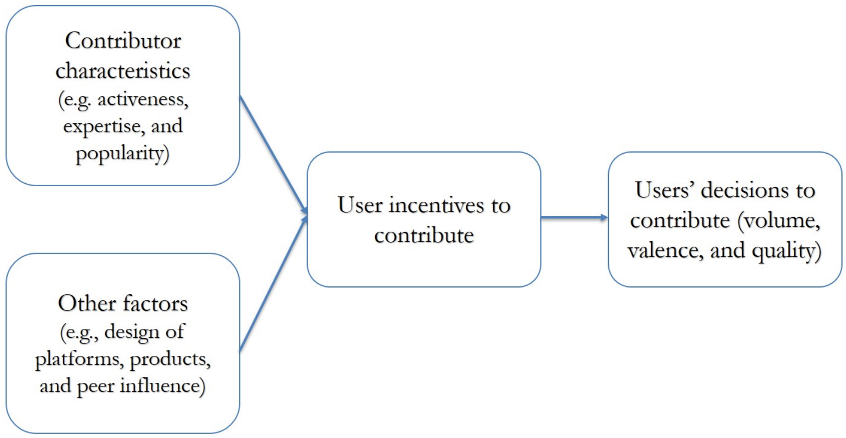
In the previous chapter we explored average impacts of the peer group size on individuals' incentives to contribute to online product reviews in the sense that we did not examine the heterogeneity in individuals, or differential impacts of peer groups. In other words, across different types of users, an enlarged population of peer review writers and audience leads to increased contribution volume, valence, and review quality. However, individuals are different in incentives to contribute, which is arguably determined by his or her characteristics including but not limited to personal preferences and experience.

It is not hard to see that individual users differ in their activeness in participation and contribution to online reviews. Literature generally observes highly skewed distributions of online activities (Wei and Xiao 2017). Active users are more self motivated in online communities than less active users, and therefore, less affected by the change in their reference groups. This implies that active users should be less affected by the merge of the two online platforms. In other words, the moderating role of a user's activeness is negative. Similarly, individuals may be distinct in their expertise or knowledge about certain products. Some users are heavy book readers while others may spend the majority of their leisure time watching movies or TV shows. The exogenous shock we considered in Chapter 3 affected the section of books (including book reviews) mainly. Therefore, it is not difficult to see that those who focused more on books and book reviews should be less influenced as they are also much more self motivated. In this chapter, we study the differential impacts of the exogenous shock by user characteristics such as a user's activeness in participation, expertise in contributions, and popularity.

Our conceptual framework is the choice model by (Hansen 1976). The idea is that the effectiveness of an influencer is moderated by environmental and contextual factors, and the interactions among these factors eventually determine the response. As illustrated by Figure 4.1, the contextual factors (or the moderating factors) we explore are contributor characteristics including activeness, expertise, and popularity. Other factors such as the platform design, products in collection, and competitions for user attention from other online platforms will also influence individual users' incentives to contribute. In addition, the effects of these additional factors are moderated by other contextual factors such as contributor characteristics. Motivated by this conceptual model, we ask whether and how the effects of the merge of Douban.com with an influential and large-scale online social network differ across different types of users.

We focus on three important aspects about an individual user, i.e., the activeness in participation, their expertise, and popularity. We use the total number of reviews

Figure 4.1: The Conceptual Frameworkd



prior to the study period and the number of followees as measures of a user's activeness. We use the number of reviews to a particular product category as the measure of an individual's expertise and the number of followers to proxy for their popularity.[1]

Interestingly, we find that the effects of the exogenous shock on either the volume, valence, or quality of reviews are smaller for individuals who had posted more reviews or followed more other users. In other words, the moderating effects of a user's activeness in participation are negative. Also interesting enough, we find that if a user had focused in writing book reviews, he or she would be more affected by the merge of two large-scale networks. More specifically, the moderating effects of a user's contributions to book reviews are positive, in sharp contrast those of other reviews are negative. Although not statistically significant, we find that one's popularity on site

[1]A caveat is that the number of followers and the number of followees are collected in 2014. Unfortunately we do not have access to the historical network data as the platform does not provide the timestamp of friendship formations.

negatively moderates the impacts of the exogenous shock. We find similar patterns from either summary statistics and regression-adjusted analysis. We conduct several robustness checks to make sure that our results are immune to several concerns.

The study is a natural extension to our understanding of the network size effects (Andreoni 2007, Zhang and Zhu 2011). We have uncovered the average impacts across different types of users in Chapter 3 and add to the literature by exploring the differential impacts of an enlarged population of reference groups by user characteristics. Our results suggest that although a larger network leads to higher incentive to contribute, the influence is not necessarily the same across different types. The findings have important practical and managerial implications. For platforms targeting at promoting contributions from users, the findings suggest that they should adopt different strategies for different users. An an example, to increase the total contributions on the platform the strategies focusing on less active users will be more effective than those targeting at more active users (or the whole population). Similarly, the platform faces a tradeoff because any promotion strategies can lead to conflicting reactions among different groups of users.

This chapter is organized as follows. We start with introducing our study context and data in Section 4.2. We discuss our research hypotheses in Section **??**. We report our empirical findings in the following section 4.3. More specifically, we start with our empirical strategies in section 4.3.1 and report findings from summary statistics in section 4.3.2 and regression-adjusted analysis in section 4.3.3. We conclude and highlight our contributions in the last section.

4.2. Evidence of Individual Heterogeneity by Observables

We study the same exogenous shock as in the previous chapter. We also focus on a relatively short time window, i.e., four weeks before and four weeks after the introduction of Douban Reading on Tencent's QZone on August 1st, 2009. An important reason we focus on this particular sample is that there was no other policy changes or major exogenous shocks to the platform. For example, Douban temporarily shut down the function of commenting on a group page in October 2009, which is not covered in our main sample.

Similarly, we focus on the group of users who posted at least one review during our study period. Table 5.1 summarizes all sampled users. We can see that users are heterogeneous in several directions. As some examples, the most active user in our sample had contributed 881 reviews by our data collection date and more than half of the sample posted no reviews at all. Similarly, the most popular user had attracted more than $80,000$ followers while the median of the follower count distribution is 33 (similar patterns for the distribution of the followee count). In addition, we observe that some users had contributed hundreds of book reviews while nothing to other categories.

We look for further evidence of heterogeneity by comparing the distribution of book review volume with that of other reviews. Figure 4.2 and 4.3 show the two distributions respectively. It is not hard to see that our sampled users do have their own expertise in review contributions. Similarly, Figure 4.4 displays the distributions of the followee count and the follower count. We can see that users are also distinct in terms of activeness in engagement and popularity.

Figure 4.2: The Distribution of Contribution Volume to *Book* Reviews

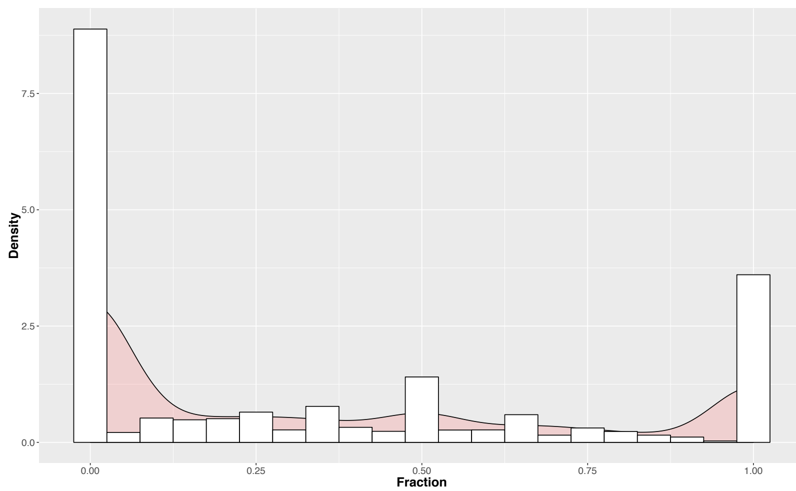


Figure 4.3: The Distribution of Contribution Volume to *Other* Reviews

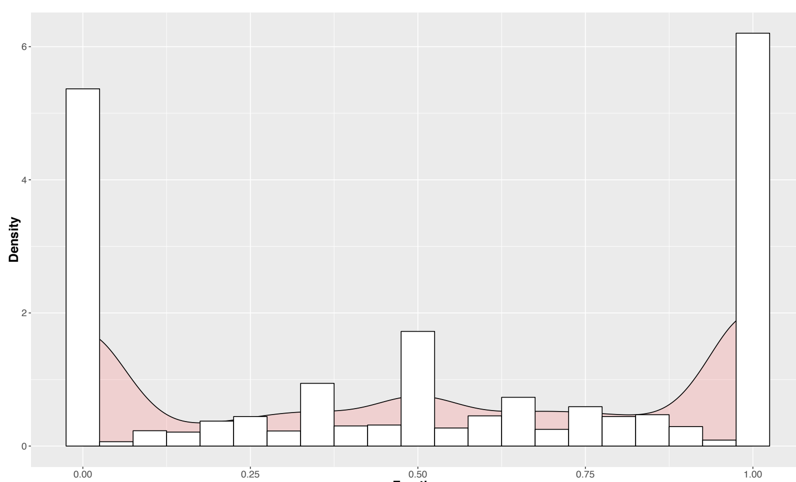
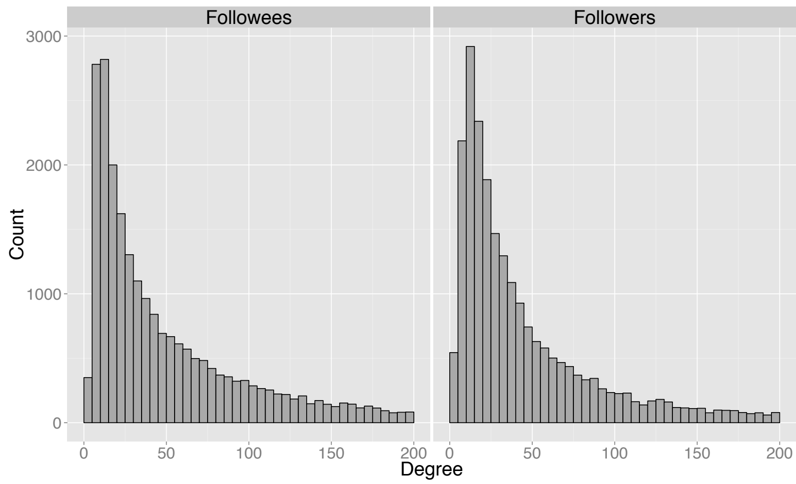


Figure 4.4: Distributions of the Followee and Follower Count



4.3. The Moderating Roles of User Characteristics

We seek answers to our research questions in this section—test our hypotheses developed in Chapter 2. We start with our main empirical strategy in Section 4.3.1 and continue with evidence from summary statistics and subsample analysis in the following section 4.3.2. In Section 4.3.3, we report the main results from regression-adjusted analysis. The last subsection 4.3.4 reports results from our robustness checks.

4.3.1. Empirical Strategies

Our main empirical strategy is a natural extension from the previous chapter. We use the introduction of Douban Reading on Tencent users' QZone as a "natural experiment" and the identification comes from the exogeneity of this merge event. To study the moderating roles of user characteristics, we are exploring how the effects of the exogenous shock vary across different types of users by some observed characteristics.[2] Our main empirical specification is a natural extension from Equation 3.1,

$$Y_{it}^{j} = \beta_0 + \beta_1 \cdot D^j \cdot D_t \cdot X_i^{\text{mod}} + \beta_2 \cdot D^j \cdot D_t + \beta_3^{'} \mathbf{X}_{it} + \beta_4 \cdot D^j + \mu_i + \nu_t + \epsilon_{it}^{j}, \quad (4.1)$$

where in addition to all variables in Equation (3.1), X_i^{mod} is a certain characteristic of the user i. In the new estimation equation, β_1 has a different interpretation. The estimates now capture the differential effects of the exogenous shock by the user characteristic X_i^{mod}. Note again that a single term of X_i^{mod} is omitted because of its collinearity with the user fixed effects μ_i. The moderating variables are summarized in Table 4.1.

4.3.2. Evidence from Subsample Analysis

We look for evidence of individual heterogeneity by starting with some subsample analysis. We aim at uncovering the moderating roles of three user characteristics, the activeness in participation, their expertise, and popularity. We first construct subsamples of users according to each of the moderating factors. Specifically, we use the number of previous reviews and the number of followees as two measures of a user's activeness. Accordingly, our first set of subsamples are three sets of users according to their review volume prior to our study period. The first subgroup consists of users

[2] In Chapter 5, we take into account the impacts of unobserved characteristics.

who had less than one review, the second less than four reviews, and the last more than four. Each group comprises of about one third of the original sample. Table 4.2 reports all regression results for each of the subsamples. More specifically, we repeat the main analysis in the previous chapter and estimate Equation 3.1 with each of the subsamples. We can see that the effects of the exogenous shock are overall smaller for more active users. For more active users, the increases in the contribution volume (Column 1 and 2 in Table 4.2), valence or review ratings (Column 3), and review quality (the last column) are all smaller.

Table 4.1: A Summary of Moderating Variables

User Characteristics	Moderating variable
Activeness	The number of reviews prior to the study period
	The number of followees
Expertise	The number of book reviews prior to the study period
	The number of other reviews prior to the study period
Popularity	The number of followers

Table 4.2: Subsample Analysis by a User's Early Reviews

	OLS estimates of the coef. for 1 (Tencent) ∗ 1 (Book)				
Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
Early # revs ≤ 1	0.007***	0.059***	0.047***	0.001	0.003*
	(0.003)	(0.020)	(0.013)	(0.001)	(0.002)
Early # revs ≤ 4	0.003	0.022	0.012	0.259e-03	0.003*
	(0.002)	(0.017)	(0.011)	(0.001)	(0.002)
Early # revs > 4	0.007*	0.039	0.027	0.002	0.001
	(0.004)	(0.031)	(0.019)	(0.002)	(0.003)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 4.3: Subsample Analysis by a User's Followee Count

	OLS estimates of the coef. for 1 (Tencent) ∗ 1 (Book)				
Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
Followee count ≤ 20	0.007***	0.054***	0.039***	0.001	0.002
	(0.002)	(0.018)	(0.013)	(0.001)	(0.001)
Followee count ≤ 51	0.005*	0.046*	0.031*	0.422e-03	0.005**
	(0.003)	(0.024)	(0.016)	(0.002)	(0.002)
Followee count ≤ 118	0.006*	0.037	0.037**	0.003**	0.001
	(0.004)	(0.027)	(0.018)	(0.002)	(0.003)
Followee count > 118	0.004	0.031	0.012	0.001	0.003
	(0.004)	(0.031)	(0.020)	(0.002)	(0.003)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Another measure of a user's activeness on the platform is the number of followees. Followees are other users a user follows. We believe that this is a good proxy of activeness because it measures how engaged a user is with activities on Douban.com. We conduct similar subsample analysis with respect to the followee count. We construct four subgroups with less than 20 followees, less than 51, less than 118, and more than 118 followees. The cutoffs are quarter percentiles of the followee count distribution. The results are reported in Table 4.3. We find similar patterns with Table 4.2.

The second user characteristic we study is a user's expertise. Arguably if a user focuses more on writing reviews for books, he or she would be more affected by the merge of Douban and Tencent's QZone as the web app only influenced book reviews directly. Therefore, we expect to observe that if a user had contributed more to book reviews, he or she would contribute event more and assign even higher and more helpful reviews. We test this conjecture by examining users according to their historical contributions to book reviews and other reviews. Table 4.4 reports the subsample analysis by the distribution of an individual's book review contributions. We separate the main sample into three categories, the user with no book reviews, less than 2 book reviews, and more than 2 book reviews. The overall pattern across volume, valence, and quality of reviews support our conjecture.

Table 4.4: Subsample Analysis by a User's Review Contributions

	OLS estimates of the coef. for $1\,(\text{Tencent}) * 1\,(\text{Book})$				
Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
	By a User's Historical Contributions to *Book Reviews*				
Hist. book revs $= 0$	0.006**	0.043**	0.034***	0.001	0.002
	(0.002)	(0.018)	(0.012)	(0.001)	(0.002)
Hist. book revs ≤ 2	0.003	0.018	0.015	0.001	0.001
	(0.002)	(0.018)	(0.012)	(0.001)	(0.002)
Hist. book revs > 2	0.011**	0.084**	0.045*	0.003	0.006
	(0.005)	(0.042)	(0.026)	(0.003)	(0.004)
	By a User's Historical Contributions to *Other Reviews*				
Hist. other revs $= 0$	0.014***	0.102**	0.078***	0.002	0.006*
	(0.004)	(0.033)	(0.022)	(0.002)	(0.003)
Hist. other revs ≤ 2	0.002	0.020	0.012	0.263e-03	0.002*
	(0.002)	(0.013)	(0.009)	(0.001)	(0.001)
Hist. other revs > 2	0.005	0.028	0.020	0.002	0.001
	(0.003)	(0.026)	(0.017)	(0.001)	(0.003)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Conversely, if a user is more interested in writing reviews in other categories, the impact of the exogenous shock will be minimal. It is not hard to see this because these users did not experience the same level of increase in the audience population of their reviews. Therefore, we would expect negative moderating roles of a user's historical contributions to reviews of other categories. Table 4.4 reports the subsample analysis and confirms our hypothesis. The more a user contributed to other reviews, the less he or she was affected by the merge event.

Last but not least, we are also interested in the moderating role of a user's popularity. We use the number of followers as the proxy for popularity. We carry out similar subsample analysis. In this case we separate the sample by a user's follower count. Specifically, we construct subsamples of users with followers less than 22, less than 52, less than 133, and more than 133. The results of estimating Equation 3.1 are reported in Table 4.5. Interestingly, we find that if a user is more popular, he or she will be less affected by the exogenous shock.

Table 4.5: Subsample Analysis by a User's Follower Count

	OLS estimates of the coef. for 1 (Tencent) ∗ 1 (Book)				
Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
Follower count ≤ 22	0.010***	0.073*	0.053***	0.247e-03	0.004**
	(0.003)	(0.019)	(0.014)	(0.001)	(0.002)
Follower count ≤ 52	0.005*	0.038*	0.030*	0.001	0.004**
	(0.003)	(0.021)	(0.015)	(0.002)	(0.002)
Follower count ≤ 133	0.001	-0.007e-03	0.002	0.003*	-0.003
	(0.003)	(0.009)	(0.017)	(0.001)	(0.003)
Follower count > 133	0.007	0.056*	0.034	0.001	0.006
	(0.004)	(0.034)	(0.021)	(0.002)	(0.004)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

4.3.3. Evidence from Regression-Adjusted Analysis

We start with the activeness of a user. A more engaged user typically spends more time on the platform. He or she may contribute more reviews and also engages more in other onsite activities. These users will be less affected by a sudden change in the population of audience or cohort review writers because their contributions are less casual compared with less active users. In this regard, we hypothesize that the exogenous shock has a smaller effect on a user's contributions in either the volume, the valence, or the quality.

We adopt two measures of a user's activeness on or engagement with the platform: the number of product reviews prior to our study period and the number of followees. Our estimation results are reported in Table 4.6 and 4.7, respectively. The estimates of β_1 in various regressions, shown in the first rows of the two tables, support our conjecture of less impact on more active users. In particular, a user who had posted more reviews before the beginning of our study period has a lower increase in contribution volume, the average and dispersion of ratings, and the quality of reviews. We find similar patterns for the other moderating characteristic, the number of followees.

Second, Douban users can have distinct interests in reviewing different types of products. A "bookworm" may have interests in writing reviews for books only, while a movie addict is only knowledgeable about and can only contribute to movie reviews. The application Douban Reading, facilitating direct access to the book section on

Douban.com, apparently increased the population of audience and review writers for books mainly. In contrast, the users who focused more on reviews in other categories did not experience the same level of growth in their reference groups. Therefore, we expect to see a larger impact of the merge event on users specialized in book reviews, but limited impact on those expert in other categories.

To formally test this conjecture, we construct two user characteristics measuring their expertise, namely the number of book reviews and other reviews prior to the study period separately. We estimate Equation (4.1) with these two moderating characteristics separately, and the results are reported in Table 4.8 and 4.9. As expected, the estimates of β_1 in Equation (4.1) for the number of book reviews are mostly positive and statistically significant, suggesting that the exogenous shock had a bigger impact on the "bookworms." In sharp contrast, the moderating effects of the number of other reviews are uniformly negative at any usual significance level.

In the last set of tests of the moderating effects, we look at the role of a user's popularity. With the similar reasoning as the moderating role of an individual's activeness, we hypothesize that the introduction of Douban Reading had a smaller impact on a more popular user. We use the number of followers as the measure of popularity and repeat the estimations of Equation (4.1). Results are reported in Table 4.10. We find that the moderating effects of the follower count are indeed negative, but not statistically significant except for the effect on the quality of reviews.

Table 4.6: Moderating Effects by the Volume of Early Reviews

Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
1 (**Tencent**) ∗ 1 (**Book**) ∗#**Early reviews**	**-0.001*****	**-0.005*****	**-0.003*****	**-0.196e-03****	**-0.050*****
	(0.289e-03)	(0.002)	(0.001)	(0.795e-04)	(0.016)
1 (Tencent) ∗ 1 (Book)	0.011***	0.070***	0.045***	0.002***	0.529***
	(0.002)	(0.014)	(0.009)	(0.001)	(0.150)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.141	0.110	0.092	0.052	0.080
Num. obs.	62,048	62,048	62,048	62,048	62,048

Table 4.7: Moderating Effects by the Number of Followees

Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
1 (**Tencent**) ∗ 1 (**Book**) ∗#**Followees**	**-0.158e-04****	**-0.103e-03***	**-0.451e-04**	**-0.194e-07**	**-0.001**
	(0.793e-07)	(0.607e-04)	(0.415e-04)	(0.286e-07)	(0.001)
1 (Tencent) ∗ 1 (Book)	0.007***	0.052***	0.034***	0.001*	0.381***
	(0.002)	(0.014)	(0.009)	(0.001)	(0.145)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.138	0.109	0.091	0.052	0.079
Num. obs.	62,048	62,048	62,048	62,048	62,048

Table 4.8: Moderating Effects by the Number of Early Book Reviews

Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
1 (**Tencent**) ∗ 1 (**Book**) ∗#**Early book reviews**	**0.001**** (0.001)	**0.009*** (0.004)	**0.005*** (0.002)	**0.343e-03** (0.260e-03)	**0.094*** (0.050)
1 (Tencent) ∗ 1 (Book)	0.004** (0.001)	0.026* (0.014)	0.022** (0.009)	0.001 (0.001)	0.111 (0.143)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.139	0.109	0.091	0.052	0.079
Num. obs.	62,048	62,048	62,048	62,048	62,048

Table 4.9: Moderating Effects by the Number of All Other Reviews Previously

Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
1 (**Tencent**) ∗ 1 (**Book**) ∗#**Early other reviews**	**-0.002***** (0.315e-03)	**-0.009***** (0.002)	**-0.005***** (0.001)	**-0.312***** (0.086e-03)	**-0.080***** (0.017)
1 (Tencent) ∗ 1 (Book)	0.011*** (0.002)	0.073*** (0.014)	0.046*** (0.009)	0.002*** (0.001)	0.558*** (0.142)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.144	0.111	0.092	0.053	0.081
Num. obs.	62,048	62,048	62,048	62,048	62,048

Table 4.10: Moderating Effects by the Number of Followers

Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
1 (**Tencent**) $*$ 1 (**Book**) $*$**#Followers**	**-0.226e-07**	**-0.166e-04**	**-0.667e-07**	**-0.708e-09**	**-0.266e-03***
	(0.151e-07)	(0.128e-04)	(0.885e-07)	(0.489e-09)	(0.137e-03)
1 (Tencent) $*$ 1 (Book)	0.006***	0.046***	0.031***	0.001*	0.327**
	(0.002)	(0.013)	(0.009)	(0.001)	(0.134)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.138	0.109	0.091	0.052	0.079
Num. obs.	62,048	62,048	62,048	62,048	62,048

4.3.4. Robustness Checks

We conduct similar robustness checks as in Chapter 3. Specifically, we separate the control group (of all other reviews) into movie reviews and music reviews. We compare each of the subgroups to the treatment group (book reviews) and repeat our main analysis. We extend our study period to 16 weeks and 32 weeks before and after the exogenous shock. We construct two subsamples with users who joined the platform at least one year before the merge of two platforms and those with less than one year tenure on site. Last but not least, we include all "silent" users who did not speak up during our study period.[3]

Results are reported in Table 4.11 through 4.17. It is not surprise that these results are not significantly different from our main results. Table 4.11 reports the estimates of the moderating effects of all five user characteristics (the number of early reviews and followees as two measures of a user's engagement with the platform, early contributions to book reviews versus other reviews as their expertise, and the number of followers as a proxy for their popularity) for the first robustness check by comparing book reviews with movie reviews. Similarly, the other tables report the similar set of regressions for other robustness checks.

[3]The main sample used throughout this dissertation consists of all users who posted at least one review during our main study period, which is four weeks before and four weeks after the exogenous shock.

Table 4.11: Robustness 1 – Comparing Book Reviews with *Movie Reviews*

Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
	Moderating factor: Activeness				
1 (**Tencent**) ∗ 1 (**Book**) ∗**#Early reviews**	**-0.821e-04**	**-0.001**	**-0.360e-03**	**-0.166e-04**	**-0.487e-04**
	(0.112e-03)	(0.001)	(0.001)	(0.458e-04)	(0.982e-04)
1 (**Tencent**) ∗ 1 (**Book**) ∗**#Followees**	**-0.601e-07**	**-0.366e-04**	**-0.443e-07**	**-0.810e-08**	**-0.399e-07**
	(0.745e-07)	(0.058e-03)	(0.398e-04)	(0.277e-07)	(0.770e-07)
	Moderating factor: Expertise				
1 (**Tencent**) ∗ 1 (**Book**) ∗**#Early book reviews**	**0.001****	**0.010****	**0.005****	**0.333e-03**	**0.001****
	(0.001)	(0.004)	(0.002)	(0.259e-03)	(0.492e-03)
1 (**Tencent**) ∗ 1 (**Book**) ∗**#Early other reviews**	**-0.282e-03****	**-0.002****	**-0.001****	**-0.066e-03***	**-0.199e-03****
	(0.109e-03)	(0.001)	(0.001)	(0.086e-03)	(0.898e-04)
	Moderating factor: Popularity				
1 (**Tencent**) ∗ 1 (**Book**) ∗**#Followers**	**-0.190e-07**	**-0.151e-04**	**-0.620e-07**	**-0.614e-09**	**-0.222e-07***
	(0.147e-07)	(0.128e-04)	(0.887e-07)	(0.461e-09)	(0.134e-07)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 4.12: Robustness 2 – Comparing Book Reviews with *Music Reviews*

Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
	Moderating factor: Activeness				
1 (**Tencent**) ∗ 1 (**Book**) ∗#**Early reviews**	**-0.001***	**-0.002**	**-0.001**	**-0.111e-03**	**-0.251e-03**
	(0.327e-03)	(0.002)	(0.001)	(0.809e-04)	(0.179e-03)
1 (**Tencent**) ∗ 1 (**Book**) ∗#**Followees**	**-0.186e-07**	**-0.352e-04**	**-0.337e-04**	**-0.736e-08**	**-0.414e-07**
	(0.669e-07)	(0.538e-04)	(0.372e-04)	(0.251e-07)	(0.735e-07)
	Moderating factor: Expertise				
1 (**Tencent**) ∗ 1 (**Book**) ∗#**Early book reviews**	**0.002*****	**0.018*****	**0.009*****	**0.494e-03***	**0.002*****
	(0.001)	(0.004)	(0.002)	(0.260e-03)	(0.481e-03)
1 (**Tencent**) ∗ 1 (**Book**) ∗#**Early other reviews**	**-0.001*****	**-0.006*****	**-0.003*****	**-0.216e-03****	**-0.001*****
	(0.354e-03)	(0.002)	(0.001)	(0.869e-04)	(0.185e-03)
	Moderating factor: Popularity				
1 (**Tencent**) ∗ 1 (**Book**) ∗#**Followers**	**-0.393e-08**	**-0.512e-08**	**0.136e-07**	**-0.311e-09**	**-0.436e-08**
	(0.144e-07)	(0.123e-04)	(0.858e-07)	(0.349e-09)	(0.123e-07)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 4.13: Robustness 3 – An Alternative Sample: June 6, 2009 – September 25, 2009

Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
			Moderating factor: Activeness		
1 (**Tencent**) ∗ 1 (**Book**) ∗**#Early reviews**	**-0.001*****	**-0.004*****	**-0.005*****	**-0.263e-03***	**-0.023**
	(0.198e-03)	(0.001)	(0.001)	(0.162e-03)	(0.020)
1 (**Tencent**) ∗ 1 (**Book**) ∗**#Followees**	**-0.189e-03*****	**-0.273e-03****	**-0.322e-04**	**-0.296e-08**	**-0.452e-03**
	(0.465e-06)	(0.532e-04)	(0.290e-04)	(0.266e-07)	(0.001)
			Moderating factor: Expertise		
1 (**Tencent**) ∗ 1 (**Book**) ∗**#Early book reviews**	**0.003*****	**0.011*****	**0.006****	**0.567e-03**	**0.040***
	(0.001)	(0.002)	(0.004)	(0.421e-03)	(0.029)
1 (**Tencent**) ∗ 1 (**Book**) ∗**#Early other reviews**	**-0.003*****	**-0.016*****	**-0.007*****	**-0.299*****	**-0.096*****
	(0.468e-03)	(0.004)	(0.002)	(0.001)	(0.015)
			Moderating factor: Popularity		
1 (**Tencent**) ∗ 1 (**Book**) ∗**#Followers**	**-0.389e-08**	**-0.279e-03**	**0.369e-08**	**-0.896e-09**	**-0.375e-03***
	(0.163e-07)	(0.193e-03)	(0.251e-07)	(0.572e-09)	(0.122e-03)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 4.14: Robustness 4 – An Alternative Sample: May 9, 2009 – October 23, 2009

Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
	Moderating factor: Activeness				
1 (**Tencent**) ∗ 1 (**Book**) ∗#**Early reviews**	**-0.360e-03**	**-0.004**	**-0.001**	**-0.259e-04**	**-0.032****
	(0.322e-03)	(0.003)	(0.001)	(0.325e-04)	(0.020)
1 (**Tencent**) ∗ 1 (**Book**) ∗#**Followees**	**-0.129e-04***	**-0.938e-04***	**-0.333e-04**	**-0.255e-08**	**-0.687e-04**
	(0.960e-05)	(0.509e-04)	(0.211e-04)	(0.396e-08)	(0.102e-03)
	Moderating factor: Expertise				
1 (**Tencent**) ∗ 1 (**Book**) ∗#**Early book reviews**	**0.001**	**0.007***	**0.004**	**0.683e-03**	**0.033**
	(0.001)	(0.004)	(0.003)	(0.700e-03)	(0.029)
1 (**Tencent**) ∗ 1 (**Book**) ∗#**Early other reviews**	**-0.001***	**-0.006****	**-0.002**	**-0.278****	**-0.066***
	(0.001)	(0.003)	(0.002)	(0.001)	(0.030)
	Moderating factor: Popularity				
1 (**Tencent**) ∗ 1 (**Book**) ∗#**Followers**	**-0.200e-07**	**-0.106e-04**	**0.878e-07**	**-0.777e-09**	**-0.368e-04**
	(0.262e-07)	(0.138e-04)	(0.886e-07)	(0.609e-09)	(0.176e-03)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 4.15: Robustness 5 – Users Joining *before* July 4, 2008

Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
	Moderating factor: Activeness				
1 (**Tencent**) ∗ 1 (**Book**) ∗**#Early reviews**	**-0.001***** (0.299e-03)	**-0.005***** (0.002)	**-0.003***** (0.001)	**-0.187e-03**** (0.811e-04)	**-0.057***** (0.016)
1 (**Tencent**) ∗ 1 (**Book**) ∗**#Followees**	**-0.209e-04**** (0.844e-07)	**-0.134e-03**** (0.651e-04)	**-0.070e-03*** (0.412e-04)	**-0.344e-07** (0.320e-07)	**-0.002**** (0.001)
	Moderating factor: Expertise				
1 (**Tencent**) ∗ 1 (**Book**) ∗**#Early book reviews**	**0.001*** (0.001)	**0.010**** (0.005)	**0.004** (0.003)	**0.411e-03*** (0.247e-03)	**0.049** (0.050)
1 (**Tencent**) ∗ 1 (**Book**) ∗**#Early other reviews**	**-0.002***** (0.325e-03)	**-0.008***** (0.002)	**-0.005***** (0.001)	**-0.298e-03***** (0.886e-04)	**-0.082***** (0.017)
	Moderating factor: Popularity				
1 (**Tencent**) ∗ 1 (**Book**) ∗**#Followers**	**-0.286e-07*** (0.156e-07)	**-0.208e-04** (0.135e-04)	**-0.901e-07** (0.950e-07)	**-0.323e-09** (0.404e-09)	**-0.353e-03***** (0.130e-03)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 4.16: Robustness 6 – Users Joining *after* July 4, 2008

Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
			Moderating factor: Activeness		
1 (**Tencent**) ∗ 1 (**Book**) ∗#**Early reviews**	**-0.239e-04** (0.001)	**-0.004** (0.005)	**0.538e-03** (0.343e-03)	**-0.372e-03** (0.444e-03)	**0.085** (0.078)
1 (**Tencent**) ∗ 1 (**Book**) ∗#**Followees**	**-0.128e-04** (0.216e-04)	**-0.725e-04** (0.162e-03)	**-0.968e-04** (0.147e-03)	**-0.733e-07** (0.585e-07)	**-0.002** (0.003)
			Moderating factor: Expertise		
1 (**Tencent**) ∗ 1 (**Book**) ∗#**Early book reviews**	**0.002** (0.002)	**0.006** (0.010)	**0.011** (0.007)	**0.146e-03** (0.001)	**0.481***** (0.179)
1 (**Tencent**) ∗ 1 (**Book**) ∗#**Early other reviews**	**-0.001** (0.001)	**-0.011**** (0.006)	**-0.003** (0.004)	**-0.001** (0.489e-03)	**-0.021** (0.087)
			Moderating factor: Popularity		
1 (**Tencent**) ∗ 1 (**Book**) ∗#**Followers**	**-0.419e-07** (0.388e-07)	**-0.277e-04** (0.286e-04)	**-0.173e-04** (0.144e-04)	**-0.324e-08** (0.489e-09)	**0.001** (0.001)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 4.17: Robustness 7 – “Silent” Users

Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
	Moderating factor: Activeness				
1 (**Tencent**) ∗ 1 (**Book**) ∗#**Early reviews**	**-0.829e-03*****	**-0.590e-04*****	**-0.388e-04*****	**-0.201e-03****	**-0.039*****
	(0.886e-04)	(0.111e-04)	(0.100e-04)	(0.801e-04)	(0.010)
1 (**Tencent**) ∗ 1 (**Book**) ∗#**Followees**	**-0.378e-05****	**-0.866e-05***	**-0.578e-05**	**-0.220e-07**	**-0.002**
	(0.870e-06)	(0.520e-05)	(0.622e-05)	(0.198e-07)	(0.002)
	Moderating factor: Expertise				
1 (**Tencent**) ∗ 1 (**Book**) ∗#**Early book reviews**	**0.798e-03***	**0.166e-03***	**0.378e-03***	**0.290e-03**	**0.062***
	(0.620e-03)	(0.125e-03)	(0.269e-03)	(0.252e-03)	(0.028)
1 (**Tencent**) ∗ 1 (**Book**) ∗#**Early other reviews**	**-0.950e-04*****	**-0.328e-03*****	**-0.320e-03*****	**-0.312*****	**-0.080*****
	(0.168e-04)	(0.140e-04)	(0.446e-04)	(0.086e-03)	(0.017)
	Moderating factor: Popularity				
1 (**Tencent**) ∗ 1 (**Book**) ∗#**Followers**	**-0.478e-08**	**-0.260e-05**	**-0.982e-08**	**-0.889e-09**	**-0.398e-04***
	(0.787e-08)	(0.101e-04)	(0.169e-07)	(0.750e-09)	(0.120e-04)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

4.4. Concluding Remarks

4.4.1. Implications

Our findings in this chapter have important implications both theoretically and managerially. First, the findings about the moderating roles of several user characteristics enhances our understanding that the contributions to online user-generated content are not homogenous across different types of users. They extend our traditional views about the private provision of public goods in the sense that individual-specific characteristics play a role in their incentives to contribute. In particular, their past experience and expertise deviates a particular individual from the average level of motivations. These in turn have important managerial implications for the third-party platforms as well as product or service providers.

First, our findings about the differential impacts of a larger audience by user characteristics suggest that platforms that rely on user contributions should adopt different promotion strategies in different user groups. The target of these platforms is to encourage the users to speak up. Therefore, in addition to our managerial suggestions from the last chapter, the results in the current chapter indicate that universal strategies that aim at all users equally may not be a good one. For a concrete example, the negative role of user activeness suggest that platforms should target at encouraging the less active users to contribute because the promotion strategies will have a bigger effect on these users (similar for those less popular users). Second, from the product or service providers' perspective, our findings, particularly the positive role of a user's expertise, suggest that they should target at the "VIP" users who specialize in the same category. For example, movie producers should encourage the movie review experts to write reviews for their products. This can be more effective in promoting sales through online reviews.

4.4.2. Summaries

As a quick summary, in this chapter we study a natural extension from the previous chapter on average treatment effects of network sizes. We have uncovered that, in Chapter 3, an enlarged population of peer groups causes individual users to post more and longer reviews, assign higher and more dispersed ratings, and post reviews of higher quality. But are these effects necessarily the same across different types of users? In particular, what are the moderating roles of some observed user characteristics? These are the research questions to which we seek answers in the current chapter.

We study three important user characteristics including a user's activeness in participation, his or her expertise in contributions, and popularity. The theoretical framework is the choice model (Hansen 1976) that conceptualizes how the moderating factors interact with our main variable of interests in affecting an individual's review writing behavior. Our identification strategy is the same as in Chapter 3. We utilize the merge between Douban.com and Tencent's QZone to uncover the moderating effects of the three user characteristics.

We find that first of all, a more active user tends to be less affected by the merge event. More specifically, if a user has contributed more in the past, the increases in volume, valence, and helpfulness are smaller than less active users. Second, also interesting enough, a user who focuses more on book reviews value the exogenous shock more than those focusing on other categories and contribute even more to book reviews, assign even higher ratings, and post even more helpful reviews. Last but not least, although not significant at the usual significance level, a more popular user (with more followers) was less affected by the merge event in the sense that all increases were smaller.

This study contributes to the online review literature by uncovering the moderating effects of user characteristics (Zhu and Zhang 2010). In addition, unlike most papers in this literature, we study individual users' incentives to contribute, and therefore focus on individual users' activities; while most other papers focus on the review- or product- level analysis. Our findings have important managerial implications. Platforms that target at promoting more active contributions should adopt different strategies for different groups of users. As an example, our findings suggest that platforms should adopt strategies to make less active users speak up, because the effects of such strategies will be bigger than strategies targeting at all users.

5. Heterogeneity in Peer Effects: An Application of Finite Mixture Models

5.1. Introduction

The theme of this dissertation is the impacts of reference group sizes on individuals' incentives to contribute to online product reviews. As we discussed in the last two chapters, the biggest challenge we face is to identify the "real" effects as in observational data (Manski 1993, Goldsmith-Pinkham and Imbens 2013), the size of a user's reference group is inherently correlated with his or her intrinsic motivations to write reviews, which is generally unobserved to researchers. Therefore, we use the exogenous shock, in particular the special structure of the merge, as a "natural experiment" to identify the impacts of network sizes on individuals' review posting behavior. In Chapter 3, we found that individuals, on average, contribute more reviews, assign higher ratings, and post more helpful reviews in a large network. Being a step forward, we found that, in Chapter 4, individuals differ in their response to the exogenous shock by some of their observed characteristics including but not limited to engagement, expertise, and popularity.

However, individuals differ not only in terms to their observed characteristics or contribution histories, but also to the extent of their unobservables. As a simple example, Douban users are different in their motivation levels. Some users are highly motivated and fascinated in writing reviews, while some others may be much less motivated and are even free riders on the platform. Or, users can also differ in the level of their knowledge about a book, a movie, or a piece of music. The heterogeneity in individuals not only post greater challenges to our identification but also is more important in terms of managerial implications. Unless we are able to reach a better understanding of individuals' heterogeneity in contributions, either observed as in Chapter 4 or unobserved as in the current chapter, can we make a more helpful managerial recommendations for platforms as well as any companies targeting at social media marketing.

In this Chapter we employ the Finite Mixture Model (FMM) (Bapna et al. 2011) to identify the heterogeneity in individuals' unobserved characteristics. More specifically, a finite mixture model separate users into segments based on users' unobserved actions (outcome variables or decisions) and characteristics (as a set of control covariates). This model is widely used in statistics and other closely related disciplines to control for an individual's unobserved heterogeneity.

We identify three types of users that exhibit different patterns of contributions. The first segment of users exhibit highest increase in their motivations to contribute after the introduction of Douban Reading on Tencent users' QZone space. The second type is a medium group in the sense that the increases in their contribution volume, valence, and helpfulness are all moderate compared to the first and the last group. The last segment is the least motivated group in that their response to the exogenous shock is not statistically significant. These findings have important managerial implications. Platforms that target at promoting more active contributions from users should look at not only the users' observed characteristics but also intrinsic motivations that are in general unknown to the platforms. These findings also suggest that online content that have been generated by individual people can be biased in the sense that only highly motivated individuals will speak up on the Internet. The content also reflects the opinions of those who have high incentives to contribute. A caveat is that when we study online user-generated content we should be more careful in the interpretation.

The findings in the current chapter speak to the results from Chapter 4. In the previous chapter, we hypothesize that user characteristics such as activeness, expertise, and popularity play a moderating role in the effects of the exogenous shock we consider in this thesis. Empirical findings support all our hypotheses. A main takeaway from these findings is that users differ in responding to the exogenous shock according to several observed characteristics. This further suggests that there must be some underlying and unobserved characteristics about a user that may also moderate the effects of an expanded population of peer reviewers or audience. The main purpose of the current chapter is to extend from the last one and use some statistical methods, FMM methods as an example, to uncover the hidden types of users. Our results indicate that there do exist such various types. Therefore, this chapter complete our understanding how a user's characteristics moderate the main effects found in Chapter 3.

This chapter makes several contributions to the literature of user-generated content, online reviews, and economics. As we discussed above, we contribution to the extensive literature of UGC by providing evidence that only highly motivated individuals will contribute to online content (Gu et al. 2007). A natural extension from the current study would be to explore the implications or outcomes of this finding about potentially biased content online. Another literature we contribute to is on online reviews (Zhang and Zhu 2011, Goes, Lin, and Au Yeung 2014, Huang, Hong, and Burtch 2016, Khern-am-nuai and Kannan 2016). Along with the previous two chapters, we add to this literature by exploring individual heterogeneity in the production of online word of mouth. We use the FMM to help identify different types of users according to their unobserved characteristics. Last but not least, we also contribute the long standing economics literature on private provision of public goods by extending our understanding to incorporate individual heterogeneity in underlying incentives.

This chapter is organized as follows. We start with a brief review of our research context and the data sets we use in our empirical analysis in Section 5.2. We continue with a detailed development of the FMM in our context in Section 5.3.1. The next section, Section 5.3.2, report our main findings and discuss. We summarize in the last section.

5.2. Research Context

5.2.1. Individual Heterogeneity in Contributions

We seek answers to our research questions using the same set of data as in the last two chapters. We study the same platform because of the following reasons. Douban provides a platform for individuals to contribute to product reviews. The platform does not sell the products themselves. Instead, they serve as an online community for individuals users to interact with each other. Therefore, the platform's incentive (be it monetary or not) is not a particular concern of contaminating individual users' incentives to contribute. Our study period is a relatively short period of time in mid 2009. Review writers in early years, like in our current context, were arguably not driven by outside resources like potentially monetary payment from third-parties or the product sellers (Goes, Lin, and Au Yeung 2014, Khern-am-nuai and Kannan 2016). We argue that during our study period intrinsic motivation was still the main reason individuals contribute to online reviews. Third and most importantly, we argued in the last two chapters, the exogenous shock to Douban network provides us a chance to identify the network size effects. Therefore, we explore the same event and use the same data sets in this chapter.

We have uncovered some interesting cases of differences in individuals' contributions by their observed characteristics. As a quick review, in Chapter 4, we found that individual users who have posted more reviews and are followed by more other users are less affected in the sense that the increases in contribution volume, valence, and helpfulness were all smaller. Also interesting enough, a user who was more active in the book section was more affected by the merge event; while a user who focused more on other reviews was less affected because apparently these users did not experience the same level of increase in their audience or peer review writers. Third, although not statistically significant, the popularity of a user plays a negative moderating role in a user's incentives to contribute to online reviews. These findings suggest individuals differ significantly in response to the exogenous shock by their observed characteristics.

5.2.2. Data and Variables

We focus on the same period of time as in the last two chapters. Specifically, we study the period four weeks before and four weeks after the exogenous shock on August 1, 2009. We study this period to control for any other policy changes on the platform. We carry out robustness checks by extending the sample to a longer period. Our dependent variables are summarized in Table 3.4. Our moderating factors are summarized in Table 4.1.

Table 5.1 reports summary statistics for the sample of users and all their reviews by the data collection date. Note that $5,823$ of $24,374$ users had posted at least one product review by November 1, 2014. Among these "active" users, the average number of reviews ever posted is around 7. Among all the reviews, about 36% are in the book section, and more than 50% are reviews of movies or TV shows. The rest are music reviews. The average rating had reached over 4 (out of 5) up to November 2014, with the average number of helpful votes greater than 7 and the percentage of helpful votes over 43%. Note that the distribution of the volume of reviews is highly skewed, with over half the population contributing nothing. This phenomenon of "specialization" is consistent with theory predictions on the private provision of public goods in social networks (Bramoullé and Kranton 2007).

5.3. Empirical Analysis

5.3.1. Empirical Strategy

Our baseline model is similar to the main specification in Chapter 3. As a quick review and for the purpose of further reference, the baseline model considered in this chapter is as follows,

$$Y_{it}^{j} = \beta_0 + \beta_1 \cdot D^j \cdot D_t + \beta_2' \mathbf{X}_{it} + \beta_3 \cdot D^j + \nu_t + \epsilon_{it}^{j}, \tag{5.1}$$

Recell that Y is one of the dependent variables in Table 3.4. The coefficient of the interaction term, β_1, captures the causal effects of an enlarged network on the outcome variable. Notice that the difference between the equation 3.1 and 5.1 is that there is no individual user dummies in Equation 5.1. The reason is that including a more granular variable will make the main equation of interests not identified.

Table 5.1: Summary Statistics of All Sampled Users and Reviews

	Statistics				
Variables	Median	Mean	s.d.	Min.	Max.
User Information					
# All reviews	0	2.570	12.603	0	881
# Groups	43	66.536	68.274	0	2,004
# Followees	36	78.926	142.174	0	2,144
# Followers	33	158.171	1,517.220	0	88,656
1 (Missing followers)	0	0.002	0.044	0	1
Length on site[a]	424	498.221	365.539	1	1,613
Book Collections					
# Reading	2	6.556	36.526	0	3,217
# Wish list	10	53.530	230.823	0	15,908
# Read	21	65.255	142.938	0	5,236
Movie Collections					
# Watching	0	3.164	8.101	0	245
# Wish list	13	72.420	204.302	0	9,530
# Watched	99	247.785	377.361	0	7,201
Music Collections					
# Listening	1	7.587	35.956	0	2,784
# Wish list	2	18.053	133.431	0	16,287
# Listened	10	87.472	323.902	0	10,049
Users			24,374		
Review Information					
Length of review[b]	513	859.241	1,966.795	0	297,620
# Helpful votes	1	7.739	76.175	0	10,324
# Non-helpful votes	0	1.009	6.162	0	455
Helpfulness votes (%)[c]	20	43.836	45.845	0	100
Rating (1 - 5)	4	4.050	0.939	1	5
1 (Missing rating)	0	0.018	0.135	0	1
1 (After Douban Reading)	0	0.489	0.500	0	1
Users			5,823		
Book reviews			14,969		
Movie reviews			21,150		
Music reviews			5,575		
All reviews			41,774		

[a]The number of days since a user's registration till Aug. 1, 2009, the date of the exogenous shock.

[b]The length of the review content, not including title.

[c]The score equals #helpful votes / (#helpful votes + #non-helpful votes).

In Equation 5.1 we assume that the effects of the exogenous shock are the same across individual users. We employ the Finite Mixture Model to relax this assumption and help us identify the unobserved segments of users. The basic assumption underlying an FMM is that individuals within a segment are homogenous in their motivations to contribute, while individuals in different segments are different in preference (Bapna et al. 2011). Using a finite mixture model we can better control for unobserved individual heterogeneity among Douban users. In addition, as we mentioned, an FMM method offers deeper managerial insights than the average effects.

We assume that there are S segments of Douban users. The segments differ in users' unobserved factors governing their preferences in contributions. There are S different sets of coefficients $\beta = \left(\beta_0, \beta_1, \beta_2^{'}, \beta_3\right)$. Let β^s denote the set of coefficients for segment $s \in \{1, 2, 3, ..., S\}$. A finite mixture model hinges on the functional form assumption of the error term ϵ_{it}^{j}. Without much loss of generality, we assume that the error term has a standard normal distribution conditional on all observables. Specifically, we assume that $\epsilon_{it}^{j} | \left(D^j, D_t, \mathbf{X}_{it}, \nu_t\right) \sim N(0,1)$. Let $f(\cdot)$ denote the probability density function of a standard normal distribution. Then the probability of observing a datum will be $f\left(Y_{it}^{j} - (\beta_0^s + \beta_1^s \cdot D^j \cdot D_t + \beta_2^{'s} \mathbf{X}_{it} + \beta_3^s \cdot D^j + \nu_t)\right)$. We let $\hat{Y}_{it}^{js} = \beta_0^s + \beta_1^s \cdot D^j \cdot D_t + \beta_2^{'s} \mathbf{X}_{it} + \beta_3^s \cdot D^j + \nu_t$ and thus the probability becomes

$f\left(Y_{it}^{j}-\hat{Y}_{it}^{js}\right)$. Hence the probability of observing a user i in segment s will be,

$$L_{i|s}=\prod_{j=T,C}\prod_{t=1}^{8}f\left(Y_{it}^{j}-\hat{Y}_{it}^{js}\right) \tag{5.2}$$

As econometricians, we do not observe which segment an individual user belongs to. We only observe their outcomes and some observed characteristics. Therefore, we use the maximum likelihood estimation method to estimate the coefficient β that maximizes the unconditional likelihood of observing the data at hand. In a standard finite mixture model, the unconditional likelihood for an individual user i will be equal to the weighted sum of the conditional likelihood of belonging to segment s. Specifically, the unconditional likelihood function will be,

$$L=\prod_{i=1}^{n}\sum_{s=1}^{S}\pi_s\cdot L_{i|s}, \tag{5.3}$$

where π_s is the weight of segment s with $\pi_s\in[0,1]$ and $\sum_{s=1}^{S}\pi_s=1$.

Instead of maximizing the likelihood function 5.3 directly, which might run into computational hurdles, we maximize the log likelihood by taking natural log of the likelihood function. The log-likelihood function looks like,

$$\ln L=\sum_{i=1}^{n}\sum_{s=1}^{S}\pi_s\cdot\ln L_{i|s} \tag{5.4}$$

The coefficient estimate $\hat{\beta}$ that maximizes $\ln L$ is the ML estimate.

5.3.2. Results

Segmentation An important question in a finite mixture model is how many segments we should separate the sample into. To determine the number of segments, we use the likelihood based information criteria including AIC and BIC for our main sample. We report the fit statistics in Table 5.2. Overall, the 3-segment model outperforms any other models in BIC and is only second to the 4-segment model in terms of AIC. However, the gain in AIC in the 4-segment model is really marginal and negligible overall. Similar to Tan, Lu, and Tan (2016), if we take into account the interpretation of the segments, we find that a 3-segment model is preferred to a 4-segment model. Specifically, with a 3-segment model, we interpret the segments as groups of users with high, mediocre, and low motivations to contribute.

We use the pseudo R^2 to infer the explanatory power of different models. We see an increase from 1-segment model to 2-segment model. But the gain in explanatory power jumps dramatically from 2-segment model to 3-segment model. Specifically, the power almost doubles from 3.8% to 7.5%. Although we observe that the pseudo R^2 keeps increasing with more segments, the gain become marginal in the models with more than three segments. This corroborates our choice of three-segment model.

Segment Characteristics We take a closer look at the segments of users by their observed characteristics, which offers us a foundation for the interpretation of various segments. Table 5.3 to 5.4 summarize these three segment separately. We look at not only the observed characteristics such as a user's networks but also his or her

Table 5.2: Fitness Statistics

Num. obs.	62,048
One-segment model	
Log likelihood	-3.269e+04
AIC	1.066e+05
BIC	1.068e+05
Pseudo R^2	0.026
Two-segment model	
Log likelihood	-2.980e+04
AIC	1.062e+05
BIC	1.066e+05
Pseudo R^2	0.038
Three-segment model	
Log likelihood	-2.800e+04
AIC	1.050e+05
BIC	1.052e+05
Pseudo R^2	0.075
Four-segment model	
Log likelihood	-2.629e+04
AIC	1.048e+05
BIC	1.053e+05
Pseudo R^2	0.080
Five-segment model	
Log likelihood	-2.590e+04
AIC	1.049e+05
BIC	1.055e+05
Pseudo R^2	0.081

information on product reviews. It is apparent that users in the third segment (Table 5.5) are more "active" than the other two segments by posting more reviews, joining more groups, and having both more followers and more followees. In addition, interestingly, these more "motivated" users wrote longer reviews and assign higher ratings. We interpret this segment (Segment III) as users with high motivations, the second segment as mediocre users and the last one as those with low motivations.

Table 5.3: Summary Statistics of Segment I

Variables	Median	Mean	s.d.	Min.	Max.
		User Information			
# All reviews	0	2.038	12.287	0	362
# Groups	36	58.092	66.243	0	190
# Followees	30	69.345	140.706	0	972
# Followers	28	139.645	1,502.465	0	9,764
1 (Missing followers)	0	0.002	0.042	0	1
Length on site[a]	368	460.364	352.687	1	669
		Review Information			
Length of review[b]	506	819.642	1,610.635	0	200,693
# Helpful votes	0	7.036	66.609	0	2,679
# Non-helpful votes	0	0.892	5.938	0	288
Helpfulness votes (%)[c]	20	40.239	42.960	0	100
Rating (1 - 5)	3.5	3.886	0.902	1	5
1 (Missing rating)	0	0.021	0.117	0	1
1 (After Douban Reading)	0	0.462	0.482	0	1
Users			1,875		

[a]The number of days since a user's registration till Aug. 1, 2009, the date of the exogenous shock.
[b]The length of the review content, not including title.
[c]The score equals #helpful votes / (#helpful votes + #non-helpful votes).

Notice that almost half of the sample fall into the low motivation segment, while less than a quarter of them are highly motivated. This observation is consistent with other studies of online user-generated content in the sense that most users are under participating. The rest analysis will be based on this segmentation.

Heterogeneous Effects We report the estimates of β_1^s in Table 5.6. The s denotes the low motivation segment when it takes the value of 1, the mediocre motivation group when it takes the value of 2, and the high motivation segment when it takes the value

Table 5.4: Summary Statistics of Segment II

Variables	Median	Mean	s.d.	Min.	Max.
User Information					
# All reviews	1	2.612	13.549	1	476
# Groups	48	70.862	66.008	0	892
# Followees	42	81.118	139.458	0	2,144
# Followers	36	170.374	1,248.013	0	23,760
1 (Missing followers)	0	0.003	0.050	0	1
Length on site[a]	466	520.348	335.178	1	892
Review Information					
Length of review[b]	520	880.325	1899.345	0	220,645
# Helpful votes	1	8.028	70.135	0	5,098
# Non-helpful votes	0	1.279	5.892	0	299
Helpfulness votes (%)[c]	20	45.698	42.235	0	100
Rating (1 - 5)	4	4.178	0.901	1	5
1 (Missing rating)	0	0.020	0.128	0	1
1 (After Douban Reading)	0	0.506	0.500	0	1
Users			1,167		

[a]The number of days since a user's registration till Aug. 1, 2009, the date of the exogenous shock.

[b]The length of the review content, not including title.

[c]The score equals #helpful votes / (#helpful votes + #non-helpful votes).

Table 5.5: Summary Statistics of Segment III

Variables	Median	Mean	s.d.	Min.	Max.
		User Information			
# All reviews	2	4.075	16.236	0	881
# Groups	56	72.374	80.234	2	2,004
# Followees	58	88.239	166.458	0	1,984
# Followers	56	170.932	1,830.350	0	88,656
1 (Missing followers)	0	0.002	0.052	0	1
Length on site[a]	520	559.305	468.348	1	1,613
		Review Information			
Length of review[b]	586	903.346	2248.001	0	297,620
# Helpful votes	3	9.032	88.560	0	10,324
# Non-helpful votes	0	1.338	8.058	0	455
Helpfulness votes (%)[c]	20	48.023	50.118	0	100
Rating (1 - 5)	4	4.306	0.947	1	5
1 (Missing rating)	0	0.011	0.208	0	1
1 (After Douban Reading)	0	0.519	0.516	0	1
Users			836		

[a]The number of days since a user's registration till Aug. 1, 2009, the date of the exogenous shock.

[b]The length of the review content, not including title.

[c]The score equals #helpful votes / (#helpful votes + #non-helpful votes).

of 3. A caveat is that the segmentation is based upon all observed covariates with no constraints in weighing the different factors.

First, we find that the introduction of Douban Reading on Tencent QZone had significantly different impacts on individuals' contribution volume. Specifically, the increases in both the number of reviews and the textual lengths of reviews are all significantly larger in high motivation segment. The increases in low motivation group are much smaller in magnitude and less statistically significant. Similarly, the changes in valence and the standard deviation of daily ratings are also getting smaller and less statistically sound from high to low motivation group. Interestingly, the increase in the quality of review follow similar fashions. Following the treatment, the mediocre segment exhibit moderate increases in all five cases. It is useful to note that the percentages of users falling into each segment are 21.56% in high motivation group, 30.09% in the mediocre segment, and 48.35% in the low motivation group. It is not surprising that almost half of the sampled users are in the l ow motivated segment while less than a quarter are highly motivated. This is consistent with the findings of highly skewed distributions of online content generation in other studies (Wei and Xiao 2017).

The findings in Table 5.6 are also in line with our findings in Chapter 4. In the previous chapter, we find that individual users exhibit different patterns in response to the exogenous shock by their observed characteristics. In particular, we find that a user who posts more book reviews is more affected by the exogenous shock. Similarly, we find that, in the current chapter, a more motivated user is more affected the event. The difference is that in the current chapter we are exploring the moderating role of a latent variable—an individual's unobserved type.

Moderating Roles of User Characteristics Similar to the idea in the last chapter, we examine the moderating roles of some user characteristics. Essentially, we are exploring the interactions between observed and unobserved user characteristics. We focus on the activeness and expertise in this section. Again, we use the number of past reviews as the measure of activeness and the number of reviews in a certain category as a measure of whether a user is an expert or not. Table 5.7 and 5.8 report the estimation results from a series of FMM regressions. Specifically, we are adding one more interacting term (either the early review quantity or early book review quantity) to the interaction term between the treatment dummy and the event dummy. It is essentially the same model as in the last chapter but we are estimating it in three cases, the high, mediocre, and low motivated groups.

Table 5.6: Heterogeneity in Segments

Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
High motivation	**0.010*****	**0.068*****	**0.052*****	**0.003****	**0.326*****
	(0.001)	(0.012)	(0.006)	(0.001)	(0.116)
Mediocre motivation	**0.007*****	**0.044*****	**0.039*****	**0.001***	**0.252*****
	(0.001)	(0.013)	(0.008)	(0.001)	(0.110)
Low motivation	**0.002**	**0.026***	**0.009**	**0.001**	**0.087**
	(0.003)	(0.020)	(0.008)	(0.001)	(0.152)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 5.7: Heterogeneity in Segments: Moderating Roles of a User's "Activeness"

	Coef. estimates for 1 (Tencent) ∗ 1 (Book) ∗ #Early reviews				
Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
High motivation	**-0.002*****	**-0.008*****	**-0.005*****	**-0.360e-03****	**-0.102*****
	(0.346e-03)	(0.001)	(0.002)	(0.101e-03)	(0.018)
Mediocre motivation	**-0.001*****	**-0.004****	**-0.003*****	**-0.212e-03***	**-0.052*****
	(0.214e-03)	(0.001)	(0.001)	(0.988e-04)	(0.128)
Low motivation	**0.001**	**-0.001**	**0.001**	**0.834e-04**	**-0.011***
	(0.001)	(0.001)	(0.001)	(0.923e-04)	(0.005)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 5.8: Heterogeneity in Segments: Moderating Roles of a User's "Expertise" in Book Reviews

	Coef. estimates for 1 (Tencent) ∗ 1 (Book) ∗ #Early book reviews				
Dep var.:	log (#Reviews)	log (Rev. length)	Avg. rating	SD ratings	Helpful votes (%)
High motivation	**0.003*****	**0.018*****	**0.009*****	**0.599e-03***	**0.200****
	(0.001)	(0.003)	(0.002)	(0.207e-03)	(0.061)
Mediocre motivation	**0.001****	**0.008****	**0.006****	**0.323e-03**	**0.090***
	(0.001)	(0.003)	(0.002)	(0.408e-03)	(0.062)
Low motivation	**0.001**	**0.003**	**0.001**	**0.934e-04**	**0.048**
	(0.002)	(0.004)	(0.002)	(0.234e-03)	(0.050)
Control variables	Yes	Yes	Yes	Yes	Yes
User fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
1 (Book)	Yes	Yes	Yes	Yes	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Interestingly, a user's motivation level plays an "increasing" role in the moderation of a user's activeness in participation. Specifically, from the last chapter we see that a user's activeness plays a negative role in moderating the effects of the exogenous shock on volume, valence, and quality. With the segmentation we identify in this chapter, the results in Table 5.7 suggest that this negative moderating role gets less significant from the highly motivated group to the low segment. In other words, if a user is more intrinsically motivated, he or she will be less affected by the exogenous shock if he or she was more active in writing reviews in the past.

Another interesting finding is about the heterogeneity in the moderating role of a user's expertise in posting book reviews. Similar to what we observe about the heterogeneity in the differential impacts of a user's activeness, we also see more significant impacts for the highly motivated group. Estimates in Table 5.8 tell us that if a user is an expert in writing book reviews, he or she will be more affected by the exogenous shock if he or she was more active in writing book reviews in the past.

5.4. Summaries

In this chapter we move one step forward from the previous two chapters by studying individuals' unobserved heterogeneity in the private provision of online reviews. We studied the average causal impacts of an enlarged network and the moderating roles of several observed user characteristics in Chapter 4 and 5 respectively. In particular, the results in Chapter 4 suggest that individuals responded differently to the merge of the two large-scale networks. It is equally important to study the unobserved and latent user type because it enhances not only our understanding of individuals' incentives to contribute to online reviews, which is the theme of this dissertation, but also the managerial implications of our findings.

The method we use to deal with the underlying latent user type is a finite mixture model, which helps us identify the segments by a user's unobserved characteristics. We use the likelihood based information criteria including AIC and BIC to help us choose the optimal number of segments. We also take into account the interpretability to determine this optimal number. The result suggests that a three-segment model performs well in AIC and BIC criteria and best in terms of interpretability.

We interpret the three segments as groups of users with low motivation, mediocre motivation, and high motivation to contribute to online reviews. We find that, interestingly, the increases in a user's contribution volume, valence, and helpfulness are the smallest and mostly insignificant across the three segments. In sharp contrast, the highly motivated segment is much more affected by the exogenous shock than the other two segments. The estimates of the causal effects are all bigger in magnitude than the average treatment effects uncovered in Chapter 3. The mediocre segment is between the two groups.

These findings enhances our understanding of an individual's incentives to contribute to online reviews. They extend our findings in the previous chapters, therefore, have important managerial implications. Consider a platform targeting at promoting more active contributions from the users, our study provides a framework they can follow to identify the underlying user types. By identifying the unobserved user types, platforms can target more accurately at the users who would respond to a particular promotion strategy most efficiently. For example, recommendations of highly motivated users for other users to follow will be more effective than a random user recommendation, because the recommended users of the former case respond more to the increase of followers or audience.

In addition, our results also speak to the interactions between observed and unobserved user characteristics. We show in this chapter that the moderating roles of some user characteristics differ across the segments we identified. These findings suggest that, as a step further from previous chapters, platforms targeting at specific groups of users should not only consider the observed and unobserved characteristics separately, but also take into account of the interactions between these two groups of characteristics. This also implies that firms can target more accurately at the users of their interests by considering both observed and unobserved characteristics simultaneously. Again, the method we use in this chapter provides a framework that is of help potentially.

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