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

Paulo Goes, Yang Wang
Eller College of Management, University of Arizona, Tucson, AZ 85721
pgoes@eller.arizona.edu, yangwang@email.arizona.edu

Zaiyan Wei
Krannert School of Management, Purdue University, West Lafayette, IN 47907, zaiyan@purdue.edu

Dajun Zeng*
Eller College of Management, University of Arizona, Tucson, AZ 85721, zeng@eller.arizona.edu

January, 2016

We study the effects of network sizes on individuals' contributions to online product reviews. Provided by either consumers or professionals, online reviews are shown to be closely correlated with consumers' purchasing decisions and product sales. Individuals have conflicting incentives of free riding and maximizing social benefits when producing online reviews. We leverage a "natural experiment," an exogenous expansion in the users population on a major third-party platform, to better understand the tradeoffs between the conflicting incentives of producing online reviews. We find that the larger population of users, a direct consequence of the exogenous shock, caused individuals to post more and longer reviews. In addition, the larger population of audience led individuals to assign higher and more diverse ratings in their reviews. However, the helpfulness or "quality" of reviews, evaluated by other users, is not affected. These results lend support to the conjecture that maximizing social capital dominates one's incentives to publish online reviews. The positive effect of network sizes on the volume of reviews implies that enlarging the reviewers population is effective in promoting more active contributions.

*Key words*: Online reviews, Social networks, Group size effects, Exogenous shocks

---

## 1. Introduction

Online reviews, provided by either consumers or third-party professionals, are shown to be closely correlated with product sales (Dellarocas 2003, 2006, Chevalier and Mayzlin 2006). The majority of online retailing platforms, including Amazon.com (Mudambi and Schuff 2010) and eBay.com (Li and Hitt 2008), allow consumers to post personal opinions on product pages. Simultaneously, platforms specialized in facilitating third-party product

* This is a preliminary draft and results may be subject to change. Please contact us before citing. Comments welcome.

reviews (such as Yelp.com, IMDb.com, and Douban.com) emerge in recent years (Chen and Xie 2005). More important, online reviews are shown to be positively related to product sales (Liu 2006, Dellarocas et al. 2007, Chen and Xie 2008, Duan et al. 2008, Forman et al. 2008, Zhu and Zhang 2010).

Interactions among review writers, often in the form of online social networking,[1] have profound impacts on their reviewing behaviors. In particular, individuals' contributions to online reviews are affected by the number of his or her friends (or followers, subscribers). Recent studies have shown that the popularity of individuals and their online friends' activities are closely correlated with their own reviews (Goes et al. 2014, Wang et al. 2015). Nevertheless, it remains inconclusive how an individual's network affects his or her review-posting behavior, or what the causal effects of social influence on individuals' behavior of writing reviews are.

Online reviews are public goods on the Internet (Duan et al. 2008). Anyone cannot be effectively excluded from "consuming" online reviews, and an individual's "consumption" of product reviews does not crowd out others' access to them. With larger group sizes, one may free ride on others' contributions and post less reviews. Classic public goods theories argue that individuals gain utilities or benefits from the level of total contributions only, and predicts less contributions with more friends (Olson 1965, Chamberlin 1974). However, individuals may, on the other hand, be encouraged to post more reviews because they receive personal satisfactions or warm glow from contributions. Recent development in theories extends the assumptions in classic models and incorporates effects of social benefits or altruism (Andreoni 1989, 1990, 2007, Andreoni and Bernheim 2009). As a consequence, individuals provide more reviews with larger group sizes. Therefore, predictions about network size effects are not clear-cut *a priori.*

In this study, we empirically examine the network size effects on users' behavior of posting online reviews. In particular, we ask which individuals' incentive dictates their private provision of online reviews, and how their contributions are affected by the change in reference group sizes. Specifically, do more friends or larger audience of an individual's review posts necessarily cause him or her to devote more efforts and post more and longer

[1] Online social networking has become a huge phenomenon globally. According to the annual report from surveys conducted by PewResearch Internet Project (`http://www.pewinternet.org/`), as of January 2014, 74% of adult Internet users use social networking services.

product reviews? Does an increase in the network size lead an individual to assign more positive and more diverse ratings? Is the helpfulness or the "quality" of reviews, voted by readers, affected by the growth in network sizes?

We seek answers to the questions by examining individual behavior of posting product reviews on Douban.com, the largest platform for third-party reviews in China. Launched on March 6, 2005, Douban.com has focused on providing the platform for consumers and professionals to write reviews and assign ratings (ranging from 1 the worst to 5 the best) for books, movies, TV shows, and music. The platform witnessed a sudden expansion in the number of registered users starting from August 1, 2009, due to the introduction of a web application, "Douban Reading," on China's largest social networking platform QZone.[2] The application granted QZone users direct access to all Douban reviews of books. This exogenous shock, through the unexpected merge of two large-scale and influential networks, provides us a unique opportunity to study the group size effects on online reviews.

We collected data from Douban.com. We obtained all relevant information from the webpages of $24,374$ Douban users on November 1, 2014 using a web data crawler. The identification of group size effects comes from a feature of the exogenous shock. Specifically, QZone users gain access to only the section of book reviews on Douban.com. In contrast, the web application does not allow direct access to other sections including reviews of movies, TV shows, or music. This unique structure naturally divides Douban reviews into two groups, book reviews as the treatment group and all other reviews as the control group. With this "natural experiment," we conduct differences-in-differences (DID) analyses that uncover the causal effects of the policy change (increase in group sizes) on individuals' contributions to product reviews and other review-related activities.

We focus on a period between July 4, 2009 and August 28, 2009, which is four weeks before and four weeks after the exogenous shock. There were no policy changes other than the introduction of Douban Reading. We first find that the exogenous expansion indeed led to increase in one's network size—more readers with more comments. We then explore the differences in certain outcomes of posting book reviews versus those of other reviews. We find supporting evidence, from both descriptive statistics and regression-adjusted analyses,

[2] QZone can be found at `http://qzone.qq.com/`. The Wikipedia page for this online network is at `http://en.wikipedia.org/wiki/Qzone`. According to "We Are Social" reports, the number of active users on QZone were more than 644 million as of May 2014, making it the second largest internet social network worldwide.

that compared to the change in other reviews, individuals post more book reviews. Our estimates imply a positive effect on the *volume* of contributions to book reviews; in other words, larger group sizes caused more private contributions. Numerically, the exogenous shock led to around 0.1% increase in the number of reviews per user per week, and about 0.7% increase in the textual length of reviews.

Analogously, we perform DID analyses exploring the causal effects on other reviewing activities and outcomes. The results indicate that, on average, the exogenous shock caused individuals to assign higher ratings (*valence* of reviews) for the products. In addition, after the exogenous shock individuals posted reviews for wider ranges of books, measured by the *variance* of review ratings. In contrast, we do not find statistically significant effects on a measure of the reviews "quality" (or the *helpfulness* of reviews evaluated and voted by other readers). We perform robustness checks to eliminate several concerns on the sample and our main specifications. In a nutshell, our findings are qualitatively consistent across samples and specifications.

This study first contributes to the literature on online reviews (Dellarocas 2003, Chevalier and Mayzlin 2006, Chen and Xie 2008, Goes et al. 2014, Wang et al. 2015). We add to the literature by exploring the causality of reference group sizes on individuals' behavior of posting online reviews. Goes et al. (2014) and Wang et al. (2015) both explore the intertemporal relations between neighbors' review posting behaviors. Although we do not explicitly study the peer effects (e.g., how neighbors' average activities affect an individual's behavior, Manski (1993), Goldsmith-Pinkham and Imbens (2013)), we empirically show how the larger audience causes changes in individual behaviors in posting online reviews, which has not been previously documented. We also contribute to the economic literature on the private provision of public goods (Olson 1965, Chamberlin 1974, Andreoni 1989). Our results provide empirical evidence that supports the hypothesis of altruism being a generic part of individuals' incentives (Zhang and Zhu 2011). Last but not least, this study contributes to the literature on exogenous shocks to complex systems (Barabási 2005, Crane and Sornette 2008, Beaman 2012). We add to this strand of literature by empirically examining the effects on a large-scale social network, which is an important and extensively studied complex system.

The paper is structured as follows. Section 2 summarizes related literature and develops our research hypotheses. We introduce the context of our research, Douban.com and the exogenous shock, in Section 3. We describe the datasets and present summary statistics in Section 4. We then provide detailed discussions of our empirical strategies in Section 5.1. We report findings and carry out discussions in Section 5.2 and 5.3 respectively. Section 6 concludes.

## 2. Related Literature and Research Hypotheses

### 2.1. Related Literature

We draw on several strands of literature: online 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.

Online product reviews, provided by either consumers or third-party professionals, have been extensively studied in the literature (see Wang et al. (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 et al. 2007, Duan et al. 2008, Forman et al. 2008, Li and Hitt 2008, Mudambi and Schuff 2010, Sun 2012). More recent studies on online reviews start exploring the role of user interactions (the peer effects or social influence) in individuals' contributions to the public goods. Goes et al. (2014) and Wang et al. (2015) are two papers closest to our study. Goes et al. (2014) study the dynamics of an individual's popularity (measured by his or her quantity of followers) and review-posting behaviors. In contrast, Wang et al. (2015) explore the intertemporal relations between an individual's review ratings and his or her neighbors' reviews prior to the formation of their friendship. Both explore the intertemporal relations between some measures of one's network and his or her contributions to online reviews. However, the causal effects of one's network on review posting are not studied in this literature. We start filling this gap by studying the effects of network sizes on individuals' contributions. Although we do not explicitly investigate the peer effects (Manski 1993), we empirically show how larger audience causes changes in individual behaviors in posting online reviews, which has not been documented yet.

We draw on a long-standing literature on the private provision of public goods (Olson 1965, Chamberlin 1974, Bergstrom et al. 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 et al. 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 (or the number of recipients) 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 et al. 2011, Ransbotham and Kane 2011, Ransbotham et al. 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 et al. 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. Hypotheses

Online reviews can be considered as public goods (Duan et al. 2008). In particular, product reviews are *non-excludable* since the product pages are generally public on the Internet and accessible to any internet users. Furthermore, an individual's access to the reviews does not effectively preclude others' abilities to access (*non-rivalry*). In the private provision of public goods, contributors receive utilities from not only the total volume of contributions but also the volume of private contributions (Andreoni 1989).

Based on the assumption that individuals gain utilities from only the total volume of contributions, early papers on public goods provision develop models that predict "free-riding" phenomenon (Olson (1965), Chamberlin (1974)). Specifically, they predict that individuals' contribution levels decrease with the group size increasing. However, pointed out by more recent studies (Andreoni 1988), these models fail to explain the extensive giving behavior observed in empirical and experimental research. Recent studies extend the assumption that individuals' utilities depend only on the total contributions, and formulate the idea of altruism (or social benefit/effect) that the utilities also depend on the level of personal contributions (Andreoni 1989, 1990, Duncan 2004). These models are proposed to address the aforementioned inconsistencies between empirical findings and theories. A fundamental prediction of the new theories is that when the group size is sufficiently large, the relative importance of pure altruism vanishes and the social effect dictates individuals' incentives to contribute. Thus with sufficiently large reference group, individuals' 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 context, product review writers gain utilities (benefits or satisfaction) from not only the stock of reviews on the platform, but also their own reviews. As the more recent theory predicts, individuals will find it more beneficial to contribute more product reviews with larger population of audience. Thus our first set of hypotheses reflects the conjecture of social effects dominating individuals' incentives to produce online reviews.

HYPOTHESIS 1A **(H1A)**. *A larger number of members in a social network cause individuals to write and post a larger number of product reviews.*

As another measure of contribution levels, the textual length of product reviews also reflects individuals' efforts devoted to providing the public good—online reviews. Similar to the number of reviews posted, theories suggest that individuals will write on average longer reviews with larger reference groups.

HYPOTHESIS 1B **(H1B)**. *An increasing number of members in a social network cause individuals to write and post on average longer product reviews.*

In addition to the *volume* effects, the size of peer groups has potential impacts on the *valence* of reviews. On third-party platforms including Douban.com, the review writers can choose an integer number or some number of stars as his or her overall rating of the product. Goes et al. (2014) find a negative correlation between the average rating and the number of followers up to the previous period. They attribute the negative relation to 1) that if individuals are more likely to post reviews, higher popularity leads to negativity bias (Ofir and Simonson 2001); and that 2) readers or consumers find negative evaluations more informative, which induces negative bias of the reviews (Bateman et al. 2011).

However, the true effect of popularity could be potentially biased by the endogeneity of the followers count. Specifically, the number of followers is arguably correlated with some unobserved heterogeneity that is captured by the error term, for example, individuals' expertise and professionalism in writing product reviews accumulated over time. Given this example, an individual tends to have more followers and posts lower ratings simultaneously over time, which leads to negative correlations between the ratings and the quantity of followers. This in turn induces negative bias of the popularity effects on product ratings assigned by the reviewers. Instead we hypothesize that the exogenous shock causes individuals to assign on average higher ratings for book reviews.

HYPOTHESIS 2 **(H2)**. *A larger number of group members increase the overall valence of ratings assigned by the review writers.*

The dispersion or variance of product ratings also has profound influence on product sales. A product with more diversified but lower average rating has higher demand subsequently (Sun 2012). Goes et al. (2014) hypothesize that due to the special structure of ratings system (with lower and upper bounds), the change in average rating leads to higher variance. Following the same logic, we hypothesize that a larger population of audience causes individuals to assign more diversified ratings.

HYPOTHESIS 3 **(H3)**. *The variance of review ratings that individuals assign is higher with a large population of 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 consumers' information distraction and final product sales (Mudambi and Schuff 2010, Cao et al. 2011). In the literature, the factors that influence the quality or helpfulness of reviews include reviewers' expertise, textual characteristics, and timing of posting online reviews in terms of the product lifecycle. We hypothesize that although individuals devote more efforts into contributions of online reviews, a larger population of readers do not have significant effects on the average helpfulness of the reviews.

HYPOTHESIS 4 **(H4)**. *As the number of group members grows, the "quality" or helpfulness of product reviews is not affected.*

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.

## 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 other networking sites such as Facebook.com and Twitter.com, the formation of friendships on Douban.com is 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.[3] 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 SNS 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.[4] Douban.com is now the largest platform for third-party online reviews in China.

[3] 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.

[4] 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/`.

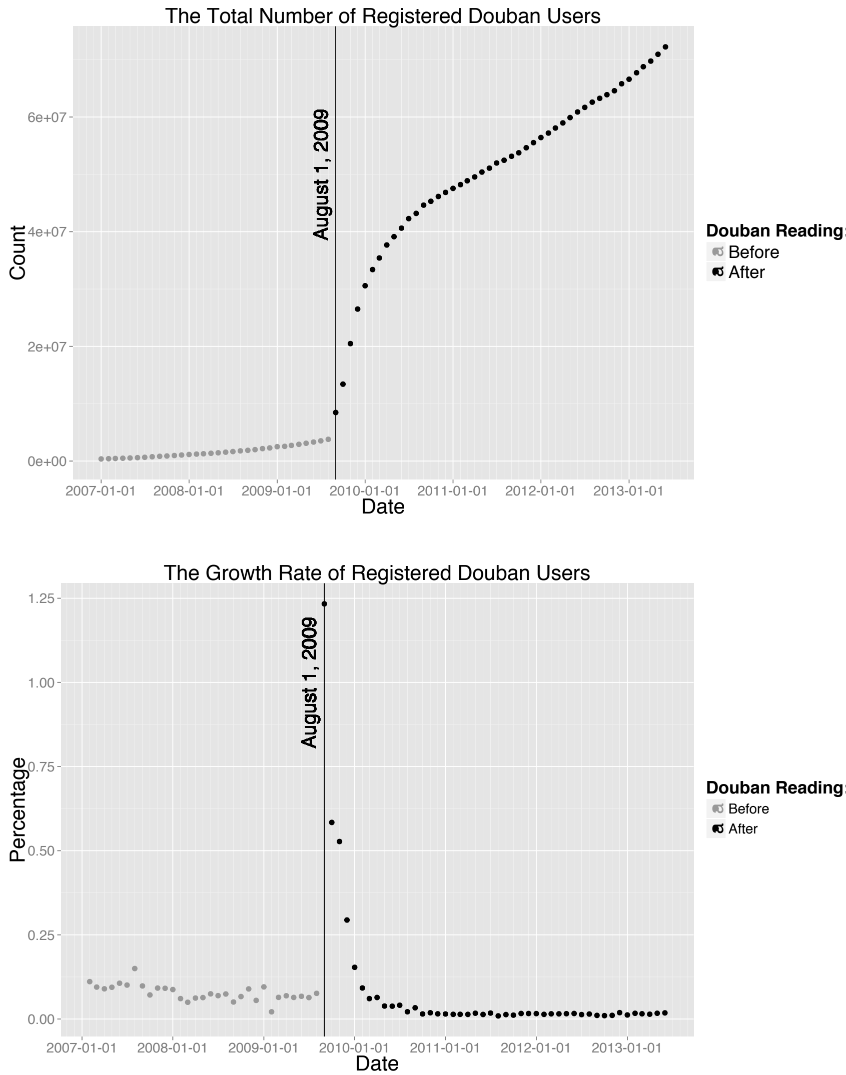
In this study we consider the introduction of "Douban Reading" on Tencent.com being an exogenous shock to Douban network. Tencent.com, the largest online social network in China, started testing customizable installations of third-party applications on their users' profile pages (called "QZone") on August 1, 2009. The first such application was Douban Reading. Figure 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. However, as its name suggests, the application did not provide direct entry into either movies or music 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.

**Figure 1** **An Illustration of "Douban Reading" Installed on a Tencent User's QZone**


A straightforward impact of this exogenous shock is on the number of registered Douban users. In Figure 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.[5] The population was more than doubled within a month.

[5] 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`.

**Figure 2 The Total Number and Growth Rate of Registered Users on Douban.com**




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.

## 4. A Summary of Dataset

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 started with 119 Douban groups and recorded all their members, originally 552, 827 individuals. We then selected 24, 374 users among the original sample. Note that only the sampled users joined Douban.com before the exogenous shock on August 1, 2009.

We crawled all publicly available user demographics on their profile pages, and all reviews and related product information.

Specifically, from the user profile page, we obtained user demographic information including age, gender, location, and registration date. We crawled all reviews of books, movies, TV shows, and music (if any) for each sampled user. For each product review, we collected the timestamp, title, full content, and all comments attached (with comments posting dates as well). We also obtained the review rating with a range between 1 (the worst) and 5 (the best), the number of helpfulness votes, and the number of non-helpfulness votes for each review.[6] In addition, we crawled all other activities such as the number of photo albums, personal notes, product collections,[7] 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.

Corresponding to each review, we downloaded all product information from the product pages. For instance, if the product is a book, we crawled the following information the author(s) name(s), publisher name, ISBN number, publishing date, the total number of pages, a brief outline of the book content, and the author(s) introduction. We also obtained the users rating of a product, ranging from 1 (the worst) to 10 (the best). This rating is based upon assignments by any Douban users that selected an integer within the range. It is different from the rating assigned in the reviews. The review rating is assigned by the review writer, with a range 1 to 5. While the rating on the product page 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.

In Table 1 we provide summary statistics for our main sample of users and all their reviews by our data collection date. Note that $5,823$ out of $24,374$ users have posted at least one product review (regardless of categories) by November 1, 2014. Among these "active" users, the average number of reviews ever posted turns out to be about 7. Among all the reviews, about 36% are in book section, and more than 50% are movies or TV shows reviews. The rest are music reviews. The average rating has reached over 4 out of

[6] The readers of a product review have the option to characterize the review as being either "helpful" or "non-helpful." The platform displays the total number of each option.

[7] Douban users can choose to display collections of books, movies, TV shows, or music on their profile pages. Products in collections are usually personal favorites including those reviewed by the corresponding individual. The collections are divided into three categories. Collections of books, as examples, are categorized into those one has read, those one is reading, and those in one's wish list.

5 up to November 2014, with the average number of positive votes greater than 7. For all sampled users, the distribution of reviews quantity is highly skewed, with more than half of them contributing nothing since their registrations. This phenomenon of "specialization" is consistent with theory predictions from the literature on private provision of public goods in social networks (Bramoullé and Kranton 2007).

**Table 1 Summary Statistics of the Cross-Sectional Data**

| | Statistics | | | | |
|---|---|---|---|---|---|
| **Variables** | Median | Mean | s.d. | Min. | Max. |
| *Users Information* | | | | | |
| # Total 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] | 2,342 | 2,416.220 | 365.539 | 1,919 | 3,531 |
| *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 | | |
| *Reviews 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 Score[c] | 0 | 6.730 | 72.852 | -115 | 10,098 |
| 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 until our data collection date.

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

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

By our data collection date, among all sampled users, the median number of followees (those one follows) and that of followers are 36 and 33 respectively. Figure 3 shows the distributions of followees count (out-degree) and followers count (in-degree). Both distributions abide by the power law or "fat-tail" phenomenon that is well documented in the literature.[8] Indeed, we notice that the maximum of followees count is $2,144$ in our sample, and that for followers is more than $88,000$.

**Figure 3** **Distributions of the Followees and Followers Count for Users in the Main Sample**

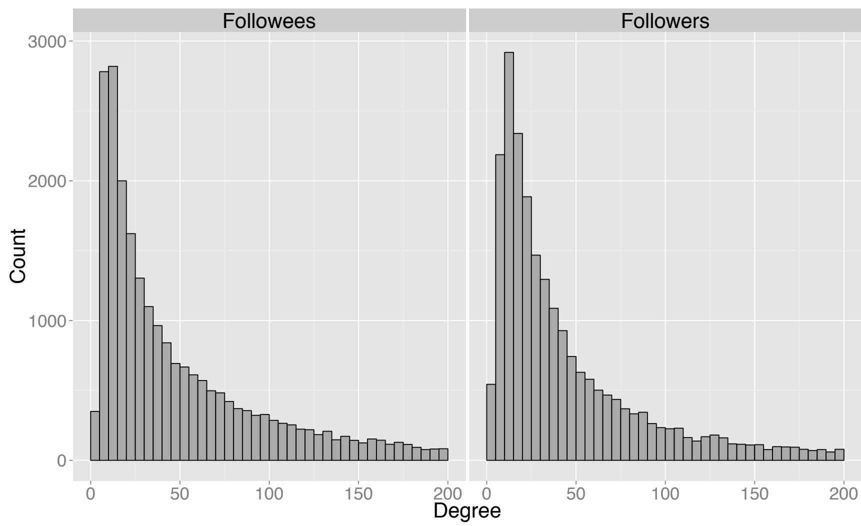



Table 2 takes a closer look at the sampled reviews categorized by types, *i.e.*, either book reviews or others. One thing to note is that more than half of sampled book reviews were posted during the four weeks after the exogenous shock, while less than 50% of other reviews (including all movie, TV shows, 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 than other types.

In our main empirical analyses in Section 5, we focus on the reviews posted by the sampled users between July 4, 2009 and August 28, 2009, which was 4 weeks before and 4 weeks after the exogenous shock. We choose this time window mainly because within this period the exogenous shock was the only policy change on Douban.com. Douban was experiencing improvements as well as strict regulations from the Chinese government in 2009. As examples, the platform introduced "Douban Station" to stream all its music to

[8] Price (1965) was the first to document such distributions in the setting of social networks. Jackson (2010) provides a thorough review and theoretical treatments on this topic.

registered users in June 2009; and starting from July 1, 2009, group members were unable to comment on or reply to posts within the group. In our sample, 23,548 users registered Douban accounts before July 4, 2009. Notice that this is slightly different from our original sample of 24,374 users who joined before August 1, 2009. We provide sample comparisons in Table 3, and results suggest that these two samples are not significantly different.

**Table 2 Summary Statistics of the Sampled Reviews by Types**

| | 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 Score[c] | 5.275 | 27.978 | 7.545 | 88.500 | 8.269 | 98.982 |
| 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 (After 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 other than those in book section, including movie, TV shows, and music reviews.

[b] The number of "helpful" clicks by review readers, likewise for "# Non-helpful votes."

[c] The score equals the difference between # helpful votes and # non-helpful votes.

**Table 3 Summary Statistics of the Main Sample Used in Regressions**

| | Main Sample | | | Original Sample | | | | |
|---|---|---|---|---|---|---|---|---|
| **Variables**: (Weekly[a]) | Median | Mean | s.d. | Median | Mean | s.d. | ***t*-stats**[b] | ***p*-values** |
| # Total Reviews | 0 | 2.612 | 12.590 | 0 | 2.570 | 12.603 | 0.365 | 0.715 |
| # Groups | 43 | 66.677 | 68.369 | 43 | 66.536 | 68.274 | 0.226 | 0.821 |
| # Followees | 36 | 79.051 | 142.276 | 36 | 78.926 | 142.174 | 0.096 | 0.923 |
| # Followers | 33 | 157.438 | 1,498.390 | 33 | 158.171 | 1,517.22 | -0.076 | 0.940 |
| 1 (Miss Followers) | 0 | 0.002 | 0.045 | 0 | 0.002 | 0.044 | 0.169 | 0.866 |
| **Users** | | 23,548 | | | 24,374 | | | |

[a] For all variables, we evaluate them on a weekly basis.

[b] In the paired two-sided T-tests our null hypotheses are that the true difference in means between the variable from the main sample and that from the original sample is zero.

# 5. Empirical Analysis

## 5.1. 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 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 (group size effects on contributions), 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 (often abbreviated as diffs-in-diffs or DID), provides a solution to the endogeneity problem (Card and Krueger 1994, Athey and Imbens 2006). The exogenous shock to Douban.com provides us a unique opportunity to apply this method to explore our research questions.[9] 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. As the superscripts suggest, we divide all Douban reviews into two groups—book reviews as the treated group and other reviews as the untreated/control group.[10] 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).

[9] The technique of diffs-in-diffs is widely adopted in economics literature (Ashenfelter 1978, Card and Krueger 1994). 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.

[10] 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.

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 $s$ $(s=1,2)$ to Douban book reviews (treatment) and other reviews (control), 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 of such variables is the user demographic information. The rationale is that the treatment effect may differ for different types of users. In this situation, a regression formulation of the DID estimator is useful to compute a *conditional* version that corrects for the effect of $X_{it}$. Specifically, our main empirical specification is

$$Y_{it}^j=\beta_0+\beta_1\cdot D^j+\beta_2\cdot D_t+\beta_3\cdot D^j\cdot D_t+\beta_4^{'}X_{it}+\epsilon_{it}^j, \tag{1}$$

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 time dummy $D_t=1$ $(t=1,2,3,)$ stands for the period after the exogenous shock on August 1, 2009. In addition, $X_{it}$ include user demographics (both time-variant and time-invariant) such as the length of time on site, user location fixed effects, or individual fixed effects.

Note that $\beta_3$ is the coefficient for the interaction term between the dummy for book reviews and the time dummy. It is the coefficient of interests, estimates of which can be interpreted as the treatment effect of the introduction of Douban Reading on QZone on the outcome variable, $Y_{it}^j$.

### 5.2. Group Size Effects on Reviews

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 (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.

**5.2.1. Larger Peer Group Sizes** A critical question is whether the introduction of Douban Reading indeed led to larger population of audience (or larger peer group sizes) for Douban reviews. Unfortunately, we are unable to observe the number of actual readers directly. However, a close proxy for the population of audience is the quantity of comments made to the reviews. More readers generally post more comments. Thus after controlling for all observed characteristics, we hypothesize that the exogenous shock led to more comments for reviews.

We focus on the comments ever made to the sampled reviews that were posted before July 4, 2009. We keep track of all comments posted between July 4, 2009 and August 28, 2009, which is our main study period. During this period, $1,110$ reviews (out of $20,539$ total reviews) received $2,123$ comments from readers. The average number of comments a review received during the period was 1.39 per week. We conduct the same DID analysis, as in Section 5.1, to explore the effect of the exogenous shock on the number of comments made. The dependent variable, $Y_{it}^{j}$ as in Equation (1), is the log of the number of comments per review per week.

The estimates of Equation (1) are reported in Table 4. We notice that the estimates of the main effect support our hypothesis that the exogenous shock led to larger population of audience. Specifically, the estimate of $\beta_3$, reported in the first row of Table 4, 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 larger due to 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 indicator for the exogenous shock as an exact proxy for the increase in the peer group sizes.

**5.2.2. 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

**Table 4 OLS Estimates of the Exogenous Shock Effects on the Quantity of Comments**

| | OLS Results | | | |
|---|---|---|---|---|
| **Dep var.:** log (# Comments) | Spec 1 | Spec 2 | Spec 3 | Spec 4 |
| 1 (**Tencent**) ∗ 1 (**Book**) | **0.918e-03**$^{**}$ | **0.918e-03**$^{**}$ | **0.918e-03**$^{**}$ | **0.918e-03**$^{**}$ |
| | (4.116e-04) | (4.114e-04) | (4.075e-04) | (3.973e-04) |
| 1 (Tencent) | -0.002$^{***}$ | -0.002$^{***}$ | -0.002$^{***}$ | -0.002$^{***}$ |
| | (3.041e-04) | (3.039e-04) | (3.003e-04) | (2.925e-04) |
| 1 (Book) | -0.001$^{***}$ | -0.001$^{**}$ | -0.001$^{**}$ | -0.001 |
| | (3.252e-04) | (3.237e-04) | (3.193e-04) | (0.463e-03) |
| Review_Age[a] | | -0.120e-03$^{***}$ | -0.157e-03$^{***}$ | -0.413e-03$^{***}$ |
| | | (0.917e-07) | (0.161e-04) | (0.125e-03) |
| Sq_Review_Age | | 0.532e-08$^{***}$ | 0.612e-08$^{***}$ | 0.248e-07$^{***}$ |
| | | (0.444e-09) | (0.739e-09) | (0.487e-08) |
| (Intercept) | 0.005$^{***}$ | 0.010$^{***}$ | 0.012$^{***}$ | 0.016$^{**}$ |
| | (2.422e-04) | (4.582e-04) | (0.001) | (0.001) |
| **User Location FE** | | | Yes | |
| **User FE** | | | | Yes |
| $R^2$ | 0.0003 | 0.001 | | |
| **Adj.** $R^2$ | | | 0.020 | 0.069 |
| **Num. obs.** | 328,624 | 328,624 | 328,624 | 328,624 |

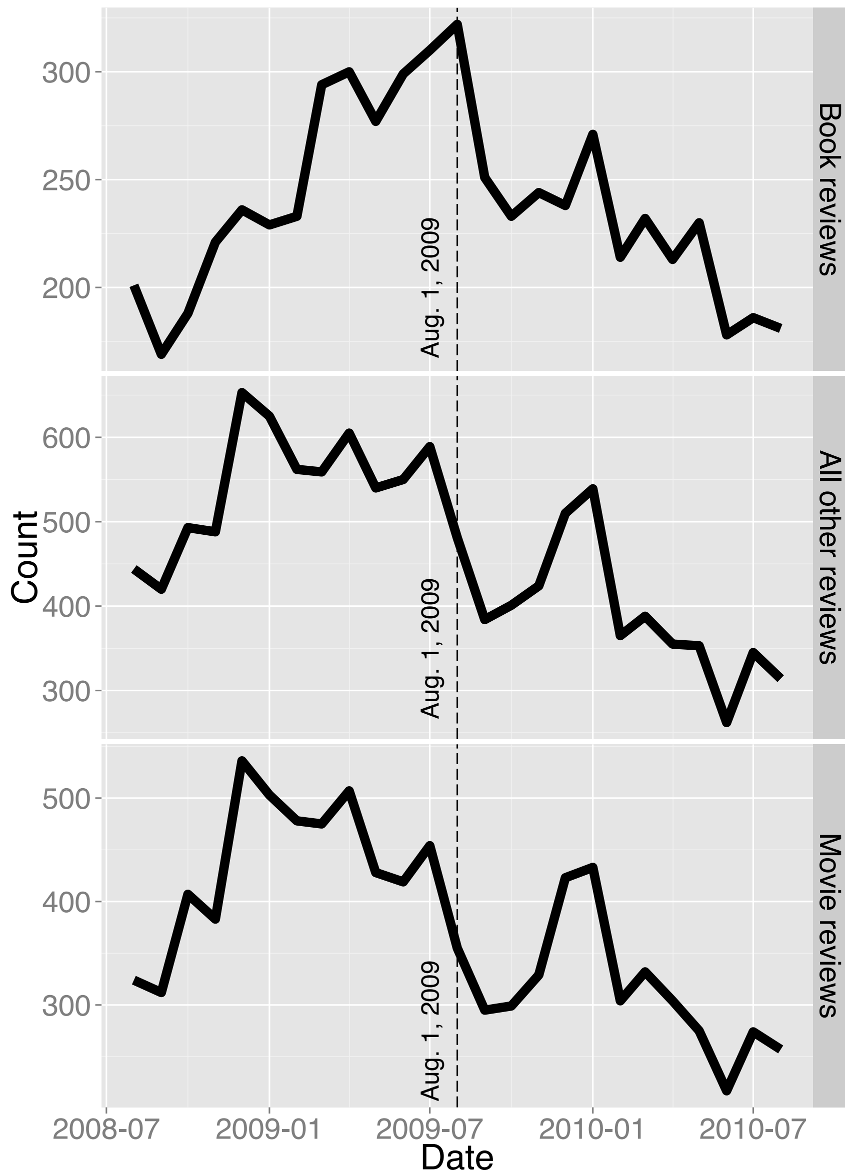
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

[a] Note that the variable "Review_Age" measures the number of weeks since the date a review was posted, and "Sq_Review_Age" is the square of it.

the untreated group. We first compare the total reviews posted by our sampled users in the two groups. Figure 4 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 counts 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; in contrast the total number of all other reviews dropped from 589 in July 2009 to 481 in August 2009 (by about 18.34%). 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 period. There are $23,548$ individuals in this subsample. They posted $1,553$ reviews with $1,226,204$ characters (or words) during the 8-week time window. Among these reviews, 585 were posted in book

**Figure 4 Monthly Total Numbers of Reviews by Review Categories**




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.

To test each of our hypotheses, we construct the dependent variables accordingly as in Table 5. Table 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.

**Table 5 A Summary of Dependent Variables**

| Hypothesis | Dependent Variable |
|---|---|
| **H1A** | Log of the number of reviews |
| **H1B** | Log of the total textual lengths of reviews |
| **H2** | Average ratings of reviews |
| **H3** | Standard deviation of review ratings |
| **H4** | Average helpfulness score[a] |

[a] The score is constructed from the votes by review readers. Specifically, all readers can vote a review being either "helpful" or "non-helpful." This variable is equal to the difference between the quantity of helpfulness votes and that of non-helpfulness votes.

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 6, suggest that compared to the difference prior to the shock, the difference afterwards was significantly bigger (in negative values) 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 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 6.

**Table 6 Summary Statistics of the Main Sample Used in Regressions**

| | 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* | | | | | | | | |
| # Reviews | 0 | 0.003 | 0.103 | 0 | 0.003 | 0.069 | -0.528 | 0.299 |
| Total textual length | 0 | 2.458 | 137.877 | 0 | 2.818 | 164.993 | -0.514 | 0.304 |
| Avg. rating | 0 | 0.008 | 0.182 | 0 | 0.010 | 0.204 | -2.313 | 0.010 |
| Avg. S.d. of rating | 0 | 0.0002 | 0.014 | 0 | 0.0003 | 0.020 | -0.708 | 0.240 |
| Avg. helpfulness score | 0 | 0.014 | 1.604 | 0 | 0.016 | 1.575 | -0.201 | 0.420 |
| *Non-book reviews* | | | | | | | | |
| # Reviews | 0 | 0.006 | 0.118 | 0 | 0.004 | 0.096 | 2.334 | 0.990 |
| Total textual length | 0 | 4.053 | 133.450 | 0 | 3.379 | 116.703 | 1.167 | 0.878 |
| Avg. rating | 0 | 0.016 | 0.263 | 0 | 0.013 | 0.240 | 2.466 | 0.993 |
| Avg. S.d. of rating | 0 | 0.0004 | 0.022 | 0 | 0.0003 | 0.019 | 1.521 | 0.936 |
| Avg. helpfulness score | 0 | 0.02 | 1.854 | 0 | 0.002 | 0.017 | 0.397 | 0.654 |
| *Difference in # reviews* | | | | | | | | |
| Book – Non-book[c] | 0 | -0.003 | 0.145 | 0 | -0.001 | 0.110 | -2.313 | 0.010 |
| *Difference in total lengths of reviews* | | | | | | | | |
| Book – Non-book | 0 | -1.595 | 190.316 | 0 | -0.561 | 200.032 | -1.149 | 0.125 |
| *Difference in avg. review rating* | | | | | | | | |
| Book – Non-book | 0 | -0.008 | 0.305 | 0 | -0.004 | 0.299 | -3.540 | <0.001 |
| *Difference in the s.d. of review rating* | | | | | | | | |
| Book – Non-book | 0 | -0.0002 | 0.026 | 0 | -0.00004 | 0.027 | -1.646 | 0.050 |
| *Difference in avg. helpfulness score* | | | | | | | | |
| Book – Non-book | 0 | -0.006 | 2.429 | 0 | -0.001 | 1.937 | -0.423 | 0.336 |
| **Users** | | | 23,548 | | | | | |
| **Weeks** | | | 8[d] | | | | | |
| **Num. obs.** | | | 376,768 | | | | | |

[a] We evaluate all variables on a weekly basis.

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

[c] This variable calculates the difference between the corresponding variable of book reviews and that of non-book reviews for an individual user in a week.

[d] Our sampling period is between July 4 and August 28, 2009, spanning an 8-week window before and after the shock.

**5.2.3. 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 7 through 11 report the main estimation results from Equation (1).[11] Each table corresponds to one hypothesis in Section 2.

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 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 (on all control variables) 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).[12] 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 (suppose continuous) 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 $\beta_3$ in Equation (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 absolute value of it is too small to have real impacts on Douban review 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

[11] 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.

[12] 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 $\exp\left(0.941e-03\right) - 1 \approx 0.941e-03$.

**Table 7 OLS Estimates of the Exogenous Shock Effects on the Quantity of Reviews**

| | OLS Results | | | |
|---|---|---|---|---|
| **Dep var.:** log (#Reviews) | Spec 1 | Spec 2 | Spec 3 | Spec 4 |
| 1 (**Tencent**) ∗ 1 (**Book**) | **0.941e-03**$^{***}$ | **0.941e-03**$^{***}$ | **0.941e-03**$^{***}$ | **0.941e-03**$^{***}$ |
| | (2.979e-04) | (2.979e-04) | (2.977e-04) | (2.749e-04) |
| 1 (Tencent) | -6.333e-04$^{***}$ | -6.503e-03$^{***}$ | -6.438e-04$^{***}$ | -3.594e-04 |
| | (2.358e-04) | (2.353e-04) | (2.349e-04) | (3.206e-04) |
| 1 (Book) | -0.002$^{***}$ | -0.002$^{***}$ | -0.002$^{***}$ | -0.002$^{***}$ |
| | (2.168e-04) | (2.168e-04) | (2.166e-04) | (2.003e-04) |
| Age$^{a}$ | | -0.664e-07 | -0.889e-07$^{*}$ | -2.121e-04$^{***}$ |
| | | (0.539e-07) | (0.541e-07) | (0.779e-04) |
| Sq_Age | | 0.742e-09$^{***}$ | 0.783e-09$^{***}$ | 0.976e-08$^{***}$ |
| | | (0.285e-09) | (0.289e-09) | (0.342e-08) |
| (Intercept) | 0.003$^{***}$ | 0.003$^{***}$ | 0.003$^{***}$ | 0.011$^{**}$ |
| | (1.763e-04) | (2.632e-04) | (2.649e-04) | (0.004) |
| **User Location FE** | | | Yes | |
| **User FE** | | | | Yes |
| $R^2$ | 0.0002 | 0.0003 | | |
| **Adj.** $R^2$ | | | 0.002 | 0.149 |
| **Num. obs.** | 376,768 | 376,768 | 376,768 | 376,768 |

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

$^{a}$ Note that the variable "Age" measures the number of weeks since a user's registration date, and "Sq_Age" is the square of it. This applies to all subsequent tables.

lengths as the dependent variable. Estimation results are presented in Table 8. 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 $\beta_3$ are the same across specifications.

In addition to the volume effects, we also estimate the causal effects on the valence of reviews. Table 9 presents 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.

We report the estimation results for the test of hypothesis H3 in Table 10. The findings support the hypothesis that the variance, or the standard deviation, of weekly review

**Table 8 OLS Estimates of the Exogenous Shock Effects on the Lengths of Reviews**

| | OLS Results | | | |
|---|---|---|---|---|
| **Dep var.:** log (Review Lengths) | Spec 1 | Spec 2 | Spec 3 | Spec 4 |
| 1 (**Tencent**) ∗ 1 (**Book**) | **6.883e-03**$^{***}$ | **6.883e-03**$^{***}$ | **6.883e-03**$^{***}$ | **6.883e-03**$^{***}$ |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| 1 (Tencent) | -4.285e-03$^{**}$ | -4.480e-03$^{**}$ | -4.426e-03$^{**}$ | -2.972e-03 |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| 1 (Book) | -0.012$^{***}$ | -0.012$^{***}$ | -0.012$^{***}$ | -0.012$^{***}$ |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Age | | -0.132e-04 | -0.343e-04 | -1.346e-03$^{**}$ |
| | | (0.401e-04) | (0.404e-04) | (0.001) |
| Sq_Age | | 0.420e-08$^{**}$ | 0.471e-08$^{**}$ | 0.692e-07$^{***}$ |
| | | (0.214e-08) | (0.217e-08) | (0.253e-07) |
| (Intercept) | 0.025$^{***}$ | 0.023$^{***}$ | 0.024$^{***}$ | 0.068$^{**}$ |
| | (0.001) | (0.002) | (0.002) | (0.034) |
| **User Location FE** | | | Yes | |
| **User FE** | | | | Yes |
| $R^2$ | 0.0002 | 0.0003 | | |
| **Adj.** $R^2$ | | | 0.002 | 0.120 |
| **Num. obs.** | 376,768 | 376,768 | 376,768 | 376,768 |

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

**Table 9 OLS Estimates of the Exogenous Shock Effects on the Ratings of Reviews**

| | OLS Results | | | |
|---|---|---|---|---|
| **Dep var.:** Avg. Rating | Spec 1 | Spec 2 | Spec 3 | Spec 4 |
| 1 (**Tencent**) ∗ 1 (**Book**) | **4.926e-03**$^{***}$ | **4.926e-03**$^{***}$ | **4.926e-03**$^{***}$ | **4.926e-03**$^{***}$ |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| 1 (Tencent) | -2.866e-03$^{**}$ | -2.953e-03$^{**}$ | -2.918e-03$^{**}$ | -2.000e-03 |
| | (0.001) | (0.001) | (0.001) | (0.002) |
| 1 (Book) | -0.008$^{***}$ | -0.008$^{***}$ | -0.008$^{***}$ | -0.008$^{***}$ |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Age | | -0.197e-04 | -0.329e-04 | -0.001$^{**}$ |
| | | (0.262e-04) | (0.264e-04) | (3.769e-04) |
| Sq_Age | | 0.281e-08$^{**}$ | 0.313e-08$^{**}$ | 0.433e-07$^{***}$ |
| | | (0.138e-08) | (0.140e-08) | (0.163e-07) |
| (Intercept) | 0.016$^{***}$ | 0.016$^{***}$ | 0.016$^{***}$ | 0.044$^{**}$ |
| | (0.001) | (0.001) | (0.001) | (0.022) |
| **User Location FE** | | | Yes | |
| **User FE** | | | | Yes |
| $R^2$ | 0.0002 | 0.0003 | | |
| **Adj.** $R^2$ | | | 0.002 | 0.102 |
| **Num. obs.** | 376,768 | 376,768 | 376,768 | 376,768 |

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

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.

**Table 10 OLS Estimates of the Exogenous Shock Effects on the Variance of Review Ratings**

| | OLS Results | | | |
|---|---|---|---|---|
| **Dep var.:** S.d. of Ratings | Spec 1 | Spec 2 | Spec 3 | Spec 4 |
| 1 (**Tencent**) ∗ 1 (**Book**) | **0.201e-03**$^{*}$ | **0.201e-03**$^{*}$ | **0.201e-03**$^{*}$ | **0.201e-03**$^{*}$ |
| | (1.241e-04) | (1.241e-04) | (1.241e-04) | (1.207e-04) |
| 1 (Tencent) | -0.145e-03 | -0.142e-03 | -0.141e-03 | -0.161e-04 |
| | (0.095e-03) | (0.095e-03) | (0.095e-03) | (0.128e-03) |
| 1 (Book) | -0.236e-03$^{***}$ | -0.236e-03$^{***}$ | -0.236e-03$^{***}$ | -0.236e-03$^{***}$ |
| | (0.857e-04) | (0.857e-04) | (0.858e-04) | (0.828e-04) |
| Age | | -0.183e-07 | -0.169e-07 | -0.755e-04$^{**}$ |
| | | (0.237e-07) | (0.231e-07) | (0.352e-04) |
| Sq_Age | | 0.715e-10 | 0.547e-10 | 0.295e-08$^{**}$ |
| | | (0.109e-09) | (0.108e-09) | (0.137e-08) |
| (Intercept) | 0.444e-03$^{***}$ | 0.001$^{***}$ | 0.001$^{***}$ | 0.004$^{*}$ |
| | (0.717e-04) | (0.125e-03) | (0.123e-03) | (0.002) |
| **User Location FE** | | | Yes | |
| **User FE** | | | | Yes |
| $R^2$ | 0.000 | 0.000 | | |
| **Adj.** $R^2$ | | | -0.001 | 0.053 |
| **Num. obs.** | 376,768 | 376,768 | 376,768 | 376,768 |

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

The last set of estimation results are presented in Table 11, used to test the hypothesis H4. We are investigating the shock effects on the "quality" or the helpfulness of the reviews from the readers' points of views. We hypothesize that the exogenous shock does not have significant effects. The results lend support to this conjecture, and imply that the true causal effect is not statistically significant at any significance level.

The findings summarized above support all our hypotheses. However, there are extra concerns that may potentially mitigate the reliability of these findings, including concerns about our samples used and empirical specifications. In the next section, we carry out robustness checks (or specification tests) according to each of these concerns.

**5.2.4. 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 (including TV shows), 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

**Table 11 OLS Estimates of the Exogenous Shock Effects on the Quality of Review Ratings**

| | OLS Results | | | |
|---|---|---|---|---|
| **Dep var.:** Avg. Helpfulness | Spec 1 | Spec 2 | Spec 3 | Spec 4 |
| $1\,(\textbf{Tencent}) * 1\,(\textbf{Book})$ | **0.004** | **0.004** | **0.004** | **0.004** |
| | (0.010) | (0.010) | (0.010) | (0.010) |
| 1 (Tencent) | -0.003 | -0.004 | -0.004 | 0.007 |
| | (0.007) | (0.007) | (0.007) | (0.010) |
| 1 (Book) | -0.006 | -0.006 | -0.006 | -0.006 |
| | (0.008) | (0.008) | (0.008) | (0.008) |
| Age | | 0.201e-03 | 0.192e-03 | -0.001 |
| | | (0.177e-03) | (0.182e-03) | (0.002) |
| Sq_Age | | 0.182e-08 | 0.197e-08 | -0.137e-04 |
| | | (0.112e-07) | (0.115e-07) | (0.167e-04) |
| (Intercept) | $0.020^{***}$ | 0.004 | 0.005 | 0.164 |
| | (0.006) | (0.008) | (0.008) | (0.129) |
| **User Location FE** | | | Yes | |
| **User FE** | | | | Yes |
| $R^2$ | 0.000 | 0.000 | | |
| **Adj.** $R^2$ | | | -0.001 | 0.015 |
| **Num. obs.** | 376,768 | 376,768 | 376,768 | 376,768 |

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

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.[13] 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 12 and 13. We find qualitatively consistent estimates of the exogenous shock effects with our main findings in Table 7 through 11.

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),

[13] 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.

**Table 12 Robustness Check I: Comparing Book Reviews with Movie Reviews**

| | OLS Results | | | | |
|---|---|---|---|---|---|
| **Dep var.**: | log (# Reviews) | log (Rev. Lengths) | Avg. Rating | SD Ratings | Avg. Helpfulness |
| 1 (**Tencent**) ∗ 1 (**Book**) | **0.862e-03**$^{***}$ | **6.460e-03**$^{***}$ | **4.772e-03**$^{***}$ | **0.177e-03**$^{*}$ | **0.005** |
| | (0.255e-03) | (0.002) | (0.001) | (0.108e-03) | (0.010) |
| 1 (Tencent) | -0.290e-03 | -2.774e-03 | -0.002 | 0.025e-03 | 0.007 |
| | (0.300e-03) | (0.002) | (0.002) | (0.119e-03) | (0.010) |
| 1 (Book) | -0.001$^{***}$ | -0.007$^{***}$ | -0.005$^{***}$ | -0.121e-03 | -0.002 |
| | (0.185e-03) | (0.001) | (0.001) | (0.753e-04) | (0.008) |
| Age | -0.192e-03$^{***}$ | -1.223e-03$^{**}$ | -0.001$^{**}$ | -0.773e-04$^{**}$ | -0.001 |
| | (0.729e-04) | (0.001) | (0.349e-03) | (0.332e-04) | (0.002) |
| Sq_Age | 0.854e-08$^{***}$ | 0.647e-07$^{***}$ | 0.376e-07$^{**}$ | 0.277e-08$^{**}$ | -0.141e-04 |
| | (0.309e-08) | (0.233e-07) | (0.149e-07) | (0.120e-08) | (0.154e-04) |
| (Intercept) | 0.010$^{***}$ | 0.057$^{*}$ | 0.035$^{*}$ | 0.004$^{**}$ | 0.174 |
| | (0.004) | (0.031) | (0.021) | (0.002) | (0.123) |
| **User FE** | Yes | Yes | Yes | Yes | Yes |
| **Adj.** $R^2$ | 0.138 | 0.114 | 0.096 | 0.057 | 0.009 |
| **Num. obs.** | 376,768 | 376,768 | 376,768 | 376,768 | 376,768 |

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

**Table 13 Robustness Check II: Comparing Book Reviews with Music Reviews**

| | OLS Results | | | | |
|---|---|---|---|---|---|
| **Dep var.**: | log (# Reviews) | log (Rev. Lengths) | Avg. Rating | SD Ratings | Avg. Helpfulness |
| 1 (**Tencent**) ∗ 1 (**Book**) | **0.424e-03**$^{**}$ | **3.404e-03**$^{**}$ | **2.541e-03**$^{**}$ | **0.906e-04** | **0.002** |
| | (0.202e-03) | (0.002) | (0.001) | (0.855e-04) | (0.008) |
| 1 (Tencent) | 0.324e-04 | -0.306e-04 | 0.285e-03 | 0.915e-07 | 0.004 |
| | (0.205e-03) | (0.002) | (0.001) | (0.075e-03) | (0.007) |
| 1 (Book) | 0.001$^{***}$ | 0.007$^{***}$ | 0.004$^{***}$ | 0.122e-03$^{**}$ | 0.010$^{*}$ |
| | (0.143e-03) | (0.001) | (0.001) | (0.055e-03) | (0.006) |
| Age | -0.124e-03$^{**}$ | -0.001$^{*}$ | -0.001$^{**}$ | -0.037e-03 | -0.001 |
| | (0.587e-04) | (0.423e-03) | (0.285e-03) | (0.229e-04) | (0.001) |
| Sq_Age | 0.589e-08$^{**}$ | 0.408e-07$^{**}$ | 0.260e-07$^{**}$ | 0.175e-08$^{*}$ | -0.407e-07 |
| | (0.274e-08) | (0.202e-07) | (0.131e-07) | (0.999e-09) | (0.902e-07) |
| (Intercept) | 0.005 | 0.030 | 0.025 | 0.001 | 0.074 |
| | (0.003) | (0.025) | (0.016) | (0.001) | (0.113) |
| **User FE** | Yes | Yes | Yes | Yes | Yes |
| **Adj.** $R^2$ | 0.119 | 0.094 | 0.080 | 0.042 | 0.005 |
| **Num. obs.** | 376,768 | 376,768 | 376,768 | 376,768 | 376,768 |

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

and between May 9, 2009 and November 22, 2009 (12 weeks before and after the shock) respectively. We report estimation results in Table 14 and 15. 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.

**Table 14 Robustness Check III: an Alternative Sampling Period Jun. 6, 2009 - Sep. 25, 2009**

| | OLS Results | | | | |
|---|---|---|---|---|---|
| **Dep var.**: | log (# Reviews) | log (Rev. Lengths) | Avg. Rating | SD Ratings | Avg. Helpfulness |
| 1 (**Tencent**) ∗ 1 (**Book**) | **0.639e-03**$^{**}$ | **4.040e-03**$^{***}$ | **3.171e-03**$^{***}$ | **0.163e-03**$^{*}$ | **0.002** |
| | (0.195e-03) | (0.001) | (0.001) | (0.091e-03) | (0.006) |
| 1 (Tencent) | -0.886e-04 | -0.256e-03 | -0.190e-03 | -0.248e-07 | 0.002 |
| | (0.228e-03) | (0.002) | (0.001) | (0.103e-03) | (0.007) |
| 1 (Book) | -0.001$^{***}$ | -0.011$^{***}$ | -0.008$^{***}$ | -0.177e-03$^{**}$ | -0.006 |
| | (0.144e-03) | (0.001) | (0.001) | (0.695e-04) | (0.005) |
| Age | -0.110e-03$^{***}$ | -0.001$^{***}$ | -0.001$^{***}$ | -0.355e-04$^{***}$ | 0.939e-04 |
| | (0.271e-04) | (0.203e-03) | (0.135e-03) | (0.126e-04) | (0.001) |
| Sq_Age | 0.250e-08$^{**}$ | 0.144e-07 | 0.953e-08 | 0.914e-09$^{*}$ | -0.425e-07 |
| | (0.121e-08) | (0.895e-08) | (0.582e-08) | (0.516e-09) | (0.366e-07) |
| (Intercept) | 0.009$^{***}$ | 0.065$^{***}$ | 0.046$^{***}$ | 0.002$^{***}$ | 0.045 |
| | (0.002) | (0.012) | (0.008) | (0.001) | (0.041) |
| **User FE** | Yes | Yes | Yes | Yes | Yes |
| **Adj.** $R^2$ | 0.122 | 0.101 | 0.085 | 0.039 | 0.018 |
| **Num. obs.** | 725,664 | 725,664 | 725,664 | 725,664 | 725,664 |

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

**Table 15 Robustness Check IV: an Alternative Sampling Period May 9, 2009 - Oct. 23, 2009**

| | OLS Results | | | | |
|---|---|---|---|---|---|
| **Dep var.**: | log (# Reviews) | log (Rev. Lengths) | Avg. Rating | SD Ratings | Avg. Helpfulness |
| 1 (**Tencent**) ∗ 1 (**Book**) | **0.608e-03**$^{***}$ | **4.001e-03**$^{***}$ | **3.175e-03**$^{***}$ | **0.148e-03**$^{**}$ | **-0.004** |
| | (0.161e-03) | (0.001) | (0.001) | (0.074e-03) | (0.007) |
| 1 (Tencent) | -0.263e-03 | -0.002 | -0.001 | -0.457e-04 | 0.003 |
| | (0.189e-03) | (0.001) | (0.001) | (0.079e-03) | (0.006) |
| 1 (Book) | -0.001$^{***}$ | -0.011$^{***}$ | -0.008$^{***}$ | -0.156e-03$^{***}$ | -0.005 |
| | (0.119e-03) | (0.001) | (0.001) | (0.582e-04) | (0.005) |
| Age | -0.536e-04$^{***}$ | -0.377e-03$^{***}$ | -0.231e-03$^{***}$ | -0.209e-04$^{***}$ | 0.001 |
| | (0.152e-04) | (0.114e-03) | (0.075e-03) | (0.761e-07) | (0.001) |
| Sq_Age | 0.106e-08 | 0.749e-08 | 0.329e-08 | 0.563e-09$^{*}$ | -0.425e-07 |
| | (0.650e-09) | (0.495e-08) | (0.319e-08) | (0.312e-09) | (0.358e-07) |
| (Intercept) | 0.006$^{***}$ | 0.045$^{***}$ | 0.030$^{***}$ | 0.002$^{***}$ | 0.006 |
| | (0.001) | (0.007) | (0.004) | (0.423e-03) | (0.027) |
| **User FE** | Yes | Yes | Yes | Yes | Yes |
| **Adj.** $R^2$ | 0.102 | 0.085 | 0.072 | 0.025 | 0.014 |
| **Num. obs.** | 1,044,384 | 1,044,384 | 1,044,384 | 1,044,384 | 1,044,384 |

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

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 16 and 17. 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.

**Table 16 Robustness Check V: Users Joining Before July 4, 2008**

| | OLS Results | | | | |
|---|---|---|---|---|---|
| **Dep var.**: | log (# Reviews) | log (Rev. Lengths) | Avg. Rating | SD Ratings | Avg. Helpfulness |
| 1 (**Tencent**) ∗ 1 (**Book**) | **0.748e-03**$^{*}$ | **5.737e-03**$^{***}$ | **3.781e-03**$^{*}$ | **1.947e-04** | **0.010** |
| | (0.390e-03) | (0.003) | (0.002) | (0.151e-03) | (0.018) |
| 1 (Tencent) | -0.154e-03 | -0.002 | -0.001 | -0.002-02 | 0.014 |
| | (0.454e-03) | (0.004) | (0.002) | (0.170e-03) | (0.017) |
| 1 (Book) | -0.002$^{***}$ | -0.013$^{***}$ | -0.009$^{***}$ | -0.274e-03$^{**}$ | -0.013 |
| | (0.227e-03) | (0.002) | (0.001) | (0.107e-03) | (0.014) |
| Age | -0.276e-03$^{*}$ | -0.002$^{*}$ | -0.002$^{**}$ | -0.131e-03$^{**}$ | -0.472e-03 |
| | (0.148e-04) | (0.001) | (0.001) | (0.603e-04) | (0.007) |
| Sq_Age | 0.107e-07$^{*}$ | 0.900e-07$^{**}$ | 0.591e-07$^{**}$ | 0.500e-08 | -0.021e-03 |
| | (0.579e-08) | (0.441e-07) | (0.282e-07) | (0.206e-08) | (0.304e-04) |
| (Intercept) | 0.019$^{*}$ | 0.132 | 0.101$^{*}$ | 0.008$^{*}$ | 0.364 |
| | (0.011) | (0.084) | (0.055) | (0.004) | (0.420) |
| **User FE** | Yes | Yes | Yes | Yes | Yes |
| **Adj.** $R^2$ | 0.132 | 0.103 | 0.090 | 0.062 | 0.015 |
| **Num. obs.** | 207,936 | 207,936 | 207,936 | 207,936 | 207,936 |

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

### 5.3. Discussions

Our findings indicate that the larger network sizes, the direct consequence of the exogenous shock, cause Douban users to publish more and longer book reviews compared to other reviews. This positive relationship, between the group size and levels of contribution to public goods, lends support to the social effect hypothesis in private provision of public goods (Andreoni 1989). Specifically, when making the decisions to post product reviews, individuals gain benefits from not only the total volume of reviews by all Douban users,

**Table 17 Robustness Check VI: Users Joining After July 4, 2008**

| | OLS Results | | | | |
|---|---|---|---|---|---|
| **Dep var.**: | log (# Reviews) | log (Rev. Lengths) | Avg. Rating | SD Ratings | Avg. Helpfulness |
| 1 (**Tencent**) ∗ 1 (**Book**) | **1.178e-03**$^{***}$ | **8.294e-03**$^{***}$ | **6.337e-03**$^{***}$ | **2.088e-04** | **-0.002** |
| | (0.382e-03) | (0.003) | (0.002) | (0.195e-03) | (0.004) |
| 1 (Tencent) | -0.001 | -0.004 | -0.004 | -0.114e-04 | -0.001 |
| | (0.446e-03) | (0.003) | (0.002) | (0.194e-03) | (0.005) |
| 1 (Book) | -0.001$^{***}$ | -0.011$^{***}$ | -0.008$^{***}$ | -0.190e-03 | 0.004 |
| | (0.288e-03) | (0.002) | (0.001) | (0.129e-03) | (0.003) |
| Age | -0.401e-03$^{***}$ | -0.002$^{**}$ | -0.002$^{**}$ | -0.104e-03 | 0.417e-03 |
| | (0.145e-03) | (0.001) | (0.001) | (0.762e-04) | (0.001) |
| Sq_Age | 0.522e-07 | 0.283e-04$^{**}$ | 0.244e-04$^{***}$ | 0.102e-07 | 0.361e-07 |
| | (0.169e-07) | (0.115e-04) | (0.776e-07) | (0.837e-08) | (0.173e-04) |
| (Intercept) | 0.009$^{***}$ | 0.055$^{***}$ | 0.036$^{***}$ | 0.002 | -0.010 |
| | (0.003) | (0.019) | (0.013) | (0.001) | (0.031) |
| **User FE** | Yes | Yes | Yes | Yes | Yes |
| **Adj.** $R^2$ | 0.174 | 0.150 | 0.121 | 0.044 | 0.016 |
| **Num. obs.** | 168,832 | 168,832 | 168,832 | 168,832 | 168,832 |

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

but also his or her private contributions (Andreoni 1990). In this sense, our findings of the positive effects are consistent with recent empirical investigations of public goods provisions (Zhang and Zhu 2011).

Our findings of positive effect on the valence of review ratings are in sharp contrast to those found in Goes et al. (2014). We attribute the disagreement to the potential endogeneity of followers count in social networks. Goes et al. (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 in-degree (*i.e.*, the number of followers) 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 provide discussions on how this issue leads to biased estimates and the rationale for the underestimation of true effects on valence.

Methodologically, the current research is among the first introducing a quasi-experimental method, DID utilizing the exogenous shock as a natural experiment (Card and Krueger 1994, Athey and Imbens 2006), into the literature on the network effects on online reviews (Chevalier and Mayzlin 2006, Wang et al. 2015), or more broadly online communities. The advantage of this method is providing us a clear and credible identification strategy to uncover the true effect of social influence on individuals' behaviors.

From more practical point of view, especially the platform's purposes, Douban.com wants to increase its users' "activeness" on site - posting more reviews. For online platforms, higher level of user participation usually leads to higher profitability. To promote more contributions from its users, our results suggest that the platform should target at increasing the population of readers and audience of its product reviews. Establishing direct access to other large-scale online social networks, such as the exogenous shock under investigation, is a plausible and effective strategy.

## 6. Concluding Remarks

A variety of online platforms that rely on user-generated content have been established in recent years. Individuals on these platforms privately contribute to a wide range of online public goods, including but not limited to articles (Wikipedia.org), microblogs (Twitter.com), and product reviews (Yelp.com, YouTube.com, and Douban.com). How does the network structure affect individuals' incentives to contribute to these online public goods? Particularly, how do more friends or larger population of audience impact one's behaviors? There are the research questions to which we seek answers in the current study.

We examine a large-scale online networking site that provides a platform for individuals to publish third-party product reviews, Douban.com. The identification of the causal effect of network sizes hinges on a sudden and unexpected merge with another large-scale and influential network, an exogenous shock to the Douban network. Using this "natural experiment," we conduct DID analysis and find that the exogenous shock causes Douban users to write more and longer book reviews. Not limited to the effects on the volume of contribution, we also find statistically significant effects on the valence of review ratings. Specifically, the exogenous shock causes individuals to assign higher and more extensive ratings of reviews. In contrast, however, we do not find significant effects on the helpfulness of reviews evaluated by readers. These findings lend support to the social effect hypothesis in the theory of private provision of public goods. Practically, our results have managerial implications for the platform to promote more active contributions to the public good - online reviews.

An important implication of our current findings is the network effect on Internet users' incentives to contribute to those user-generated contents in online communities. We focus on the network size effects in this study. However, how does one's network position affect his or her contribution levels? What are the impacts of his or her neighbors' contributions? In our data, we notice that less than 25% of the sampled users ($5,823$ out of $24,374$) published product reviews during our two-year study period. What are the factors that contribute to this skewness in review posting behavior? As a future direction, answers to these questions about network effects on contributions to user-generated contents are worth pursuing.

## References

Abadie, A. 2005. Semiparametric Difference-in-Differences Estimators. *Review of Economic Studies* **72**(1): 1–19.

Andreoni, J. 1989. Privately Provided Public Goods in a Large Economy: The Limits of Altruism. *Journal of Public Economics* **35**(1): 57–73.

Andreoni, J. 1989. Giving with Impure Altruism: Applications to Charity and Ricardian Equivalence. *Journal of Political Economy* **97**(6): 1447–1458.

Andreoni, J. 1990. Impure Altruism and Donations to Public Goods: A Theory of Warm-Glow Giving. *Economic Journal* **100**(401): 464–477.

Andreoni, J. 2007. Giving Gifts to Groups: How Altruism Depends on the Number of Recipients. *Journal of Public Economics* **91**(9): 1731–1749.

Andreoni, J., and B. D. Bernheim. 2009. Social Image and the 50-50 Norm: A Theoretical and Experimental Analysis of Audience Effects. *Econometrica* **77**(5): 1607–1636.

Ashenfelter, O. 1978. Estimating the Effect of Training Programs on Earnings. *Review of Economics and Statistics* **6**(1): 47–57.

Athey, S., and G. Imbens. 2006. Identification and Inference in Nonlinear Difference-In-Differences Models. *Econometrica* **74**(2): 431–497.

Barabási, A. L. 2005. The Origin of Bursts and Heavy Tails in Human Dynamics. *Nature* **435**(7039): 207–211.

Bateman, P. J., P. H. Gary, and B. S. Butler. 2011. The Impact of Community Commitment on Participation in Online Communities. *Information Systems Research* **22**(4): 841–854.

Beaman, L. A. 2012. Social Networks and the Dynamics of Labour Market Outcomes: Evidence from Refugees Resettled in the U.S. *Review of Economic Studies* **79**(1): 128–161.

Bergstrom, T., L. Blume, and H. Varian. 1986. On the Private Provision of Public Goods. *Journal of Public Economics* **59**(2): 299–308.

Bramoullé, Y. and R. Kranton. 2007. Public Goods in Networks. *Journal of Economic Theory* **135**(1): 478–494.

Cao, Q., W. Duan, and Q. Gan. 2011. Exploring Determinants of Voting for the "Helpfulness" of Online User Reviews: A Text Mining Approach. *Decision Support Systems* **50**(2): 511–521.

Card, D., and A. B. Krueger. (1994). Minimum Wages and Employment: A Case Study of the Fast Food Industry in New Jersey and Pennsylvania. *American Economic Review* **84**(4): 772–793.

Crane, R., and D. Sornette. (2008). Robust Dynamic Classes Revealed by Measuring the Response Function of a Social System. *Proceedings of the National Academy of Sciences* **105**(41): 15649–15653.

Chamberlin, J. 1974. Provision of Collective Goods as a Function of Group Size. *American Political Science Review* **68**(2): 707–716.

Chen, Y., and J. Xie. (2005). Third-Party Product Review and Firm Marketing Strategy. *Marketing Science* **24**(2): 218–240.

Chen, Y., and J. Xie. (2005). Online Consumer Review: Word-of-Mouth as a New Element of Marketing Communication Mix. *Management Science* **54**(3): 477–491.

Chevalier, J. A., and D. Mayzlin. (2006). The Effect of Word of Mouth on Sales: Online Book Reviews. *Journal of Marketing Research* **43**(3): 345–354.

Dellarocas, C. 2003. The Digitization of Word of Mouth: Promise and Challenges of Online Feedback Mechanisms. *Management Science* **49**(10): 1407–1424.

Dellarocas, C. 2006. Strategic Manipulation of Internet Opinion Forums: Implications for Consumers and Firms. *Management Science* **52**(10): 1577–1593.

Dellarocas, C., X. Zhang, and N. F. Awad. 2007. Exploring the Value of Online Product Reviews in Forecasting Sales: The Case of Motion Pictures. *Journal of Interactive Marketing* **21**(4): 23–45.

Duan, W., B. Gu, and A. B. Whinston. 2008. Do Online Reviews Matter? An Empirical Investigation of Panel Data. *Decision Support Systems* **45**(4): 1007–1016.

Duncan, B. 2004. A Theory of Impact Philanthropy. *Journal of Public Economics* **88**(9-10): 2159–2180.

Forman, C., A. Ghose, and B. Wiesenfeld. 2008. Examining the Relationship Between Reviews and Sales: The Role of Reviewer Identity Disclosure in Electronic Markets. *Information Systems Research* **19**(3): 291–313.

Goes, P., M. Lin, and C. Au Yeung. 2014. "Popularity Effect" in User-Generated Content: Evidence from Online Product Reviews. *Information Systems Research* **25**(2): 222–238.

Goldsmith-Pinkham, P., and G. W. Imbens. 2013. Social Networks and the Identification of Peer Effects. *Journal of Business and Economic Statistics* **31**(3): 253–264.

Gu, B., P. Konana, R. Rajagopalan, and H-WM Chen. 2007. Competition among Virtual Communities and User Valuation: The Case of Investing-Related Communities. *Information Systems Research* **18**(1): 68–85.

Imbens, G.W. and J. M. Wooldridge. 2009. Recent Developments in the Econometrics of Program Evaluation. *Journal of Economic Literature* **47**(1): 5–86.

Jackson, M. O. 2010. Social and Economics Networks. *Princeton University Press.*

Li, X., and L. M. Hitt. 2008. Self-Selection and Information Role of Online Product Reviews. *Information Systems Research* **19**(4): 456–474.

Liu, Y. 2006. Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue. *Journal of Marketing* **70**(3): 74–89.

Ma, M., and R. Agarwal. 2007. Through a Glass of Darkly: Information Technology Design, Identity Verification, and Knowledge Contribution in Online Communities. *Information Systems Research* **18**(1): 42–67.

Manski, C. F.. 1993. Identification of Endogenous Social Effects: The Reflection Problem. *Review of Economic Studies* **60**(3): 531–542.

Mudambi, S. and D. Schuff. 2010. What Makes a Helpful Review? A Study of Customer Reviews on Amazon.com. *MIS Quarterly* **34**(1): 185–200.

Ofir, C., and I. Simonson. 2001. In Search of Negative Customer Feedback: The Effect of Expecting to Evaluate on Satisfaction Evaluations. *Journal of Marketing Research* **38**(2): 170–182.

Olson, M. 1965. The Logic of Collective Action: Public Goods and the Theory of Groups. Harvard University Press.

Price, D. J. S. 1965. Networks of Scientific Papers. *Science* **149**: 510–515.

Ransbotham, S., and G. C. Kane. 2011. Membership Turnover and Collaboration Success in Online Communities: Explaining Rises and Falls from Grace in Wikipedia. *MIS Quarterly* **35**(3): 613–627.

Ransbotham, S., G. C. Kane, and N. H. Lurie. 2012. Network Characteristics and the Value of Collaborative User-Generated Content. *Marketing Science* **31**(3): 387–405.

Sun, M. 2012. How Does the Variance of Product Ratings Matter? *Management Science* **58**(4): 696–707.

Wang, C., X. Zhang, and I. Hann. 2015. Socially Nudged: A Quasi-Experimental Study of Friends' Social Influence in Online Product Ratings. *Information Systems Research*. Forthcoming.

Wooldridge, J. 2002. Econometric Analysis of Cross Section and Panel Data. The MIT Press.

Xu, L., T. Nian, and L. Cabral. 2014. What Makes Geeks Tick? A Study of Stack Overflow Careers. *Working paper.*

Zhang, X., and F. Zhu. 2011. Group Size and Incentives to Contribute: A Natural Experiment at Chinese Wikipedia. *American Economic Review* **101**(4): 1601–1615.

Zhu, F., and X. Zhang. 2010. Impact of Online Consumer Reviews on Sales: The Moderating Role of Product and Consumer Characteristics. *Journal of Marketing* **74**(2): 133–148.