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Completed Research Paper

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Abstract

Although user-generated content (UGC) is prevalent these days, high-quality UGC is still desired by readers and is crucial for the development of a website. Therefore, how to encourage users to produce high-quality content becomes a critical issue for UGC platforms. Using travel blogs collected from Lvmama.com, a leading online travel agency (OTA) in China, we investigated the effects of money-based incentives on user effort to generate high-quality content and its performance in the long run. The launch of money-based incentives after several years of running of the platform provides an ideal natural experiment setting. We applied the regression discontinuity design, and the results show that both user effort and UGC quality increased after the incentive program was released. However, the UGC quality declined quickly after that. This study concludes by presenting theoretical and managerial implications for both research and practice.

Keywords: UGC quality, money-based incentive, UGC motivation, natural experiment

Introduction

User-generated content (UGC) is currently playing a vital role in people's daily lives, especially in decision making (Liu, 2006; Zhou and Duan, 2016; Zhu and Zhang, 2010). For UGC websites, the quantity and quality of UGC is an assurance to maintain their current users and attract new ones (Goes et al., 2016; Liu and Park, 2015). However, UGC such as product reviews and travel blogs is a typical type of public good that individuals can use without being required to contribute (Chen et al., 2010). Furthermore, the quality of UGC is out of control since it is generated by a large number of users with different levels of expertise. Poor-quality UGC is inefficient in providing information for readers and leads to the issue of information overload, which presents a barrier for readers to quickly locate the useful information. Therefore, how to motivate users to continuously contribute high-quality content becomes a critical issue for UGC websites.

Many UGC websites, such as ecommerce websites, movie-review websites, and online travel agencies (OTAs), deploy online incentives to encourage user activities (Zhang et al., 2016). While extant studies provided consistent evidence that online incentives exert a positive influence on user effort in contributing more content (Cavusoglu et al., 2015; Goes et al., 2016; Hamari, 2017), little attention has been paid to UGC quality. The numerous users and the introduction of online incentives result in overwhelming UGC. Hence, information searchers (potential consumers) spend increasing time on locating high-quality content to make decisions. Under such circumstances, high-quality content plays a key role. Therefore, most UGC websites try to encourage and screen out the high-quality UGC with the help of crowds. For instance, they deploy the "like" function that enables readers to praise the high-quality reviews and utilize money-based incentives to encourage users to exert more effort when writing reviews. Our study aims to reveal whether money-based incentives work for improving UGC quality.

Data from Lvmama.com, a leading OTA in China, were employed in this study. Lvmama.com launched a money-based incentive called Travel Treasure to encourage users to contribute high-quality travel blogs. In this program, qualified travel blogs recognized by the official website can receive money rewards. Because Lvmama.com had run for several years before the launch of this incentive program, it provides a natural experiment setting for this study to investigate the effects of this reward program.

Two main findings were drawn from this study. First, the money-based incentive program increases user effort in UGC quality improvement. Second, UGC quality increases at the beginning stage of the program but quickly decreases after that. These findings have significant theoretical contributions and managerial implications regarding online incentives and user effort intention.

The rest of this paper begins with an overview of the related literature, which is followed by hypotheses development. The data section illustrates the research context and shows model-free evidence. The empirical analysis section presents the econometrics analysis. We conclude the paper in the last section by revisiting the findings with discussions.

Literature review

This study relates to two important and expansive streams of research in the literature: WOM and online incentives. First, travel blogs are a kind of UGC and eWOM, and we analyze users' motivations to contribute under a theoretical framework. Second, money-based rewards are a kind of online incentive among UGC websites. Hence, we review the literature relevant to online incentives and user effort.

Motivation to contribute

Lovett et al. (2013) developed a WOM theoretical framework by summarizing previous studies and concluded three major drivers that motivate users to produce WOM. The three major drivers are social, functional, and emotional. We thus introduce this WOM theoretical framework to understand users' motivation in online contributions.

First are social drivers. As Lovett et al. (2013) and Luo et al. (2017) suggested, users have the desire to send signals to others about their status, expertise, and uniqueness. eWOM is a fast channel for users to show and enhance their expertise level among a large audience. Thereby, users are more likely to engage in posting eWOM on products or services that allow for them to gain recognition or reputation from peers or the official website (Berger and Heath, 2007; Cheema and Kaikati, 2010). Thus, the social driver is salient in explaining users' motivations to contribute, especially for high-quality content, as the number of "helpful votes" or "likes" received from readers can promote users' statuses and online reputation.

Second are functional drivers. This driver is related to the need to acquire and supply information (Anand and Shachar, 2011; Godes and Mayzlin, 2004; Mudambi and Schuff, 2010). The fundamental function of WOM is to reduce information asymmetry (Ba and Pavlou, 2002). Among the overwhelming number of online reviews, readers (potential consumers) are searching hard for high-quality reviews to make decisions. During this process, the supply of high-quality content plays a key role, and users are more likely to contribute high-quality content in high-involvement product markets with superfluous reviews (Peres, Muller, and Mahajan, 2010). To encourage frequent contributions and high-quality content, UGC websites usually deploy online incentives.

Third are emotional drivers. To share one's positive or negative feelings is a basic attribute of WOM (Berger and Milkman, 2012; Nardi et al., 2004; Peters and Kashima, 2007). This driver is particularly important in online situations and is driven by consumers' satisfaction degree for a product or service.

As UGC and social media become increasingly important in practice, eWOM, such as product reviews and travel blogs, gain significant attention from academia (Yen and Tang, 2015). In addition to the above three divers, extant studies have identified the following motives: social benefits (Yoo et al., 2013), economic incentives (Yoo et al., 2013), self-enhancement (Berger and Iyengar, 2013; Yoo et al., 2013), the expression of negative feelings (Hennig-Thurau et al., 2004), affiliation and a sense of belonging (Chen and Kirmani, 2015; Cheung and Lee, 2012), advice-seeking (Hennig-Thurau et al., 2004), altruism (Cheung and Lee, 2012), and persuasion (Chen and Kirmani, 2015).

Online incentives and user effort

The quantity and quality of user-generated content are crucial in the development of a website, but UGC is a public good that users can use for free (Chen et al., 2010). Thereby, encouraging users to contribute is a challenge for UGC websites.

In order to encourage users to frequently contribute blogs or reviews (quantity), UGC websites usually deploy incentive hierarchies, through which users can achieve increasingly higher statuses by accomplishing progressively difficult tasks (Liu et al. , 2018). In this system, the status of each user can be identified according to the uniform ranking system in which users can easily be compared with each other with their ranks (Goes et al., 2016). Usually, each badge corresponds to each rank and is designated by the website with the explicit criterion. The badges that users obtain are prominently displayed on their public profiles and can be viewed by their peers, which serve as symbols of users' statuses in a community (Anderson et al., 2015). A higher status represents greater glory, authority, and influence among peers (Anderson et al., 2015; Sailer et al., 2017).

Extant studies from several research fields confirmed the positive effects of online incentives on user effort (Cavusoglu et al., 2015; Goes et al., 2016; Liu et al., 2016). As Hamari (2017) stated, glory-based badges that represent statuses place participants in a gamified environment and increase their engagement intention. For instance, Goes et al. (2016) analyzed a dataset of online Q&A users and indicated that although glory-based incentives motivate users to contribute more, their contributory effort drops significantly after the statuses are obtained. Similarly, Liu et al. (2016) observed that the positive effect of glory-based badges is temporary and decreases with time using a dataset of online travel agency users. Cavusoglu et al. (2015) empirically examined the extent to which participants are motivated by earned badges and revealed a positive effect of badges on voluntary participation. Liu et al. (2018) revealed that users are more eager for the quick upgrade of their statuses when at a lower status.

However, as Anderson et al. (2013) discussed, although online incentives such as badges motivate users to increase their activities, it brings up the question regarding how these incentives affect the quality of their contributions. To encourage users to contribute high-quality content (quality), several incentives are usually adopted in practice: "helpful votes", "likes", and "expert reviews". Helpful votes or likes are recognition from peers (Baek et al., 2012; Fang et al., 2016). Kwok and Xie (2016) showed that the number of helpful votes that a review receives can be affected by the poster's status and other characteristics. Fang et al. (2016) found that the perceived value of online reviews (represented by helpful votes) is correlated with text readability and reviewer characteristics. An expert review is recognition from the official website, which can be more powerful than peer recognition in encouraging users to contribute high-quality content (Zhang et al., 2016). The extant studies mainly explored the influence of glory-based incentives (badge ranks) on user effort, but there is a lack of studies that investigate the influence of money-based incentives on user effort and UGC quality. We thus aim to fill this research gap and examine the efficiency of money-based incentives on encouraging user activities and UGC quality.

Hypotheses development

Since online incentives might influence user effort, which will ultimately affect the quality of UGC, hypotheses are developed for both user effort and UGC quality.

Goals and user effort

Rewards earned from online contributions are a powerful motivator within a community (Anderson and Brown, 2010; Anderson et al., 2015). Research has shown that individuals are motivated to approach rewards or goals (Elliot, 2006; Hull, 1932), and the motivation to achieve them intensifies as they are approaching (Kivetz et al., 2006; Wadhwa and Kim, 2015).

As the rewards program is issued, users are encouraged and motivated to achieve each reward. The pursuit of rewards can serve as goals and lead to goal-directed online behaviors (Cheema and Bagchi, 2011). According to Goal-setting Theory, participant effort will change before and after goal-seeking (Koo and Fishbach, 2008). Within a money-based incentive environment (after the rewards program is issued), users work hard to obtain each award. The desire for such rewards induces users to exert more effort on their blogs than before the rewards program was issued.

According to Prospect Theory (Kahneman and Tversky, 1979; Mcdermott et al., 2008; Tversky and Kahneman, 1992), rewards act as the reference point for users who post travel blogs after the rewards program was issued. Wang et al. (2017) revealed that the effort paid to a task can reinforce the evaluation and the subjective expectation of its performance. Accordingly, the more effort that a user exerted in writing a travel blog, the higher expectation he or she has on the blog, which thereby reinforces the user's expectation of achieving the award (Brehm and Self, 1989; Wang et al., 2017). Therefore, users are more motivated to contribute after the rewards program was issued compared to before when there are no incentives. Accordingly, we hypothesize the following:

H1: User effort on the platform increases after the release of a money-based incentive program.

Official recognition and UGC quality

Sharing one's experiences in an online community is largely a public good due to its positive externalities (Chen et al., 2010; Goes et al., 2016). For UGC websites, the key to resolving this public good problem and encouraging user contributions is to offer rewards through which users can internalize certain benefits of their contributions and fulfill their self-fulfillment demand (Hennig-Thurau et al., 2004). Different from most UGC websites, Lvmama offers money-based rewards.

Before the rewards program was issued, users were less motivated to improve the quality of their blogs due to the lack of efficient incentives. In this situation, high-quality blogs and poor-quality blogs are indifferent, both of which cannot earn rewards. Therefore, users' efforts and intentions to improve the quality of their contributions are weak. However, after the reward policy issues, earning the rewards can act as goals and lead to goal-directed behaviors. Users are motivated to try their best to earn the rewards, especially for the money-based rewards. According to the rewards policy, users can earn money from posting travel blogs only if their blogs are officially recognized as "recommendations" and "beautiful/helpful". As a result, a poor-quality blog requires less effort and has a low probability to earn a reward, while a high-quality blog needs more effort and has a high probability to earn a reward. To increase the probability of being recognized as a "recommendation" and "beautiful/helpful", users need to ensure or improve the quality of their blogs. Therefore, exerting more effort to generate high quality blogs becomes a better choice. As a result, the quality of UGC on the platform will increase. We thus propose the following:

H2: The UGC quality on the platform improves after the release of the money-based incentive program.

Data and model-free evidence

Research context

Lvmama.com is one of the leading OTAs in China, and it created a blog section for users to share their travel experiences approximately 2013. In September 2014, the company launched a money-based incentive program named Travel Treasure to encourage users to contribute more high-quality content. The first season of this program was concluded at the end of 2014, and the second season was launched in May 2015. On May 5th, 2015, an announcement of the second season of *Travel Treasure* was released. The announcement stated that users could receive reward points equal to 100 RMB for each qualified blog published between May 10th, 2015, and December 31st, 2015. The points can be applied to purchase any travel products (e.g., air tickets, hotels, tour packages, etc.) on Lvmama.com without any limitation except encashment. It means that the coupon can be similar to the role of cash. To be a qualified blog, the blog must include the label "I am an expert" in the title and should be officially recognized as a "*recommendation*" and "*beautiful* / *helpful*". "*Recommendation*" means that this blog is thought to be of high quality, "*helpful*" represents that this blog provides some useful tips for readers, and "*beautiful*" indicates that this blog provides enough beautiful photos.

Data collection and variables

Data collection was conducted on January 15th, 2018, and all historical travel blogs were retrieved. This study only uses the information of travel blogs posted in 2015 for two reasons. First, the first season only lasted for about three months, while the second season lasted for approximately 8 months. The longer period enables us to perform deeper analysis. Second, although Lvmama also launched the third season and fourth season, there are rarely gaps between seasons. The third season began on January 5th, 2016, and ended on December 31st, 2016. The fourth season began on January 1st, 2017, and ended on December 31st, 2017 Therefore, the year of 2015 that contains 4 months with no rewards program period and 8 months of the rewards program running period becomes the best period for this study to investigate the effect of this rewards program on the platform.

Moreover, 6,048 travel blogs were published in 2015. The data include the blog title, blog content, posting date, author, recommendation label, helpful label, beautiful label, number of views, number of likes, tour departure date (if reported), tour return date (if reported), etc.

User effort in writing blogs is measured by the text length (*TL*), which is the number of words in the blog. Text length is the most intuitive measurement of effort since longer text certainly takes more effort (Godes and Silva, 2012; Liu et al., 2018). The number of photos (*Photo*) uploaded in the blog is introduced as another measurement of user effort. Although uploading more photos also takes more effort due to the photo selection and photo arrangement, it obviously takes less effort than writing words. We thus use it for the robustness check.

Table 1. Summary statistics of interested variables

Variable	Obs.	Mean	Std. Dev.	Min	Max
TL	6,048	5.300	5.7516	0	32.767
LPV	6,048	1.637	12.9022	0	654.909
Photo	6,048	59.502	75.8077	0	1,186

Since it is difficult to directly measure the quality of blogs, this study employes the number of likes per thousand views (*LPV*) to measure the quality. The "likes" function is a kind of usefulness/helpfulness voting system. A like means that a reader was attracted by the blog and praised it, which indicates that this blog is helpful to him/her. Therefore, the number of likes can serve as a valid proxy for blog quality. Since the number of likes is correlated with the quality and the time elapsed since the blog was published, we used the number of likes per thousand views (*LPV*) in this study. Table 1 provides the summary statistics of the variables of interest, where *TL* is measured in thousands.

Identification strategy

The main purpose of this study is to explore the effect of launching a rewards program on user efforts in generating high-quality content. Since all users on the platform can join this rewards program to earn money by writing high-quality blogs, all of them were treated as individuals, which means that all users were supposed to change their behavioral patterns immediately after the shock of the rewards program. As a result, the regression discontinuity design (RDD) becomes an ideal method to identify the impacts of launching such a rewards program on user activities. Moreover, it is obviously a sharp RDD.

The running variable in RDD in this study is time. The announcement date of the rewards program (May 5th, 2015) is selected as the cutoff. To the best of our knowledge, there were no other events that happened in 2015 that might influence user activities. Thereby, the results will not be influenced by other exogenous shocks and users were not able to know the release date of this program in advance.

We use the announcement date rather than the effective date (May 10th, 2015) of the rewards program for two reasons. First, blogs should be officially evaluated to decide whether they are qualified, and the review process takes approximately 7 days. Therefore, users tend to take part in the program earlier than the effective date. Second, using the announcement date of policies, earnings, and other events is a common practice, especially in the decision-making behaviors such as investor reactions and information demand (Dellavigna and Pollet, 2009; Drake et al., 2012). In addition, we perform additional tests using the cutoff of May 10th, 2015, and the results support our selection.

Model-free evidence

We first provide some model-free evidence by drawing regression discontinuity plots. Two critical issues in RDD can lead to a biased estimation: bandwidth choice and the order of the polynomial. Although there are several algorithms to calculate the optimal bandwidth, it is better to provide more results with different bandwidth choices for robustness. Hence, four different bandwidths are selected in this study: 30, 60, 90, and 120. In addition, we also perform the MSE-optimal bandwidth choice and CER-optimal bandwidth choice with several kernels, and the results are within the range of these four bandwidths. We also provide results up to the fourth-order polynomial.

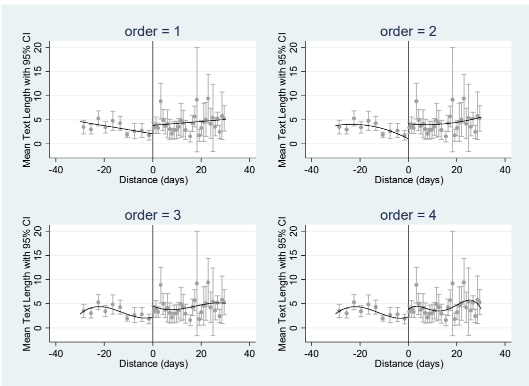

Figure 1. Mean text length against time with bandwidth = 30

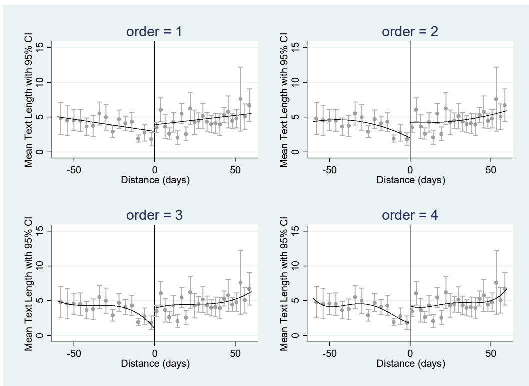

Figure 2. Mean text length against time with bandwidth = 60

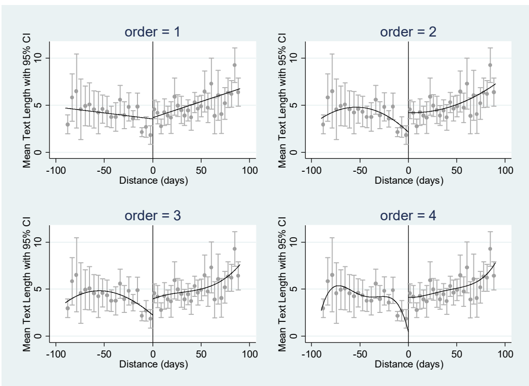

Figure 3. Mean text length against time with bandwidth = 90

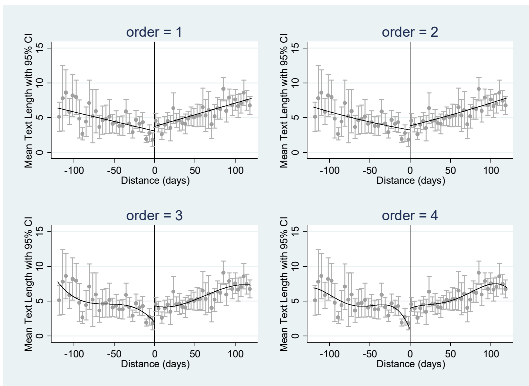

Figure 4. Mean text length against time with bandwidth = 120

The plots of mean text length against time with fitted curves are shown in Figures 1-4, where *Distance* represents the number of days to the cutoff day (May 5th, 2015). All 16 plots in these four figures show a clear positive jump at the cutoff, thus indicating that the release of the rewards program did increase user efforts on the platform.

Figures 5-8 present the plots of the mean *LPV* against time with fitted curves. Most of these plots show a clear positive jump at the cutoff except the plots in Figure 8, which reports the plots with a bandwidth of 120. It is reasonable that this bandwidth might be too large for RDD to estimate. The effect might decrease along with time, or the effect might be influenced by some unobserved random events. In fact, neither of the two optimal bandwidth choice algorithms suggests a large bandwidth for *LPV* (the largest one is approximately 60). Therefore, the plots suggest that the release of the rewards program increases the quality of the travel blogs on the platform.

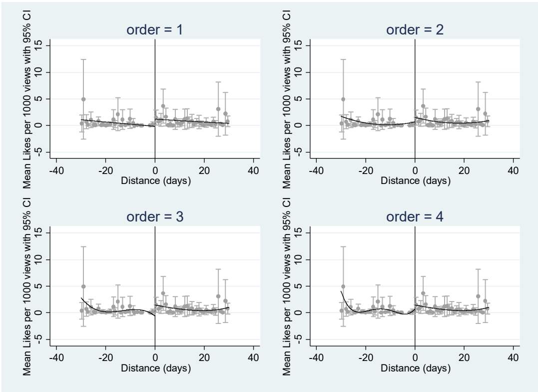

Figure 5. Mean LPV against time with bandwidth = 30

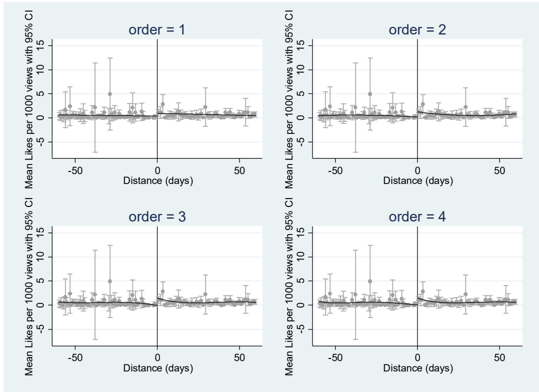

Figure 6. Mean LPV against time with bandwidth = 60

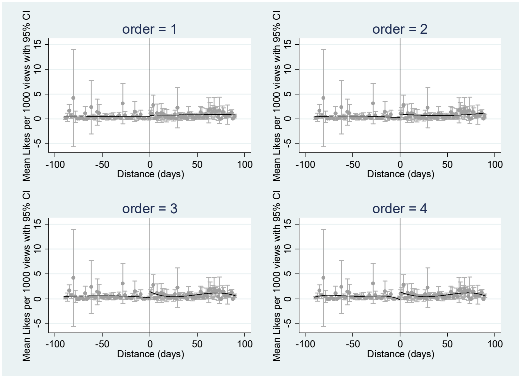

Figure 7. Mean LPV against time with bandwidth = 90

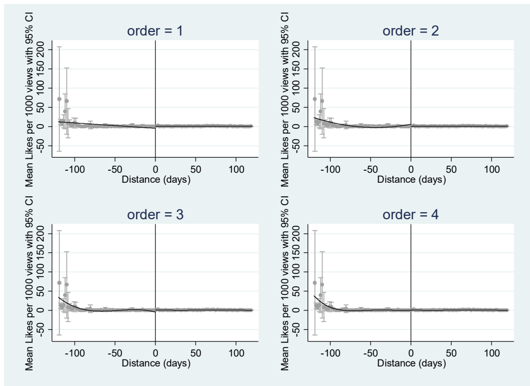

Figure 8. Mean LPV against time with bandwidth = 120

Empirical analysis

Econometrics model

The model-free evidence shows a significant effect of the rewards program. We thereby designed a regression discontinuity model to empirically investigate this effect further. The econometrics model is as follows (equation (1)).

$$y_i = \beta_0 1(Release_i) + 1(Release_i)\sum_{p=1}^{\bar{p}} \beta_{1,p}(|Distance_i|)^p + \left(1 - 1(Release_i)\right)\sum_{p=1}^{\bar{p}} \beta_{2,p}(|Distance_i|)^p + \mathbf{X}_i\boldsymbol{\gamma} + \varepsilon_i \quad (1)$$

In model (1), the dependent variable y_i represents the three interested variables of blog i: *TL*, *LPV*, and *Photo*. $1(Release_i)$ is a dummy variable indicating whether blog i is posted after the cutoff day (1 for after, 0 for before). $Distance_i$ represents the days from when blog i was posted to the cutoff day, and $\sum_{p=1}^{\bar{p}} \beta_{1,p}(|Distance_i|)^p$ is a $\bar{p}$-order polynomial of *Distance*. $\mathbf{X}_i$ is a set of control variables, while ε_i is the random error. The individual fixed effect is not included in this model since this study aims to investigate the performance of the rewards program on the platform, namely, the change of user efforts and UGC quality before and after the lunching of the rewards program. The effects of the rewards program on the individual level are beyond this study.

Results

For the dependent variable of text length (*TL*), two control variables are included. One is the total days of the whole tour. The more days that a tourist spent on a tour, the more things that he/she can do, and thereby, they can write more when posting travel blogs. The other is the number of days that elapsed from the return date of a tour and the blogging date since it is more difficult to recall things that happened a longer time ago.

The weighted least squares method is applied to estimate the model, and the weight is the inverse of the absolute distance. Up to the second-order polynomial is estimated in this study (Goes et al., 2016; Nunes and Drèze 2006) since high-order polynomials could be misleading (Gelman and Imbens 2014). We run 8 regressions (four different bandwidth × two different orders), and the results are reported in Table 2. Only β_0 is reported for clarify since we mainly focus on the instantaneous effect of the rewards program.

Table 2. Results for text length

Bandwidth	**30**	**60**	**90**	**120**
Order = 1	1.980(0.532)***	1.737(0.465)***	1.425(0.427)***	1.421(0.401)***
Order = 2	2.107(0.655)***	2.132(0.563)***	2.106(0.514)***	1.790(0.487)***
# of obs. (Left)	359	693	918	1,167
# of obs. (Right)	425	870	1,356	1,956

*** p<0.01, ** p<0.05, * p<0.1, Robust standard errors are reported in parentheses

As reported in Table 2, the $\beta_0 s$ are significantly positive in all eight models. This result indicates that the release of the money-based incentive program significantly increases user effort in writing blogs on the platform. In particular, the average increment of the text length per blog is approximately 2,000 words after the reward program was released. As the average text length for blogs posted in 2015 is approximately 5,300 words, this increment is quite magnificent. Thus, H1 is supported.

For the dependent variable of *LPV*, we also introduce two control variables: *TL* and *Photo*. Blogs with more words and more photos may contain more information about the tour, and thereby, they have a higher probability to provide the reader with more useful information. As a result, these blogs would receive more likes from the readers. We also run 8 regressions with WLS, and the results are reported in Table 3.

Table 3. Results for LPV

Bandwidth	**30**	**60**	**90**	**120**
Order = 1	0.802(0.308)***	0.725(0.261)***	0.700(0.249)***	1.813(0.386)***
Order = 2	0.670(0.421)	0.837(0.332)**	0.807(0.299)***	-0.521(0.512)
# of obs. (Left)	362	697	923	1174
# of obs. (Right)	425	872	1359	1961

*** p<0.01, ** p<0.05, * p<0.1, Robust standard errors are reported in parenthesis

As shown in Table 3, the $\beta_0 s$ are significantly positive in most of the results, most of which are approximately 0.8 except for the one in the model with the 120 bandwidth and the first-order polynomial. Since the mean of the *LPV* is 3.489, an increment of 0.8 represents a magnificent effect. Thereby, our H2 investigating the positive effect of the rewards program on UGC quality on the platform is generally supported. However, the instantaneous effect of the rewards program on UGC quality will decrease over time according to the plots (Figure 5-8). One possible explanation is that users did not know the standard of being qualified blogs at the beginning, and hence, they tried their best to meet the requirements and increase the probability. After a period, users were able to learn the standard by reading the qualified blogs or from their successful experiences and adjust the level of effort to maximize profits. They may find that a longer text will have a higher probability to receive certification, while a higher-quality text will not. Therefore, the optimal strategy is writing longer text to win the rewards. Since the decrement of *LPV* does not influence the chance of winning rewards, the users do not care about it.

Robustness check

To further validate the robustness of our main results, we perform the following two robustness checks. We first apply the higher-order polynomial in the regression discontinuity model. To ensure there are enough observations to be estimated, we do not run regressions for the bandwidth of 30. The results are reported in Tables 4-5, which are consistent with our main results.

Table 4. Results for text length with higher-order polynomial

Bandwidth	**60**	**90**	**120**
Order = 3	2.046(0.639)***	2.045(0.590)***	2.224(0.556)***
Order = 4	2.024(0.670)***	1.970(0.612)***	2.117(0.580)***
# of obs. (Left)	693	918	1,167
# of obs. (Right)	870	1,356	1,956

*** p<0.01, ** p<0.05, * p<0.1, Robust standard errors are reported in parenthesis

Table 5. Results for LPV with higher-order polynomial

Bandwidth	**60**	**90**	**120**
Order = 3	0.906(0.401)**	0.932(0.363)**	1.588(0.447)***
Order = 4	0.902(0.450)**	0.925(0.399)**	1.651(0.472)***
# of obs. (Left)	697	923	1,174
# of obs. (Right)	872	1,359	1,961

*** p<0.01, ** p<0.05, * p<0.1, Robust standard errors are reported in parenthesis

We then replace the text length with the number of photos in the blog. Uploading photos and arranging them also takes effort, although it may be less than writing words. Therefore, we perform all analyses using the number of photos as the dependent variable, including plots and regressions. The results are not reported due to the page limit, and they are consistent with the results obtained from using the text length. Thereby, our hypotheses are again supported.

We also replace the announcement date with the effective date as the cutoff. Neither the plots nor the regression discontinuity results show a significant instantaneous effect (the results are not reported due to the page limit). This result provides evidence to support our selection of the cutoff.

Conclusions

Using a dataset collected from a leading travel platform in China and applying the regression discontinuity design, our study reveals the positive effects of money-based incentives on user efforts and UGC quality. First, user efforts as represented by the text length increase after the rewards program was released and lead to an almost 40% instantaneous increment. Second, the quality of UGC increases at the beginning of the rewards program and declines over time.

This study represents one of the first attempts to investigate the effect of money-based incentives on the quality of UGC, while prior studies mainly focus on the effect of glory-based incentives on the quantity of UGC (Cavusoglu et al., 2015; Goes et al., 2016; Hamari, 2017). Unlike the glory-based incentives, the money-based incentives involve money. In the Maslow's hierarchy of needs, the money is more like the lower level of physiological needs, whereas the glory is more like the higher level of needs such as self-actualization. Therefore, it is obviously that the money reward could attract more people than the glory reward since there are more individuals having the physiological needs. Our results show users are strategic in the money-based incentives. They pretend to take more effort by writing more words and posting more photos to earn money, but the true quality measured by the number of likes does increase in long term. Another theoretical contribution to the literature of this study is the effort is measured by the quality, whereas extant literature mainly pay attention to the quantity of UGC (Cavusoglu et al., 2015; Goes et al., 2016; Hamari, 2017). For example, users' effort in Goes et al. (2016)'s work is measured by the number of questions answered. In fact, the quality is more important than the quantity since all people need high quality information but not many low quality information. Therefore, it is more important to understand why do users contribute high quality UGC. This study shed a light on the future investigation on the UGC motivation.

Our results yield direct implications for UGC platforms to encourage users to generate more high-quality content. First, the powerful effect of money-based incentives results in a 40% increment in text length on the platform, which largely increases the reading load of information searchers. Therefore, we suggest that the platform set a maximum number of words for each blog. The length limit will encourage the users to take more effort to improve the quality instead of merely including more information. Additionally, the platform should consider more about the content quality rather than the length when officially recognizing qualified blogs. Second, the positive jump of UGC quality after the rewards program release suggests that the rewards program does have a positive effect on UGC quality. However, the quick decline indicates that the incentive does not last long. One possible explanation is that users might learn from experience and minimize their effort levels. Hence, the platform should design a better incentive system to encourage user activities over the long run. For example, only the users that were in the top 10% of likes can get the rewards.

This study has several limitations. First, UGC quality is represented only by the like ratio, and user effort is measured only by the text length and the number of photos. More measurements should be introduced to investigate deeper, such as readability, sentiment, etc. Second, an author-specific fixed effect is not included in this study. Unobservable author specific heterogeneity might have an impact on both user efforts and UGC quality. Although we only focus on the change of user activities on the platform before and after the rewards program was released, the inclusion of a user-specific fixed effect would enable us to better understand the underlying reasons of efforts and quality increments. Third, the reason why UGC quality declines quickly is not further explored in this study, which can be an interesting future direction.

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