PACIS 2023 Proceedings

Pacific Asia Conference on Information Systems (PACIS)

7-8-2023

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Completed Research Paper

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Abstract

The "quality threshold for monetary incentive" mechanism is a common practice in online review platforms. However, the effect of the quality threshold is still not clear in the extant literature. This study attempts to investigate how the introduction of the quality threshold affects content quality. Based on the Anchoring Effect theory, this study first derives some theoretical conclusions based on theoretical models and then conducts a natural experiment to test the conclusions. The findings show that after introducing the quality threshold, (1) the proportion of content with the threshold-level quality will increase; (2) the proportion of content higher than the quality threshold is reduced when there is the "Anchoring Effect". Moreover, the empirical study also shows that the quality threshold leads to an overall negative effect on the average review quality. Our findings are meaningful to the stakeholders of the online review platforms.

Keywords: Online review platform; quality threshold; monetary incentive; anchoring effect; content quality

Introduction

Nowadays, many online review platforms use monetary incentives to motivate reviewers to contribute valuable reviews (Zhang et al., 2020). However, extant studies show evidence that monetary incentives may backfire and reduce content quality (Sun et al., 2017; Yu et al., 2018). Thus, inducing high-quality content remains challenging (Fang & Liu, 2018). A popular method on online review platforms is introducing a "quality threshold" policy for monetary incentives: the contributors could get monetary incentives only when the content quality reaches the quality threshold (Khern-am-nuai et al., 2018). For example, Kmart, which is one of the largest retailers in America, offers 500 points (around $0.50) for each review if the review posted in its online review platforms meets the minimum length requirement for rewards. Many leading platforms in China, such as Meituan.com, JD.com, Taobao.com, Suning.com, etc., also adopt "quality threshold for monetary incentives". Specifically, Suning.com and JD.com both require at least 10 Chinese characters in each review for monetary incentives.

Although the "quality threshold for monetary incentive" mechanism is a common practice in online review platforms, the effect of the quality threshold on content quality is still not clear in the extant literature. Khern-am-nuai et al. (2018) find that when reviewers are promised 25 loyalty points for each review with at least 50 characters, reviewers spend less effort and write shorter reviews. However, it is hard to distinguish whether the "backfire" effects are caused by the "crowding out" effect of monetary incentive or by the quality threshold (i.e., at least 50 characters). A couple of studies have investigated various quality control mechanisms but not the "quality threshold for reward" policy. For example, Yu et al. (2018) study a mechanism that only incentivizes the highest quality content, claiming that such a mechanism might ensure content quality. Wang et al. (2012) indicate that performance-contingent rewards (proportional to content quality) will improve content quality. In a nutshell, it is still not clear on the impact of quality threshold on content quality. There is still a research gap in understanding the effect of the quality threshold for monetary incentives on content quality.

To fill the research gap, this study attempts to investigate how the introduction of the quality threshold affects content quality. According to the psychological literature, the quality threshold quality acts as a reference point and might affect contributors' motivation (Fang & Liu, 2018). The Anchoring Effect theory claims that people often make estimates by starting from an initial value, or an anchoring point, and then adjusting it to produce a final estimate. This phenomenon is called anchoring. However, the adjustment is usually insufficient, resulting in a final estimate that is biased towards the initial value, which is known as Anchoring Effect (Tversky & Kahneman, 1974). For instance, when asked to estimate the percentage of African countries in the United Nations, people who first judged whether the correct value was higher or lower than 65 gave higher estimates than those who first judged it against 10. The former group used 65 as their anchoring point and the latter group used 10, and their insufficient adjustments led to estimates that were closer to their anchors (Cervone & Peake, 1986). The quality threshold is a salient presented reference point. According to the Anchoring Effect theory, the contributors might decide their content quality by starting from the reference point, or called anchoring point, and then adjust to their final decision about the quality. Therefore, the quality of contribution is biased toward the quality threshold (Tanford et al., 2019; Tversky & Kahneman, 1974). Based on this theory, we first build several theoretical models: a benchmark model and two quality control models without and with the "Anchoring Effect", respectively. We then conduct a natural experiment by collecting more than 2 million reviews from *Suning.com*, to test the conclusions drawn from our models.

This study has several interesting findings. Our theoretical model shows that after introducing the quality threshold, (1) some contributors will increase their content quality to the quality threshold, thus increasing the proportion of content with exactly the threshold-level quality. (2) The proportion of content higher than the quality threshold is unaffected when there is no "Anchoring Effect" but reduced when there is the "Anchoring Effect". Our empirical results support the conclusions of the quality control model with the "Anchoring Effect". Moreover, the empirical study also shows that (3) the quality threshold leads to an overall negative effect on the average review quality. Therefore, our findings indicate that the quality threshold plays the role of "anchoring point" for the contributors. Introducing the quality threshold for monetary incentives could even harm the content quality.

To the best of our knowledge, this is the first research to investigate the effect of the quality threshold on content quality. This study could contribute to the literature by providing theoretical analysis and solid empirical evidence of the negative effect of quality threshold on content quality. This study may also deepen our understanding of the effect of "quality threshold", as well as the application of the Anchoring Effect theory in the online review context. Our findings are also meaningful to the stakeholders of the online review platforms.

Theoretical Background

Online communities, such as Wikipedia, YouTube, Facebook, Instagram, online forums, and review sites, have become increasingly influential in various aspects of our lives in recent years (Liu & Feng, 2021). These online communities are heavily related to the success of many companies (e.g. Apple, Oracle, Alibaba) (Bahtar & Muda, 2016; Timoshenko & Hauser, 2019). The content in these communities, such as blogs, reviews, videos, etc., is generated by their users, which is referred to as user-generated content (UGC) (Ahn et al., 2016; Yi et al., 2019). Among these contents, reviews on product reviews sites (e.g. Yelp, TripAdvisor, RottenTomatoes) or e-commerce sites (e.g. Alibaba, Amazon) is one of the most common UGC. (Luca & Zervas, 2016; Zhang et al., 2020). UGC in the website platform is often undersupplied since it is a type of public good contributed by volunteers (Burtch et al., 2018; Huang et al., 2019).

Monetary incentive is one of the essential interventions to motivate contributors to share more (Qiao et al., 2020). A primary stream of literature discusses how monetary incentives affect UGC contribution volume. Though platforms might succeed in increasing contribution volume through monetary incentives when the incentive is sufficiently high (Liu & Feng, 2021), Garud and Kumaraswamy (2005) claim that the quality is not guaranteed, and the information may be overloaded. Content quality is of prime concern on UGC platforms, which is widely discussed in the literature (Burtch et al., 2022; Sun et al., 2017). The method to measure quality may vary depending on the types of UGC. In online review platforms, many variables are used to measure review quality, such as text length, helpfulness, lexical density, and lexical richness (Fang & Liu, 2018; Qiao et al., 2020; Yu et al., 2018; Zhang et al., 2020). Extant studies provide evidence that monetary incentive mechanisms will increase contribution volume at the cost of its quality (Khern-am-nuai et al., 2018; Yu et al., 2018). For example, Wang et al. (2016) conduct a quasi-natural experiment, showing that introducing completion-contingent monetary incentives will significantly increase review volume, while the impact of monetary incentives on helpfulness is not supported.

A few empirical studies argue that monetary incentives fail to incentive content quality since the mechanism is completion-contingent instead of performance-contingent (Wang et al., 2012). Therefore, some researchers focus on monetary incentive mechanisms in which monetary rewards can only be obtained by satisfying requirements of quality. Yu et al. (2018) argue that such a design may enhance people's intrinsic motivation by signaling their inherent capability in the related area, ensuring content quality. Some literature studies monetary incentives conditional on quality, but the quality requirements are not based on the quality threshold. Cabral and Li (2015) investigate the conditional rebates on eBay and find that they will increase the contribution rate but cannot trigger unbiased feedback. Wang et al. (2012) also indicate that performance-contingent rewards will improve content quality. In the articles discussed above, they do not set a specific quality threshold to get monetary rewards. Instead, they either only reward the content with the highest quality (Yu et al., 2018), measure the content quality in ways that are not clearly visible to the contributors (Cabral & Li, 2015), or offer monetary incentives proportional to quality (Wang et al., 2016). Two studies are pretty relevant to ours which study monetary incentive mechanisms with a clear contribution threshold. Khern-am-nuai et al. (2018) find that when reviewers are promised 25 loyalty points for each review they submit with the requirement (at least 50 characters), reviewers spend less effort and write shorter reviews. Sun and Zhu (2013), which investigates the ad-revenue-sharing program requiring participants to meet the minimum contribution, find that participants' contribution increases while the nonparticipants' contribution declines slightly over time. However, they mainly focus on the effect of monetary incentives and have not discussed the effect of the quality threshold. The impact of the quality threshold on content quality is still unclear.

Several theoretical models study the effect of monetary incentive mechanisms on UGC contribution. Since UGC is produced by volunteers (Bahtar & Muda, 2016; Timoshenko & Hauser, 2019), one of the most relevant models is the prosocial model developed by (Bénabou & Tirole, 2006). They distinguish between intrinsic motivation and extrinsic motivation for contribution, and assume that contributors differ in their intrinsic motivation and that monetary incentives are a form of extrinsic motivation. These assumptions are adopted by many subsequent studies as well as the benchmark model in our paper (Liu & Feng, 2021). Few studies model the quality control mechanism in the UGC context. Ma et al. (2009) is a closely related study that models the UGC firm's quality control decision on users' behavior. Ghosh and McAfee (2011) study the fixed monetary reward mechanism and find that it will result in a large amount of contribution with worse average quality. But different from their quality control mechanism, which only permits high-quality content, we allow all contributors to contribute. And we also consider the "Anchoring Effect" caused by the quality threshold to extend our benchmark model.

According to the literature, the quality acts as a reference point and may lead to an "Anchoring Effect" (Tversky & Kahneman, 1974). The "Anchoring Effect" refers to the tendency to anchor a decision at an initial value and fail to make sufficient upward or downward adjustments to the true value (Tanford et al., 2019; Tversky & Kahneman, 1974). Such an insufficient adjustment will affect their judgment of their performance capabilities, thus affecting their task persistence and performance (Cervone & Peake, 1986). Researchers have paid attention to many aspects of the impact of the "Anchoring Effect" on judgment and decision-making tasks(Furnham & Boo, 2011), such as legal judgment (Englich & B., 2006; Enough & Mussweiler, 2001), purchase decisions (Ariely et al., 2003), prediction (Critcher & Gilovich, 2008), negotiation (Galinsky & Mussweiler, 2001), etc., all of which show that the "Anchoring Effect" has a strong robustness. However, the existing literature does not explore whether the introduction of the quality threshold in online UGC platforms causes an "Anchoring Effect", nor does it explore the effect of quality threshold on the overall average quality if the quality threshold leads to an "Anchoring Effect". Thus, it is necessary to further explore the existence and influence of the "Anchoring Effect" on UGC platforms. In online review platforms, the quality threshold might serve as an anchoring point. The contributors who contribute lower than the quality threshold may fail to make a downward adjustment and will contribute at higher quality. However, the contributors who contribute higher than the quality threshold may fail to make a sufficient upward adjustment and thus contribute at a lower quality. When combining these two effects, the overall impact of quality threshold on content quality may even be negative. This theory is quite relevant to our study thus we will introduce it into our paper.

In summary, few studies investigate the effect of the quality threshold for monetary incentives on content quality. Therefore, we examine the impact of the quality threshold on content quality based on Anchoring Effect theory in this paper.

Analytical Model

In this section, we first build a benchmark model without quality control, and extend it to quality control models, including one model with no "Anchoring Effect" and the other with "Anchoring Effect". Then we obtain contributors' strategies in these models. We investigate how the quality threshold affects content quality by comparing contributors' behavior in different scenarios. We also do a simulation to investigate how the introduction of the quality threshold affects the distribution of content quality.

Benchmark Model

We study the behavior of contributors who decides to contribute content to the UCG platforms. The generated content varies in quality, which is denoted by $q_i \geq 0$. When there are no monetary rewards, the utility of contributor i is equal to the intrinsic motivation minus the contribution cost.

The contributors vary in their intrinsic motivation since they differ in intrinsic valuation for generated content quality denoted by v_i. It determines the degree to which the quality of content translates to contributor i's utility (Bénabou & Tirole, 2006; Ma et al., 2009). Contributing the content also entails a cost $c(q_i)$. Following the literature, the cost function satisfies $c(0) > 0, c(q_i)' > 0, c(q_i)'' > 0$ (Frey & Oberholzer-Gee, 1997; Liu & Ho, 2018). We adopt $c(q_i) = c + kq_i^2$ as contributor i's cost where $c > 0$ and $k > 0$ (Ghosh & Hummel, 2014; Shen et al., 2022). Here c is the fixed net cost, and k is the marginal cost which may reflects the difficulty to contribute.

We first consider a benchmark model where each contributor can get a fixed reward m from the UGC platform. A typical example is a coupon offered by e-commerce platforms (e.g., Amazon.com, jd.com) to motivate reviewers' contributions. Therefore, the contributor i's utility is as follows:

$$U_i(q_i) = v_i q_i + m - (c + kq_i^2)$$

By maximizing the utility function, we can obtain contributors' strategies which are summarized in Proposition 1.

Proposition 1. Contributors with $v_i > 2\sqrt{k(c - min\{c, m\})}$ will contribute and contribute at $q_i{}^* = \frac{v_i}{2k}$.

We visualize Proposition 1 in Figure 1. As shown in Figure 1, when $m \leq c$, only contributors with $v_i > 2\sqrt{k(c - m)}$ will contribute. The level of content quality is positively related to the intrinsic valuation for generated content quality. In addition, the higher the level of monetary incentives, the more contributors will contribute. When $m > c$, all of the contributors will contribute.

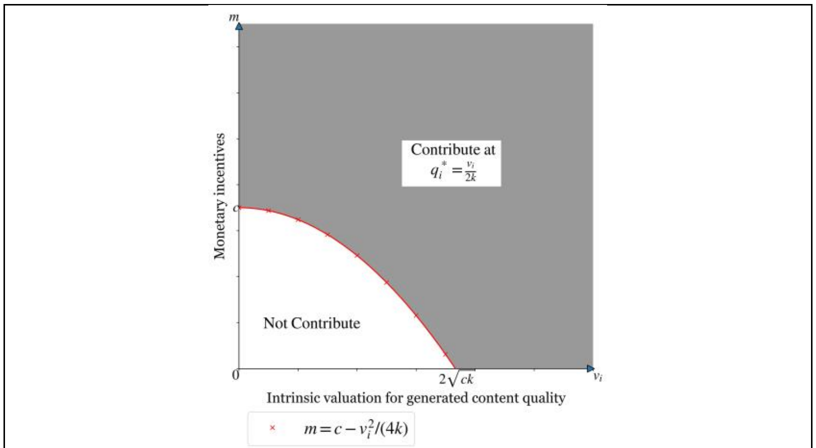


Figure 1. Contributors' Strategies in Benchmark Model

Quality Control Model

When there is no "Anchoring Effect"

Now we consider the situation where the platform introduces the quality threshold q_t to control the content quality. Contributors who contribute more than the quality threshold are eligible for monetary rewards. Otherwise, they cannot be rewarded by the UGC platforms. We do not add the "Anchoring Effect" to our model here. Thus, the utility of contributor i can be represented as:

$$U_i(q_i) = \begin{cases} v_i q_i - (c + kq_i^2) & q_i < q_t \\ v_i q_i + m - (c + kq_i^2) & q_i \geq q_t \end{cases}$$

Each contributor chooses the content quality to maximize his or her utility. When $U_i' = v_i q_i - (c + kq_i^2)$, the optimal decision is $q_i = \frac{v_i}{2k}$, and the participation constraint ($U_i' > 0$) is $v_i > 2\sqrt{ck}$. Note that contributors with $v_i \geq 2kq_t$ have $\frac{v_i}{2k} \geq q_t$, that is to say, they either contribute no less than q_t or not contribute. Therefore, if $2kq_t < 2\sqrt{ck}$, no one will contribute lower than the threshold, regardless of the level of monetary incentives. To be simple, we assume $q_t > \sqrt{c/k}$ in this paper, but all of our main results still hold when $q_t \leq \sqrt{c/k}$. Under the constraint of $q_t > \sqrt{c/k}$, the contributors' strategies are summarized in Proposition 2.

Proposition 2. When introducing the quality threshold with no "Anchoring Effect":

(1). Contributors with $v_i > 2kq_t$ will contribute at $q_i^* = \frac{v_i}{2k} > q_t$;

(2). Contributors with $\hat{v} < v_i \leq 2kq_t$ will contribute equal to $q_i^* = q_t$;

(3). There will be contributors with $\bar{v} < v_i \leq \hat{v}$ who will contribute at $q_i^* = \frac{v_i}{2k} < q_t$ only if $m < \left(\sqrt{c} - \sqrt{k}q_t\right)^2$;

(4). Users with $0 \leq v_i \leq \bar{v}$ will not contribute.

Note that $\hat{v} = 2kq_t - 2\sqrt{km} > \bar{v} = 2\sqrt{ck}$ when $m < \left(\sqrt{c} - \sqrt{k}q_t\right)^2$, and $\hat{v} = \bar{v} = max\left\{\frac{c - m + kq_t^2}{q_t}, 0\right\}$ when $m \geq \left(\sqrt{c} - \sqrt{k}q_t\right)^2$.

We visualize Proposition 2 in Figure 2. As shown in Figure 2, when $m \leq \left(\sqrt{c} - \sqrt{k}q_t\right)^2$, some contributors will contribute lower than the quality threshold and cannot get monetary rewards. When $\left(\sqrt{c} - \sqrt{k}q_t\right)^2 < m \leq c + kq_t^2$, contributors either do not contribute or contribute no less than the quality threshold. And as the level of monetary incentives increases to $m > c + kq_t^2$, all users will contribute at a quality no less than the quality threshold.

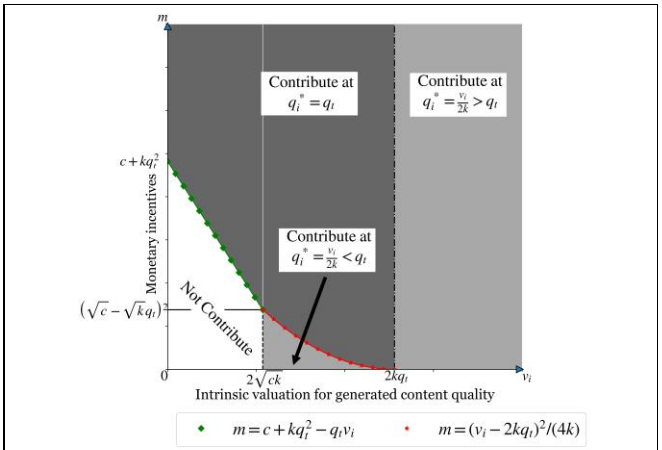


Figure 2. Contributors' Strategies in Quality Control Model with no "Anchoring Effect"

When there is an "Anchoring Effect"

In addition to the direct constraint set by the quality threshold, it acts as a reference point. It might lead to an "Anchoring Effect", which changes the human decision-making processes (Furnham & Boo, 2011). The "Anchoring Effect" refers to the tendency to anchor a decision at an initially presented value or parameter and fail to make sufficient upward or downward adjustments to the true value. Therefore, the final modified value is biased toward the anchor values (Tversky & Kahneman, 1974). In our research context, the true value refers to the contributor i's intrinsic valuation for generated content quality which is not modified by the quality threshold. According to the Anchoring Effect theory, the presented quality threshold signals an initial valuation $v_a(q_t)$ for generated content quality

a. If $v_i < v_a$, the contributor makes a downward adjustment $(v_i - v_a) < 0$, which is insufficient, leading to $v_a + \alpha(v_i - v_a) > v_a + (v_i - v_a) = v_i$. In other words, the modified valuation for generated content quality is higher than the true intrinsic valuation for generated content quality.

b. If $v_i = v_a$, there is no need for the contributors to adjust since $v_a + \alpha(v_i - v_a) = v_a = v_i$. In other words, the initial signal valuation for generated content quality triggered by the quality threshold equals the true intrinsic valuation for generated content quality.

c. If $v_i > v_a$, the contributor makes an upward adjustment $(v_i - v_a) < 0$, which is insufficient, leading to $v_a + \alpha(v_i - v_a) < v_a + (v_i - v_a) = v_i$. In other words, the modified valuation for generated content quality is lower than the true intrinsic valuation for generated content quality.

Considering the "Anchoring Effect", the utility function for contributor i is as follows:

$$U_i(q_i) = \begin{cases} [v_a + \alpha(v_i - v_a)]q_i - kq_i^2 & q_i < q_t \\ [v_a + \alpha(v_i - v_a)]q_i + m - kq_i^2 & q_i \geq q_t \end{cases}$$

Each contributor chooses the content quality to maximize his or her utility. Contributors' strategies are summarized in Proposition 3.

Proposition 3. When introducing the quality threshold with the "Anchoring Effect":

(1). Contributors with $v_i > 2kq_t$ will contribute at $q_i^* = \frac{\alpha v_i}{2k} + (1 - \alpha)q_t > q_t$;

(2). Contributors with $\hat{v}' < v_i \leq 2kq_t$ will contribute at $q_i^* = q_t$;

(3). There will be contributors with $\bar{v}' < v_i \leq \hat{v}'$ who will contribute at $q_i^* = \frac{\alpha v_i}{2k} + (1-\alpha)q_t < q_t$ only if $m < \left(\sqrt{c} - \sqrt{k}q^t\right)^2$;

(4). Users with $0 \leq v_i \leq \bar{v}$ will not contribute.

Note that $\hat{v}' = 2kq_t - \frac{2\sqrt{km}}{\alpha} > \bar{v}' = \frac{2(\sqrt{ck}+k(\alpha-1)q_t)}{\alpha}$ when $m < \left(\sqrt{c} - \sqrt{k}q_t\right)^2$, and $\hat{v}' = \bar{v}' = max\left\{\frac{c-m+kq_t^2+2k(\alpha-1)q_t^2}{\alpha q_t}, 0\right\}$ when $m \geq \left(\sqrt{c} - \sqrt{k}q_t\right)^2$.

We visualize Proposition 3 in Figure 3. As shown in Figure 3, some contributors will contribute lower than the quality threshold and cannot get monetary rewards when $m < \left(\sqrt{c} - \sqrt{k}q_t\right)^2$. When the level of monetary incentives increases to $\left(\sqrt{c} - \sqrt{k}q_t\right)^2 \leq m < c + (2\alpha - 1)kq_t^2$, no one will contribute lower than the quality threshold. And as the level of monetary incentives increase to $m > c + (2\alpha - 1)kq_t^2$, all contributors will contribute and get monetary rewards.

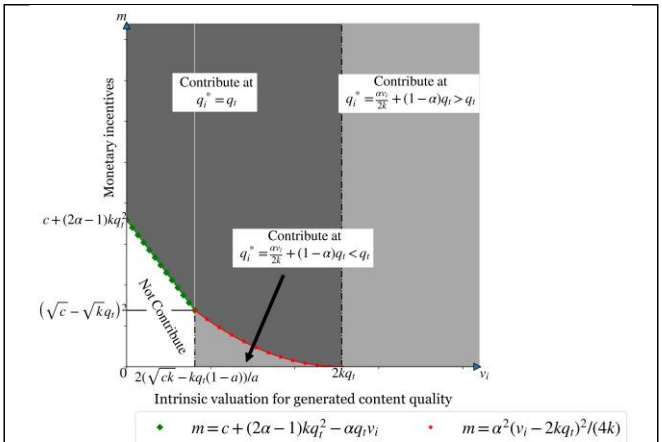


Figure 3. Contributors' Strategies in Quality Control Model with "Anchoring Effect"

The Effect of Quality Threshold on Content Quality

In this part, we discuss how the quality threshold affects the content quality in the UGC platforms. From Proposition 2 and Proposition 3, we know that the introduction of quality threshold divides the users into four categories in which there are three kinds of contributors according to their level of content quality. Contributors in the first group will contribute higher than the quality threshold; Contributors in the second group will contribute equal to the quality threshold; Contributors in the third group will contribute lower than the quality threshold; Users in the four group do not contribute. According to these categories, we analyze how the contributors are affected by the quality threshold by comparing contributors' strategies in the no quality control scenario with those in the quality control scenario.

We first compare contributors' strategies in Proposition 2 with Proposition 1 to obtain the impact of quality control with no "Anchoring Effect" on contributors' strategies.

Lemma 1. After the introduction of quality threshold when there is no "Anchoring Effect":

(1). Contributors with $v_i > 2kq_t$ will sustain their content quality which is higher than the quality threshold;

(2). Contributors with $\hat{v} < v_i \leq 2kq_t$ will increase their content quality to the quality threshold;

(3). There will be contributors with $\bar{v} < v_i \leq \hat{v}$ who will sustain their content quality which is lower than the quality threshold only if $m \leq \left(\sqrt{c} - \sqrt{k}q_t\right)^2$;

(4). Users with $0 \leq v_i \leq \bar{v}$ either change from contributing to not contributing or keep not contributing.

As illustrated by Lemma 1, the quality threshold either has no effect (Lemma 1(1,3)) or increases the content quality (Lemma 1(2)) contributed by contributors. Since the quality threshold might reduce the overall contributors (Lemma 1(4)), the average content quality will increase when there is no "Anchoring Effect" as shown in Corollary 1.

Corollary 1. After the introduction of the quality threshold when there is no "Anchoring Effect", the average content quality will increase.

We then compare contributors' strategies in Proposition 3 with Proposition 1 to obtain the impact of quality control with "Anchoring Effect" on contributors' strategies.

Lemma 2. After the introduction of quality threshold when there is an "Anchoring Effect":

(1). Contributors with $v_i > 2kq_t$ will decrease their content quality to a level that is higher than the quality threshold;

(2). Contributors with $\hat{v}' < v_i \leq 2kq_t$ will increase their content quality to the quality threshold;

(3). There will be contributors with $\bar{v}' < v_i \leq \hat{v}'$ who will increase their content quality to a level that is lower than the quality threshold;

(4). Users with $0 \leq v_i \leq \bar{v}'$ will either change from contributing to not contributing or keep not contributing.

As illustrated by Lemma 2, different from the scenario without the "Anchoring Effect", the quality threshold might either decrease (Lemma 2(1)) or increase (Lemma 2(2,3)) the content quality contributed by contributors when there is an "Anchoring Effect". Therefore, the average quality runs a risk of being decreased by the quality threshold in the UGC platforms.

Corollary 2. After the introduction of the quality threshold when there is an "Anchoring Effect", the average content quality might be either increase or decrease.

Simulation

To further understand the difference between the scenario with no "Anchoring Effect" and the scenario with an "Anchoring Effect", we do a simulation in this section. To focus on more general cases, let $m < \min\left\{\left(\sqrt{c} - \sqrt{k}q_t\right)^2, c\right\}$, that is, not all users will contribute in the benchmark model, and some contributors will contribute lower than the quality threshold in the quality control model. As suggested by previous literature, the UGC follows the Participation Inequality rule, also known as the 90-9-1, meaning that 90% of the users just "lurk" on the site, 9% of users contribute little content and 1% of users contribute actively (Darnell, 2011; Sun et al., 2017). Following the literature, we assume that the distribution of the intrinsic valuation for generated content quality is a power law distribution, that is $f(v_i) = \gamma {v_i}^{-\beta-1}$ (Cha et al., 2007; Gangadharbatla & Valafar, 2017). Therefore, the distribution of the content quality in the benchmark model is:

$$f(q_i) = \begin{cases} \gamma\,(2kq_i)^{-\beta-1} & q_i \geq \sqrt{\dfrac{c-m}{k}} \\ 0 & q_i < \sqrt{\dfrac{c-m}{k}} \end{cases}$$

The distribution of the content quality in the quality control model with no "Anchoring Effect" is:

$$f(q_i) = \begin{cases} \gamma(2kq_i)^{-\beta-1} & q_i > q_t \\ \infty, & q_i = q_t \\ 0 & q_t - \sqrt{\dfrac{m}{k}} \leq q_i < q_t \\ \gamma(2kq_i)^{-\beta-1} & \sqrt{\dfrac{c}{k}} \leq q_i < q_t - \sqrt{\dfrac{m}{k}} \\ 0 & q_i < \sqrt{\dfrac{c}{k}} \end{cases}$$

The distribution of the content quality in the quality control model with the "Anchoring Effect" is:

$$f(q_i) = \begin{cases} \gamma\left(\dfrac{2k(q_i + (\alpha - 1)q_t)}{\alpha}\right)^{-\beta-1} & q_i > q_t \\ \infty & q_i = q_t \\ 0 & q_t - \sqrt{\dfrac{m}{k}} \le q_i < q_t \\ \gamma\left(\dfrac{2k(q_i + (\alpha - 1)q_t)}{\alpha}\right)^{-\beta-1} & \sqrt{\dfrac{c}{k}} \le q_i < q_t - \sqrt{\dfrac{m}{k}} \\ 0 & q_i < \sqrt{\dfrac{c}{k}} \end{cases}$$

In both cases, the $f(q_t)$ increases dramatically at $q_i = q_t$, which means that the amount of contribution with content quality equal to the quality threshold will increase either with or without the "Anchoring Effect". In specific, the probability of contributing at the quality threshold is $P(q_t) = \int_{q_t-\sqrt{\frac{m}{k}}}^{q_t} \gamma(2kq_i)^{-\beta-1} dq_i$ in the scenario of quality control with no "Anchoring Effect", and $P(q_t) = \int_{q_t-\sqrt{\frac{m}{k}}}^{q_t} \gamma\left(\frac{2k(q_i+(\alpha-1)q_t)}{\alpha}\right)^{-\beta-1} dq_i$ in the scenario of quality control with the "Anchoring Effect". In our simulation, $c = 0.1, k = 0.55, m = 0.01, q_t = 0.65, \alpha = 0.65, \beta = 0.3, \gamma = 0.1$. We eliminate the point at $q_i = q_t$ in Figure 4 and Figure 5. The pictures are shown as follows.

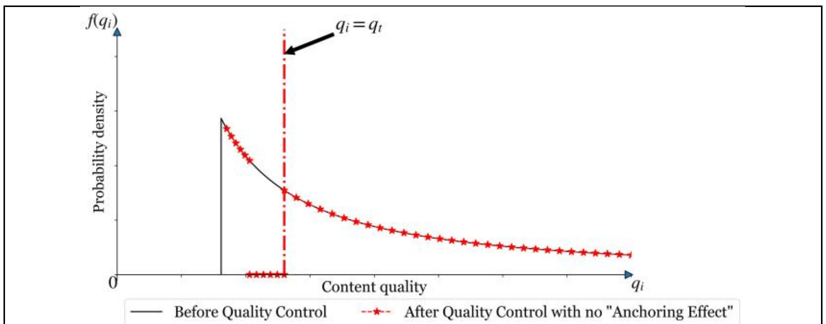


Figure 4. Distribution of Content Quality before and after Quality Control with no "Anchoring Effect"

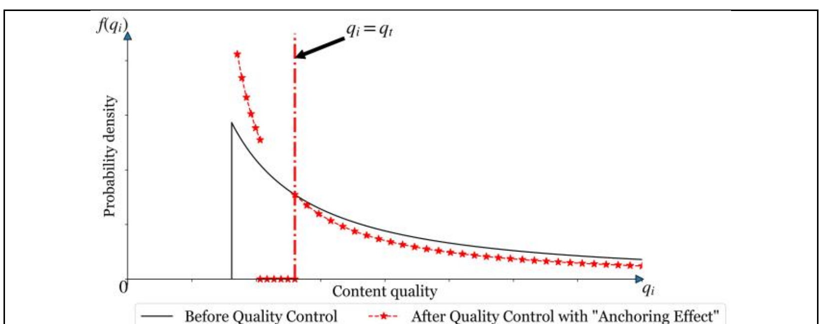


Figure 5. Distribution of Content Quality before and after Quality Control with "Anchoring Effect"

Figure 4 is consistent with Lemma 1. Since contributors who will contribute higher than the quality threshold will sustain their behaviors (Lemma 1(1)) and no contributors will increase their content quality higher than the quality threshold, thus the distribution of $q_i > q_t$ is not changed. Only the contributors who contribute lower than the quality threshold are affected by the quality threshold, leading to changes in the distribution of according content quality. Since some contributors will jump content quality to the quality threshold and some will stop contributing, the proportion of content with quality lower than the quality threshold will decrease. Based on Figure 4 and Lemma 1, we then propose the following Corollary:

Corollary 3. After the introduction of the quality threshold when there is no "Anchoring Effect": (1). The proportion of content with the level of quality higher than the quality threshold is increased; (2). The proportion of content with the level of quality equal to the quality threshold is increased.

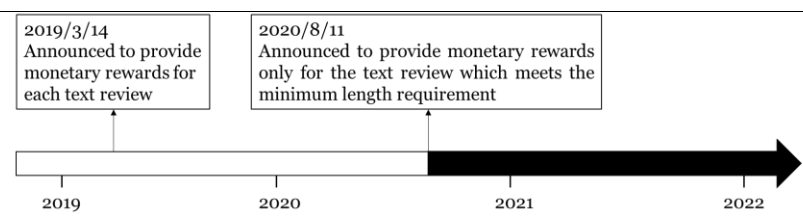
Based on the assumption of the distribution of intrinsic valuation for generated content quality, Figure 5 provides us with more implications than Lemma 2. Lemma 2(1) suggests that contributors who contribute more than the quality threshold will decrease their content quality after introducing the quality threshold. Since the probability density decreases as the intrinsic valuation for generated content quality increases, the proportion of the content for all $q_i > q_t$ will decrease. Therefore, when an "Anchoring Effect" exists, the quality threshold might reduce high-quality content and thus harm the UGC platforms. Based on Figure 5 and Lemma 2, we then propose the following Corollary.

Corollary 4. After the introduction of the quality threshold when there is an "Anchoring Effect": (1). The proportion of content with the level of quality higher than the quality threshold might be decreased; (2). the proportion of content with the level of quality equal to the quality threshold might be increased.

Empirical Study

The analytical models in the previous section show that the quality threshold has different effects on the content quality depending on whether there is an "Anchoring Effect" or not. Specifically, without the "Anchoring Effect", the quality threshold raises the average quality (Corollary 1) and may increase the proportion of high-quality content (Corollary 3(1)). However, with the "Anchoring Effect", the average quality may either be decreased or increased (Corollary 2) and the proportion of high-quality content may be decreased (Corollary 4(1)) by the quality threshold. Therefore, this section conducts natural experiments to explore which models are more consistent with reality. The empirical analysis can help to verify the previous model's conclusions and test whether there is an "Anchoring Effect".

We conduct a natural experiment in *Suning.com*, one of the leading online marketplaces in China, which offers us an ideal experimental setting for this study. On Suning.com, consumers could post reviews for the goods they purchased after transactions. As illustrated in Figure 6, on March 14, 2019, *Suning.com* announced a monetary incentive program: If a consumer posts a review for the purchased goods above CNY 10 with 45 days after a transaction, he/she will get a cash-equivalent credit (*YunZuan*) worth approximately CNY 0.2. The cash-equivalent credit could be used instead of money in future transactions. On August 11, 2020, *Suning.com* announced a "quality threshold" modification to the monetary incentive program: A reviewer can get the reward only if the review text contains ten or more Chinese characters. Note that the requirement to get the rewards is displayed in the reviewer's writing process, and the platforms' monetary reward is paid automatically. Therefore, the introduction of the "quality threshold" policy offers us a great opportunity to investigate the effect of the quality threshold on review quality.



Notes. *Announcements for monetary incentive programs for reviews before March 14, 2019, are not available on suning.com. However, as the announcement on March 14 2019 stated, the platform had already provided monetary rewards for some reviews before March 14, 2019.*

Figure 6. Timeline of Monetary Incentive Programs for Text Reviews on Suning.com

Data Collections and Variables

We develop a crawler using *Python* to collect reviews between 2019 and 2021 from *Suning.com*. To provide a solid data foundation for this study, we collect 2,470,011 reviews of more than 20,000 goods types in 175 categories. The data is cleaned in the following steps: (1) We exclude the reviews of products that cost less than CNY 10, since the incentive program only targeted products that cost more than CNY 10. (2) We eliminate all the default reviews. (3) We remove duplicate reviews and retain only one of them. A review is considered a "duplicate review" if it had identical user information, product information, and review content as another review. (4) We discard reviews that are likely to be bought by sellers. We identify a review as "purchased content" if it was posted by different users in the same store at the same time. For each group of "purchased content", we keep only one of the duplicate reviews. (5) We filter the dataset and only keep the goods that have both reviews before and after August 11, 2020, to control the impact of goods type on our results. The final dataset has 1,307,827 reviews. We classify the final dataset into two subsets: one contains the reviews posted before August 11, 2020, and the other contains reviews posted after that time.

Figure 7 shows the information we collect from the online platform. Table 1 reports the variable definitions and summary statistics, and Table 2 provides correlations between the variables. Since the quality threshold policy is based on the text length, we measure the review quality by the *Text Length* (i.e., the number of Chinese characters) of reviews, which is also adopted by previous studies (Yu et al., 2018). The other variables are used as control variables.

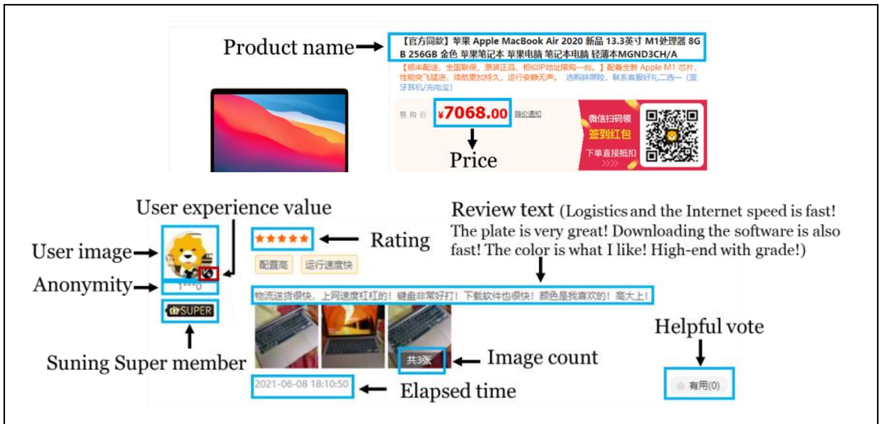


Figure 7. The Information of Review

	Variable Definitions	Mean	Min.	Max.	Std. dev	N
Text Length	The number of Chinese characters in each review.	25.72	1	581	28.05	1,307,827
Price	Price of the product associated with the review.	794.98	10	278,000	2,207.81	1,307,827
Rating	Star rating given to the product in the review.	4.87	1	5	0.63	1,307,827
Super Member	VIP privilege.	0.31	0	1	0.46	1,307,827
Experience Value	Users' purchase experience.	2.80	0	5	1.29	1,307,827

Table 1. Variable Definitions and Summary Statistics

	Text Length	Price	Rating	Super Member	Experience Value
Text Length	1	0.140	-0.078	-0.100	-0.075
Price		1	0.040	-0.120	-0.053
Rating			1	0.011	0.048

Super Member				1	0.390
Experience Value					1

Table 2. Correlation between Variables

Empirical Models

We adopt the *regression kink design* (*RKD* or *RK design*) to estimate the impact of the quality threshold (Landais, 2015). *RKD* exploits a change in slope at the likelihood of being treated at a kink point and is commonly used to identify the causal effect in settings where the regressor of interest is a kinked function of a running variable.

On *Suning.com*, the modification of the incentive program was suddenly launched on August 11, 2020. However, it may need some time for the modified incentive program to be known by the consumers, as suggested by (Sun & Zhu, 2013). Thus the effect of the quality threshold on the reviews could be a function of the running time. The longer the time after the launch of the quality threshold policy, the stronger the effect of the quality threshold could be. In other words, the effect of the quality threshold policy on review quality could be a kinked function of the running time, with the kink point on August 11, 2020. Therefore, the *RKD* model is a reasonable method to identify the impact of the modified incentive program.

In this study, we first investigate the effect of the quality threshold on the overall review quality regarding the average text length. The *RKD* estimation estimates the change in the slope of the conditional expectation function of the outcome given the running variable at the kink. In our model, the outcome Y is the average text length, the running variable is the time, and the kink is August 11, 2020. Following (Landais, 2015), this can be done by running parametric polynomial models of the form:

$$E(Y|W = w) = \mu_0 + \sum_{p=1}^{\bar{p}}\left[\gamma_p(w-k)^p + v_p(w-k)^p \cdot D\right] + \gamma X \text{ where } |w-k| \leq h, \tag{1}$$

where W is the running time; $D = 1$ if $W > k$ is an indicator for being above the kink threshold, i.e., after the modified incentive program was launched; h is the bandwidth size, which indicates the period needed for the modified incentive program to take effect fully; X is the set of control variables that contains Price, Rating, Super Member and User Experience Value; γ is the parameter vector of the control variables; the change in the slope of the conditional expectation function is given by v_1.

Our data fail to get the reviewer ID to track contributors' behavior before and after the quality control program. But we can take a look at how the distribution of content quality changes. To achieve this research goal, we extend the *RKD* model to estimate the quality threshold's treatment effect on the review quality distribution. Let $Q_\tau(Y|W = w)$ as the conditional proportion of the reviews with quality τ given the running variable. Then we estimate the treatment effect by the following model:

$$Q_\tau(Y|W = w) = \mu_0 + \sum_{p=1}^{\bar{p}}\left[\gamma_{\tau p}(w-k)^p + v_{\tau p}(w-k)^p \cdot D\right] + \gamma X \text{ where } |w-k| \leq h, \tag{2}$$

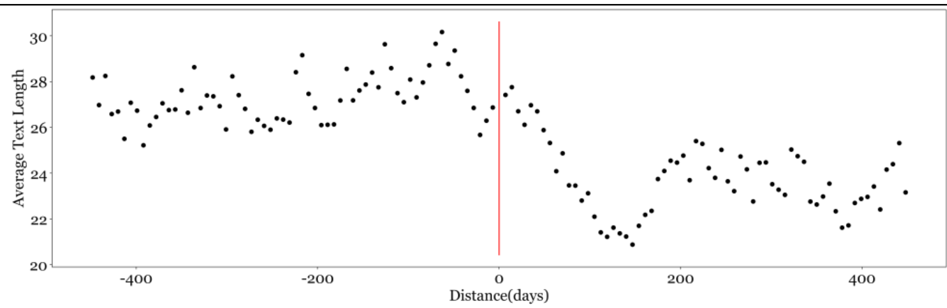
where $v_{\tau 1}$ indicates the change in the proportion of the reviews with quality τ.

Results

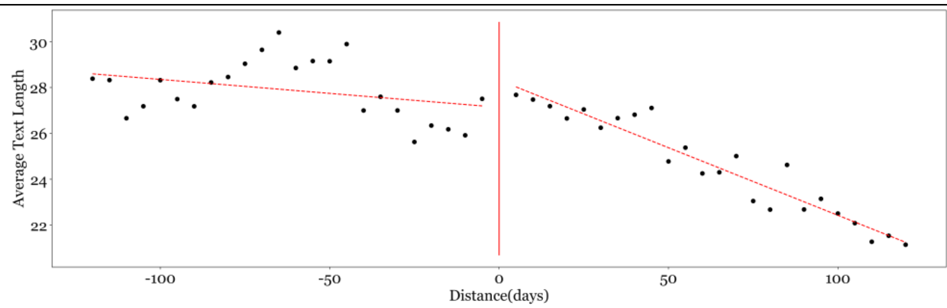
We first report model-free statistics and visualizations of the effect of the quality threshold. Then we conduct the *RKD* estimation and report the results.

Treatment Effect on the Review Quality

Figure 8 provides graphical evidence by drawing the average text length against time, where the horizontal axis *Distance* represents the number of days to the kink (August 11, 2020). Figure 8(1) shows that the average content quality first decreased over time (around four months) and then fluctuated at a lower level of review quality after introducing the quality threshold. Based on Figure 8(1), we then draw the change in average content quality over four months to verify the RKD model adopted in our paper. Figure 8(2) shows a clear drop in slope starting from the kink. This indicates that the introduction of the effect of the quality threshold is stronger on the platform over time during a relatively short time.



(1) Bandwidth = 420 Days



(2) Bandwidth = 120 Days

Figure 8. Average Quality against Time

Table 3 reports the *Average Text Length* before and after the quality control. As shown in Table 3, the average text length decreases after the platform announces the quality threshold policy. For example, as reported in the "Bandwidth=120 Days" columns, the average text length within 120 days before the quality control is 27.76, while the average text length within 120 days after the quality control drops to 24.13. Table 3 also shows that the longer the quality threshold program was introduced, the more the average text length decreased. As shown in the row "After Quality Control", the Average Text Length drops from 26.23 (60 days) to 24.13 (120 days), and then to 23.48 (180 days).

	Bandwidth = 60 Days	Bandwidth = 120 Days	Bandwidth = 180 Days
Before Quality Control	27.19	27.76	27.88
After Quality Control	26.23	24.13	23.48
The Change	0.96	3.63	4.40

Table 3. Average Text Length before and after Quality Control

Whether the results in Table 3 are significant requires more statistical tests. We conduct the *RKD* estimation in Equation (1) and report the result in Table 4.

	Bandwidth = 60 Days	Bandwidth = 120 Days	Bandwidth = 180 Days
Estimated Kink v_1	0.0123 (0.0108)	-0.0169***(0.0035)	-0.0263***(0.0019)

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

Table 4. Treatment Effect of Quality Threshold on Review Quality

As shown in Table 4, the *Estimated Kink* v_1 are significantly negative when the Bandwidth equals 120 days or 180 days after controlling all the control variables (including Price, Rating, Super Member, and User Experience Value). In summary, (1) the quality threshold policy significantly decreases the average review quality. It supports the conclusion in corollary 2, which indicates that the average quality content might be reduced on account of the "Anchoring Effect" after introducing the quality threshold; and (2) the quality threshold gradually takes effect after the policy was launched. This could also be the reason why the *Estimated Kink* v_1 is non-significantly when the Bandwidth equals 60 days.

Treatment Effect on the Distribution of Quality

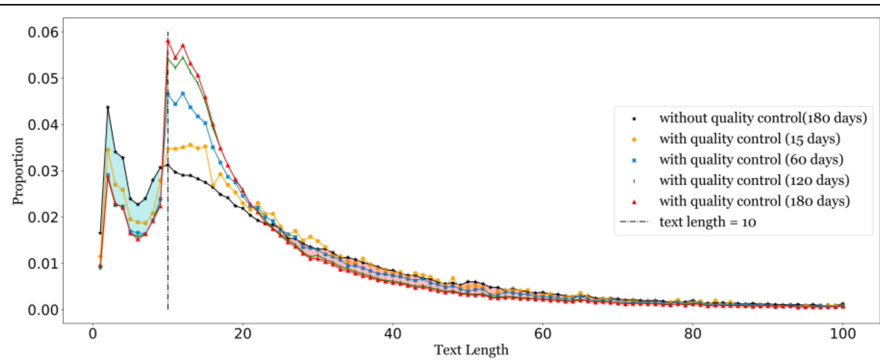
The results in the previous section are counterintuitive. Intuitively, the quality threshold policy may at least urge the reviewers who post less than 10 Chinese characters to 10 or more characters. What is the reason that the quality threshold reduces the average review quality? Does the quality threshold discourage the reviewers who post long reviews? To further understand these questions, we first illustrate the distribution of the review text length in Figure 9. The horizontal axis is the review text length, and the vertical axis shows the probability density of the reviews with specified text length. We draw the probability density curves of the reviews within 180 days before, and 15, 60, 120, and 180 days after the quality threshold announcement day (August 11, 2020) separately. Figure 9 shows that:

(1) When the text length is less than 10 characters, the probability density curve of 180 days before is higher than that of 15 days after, and then higher than that of 60, 120, and 180 days after.

(2) On the contrary, when the text length is between 10 and 23 characters, the probability density curve of 180 days before is lower than that of 15 days after, and then lower than that of 60, 120, and 180 days after. In other words, the quality threshold policy gradually decreases the proportion of 1~9 character reviews over time, and gradually increases the proportion of 10~23 character reviews over time. From the perspectives of (1) and (2), the quality threshold has a positive effect on the review quality.

(3) Interestingly, when the text length is more than 23 characters, the probability density curve of 180 days before becomes once again higher than that of 60 days after, and then higher than that of 120 and 180 days after. In other words, the quality threshold policy gradually decreases the proportion of long reviews (over 23 characters) and shows a negative effect on the review quality.

In summary, the quality threshold is a double-edged sword for the review quality. On the one hand, the quality threshold may urge the reviewers who post less than 10 Chinese characters to post more to reach the threshold. On the other hand, the quality threshold may also discourage the reviewers who post long reviews with 23 or more Chinese characters from posting less. Combining these two effects, the quality threshold shows an overall negative effect on the review quality. The results are consistent with the Anchoring Effect theory. That is, the quality threshold plays not only a role of "threshold" but also a role of "anchoring point" for the reviewers.



Notes. *We only show the distribution of reviews with less than 100 characters to clarify the figure. All of the graphical evidence hold if we include all text lengths in the picture.*

Figure 9. The Distribution of Review Quality

To further verify the significance of the results reported in Figure 9, we conduct the *RKD* estimation in Equation (2). Table 5 reports the estimated kink of the proportion of reviews with specified text length. As shown in Table 5, the estimated values in the row "Text Length 10~19" are significantly positive. This shows that the quality threshold policy significantly increases the proportion of reviews with moderate text length (equal to or slightly higher than the threshold). Thus, the conclusion in Corollary 3(2) and Corollary 4(2) are supported. However, the other estimated values are either significantly negative or non-significant. The results are consistent with Lemma 2(1) and support Corollary 4(1): when there is an

"Anchoring Effect", the quality threshold reduces the proportion of high-quality content; thus, the proportion of reviews with text length far more than the threshold is reduced.

Text Length	Bandwidth = 60 Days	Bandwidth = 120 Days	Bandwidth = 180 Days
0~9	-0.0539***(0.0153)	-0.0259***(0.0074)	-0.0023(0.0036)
10~19	**0.0405*(0.0216)**	**0.0850***(0.0073)**	**0.0598***(0.0042)**
20~29	-0.0548***(0.0193)	-0.0260***(0.0066)	-0.0212***(0.0034)
30~39	0.0161(0.0125)	-0.0108**(0.0044)	-0.0102***(0.0024)
40~49	0.0020(0.0090)	-0.0168***(0.0035)	-0.0122***(0.0018)
50~100	0.0499***(0.0150)	-0.0062(0.0058)	-0.0101***(0.0030)
100~	-0.0002(0.0074)	0.0004(0.0030)	-0.0037**(0.0016)

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

Table 5. Treatment Effect of the Quality Threshold on the Distribution of Quality

Discussions

The literature lacks an investigation of the impact of quality threshold on content quality. One primary objective of this paper is to argue that the quality threshold might induce an "Anchoring Effect". Thus the "quality control" program might even hurt content quality. We first develop a benchmark model with no quality threshold, then introduce the quality threshold without and with the "Anchoring Effect" into the benchmark model, respectively. We drive the optimal content quality of contributors and examine how the quality threshold affects contributors' behavior and average content quality in the UGC platforms. We find that the proportion of content with quality equal to the quality threshold will increase since some contributors will be forced to increase content quality to get monetary rewards. However, the proportion of high-quality content might be reduced when the quality threshold serves as an anchor and induce the "Anchoring Effect". Additionally, we develop a crawler and collect more than 2 million reviews from *Suning.com* both before and after the announcement of the quality threshold policy. Our analysis supports the findings of the quality control model with the "Anchoring Effect". Moreover, our empirical evidence also shows that the quality threshold policy does not take effect immediately after the announcement. The policy requires a relatively long time to take effect among the reviewers.

To the best of our knowledge, this is the first research to investigate the effect of the quality threshold on content quality (Burtch et al., 2022; Cabral & Li, 2015; Wang et al., 2016). Based on theoretical models and a natural experiment with millions of review records, this study contributes to the literature by showing the negative effect of quality threshold on content quality. This study also deepens our understanding of the effect of "quality threshold": the quality threshold plays as an "anchoring point" and has a bi-directional effect on the reviewers. These findings contribute to the UGC literature, especially the literature on the "crowding out effect", i.e., the monetary incentive may reduce the content quality (Bénabou & Tirole, 2006; Lepper et al., 1973; Liu & Feng, 2021). Moreover, this study extends the "Anchoring Effect" literature by applying the "Anchoring Effect" theory in the online review context (Furnham & Boo, 2011; Tanford et al., 2019; Tversky & Kahneman, 1974).

This research also has several practical implications. First, the stakeholders of UGC platforms should decide whether to introduce a quality threshold on content quality with caution. The quality threshold may decrease the overall content quality. Second, the quality threshold may play as an "anchoring point" and discourage the contributors from posting high-quality content. However, high-quality content with rich information is much more important for potential consumers and the development of online platforms. Third, our results also show that the quality threshold policy requires a relatively long time to gradually take effect after the announcement. If the stakeholders of an online review platform hope to launch a monetary incentive policy, our findings are helpful for them to understand the effect of the policy correctly.

This study is not without limitations. First, our theoretical models do not analyze how the average quality changes in the quality control model with the "Anchoring Effect" under different parameters. Second, due to our research setting and dataset, we use only text length to measure review quality. In the future, more variables, such as helpfulness", could be used to measure review quality. Third, the reviewer ID is encrypted in our dataset, thus it is not possible to identify the individuals. Future studies should collect individual-level datasets to investigate the effect of the quality threshold policy on reviewers' behavior. Finally, both platform owners and sellers can implement measures to enhance review quality. Future research should employ more methods to control for the effect of seller measures on our analysis.

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