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Implications of Rewards and Punishments for Content Generations by Key Opinion Leaders

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Abstract: Nowadays, e-commerce platforms have increasingly relied on contents generated by key opinion leaders to engage customers and drive product sales. To stay on top of the growth, e-commerce content platforms have introduced rewards and punishments policies to ensure content quality. However, effectiveness has remained less clear. Besides, there is a dearth of research that focuses on such performance-based output control in the extant platform governance and user-generated content (UGC) literature. In this study, based on the reinforcement theory and UGC literature, we investigate the effects of monetary rewards and punishments on the quantity and quality of contents generated by KOLs in the e-commerce content platform context. Using data collected from JD WeChat Shopping Circle, we empirically testified our hypotheses. Our results indicate that punishments significantly increase the quantity and quality of content generated by KOLs. Monetary rewards only have significantly positive effects on the quality of KOLs' generated content. Nevertheless, the magnitude of the effects of monetary rewards is larger compared with that of punishments. Theoretical and practical implications are discussed.

Keywords: generated contents, key opinion leaders, output control, platform governance

1. INTRODUCTION

Recently, with the increasingly saturated online shopping markets and consumption upgrades, the fusion of e-commerce and online contents has been a growing trend in Chinese e-commerce and has become a new driver of customer engagement and product sales for e-commerce platforms[†]. Rather than conventional price or product differentiation strategies, e-commerce platforms now have invested heavily to develop content platforms[‡] and foster key opinion leaders (KOLs) in generating product-related content. For example, Taobao, the most popular online shopping market in China, has developed more than twenty content channels within its mobile application, such as Taobao Headlines, Weitao, good goods, love shopping, must-buy lists, Taobao Live, and life research institute[§]. For Taobao live streaming alone, the single content channel generated a sales volume of RMB 100 billion in 2018, growing nearly 400% year-on-year[**]. The key to achieve, sustain, and further facilitate such growth relies on the continuous output of high-quality contents generated by KOLs. Therefore, it is imperative for e-commerce content platforms to formulate effective mechanisms to ensure both the quantity and quality of content outputs by KOLs.

The rewards and punishments are two common mechanisms adopted by e-commerce content platforms in practice. E-commerce content platforms use monetary rewards to prize KOLs who generate high-quality content.

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[†] https://technode.com/2019/05/14/content-emerges-as-new-driver-of-chinese-e-commerce/

[‡] We refer content platforms developed by e-commerce platforms as *e-commerce content platform* hereafter.

[§] https://www.parklu.com/tmall-taobao-influencer-marketing/

[**] https://technode.com/2019/04/01/taobao-live-ambitious-boost-plan/

Meanwhile, they would also punish KOLs for not generating quality content in a given period. For instance, Alibaba content platform launches multiple monetary incentive policies to reward KOLs to continuously generate high-quality contents, such as dynamic commission rewards[††], and punishment policies to remove KOLs' identity for not generating quality content within a month. Nevertheless, the effectiveness remains less clear. While it is institutive that monetary rewards can improve the quality of contents generated by KOLs, such an increase may be pseudo. Because the criteria are partially based on customer engagement, such as the number of readings and likes by customers, some of the KOLs may buy likes from third parties in an attempt to obtain the desirable rewards. As such, monetary rewards can be counterproductive for engaging customers and driving product sales. Besides, the effects remain less certain for punishments. Although punishing KOLs for removing their identities and limiting their access to platform resources can potentially deter undesirable behaviors by KOLs, the punishment can also negatively impact KOLs' motivations and thus crowd out KOLs to competing platforms. Thus, getting clear about the effects of rewards and punishments on content generations by KOLs is consequential for e-commerce platforms to successfully grasp the trends of content transformation.

Platform governance literature mainly focuses on policies and mechanisms implemented by a platform owner to influence and coordinate the interaction between the two sides[1] and has investigated how to leverage various policies or mechanisms (including pricing[2-3], control[4], and technical designs[1] [5-6]) to foster complementor innovations and strengthen network effects. In particular, previous studies suggest that platform owners should apply a certain level of control without excessively intervening complementor autonomy [7-8] so that the platform can appropriate the value of generativity [9]. However, although prior literature has given some prescriptions in terms of how to balance the tension, such as standardized process and tools, graduated control regimes and self-selection of the desired level of control by complementors[7-8], there is lack of study to quantify the effects of control mechanisms rather than qualitative descriptions. Moreover, the performance-based output control – a platform owner rewards or punishes complementors based on the quality of their outputs – which is a widely used control mechanism in content platforms – has been received limited attention in the platform governance literature.

The user-generated content (UGC) literature has started to examine how monetary incentives and non-monetary incentives (such as badges and social norms), as well as their combinations, affect the quantity and quality of UGC[10-15]. While most studies have found that monetary incentives significantly increase the quantity of UGC[10][15], some studies have demonstrated that monetary incentives can crowd out content generators' intrinsic motivations and thus reduce the quality of their generated contents [13]. Nevertheless, prior literature largely focuses on the quantity-based monetary rewards in the context of online product reviews. There is a dearth of research on the implications of performance-based monetary rewards for content generations by key opinion leaders (KOLs) in the context of e-commerce content platforms. Moreover, in contrast to retaining and incentivizing KOLs by monetary rewards, e-commerce content platforms also use punishment policies to remove the identity of KOL for not satisfying the quality criteria predefined by the platform. To our best knowledge, such punishments are understudied in the UGC literature.

Therefore, to address the above gaps, we are motivated to ask three research questions:

1. *How do monetary rewards affect the quantity and quality of content generated by KOLs in the context of e-commerce content platforms?*
2. *How do punishments affect the quantity and quality of content generated by KOLs in the context of e-commerce content platforms?*
3. *What is the relative effectiveness of monetary rewards and removing punishments on quantity and quality of contents generated by KOLs?*

[††] https://www.yuque.com/u229647/alczzptdrbps/zt3l4w

We next draw from the reinforcement theory as our overarching theoretical lens to define our core constructs and justify how and why monetary rewards and punishments affect the quantity and quality of contents generated by KOLs. We collected 128,614 contents generated by 465 KOLs from JD WeChat Shopping Circle, the largest e-commerce content platform embedded in WeChat, from January 1, 2017, to December 31, 2018. By leveraging the introduction of double commission subsidy and removing policy by JD WeChat Shopping Circle as quasi-experiment settings, we applied the difference-in-differences (DID) approach to empirically test our hypotheses. We found that while punishments significantly increase the quantity and quality of contents generated by KOLs, monetary rewards only have significantly positive effects on the quality of KOLs' generated content. Nevertheless, the magnitude regarding the effects of monetary rewards is larger compared with that of punishments. Theoretical and practical implications are also discussed.

2. THEORETICAL AND HYPOTHESIS DEVELOPMENT

2.1 Reinforcement theory

The reinforcement theory explains the strength of an individual's behavior as a function of its consequences [16]. The theory assumes that individuals are learning agents that would adjust behaviors according to consequences of the behavior and the consequences are assumed as instrumental to the individual. Accordingly, behaviors followed by pleasurable consequences (rewards) are strengthened and tend to be repeated, while behaviors followed by unpleasant consequences (punishments) are weakened and are less likely to be repeated [17-18]. Such effects diminish with the temporal distances between rewards or punishments to behavior[17].

We apply the concepts of rewards and punishments, as well as the underlying theoretical arguments between rewards or punishments and individual behaviors from the reinforcement theory to develop our theoretical model. Rewards refer to adding a reward after the desired behavior is made and thus act as a positive reinforcer to increase the strength of the behavior. Punishments denote to adding a punishment or sanction after an undesired behavior is made and thus decrease the strength of the behavior [16]. For e-commerce content platform owners, a desired behavior of KOLs is continuously generating high-quality content that improves consumer engagements and product sales[19-20]. Undesired behavior is not generating high-quality content given a period. Accordingly, we conceptualize the behaviors of KOLs as the quantity and quality of contents. In reference to previous UGC literature, we define *content quantity* as the volume of contents generated by a KOL [10][13][15] and *content quality* as the perceived informativeness of content by users and the platform[21]. Besides, we conceptualize rewards as *monetary rewards* a platform owner gives to a KOL after the KOL generates high-quality or high-performing content [13]. Meanwhile, we conceptualize *punishments* as removing the identity of a KOL and limiting a KOL's access to platform resources for not generating high-quality content in a given period.

2.2 Monetary rewards and content generations by KOLs

The monetary rewards are monetary prizes a platform owner gives to KOLs to recognize their efforts or excellence in generating high-quality content[13] with a high level of consumer engagement and conversion rate. According to the reinforcement theory, the monetary reward would act as a positive reinforcer to increase the strength of the desired content-generating behavior[16], increasing both quantity and quality of contents generated by KOLs.

Particularly in the e-commerce content platform context, monetary rewards are consequential in influencing KOLs' content-generating behaviors because KOLs rely on contents to obtain commissions and collaboration with brands. If consumers buy products through clicking the product link KOLs share in his or her content, the KOL will receive commissions of a certain percentage. Besides, another major source of KOLs' income is a collaboration with brands. The collaboration depends on the historical performance of a KOL (including quantity and quality of generated contents). Under such circumstances, the introduction of monetary rewards by the platform means that KOLs can not only increase their amount of commissions and collaboration opportunities with brands through generating more high-quality content but also can enjoy the monetary subsidies provided by platforms in appreciating their high-quality content generation behavior. In other words, the intrinsic and extrinsic motivations of KOL are both strengthened by rewarding their high-quality content generation behaviors [13][15]. As such, both the quantity and quality of contents generated by KOLs are expected to increase. Accordingly, we hypothesize the following:

Hypothesis 1a. *The introduction of monetary rewards increases content quantity by key opinion leaders.*

Hypothesis 1b. *The introduction of monetary rewards increases content quality by key opinion leaders.*

2.3 Punishments and content generations by KOLs

The punishments refer to the identity of a KOL being removed from a content platform for not generating high-quality content in a given period. It is worth noting that the removal does not mean the punished KOL can no longer generate contents in the platform but means that the identity or status of a KOL would be removed and the KOL would have limited access to the platform resources, such as online traffic support and collaborations with brands. Besides, the KOL cannot enjoy any monetary rewards.

Previous online review literature has demonstrated that reviewers' identity is important peripheral information cues for consumers to evaluate the helpfulness of a review and make following purchase decisions[22-23]. KOL identity represents a content generator's rich product knowledge and professional skills in discovering and recommending quality products[24], and thus are important means to influence consumers' following purchases of a KOL's recommended products. The number of following purchases further determines the number of commissions a KOL can earn. As such, the removal of KOL identity would have consequential effects on the income of a KOL. Thereby, the punishments act as an anxious stimulus to reduce the strength of the undesired content-generating behavior [16]. In other words, after the introduction of the punishments, KOLs would increase the quantity and quality of their generated content to avoid the unpleasant consequences of being punished. Therefore, we hypothesize that:

Hypothesis 2a. *The introduction of punishments increases content quantity by key opinion leaders.*

Hypothesis 2b. *The introduction of punishments increases content quality by key opinion leaders.*

3. METHODOLOGY

3.1 Research context

We chose JD WeChat Shopping Circle as our research context. JD WeChat Shopping Circle is an online shopping content sharing platform introduced by a Chinese e-commerce giant JD.com with WeChat[‡‡] in May 2015 and has been growing as the largest content communities for product sharing and recommendation on WeChat[§§]. In the JD WeChat Shopping Circle, WeChat users and key opinion leaders (KOLs) can post reviews on products, recommend products available from JD.com, and share shopping experiences in any of twenty-five interest groups or circles, such as beauty, photography, books and maternal and child product circles[***]. The generated content by users and KOLs can be attached with a link that directs consumers to JD WeChat Shopping, a shopping function of WeChat that allows users to buy products from JD.com without leaving WeChat, to complete purchasing seamlessly. If consumers buy products through the link a user or KOL shares, the user or the KOL can have a commission of a certain percentage. Moreover, after years of development, the Shopping

‡‡ WeChat is a Chinese multi-purpose messaging, social media, and mobile payment app developed by Tencent.

§§ https://www.marketingtochina.com/jd-wechat-store-one-year-anniversary-a-touch-of-circles-marketing/

*** https://www.chinadaily.com.cn/a/201903/27/WS5c9b16e8a3104842260b2de0.html

Circle has attracted and retained a large number of users, as well as desirable converted purchases. As of May 2018, JD WeChat Shopping Circle has accumulated more than 10 million users and more than 50 million user-generated content. Meanwhile, the monthly gross merchandise volume (GMV) achieved through generated content in Shopping Circle is over 100 million RMB.

JD WeChat Shopping Circle is a suitable empirical setting for several reasons. First, in contrast to user-generated content platforms that largely relies on users voluntarily generate contents, the Shopping Circle, as a typical online shopping content sharing platform introduced by traditional e-commerce firms, plays an active role in managing KOLs in terms of their generated contents. The generated contents by KOLs are vital in stimulating consumers' purchases[†††] and thus are important means to boost and sustain the revenue growth of JD WeChat Shopping. Thereby, the Shopping Circle has taken various mechanisms to regulate KOLs' content-generating behavior in an attempt to increase the quantity and quality of generated contents, as well as prompting more following buys. This objective is aligned with our theoretical consideration of output control mechanisms in the e-commerce content platform context.

Second, the double commission subsidy policy and the removing policy carried out by JD WeChat Shopping Circle provide a rare opportunity to investigate and compare the effects of monetary rewards and punishments on KOLs' content-generating behaviors in a single setting. The double commission subsidy was introduced by the JD fashion division to incentivize KOLs specialized in fashion to generate more high-quality content related to fashion products, such as clothes, shoes, jewelry, and luxury on August 8, 2018. The reward policy is a performance-based reward that gives KOLs a double commission based on the number of following buys through their generated contents. The policy is effective during the period between August 8 to December 31, 2018. JD WeChat Shopping Circle also introduced a removing policy to regulate KOLs' content-generating behaviors on July 27, 2017. KOLs were required to have at least one content recognized by the platform as high quality in three months. Otherwise, a KOL would be removed from JD WeChat Shopping Circle, meaning that the level of a KOL would be reduced and could no longer enjoy the privileges as a KOL including the financial and traffic support, and cooperation opportunities with brands. These privileges are directly linked to the number of commissions a KOL can earn from a content platform. Besides, the two policies are largely exogenous to KOLs, and therefore minimizes endogeneity concerns. Moreover, the periods of the two policies do not overlap, thus eliminating the confounding effects between different policies.

We collected data from JD WeChat Shopping Circle from January 1, 2017, to December 31, 2018. The dataset consists of 128,614 contents generated in all of the twenty-four interest groups by 465 KOLs. The data covers the demography of content generators (including the nickname, ID, gender, and level) and content details (including the date, belonged interest groups, contents, number of likes, and whether being recognized by the platform).

3.2 Research design

We exploit the introduction of a double commission subsidy policy and removing policy by JD WeChat Shopping Circle as an exogenous shock for the quasi-experiment. Recall that the double commission subsidy policy aimed at KOLs specialized in the fashion category. Thus, the introduction of the reward policy allows us to compared the quantity and quality of generated contents by KOLs affected by the reward policy (that is KOLs that are specialized in the fashion category) with the quantity and quality of generated contents by KOLs not affected by the reward policy (that is KOLs that are not specialized in the fashion category). Meanwhile, the removing policy was for KOLs who had not generated qualified content within the last three months. Accordingly, the introduction of the punishment policy allows us to compare the quantity and quality of generated contents by KOLs affected by the punishment policy (that is KOLs who had not qualified content in

[†††] https://jingdaily.com/nielsen-china-impulsive-shopping-comes-from-social-commerce/

last three months) and quantity and quality of generated contents by general users not affected by the punishment policy. The quasi-experiment needs to identify the treatment group and control group to estimate the treatment effects on which we next elaborate.

For the reward policy, we identified treatment groups as KOLs who were specialized in fashion product categories and had not generated content in other product types. We label the treatment group as a *RewardAffected* group. There were five interest groups related to fashion products – the circle of cloth matches, sporting goods, shoes and bags, accessories, and child clothes. KOLs who had not generated content in the five interest groups before and after the reward policy was viewed as not affected by the policy and thus were identified as the control group which is labeled as *RewardNotAffected* group. Consistent with the period of JD WeChat Shopping Circle in assessing KOLs' content-generating behavior, we define a six-month period – three months before the reward policy, May 8, 2018, as the pre-policy period and three months after the reward policy, November 8, 2018, as the post-policy period. Our final sample for the reward policy includes 35 KOLs in the treatment group and 137 KOLs in the control group, each observed over a six-month period. Our unit of analysis is the KOL-quarter combination.

For the punishment policy, we identified the treatment group as KOLs who were affected by the removing policy – that is KOLs who had not generated qualified content recognized by the Shopping Circle in the last three months before the policy. The treatment group was matched with the control group of comparable general users. The comparable general users refer to content generators who had not applied for KOLs but were qualified candidates – having more than 1000 followers and at least 30 generated content. Accordingly, we identified 162 KOLs in the treatment group and 64 general users in the control group. Each of them was observed over six months – three months before the punishment policy, April 27, 2017, and three months after the punishment policy, October 27, 2017. The treatment group and control group for the punishment policy are labeled as *PunishmentAffected* group and *PunishmentNotAffected* group.

3.3 Variables and measurement

Our dependent variables are the quantity and quality of generated content by content generators (including KOLs and general users). The *content quantity* (ContentQuantity) is measured by the number of generated contents by content generator *i* in quarter *t*. Following previous literature on user-generated content that uses the number of likes or helpfulness votes provided by other users as a proxy for the quality of product reviews [13], we first measure *content quality* by the number of likes content generator *i* received in quarter *t* (NumLikes). Our second measure of content quality is the ratio of qualified content selected by the platform (RatioSelected) which is operationalized by the number of qualified contents divided by the total number of generated contents of content generator *i* in quarter *t*. JD WeChat Shopping Circle has a predefined standard for high-quality content and would accordingly select and tag qualified content daily. The standards are specified in terms of different types of contents, including product lists, product recommendations, product reviews, videos, cloth matches, and general information. Take product recommendation for an example, the criteria are a length of more than 300 words, clear product pictures, products from diversified brands, product links to JD.com, and a well-designed layout. Thus, if a content is selected by the platform, we can assume the content meets the standard and is of high quality. We then log-transformed the values of ContentQuantity, NumLikes, and RatioSelected to address the skew in distributions.

The effects of monetary rewards and removing punishments are examined using dummies in difference-in-difference settings. For the monetary reward, a dummy *PostReward* takes a value of 0 for the quarter before the reward policy and a value of 1 for the quarter after the reward policy. A dummy *RewardAffected* takes a value of 1 for KOLs affected by the reward policy, and a value of 0 for KOLs not affected by the reward policy. Similarly, for removing punishment, a dummy *PostPunishment* takes a value of 0 for the quarter before the punishment policy and a value of 1 for the quarter after the punishment policy. A dummy *PunishmentAffected* takes a value of 1 for KOLs affected by the punishment policy, and a value of 0 for general users not affected by the punishment policy. Details about constructing these groups are provided in section 4.2.

We also controlled for the gender and level of content generators to include their effects on the quantity and quality of generated content[25]. A dummy *Gender* takes a value of 1 for female, and a value of 0 for male. A dummy *Level* takes a value of 1 for high levels (levels above six), and a value of 0 for low levels (levels below five). Table 1 and Table 2 summarize the descriptive statistics and correlations of reward and punishment sample correspondingly.

Table 1. Descriptive statistics and correlations for reward sample

Variables	Mean	S.D.	Min.	Max.	1	2	3	4	5	6
1.RewardAffected	0.10	0.30	0	1	1.00					
2.Gender	0.65	0.48	0	1	0.17*	1.00				
3.Level	0.90	0.31	1	1	-0.07	-0.09	1.00			
4.ContentQuantity	0.88	1.37	0	6.02	0.25*	0.10	0.01	1.00		
5.NumLikes	1.56	2.39	0	9.26	0.16*	0.13*	-0.05	0.82*	1.00	
6.RatioSelected	0.15	0.36	0	1	0.02	0.08	0.01	0.57*	0.73*	1.00

Note: The number of observations is 344; * denotes significance at the 5% level.

Table 2. Descriptive statistics and correlations for punishment sample

Variables	Mean	SD	Min	Max	1	2	3	4	5	6
1.PunishmentAffected	0.36	0.48	0	1	1.00					
2.Gender	0.66	0.47	0	1	-0.01	1.00				
3.Level	0.81	0.39	0	1	0.25*	0.05	1.00			
4.ContentQuantity	3.54	1.38	0	5.87	0.17*	0.05	-0.04	1.00		
5.NumLikes	7.59	2.79	0	11.53	0.24*	0.09*	0.09	0.80*	1.00	
6.RatioSelected	0.84	0.37	0	1	0.25*	0.05	0.07	0.59*	0.68*	1.00

Note: The number of observations is 452; * denotes significance at the 5% level.

3.4 Difference-in-differences model specifications

We estimate the differences between the pre-reward period and the post-reward period for the *RewardAffected* and *RewardNotAffected* groups, as well as the differences between the pre-punishment period and post-punishment period for the *PunishmentAffected* and *PunishmentNotAffected* groups using a DID approach. By comparing the relative difference between the group affected by policy and the comparison group not affected by a policy, both before and after the exogenous shock of a policy change, we can infer the average treatment effects of a policy. We specify the following models:

$$Y_{it} = \beta_0 + \beta_1 PostReward_t \times RewardAffected_i + \beta_2 Gender_i + \beta_3 Level_{i,t} + u_i + T_t + \varepsilon_{i,t}, \quad (1)$$

$$Y_{it} = \beta_0 + \beta_1 PostPunishment_t \times PunishmentAffected_i + \beta_2 Gender_i + \beta_3 Level_{i,t} + u_i + T_t + \varepsilon_{i,t}, \quad (2)$$

where *i* is the content generator index and *t* is the quarter index, Y_{it} denotes to our outcome of interests including ContentQuantity, NumLikes, and RatioSelected for content generator *i* on quarter *t*, *RewardAffected* and *PunishmentAffected* are dummy indicators with a value of 0 for the control groups, and a value of 1 for the treatment groups, u_i are content generator fixed effects, and T_t is time fixed effects. Because the fixed effects of the content generator and time are collinear with the main effects of *PostReward*, *RewardAffected*, *PostPunishment*, and *PunishmentAffected*, we exclude them from our equations. The coefficient of the interaction, β_1, is the coefficient of interest, which can be interpreted as the relative changes of the treatment group caused by the treatment in comparison with the control group.

4. RESULTS

4.1 Effects of monetary rewards

Table 3 shows the effects of monetary rewards on the quantity and quality of generated content by KOLs. The coefficients of the interaction between *RewardAffected* and *PostReward* in the models for the number of likes and ratios of selected content by the platform are positive and significant, whereas the coefficient of the interaction term in the model for content quantity is positive but not significant. The results show that the introduction of monetary reward resulted in about 155% greater increases in the number of likes received by users and about 36.4% greater increase in the ratio of qualified content selected by the platform. However, there were no significant increases in the quantity of contents generated by KOLs. Therefore, H1a is not supported and H1b is supported.

Table 3. Results of the effects of monetary reward

Variables	Model 1	Model 2	Model 3
	ContentQuantity	NumLikes	RatioSelected
PostReward X RewardAffected	0.405 (0.85)	1.551** (2.18)	0.364*** (3.26)
Gender	-0.027 (-0.19)	0.164 (0.69)	0.005 (0.13)
Level	0.263 (1.23)	0.008 (0.02)	0.052 (0.97)
Content generator fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Number of observations	344	344	344
R-squared	0.225	0.203	0.169

Note: * $p<0.10$; ** $p<0.05$; *** $p<0.01$; standard errors reported in parentheses.

4.2 Effects of removing punishments

Table 4 shows the effects of removing punishment on the quantity and quality of generated content by KOLs. The coefficients of the interaction between *PunishmentAffected* and *PostPunishment* in all the models are positive and significant. In particular, the introduction of removing punishment resulted in about 54.6% greater increases in quantity of content generated by KOLs, about 122% greater increases in number of likes received by users, and about 16% greater increases in the ratio of qualified content selected by the platform, indicating that the removing punishment increases both quantity and quality of contents generated by KOLs. Therefore, H2a and H2b are supported.

Table 4. Results of the effects of removing punishments

Variables	Model 4	Model 5	Model 6
	ContentQuantity	NumLikes	RatioSelected
PostPunishment X PunishmentAffected	0.546* (1.82)	1.218** (2.03)	0.160** (2.03)
Gender	0.173 (1.25)	0.540** (2.03)	0.036 (1.00)
Level	-0.359* (-1.77)	0.439 (1.04)	0.057 (0.98)
Content generator fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Number of observations	452	452	452
R-squared	0.041	0.072	0.076

Note: * $p<0.10$; ** $p<0.05$; *** $p<0.01$; standard errors reported in parentheses.

4.3 Comparison of effects of monetary rewards and removing punishments

Table 5 summarizes the effects of monetary rewards and removing punishments. As indicated by the table, monetary reward and removing punishment can increase the quality of content generated by KOLs in terms of the number of likes received by users and the ratio of qualified contents selected by the platform, wherein the magnitude is greater for monetary reward. Moreover, removing punishments significantly increases the quantity of content generated by KOLs whereas the effects of monetary rewards on content quantity are not evident.

Table 5. Summary of effects of monetary rewards and removing punishment

Variables	ContentQuantity	NumLikes	RatioSelected
RewardAffected	0.405	1.551**	0.364***
	(0.84)	(2.18)	(3.26)
PunishmentAffected	0.546*	1.218**	0.160**
	(1.83)	(2.03)	(2.03)

Note: * p<0.10; ** p<0.05; *** p<0.01; standard errors reported in parentheses.

5. DISCUSSIONS

This study investigates the effects of monetary rewards and punishments on quantity and quality of contents generated by key opinion leaders in the context of e-commerce content platforms. We found that the introduction of monetary rewards significantly increases the content quality by KOLs reflected as about 155% greater increases in the number of likes received by users and about 36.4% greater increase in the ratio of qualified content selected by the platform. But the effect is not evident on content quantity by KOLs. In contrast, the introduction of punishments results in about 54.6% greater increases in the content quantity by KOLs, as well as greater increases in KOLs' content quality (about 122% greater increases in number of likes received by users, and about 16% greater increases in the ratio of qualified content selected by the platform). Although monetary rewards cannot significantly increase content quantity, the magnitude of its effects on content quality is higher in comparison with punishments. We next reflect on how these findings contribute to theory and practice.

First, we contribute to the platform governance literature by incorporating the performance-based output control as an important but understudied form of the control mechanism and justifying how it affects complementors' innovation behaviors. Previous platform governance literature has investigated the tension between control and autonomy [7-8] and yielded qualitative prescriptions to tackle the tension. Nevertheless, although various control mechanisms have been discussed in prior literature [1], such as input control and process control, there is a dearth of research on the performance-based output control (that is, a platform owner rewards or punishes complementors based on the quality of their outputs), as well as its subsequent effects on complementors' behaviors. In particular, we investigate the effects of rewards and punishments on KOLs' content-generating behavior in the context of e-commerce content platform. Our findings on how rewards and punishments affect the quantity and quality of contents generated by KOLs greatly supplement existing platform governance literature.

Second, we contribute to the UGC literature by exploring the effects of performance-based monetary rewards and punishments on the quantity and quality of content generations by KOLs. Previous UGC literature mainly focuses on the quantity-based monetary rewards in the context of online product reviews and largely ignores punishments as an alternative mechanism to regulate content generators' behavior[10-15]. In contrast, we focus on the performance-based monetary rewards and punishments for content generations by key opinion leaders (KOLs) in the context of e-commerce content platforms. While the literature has demonstrated that quantity-based monetary rewards increase content quantity, we found that performance-based monetary rewards increase content quality. Moreover, punishments increase both the quantity and quality of contents generated by KOLs. These findings help clarify the effects of different approaches of monetary rewards and add punishments to discussions of motivating content generations.

Our findings also have several practical implications. First, e-commerce content platforms should use different approaches to monetary rewards to encourage KOLs' content contribution according to strategic purposes. Quantity-based monetary rewards increase content quantity, whereas performance-based monetary rewards increase content quality. Second, punishments are alternative mechanisms in regulating KOLs' content generations. After attracting a certain number of KOLs, e-commerce content platforms can use punishment mechanisms, such as removing KOL identity, to ensure the quantity and quality of content generations, thereby engaging consumers and increasing product sales.

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