Dec 12th, 12:00 AM

Content Platform Management of Creator Advertising: A Multi-Method Study

Xu Zhang
Fudan University, zhang_x21@m.fudan.edu.cn

Yifan Dou
Fudan University, yfdou@fudan.edu.cn

Content Platform Management of Creator Advertising: A Multi-Method Study

Short Paper

The bulk of the study is conducted by a student

Xu Zhang
School of Management,
Fudan University
670 Guoshun Road, Yangpu District,
Shanghai
zhang_x21@m.fudan.edu.cn

Yifan Dou
School of Management,
Fudan University
670 Guoshun Road, Yangpu District,
Shanghai
yfdou@fudan.edu.cn

Abstract

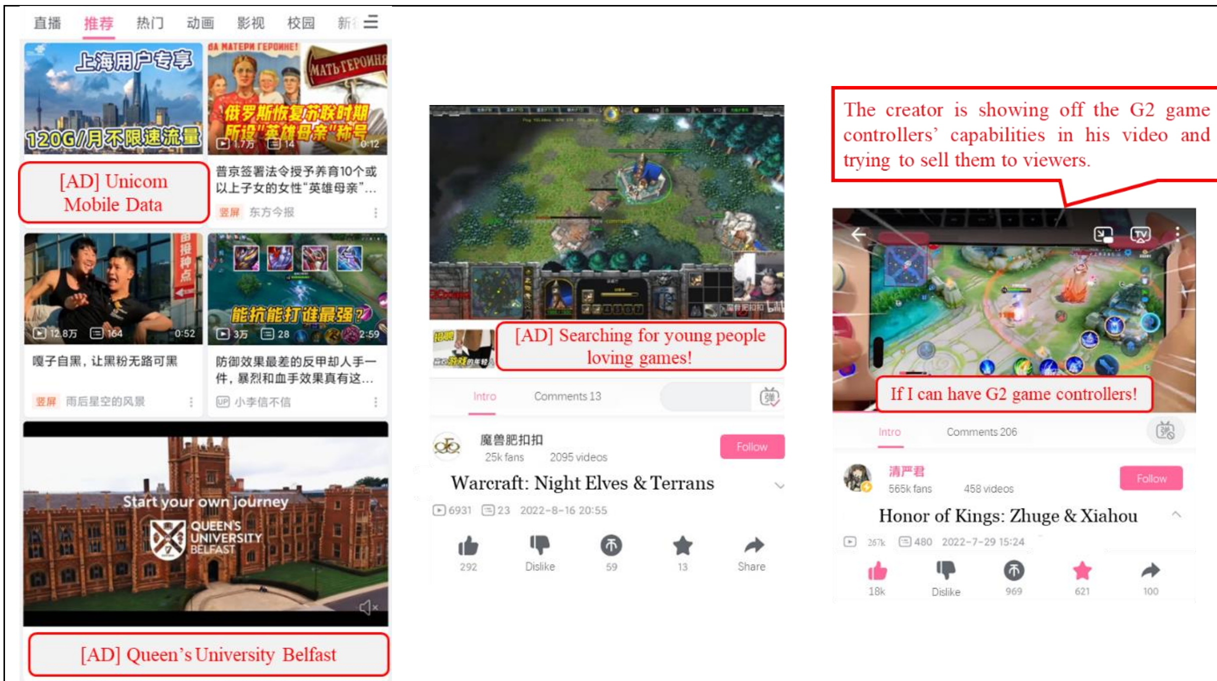
The rise of the content platforms has led to the new opportunity of advertising through the content creators, which, however, causes the strategy tradeoff for the platform owner. On the one hand, allowing creators to embed sponsored ads (CADS) may undermine the platform's own ad sales (PADS); On the other hand, the platform might benefit from CADS through commissions. We develop a game-theoretical model to examine this tradeoff. We find that allowing CADS might be optimal for the platform, depending on the qualities of PADS and CADS. In addition, we show that the strategic relationship between PADS and CADS can be substitutable, complementary, or independent from each other, which is endogenously determined by the platform's profit-maximizing decisions. We then conduct a case study based on the data collected from Bilibili to verify our analytical findings.

Keywords: creator economy, platform, advertising, analytical modeling

Introduction

The last decade has witnessed the phenomenal prosperity of the creator economy. Among the pioneer platforms, TikTok records more than 1 billion active users every month, and the content platforms have become a primary part of life for people around the world because of the creativity and authenticity of the creators (Prang, 2021). With their tremendous success and immersive influences, creators have received growing attention from advertisers. It is reported that 72% of brands had a six-figure line in their influencer marketing budget in 2018 (Arnold, 2018). It is also estimated that big-name stars earn $100,000 or more for a single YouTube video or Instagram photo posting (Kapner and Terlep, 2019).

In this paper, we identify two types of on-platform ad services: the one provided by the platform (PADS, such as traditional banner ads and pre-rolls) and the one provided by the creators (CADS, which is often embedded, somehow artistically, in the creator's content). Specifically, PADS can be categorized into two types, type-A (Figure 1a) and type-B (Figure 1b). For type-A PADS, the ads will be displayed on the portal page, such that the ads are not necessarily connected to any individual creators. In contrast, type-B PADS are often attached to a specific creator and show up next to the creator's content. For CADS, creators often work with brands in the designing process (The Economist, 2022) to enhance their artistic effects, as Figure 1c shows.



(a). Type-A PADS **(b). Type-B PADS** **(c). CADS**

Figure 1. Examples of PADS/CADS on Bilibili

In this paper, we ask: should CADS be allowed by platforms (i.e., a dual mode)? If so, how should the platform coordinate CADS with PADS?

A growing literature on platform studies has been investigating the dual mode problem. However, little attention has been paid specifically to the platform context of content creation. Hagiu, Teh, and Wright (2021) is one pioneering work from the retailing platform perspective, but their model only assumes that consumers are homogenous in willingness to pay (WTP), which is less relevant in the creator economy due to the great different advertisers' marketing targets and the creators' popularities. Furthermore, once the platform adopts the dual mode, it will face a key tradeoff between the platform's investment (i.e., the first-party investment) and the creators' production (i.e., the third-party participation), which is critical for the platform's dual mode decision. Hagiu and Spulber (2013) have discussed this coordination problem in two-sided markets by adjusting the first-party investment with an exogenously given relationship between first-party content and third-party participation. However, we find that the relationship between PADS and CADS endogenously depends on the platform's strategy. Though PADS and CADS are mutually exclusive from each other, they are not necessarily substituted (Mantin, Krishnan, and Dhar, 2014). In fact, Ghose, Smith and Telang (2006) have explored the relationship between mutually exclusive products (specifically speaking, used books and new books) in an empirical way earlier in this century, and concluded that used books may not a substitute for new books. Inspired by the former works, to clarify the strategic relationship between CADS and PADS, we built a theoretical model first and then found some empirical evidence to support the analytical results by conducting a case study on Bilibili (a leading content platform in China).

Model

A group of creators contributes content to viewers through a content platform (e.g., YouTube, TikTok, Bilibili). A pool of potential advertisers can access either the platform or content creators. We consider a model of 5 stages, which is inspired by Wauthy (1996) and Bhargava (2021). In stage 1, the platform invests in the quality of PADS, q_{P}, and the redistributive level, r. If r is positive, the platform will share its revenue with the creators, otherwise, the platform will charge commissions from the creators. In stage 2, the platform and creators set their ads prices (denoted by p_{P} and p_{C}) simultaneously. In stage 3, the advertisers arrive and choose between PADS and CADS (the market shares are denoted by S_{P} and S_{C}, respectively), they can also choose to opt out; In stage 4, the content creators optimize the volume of content (Q) to produce; Finally, viewers come to consume the content while viewing the ads from both the platform and the creators. Next, we solve the model through backward induction.

Stage 5: Demand from Viewers

We follow the literature to assume that $Views = \beta Q - \varepsilon A'$ in which β and ε are both positive constants and A' is the number of ads (Dewan et al., 2002). This equation suggests that $Views$ increases with the content offerings (i.e., more content, more views) while decreasing with ad exposures (i.e., more ads, fewer views).

As a routine of the ad industry, the number of views plays a central role in determining the potential of the advertising service, which is given by $A = \mu \cdot Views$ (coefficient $\mu > 0$). An equilibrium is reached when $A' = \phi A$ where $0 \leq \phi \leq 1$. Combining the two equations above gives $A = (\mu\beta/(1 + \varepsilon\phi\mu))Q$, which reduces to $A = \alpha Q$ where $\alpha = \mu\beta/(1 + \varepsilon\phi\mu)$.

Stage 4: Creators' Content Production Decision

The creators' profit depends on three parts: 1) CADS revenue ($p_{\mathrm{C}}S_{\mathrm{C}}A$), 2) revenue sharing from the platform or the commissions paid to the platform (depending on the sign of r again), and 3) the loss due to embedding more ads in their content (in which δ represents the viewers' disutility against the creators' ads). Collectively, a representative creator's profit is given as Equation (1) below:

$$\pi_{\mathrm{C}}(Q) = p_{\mathrm{C}}S_{\mathrm{C}}A + rQ - \delta S_{\mathrm{C}}A. \tag{1}$$

We assume that the creators' content production increases with the profit per unit of content (π_{C}/Q) (Li, Shi, and Zhao, 2021). We consider a simplified linear form to characterize the overall participation of creators, $Q = w(\pi_{\mathrm{C}}/Q) = w(r + \alpha(p_{\mathrm{C}} - \delta)S_{\mathrm{C}})$, in which w is the sensitivity of creators' content production to the profit per content unit.

Stage 3: Advertisers' Decision

For a specific advertiser, we assume that the demand for the advertiser's product is $D = \gamma \cdot e$, where e is the marketing effort, and γ represents the inverse of the difficulty of selling. Assuming that the product margin is ρ , so we have the advertiser's revenue is $u = \rho \cdot \gamma \cdot e$. Considering that the higher the margin, the harder the product to sell, we can set $\rho \cdot \gamma = 1$, which gives $u = e$. We further assume selective potential, s, as the limit of demand such that for a specific product, the advertiser's revenue is $u_{\mathrm{i}} = \min\{e, s_{\mathrm{i}}\}$.

Now the advertiser faces two advertising services: the PADS with quality q_{P} and the CADS with quality q_{C}. Their prices are p_{P} and p_{C}, respectively. The advertisers' decisions are subject to individual rationality (IR) and incentive compatibility (IC) constraints. If an advertiser chooses the PADS and the PADS happens to be of superior quality (compared with the CADS), we have the IR condition, $\min\{v, q_{\mathrm{P}}\} - p_{\mathrm{P}} \geq 0$, and the IC condition, $\min\{v, q_{\mathrm{P}}\} - p_{\mathrm{P}} \geq \min\{v, q_{\mathrm{C}}\} - p_{\mathrm{C}}$. We normalize the potential size of the advertising service market with $A = 1$. The demand functions are then $S_{\mathrm{P}} = 1 - (q_{\mathrm{C}} - p_{\mathrm{C}} + p_{\mathrm{P}})$, $S_{\mathrm{C}} = q_{\mathrm{C}} - 2p_{\mathrm{C}} + p_{\mathrm{P}}$. We can similarly derive the demand functions in the opposite case (the PADS is of inferior quality).

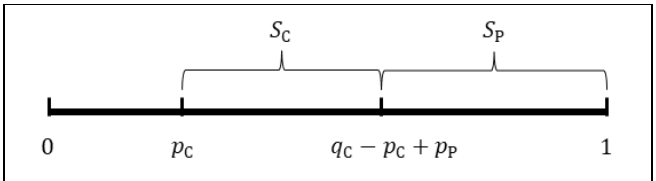


Figure 2. Advertisers' Demand

Stage 2&1: Platform's Decision

We follow the literature (e.g., Gupta, 2009) to assume that the platform's payoff consists of three parts: 1) ads revenue from PADS (denoted by $p_{\mathrm{P}}S_{\mathrm{P}}A$), 2) revenue shared to creators or the commission gained from creators (depending on the sign of r), and 3) the loss due to viewers' aversion to the PADS (denoted by $\lambda S_{\mathrm{P}}A$ where λ represents the degree of viewer's disutility against PADS). The platform's profit function is given as Equation (2) below:

$$\pi_{\mathrm{P}} = p_{\mathrm{P}}S_{\mathrm{P}}A - rQ - \lambda S_{\mathrm{P}}A. \tag{2}$$

Based on Equations (1) and (2), the creators and platform choose the prices. Meanwhile, the platform also decides the redistributive level and chooses the investment level on PADS. In this short paper, we assume that $\lambda = \delta = 0$, under which Lemma 1 always holds in equilibrium (the proof is omitted due to page limit but available upon request):

Lemma 1. *In equilibrium, if* $q_{\mathrm{P}} > q_{\mathrm{C}}$, *both* $q_{\mathrm{P}} - p_{\mathrm{P}} \geq q_{\mathrm{C}} - p_{\mathrm{C}}$ and $p_{\mathrm{P}} \geq p_{\mathrm{C}}$ *always hold; Otherwise, both* $q_{\mathrm{P}} - p_{\mathrm{P}} \leq q_{\mathrm{C}} - p_{\mathrm{C}}$ and $p_{\mathrm{P}} \leq p_{\mathrm{C}}$ *always hold.*

Analysis

For the convenience of subsequent analysis, we start with the definition of substitutes, complements, and independence between PADS and CADS.

Definition 1. *If* $\partial S_{\mathrm{C}}/\partial q_{\mathrm{P}} \geq 0$ *and* $\partial p_{\mathrm{C}}/\partial q_{\mathrm{P}} \geq 0$ *(respectively, if* $\partial S_{\mathrm{C}}/\partial q_{\mathrm{P}} \leq 0$ *and* $\partial p_{\mathrm{C}}/\partial q_{\mathrm{P}} \leq 0$*), we identify that PADS and CADS are strictly complements (substitutes). And they are strictly independent of each other if* $\partial S_{\mathrm{C}}/\partial q_{\mathrm{P}} = 0$ *and* $\partial p_{\mathrm{C}}/\partial q_{\mathrm{P}} = 0$. *Note that* q_{P} *is endogenously determined by the platform.*

In practice, PADS and CADS are complements (substitutes or independent) if $\partial \mathrm{R_C}/\partial \mathrm{q_P} > 0$ (respectively, if $\partial \mathrm{R_C}/\partial \mathrm{q_P} < 0$ or $\partial \mathrm{R_C}/\partial \mathrm{q_P} = 0$). It should be noted that the $\mathrm{R_C}$ is CADS revenue, which equals p_{C} times S_{C}.

Setting Ads Price

We benchmark our analysis with a non-dual mode under which the platform forbids the creators to embed ads in the content creation.

Non-Dual Mode

When there's only PADS with p_{P} and q_{P}, the demand will be $S_{\mathrm{P}} = 1 - p_{\mathrm{P}}$, and the profit function will be $\Pi_{\mathrm{b}} = S_{\mathrm{P}} \cdot (p_{\mathrm{P}} - \lambda)$. When $q_{\mathrm{P}} > (1+\lambda)/2$, the optimal price is ${p_{\mathrm{P}}}^* = (1+\lambda)/2$ and the equilibrium profit is then $\Pi_{\mathrm{b}}^* = (1-\lambda)^2/4$. When $q_{\mathrm{P}} < (1+\lambda)/2$, we have ${p_{\mathrm{P}}}^* = q_{\mathrm{P}}$ and $\Pi_b^* = -{q_{\mathrm{P}}}^2 + q_{\mathrm{P}}(1+\lambda) - \lambda$.

Dual Mode

q_{P} and q_{C}	S_{P}	p_{P}	S_{C}	p_{C}	Relationship
$0 < q_{\mathrm{P}} \le 1/6$ $\max\{q_{\mathrm{P}}, 1/2\} < q_{\mathrm{C}} \le 1$	$1/2 - q_{\mathrm{P}}$	q_{P}	$1/2$	$1/2$	Independent
$0 < q_{\mathrm{P}} \le 1$ $3q_{\mathrm{P}} < q_{\mathrm{C}} \le 1/2$	$q_{\mathrm{C}} - q_{\mathrm{P}}$	q_{P}	$1 - q_{\mathrm{C}}$	q_{C}	Independent
$1/6 < q_{\mathrm{P}} \le 3/4$ $\max\{q_{\mathrm{P}}, (3q_{\mathrm{P}}+3)/7\} < q_{\mathrm{C}} \le 1$	$(2q_{\mathrm{P}}+2)/7$	$(q_{\mathrm{P}}+1)/7$	$(4-3q_{\mathrm{P}})/7$	$(4-3q_{\mathrm{P}})/7$	Substitutes
$0 < q_{\mathrm{P}} \le 1$ $q_{\mathrm{P}} < q_{\mathrm{C}} \le \min\{3q_{\mathrm{P}}, (3q_{\mathrm{P}}+3)/7\}$	$2q_{\mathrm{C}}/3$	$q_{\mathrm{C}}/3$	$1 - q_{\mathrm{C}}$	$4q_{\mathrm{C}}/3 - q_{\mathrm{P}}$	Substitutes
$3/4 < q_{\mathrm{P}} \le 1$ $q_{\mathrm{P}} < q_{\mathrm{C}}$	$2q_{\mathrm{P}} - 1$	$1 - q_{\mathrm{P}}$	$1 - q_{\mathrm{P}}$	$1 - q_{\mathrm{P}}$	Substitutes

Table 1. Equilibrium Demands and Equilibrium Prices of CADS and PADS ($q_{\mathrm{C}} > q_{\mathrm{P}}$)

First, consider the case when CADS is of superior quality, $q_{\mathrm{C}} > q_{\mathrm{P}}$. The demand functions are then $S_{\mathrm{C}} = 1 - (q_{\mathrm{P}} - p_{\mathrm{P}} + p_{\mathrm{C}})$ and $S_{\mathrm{P}} = (q_{\mathrm{P}} - p_{\mathrm{P}} + p_{\mathrm{C}}) - p_{\mathrm{P}}$, respectively. The profit functions will be $\pi_{\mathrm{C}} = S_{\mathrm{C}} \cdot (p_{\mathrm{C}} - \delta) + r/\alpha$ and $\pi_{\mathrm{P}} = S_{\mathrm{P}} \cdot (p_{\mathrm{P}} - \lambda) - r/\alpha$, respectively. The equilibrium is derived in Table 1.

Similarly, we can derive the equilibrium when the PADS is of superior quality, $q_{\mathrm{C}} < q_{\mathrm{P}}$, which is symmetric to Table 1 above.

The last column of Table 1 gives the following Proposition 1, which uncovers the strategic relationship between PADS and CADS from the platform's perspective. Unlike the literature where the relationship is often predefined (e.g., Hagiu and Spulber, 2013), Proposition 1 implies that the relationship between PADS and CADS is subject to the platform's strategy – an endogenous decision.

Proposition 1. *PADS and CADS could be either substitutable, complementary, or independent from each other, depending on their qualities (see Table 1).*

The Optimal Redistributive Level

We then derive the optimal investment level over PADS. Note that the platform chooses the quality q_{P} and the redistributive level simultaneously. Note that the platform is still open to the non-dual mode. That is, observing the revenue from the ad pricing equilibrium above, the platform is still capable of forbidding the creators to post sponsored content (e.g., videos with commercial promotions are not allowed).

The optimal platform strategy is given by Proposition 2 below. Interestingly, we find that the platform always allows CADS under the optimal strategy, but the implementation is divided into two different cases, depending on the quality of CADS, q_{C}. We illustrate the key idea in Figure 3. For a given pair of $\{q_{\mathrm{P}}, q_{\mathrm{C}}\}$, the dark area represents the region in which the platform would end up allowing on-platform advertising from creators. We then optimize q_{P} as a function of q_{C}, resulting in a non-monotonic, piece-wise curve of q_{P}^*.

Proposition 2. *The optimal q_{P} always falls in the adoption area, suggesting that for all q_{C}, the platform should allow CADS.*

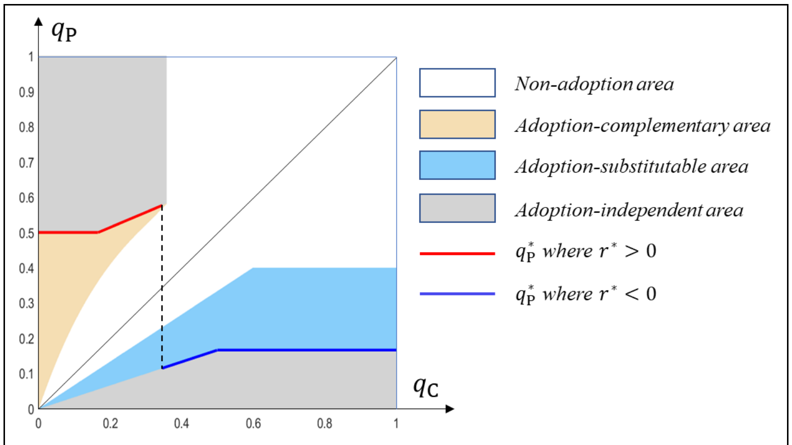


Figure 3. The Adoption of Dual Mode

Interestingly, the optimal PADS quality is always located at the interface between the independent area and the other areas, which means that PADS quality will never have an impact on CADS revenue in equilibrium.

Moving on to the optimal redistributive level. Specifically, if $r^* > 0$, the platform pays creators for the content contribution; If $r^* < 0$, the platform charges creators for their on-platform advertising. Following Proposition 3 provides the result.

Proposition 3. *When $q_C > q_P^*$, the platform charges creators for their on-platform advertising ($r^* < 0$, the blue curve in Figure 3); Otherwise, the platform pays creators for the content contribution ($r^* > 0$, the red curve in Figure 3).*

The implication of Proposition 3 is vital to the creator economy: The creators and platform are never rivals in competing for advertisers' sponsorship, if the platform configures the strategy optimally – If CADS are of superior quality (e.g., ultra-popular video contributors), then it is optimal for the platform to allow their sponsored contents while charging a commission; Otherwise, if most CADS are of inferior quality (e.g., grass-root contributors), then the platform should help them with revenue sharing to attract more contributors, in which way the viewer base is maximized.

The value of the insights above is further highlighted when thinking of the opposite: If the platform hosts super-popular contributors, it is unwise to forbid them from uploading sponsored content; Besides, it is not optimal, either, to start charging the grass-root creators from posting sponsored contents. In general, the platform should base the strategy on q_P and q_C, which means that the platform-creator relationship might evolve dynamically as their ad qualities improve over time.

Case Study

As a quick real-world check of our analytical findings, we conducted a case study based on a dataset from Bilibili, one of the leading content platforms in China. Our goal is to show that, as our central argument in Proposition 1 and Figure 3, regardless of whether PADS quality is higher than CADS quality, the PADS quality will not cause significant changes in CADS revenue.

Data

Our data are compiled from publicly available information on Bilibili and its affiliated CADS market––– Huahuo. We worked with an analytical company, Xinzhan, to collect the data. We first randomly sampled 100 creators who had sold CADS in July 2022. We then defined the following four segments of creators based on their numbers of fans: below 100,000, 100,000 to 500,000, 500,000 to 1 million, and more than 1 million. We found that the distribution ratio of the sampled creators in the above four segments is about 1:2:1:1. We then randomly selected a total of 1,000 creators in the four segments according to the above distribution ratio. Further, we cleaned the data by removing creators who did not offer CADS prices, leaving

567 creators. For each creator, we collected the following information: CADS price offer, CADS sales (within the last month), average views of the last five videos, number of fans, the total historical likes, the total number of historical videos, creation category, the institution certification and famous-creator certification. It should be noted that videos with keywords such as "Qiafan" (a Chinese internet slang that means the creator is making money, perhaps disgracefully, from showing ads to fans) appearing more than three times on the bullet screen will be identified as CADS related videos. We counted the number of CADS related videos to obtain the CADS sales. Other variables are available from the creators' home pages.

We used the product of CADS price and CADS sales as the CADS revenue (denoted as $CADSRevenue$), which is the dependent variable. What's more, it is important to clarify how to measure the PADS quality (denoted as $PADSQuality$) that is the main independent variable. Generally speaking, the PADS quality is determined by two dimensions, ad tech and exposure. Since we have used the cross-sectional data, ad tech will not change, so that the PADS quality is directly related to the exposure. We took views to represent the exposure, and that's pretty intuitive.

The quality of type-A PADS depends on the platform's ad tech and overall page views on the platform, and the ad tech and overall page views are both not easy to change in a short term. Therefore, it is hard to analyze the strategic relationship between type-A PADS quality and CADS revenue with cross-sectional data. The quality of type-B PADS depends on the platform's ad tech and the page views of its related creators, and the page views above-mentioned can be different among creators. Considering this limitation, we focus on type-B PADS in our case study. It should be noted the type-B PADS quality is almost always lower than its corresponding CADS quality, because the latter combines the creator's creativity and endorsement with the same exposure as the former. Therefore, subsequent analysis can only verify whether significant changes in CADS revenue caused by type-B PADS quality exist when PADS is of inferior quality. We used the average views of the last five videos to represent the type-B PADS quality attached to a specific creator.

We used the number of fans to represent the viewer base (denoted as $ViewerBase$) for a specific creator, and used the ratio of the total historical likes to the total number of the historical videos to show the popularity of video content (denoted as $AveLikes$) for a specific creator. Considering there might be differences about the advertising market among categories, we calculated the average PADS quality of each category (denoted as $CategaryPADSQ$) as a control. If the creator is an institution such as a university or a company, the institution certification (denoted as $InstitutionCertification$) will be "1", otherwise it will be "0". Similarly, if a creator is famous enough to meet the platform's criteria, the famous-creator certification (denoted as $FamousCreatorCertification$) will be "1", otherwise it will be "0".

Variable	Obs.	Mean	St. dev.	Min	Max
$CADSRevenue$	567	1.414	8.341	0	140
$PADSQuality$	567	22.160	38.892	0.001	405.600
$ViewerBase$	567	78.513	87.973	1.183	818.928
$AveLikes$	567	2.090	3.139	0.001	30.874
$CategaryPADSQ$	19	22.160	8.598	1.500	40.600
$InstitutionCertification$	567	0.028	0.166	0	1
$FamousCreatorCertification$	567	0.850	0.357	0	1

Table 2. Summary Statistics

$$CADSRevenue_i = \Gamma \cdot PADSQuality_i + \Psi \cdot ViewerBase_i + \boldsymbol{\Omega} \cdot \boldsymbol{X_i} + Constant. \quad (3)$$

Above is our regression model, the dependent variable is the $CADSRevenue$. The independent variables are $PADSQuality$, $ViewerBase$, and a vector of other control variables, $\boldsymbol{X}$. Our control variables include $AveLikes$, $CategaryPADSQ$, $InstitutionCertification$, and $FamousCreatorCertification$. Γ, Ψ, and $\boldsymbol{\Omega}$ are the parameters or parameter vector to be estimated. It should be noted that we have checked the variance inflation factor (VIF), and there is no collinearity between the independent variables. In addition, because that many creators got zero from CADS, we conducted a Tobit regression, which can handle such a situation.

Results

	(1)	(2)	(3)	(4)	(5)
$Constant$	-53.02*** (6.351)	-52.88*** (6.407)	-61.27*** (9.281)	-59.30*** (9.168)	-65.62*** (12.650)
$PADSQuality$	0.0996 (0.0534)	0.1030 (0.0590)	0.0880 (0.0599)	0.0828 (0.0598)	0.0809 (0.0599)
$ViewerBase$	0.101*** (0.0230)	0.102*** (0.0234)	0.104*** (0.0235)	0.106*** (0.0236)	0.104*** (0.0237)
$AveLikes$		-0.119 (0.828)	-0.237 (0.844)	-0.272 (0.842)	-0.338 (0.851)
$CategaryPADSQ$			0.393 (0.272)	0.339 (0.272)	0.341 (0.272)
$InstitutionCertification$				-127.2 (5335.8)	-125.5 (8101.0)
$FamousCreatorCertification$					7.315 (9.279)
No. of observations	567	567	567	567	567
Pseudo R^2	0.044	0.044	0.047	0.051	0.052

Table 3. Tobit Regression Results

*Notes. The dependent variable is $CADSRevenue$. Standard errors are listed in parenthesis; ***, ** and * denote significance at 0.001, 0.01 and 0.05, respectively.*

The above analysis shows that when CADS is of superior quality, there're no significant changes in CADS revenue caused by PADS quality can be found. The difference in CADS revenue is mainly driven by the viewer base. That's basically consistent with our analytical results.

Conclusion

Although PADS and CADS are mutually exclusive, the strategic relationship between CADS and PADS is not that intuitive. Our analytical results suggest that CADS and PADS could be either complements, substitutes, or independent from each other, depending on the platform's endogenous decisions. From the strategic level, under specific assumptions, we show that the platform should always allow on-platform advertising from content creators if the platform can configure the platform strategies (i.e., quality of PADS and the redistributive level) optimally. From the implementation level, if the platform hosts super-popular contributors, it is unwise to forbid them from uploading sponsored content. At this point, the platform should just take commissions from them. Besides, it is not optimal, either, to start charging the grass-root creators for posting sponsored content. In fact, the platform should pay them for their content creation.

Our analytical model suggests that CADS and PADS are independent of each other in equilibrium, and we have found some empirical evidence for it from the case study of Bilibili. When PADS quality is lower than CADS quality, we didn't find any significant changes in CADS revenue caused by the PADS quality according to Tobit regression results. Future studies may consider moving forward to verify the above idea when PADS is of superior quality.

References

Arnold, A. (2018). How Brands Can Improve Influencer Marketing to Remain in Touch with Consumers. Forbes.

Bhargava, H. K. (2021). The Creator Economy: Managing Ecosystem Supply, Revenue Sharing, and Platform Design. Management Science.

Dewan, R., Freimer, M., & Zhang, J. (2002, January). Managing Web Sites for Profitability: Balancing Content and Advertising. In Proceedings of the 35th Annual Hawaii International Conference on System Sciences (pp. 2340-2347). IEEE.

Ghose, A., Smith, M. D., & Telang, R. (2006). Internet exchanges for used books: An empirical analysis of product cannibalization and welfare impact. *Information systems research*, *17*(1), 3-19.

Gupta, S. (2009). Customer-based Valuation. Journal of Interactive Marketing, 23(2), 169-178.

Hagiu, A., & Spulber, D. (2013). First-party Content and Coordination in Two-sided Markets. Management Science, 59(4), 933-949.

Hagiu, A., Teh, T. H., & Wright, J. (2021). Should Platforms be Allowed to Sell on Their Own Marketplaces?. Available at SSRN 3606055.

Kapner, S., & Terlep, S. (2019). Online Influencers Tell You What to Buy, Advertisers Wonder Who's Listening. WSJ.

Li, X., Shi, M., & Zhao, C. Y. (2021). Incentivizing Mass Creativity: An Empirical Study of the Online Publishing Market. Available at SSRN 3842153.

Mantin, B., Krishnan, H., & Dhar, T. (2014). The Strategic Role of Third - party Marketplaces in Retailing. Production and Operations Management, 23(11), 1937-1949.

Prang, A. (2021). TikTok Tops 1 Billion Monthly Users. WSJ.

The Economist (2022). Schumpeter: Creative Seduction. The Economist

Wauthy, X. (1996). Quality Choice in Models of Vertical Differentiation. The Journal of Industrial Economics, 345-353.