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The effect of advertising strategies on a short video platform: evidence from TikTok

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Abstract

Purpose – There are two major strategies for short video advertising which are KOL (key opinion leader) endorsement and in-feed advertising. The authors aim to research the effectiveness of these two strategies for heterogeneous sellers.

Design/methodology/approach – The study employed a data set of users from Douyin. Using an endogenous treatment model, the study empirically examines the two strategies' effectiveness in attracting product traffic for online retailors at a short video app Douyin (TikTok).

Findings – The results show that the performance of in-feed advertising is higher when the seller's product is of lower price and when the seller has smaller cumulative video exposure. In addition, KOL endorsement is effective regardless of the product price, but performs better when the seller has larger cumulative video exposure.

Originality/value – To the best of the authors' knowledge, this study is one of the first to explore the interaction effects of two major advertising strategies, KOL endorsement and in-feed advertising on short video platforms. The findings provide important theoretical contributions and practical implications.

Keywords Short video marketing, In-feed advertising, KOL endorsement, Social commerce, TikTok (Douyin), Douyin marketing

Paper type Research paper

1. Introduction

With the continuous development of social commerce, short video platform has gradually become another area of e-commerce (Mhalla *et al.*, 2020). Launched by ByteDance in September 2016, TikTok (Douyin) is now one of the leading short video mobile apps by number of downloads as well as active users, which allows users to browse other-created contents and post self-created videos (ByteDance, 2018). According to the 2019 data report, Douyin has more than 400 million daily active users. Especially during the epidemic period, merchants prefer to conduct short video sales on Douyin. The main reason is the decentralized delivery mechanism of Douyin, when the system engine receives videos uploaded by users; it analyzes the interests of the user, sorts them, and recommends relevant short videos (Maharjan, 2019). The recommendation mechanism calculates the tag of each uploaded video and classifies the videos according to their category characteristics. It then maps the label of video to users with the same label. Thus, Douyin realized the accurate positioning based on big data algorithms, which further promotes short video marketing (Lu, 2019).

Presently, revenue streams of Douyin mostly from advertisement display and campaigns (Chen, 2017). In-feed advertisements and KOL (key opinion leader) endorsement are two primary advertising tools on Douyin. The in-feed advertisement service, which began in 2016, incorporates advertising messages into the short video (Chen, 2019). Advertising messages are shown underneath short videos, implanting product links in advertising content and thus making it more accessible to users (Plate 1). When a user clicks on the product link or according to times of advertising exposure, the platform charges sellers a service fee (Zhang and Osawa, 2019). KOL endorsement, another advertising tool offered by Douyin, was

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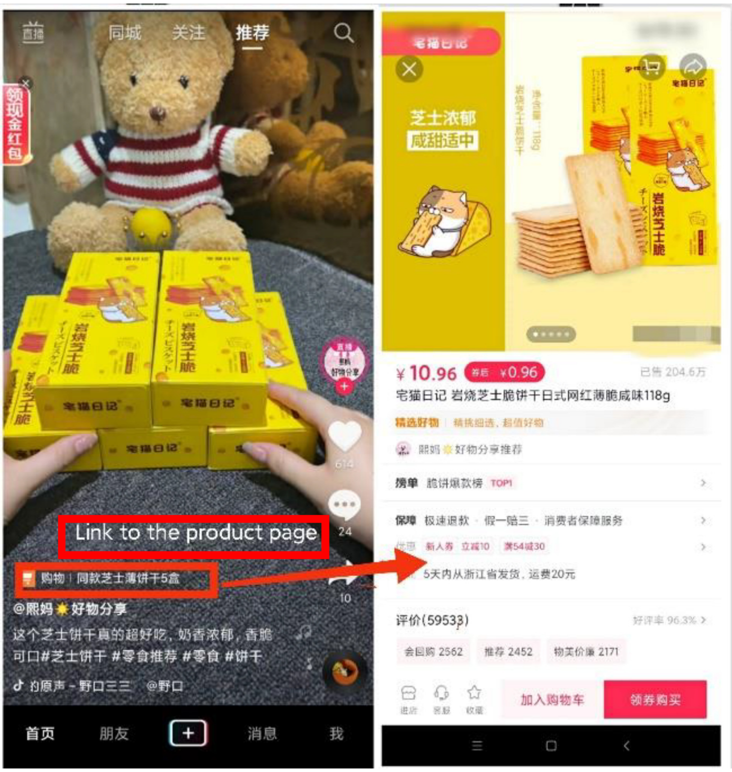

Plate 1.
Illustration of in-feed ads

proposed in 2018 (Windels *et al.*, 2018). The endorser posts short videos of different products to redirect traffic to the seller's website, and they receive a commission based on the effect of ads and the number of followers they own (Plate 2). Essentially, sellers post tasks for products they want to promote on Ocean Engine. Then, the endorsers can contact sellers to discuss the products details, and finally post short videos on Douyin to share the product information such as user experience (Zimmer and Scheibe, 2019). Given the great value of advertising on short video platforms, both researchers and practitioners pay increasingly more attention to this field.

Existing literature mainly focus on investigating the effect of single advertising tool to improve firm performance (Fan *et al.*, 2017; Farivar *et al.*, 2021) or understanding factors of the advertising enhancing consumer and product interaction (Kiss and Bichler, 2008; Li and Du, 2011). Besides, several researches have begun to explore the consumer heterogeneity to certain advertising method (Blake *et al.*, 2015; Hamouda, 2018). However, it is little known that the heterogeneity of sellers has an impact on the choice and effect of different advertising tools to attract customers. It is largely silent on why or when one selling channel is or should be chosen over another (Choi *et al.*, 2020). Therefore, the purpose of this paper is to fill this gap in the literature by jointly studying the differential effects of in-feed advertisements and KOL endorsement for heterogeneous sellers promoting their products. Overall, we respond to the following questions: Are these advertising strategies effective in increasing website traffic? What types of sellers are

Plate 2.
Illustration of KOL endorsement

better suited for in-feed advertisements or KOL endorsement? How these strategies work differently across different products?

There are two implications of this paper. First, the study extends the conclusions on how advertising strategies work in influencing individual sellers' traffic on a short- video sharing platform. Our results reveal the relative advantages of the two models in affecting traffic as well as examine the interaction between the two types of advertising and also advance the understanding of the research on the two main advertising methods. Second, we consider the two advertising tools by examining two key variables—product price and video count, which is an obvious indicator for customers to captures how the customer is responding to the transactions. Our conclusions provide an important reference for the seller's advertising selection and the platform's strategic guidance.

The rest of the study is planned as following. Section 2, we review the relevant theoretical literature. Section 3 develops the theoretical background and proposes our research hypothesis. Section 4 introduces the dataset and illustrates the model-free. Section 5 provides research methodology and identification strategies for the results and additional robustness check. In the next section, we discuss results with theoretical and practical implications. Finally, we conclude the study with limitations and future directions of this research.

2. Literature review

In this section, we discuss the current research development of two advertising strategies and online traffic as well as business model on short video platforms respectively.

2.1 Two advertising strategies

This research focuses on the growing literature on short video advertising in the e-business context. A few studies have concentrated on in-feed advertising (Cowley and Barron, 2008; Tutaj and Van Reijmersdal, 2012; Smith, 2014; Fan *et al.*, 2017; Xiao and Zhang, 2022). Recent empirical work has examined in-feed ads receive higher click-through rates and consumer engagement (Fan *et al.*, 2017; Aribarg and Schwartz, 2020), as well as perceived as less persuasion motivation (Tutaj and Van Reijmersdal, 2012; Wojdynski and Evans, 2016). To be specific, Aribarg and Schwartz (2020) combined clickstream, eye movement with survey data and found that in-feed ad generates a higher click-through rate because it is better fits in the surrounding content. Fan *et al.* (2017) found in-feed advertising leverage their social nature to reduce advertising persuasion motivation and improve consumers to view and even like, share and comment on these advertising as the same as other social media messages through an online survey. Tutaj and Van Reijmersdal (2012) discovered the direct form of traditional media advertising showed more negative effects on product response than the indirect form. They argued that in-feed advertising is more successful because they take a subtle form and show less persuasion motivation. In addition, Xiao and Zhang (2022) examined the in-feed advertising persuasion motivation based on Baidu archived-data analysis. They found implicit persuasion motivation matched with convergent consumer browsing modes can improve advertising performance. However, the above studies are conducted in the context of online search engine advertising, and this paper researches in-feed advertising on a short video sharing environment.

Literature on KOL endorsement has been scant. Previous researches discuss KOL endorsement are based on online word-of-mouth marketing (Li and Du, 2011; Farivar *et al.*, 2021). Their researches indicate that employing the close relationship between KOL and his followers to influence consumers, it is likely to provide useful information and positive word-of-mouth (WOM) to consumers, which is the key to demonstrate the effectiveness of KOL endorsement (Che *et al.*, 2017). Their findings also have shown a retailer's internal WOM has a limited influence on sales, while external WOM sources (e.g. KOL) have a significant impact on sales (Wang *et al.*, 2020). Each good KOL has its extensive experience and knowledge background in the individual field, and if they can spread positive WOW for products, most of them could gain the attention of their followers (Farivar *et al.*, 2021). Similarly, the use of KOL to endorse goods or services on social media platform has been proved to have a positive impact on traffic and profits (Wang *et al.*, 2020), which attaches the image of a KOL to the product and attracts consumer to view and purchase. At the same time, KOL will use their social accounts to gain the attention of their customers before trading to ensure smooth sales and promotion of their products (Li and Du, 2011). However, the above studies on KOL endorsement all discuss the effectiveness and principles from an overall perspective, whereas in our context, the effectiveness of KOL endorsement on sellers and products are subdivided.

2.2 Online traffic

Our study is related to the growing literature that explores different factors on online traffic. Traffic is one of the most important indicators of the effectiveness of a marketing strategy. Because the seller's marketing performance is closely related to the amount of online traffic, such traffic may be translated into sales and income (Fan *et al.*, 2017). Due to the importance of online traffic, researchers have the motivation to study online traffic. For example, Chatterjee *et al.* (2003) examined the click proneness across consumers and explored the effects of repeated exposure based on the number of advertisements. Sun *et al.* (2020) used Taobao-level transaction data set and found indirect effect of product price on future online traffic. Besides, other related factors, such as brand reputation (Sari and Yulianti, 2019), product variety, seller tenure and the number of fans (Yuan *et al.*, 2021) can affect traffic generation. We extend this body of literature and examine how the two advertising strategies concurrently impact online traffic.

2.3 Business model for short video platform

In the modern days, advertising is still the main business model in the short video industry (Jiang and Zhang, 2020). The “Douyin” platform combines short video and traditional e-commerce, producing an innovative business model (Bian and Zhu, 2020). The business model connecting the platform and e-commerce is doomed to the heavy profit nature of the platform, namely, the platform will associate users with recommended products through algorithms and creators they follow (Zhang 2021). For instance, on 16 January 2019, an e-commerce platform called “Buy at Ease” (Fang Xin Gou) which comes from ByteDance, the same mother company with Douyin, was connected to the platform, and creators were allowed to add the products from shops in “Buy at Ease” to merchandise windows could be embedded into their videos. Profits from commodity sales would be shared by producers, platforms and creators in a certain proportion (Van Dijck *et al.*, 2018; Zhang, 2021). The business model is also the current mainstream model of short video platform represented by Douyin.

Overall, this research contributes to the literature in the following ways. First, previous literature on in-feed advertising has focused on the context of online search engines, such as Google and Baidu. However, it is different on the mechanism of the in-feed advertisement on short video platform, which allows consumers to engage, e.g. like, comment and share. Therefore, this article fills this gap by exploring the mechanism and effectiveness of in-feed advertising on short video platforms. Second, in the previous literature, KOL endorsement has not been fully studied. We inspect the effect of KOL endorsement and compare its effectiveness to in-feed advertising. Third, previous researchers studied the isolated effects of a single advertising strategy, but ignored the interaction of different advertising strategies. Our research emphasizes the usage of differentiated advertising strategies to maximize the effect according to the heterogeneous characteristics of sellers. To our knowledge, this study is one of the first empirical studies of the economic effect of advertising tools on short video platforms, which rely on advertising as their primary source of revenue.

3. Theoretical background and hypotheses

3.1 Effect of in-feed advertising

In-feed advertising on short video platforms such as Douyin release promotional videos to match users through certain tags, such as gender, age, interest and city, etc., while also allowing products to better expose themselves in the decision-making process of customer satisfaction. The matching view in the advertising literature indicates that advertisements will provide matching information according to the characteristics of target consumers, that is, advertisements contain content about product characteristics and related information, which is crucial to matching the different tastes and expected prices of potential consumers. For instance, web search engines are based on the idea, which could sort the search results based on the relevance between the user query and the returned web pages (Panniello *et al.*, 2016).

In short video platforms, the correlation between the user profile and the video is often used to predict which items are likely to match the interests of users. Likewise, the relevance between interests and in-feed advertising may also influence the level of acceptance of short video advertising (Fan *et al.*, 2017). After consumers click to the video, sellers can pay for the promotion of the video and re-advertise to consumers based on the browsing history, thus increasing the chances that consumers will visit the store and browse the products by clicking on the link of the video (Chen *et al.*, 2017). Hence, we expect that in-feed advertising could divert the attention of consumers to product pages and effectively increase the traffic of their products, which proposes the hypothesis as follows.

H1. In-feed advertisements have a positive effect on increasing product traffic.

3.2 Effect of KOL endorsement

Unlike in-feed advertising, KOL endorsement relies on social influence to spread positive attitudes toward products, but clients are not necessarily having purchase intention from the first (Egger, 2016). Like other ways in which social advertising effects, KOL endorsement is verified through social networks which based on a current fan base (Bakshy *et al.*, 2012), and intended to attract consumer attention and change the attitudes or behaviors of the recipient (Starr and MacMillan, 1990).

Basically, KOL endorsement spread a positive word-of-mouth, especially online WOM, that represents a positive attitude to products or sellers. Existing research has indicated that positive WOW has a significant effect on directing traffic to e-commerce platforms (Godes and Mayzlin, 2004; Chevalier and Mayzlin, 2006). However, unlike traditional e-commerce platforms where the consumers and the sellers are most likely strangers to each other, when endorsers post a video about product promotion, they spread positive word-of-mouth to fans who share similar interests and values as well as those who have a social relationship with the endorser. Findings from social psychology have long confirmed that users are influenced and persuaded by people they adore and to whom they resemblances (Cialdini and Rhoads, 2001). Given the connection between endorsers and recipient of information, potential buyers may be tempted by a positive attitude (Lundgren and Prislin, 1998) to receive endorser opinions and visit the product. Therefore, we expect KOL endorsement to have a positive impact on attracting potential consumers to the store. Therefore, we provide the following assumptions:

H2. KOL endorsement has a positive effect on increasing product traffic.

3.3 Moderating effect of product price

In our research context of short videos, KOLs commonly share their opinions on endorsed products with a large volume of visitors on short videos platforms (Park and Lee, 2008). This may induce short video visitors' concern about the reputation and discount of products, e.g. product brand or product price. Chen *et al.* (2019) find that online visitors tend to care product price as well instead of limiting themselves to the endorser and the video content while browsing short videos. In order to attract visitors attention in limited time, sellers would seek help from the price of endorsed products. McKnight and Kacmar (2006) argue that the most important factor in advertising strategy is product price. Price can be defined as a signal consumer's perception of the reputation and discount of a product, reflecting nothing about the advertising itself. Therefore, it is necessary to explore the interaction between product price and different advertising strategies.

Product price had main and interaction effects on purchase intention (Park and Lee, 2008), and intention to click (Flores *et al.*, 2014). In low product price situations, individuals are more motivated to analyze and understand the meaning of the information provided by in-feed advertising by the incentive of attractive price (e.g. Phelps and Thorson, 1991; Warrington and Shim, 2000). Contrarily, high product price often leads to less motivation (Kaufman *et al.*, 1999). For the meantime, as discussed above, short video platform places advertising in the context of an entertainment experience, then the placement hides the motivation to persuade consumers (Cowley and Barron, 2008). Therefore, the combination of less persuasive motivation on in-feed advertising and more exploration motivation on low price led to more intention to click. We expect that consumers will gradually accept the information of products with low price through browsing short videos. Meanwhile, from a profit perspective, lower-priced products, which are limited by brand, are better suited to advertise in-feed to match potential consumers, which propose our following hypothesis.

H3a. For lower-priced products, in-feed advertising has a more significant effect on product traffic.

Unlike in-feed advertising, KOL endorsement attracts traffic through social influence. As we argued above, KOL endorsement is generally effective in building positive word-of-mouth among consumers. Nevertheless, this positive impact can vary depending on endorsed products. We believe that prices could complement social impact processes as a signal of quality and reputation. For example, consumers infer the level of a brand by observing historical prices. It also means that the price signs brand degree (Erdem *et al.*, 2008).

From a motivated reasoning perspective, Fu *et al.* (2018) find that consumers are more susceptible to less stereotypical persuasion attempts under defense motivation. These consumers are willing to pay higher prices and show greater trust in endorsers who use less stereotypical persuasion attempts. As a result, price and other objective signals could make these consumers more responsive to endorsement, which is the preference of precision and defensive consumers. Furthermore, Chen *et al.* (2012) suggest that impression-oriented consumers tend to select and focus on the price information of a product. Generally, consumers have a favorable impression of brand products or sellers with high reputation (Elfenbein *et al.*, 2012), and accept that high-value products posted by endorsers in their videos. Hence, we suggest that KOL endorsement is an effective way to attract the attention of consumers and appeal to them to purchase products for the high-priced products. We propose the following:

H3b. For higher-priced products, KOL endorsement has a more significant effect on product traffic.

3.4 Moderating effect of cumulative videos

The effects of advertising are often difficult to achieve in a short period of time and usually take longer to accumulate, so the exposure time required to produce these effects is longer. As noted in the literature, there is a cumulative media effect when repeated exposure to television as well as the press, and that effect has a diffused impact on our values and views on the long-term socialization progression (Irwin and Van Holsteyn, 2008). Similarly, the cumulative effect of short video ad exists all the time, then the consumer trust and conversation on advertising can cumulate over time. However, researchers also discovered advertising repetition can also bore consumers and engender negative attitudes towards the product (Campbell and Keller, 2003). Given the special delivery mechanism of short videos, the platform will not recommend or display the video again if consumers dislike or even skip this video. In this case, there are few negative effects of repeated advertising. Hence, we can consider cumulative exposure of short video advertising over several days in a row to see certain forms of advertising effects that result from repeated long-term or short-term campaign exposures.

Yuan *et al.* (2021) confirm that the cumulative effect may form attitudes and beliefs both within and across consumers, for instance consumer trust, expression norms as well as tolerance of viewing advertisements. Consequently, cumulative exposure generated by either in-feed advertising or KOL endorsement could be effective in attracting customers who already have an impression of the product. This argument is consistent with previous literature of banner advertising marketing, by which consumers tend to develop a preference for products simply since they are familiar with them (Chatterjee *et al.*, 2003; Drèze and Hussherr, 2003). Thus, the following hypotheses are proposed:

H4a. For products with more cumulative videos, in-feed advertising has a strong positive effect on product traffic.

H4b. For products with more cumulative videos, KOL endorsement has a strong positive effect on product traffic.

The proposed research model is demonstrated in Figure 1.

4. Methodology

4.1 Data and variables

We examine the effect of in-feed advertising and KOL endorsement based on a panel data provided by Douyin, one of the largest and most successful short video platforms in the world. The dataset contains 300 randomly sampled products, with daily data across 60 days from August 2020 to October 2020. This panel data is unbalanced as some sellers just entered the platform during the research period. To capture the effects of both strategies in a same time horizon, we eliminate products with less than our period activities in the dataset, and we ended up having 180 products in our sample. Next, we provide detailed descriptions of the variables in the dataset. Table 1 present the summary statistics of the variables.

4.2 Model-free

We use the data to present some model-free analysis. First, a large proportion of sellers who adopted advertising are using strategies dynamically rather than blindly. Table 1 and Figure 2 displays the proportion and distribution of each advertising strategy used by sellers. For instance, it started with 46.67% of sellers use KOL endorsement (KOL refers to those accredited by MCN), but over time, whereas 75% of them used it at the end of the study period. The number of sellers using KOL endorsement has increased gradually and significantly. By contrast, only 32.67% of sellers use in-feed advertising at the beginning, whereas the sellers increased over time, but the trend has been steady and slow (Table 2).

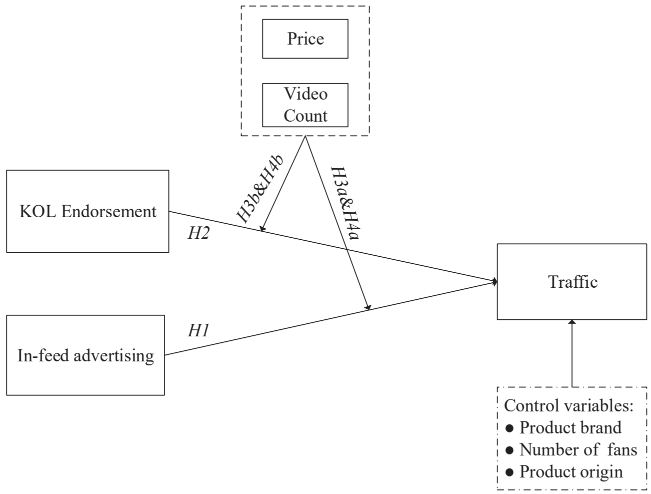

Figure 1.
Theoretical model

Table 1.
Key variable description

Variable type	Variable	Variable definition
Dependent	Traffic	Total number of unique visitors that visited the product page of a seller website in a given day
Independent	In-feed	Binary variable indicating whether sellers have adopted in-feed advertising or not in a given day; in-feed = 1 if in-feed advertising is used; otherwise, in-feed = 0
	KOL	Binary variable indicating whether sellers have adopted kol endorsement or not in a given day; kol = 1 if kol endorsement is used; otherwise, kol = 0
Moderating	Video count	Cumulative Total number of different products posted videos by a seller within a day
	Product price	The price at which the seller sells the product within a day
Control	Fans	Total number of the fans a seller has in a given day
	Brand	Binary variable indicating whether product have a brand name or not in a given day; brand = 1 if have a brand name; otherwise, brand = 0
	Small shop	A dummy variable indicating whether the product is derived from small shop of douyin; Small shop = 1 if a product is derived from small shop of douyin; otherwise, small shop = 0
	Taobao	A dummy variable indicating whether the product is derived from Taobao; Taobao = 1 if a product is derived from Taobao; otherwise, Taobao = 0
	Jingdong	A dummy variable indicating whether the product is derived from Jingdong; Jingdong = 1 if a product is derived from Jingdong; otherwise, Jingdong = 0

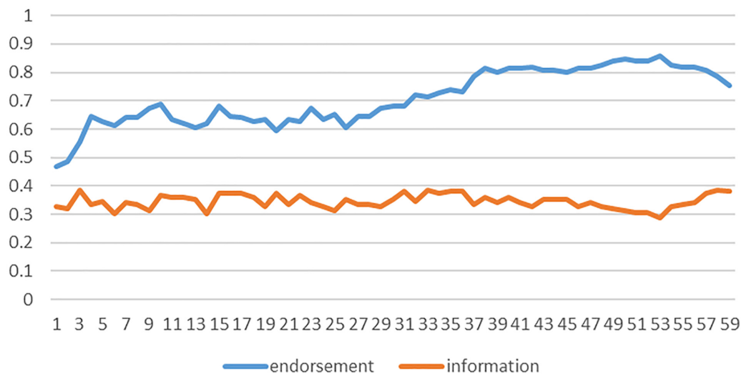

Figure 2.
Trend of sellers with strategy adoption frequency

Next, we verify whether the adoption of the advertising strategies is related to the seller's personal behavior, such that sellers with expensive products are partial to adopt advertising tools. Figure 3 reveals the distribution of seller characteristics, where price level led to the adoptions of diverse advertising methods. This picture shows the product price is not necessarily a reason for the seller to choose either or both strategies. Also, we study traffic distribution across different strategy sets. As shown in Figure 4, sellers with KOL endorsement have attracted more traffic than those with in-feed advertising, at the same time, sellers with two strategies even attract more traffic. This result preliminarily proves that KOL endorsement has a greater influence in traffic than in-feed advertising, but in-feed advertising can increase traffic above and beyond KOL endorsement.

Third, we examine the seller's monthly traffic and sales distribution. Traffic is highly correlated with a correlation coefficient of 0.55 with sales. Figure 5 shows the scatterplot of

Table 2. Variable descriptive statistics

Variable	*N*	Mean	SD	Min.	Max.
Traffic	10,800	24,036.436	54,923.864	0	1,441,000
Video	10,800	152.869	430.604	0	3,719
KOL	10,800	0.69	0.457	0	1
In-feed	10,800	0.35	0.475	0	1
Brand	10,800	0.37	0.484	0	1
Price	10,800	38.21	43.451	3.9	229
Small shop	10,800	0.78	0.414	0	1
Taobao	10,800	0.2	0.4	0	1
Jingdong	10,800	0.02	0.14	0	1
Fans	10,800	8287,993.7	14,472,428	2,650	25,450,000

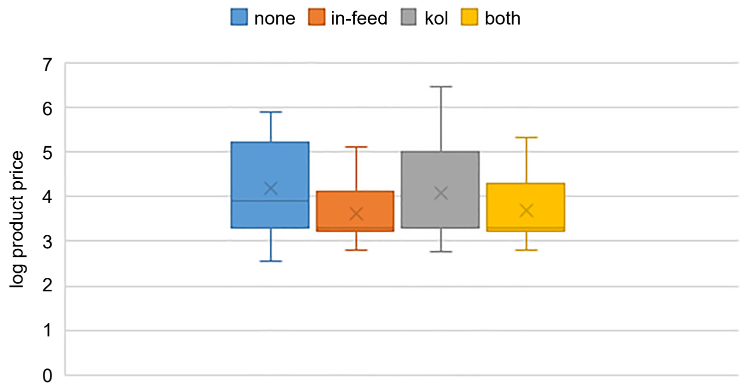

Figure 3. Distribution of product price

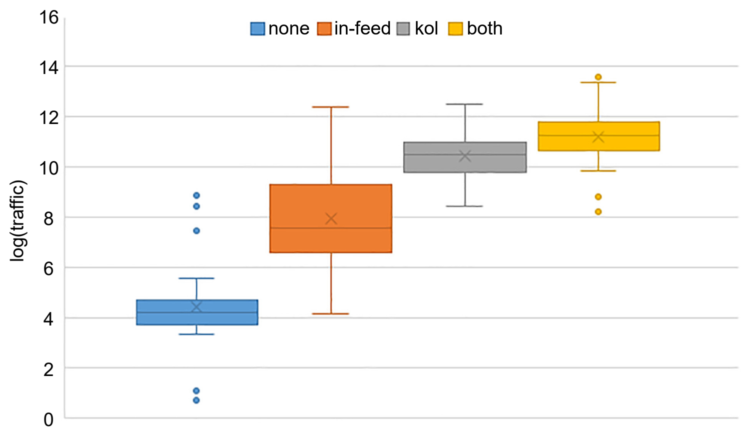

Figure 4. Distribution of traffic by ad

traffic and sales, the results indicate that online traffic has a positive effect on sellers' sales. Also confirms that seller's profit income is closely related to its capability to appeal traffic (Perdikaki *et al.*, 2012), which may be translated into sales and revenue (Fich, 2004).

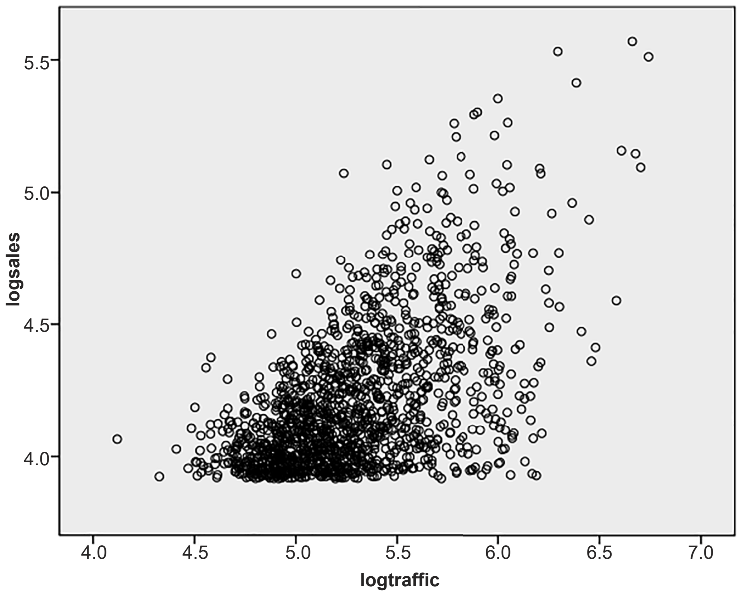

Figure 5.
Scatterplot of traffic and sales

4.3 Model specification

As mentioned above, we assume that the advertising strategy has an impact on product traffic. To solve the potential endogenous issues, we employed the endogenous treatment effects model with an ordered outcome (Tsuchiya, 2010). Our model includes advertising strategy choice as an endogenous treatment variable, and we estimate the equations simultaneously instead of following a two-stage estimation approach of sample selection and treatment model. Thus, our full models based on traffic equation and advertising strategies selection equation. We establish the full model as following:

$$Y_{it}^{*} = \log(\lambda_{it}) = \mathrm{In} - \mathrm{feed}_{it}Z_1 + \mathrm{KOL}_{it}Z_2 + \mathrm{Xit}\beta + \vartheta_i + u_{1it}, \tag{1}$$

$$Z_{1it} = w_i\gamma + u_{2it} \qquad \mathrm{In} - \mathrm{feed}_{it} = 1 \;\text{ if }\; Z_{1it} > 0, \mathrm{In} - \mathrm{feed}_{it} = 0 \;\text{ otherwise}, \tag{2}$$

$$Z_{2it} = w_i\gamma + u_{3it} \quad \mathrm{KOL\ \ endorsement}_{it} = 1 \;\text{ if }\; Z_{2it} > 0, \mathrm{KOL}_{it} = 0 \;\text{ otherwise}, \tag{3}$$

Z_{1it} is a dichotomous variable with a value of 1 for sellers who make the choice of in-feed advertising strategy, and 0 otherwise, and the same is true for Z_{2it}. X_{it} is a vector of outcome covariates, $\vartheta_i \sim N(0, \sigma\vartheta)$ is the random effects capturing individual seller heterogeneity. *wi* is a vector of endogenous treatment covariates, β and γ are unknown parameters, while u_{it} are the error terms.

Specifically, the traffic equation includes the sellers choose advertising strategies, which is a function of advertising strategies and other characteristics of sellers. We assess the impact on traffic based on product price level, brand, number of cumulative videos, and fans, all of which reflect different aspects that influence traffic. The traffic model showed as equation (1).

Then, for the selection model, we find different strategies that are driven by seller-specific characteristics that indicate their propensity to advertising strategies. Since we have two binary choice variables, we use a binary probability model that allows for correlated interference in multiple equations, which is the same as a seemingly uncorrelated regression model. Both the selection probability of in-feed advertising and KOL endorsement were estimated at the same time. So, we take the probability of In-feed ad advertising and KOL endorsement as explained variable, and defines it as a discrete binary variable. We propose the selection model displayed as equations (2) and (3).

5. Results

First, we control for selection bias and the results are presented in Table 3, in which we investigate whether seller characteristics are related to their choices of in-feed advertising and/or KOL endorsement. Our analysis indicates that price has positive, significant effects on the choice of in-feed with an estimated coefficient of 0.002 ($p < 0.01$). The coefficient estimation of price for KOL endorsement is −0.001, and is highly negative significant ($p < 0.01$). This finding indicates that seller with a higher product price is more likely to adopt in-feed than those with lower product price. Instead, seller with a lower product price is inclined to select KOL endorsement.

Moreover, sellers' choices of strategies also vary according to the product brand, the number of fans, and product origin. Product brand has a positive effect on the likelihood of using KOL endorsement, with coefficient estimate of 0.179 ($p < 0.05$), but has no significant effect on in-feed ads. It shows that sellers with brand product are more likely to use KOL endorsement, but not necessarily to use in-feed. The number of fans has a positive significant effect on in-feed ads, with a coefficient estimate of 0.010 ($p < 0.01$), but has no significant effect on using KOL endorsement, suggesting that sellers with more fans are more likely to use in-feed advertising. In sum, product price and the number of fans play a role in sellers' choices of in-feed ad, while sellers' decisions of using KOL endorsement are affected by price and brand. Sellers located in the Taobao are relatively more likely to use KOL endorsement, while sellers located in Jingdong are less likely to use KOL endorsement and more likely to use in-feed ads.

Additionally, Table 4 shows the results of the model. We start from the Base Model with only the control variables, estimated coefficient for all variables are significant. Then, in the Interaction Model (I), estimated coefficient for KOL endorsement is 0.616 and it is highly significant ($p < 0.01$). The coefficient of in-feed advertising is estimated to be 0.226, which is also highly significant ($p < 0.01$). Therefore, KOL endorsement and in-feed advertising are both effective strategies in increasing product traffic. Hypothesis 1 and 2 are both supported. Also, we can see the the distribution of traffic according to the employment of the strategies (Figures 1 and 2). We can find that sellers with in-feed advertising have lower mean traffic than sellers with KOL endorsement, which is consistent with the results of the model, suggesting that KOL endorsement has a higher marginal effect on traffic than in-feed advertising. Fans, video count and price are all positive significant in increasing traffic. The estimated coefficients are 0.226 ($p < 0.01$), 1.298 ($p < 0.01$) and 0.997 ($p < 0.01$) respectively.

Variable	Endorsement	In-feed
Price	−0.001*** (0.0004)	0.002*** (0.0004)
Brand	0.179** (0.035)	0.017 (0.034)
Fan	0.007 (0.006)	0.010*** (0.0008)
Taobao	0.182*** (0.047)	0.006 (0.041)
Jingdong	−0.224 (0.105)	0.179** (0.107)
Constant	0.477*** (0.021)	−0.575*** (0.021)

Note(s): Total number of observation $N = 10{,}800$
All the continuous variables are log-transformed
Standard error in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 3. Bivariate probit regression

Variable	Base model	Interaction model (I)	Interaction model (II)	Interaction model (III)
Video	1.911*** (0.028)	1.298*** (0.031)	1.472*** (0.052)	1.131*** (0.037)
Fans	0.263*** (0.007)	0.226*** (0.007)	0.226*** (0.007)	0.018*** (0.005)
Price	1.012*** (0.009)	0.997*** (0.008)	0.992*** (0.008)	0.525*** (0.006)
KOL		0.616*** (0.167)	0.619*** (0.016)	0.177*** (0.012)
In-feed		0.226*** (0.004)	0.227*** (0.005)	0.072*** (0.003)
KOL * In-feed			−0.404*** (0.009)	
KOL *video				0.270*** (0.001)
In-feed *video				−0.002*** (0.0003)
KOL *price				−0.0007 (0.003)
In-feed *price				−0.305*** (0.016)
Constant	−3.304*** (0.101)	−5.225*** (0.105)	−5.219*** (0.106)	−0.417*** (0.072)
Observations	10,800	10,800	10,800	10,800
R-square	0.302	0.356	0.356	0.371

Note(s): All the continuous variables are log-transformed
Standard error in parentheses
$*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table 4.
Traffic equation estimates for advertising strategies

In the Interaction Model (II), the estimated coefficient for the interaction term of in-feed advertising and KOL endorsement is −0.404, and it is highly significant ($p < 0.01$). It shows that in-feed advertising has a smaller marginal effect on product traffic when it is adopted together with KOL endorsement. In the same way, KOL endorsement has a smaller marginal effect on improving product traffic when tied with in-feed advertising. Thus, the effects of the two advertising strategies are partially substitutive.

The Interaction Model (III) shows that how these two advertising strategies work with the different level of product price. First, in-feed advertising is more sensitive to price, and lower-priced products are more suitable for in-feed advertising, with the coefficient of the interaction term is −0.305 ($p < 0.1$). Therefore, hypothesis 3(a) is also supported, which suggests that price is disposed to be a traffic generation mechanism rather than a signaling mechanism when using in-feed advertising. Nonetheless, the interaction term between KOL endorsement and price is not significant. Hypothesis 3(b) is not supported. We find that KOL not only endorser higher-priced products in their videos, also post cheaper and practical products to attract more consumers, which result in price being irrelevant to how KOL endorsement impacts traffic.

The results also show that KOL endorsement is more effective for sellers with more videos accumulation, the coefficient of the interaction term between KOL endorsement and video is 0.27 ($p < 0.01$). So, Hypothesis 4(a) is supported. In-feed advertising appears equally significant when interacting with video count, but its effect is negative (−0.002, $p < 0.01$). Therefore, Hypothesis 4(b) is not supported. This finding suggests that, compared to sellers with more videos, sellers with less video's accumulation are likely to have more advantage by means of in-feed advertising, this contrasts with KOL endorsement which more cumulative videos could to some extent bring marginal benefit.

5.1 Robustness check

To further test the main effect of these two advertising methods in increasing traffic, we use the matching technique as a robustness check. We match all sellers with similar characteristics and compare the effect of each strategy on traffic. Basically, we match the data according to seller previous level of traffic, the amount of video previously posted, brand level, the average number of fans, and product price. Because of the presence of two binary choice variables, at first, we match sellers who have similar characteristics as well as the same decision to adopt the strategy, and then the adoption of other strategy as a treatment. Specifically, we performed two matching procedures. One is to match sellers who only adopt KOL endorsement with sellers who do not use any strategy; the second is to match sellers who only adopt in-feed advertising with sellers who do not employ any strategy. Our study uses the log-transformed traffic variable as the outcome variable, then estimate the after treatment effect for each strategy on the results.

Table 5 presents the specific propensity score matching results for the two processes. From the first matching result we can find that the after treatment effect of adopting in-feed advertising is extremely significant when log-transformed traffic is used as the outcome variable (t-stat = 42.61). While for the second matching we find a significant after-treatment effect using KOL endorsement for traffic (t-stat = 2.05). To confirm the accuracy of the matching procedure, we also examined whether the covariates between the treatment and control groups were balanced in the pre-competition and post-competition situations and showed that the matching results were valid. Furthermore, we conducted same regression model based on the matched samples (Table 6), and the results were consistent with the results of the main study, which further proved the effectiveness of our results.

6. Discussions

6.1 Key findings

Our analysis confirms that both in-feed advertising and KOL endorsement play an important role in boosting traffic, with KOL endorsement being more effective than in-feed advertising. Also, we find that the two types of advertising methods are mutually substituted. Although sellers who adopt both in-feed advertising and KOL endorsement can increase more traffic than employ only one of them, when using other advertising tools at the same time, the marginal effect of in-feed advertising and KOL endorsement is low. Some potential customers

Outcome variable	Sample	Treated	Controls	Difference	Standard error	*T*-stat
In-feed Adoption vs No Advertising						
Log (Traffic)	Unmatched	8.814	3.801	5.014	0.067	74.29
	ATT	7.621	3.801	3.820	0.089	42.61
KOL endorsement Adoption vs No Advertising						
Log (Traffic)	Unmatched	7.809	7.107	0.702	0.082	8.57
	ATT	7.809	7.621	0.188	0.092	2.05

Table 5. Propensity score matching: advertising adoption vs no advertising

Variable	Model
In-feed	3.179*** (0.136)
KOL	1.321*** (0.071)
KOL * video	0.204** (0.098)
KOL * price	0.085 (0.08)
In-feed *video	−0.262*** (0.038)
In-feed *price	−0.118*** (0.024)
Video	1.024*** (0.026)
Fans	0.094*** (0.012)
Price	0.101*** (0.019)
Constant	−1.619*** (0.172)
Observations	4,721
R-square	0.325

Table 6. Propensity score matching: traffic equation estimates

may be exposed to both advertising mechanisms at the same time, thereby reducing the marginal effect of each tool. Moreover, we further study the differential effects of the two advertising tools for products at different price levels. Results turn out that in-feed advertising is more effective in improving traffic for a low-price product, but has no significant effect on KOL endorsement. One explanation is that key opinion leaders in a short video from Douyin are different from celebrity in TV and so on. Douyin is a younger, more fashionable social platform for short videos, where the KOL is more accessible to the public and has more interaction with fans. Therefore, it is different from celebrities who endorse products with higher prices, KOL are not sensitive to the price of the recommended product. Besides, KOL endorsement increases online traffic more effectively in the case of more accumulated videos, while the cumulative effect on in-feed advertising is opposite. The result shows that the key role of in-feed advertising is in order to match potential users, in other words, if the same product ads appear many times, consumers will suffer from visual fatigue and thus reduce the click rate, which is consistent with the discovery by Tutaj and Van Reijmersdal (2012).

6.2 Theoretical implications

This study extends the literature in three ways. Firstly, our study can enrich existing literature by investigating in-feed advertising on a new context (short video platform). Our research shows that the mechanism of in-feed advertising attracting traffic by matching potential customer tags (according to their engagement behaviors), which is different from online search engine that matching based on the search history. Secondly, the study of KOL endorsement has been relatively silent in the previous literature. So, we not only researched KOL endorsement but also compared its effects to in-feed advertising. Thirdly, prior literature has only concentrated on the isolated effect of a separate advertising tool and ignores the interactions or relative influence of different advertising strategies. The study emphasizes the benefits of retailers adopting different advertising strategies because they have different characteristics. For all we know, this paper is one of the first empirical studies to inspect the two main advertising effectiveness based on heterogeneous seller on a short video platform that. Thus, we expand the boundary of advertising strategy application scope.

6.3 Practical implications

We provide significant practical implications not only to sellers but to Douyin application. First, in general, KOL endorsement is a more useful method to attract traffic than in-feed advertising in Douyin short video platform. Therefore, if sellers are looking for ways to improve traffic or sales, KOL endorsement is usually more popular than in-feed advertising. In a way, other short video platform, such as Kuaishou, should also consider embracing KOL endorsements at the same time.

Second, we find that the effect of in-feed advertising is stronger for sellers with lower products price. In a short run, sellers with higher product price are better to engage in more energy than lower-price sellers—as to reduce product capacity to reduce intuitive price, so that the consumers feel the price is worthwhile. So, high-price sellers should give more consideration to prices and offer more competitive prices than low-price sellers.

Third, we suggest that sellers post fewer videos previous, perhaps, expect a substantial increase in traffic from in-feed advertising. More cumulative videos are likely to make these potential customers—unattractive through in-feed advertising—pause the final purchase decision. On the contrary, customers attracted through KOL endorsement have a word-of-mouth effect and have confidence in the product recommended by KOL. Thus, they will be more accepting of multiple cumulative videos of the product.

Fourth, from the perspective of short video platform, our study helps managers better understand the advertising tools and improve the design of it. Specifically, as low-price products are more capable of attracting traffic through in-feed advertising, Douyin should attempt to introduce the in-feed advertising tool to sellers with low price. Furthermore, sellers with more cumulative videos, platforms could help them excavate an effective key opinion leader as well to better compete with others.

6.4 Limitation and future scope

Our research has several limitations. First, due to the limitation of statistical mechanism, cumulative videos refer to an aggregate of short videos from products to Douyin, without distinguishing how much of them are KOL endorsement or in-feed advertising. Future work could investigate whether various kinds of cumulative video number will have different conclusions. Second, our data is based on all product categories. But sellers and buyers may react in a different way to different product categories. In the future, it would be interesting to see if the same results are found across different product categories. For example, we can see if there is a difference between the effects of two advertising tools on hedonic and utilitarian products.

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