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Motivated Endeavor in Catching Attention: The Impact of Conversion Tool on Sponsored Post Engagement

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ABSTRACT

Social media influencer marketing has grown substantially in the last decade and is a major advertising channel for many brands. Nowadays, social media platforms are taking embedded interactive traffic conversion tools (e.g., product tags in Instagram) to reduce the steps between sponsored posts and final purchases to improve conversion rates. However, given the simultaneous potential for increased conversion rates and user aversion to advertisements, it is unclear how the adoption of the novel tool affects sponsored post engagement. In this study, we explore an exogenous comment component launch on a popular social media platform in China (i.e., Xiaohongshu). Our empirical results suggest that the adoption of the comment component increases sponsored post engagement, which is reflected in the increment of likes, favorites, and comments. We further explore the potential mechanism from the theoretical perspective of the motivation-opportunity-ability (MOA) framework and find that influencers get motivated endeavor to their posts with longer text and more positive emotions to catch attention. Our findings have novel and important implications for stakeholders of social e-commerce.

Keywords: Social media, influencer marketing, conversion tool, sponsored post engagement, influencer effort.

INTRODUCTION

As consumers grow increasingly wary of traditional forms of advertising and spend more time on social media, this has led to an increasing number of marketers turning to social media (e.g. Facebook, Instagram, Xiaohongshu, TikTok) influencers. By 2023, the global influencer marketing market value stood at 21.1 billion U.S. dollars (Statista, 2023). In influencer marketing, firms select and incentivize online influencers to engage their followers on social media in an attempt to promote the firm's offering and influencers integrate the products into their content to generate social media engagement among their followers. However, beyond engagement, optimizing the conversion funnel has become a crucial goal for both influencers and brands. The conversion funnel represents the journey a potential customer takes from becoming aware of a product to completing a purchase (Hoban & Bucklin, 2015). Streamlining this process can significantly enhance marketing effectiveness. Major platforms are continuously seeking ways to shorten the conversion path between sponsored posts and final purchases and improve brand conversion rates. For example, Instagram Swipe Up allows Instagrammers with more than 10,000 followers to add a link that their followers can get to by swiping up while watching their stories. Similarly, platforms like Xiaohongshu and TikTok have introduced features that allow influencers to embed short introductions related to the sponsorship brand at the top of the comment section, with a link that directly redirects to the brand's page.

With the adoption of traffic conversion tools related to sponsorship brands in sponsored posts, how they affect the engagement of influencers' posts remains an open question. The adoption of traffic conversion tools may change people's situational processing of available information, which can entail two opposite effects. On the one hand, the use of available information while engaging with the content may become more efficient and targeted. The traffic conversion tool can provide immediate access to additional brand information, potentially increasing users' understanding and interest in the brand. This streamlined access to relevant brand information can lead to higher engagement levels, as users find the content more informative and useful (Chu & Kim, 2011; De Vries et al., 2012). On the other hand, the addition of traffic conversion tools further enhances the display of brand information. More obvious sponsoring brand information may enhance users' advertising awareness and persuasive knowledge (Cao & Belo, 2023; Choi et al., 2018). This may reduce users' favorability towards influencers, leading to decreased engagement in their sponsored posts. If that's the case, it could diminish the marketing effectiveness of the brands involved. In social media setting, engagement is usually captured by the number of interactions (e.g., likes, favorites, and comments), which is a highly relevant performance indicator that advertisers and influencers seek to optimize (Leung, Gu, & Palmatier, 2022). Therefore, it is crucial to investigate the following research question: How does the adoption of the traffic conversion tool affect sponsored post engagement? And why?

To answer these questions, we leverage the exogenous shock in a popular social media platform Xiaohongshu in China which launched a comment component for sponsored posts on June 6, 2022. The comment component allows for a brief promotion about the cooperating brand and is displayed at the top of the comment section of the sponsored post, with a link that can directly redirect to the related brand's page. We collected data from March 10, 2022 to January 1, 2023 covering 3 months before and 6 months after the novel tool launch. There are 933 influencers belonging to 2 categories in our dataset. We obtain their sponsored posts' engagement (e.g., likes, comments, and favorites). Our identification is based on the difference-in-differences (DID) model with influencers' staggered adoption.

Our analysis reveals important findings regarding the impact of the adoption of the comment component on sponsored posts engagement and their content creation strategies. First, we find that the number of likes, comments, and favorites on average increased by 68.3%, 43.3%, and 56.9%, respectively. To better understand the increase in engagement with sponsored posts, we draw upon the Motivation-Opportunity-Ability (MOA) theory to analyze influencers' content creation behaviors (Batra & Ray, 1986; Maclnnis et al., 1991). After the adoption of the comment component, influencers, motivated to boost brand conversion rates and post engagement, put more effort into sponsored post creation by extending the textual length and enhancing the emotional appeal of their posts. Furthermore, we explore the heterogeneity in influencers' efforts by analyzing the impacts of follower count (Opportunity) and the proportion of sponsored posts (Ability) on their exerted efforts. We find that as the number of followers increases or the proportion of sponsored posts prior to the event increases, the degree of effort exerted by influencers decreases.

This research contributes to extant literature in several ways. First, we contribute to the literature on social media influencer marketing by documenting causal evidence of the effects of the adoption of the traffic conversion tool. Second, we contribute to conversion funnel optimization literature by demonstrating how traffic conversion tools in social media posts can significantly enhance engagement metrics. This underscores the importance of integrating seamless conversion tools in digital marketing strategies to improve conversion rates and marketing effectiveness. From a practical perspective, our findings provide significant implications for influencers and marketers.

CONCEPTUAL BACKGROUND

Influencer Marketing

Many existing studies in influencer marketing mainly explore how the characteristics of sponsored posts or influencers affect the engagement of posts. Hughes et al. (2019) show that blogger characteristics and blog post content including the blogger's expertise, campaign advertising intent, and posts' hedonic content, affect online engagement differently. Leung et al. (2022) draw on a communication model to examine how factors related to influencers, followers, and posts determine influencer marketing effectiveness. The findings show that influencer originality, follower size, and sponsor salience enhance effectiveness, and posts that announce new product launches diminish it. Rizzo et al. (2024) demonstrate that high-arousal language increases engagement with micro-influencers, but reduces engagement with macro-influencers, seemingly because it makes micro- (macro-) influencers appear more (less) trustworthy. In addition, Tian et al. (2014) and Wies et al. (2023) specifically investigate the impact of influencers' follower count. They find that midtier influencers have the highest gain in impressions for each incremental follower and engagement with sponsored content. Wies et al. (2023) demonstrate an inverted U-shaped relationship between influencers' follower counts. Higher content customization and lower familiarity with the sponsored brand signal that influencers value their relationships with followers and thereby flatten the inverted U-shaped relationship.

While extensive literature exists on the impact of influencers and posts' characteristics on sponsored post engagement, few studies explore how the adoption of traffic conversion tools which are used to shorten the conversion funnel in social media affects influencer content creation and post engagement. Therefore, we aim to explore the direct effects of the adoption of the tool on engagement metrics and how influencers adjust their efforts in terms of post length and emotional tone in response to the new tool.

Conversion Funnel

The conversion funnel, representing the customer journey from awareness to purchase, is a crucial framework in digital marketing (Hoban & Bucklin, 2015). Optimizing this funnel involves various strategies and tools aimed at reducing friction points and streamlining the process, thus enhancing conversion rates and overall marketing effectiveness. There have been several studies exploring how to design and optimize conversion funnels. Hoban and Bucklin (2015) investigate the impact of internet display advertising on different stages of the purchase funnel. Batra and Keller (2016) discuss the integration of various marketing communication tools and their impact on consumer behavior. They explore how combining different marketing elements, such as advertising, public relations, and direct marketing, can create a synergistic effect that enhances overall marketing effectiveness. Edelman (2010) underscores the significance of direct response mechanisms, highlighting how these tools can significantly shorten the path to purchase and enhance conversion rates. These tools provide consumers with immediate access to product pages or further information, reducing the effort required to move from interest to action.

The existing literature provides a solid foundation for understanding the impact of various marketing strategies on the conversion funnel. However, there is limited research on the specific impact of these tools within the context of influencer marketing. Our study addresses this gap by examining the effects of the traffic conversion tool adoption integrated into influencer-sponsored posts on engagement. Specifically, we aim to investigate how the implementation of a comment component that provides direct brand links influences both the content creation strategies of influencers and the engagement metrics of their posts.

RESEARCH CONTEXT AND DATA

Research Context

We obtained data from Xiaohongshu, a large social media platform in China. Xiaohongshu has reached 200 million monthly active users in China in September 2023 (Statista, 2023b). Users on the platform share detailed product reviews, lifestyle tips, and personal experiences, creating a trusted community for consumers to make informed purchase decisions. Xiaohongshu allows influencers to post sponsored notes. For all sponsored posts, a logo with a collaborative brand must be displayed in the bottom left corner of the image or video. In order to better improve the conversion efficiency of sponsored posts, Xiaohongshu launched a comment component for sponsored posts on June 6, 2022, as shown in Figure 1. If the comment component is used, a brief promotion about the cooperating brand will be displayed in the first comment section of the sponsored post, accompanied by a link that can directly redirect to search, store, or purchase related products. The brand and influencer need to reach a consensus on whether to use the comment component. The brand needs to choose whether the influencer needs to display brand information in the comment section when placing commercial cooperation orders.

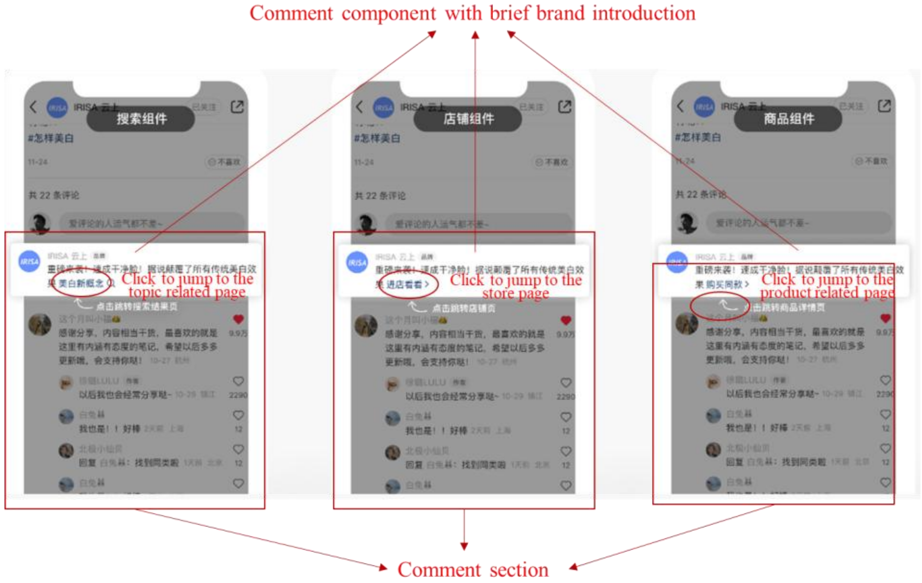

Figure 1: Examples of comment component

Data

We selected influencers with over 100,000 followers which belong to the mid-to-large-tier to ensure the representativeness of the sample. We choose two types of influencers: beauty and fashion influencers. We obtain basic information about these influencers. The proportion of beauty and fashion influencers on Xiaohongshu is more than 20% (Statista, 2024). They are the most popular types of influencers on Xiaohongshu. Next, we obtained data on all the posts posted by these influencers from March 10, 2022 to January 1, 2023 (as shown in Figure 2), including the publication time; the post engagement (comments, likes, and favorites) and so on. We only retain influencers who had posted sponsored posts before the comment component was launched, so our final sample includes 933 influencers. During our sample period, a total of 551 influencers had used (at least once) the comment component. Table 1 provides the definitions and descriptive statistics of key variables.

Figure 2: The timeline of the observation window

Table 1: Definitions and summary statistics of variables.

Variables	Operationalization	Mean	Std. dev.	Min	Max
Dependent variables					
logAveLikes	The average number of likes the influencer received in that month's sponsored posts (logged after adding 1)	5.156	3.078	0	11.986
logAveComs	The average number of comments the influencer received in that month's sponsored posts (logged after adding 1)	3.336	2.082	0	8.716

logAveFavs	The average number of favorites the influencer received in that month's sponsored posts (logged after adding 1)	4.225	2.665	0	11.604
Independent variable					
Treated	A dummy variable; =1 if the influencer has already used at least one comment component by that month; =0 for nonadopters	0.591	0.492	0	1
Mediator variables					
AveScore	The average score of positive emotions in that month's sponsored posts	0.345	0.195	0	0.622
logAveChars	The average length of characters in that month's sponsored posts (logged after adding 1)	4.431	2.558	0	7.304

EMPIRICAL ANALYSIS

Using the observation data we obtained, we first examine the average treatment effect of using the comment component on the number of sponsored posts comments, likes, and favorites. Then, we will explore the mechanism in the next section.

Empirical Model

We focus on estimating the changes in the post engagement of posts before and after the influencer adopts the comment component. We use the DID model to estimate the impact of using the comment component feature based on the time changes of the influencer's first use of the comment component feature. To estimate the causal effect of the adoption of comment components on the post engagement, we use a two-way fixed effects (TWFE) model. The TWFE model with the DID specification controls for the time-invariant confounders with the user-fixed effects and the common time confounders using the time-fixed effects that capture the month-specific temporal shocks. We index users by i and index time (event months) by t. As different users start to use the comment component feature at different times, we use a DID setup with staggered adoption as follows:

$$Y_{it} = \alpha + \beta Treated_{it} + \gamma_i + \delta_t + \varepsilon_{it} \tag{1}$$

Here, Y_{it} is a dependent variable that denotes the average engagement of posts received by influencer i at time t, including comments, likes, and favorites. The independent variable of interest is $Treated_{it}$, a binary variable indicating whether influencer i is a comment component feature user at time t, and it is equal to one if he or she started to use the comment component feature and zero otherwise. Specifically, γ_i denotes the user fixed effects. The term δ_t represents the time fixed effects, and ε_{it} is an error term.

We employ two additional analyses to showcase the robustness of our findings in Section 6. First, we use a DID model with leads and lags (i.e., the event-study estimate), which is suggested to be more reliable than the canonical two-by-two DID estimate that assumes the treatment effect is constant over time. Second, we leverage the behavioral data observed prior to the treatment time and employ the PSM to match the current feature user with the untreated users to improve the comparability between the treatment and control groups.

Main Results on Post Engagement

Table 2 shows the result of the estimation. We find that, on average, influencers tend to receive more comments, likes, and favorites for sponsored posts after adopting the comment component feature. Specifically, the positive impact on the engagement of sponsored posts is significant. After adopting the comment component, the average likes of sponsored posts in each event month increased by 68.3%, a 43.3% increase in comments, and a 56.9% increase in favorites.

Table 2: Treatment effect of the comment component adoption on post engagement.

	Dependent variables		
	logAveLikes	*logAveComs*	*logAveFavs*
Treated	0.683*** (0.100)	0.433*** (0.063)	0.569*** (0.086)
Influencer FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	9330	9330	9330
Number of influencers	933	933	933

R^2	0.042	0.037	0.043

Notes: Robust standard errors clustered by influencers are in parentheses. FE, fixed effect.
* p < 0.10, ** p < 0.05, *** p < 0.01

MECHANISM EXPLORATION

Although our main analysis shows that using comment components in sponsored posts leads to a positive average treatment on post engagement, it is important to explore the underlying mechanism behind the effect. More display of brand information is often believed to enhance the persuasive knowledge of followers (Boerman et al., 2017; Cao & Belo, 2023; Choi et al., 2018), causing negative emotions, which is not conducive to increasing the engagement of posts. Therefore, drawing on the theoretical perspective of the Motivation-Opportunity-Ability (MOA) framework (Batra & Ray, 1986; Maclnnis et al., 1991), we infer that influencers have adjusted their content to reduce advertising perception and persuasive knowledge (as shown in Figure 3). The MOA framework provides a comprehensive lens to examine how influencers' efforts in content creation are influenced by their motivations, and moderated by opportunities and abilities. In our context, the efforts of influencers are mainly reflected in the posts they publish. The length of the content is indicative of the amount of information conveyed. Longer posts can provide more comprehensive information, making them more valuable to users (De Vries et al., 2012; Lou & Yuan, 2019). Similarly, content with positive sentiment is more likely to engage users as it creates a favorable emotional response (Berger & Milkman, 2012; Stieglitz & Dang-Xuan, 2013). So we use the character length of the post and the positive sentiment score of the post as proxy variables for influencers' efforts. We study the treatment effect of the comment component feature adoption on AveScore and logAveChars, and its subsequent effect on post engagement.

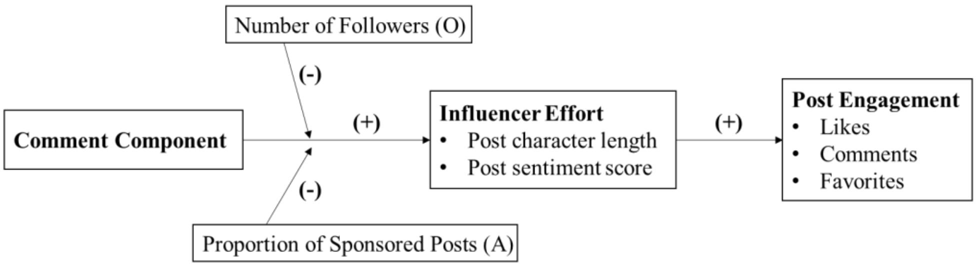

Figure 3: Conceptual framework

Mediation Effect of Influencers' Effort (M)

The motivation to boost brand conversion rates and post engagement after the adoption of comment components is rooted in influencers' desire to maintain a positive relationship with their followers while promoting sponsored content. Influencers may realize that an overt display of brand information can lead to persuasion knowledge among followers, reducing engagement (Boerman et al., 2017; Friestad & Wright, 1994). Consequently, their motivation is to strike a balance between promoting the brand and maintaining follower engagement. This balance is achieved by crafting longer posts with more positive sentiment, which helps to mask the persuasive intent of the content and fosters a more genuine connection with the audience (Berger & Milkman, 2012; De Vries et al., 2012; Lou & Yuan, 2019).

Table 3: Effect of the comment ccomponent adoption on effort and its mediation effect on post engagement.

	Dependent variables				
	AveScore	*logAveChars*	*logAveLikes*	*logAveComs*	*logAveFavs*
Treated	0.047*** (0.006)	0.553*** (0.080)	0.038 (0.039)	0.028 (0.026)	0.048 (0.042)
AveScore			10.822*** (0.430)	6.156*** (0.283)	9.667*** (0.425)
logAveChars			0.249*** (0.032)	0.211*** (0.021)	0.123*** (0.032)
Influencer FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	9330	9330	9330	9330	9330
Number of influencers	933	933	933	933	933
R^2	0.034	0.033	0.877	0.855	0.799

Notes: Robust standard errors clustered by influencers are in parentheses. FE, fixed effect.
* p < 0.10, ** p < 0.05, *** p < 0.01

As shown in Table 3, on average, the comment component adoption encourages influencers to post longer or more positive posts. In addition, we find that an increase in character length or an increase in positive emotions has a positive impact on the post engagement. And the positive impact of the adoption of the comment component on sponsored post engagement is entirely mediated by the positive sentiment score and character length of the posts. Consistent with previous literature, posts with more positive emotions tend to generate higher levels of engagement (Berger & Milkman, 2012; Stieglitz & Dang-Xuan, 2013).

Heterogeneous Treatment Effect

Heterogeneous Treatment Effect by Number of Followers (O)

The commercial opportunities that influencers with different follower numbers can obtain are different, so we use follower numbers before the event as a proxy variable for opportunity (logNumFans). We add the interaction between the treatment status dummy (Treated) and logNumFans. As shown in Table 4, regardless of the number of followers, influencers will increase character length or positive emotions in the text content. However, compared to influencers with more followers, influencers with fewer followers tend to cherish opportunities more. Due to their strong connection with followers, they may be more concerned about the negative emotions generated by overt advertising (Tian et al., 2024; Wies et al., 2023) and thus put in more effort to reduce advertising perception. In addition, the positive impact of adopting the comment component on engagement will decrease as the number of followers increases, because influencers with higher followers put in less effort likely stems from an over-reliance on their established follower base.

Table 4: Heterogeneous treatment effect by number of followers.

	Dependent variables				
	AveScore	*logAveChars*	*logAveLikes*	*logAveComs*	*logAveFavs*
Treated	0.352*** (0.058)	4.391*** (0.744)	6.735*** (1.012)	3.730*** (0.616)	5.600*** (0.877)
Treated×NumFans	-0.025*** (0.005)	-0.315*** (0.060)	-0.497*** (0.082)	-0.271*** (0.050)	-0.413*** (0.071)
Influencer FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	9330	9330	9330	9330	9330
Number of influencers	933	933	933	933	933
R^2	0.038	0.036	0.047	0.041	0.048

Notes: Robust standard errors clustered by influencers are in parentheses. FE, fixed effect.
* p < 0.10, ** p < 0.05, *** p < 0.01

Heterogeneous Treatment Effect by Influencers' Commercial Ability (A)

The commercial ability of influencers who publish different proportions of sponsored posts varies, and we use the proportion of sponsored posts published before the event to measure their commercial ability. We add the interaction between the treatment status dummy (Treated) and the proportion of sponsored posts to the total number of posts three months prior to the introduction of comment component (PorSponsor).

Table 5: Heterogeneous treatment effect by proportion of sponsored posts.

	Dependent variables				
	AveScore	*logAveChars*	*logAveLikes*	*logAveComs*	*logAveFavs*
Treated	0.086*** (0.008)	1.066*** (0.106)	1.436*** (0.131)	0.824*** (0.082)	1.146*** (0.112)
Treated×PorSponsor	-0.219*** (0.026)	-2.832*** (0.345)	-4.153*** (0.419)	-2.155*** (0.248)	-3.186*** (0.351)
Influencer FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	9330	9330	9330	9330	9330
Number of influencers	933	933	933	933	933
R^2	0.041	0.040	0.052	0.043	0.051

Notes: Robust standard errors clustered by influencers are in parentheses. FE, fixed effect.
* p < 0.10, ** p < 0.05, *** p < 0.01

The results, shown in Table 5, indicate that influencers with lower commercial ability tend to put in more effort to change their sponsored posts after adopting the comment component. This increased effort results in a greater increase in engagement for their sponsored posts. In contrast, influencers with higher commercial ability (i.e., those who posted a higher proportion of sponsored posts before the event) may even reduce their efforts when adopting the comment component which can lead to a decrease in engagement. They might perceive the marginal benefit of additional effort as lower compared to those with lower commercial ability. As a result, they may choose to allocate their efforts elsewhere, believing that their established credibility and influence can carry their posts without needing substantial adjustments or added effort (Rust et al., 2002).

ROBUSTNESS CHECKS

Dynamic Treatment Effect

We employ an extension of the DID model by including multiple leads and lags to examine the mediation effect of influencer effort and the overall treatment effect parallel trend assumption. This practice can assess whether users who are treated at different times follow the parallel trend during the pretreatment period. We do this by adding a set of dummy variables to trace out the month-by-month treatment effect as follows:

$$Y_{it} = \alpha + \beta_1 Treated_{it}^{-7} + \beta_2 Treated_{it}^{-6} + \beta_3 Treated_{it}^{-5} + \cdots + \beta_{11} Treated_{it}^{3} + \beta_{12} Treated_{it}^{4} + \beta_{13} Treated_{it}^{5} + \gamma_i + \delta_t + \varepsilon_{it}$$

Here, the series of dummy variables $\{Treated_{it}^{-7}, Treated_{it}^{-6}, \cdots, Treated_{it}^{4}, Treated_{it}^{5}\}$ is defined by the influencer i's adoption status at time t. The variable $Treated_{it}^{-k}$ equals one for influencer i in the kth month before his or her adoption month, whereas $Treated_{it}^{k}$ equals one for influencer i in the kth month since his or her adoption month. Earlier and later time periods outside the range [-8, 5] are pooled in the periods of the 8th month before and the 5th month after the adoption month, respectively. We detrend all the relative time parameters relative to the month right before the adoption (i.e., $Treated_{it}^{-8}$ is the baseline).

As shown in Figure 4, we visualize the event monthly dynamic treatment effect estimates on influencers' effort and posts' engagement (likes, comments, favorites) with 95% confidence intervals. The nonsignificant relative time coefficients before the adoption time suggest that the untreated users (who had not yet or had never adopted the comment component feature) follow the parallel trend as the treated users and serve as a reasonably good counterfactual.

Propensity Score Matching

In order to improve the comparability of the control group, we use propensity score matching to match comment component adopters during the sample period with the nonadopters with similar covariate distributions. Firstly, we model the influencer's decision to adopt comment components as a function of pretreatment covariates. We use the total number of posts posted by influencers $PreNum_i$, the average number of favorites $PreAveFav_i$, likes $PreAveLike_i$, and comments $PreAveCom_i$, and the number of fans $PreFan_i$ as covariates in the three months prior to the launch of the comment component. The second step performed matching based on the estimated propensity scores. We use no replacement 1:1 nearest neighbor matching with a radius of 0.001. As can be seen in Table 6, the matched groups are balanced as the standardized bias gets smaller. For matching to be acceptable, the absolute standardized bias after matching should be less than 20%. The bias is less than 5% for all predicting variables in our sample. We can see that there is no significant pretreatment difference between the treatment group and the control group. After matching, our treatment and control groups comprised 290 influencers respectively.

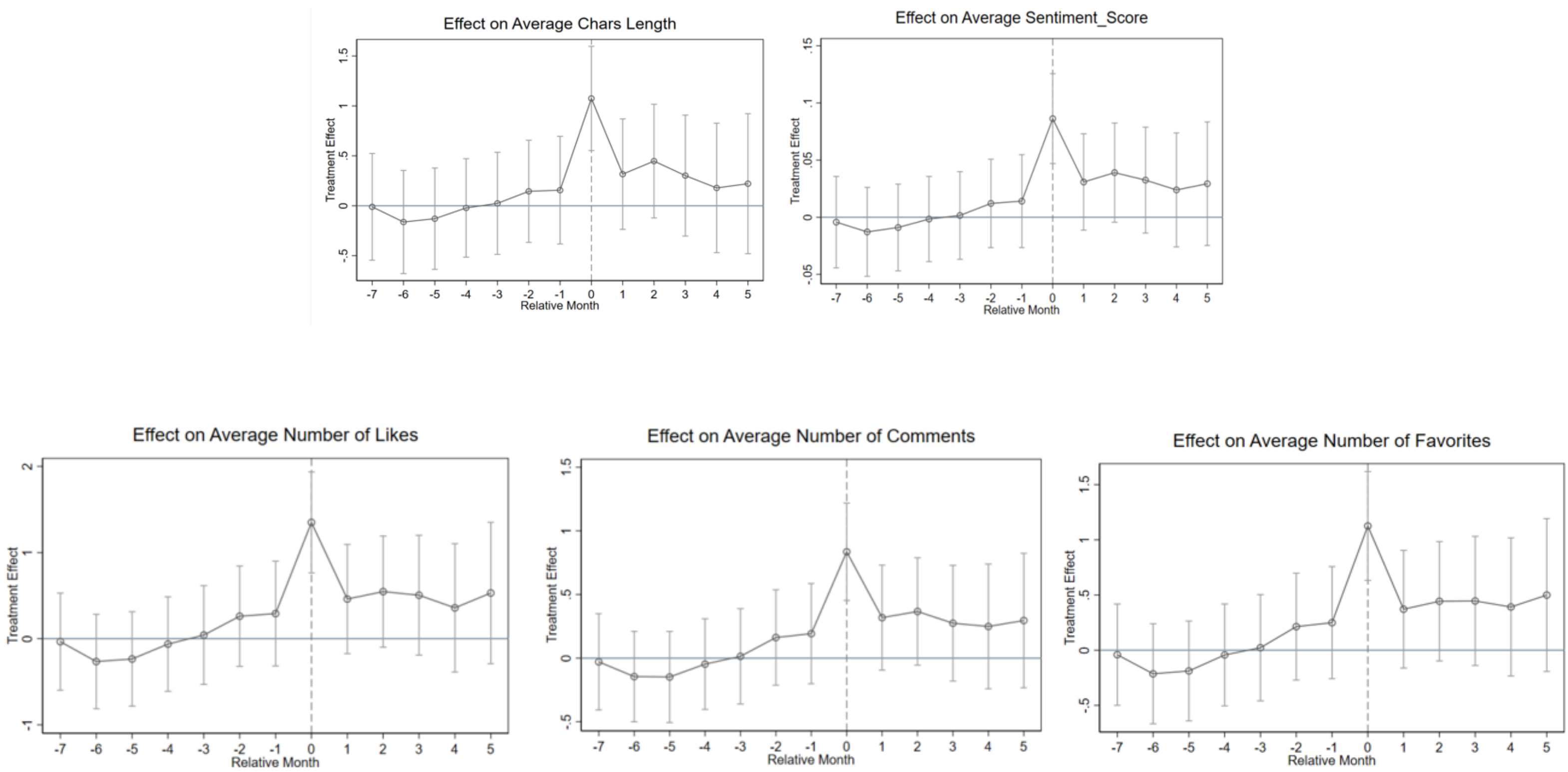

Figure 4: Coefficients of the dynamic treatment effect with leads and lags

Table 6: Covariate balance before and after matching.

Variable	Unmatched	Mean		Bias	Reduct	t-test	
	Matched	Treated	Control	(%)	bias(%)	t	p>|t|
$logPreNum_i$	U	3.765	3.724	8.1	48.8	3.89	0.000
	M	3.741	3.762	-4.1		-1.63	0.104
$logPreAveFav_i$	U	6.334	6.076	19.5	86	9.30	0.000
	M	6.276	6.239	2.7		1.05	0.293
$logPreAveLike_i$	U	7.416	7.241	15.2	82.7	7.30	0.000
	M	7.352	7.382	-2.6		-1.01	0.314
$logPreAveCom_i$	U	4.449	4.262	20.9	88.3	9.96	0.000
	M	4.303	4.325	-2.4		-0.98	0.329
$logPreFan_i$	U	12.170	12.174	-0.4	-273.5	-0.21	0.834
	M	12.188	12.171	1.7		0.64	0.522

Based on the matched samples, we estimate the DID model again. As shown in Table 7, the adoption of the comment component has a significant positive impact on mediating variables and post engagement, which is consistent with previous results, indicating that our results are robust.

Table 7: Treatment effect after matching.

	Dependent variables				
	AveScore	*logAveChars*	*logAveLikes*	*logAveComs*	*logAveFavs*
Treated	0.048*** (0.008)	0.558*** (0.106)	0.662*** (0.132)	0.456*** (0.083)	0.545*** (0.113)
Influencer FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	5800	5800	5800	5800	5800
Number of influencers	580	580	580	580	580
R^2	0.033	0.032	0.038	0.034	0.038

Notes: Robust standard errors clustered by influencers are in parentheses. FE, fixed effect.
* p < 0.10, ** p < 0.05, *** p < 0.01

GENERAL DISCUSSION

This study investigates the impact of a traffic conversion tool—specifically, the comment component with embedded links—on the engagement of influencer-sponsored posts. The findings show that this tool significantly boosts engagement. Influencers adapt by enhancing post length and emotional appeal, which further drives engagement. It provides empirical evidence that the adoption of such tools increases engagement while showing how influencers adjust content strategies within the Motivation-Opportunity-Ability (MOA) framework. Additionally, it offers practical insights for influencers and marketers: extending post length and heightening emotional appeal maximize the effectiveness of conversion tools, enabling smoother transitions from engagement to purchase.

REFERENCES

Batra, R., & Keller, K. L. (2016). Integrating marketing communications: New findings, new lessons, and new ideas. *Journal of Marketing*, *80*(6), 122-145. https://doi.org/10.1509/jm.15.0419

Batra, R., & Ray, M. L. (1986). Situational effects of advertising repetition: The moderating influence of motivation, ability, and opportunity to respond. *Journal of Consumer Research*, *12*(4), 432-445. https://doi.org/10.1086/208528

Berger, J., & Milkman, K. L. (2012). What makes online content viral? *Journal of Marketing Research*, *49*(2), 192-205. https://doi.org/10.1509/jmr.10.0353

Boerman, S. C., Willemsen, L. M., & Van Der Aa, E. P. (2017). “This post is sponsored” effects of sponsorship disclosure on persuasion knowledge and electronic word of mouth in the context of Facebook. *Journal of Interactive Marketing*, *38*(1), 82-92. https://doi.org/10.1016/j.intmar.2016.12.00

Cao, Z., & Belo, R. (2023). Effects of explicit sponsorship disclosure on user engagement in social media influencer marketing. *Forthcoming, MIS Quarterly*. https://ssrn.com/abstract=4533152

Choi, D., Bang, H., Wojdynski, B. W., Lee, Y.-I., & Keib, K. M. (2018). How brand disclosure timing and brand prominence influence consumer's intention to share branded entertainment content. *Journal of Interactive Marketing*, *42*(1), 18-31. https://doi.org/10.1016/j.intmar.2017.11.001

Chu, S.-C., & Kim, Y. (2011). Determinants of consumer engagement in electronic word-of-mouth (eWOM) in social networking sites. *International journal of Advertising*, *30*(1), 47-75. https://doi.org/10.2501/IJA-30-1-047-075

De Vries, L., Gensler, S., & Leeflang, P. S. H. (2012). Popularity of brand posts on brand fan pages: An investigation of the effects of social media marketing. *Journal of Interactive Marketing*, *26*(2), 83-91. https://doi.org/10.1016/j.intmar.2012.01.003

Edelman, D. C. (2010). Branding in the digital age: You're spending your money in all the wrong places. *Harvard Business Review*, *88*(12), 64-69.

Friestad, M., & Wright, P. (1994). The persuasion knowledge model: How people cope with persuasion attempts. *Journal of Consumer Research*, *21*(1), 1-31. https://doi.org/10.1086/209380

Hoban, P. R., & Bucklin, R. E. (2015). Effects of internet display advertising in the purchase funnel: Model-based insights from a randomized field experiment. *Journal of Marketing Research*, *52*(3), 375-393. https://doi.org/10.1509/jmr.13.0277

Hughes, C., Swaminathan, V., & Brooks, G. (2019). Driving brand engagement through online social influencers: An empirical investigation of sponsored blogging campaigns. *Journal of Marketing*, *83*(5), 78-96. https://doi.org/10.1177/0022242919854374

Leung, F. F., Gu, F. F., Li, Y., Zhang, J. Z., & Palmatier, R. W. (2022). Influencer marketing effectiveness. *Journal of Marketing*, *86*(6), 93-115. https://doi.org/10.1177/00222429221102889

Leung, F. F., Gu, F. F., & Palmatier, R. W. (2022). Online influencer marketing. *Journal of the Academy of Marketing Science*, *50*(2), 226-251. https://doi.org/10.1007/s11747-021-00829-4

Lou, C., & Yuan, S. (2019). Influencer marketing: How message value and credibility affect consumer trust of branded content on social media. *Journal of Interactive Advertising*, *19*(1), 58-73. https://doi.org/10.1080/15252019.2018.1533501

Maclnnis, D. J., Moorman, C., & Jaworski, B. J. (1991). Enhancing and measuring consumers’ motivation, opportunity, and ability to process brand information from ads. *Journal of Marketing*, *55*(4), 32-53. https://doi.org/10.1177/002224299105500403

Rizzo, G. L. C., Ordenes, F. V., Pozharliev, R., De Angelis, M., & Costabile, M. (2024). How high-arousal language shapes micro- versus macro-influencers' impact. *Journal of Marketing*. https://doi.org/10.1177/00222429231207636

Rust, R. T., Moorman, C., & Dickson, P. R. (2002). Getting return on quality: revenue expansion, cost reduction, or both? *Journal of Marketing*, *66*(4), 7-24. https://doi.org/10.1509/jmkg.66.4.7.18515

Statista. (2023). *Influencer marketing worldwide - statistics & facts*. Retrieved from https://www.statista.com/topics/2496/influence-marketing/#topicOverview （accessed 16 June 2024)

Statista. (2023b). *Number of monthly active users of Xiaohongshu app in China from December 2020 to September 2023*. Retrieved from https://www.statista.com/statistics/1327421/china-xiaohongshu-monthly-active-users/ （accessed 16 June 2024)

Statista. (2024). *Share of key opinion leaders (KOLs) on Xiaohongshu in China in 2023, by vertical*. Retrieved from https://www.statista.com/statistics/1327383/china-popular-xiaohongshu-key-opinion-leader-verticals/ （accessed 16 June 2024)

Stieglitz, S., & Dang-Xuan, L. (2013). Emotions and information diffusion in social media—sentiment of microblogs and sharing behavior. *Journal of Management Information Systems*, *29*(4), 217-248. https://doi.org/10.2753/MIS0742-1222290408

Tian, Z., Dew, R., & Iyengar, R. (2024). Mega or micro? Influencer selection using follower elasticity. *Journal of Marketing Research*, *61*(3), 472-495. https://doi.org/10.1177/00222437231210267

Wies, S., Bleier, A., & Edeling, A. (2023). Finding goldilocks influencers: How follower count drives social media engagement. *Journal of Marketing*, *87*(3), 383-405. https://doi.org/10.1177/00222429221125131