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What Influences Influencers? Hiding Popularity Signals and Influencer Behavior

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Short Paper

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Abstract

The burgeoning popularity of social media has shifted how social media users share and seek information through online platforms. Social media users are often motivated to show the "perfect side" of themselves on the platform, resulting in sharing manipulated appearances and positive aspects of their lives in order to garner more "likes" when comparing their popularity to others. Thus, social media users may often face inauthentic information, which may affect their behaviors on the platform. In this study, we utilize a change in Instagram policy—where they hide the number of likes from the platform—which started in September 2019 in East Asia. Specifically, we examine influencers' post-generating behavior and post characteristics (e.g., whether it is focused on product vs influencers themselves and the degree of image manipulation). The results show that the number of endorsement postings increases, and influencers are more likely to generate influencer-focused postings after the intervention. In addition, we find that such effects are accentuated when influencers have a the larger follower base. Lastly, our findings suggest that the economic benefit (e.g., total weekly sales) that influencers gain increases after the intervention; however, such an effect is attenuated with influencers having a larger number of followers.

Keywords: Influencer Marketing, Popularity Signal, Social Media, Product Endorsement, Quasi-experiment.

Introduction

The *number of likes or followers* on social media has been considered an important metric in (personal) branding, representing a person's or brand's popularity, profitability, and more generally the effectiveness of a post (De Cristofaro et al. 2014). Influencers who generate profit by collaborating with brands based on their reputation among their own audience (McQuarrie et al. 2012) try to garner more likes to elevate their influence within the community. In this regard, social media influencers are often motivated to make their newsfeeds "perfect"(e.g., share only positive aspects of their life, and manipulate their appearances). As a result, influencers' trustworthiness and authenticity are often called into question due to their susceptibility to deliberate manipulation (Costello and Biondi 2020).

Instagram, one of the largest influencer platforms in the world, launched a trial test of hiding the number of likes in order to mitigate the negative consequences of the like-seeking behavior of the platform users including both regular users and influencers. During the test, users who post content are able to observe the number of likes they received, however, their followers can only observe a single username and the phrase "others" as an indication of the likes a post received, instead of the explicit number who liked the post. In other words, customers or brands are not able to check the exact number of likes of influencers' postings after the new policy has been implemented during the trial test period but influencers still can track the feedback from followers.

Recent studies revealed that removing the public display of the number of likes has important positive effects, including alleviating the social pressure of generating posts to garnering more likes for social media users (non-influencers), which in turn positively affects user's mental health (Reddy and Yelchuri 2019). At the same time, it alters the context in which influencers operate. Along with the number of followers, the number of likes or the engagement ratio (i.e., number of likes/number of followers) are commonly used reference mechanisms when testifying an influencer's quality (Jang et al. 2020). Importantly, a public display of likes sends a popularity signal to potential consumers as well as the brands. Thus, our study seeks to investigate how this platform design change (hiding the number of likes) impacts influencers—active social media users who gain profit from a partnership with brands—in social media?

By collaborating with one of the leading influencer-based e-commerce platforms in Asia, our paper scrutinizes the impact of hiding the number of likes on influencers' endorsement posting behavior and its economic impact. We examine how influencers' post-generating behavior and post characteristics change (e.g., whether it is focused on products vs influencers themselves and the degree of image manipulation) when the public display of popularity feedback become private. We further extend our analyses by looking into how such influencers' behaviors are moderated by influencers' status (i.e., number of followers) prior to the intervention. Finally, our study examines how the visibility of number of likes affects the performance of the influencers' postings (e.g., sales).

Theoretical Background

Though the intent of social platforms when they first emerged was to connect individuals online, more recently concerns that have emerged in parallel with the growth of social media around mental health have come to light. Appel et al. (2016) corroborated that users on social media who have constantly experienced unflattering social comparison and envy, leads them to suffer from depression. The upward comparison when users see posts of others living a better life than themselves has also caused people to have lower self-esteem (Jan et al. 2017).

Given that positive feedback (e.g., Facebook or Instagram likes) constitutes a highly visible way of obtaining rewards and recognition, a considerable number of users in social media have been engaged in like-seeking behaviors. To receive more attention in social media, users often enhance their appearance by leveraging self-editing tools and try to highlight only positive aspects of their life (Chae 2017). Despite the numerous studies that have investigated the negative effects of social media feedback and usage, far less attention has been devoted to identifying effective solutions that can curb problematic social media usage. An exception to this is Instagram's removal of the source of the problematic social comparison, i.e., the removal of the public display of the number of likes a post receives. We leverage this policy change to explore how removing the display of the popularity signal impacts influencers' behavior – an important set of social media users, whose behavior may be significantly impacted by this intervention.

Previous research argues that users appear to rely on image-related utility, wherein utility is motivated by the perception of others and related to status-seeking as their popularity on the platform increases (Toubia and Stephen 2013). Unlike regular social media users (i.e., non-commercial users), influencers can gain economic benefit from their reputation built on the platform (McQuarrie et al. 2012). One strategy that influencers have used is partnering with brands, i.e. the posting of sponsored (in contrast to organic) content. However, recent studies have highlighted that decisions to share endorsement postings might hurt influencers' reputation which negatively affects their image-related utility (Hung et al. 2011). The trade-off between the increased intrinsic utility(e.g., revenue from the partnership) and the potential risk of losing image-related utility (e.g., audience engagement) facilitates influencers to balance the amount of organic and sponsored postings (Fainmesser and Galeotti 2019). In this regard, we first look into how hiding the number of likes affects influencers' intention to share endorsement postings.

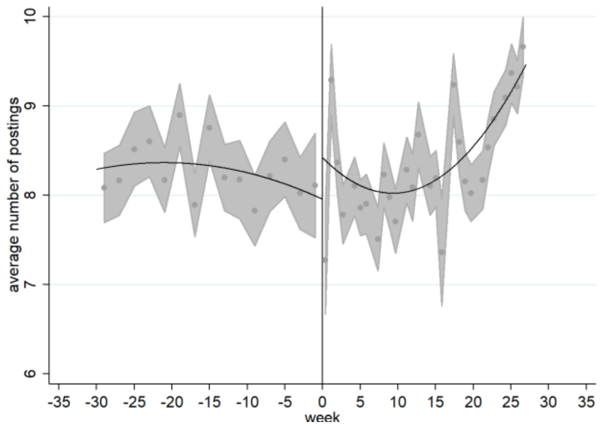
Since the engagement rate of endorsement postings may subsequently affect the influencer's future relationship with followers, as well as a partnership with the brands, social risk (i.e., potential loss of respect, and/or friendship) of reputation encourages influencers to generate authentic and credible content. For instance, if a follower is dissatisfied with the product recommended by influencers or perceives that the posting is not authentic, it may damage their reputation. Engagement rate (i.e., number of likes) has served as the key metric for influencer quality, as a surge of recent anecdotes affirms that unethical influencers either plant or pay to obtain followers – a previously used metric for influence quality – to gain reputation. Even though the adoption of a new design feature in social media (i.e., hiding the number of likes) may dampen malicious aspects of social comparison among regular users(i.e., non-commercial users) and encourage users to reveal a true depiction of themselves (Visca 2020), we suggest that hiding number of likes may affect influencers' behavior differently. Our study elucidates the effects of the visibility of number of likes on influencer's posting behavior (e.g., the quantity of endorsement posting, product vs influencer-focused posting, authenticity level) and consumers' responses to endorsement postings. To the best of our knowledge, this paper is the first empirical attempt on the design aspect of social media on influencers' behavior.

Research Context and Data

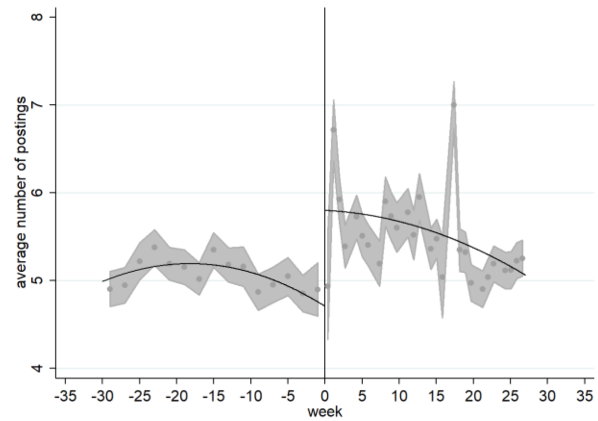
Our research partner is EcomCo, a leading mobile commerce company based in Asia. EcomCo sells a wide selection of cosmetic products. Different from conventional ecommerce platform, however, EcomCo. explicitly leverages influencer marketing by actively cooperating with various types of social influencers to promote products offered in the platform. Specifically, an influencer marketing campaign in EcomCo. starts by an individual requesting approval to EcomCo. to become an influencer. Influencers may generate content in their own way to maximize advertising value.

We utilize a quasi-experimental design, wherein our dependent variables are measured over time for Instagram users before and after the policy change. While difference-in-differences (DID) seems to be useful estimation strategy to compare influencers' posting behavior before and after the intervention, all individuals of the study population are exposed to the intervention, and separate control group is not available in the empirical setting. Thus, following previous literatures, we use *a single-group interrupted time-series* experimental design (Cavusoglu et al. 2016) to compare how influencers change their posting behaviors when the number of likes is no longer exposed to their followers. We obtained different types of influencers' posting data at multiple consecutive points before and after the intervention of the new policy. Figure 1 shows model free evidence, wherein the total number of postings, including endorsement and non-endorsement postings generated by influencers exhibit slight positive jump around the policy change, whereas endorsement postings show significant positive jump[1].

[1] Due to the page limit, we did not present graph on non-endorsement postings. It is available upon request.



(a) Total Number of Postings



(b) Number of Endorsement Postings

Figure 1. Weekly Trends of Number of Postings

In this study, we focus on users (i.e., both influencers and consumers) registered in EcomCo. who are based in South-East Asia (i.e., Indonesia and Philippines) and actively use Instagram. We first extract influencers who generated sales at least 10 times with their endorsement postings before and after the intervention. We also identify consumers who registered to EcomCo. before the policy change. Our dataset consists of all posting information generated by 1,317 influencers from September 2019 to January 2020 (16 weeks), wherein the new policy (i.e., hiding number of likes) was implemented in South-East Asia on November 15, 2019. The posting data consist of 13,449 endorsement postings on 1,702 products. We also collect individual purchase transactions made by 207,093 consumers. We aggregate influencers' posting and consumers' purchase data at a weekly level. Table 1 provides the descriptions of our key variables along with their summary statistics.

Table 1. Variable Description and Summary of Statistics

Variables	Description	Mean	Std.	Min	Max
$ln(NumPosting)_{it}$	Log-transformed number of endorsement postings generated by an influencer i in week t	0.191	0.391	0	3.296
$ln(InfluencerFocused)_{it}$	Log-transformed number of influencer-focused endorsement postings generated by an influencer i in week t	0.099	0.276	0	2.398
$ln(ProductFocused)_{it}$	Log-transformed number of product-focused endorsement postings generated by an influencer i in week t	0.154	0.374	0	2.708
$ln(FakeFacePred)_{it}$	Log-transformed average predictive score of whether the image is manipulated.	0.044	0.125	0.001	0.684
$ln(Sales)_{it}$	Log-transformed average number of sales generated by an influencer i at week t (normalized by the number of weekly postings generated by an influencer i at week t)	1.227	0.711	0	4.875
$AfterPolicy_{it}$	A binary variable indicating whether it is after the intervention	0.500	0.505	0	1
$\ln(NumFollower)_{it}$	Log-transformed number of followers of influencer i in week t	9.729	1.230	7.834	15.563

To detect how influencer's endorsement posting characteristics (e.g., product-focused vs influencer-focused, photo manipulation) are affected by policy change, we obtain images embedded in influencer-generated posting content. Specifically, we use deep learning-based face detection strategy to identify whether the image contains influencers' face. We define the endorsement posting is influencer focused if its image contains influencers' face. Otherwise, we define the endorsement posting as product focused posting. In addition, we estimate the predicted value of image fakeness by leveraging CNN-based EfficientNet algorithm CNN (Bonettini et al. 2021), a class of artificial neural networks, has been widely used in the field of computer vision tasks such as image or video recognition. To efficiently scale the dimensions of the neural network, Bonettini et al. (2021) leverage EfficientNet architecture, in which they uniformly scale number of layers in the network, number of channels in a convolutional layer, and resolution of the images of neural networks using a compound coefficient. We incorporated the model wherein trained by using face images extracted from 119,000 images which are identified as original (i.e., without photo manipulation strategy) and fake faces (i.e., with photo manipulation strategy-face swap algorithms). The extracted face images from the training datasets comprise a set of diverse actors (e.g., gender, skin tone, age, etc) with arbitrary backgrounds. To analyze endorsement postings data, we adopted a pre-trained fake photo detection algorithm[2]. We also collect the number of followers of each influencer.

Analyses and Results

Effectiveness of Hiding Number of Likes on Influencers' Posting Behavior

We first examine the impact of hiding number of likes function on influencers' posting behavior in terms of number of postings, whether the posting is product- or influencer-focused, and the level of authenticity (as measured by the *FakeScor*e). In addition, we explore how such effects are moderated by influencers' characteristics (i.e., influencers' status). We also probe into the impact of hiding number of likes feature on engagement with the post, specifically with regards to how this policy change influences product sales.

We utilize a regression discontinuity design (RDD), a quasi-experimental design that has become increasingly popular in economics, statistics, and political science (Imbens and Lemieux 2008). A RDiT elicits the causal effects of interventions by assigning a cutoff above or below (in our case, before or after) which an intervention is assigned. By comparing observations lying close to either side of the cutoff, it is possible to estimate the average treatment effect in environments in which randomization is infeasible. To that end, we utilize observations 8 weeks before and after the policy change to conduct RDD analyses. Following (Gottlieb et al. 2016), we estimate the standard parametric RDD equations of the form:

$$y_{it}^{*} = \beta_0 + \beta_1 After_t + \sum_{k=1}^{3} \gamma_k Week_t^k + \sum_{k=1}^{3} \delta_k Week_t^k * After_t + e_{it} \qquad (1)$$

where $y_{it}^{*} = y_{it} - \bar{y}_i$ is the adjusted outcome for influencer i in week t. Dependent variables are total number of weekly postings, the number of influencer-focused weekly postings, the number of product-focused weekly postings, and degree of manipulation. These variables are log-transformed, as they are highly skewed. $After_t$ is a dummy variable indicating if the observations occurred after the policy change. The coefficient of $After_t$ (i.e., β_1) captures the discontinuity in posting behaviors around the policy intervention. The estimated results of effectiveness of policy change on posting behaviors are presented in Table 2[3].

In terms of the number of postings, the coefficient of $After$ is positive and significant (p<0.01), suggesting that the number of postings increased after the policy change. The results may be indicative of the fact that influencers may be more inclined to frequently expose the products through endorsement postings as the number of likes, which may play role as a peripheral cue that may influence consumers' perception towards posting and products, is no longer visible to consumers. Also, with respect to the influencer-focused and product-focused postings, the estimated coefficient of $After$ in the second column is positive and significant at 0.01 level, whereas it is negative and significant at 0.01 level in the third column, suggesting

[2] We also tried alternative photo manipulation detection algorithms (e.g., face warp algorithms, Error Level Analysis) and confirm that our results remain consistent (Krawetz and Solutions 2007; Wang et al. 2019).

[3] In order to ensure our results, we also performed two-way fixed effect by controlling influencer and time fixed effects. Results are qualitatively consistent with our main analyses. Results are available upon request.

that influencers are more likely to generate influencer-focused postings after the intervention. Lastly, in relation to the level of authenticity, the estimated coefficient of $After$ is positive and significant (p<0.01), suggesting that influencers are more likely to generate postings with manipulated images after the policy change to beautify themselves and enhance posting quality.

Table 2. Estimated Results for the Impact of Hiding Number of Likes Function on Influencer's Posting Behavior

Variables	Number of Posting	Influencer Focused	Product Focused	Fake Score
$After$	0.199***	0.118***	-0.547***	0.026***
	(0.019)	(0.055)	(0.0863)	(0.009)
Time trend control	YES	YES	YES	YES
Constant	0.123***	0.714***	0.567***	0.021***
	(0.011)	(0.041)	(0.021)	(0.005)
Observations	21,072	21,072	21,072	21,072
R-squared	0.051	0.058	0.031	0.048

*Note: Standard errors are in parentheses; *** p < 0.01, ** p < 0.05, and * p < 0.1.*

Next, we further look into how moderating effect of influencer characteristics (i.e., the number of followers) on the effectiveness of policy change on influencers' posting behavior. Influencers with different social status may exhibit distinctive responses to the policy change as greater followers imply larger audience for their postings. The estimated results are presented in Table 3[4]. The estimated coefficient of interaction between $After$ and $\ln(NumFollower)$ in the first column is positive and significant at 0.01 level, suggesting that macro influencers who encompass larger number of followers generate more endorsement posting compared to influencers with small follower base. In addition, the results in the second and third columns suggest that macro influencers generate more (less) influencer-focused (product-focused) postings. The results show that macro influencers tend to expose themselves more often on the endorsement postings after the number of likes are invisible to their followers. Lastly, the estimated coefficient of interaction between $After$ and $\ln(NumFollower)$ in the fourth column is positive and significant at 0.01, implying that macro influencers are more likely to manipulate photos to enhance attractiveness of the posting image.

Table 3. Estimated Results for Moderating Effect of Number of Followers

VARIABLES	Number of Posting	Influencer Focused	Product Focused	Fake Score
$After$	0.087***	0.073***	-0.108***	0.041**
	(0.009)	(0.013)	(0.008)	(0.013)
$After * ln\ (NumFollower)$	0.011***	0.025***	-0.011***	0.006***
	(0.002)	(0.004)	(0.002)	(0.001)
$\ln(NumFollower)$	-0.004	-0.009**	0.007**	-0.027***
	(0.003)	(0.003)	(0.003)	(0.006)
Time trend control	YES	YES	YES	YES
Constant	0.496***	0.975***	0.355***	0.569***
	(0.071)	(0.142)	(0.021)	(0.066)
Observations	21,072	21,072	21,072	21,072
R-squared	0.077	0.065	0.050	0.048

*Note: Standard errors are in parentheses; *** p < 0.01, ** p < 0.05, and * p < 0.1.*

Economic Impact of Hiding Number of Likes

[4] Similar to previous analyses, we also corroborated results by incorporating influencer and time fixed effects. Results are qualitatively consistent with our main analyses. Results are available upon request.

Next, we turn our attention to the economic impact of hiding number of likes function. Specifically, we quantify the difference in sales after the number of likes in Instagram postings is no longer visible to users. We also probe into the differential impact of the number of followers, as consumers may respond differently to hiding number of likes function depending on the influencers' social status.

The estimated results are presented in Table 4[5], wherein the first column shows the main effect of the policy change, and the second column shows the interaction effect of number of followers[6]. The estimated coefficient of $After$ is positive and statistically significant, indicating that the policy change positively affects the product sales in influencer marketing. However, its effect becomes significant based on the influencers' number of followers. The estimated coefficient of the interaction between $After$ and $\ln(NumFollower)$ in the second column is negative and significant at 0.01 level, suggesting that the positive impact of intervention is attenuated with the number of followers with respect to sales.

Table 4. Estimated Results of Economic Impact of Hiding Number of Likes

VARIABLES	Sales	Sales
$After$	0.023** (0.010)	0.119*** (0.014)
$After * ln\ (NumFollower)$		-0.028*** (0.004)
$\ln(NumFollower)$	0.033*** (0.002)	0.042*** (0.003)
Time trend control	YES	YES
Constant	-0.211*** (0.023)	-0.744*** (0.031)
Observations	21,072	21,072
R-squared	0.021	0.017

*Note: Standard errors are in parentheses; *** p < 0.01, ** p < 0.05, and * p < 0.1.*

Robustness Check

To effectively control for other extraneous factors that may affect influencers' posting behavior (i.e., the number of postings) and establish valid causality, we performed propensity score matching (PSM) in combination with difference-in-difference estimation as a robustness check. Given that this approach requires a counterfactual as a control group, we obtained additional data on influencers who are based in New Zealand. Instagram rolled out the new policy of hiding number of likes in New Zealand along with 6 other countries (i.e., Australia, Brazil, Canada, Ireland, Italy, and Japan) 4 months (i.e., July 18, 2019) prior to expanding it globally. To determine whether a notable difference exists in influencers' posting behavior after the implementation of the new policy, we compared posting behaviors generated by influencers who are based in New Zealand (152 influencers) and other countries between July and November 2019.

To implement PSM, we leverage data on 152 influencers who are based in New Zealand between January 2019 to November 2019. We also obtained the number of postings generated by influencers in other countries (mostly in East Asia) in the same period. We calculate propensity scores based on the basis of the estimates from the logit model, where the outcome is equal to 1 if the influencer is based in New Zealand; otherwise, it is labeled a value of 0. The independent variables include influencer characteristics, such as their number of followers, performance score generated by the company, registration date, age, gender, and historical sales. Also, we employed their historical endorsement posting behavior, including proportion of skin care product versus makeup products, proportion of video versus image, and the number of active social media they use. We then performed one-to-one nearest-neighbor matching with the estimated propensity scores and ensured matching quality by carrying out t-test on matching variables. The estimated results are reported in Table 5. The estimated coefficient of interaction between $After$ and $Treat$ is positive and significant at 0.01 level, suggesting that hiding number of likes increases the number of postings generated by influencers. The results corroborate our main finding.

Table 5. Estimate Results of Difference-in-Difference Analyses

VARIABLES	Sales	Number of Posting	Influencer Focused	Product Focused	Fake Score

[5] We corroborated the results by using two-way fixed effect, incorporating influencer and time fixed effects. Results are available upon request.

[6] Full results are available upon request

$After * Treat$	0.296*** (0.015)	0.142*** (0.025)	0.250** (0.082)	-0.251*** (0.011)	0.055*** (0.004)
$After$	-0.069*** (0.011)	-0.033** (0.014)	0.051** (0.023)	-0.049*** (0.010)	-0.013*** (0.002)
$Treat$	-0.800 (0.710)	0.132 (0.214)	0.139 (0.079)	0.088 (0.111)	0.010 (0.021)
Constant	2.325*** (0.260)	0.644*** (0.065)	0.960*** (0.191)	1.352*** (0.159)	0.219*** (0.021)
Observations	4,864	4,864	4,864	4,864	4,864
R-Square	0.111	0.102	0.088	0.078	0.041

*Note: Standard errors are in parentheses; *** p < 0.01, ** p < 0.05, and * p < 0.1.*

Relative Time Model

In addition, we validated the matching results by using relative time model[7]. With the matched sample (i.e., total 304 influencers), we conducted difference-in-difference estimation to approximate variances in number of postings before and after the implementation of the new policy.

Discussions

User feedback systems (e.g., likes) have served as a core function within social media which enhances users' interaction with others. Whereas researchers have increasingly focused attention to problematic social media usage, e.g. negative impact on the mental health of social media users (e.g., depression, envy, etc), far less attention has been devoted to identifying effective solutions that can help individuals alleviate pressure in social media. In this paper, we formally investigated how the social media design (e.g., visibility of the number of likes) affects users' behavior on social media. Specifically, our study examined how hiding the number of likes affects active social media users (i.e., influencers) post-generating behavior. We observe that the number of endorsement posts significantly increases after the policy change, meanwhile, it appears that such a policy cultivates influencers to reveal themselves (i.e., including their face) in the endorsement posting. Interestingly, we also find that influencers are more likely to manipulate content (e.g., using filters) after the policy change. This change in the nature of posts by influencers suggests that perhaps alleviating one source of social comparison may lead to other means of social comparison, i.e. altering one's image. Further, our findings elucidate that hiding the number of likes has a positive impact on posting influencer's economic benefit). However, this pattern was attenuated with macro influencers.

This work contributes to the growing stream of work on influencer marketing. To the best of our knowledge, our research is among the first to empirically examine the impact of hiding the number of likes on active social media users (i.e., influencers) posting behavior by employing a deep learning-based content analysis methodology. Our study provides guidance to identify the right influencers within social media wherein these explicit descriptions of feedback that influencers received disappear and provides important insights for marketers who attempt to interact with customers via social media in which one of the reference schemes (e.g., number of likes) of influencers' quality has disappeared.

This research is a work in progress. We are at the stage of developing theoretical framing. In addition, we plan to empirically analyze the effectiveness of hiding number of likes in short-term versus long-term. Specifically, we attempt to delve into the immediate effect of policy change and whether such effects are accentuated or attenuated over time. In addition, we further investigate how effectiveness of policy change is moderated by the number of likes (i.e., degree of posting engagement) on influencers' posting behavior and product sales. Lastly, we are collecting additional data regarding non-endorsement postings generated by influencers to compare how influencers exhibit different posting behaviors on endorsement versus non-endorsement postings.

[7] Results for matching and relative-time model are available upon request.

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