

Revenue Generation Through Influencer Marketing

Maximilian Beichert, Andreas Bayerl , Jacob Goldenberg, and Andreas Lanz 

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Abstract

Direct-to-consumer firms increasingly believe that influencer marketing is an effective option for seeding. However, the current managerially relevant question for direct-to-consumer firms of whether to target low- or high-followerhip influencers to generate immediate revenue is still unresolved. In this article, the authors' goal is to answer this question by considering for the first time the whole influencer-marketing funnel, that is, from followers on user-generated content networks (e.g., on Instagram), to reached followers, to engagement, to actual revenue, while accounting for the cost of paid endorsements. The authors find that low-followerhip targeting outperforms high-followerhip targeting by order of magnitude across three performance (return on investment) metrics. A mediation analysis reveals that engagement can explain the negative relationship between the influencer followerhip levels and return on investment. This is in line with the rationale based on social capital theory that with higher followerhip levels of an influencer, the engagement between an influencer and their followers decreases. These two findings are derived from secondary sales data of 1,881,533 purchases and results of three full-fledged field studies with hundreds of paid influencer endorsements, establishing the robustness of the findings.

Keywords

influencer marketing, creator economy, user-generated content networks, social media, paid endorsements, sales, ROI

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Influencer marketing garners significant attention: it quickly grew into a \$17.4 billion industry by 2023 (Collabstr 2023), with more than 80% of companies in the U.S. using influencers for marketing purposes (Influencer Marketing Hub 2023). The most prominent user-generated content network for both brands and influencers is Instagram, counting 3.8 billion annual sponsored postings (Klear 2022). According to marketers, sales is the leading goal of influencer marketing (Statista 2023). Particularly for direct-to-consumer (DTC) firms, identifying influencers who drive positive return on investment (ROI) remains the biggest challenge when considering influencer marketing as a revenue channel (Influencer Marketing Hub 2023).

Despite the fact that revenue generation is the most important goal of budget allocation in influencer marketing (Brown 2023), research has focused on other outcome variables such as content consumption (e.g., Yoganasimhan 2012), content interaction (e.g., Hughes, Swaminathan, and Brooks 2019; Leung et al. 2022; Wies, Bleier, and Edeling 2023), content reposting (e.g., Peng et al. 2018), and follow-backs (Lanz et al. 2019).

These outcome variables, while important and worthy of consideration, are not the main focus of practitioners (Statista 2023), especially DTC firms. We may assume that revenue has not been examined as an outcome variable despite its primacy due to the significant challenge of obtaining data about how much was sold through influencer campaigns on a granular level.

Another crucial yet missing variable in the equation is the cost: the existing literature has predominantly overlooked the cost aspect, and there is a noticeable dearth of published

Maximilian Beichert is Postdoctoral Research Fellow, Mannheim Business School, University of Mannheim, Germany (email: maximilian.beichert@uni-mannheim.de). Andreas Bayerl is Assistant Professor of Marketing, Erasmus School of Economics, Erasmus University, The Netherlands (email: bayerl@ese.eur.nl). Jacob Goldenberg is Full Professor of Marketing, Arison School of Business, Reichman University, Israel, and Visiting Professor, Columbia Business School, Columbia University, USA (email: jgoldenberg@runi.ac.il). Andreas Lanz is Assistant Professor of Digital Marketing Analytics, Faculty of Business and Economics, University of Basel, Switzerland (email: andreas.lanz@unibas.ch).

research on the effect of paid endorsements. Neglecting the incorporation of costs cannot result in an effective evaluation of the influencer endorsement (Batra and Keller 2016).

Although some notable contributions have emerged, including Hughes, Swaminathan, and Brooks (2019), Leung et al. (2022), and Wies, Bleier, and Edeling (2023), shedding light on the cost aspect, they do not examine the influencers' impact on revenue generation. Calls for studying influencers using more relevant outcome variables—such as revenue—have repeatedly been made (e.g., Hughes, Swaminathan, and Brooks 2019).

The current article attempts to fill this gap and explore revenue as a key outcome variable in influencer marketing research, addressing the effectiveness of influencer endorsements in driving financial returns for DTC firms. We are not aware of prior work that jointly considers the cost and revenue aspects empirically.

A widely acknowledged debate is ongoing in the literature regarding the effectiveness of high-follower versus low-follower influencers in user-generated content networks. Yet few articles point out the value of low-follower influencers (e.g., Galeotti and Goyal 2009; Lanz et al. 2019; Watts and Dodds 2007). At this stage, most of the seeding literature in marketing recommends targeting high-follower influencers, that is, hubs (e.g., Goldenberg et al. 2009; Hinz et al. 2011; Leung et al. 2022).

A crucial observation for understanding this debate is that the findings supporting the effectiveness of low-follower influencers are based only on *unpaid* endorsements (i.e., the influencers do not receive any monetary compensation for their actions), leaving the question open as to whether the same holds true for *paid* endorsements. In paid endorsement situations, influencers work for brands to promote products or services, and influencers with higher followership have the ability to drive more significant brand exposure and consumer engagement due to their larger audience reach. There is more and more evidence for the advantage of high follower influencers in such paid endorsements (e.g., Hughes, Swaminathan, and Brooks 2019; Leung et al. 2022). However, there is no evidence in the literature that low-follower influencers offer the same advantage in paid endorsements as high-follower influencers. Low-follower influencers might be perceived as less popular (e.g., De Veirman, Cauberghe, and Hudders 2017), less credible (e.g., Goldenberg et al. 2009), and having lower status (e.g., Labrecque et al. 2013).

In contrast, based on social capital theory (Van den Bulte and Wuyts 2007; Wasko and Faraj 2005), we posit that the higher the influencer followership level, the lower the engagement between the influencer and their followers; hence the influencer's performance is expected to be less effective. In analyzing the engagement *before* the sponsored posting, we closely follow social capital theory, which for engagement formulates concepts of commitment and reciprocity in social networks. We separate this engagement between the influencer and their followers with (1) follower engagement and (2) influencer engagement, both of which are expected to be negatively associated with influencer followership levels.

In this work we engage the debate by testing the two possible strategies (focus on low- vs. high-follower influencers) in the context of paid endorsements to fully understand the potential value in user-generated content networks. In contrast to previous work, we consider the entire influencer-marketing funnel for paid endorsements in the context of DTC firms—from followers on user-generated content networks (e.g., on Instagram), to reached followers, to engagement, *all the way to actual revenue*, while accounting for the cost of paid endorsements—using a combination of secondary revenue data and three full-fledged field studies.

To align with common business practice at DTC firms, we conducted a survey among senior influencer-marketing managers in such firms to uncover the most important performance (ROI) metrics (see Web Appendix A), which we find to be (1) revenue per follower, (2) revenue per reach, and (3) return on influencer spend (ROIS). We test the effect on these three measures.

We combine both empirical and field studies. On the one hand, we use a data set from one of Europe's leading DTC firms that includes 2,808 influencer-specific discount codes, allowing us to attribute 1,881,533 sold products (with total value over €17 million in revenue) to 2,808 unique sponsored postings on Instagram by 1,698 nano-, micro-, and macro-influencers (three influencer followership levels, where “nano-influencers” refers to low-follower influencers and “macro-influencers” refers to high-follower influencers; e.g., Van den Bulte and Wuyts 2007). On the other hand, collaborating with two DTC firms, we run three distinct field studies with a total of 319 paid nano- and macro-influencers (also on Instagram).

Our consistent result is that nano-influencers provide a significantly higher ROI than macro-influencers, namely by order of magnitude across empirical and field evidence. Note that we can rule out the impact of Instagram's algorithm by also accounting for actually reached followers, resulting in the same findings. Additionally, we use propensity score matching to make nano- and macro-influencers comparable, particularly in terms of their followers' characteristics. Furthermore, in a parallel mediation analysis (e.g., Xu, Mehta, and Dahl 2022), we find that the negative effect of the number of followers on all three ROI metrics is partially mediated by the (follower and influencer) engagement before the sponsored posting, and this can explain up to 51% of the direct effect.

We delve into the two mediators by investigating the interaction between the influencer and their followers in the five postings before the sponsored posting and observe higher engagement for nano-influencers. We use language style matching (LSM) to further analyze an influencer's relationship with their followership and find that nano-influencers match the communication style of their followers far better than macro-influencers do.

Interestingly, our results do not mean that past articles reporting the advantage of high-follower influencers are necessarily wrong. A likely explanation of the emerging shift is the mere

dramatic growth of user-generated content networks (Facebook, for example, grew from 900 million users in Q1 2012 to almost 3 billion users in Q1 2022; Meta 2022). This leads to a situation in which high-followerhip influencers today have many more followers (by three orders of magnitude) than in the past (i.e., millions instead of thousands). From this we conclude that high-followerhip influencers from the past now fall into the low-followerhip category. Another reason for a potential shift is that past literature has not examined more relevant (and complex) measures like ROI, mainly because revenue and associated costs were not readily available to researchers.

The rest of this work is organized as follows: In the next section we examine the related literature before empirically investigating low- versus high-followerhip targeting based on secondary revenue data. This also includes assessing the relationship between influencers and their followers using textual analysis and LSM on followers' comments and influencers' replies. Then we replicate the main empirical investigation via three field studies. We conclude with a discussion of our findings and offer directions for future research.

Background

This work is related to three aspects of influencer marketing. The first focuses on the various existing seeding policies. The second facet involves the different returns on seeding, which we evaluate with a focus on user-generated content networks. Finally, the third facet covers the role of the engagement of both the influencer and the followers in seeding processes.

Seeding Policies

Typically, for seeding campaigns the targets are classified according to the (in)degree, or number of followers, since this metric is always readily available (Shriver, Nair, and Hofstetter 2013). In business practice, influencer followerhip levels are commonly defined as nano-, micro-, and macro-influencers (see Web Appendix B). Following this rationale, high-followerhip influencers (macro-influencers) are simply the most connected users of a network, whereas low-followerhip influencers (years later defined as nano-influencers) are the least connected ones (Van den Bulte and Wuyts 2007).

Although prior research in the seeding literature in marketing is not fully aligned in its policy recommendation, while typically focusing on unpaid endorsements, the vast majority suggests targeting high-followerhip influencers. For instance, Hinz et al. (2011) find it to be more effective than targeting fringes or individuals with high betweenness, a result that is in line with many other publications (e.g., Chen, Van der Lans, and Phan 2017; Goldenberg et al. 2009; Hinz et al. 2011; Leung et al. 2022; Libai, Muller, and Peres 2013; Yoganarasimhan 2012).

In contrast, only a few works suggest targeting low-followerhip influencers. For example, when benchmarked in an analytical model and a computer simulation, low-

followerhip influencers outperform high-followerhip influencers when the dissemination process is about information sharing (e.g., Galeotti and Goyal 2009; Watts and Dodds 2007). This is possibly due to the average influential power of influencers decreasing with an increase in their number of friends (Katona, Zuscovsek, and Sarvary 2011). Similarly, Moldovan et al. (2017) derive stronger opinion leadership among leaders in small, strong-tie groups, whereas leaders become less effective the larger the group and the weaker the ties. Lanz et al. (2019) provide further empirical evidence, demonstrating that the return in terms of follow-backs is higher on low-followerhip influencers. It is crucial to recognize that the conclusions drawn from Lanz et al. are limited to (1) self-promotion, (2) unpaid endorsements, (3) a one-to-one outreach, and (4) follow-backs as dependent variable, and this may not capture the profitability across influencers with different followerhip levels for DTC firms.

Hence, the matter arises as to whether in business practice—which relies predominantly on paid endorsements—the recent shift toward low(er)-followerhip influencers (Haenlein et al. 2020), which goes against the bulk of the seeding literature in marketing, is worthwhile. In this work, we investigate this business practice by comparing low- versus high-followerhip targeting, namely *in the context of paid endorsements*.

Return on Seeding

Prior research on seeding has mainly focused on building awareness, and rarely on adoption, let alone generating sales or considering costs (as can be seen in the “Costs” and “Revenue” columns of Table 1). Awareness, as a first step in the customer journey, can stimulate consumers in the preference-formation stage (Hamilton et al. 2021), and it has been operationalized—in the context of user-generated content networks—with content consumption (e.g., Yoganarasimhan 2012), content interaction (e.g., Hughes, Swaminathan, and Brooks 2019; Leung et al. 2022; Wies, Bleier, and Edeling 2023), content reposting (e.g., Peng et al. 2018), and follow-backs (Lanz et al. 2019). Although some research has covered later stages of the customer journey, such as adoptions (e.g., Goldenberg et al. 2009) or registrations (e.g., Katona, Zuscovsek, and Sarvary 2011), the clean attribution to sales on an influencer level has not been considered (as can be seen in the “Key Dependent Variable” column of Table 1).

In our literature review, we identified several working papers on influencer marketing, including Bairathi and Lambrecht (2023), Gu, Zhang, and Kannan (2023), Hughes, Soni, and Swaminathan (2023), Huh, Zhang, and Kannan (2023), Tian, Dew, and Iyengar (2023), and Yang, Zhang, and Zhang (2023). However, none of these papers specifically focus on DTC firms, and their dependent variable does not include revenues. Hughes, Soni, and Swaminathan; Bairathi and Lambrecht; and Tian, Dew, and Iyengar primarily focus on engagement as their main dependent variable. Yang, Zhang, and Zhang mainly focus on video content, movement, and timing of product placement of mature macro-influencers. Huh, Zhang, and Kannan

Table 1. Empirical Studies Investigating the Impact of Followership Levels on Outcomes.

Author(s) (Year)	Data			Setting			Methods Used			Model Characteristics				
	Source	No. of Users on Platform	Endorsements	Paid	Followership Levels	Textual Analysis	Computer Vision	Field Studies	Influencers' Avg. No. of Followers (Mean Indegree Connections)	Key Dependent Variable	Costs	Revenue	Reach	Variables
Goldenberg et al. (2009)	Cyworld	7 million	No	No	Yes	No	No	No	19	Product adopters	No	No	No	No
Hinz et al. (2011)	Similar to Facebook	6.3 million	No	No	Yes	No	No	Yes	21	Conversion rate	No	No	No	Yes
Katona, Zubcsek, and Sarvary (2011)	Social network	N.A.	No	No	Yes	No	No	No	206	Adoption likelihood	No	No	No	No
Yoganarasimhan (2012)	YouTube	97 million	No	No	Yes	No	No	No	9	Diffusion rate	No	No	No	No
Libai, Muller, and Peres (2013)	12 networks	N.A.	No	No	Yes	No	No	No	10	Social value	No	No	No	No
Moldovan et al. (2017)	2 mobile networks	N.A.	No	No	Yes	No	No	No	N.A.	Churn rate	No	No	No	No
Gong et al. (2017)	Sina Weibo	392 million	No	No	Yes	No	No	Yes	2,111,873	Views	No	No	No	No
Chen, Van der Lans, and Phan (2017)	1 social network	42,852	No	No	Yes	No	No	No	N.A.	Reach	No	No	No	Yes
Peng et al. (2018)	Twitter and Didi	316 million	No	No	Yes	No	No	No	4,553	Content sharing	No	No	No	No
Lanz et al. (2019)	SoundCloud	82 million	No	No	Yes	No	No	No	3,718	Follow-backs	No	No	No	No
Hughes, Swaminathan, and Brooks (2019)	Facebook and blogs	2.5 billion	Yes	Yes	Yes	Yes	No	No	21,246	Engagement	Yes	No	No	No
Valsesia, Proserpio, and Nunes (2020)	Twitter and Instagram	206 million, 1.04 billion	No	No	Yes	Yes	No	Yes	3,224	Perceived influence	No	No	No	Yes
Leung et al. (2022)	Sina Weibo	582 million	Yes	Yes	Yes	Yes	No	No	4,360,000	Engagement	Yes	No	No	Yes
Wies, Bleier, and Edeiling (2023)	Instagram	1.28 billion	Yes	No	Yes	No	No	No	178,983	Engagement	Yes	No	No	Yes
Bairathi and Lambrecht (2023)	Instagram	1.89 billion	Yes	No	Yes	No	No	No	N.A.	Engagement	No	No	No	No

(continued)

Table 1. (continued)

Author(s) (Year)	Data			Setting			Methods Used			Model Characteristics				
	Source	No. of Users on Platform	Endorsements	Paid	Followership Levels	Textual Analysis	Computer Vision	Field Studies	Influencers' Avg. No. of Followers (Mean Indegree Connections)	Key Dependent Variable	Costs	Revenue	Reach	Variables
Hughes, Soni, and Swaminathan (2023)	Instagram	1.89 billion		Yes	Yes	No	No	No	N.A.	Engagement	No	No	No	
Huh, Zhang, and Kannan (2023)	YouTube	2.29 billion		Yes	Yes	No	No	No	N.A.	Sales	Yes	Yes	No	
Tian, Dew, and Iyengar (2023)	TikTok	900 million		Yes	Yes	Yes	Yes	No	486,169	Engagement	No	No	Yes	
Gu, Zhang, and Kannan (2023)	Douyin	600 million		Yes	Yes	No	Yes	No	N.A.	Sales	No	(Yes)	Yes	
Yang, Zhang, and Zhang (2023)	Douyin	600 million		Yes	Yes	No	Yes	No	1,617,806	Sales	No	(Yes)	No	
This study	Instagram	1.89 billion		Yes	Yes	Yes	Yes	Yes	52,849	Performance (ROI) metrics	Yes	Yes	Yes	

Notes: N.A. = not available. Projects with "(Yes)" use the number of items sold, not the actual revenue in monetary terms.

focus on video content in a gaming context with a focus on offline sales, while Gu, Zhang, and Kannan do not incorporate incurred costs and instead focus on the dynamics of livestreaming.

Our research emphasizes the importance of considering both generated revenues and incurred costs, particularly using revenue per follower, revenue per reach, and ROIS as dependent variables. This approach goes beyond existing literature that primarily uses engagement as the main dependent variable. This is noteworthy, as engagement has been criticized as an inadequate predictor of sales conversion, echoing common industry concerns about engagement metrics (Yang, Zhang, and Zhang 2023).

Since the consideration of costs of paid endorsements is typically outside the scope of prior research (as can be seen in the “Paid Endorsements” column of Table 1), Hughes, Swaminathan, and Brooks (2019) call for further research to investigate “the direct impact of a blog post on consequential outcomes, such as sales and ROI” (p. 93), where ROI requires the consideration of not only revenue but also the associated costs of paid endorsements.

In summary, as can be inferred from Table 1, by considering sales (i.e., revenue), costs, and performance (ROI) metrics in paid endorsements (that were not examined before), we respond to this call in the context of DTC firms for which influencer marketing is a direct revenue channel, typically on Instagram, which is also our focus here (no other user-generated network is as popular among marketers for these purposes; Statista 2023).

Engagement of the Influencer and Followers

The literature shows that despite the importance of weak ties in building a large following—one can maintain only 150 friendships in an offline setting (Dunbar 1998)—it is the strong ties between influencer and followers that facilitate purchase intention (e.g., Aral and Walker 2014; Katona, Zubcsek, and Sarvary 2011).

Granovetter (1973) portrays tie strength in the context of mere information dissemination as a combination of time spent (the commitment) and the intensity of emotions involved in the reciprocal relationship. Hence, maintaining strong relationships, or ties, is “costly” (Hill and Dunbar 2003). Although prior research has revealed that in an online setting the number of connections can easily exceed 150, the same interaction frequencies are valid for both online and offline settings (Dunbar et al. 2015).

Concerning degrees of friendship, Dunbar (2018) differentiates among various definitions of what a “friend” is (ranging from very close friends to just acquaintances). By design there is no differentiation among connections in user-generated content networks. Therefore, users are able to connect to multiple “friends” at all levels. This means that there are different degrees of friendship among connections; namely, between “friends” in an online setting there is heterogeneity in terms of engagement. Based on social capital theory (Van den Bulte

and Wuyts 2007), *commitment* and *reciprocity* are concepts of engagement in social interactions, constituting the two pillars of relational capital according to the integrative framework for understanding online information-sharing behavior (e.g., Wasko and Faraj 2005).

Commitment is closely linked to the engagement of future interactions and originates from frequent exchange; it refers to a person’s psychological attachment and loyalty to a specific individual (Coleman 1988). Interactions are motivated by a sense of obligation within personal relationships (Constant, Kiesler, and Sproull 1994). It involves a willingness to devote time, effort, and resources to maintain and strengthen the relationship. In the presence of strong ties and more personal relationships, users are less reluctant to engage with postings (Levin and Cross 2004). High level of commitment to an influencer would mean that a follower is actively engaging with the influencer’s postings, sharing them, and providing feedback in the form of comments. Just the act of writing a comment by a follower is a somewhat strong form of commitment, let alone sharing a posting with one’s own followers, or friends. In contrast, a low level of commitment would imply that the follower is less engaged and may simply be passively following the influencer without any interaction.

Reciprocity is linked to the concept of tie strength (e.g., Aral and Walker 2014). At its core, reciprocity embodies a feeling of shared obligation, leading people to typically return the favors done for them, which in turn promotes continuous supportive interactions, as highlighted by Shumaker and Brownell (1984). This conceptualization of how two individuals interact has mainly been investigated and formulated with regard to frequency of engagement (Brown and Reingen 1987; Godes and Mayzlin 2004; Weimann 1983), where strong ties can result in more than double the volume of engagement than weak ties (e.g., Blight, Jagiello, and Ruppel 2015; Lee, Hosanagar, and Nair 2018). However, the volume of engagement is also dependent on the number of followers. With increasing followership levels, influencers accumulate—and need to maintain—new followers, thereby weakening overall tie strength (i.e., their existing degrees of friendship). More specifically, since maintaining these relationships is “costly” (Hill and Dunbar 2003), engagement frequency with each follower decreases (Sutcliffe, Binder, and Dunbar 2018).

Along these lines, to operationalize commitment and reciprocity—this concept of engagement through interactions—we use (1) follower engagement and (2) influencer engagement, both of which are expected to be *negatively* associated with influencer followership levels. We expect that low-followership influencers outperform high-followership influencers in terms of revenue per follower and ROI, because the higher the influencer’s followership level, the lower the engagement between the influencer and followers.

We first test this expectation by looking at secondary data with a multitude of influencers across followership levels for our comparison of the two seeding policies. We employ a parallel mediation analysis to shed light on the mechanism

underlying superior performance of either seeding policy across three different performance (ROI) metrics. Subsequently, to provide further robustness, we conduct three field studies across different settings to again compare the two seeding policies: In the first study, we keep the content of the sponsored posting as stylized as possible. In the second study, we allow for some freedom in content creation to make the sponsored posting more realistic. Finally, in the third study, we allow for full freedom in the creation of the sponsored posting.

Low- Versus High-Followership Targeting: Empirical Evidence

The purpose of this study is to empirically investigate the effectiveness of targeting low- versus high-followership levels. We start with model-free evidence on differences in ROI, and then we present a parallel mediation analysis to examine the underlying mechanism.

Data

One of Europe's leading DTC fashion firms provided us with a data set that includes 2,808 influencer-specific discount codes created between 2018 and 2021. These codes were distributed by 1,698 influencers via sponsored postings to their followers who, in turn, could use them to purchase products at a discount in the firm's e-commerce store, the typical setting for DTC firms to generate direct revenue through influencer marketing. The discount codes enable us to cleanly attribute 1,881,533 sold products (valued at over €17 million in total revenue) to 2,808 sponsored postings on Instagram by 1,698 influencers (each posting received an influencer-specific—i.e., unique—discount code; hence there are also 2,808 discount codes).

Initially, influencers are invited based on evaluations of the influencer-product fit on a rolling basis. Once influencers agree to participate in a campaign, they receive their designated discount code and payment. Receiving the discount code and the payment is highly automated for nano- and micro-influencers, whereas for macro-influencers a more personal and thus work-intense approach is common. Figure 1 shows an example from our data in which two influencers posted in their feed with such a discount code (see Web Appendix C for a more detailed outline of the comments). Given that influencer-marketing platforms and other specialized third-party service and data providers enable marketers to not only find but also work with hundreds of nano-influencers at the same time and efficiently leverage their potential at the labor cost of handling only one macro-influencer, we can make one-to-one comparisons of influencers, just as in Figure 1. This is also confirmed by a survey among senior influencer-marketing managers at DTC firms (see Web Appendix A for details; see also Web Appendix D demonstrating that, by definition, there is a corner solution, namely to select either nano- or macro-influencers).

Instagram, one of the biggest user-generated content networks in the domain of visual content, has become much more than an application for the purpose of editing photos as well as videos and

distributing them to friends. Today, Instagram users obtain relevant information about potential purchases through the content uploaded to the network, whether it stems from friends, influencers, or brands. This content comes in the form of feed postings (see Figure 1) or stories, with the latter only available for a short time. Typically, the feed postings and stories can be seen, liked, commented on, and shared by Instagram users as the messages find their way into their timelines.

In the case of influencers uploading the content, the sponsored feed postings and stories typically contain personalized UTM tracking URLs (i.e., influencer-specific links) that point to the firm's e-commerce store and/or influencer-specific discount codes that followers can use in that store (where the former reduces conversion friction). Hence, the funnel does not end with the followers' engagement with the sponsored posting after having seen it; the funnel continues with the followers landing in the firm's e-commerce store and eventually purchasing products in it. For this reason, we consider the whole influencer-marketing funnel, that is, from followers on Instagram, to reached followers, to engagement with the sponsored posting, and to actual revenue.

Along these lines, our data set is quite rich, as it features 2,808 influencer-specific (and thus unique) discount codes through which 1,881,533 products have been purchased; hence it allows for the calculation of ROI metrics for each of the 1,698 influencers in the data set (who differ in their number of followers). To make sure we are aligned with common business practice among DTC firms and are examining the most relevant parameters, we conducted a survey among senior influencer-marketing managers in such firms to uncover the most important ROI metrics (see Web Appendix A), which we find to be (1) revenue per follower, (2) revenue per reach, and (3) ROIS (see Table 2 for further details). We use these metrics as our main dependent variables.

For example, the low-followership influencer (nano-influencer) of the sponsored posting from Figure 1, Panel A, on April 21, 2020, had 6,632 followers at this point. The influencer generated €2,456 in revenue. Thus, we calculate the revenue per follower as €0.37. Then consider the high-followership influencer (macro-influencer) in Figure 1, Panel B, who posted on September 4, 2018, having 258,055 followers. Her sponsored posting generated €1,968 in revenue, and hence the revenue per follower is €0.008. Concerning the other two performance (ROI) metrics for this nano-influencer and macro-influencer, the revenue per reach is €1.29 versus €0.04, and the ROIS is 27.23 versus 0.01. Note that the influencers' number of followers reached and the payment are not directly observed in the secondary data but are inferred from industry sources (see Web Appendix E and Web Appendix F).

Table 2 provides descriptive statistics on all 1,698 influencers, as well as mean values for each influencer type, including nano-, micro-, and macro-influencers. Concerning the number of followers at the point in time of the actual sponsored posting, our data set covers a broad range, from influencers with 1,219 followers to those with 1.4 million followers (mean = 52,849; median = 19,004). We classify influencers according

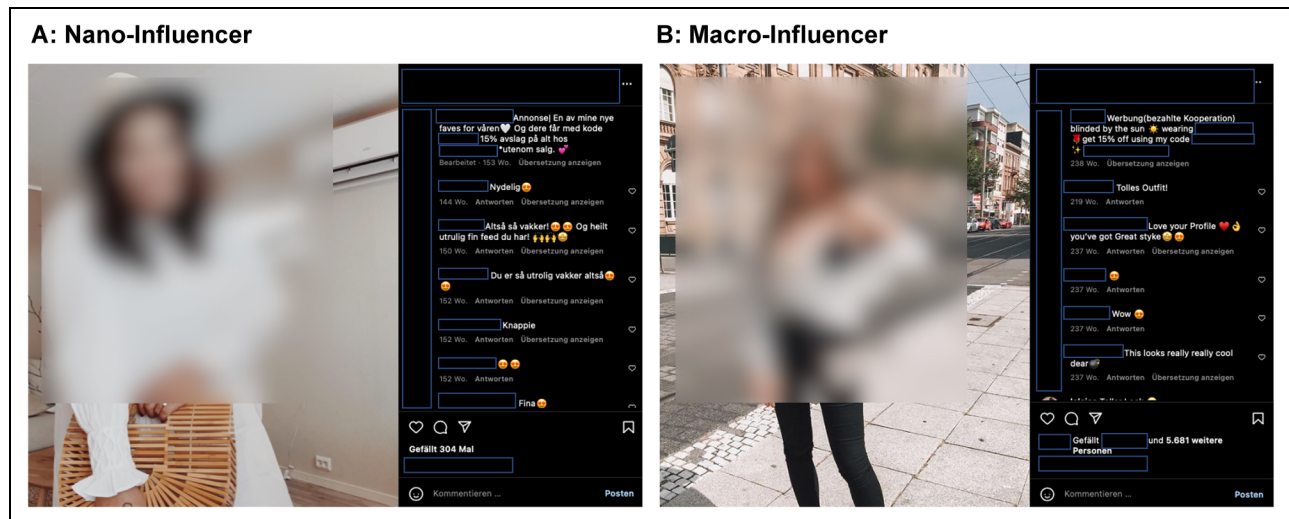


Figure 1. Examples of Feed Posting with an Influencer-Specific Discount Code.

to the distribution of number of followers in the data set; hence nano-influencers are the bottom 25% (first quartile) and macro-influencers are the top 25% (4th quartile), with micro-influencers making up the middle 50% (2nd and 3rd quartiles). More specifically, nano-influencers have between 1,219 (minimum) and 8,496 (first quartile) followers, and macro-influencers have between 49,845 (third quartile) and 1.4 million (maximum) followers; their mean number of followers amounts to 5,034 and 160,740, respectively. Concerning revenue per follower in euros, the revenues lie between 0 and 23 (mean = .117; median = .030), and the mean revenue per follower for nano-influencers is higher by one order of magnitude than that of the macro-influencers, that is, .265 versus .049. In fact, when exploring the relationship between influencer followership levels and revenue per follower, we find a monotonically decreasing pattern across the three influencer types, that is, from .265 (nano-influencers) to .080 (micro-influencers) to .049 (macro-influencers). The same holds true for revenue per reach (.881 to .305 to .237) and ROIS (17.85 to 5.98 to 4.67).¹

We demonstrate model-free evidence of the superiority of nano-influencers with respect to revenue relative to cost in a funnel comparison (see Figure 2). We observe a monotonically decreasing pattern from nano- to macro-influencers.

We analyzed data in other contexts (entertainment and gaming) as well as on other user-generated content networks such as YouTube and TikTok (see Appendix A) and found the exact same pattern. This contradicts the common (mostly implicit) assumption in the seeding literature in marketing that this pattern is increasing instead of decreasing (e.g., Hinz et al. 2011).

The findings from Table 2 provide new supportive evidence that low-followership targeting outperforms high-followership targeting in terms of ROI. Above and beyond this finding, we

expect that engagement—that is, follower and influencer engagement *before* the sponsored posting—must mediate this relationship between the number of followers and ROI. We focus on the five postings before the sponsored posting to capture a campaign-independent measure of engagement between the influencer and their followers.

For this engagement—that is, the engagement *before* the sponsored post—we divide, on the one hand, the total number of the followers' comments and likes by the influencer's number of followers ("follower engagement") and, on the other hand, the total number of the influencer's replies by the influencer's number of followers ("influencer engagement"). Note that influencer engagement does not include likes, as the influencer engages just through comments with the followers and is always simply replying to the follower's comments as well as to the comments on comments, and so forth; hence we use the term "replies" instead of "comments" for influencers. Also note that both engagement measures incorporate the mean engagement on these five postings—that is, the number of likes and comments (and replies in the case of "influencer engagement")—divided by the mean number of followers; thus five (time-varying) values go into the numerator and denominator, namely from the respective five posting dates. Hence, we take a granular, dynamic approach when measuring the mediators.

Table 2 shows that the influencer engagement before the sponsored posting by the nano-influencers is on average higher by one order of magnitude than that of macro-influencers, that is, .003 versus .0001. Concerning the follower engagement, we find the same pattern: for nano-influencers it is one order of magnitude higher, that is, .147 versus .058. Consider the example influencers from Figure 1: For the nano-influencer (Panel A), influencer engagement is .0018 and follower engagement is .0019. The macro-influencer (Panel B) shows an influencer engagement of .00017 and a follower engagement of .00059; hence the qualitative conclusion holds in terms of the order-of-magnitude difference.

¹ Note that the revenue per buyer is constant and without pattern across influencer type (110 to 119 to 117).

Table 2. Variable Description and Descriptive Statistics.

Variable Notation	Description of the Variable	Total Sample (n = 2,808)				Mean for Each Influencer Type		
		Mean	Median	Min.	Max.	Nano	Micro	Macro
Dependent Variables								
Revenue per follower	Revenue in euros achieved through the discount code shared by an influencer divided by the number of followers	.117	.030	0	23	.265	.080	.049
Revenue per reach	Revenue in euros achieved through the discount code shared by an influencer divided by the number of followers who actually saw the sponsored posting (see Web Appendix E)	.429	.117	0	75	.881	.305	.237
ROIS	Return on influencer spend = (Revenue – Cost)/Cost (see Web Appendix F)	8.552	1.658	–.999	1,590	17.850	5.977	4.668
Independent Variable								
Followers	Number of followers (indegree) the influencer had on the day of the sponsored posting	52,849	19,044	1,219	1,399,480	5,034	22,135	160,740
Mediator Variables								
Follower engagement	(Number of likes + Number of comments by followers)/Number of followers (on the five postings before the sponsored posting)	.088	.063	.0004	2.269	.147	.073	.058
Influencer engagement	Number of replies/Number of followers (on the five postings before the sponsored posting)	.001	.0003	.000	.047	.003	.001	.0001
Control Variables								
Influencer characteristics								
Following	Number of outdegree connections of an influencer	1,068	750	15	7,502	1,082	1,215	759
Media count	Total number of feed postings on the influencer's Instagram profile before ad posting	710	488	7	5,962	398	716	1,000
Days on platform	Days between the ad posting and the influencer's first feed post	1,715	1,706	1	3,769	1,643	1,691	1,834
Interest in focal brand	Postings mentioning focal brand	11	5	1	254	7	12	13
Sponsored postings	Number of sponsored postings	123	49	0	1,615	49	121	197
Tone in previous postings	LIWC (Linguistic Inquiry and Word Count) tone of the five postings before the sponsored posting	54	50	17	99	50	54	55
Beauty score	Score generated by training a convolutional neural network model based on the SCUT-FBP5500 database to predict the beauty score of the influencers	2.167	2.161	1.213	3.442	2.164	2.160	2.183
Follower characteristics								
Followers' age	Average age of followers	27	27	20	36	26	28	27
Female followers	Share of female followers	.604	.602	.070	.976	.589	.595	.639
Caucasian followers	Share of Caucasian followers	.821	.831	.414	.976	.849	.817	.802

(continued)

Table 2. (continued)

Variable Notation	Description of the Variable	Total Sample (n = 2,808)				Mean for Each Influencer Type		
		Mean	Median	Min.	Max.	Nano	Micro	Macro
Fashion focus	Fashion interest of followers (1 = highest, 10 = lowest)	1.492	1	1	10	1.282	1.477	1.726
Home country focus	Share of followers in the influencer's home country	.396	.389	0	.936	.441	.390	.365
Geographic/demographic overlap	Gini index of geographical closeness to the influencer (0 = geographically spread apart, 1 = geographically concentrated)	.471	.492	.040	.725	.517	.462	.444
Sponsored/nonsponsored comparison	Difference between engagement rate of the five (nonsponsored) postings and the sponsored posting (neg. = sponsored content is better, pos. = nonsponsored content is better)	.002	.001	-.274	.839	-.004	.003	.007
Follower activity	Activity score (based on past liking and commenting behavior, and time spent on platform) of followers provided by Instagram API	.650	.670	.120	.960	.730	.619	.632
Posting characteristics								
Likes	Number of likes on sponsored posting	2,805	1,010	75	136,863	637	1,355	7,813
Comments	Number of comments by the followers on sponsored posting	64	40	0	10,058	52	53	98
Replies	Number of comments by the influencer on sponsored posting	17	8	0	253	17	18	15
Discount	Discount amount the code allowed (15%, 20%, 25%, 30%)	.200	.200	.150	.300	.193	.198	.209
Posting length	Character count of posting length of the sponsored posting	334	247	19	4,732	303	362	306
Tone of ad	LIVC tone of sponsored posting	56	59	7	99	53	57	58
Visual complexity	Approximated by the number of kilobytes	2×10^{-5}	2×10^{-5}	0	2×10^{-4}	2×10^{-5}	2×10^{-5}	2×10^{-5}
Visual balance	Euclidean distance symmetrical	114	115	32	177	112	115	115
Image clarity	Extent to which the image conveys clear (vs. dull) colors	.442	.423	.019	.984	.437	.448	.435
Image sharpness	Amount of detail an image produces	2,316	1,787	102	15,269	2,276	2,333	2,319
Face shown	One or multiple faces shown in the image	.812	1	0	1	.795	.806	.839

Notes: We also control for the following four nonnumerical variables: campaign focus area (Benelux, DACH [Germany, Austria, Switzerland], Mediterranean, Nordic, other), whether the influencer posted during the weekend, the time of day that the influencer posted, and the period of year the influencer posted. Nano-influencers are the influencers from the lowest quartile w.r.t. to followers, macro-influencers are the ones from the highest quartile, and micro-influencers are the ones in between.

To limit the influence of confounding variables on ROI, we include a range of influencer characteristics, follower characteristics, and posting characteristics as control variables (see Table 2 for more details of the variables and how they were measured): (1) following, (2) media count, (3) days on platform, (4) interest in focal brand, (5) sponsored postings, (6) tone in previous postings, (7) beauty score, (8) followers' age, (9) female followers, (10) Caucasian followers, (11) fashion focus, (12) home country focus, (13) geographic/demographic overlap, (14) sponsored/nonsponsored comparison, (15) follower activity, (16) likes, (17) comments,

(18) replies, (19) discount, (20) posting length, (21) tone of ad, (22) visual complexity, (23) visual balance, (24) image clarity, (25) image sharpness, (26) face shown, (27) campaign focus area, (28) weekend, (29) time of day, and (30) time of year. For the correlation matrix of these variables, see Appendix B.

Analysis

To investigate the mechanism underlying the superior performance of low-follower targeting, we conduct a mediation

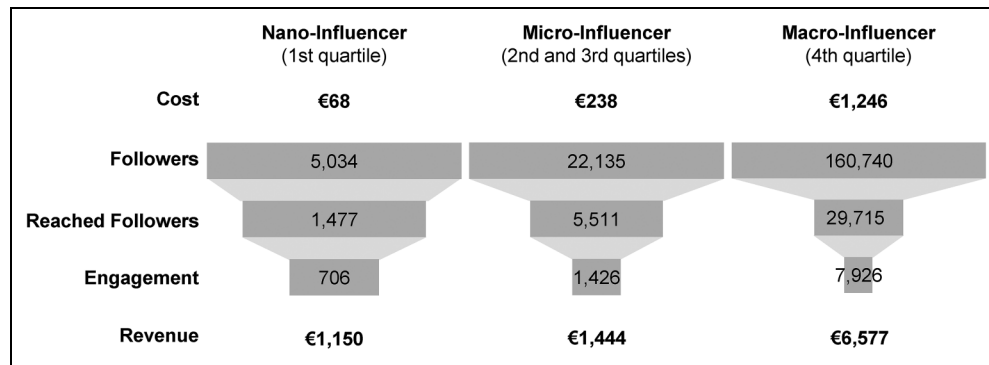


Figure 2. Funnel Comparison of Nano-, Micro-, and Macro-Influencers.

Notes: Engagement is the number of likes, comments, and replies.

analysis with two mediators in parallel² (e.g., Xu, Mehta, and Dahl 2022): the follower and influencer engagement. Note that we focus on revenue per follower, because the mechanism underlying the superiority is most likely independent of the costs for the paid endorsement. Nevertheless, for robustness, we run the models also with the two other ROI metrics, that is, with ROIS (which accounts for costs) as well as revenue per reach (which accounts for inactive followers and the impact of Instagram's algorithm, such that it only considers the followers who viewed the sponsored posting).

First, we run a total-effect model by including the (log-transformed) number of followers as the independent variable and the (log-transformed) revenue per follower as the dependent variable (see Figure 3). Note that we use the full data set with 2,808 influencer-specific discount codes attributing 1,881,533 sold products (totaling more than €17 million in revenue) to 2,808 sponsored postings on Instagram by 1,698 influencers. Also note that we include the full range of influencer-, follower-, and posting-related control variables (see Table 2).

Then we run a bootstrapped parallel mediation model, providing a robust way to test the significance of the indirect effects (e.g., Xu, Mehta, and Dahl 2022), using as parallel mediators the follower and influencer engagement on the five postings before the sponsored posting (see Figure 3). Again, we use the full data set and include the full range of influencer-, follower-, and posting-related control variables for the mediation model (see Table 2).

Results

When running the total-effect model including all control variables, we find a significant negative association between the (log-transformed) number of followers and the (log-transformed) revenue per follower: the total effect is -0.453 ($p < .01$). This finding is in line with the monotonically decreasing pattern across

the three influencer types (see Table 2), from €0.265 (nano-influencers) to €0.080 (micro-influencers) to €0.049 (macro-influencers).

When we run the parallel mediation model using the bootstrapping procedure (Hayes and Preacher 2013) including all control variables, the previously significant and negative total effect becomes closer to zero: the direct effect is -0.297 ($p < .01$). The parallel mediation analysis reveals that the effect of the number of followers on revenue per follower is partially mediated by follower engagement and influencer engagement, since the direct effect of the number of followers on the revenue per follower becomes closer to zero but stays significant. In Appendix C we illustrate the coefficients for all included control variables, which we discuss in more detail in Web Appendix G.

To better understand this result, we calculate the indirect effects (mediating effects) of the number of followers on the revenue per follower via the two mediators. A bootstrap confidence interval of the total indirect effect obtained by resampling the data 1,000 times (with number of followers as the independent variable, follower engagement and influencer engagement as the mediators, and revenue per follower as dependent variable) did not include zero (engagement = -0.156 , 95% confidence interval [CI] = $[-0.163, -0.107]$). Notably, the two indirect effects are also significant (follower engagement = -0.133 , 95% CI = $[-0.171, -0.135]$; influencer engagement = -0.023 , 95% CI = $[-0.042, -0.007]$). Hence, the mediation path for follower engagement contributes 85% to the total indirect effect, and the mediation path for influencer engagement 15%, accordingly.

The mediating effects become even stronger when replacing the dependent variable of revenue per follower with the two other ROI metrics, namely the revenue per reached follower (see Table 3, Model 2) and ROIS (see Table 3, Model 3), providing robustness of the findings. Across Models 1 to 3, engagement can explain the negative relationship between the number of followers and ROI.³ Even though from Model 1 to Model 3 the indirect effects become much stronger, the proportion and hence the contribution of the two mediation paths (follower

² Both mediators are tested simultaneously as potential explanations for the relationship between the independent and dependent variables. This type of analysis can provide insights into the underlying mechanism through which the independent variable affects the dependent variable.

³ Concerning revenue per buyer, we do not observe a significant relationship between the number of followers and the revenue per buyer.

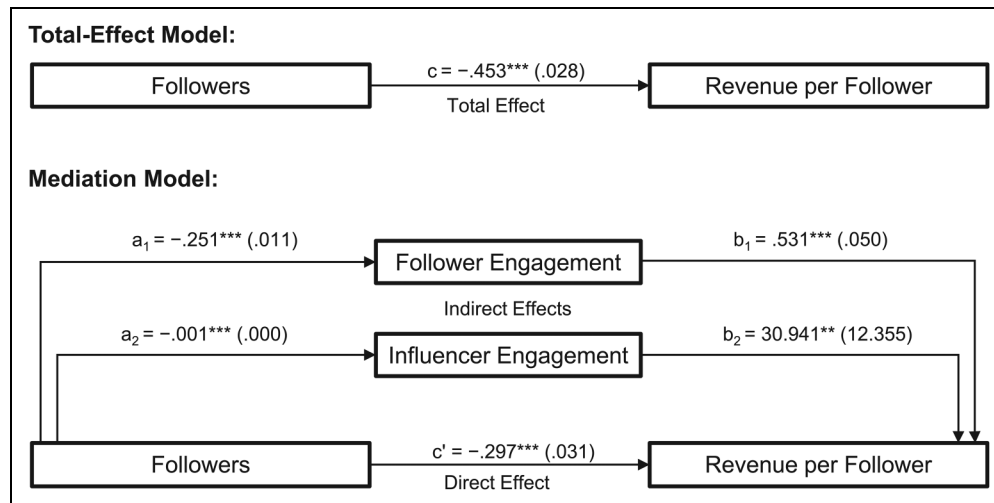


Figure 3. Total-Effect and Mediation Models for Revenue per Follower.

Notes: Standard errors are in parentheses. All models include the full range of influencer-, follower-, and posting-related control variables.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

and influencer engagement) to the indirect effects stay roughly the same. We also test for multicollinearity: the values of the variance inflation factor across Models 1 to 3 are all below four, which meets the threshold of less than five (Gareth et al. 2013).

Note that the revenue per reached follower incorporates effects of Instagram's algorithm, whose invisible hand sometimes allocates more or fewer views to a certain posting (Haenlein et al. 2020). By looking at the revenue per reached follower, we incorporate this difference and can thus rule out the possibility that our results are driven by Instagram's algorithm. Looking at reached followers also accounts for potential tie inactivity. ROIS demonstrates a further perspective on the generalizability of our findings by accounting for costs of paid endorsements.

To provide additional robustness we conducted 12 robustness checks regarding four different follower-engagement metrics in our mediation models, which we test with each of the three considered dependent variables (i.e., revenue per follower, revenue per reach, and ROIS, hence 12 robustness checks). These four follower-engagement metrics are based on comments and likes, where we categorize comments as either positive or negative (around 70% of comments are positive). First, instead of adding up the number of likes and comments, we add up only likes and *positive* comments. Second, we use only the number of likes, and, third, we use only the number of comments. For all these three new metrics, the qualitative conclusions of the mediation models stay the same. Fourth, we also use the number of likes and comments as two separate mediators. While we still find a significant mediation, the comments mediator is significant (only) at the .15 level (see Web Appendix H).

A potential bias is a self-selection bias as a result of influencers who choose to work with a firm, which can limit the generalizability of the influencer's audience and the impact

of the firm's marketing efforts. To examine this self-selection of influencers into working with the focal firm, we closely follow the marketing literature using propensity score matching (e.g., Deng, Lambrecht, and Liu 2022; Kumar et al. 2016) and show that when matching (quartile-split), via advanced covariate-balancing-propensity-score matching (Imai and Ratkovic 2014), low-follower-ship influencers with high-follower-ship influencers, the former significantly outperform the latter across all ROI metrics (revenue per follower: $\beta = -8.739$, $SE = .353$, $p < .001$, $R^2 = .440$, adjusted $R^2 = .439$; revenue per reached follower: $\beta = -29.104$, $SE = 1.117$, $p < .001$, $R^2 = .438$, adjusted $R^2 = .437$; ROIS: $\beta = -620.160$, $SE = 25.11$, $p < .001$; $R^2 = .438$, adjusted $R^2 = .437$). The results point to the same direction as in our total-effect and mediation models (see Web Appendix I for details). Furthermore, to rule out biases concerning the type of products sold, we find that the average price for items sold is the same across followership levels and ranges between €27.16 and €28.15. This suggests that there are no differences in products sold (in terms of their price and thus revenues).

Therefore, our findings from the empirical investigation are twofold: First, low-follower-ship targeting outperforms high-follower-ship targeting by order of magnitude. Second, a parallel mediation analysis reveals that engagement can explain the negative relationship between number of followers and three relevant ROI metrics.

Additional Evidence for Engagement: Textual Analyses

Linguistic Inquiry and Word Count (LIWC) categories across followership levels. For all five influencer postings before the sponsored posting (in analogy to the mediators), we analyze the followers' comments and the influencers' replies. These

Table 3. Total-Effect and Mediation Model.

	Model 1		Model 2		Model 3	
	Revenue per Follower		Revenue per Reach		ROIS	
	log(Revenue/Followers)		log(Revenue/Reached Followers)		log((Revenue – Cost)/Cost + 1)	
	No Mediators	With Mediators	No Mediators	With Mediators	No Mediators	With Mediators
Follower	–.453***	–.297***	–.332***	–.175***	–.303***	–.147***
Mediators Included						
Follower engagement	No	Yes	No	Yes	No	Yes
Influencer engagement	No	Yes	No	Yes	No	Yes
Control Variables						
Influencer characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Follower characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Posting characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,808	2,808	2,808	2,808	2,808	2,808
R ²	.319	.350	.273	.307	.262	.296
Adjusted R ²	.310	.341	.263	.297	.252	.286
Res. std. error	1.393	1.361	1.395	1.363	1.393	1.361
F-statistic	35.101***	38.293***	28.112***	31.386***	26.596***	29.841***

*p < .1.
 **p < .05.
 ***p < .01.

570,603 comments and 136,714 replies came in 16 different languages, which we translated to English. On the translated comments and replies, we use the English version of the LIWC dictionary (Boyd et al. 2022; Pennebaker, Francis, and Booth 2001). LIWC is a dictionary-based text classification method and is regularly used in marketing research (see Hartmann et al. 2019).

Since we expect (and find) a lower engagement with higher number of followers, we would also expect shorter comments by followers and shorter replies by influencers (i.e., a lower word count), as well as lower information richness (i.e., fewer words per sentence). Similarly, with a higher number of followers and thus lower engagement, we would expect such influencers to show decreased values with respect to the LIWC word categories of “emotional tone,” “authenticity,” “personal pronouns,” “social processes” (i.e., social behavior and social referents), “affect,” “positive emotions,” “affiliation,” and “net-speak” (i.e., conversational language).

We assess whether this expectation holds between the number of followers of an influencer and the respective LIWC category with a regression on the aggregated five postings (for each posting we calculated the median value of the respective LIWC category), while including the full range of influencer- and follower-related control variables (see Table 2):

$$\text{LIWC category} = \text{constant} + \beta_1 \log(\text{number of followers}) + \text{controls} + \epsilon.$$

Indeed, the regression results confirm our expectations (see Table 4), at least when considering the followers’ comments. Influencers seem to communicate rather similarly across followership levels, as most of the coefficients are either insignificant or do not reveal a clear pattern (see right column of Table 4). Also, in the descriptive data we see differences in how many comments the postings receive across influencer followership levels, but not with respect to how many replies there are (see Table 2). Therefore, the reply behavior of influencers across followership levels seems to be rather stable in absolute terms with respect to how many replies they write and how they write these replies.

In line with the main contributing mediator, namely follower engagement, of our mediation analysis, it is the followers of lower followership levels who indicate significantly more signs of authentic and positive language in their commenting behavior compared with higher followership levels. Additional indicators pointing in the same direction in a significant way are the LIWC categories “word count,” “words per sentence,” “personal pronouns,” and “social processes.” This provides additional evidence for the higher engagement and social interactions in the form of more personal relationships of followers of low-followership influencers with the influencer.

LSM between influencers and followers. Everyone has a unique language style, which is less about what we say (i.e., the content) and more about how we say it. According to

Table 4. Textual Analysis of Follower Comments and Influencer Replies.

LIWC Categories	Expectation	Follower Comments (n = 570,603)	Influencer Replies (n = 136,714)
Word count	↓	-.10***	.02
Words per sentence	↓	-.07***	.04
Emotional tone	↓	-.46***	-1.91***
Authenticity	↓	-1.53***	.66
Personal pronouns	↓	-.46***	-.07
Social processes	↓	-1.02***	-2.54***
Affect	↓	-.13***	-1.03
Positive emotions	↓	-.26***	.59***
Affiliation	↓	-.04***	.10***
Netspeak	↓	-.09***	.61***

* $p < .1$.** $p < .05$.*** $p < .01$.

Humphreys and Wang (2018), the matching of language styles between two individuals is necessary for the development of social relationships. To assess the degree of LSM, we analyze the similarity between followers' comments and influencers' replies based on the well-established LSM metric (Gonzales, Hancock, and Pennebaker 2010). Following the formula for calculating LSM (Ireland and Pennebaker 2010), for each influencer, we calculate the relative similarity in the use of eight function word categories between the followers' comments and the influencers' replies across the previous five postings. For example, for the function word category of prepositions, for each influencer i we calculate:

$$LSM_{i, prep} = 1 - \frac{|\text{prep}_{\text{follower comments}} - \text{prep}_{\text{influencer replies}}|}{\text{prep}_{\text{follower comments}} + \text{prep}_{\text{influencer replies}} + .0001}$$

We then average across the eight function word categories to create a composite measure of LSM for each influencer:

$$LSM_i = \text{avg}(LSM_{i, prep} + LSM_{i, article} + LSM_{i, auxverb} + LSM_{i, adverb} + LSM_{i, conj} + LSM_{i, ppron} + LSM_{i, ipron} + LSM_{i, negate})$$

If, as we expect (and find), there is greater closeness and cohesiveness between followers and influencers with lower followership levels, we would also expect a higher LSM above and beyond purely writing about the same content.

Indeed, the LSM metric for nano-, micro-, and macro-influencers is .886, .868, and .855, respectively. Nano-influencers show significantly higher LSM than micro-influencers ($p = .023$) and macro-influencers ($p < .01$). We further find that the level of LSM is positively, albeit not highly significantly, correlated with all our dependent variables ($\text{corr} = .03$; $p > .1$). Note that this may be due to the comments

on Instagram generally being short, which makes it challenging for LSM to always detect similarities. In line with the LIWC category results, this finding further illustrates the more personal relationship expressed in the engagement of the low-followerhip influencer and their followers.

Discussion

Looking at secondary data with a large number of influencers across followership levels to compare the two seeding policies, we find that macro-influencers in our data have 32 times more followers but generate only about four times as much revenue. Consequently, the revenue per follower is five times higher for nano-influencers: .265 versus .049 (see Table 2). We demonstrate this superiority across three ROI metrics, including ROIS, which accounts for costs of paid endorsements.

Even though we try to control for all potentially relevant outside factors, endogeneity still poses a threat to our results. The main difference from the secondary data is that in the field studies we can hold many variables constant. Some of them we can control for only in the secondary data and only to a certain degree. For example, in the secondary data, we cannot control for (1) influencers posting the specific content on other social media channels such as YouTube, TikTok, or Snapchat. We cannot control for (2) the timing dimension in a clean way; in particular, it could be that at the time of the sponsored posting, the e-commerce store had more interesting products available. Furthermore, we cannot control for (3) whether discount codes are publicly shared on third-party websites (e.g., deal-sharing platforms). We cannot fully (although we try to) control for (4) the text and visuals of the sponsored postings. And, most importantly, we cannot exactly control for (5) the products advertised.

The purpose of the next section is to rule out these alternative explanations in a controlled environment with three field studies, namely, not to allow for influencer cross-posting, prevent dissemination on deal-sharing platforms, keep the timing in terms of posting period the same for all, and provide a discount code only for a specific set of products with a short expiry time.

Low- Versus High-Followerhip Targeting: Three Field Studies

This section consists of three field studies—in full-fledged field settings—and provides robustness concerning the superior performance of low-followerhip targeting. The effects replicate across different settings, while we controlled for relevant factors, as outlined previously. We ran a total of three field studies in which the settings varied in terms of product domain, brand, freedom of content creation, followership levels, payment, and attribution to sales. In the first study, we kept everything constant except for the number of followers. In the second study, we allowed for some freedom in content creation to make it more realistic. Finally, in the third study, we allowed for full freedom in content creation.

We again collaborated with DTC firms to obtain information on the entire funnel, that is, one in the domain of fashion (consistent with the empirical investigation; Studies 1 and 2) and a second in the domain of beauty (Study 3). These two domains are the most prominently advertised on Instagram (Haenlein et al. 2020).

In the field studies, sales are attributed in two different ways: influencer-specific discount codes that followers can use in the respective firm's e-commerce store (consistent with the empirical investigation; Studies 1 and 2) and personalized UTM tracking URLs (i.e., influencer-specific swipe-up links) that point to that store, which reduce conversion friction (Study 3).

Overview of the Field Studies

Study 1. In the first field study (fashion domain), we provided influencer-specific discount codes that worked for only two days, limiting the risk of it being shared throughout the internet. Also, the goal was to keep the content of the sponsored postings practically the same across all participating influencers. For this reason, the briefing instructions for the influencers were to not show their face in the posting. DeBono and Telesca (1990) demonstrated that attractiveness of the source of an advertising message matters. By not showing the face, we wanted to limit its influence altogether.

Study 2. In the second field study (also in the fashion domain), we again provided influencer-specific discount codes but relaxed the setting to be more realistic by having sponsored postings with the influencers' faces present.

Study 3. In the third field study (beauty domain), we investigate another type of attribution to sales—that is, influencer-specific swipe-up links, which reduce conversion friction—but without a discount code. This enables followers to go directly from an influencer's posting to the respective firm's e-commerce store. At the time of the experiment, the swipe-up feature was available only for influencers starting at 10,000 followers, which is why our low-follower influencers have considerably more followers in this last field study (and are thus more professional). Once more, we had sponsored postings with the influencers' faces present, but in addition, we asked

participating influencers to use the beauty product and show a before/after effect. For details of the timeline and execution of Studies 1, 2, and 3, see Appendix D and Web Appendix J.

Data

We collaborated with two major influencer-marketing platforms (specialized third-party service and data providers), one for Studies 1 and 2 and a second for Study 3. This allowed us to take a bird's-eye view and consider all available influencers in a given country market, that is, in Germany for Studies 1 and 2 and in the United Kingdom for Study 3.

In the field studies we granted access only to influencers in the campaign from the bottom 25% (low-follower influencers) and the top 25% (high-follower influencers) on the respective influencer-marketing platform. Note that in Study 3, we established a lower boundary and considered only influencers with a minimum of 10,000 followers to be able to use the swipe-up link, which at that time was available on Instagram only for influencers with at least 10,000 followers. This also remedies the critique of choosing less professional and hence less mature influencers. Nevertheless, especially in smaller country markets, marketers heavily rely on low-follower influencers with less than 10,000 followers (which is covered in Studies 1 and 2).

Therefore, in Studies 1 and 2 the average number of followers of participating low-follower influencers is lower (see Table 5), at 1,009 ($n=68$) and 1,863 ($n=60$) respectively, whereas in Study 3 it is higher, at 11,481 ($n=36$). Concerning high-follower influencers, the average number of followers is 57,450 ($n=70$), 71,459 ($n=54$), and 50,142 ($n=31$) for Studies 1, 2, and 3. Whereas in Studies 1 and 2, the high-follower influencers have around 40 to 50 times the followers of the low-follower influencers, in Study 3, high-follower influencers are bigger by a factor of around four to five. In total, there are 319 low- and high-follower influencers in the three field studies.

We applied a "first-come, first-served" principle after using the respective influencer-marketing platform to contact 1,472, 5,272, and 810 low-follower influencers as well as 1,763, 4,557, and 1,177 high-follower influencers for Studies 1, 2, and 3, respectively. Note that we find no structural differences

Table 5. Overview of the Three Field Studies.

Study	Industry	Campaign Focus	Network and Type	Time Period	Market	Low-Follower Influencers			High-Follower Influencers		
						n	Mean Follower	Mean Compensation	n	Mean Follower	Mean Compensation
1	Fashion	Sneaker	Instagram Story	June 2020	Germany	68	1,009	€20	70	57,450	€60
2	Fashion	Sneaker	Instagram Story	October 2020	Germany	60	1,863	€30	54	71,459	€60
3	Beauty	Makeup	Instagram Story	June 2021	UK	36	11,481	£250	31	50,142	£850

among the influencers due to the “first-come, first-served” principle (see Web Appendix K for details and Web Appendix L for sample campaign material). Eventually, a total of 319 influencers participated and were compensated accordingly.

As compensation, the respective firms provided influencers with a voucher for their e-commerce store, which varied according to the influencer type. For Studies 1 and 2, we followed market compensation on the focal platform, and for Study 3, we adopted the collaborating company’s typical compensation for low-follower influencers (see Table 5). Compensation levels in Study 3 were also higher, because of higher requirement (i.e., show before/after effect, three stories instead of just one, and video content instead of only an image). To clearly attribute the sold products, each influencer received an influencer-specific discount code that followers could use in the respective firms’ e-commerce store (Studies 1 and 2) and an influencer-specific swipe-up link that pointed to that store (Study 3 only). Hence, the funnel does not end with the engagement with the sponsored posting after viewing; it continues to a landing in the brand’s e-commerce store and eventually to the purchase of a product in it.

Analysis

For all three field studies, we calculate the mean revenue per follower for both low- and high-follower influencers. Additionally, the number of reached followers was made available to us by the influencers, because it was a condition in the briefing instruction to share this (private) information through a screenshot with us.

Results

In Study 1, in which we provided influencer-specific discount codes, targeting low-follower influencers results in mean revenue per follower of .008, compared with only .00007 when targeting high-follower influencers. In Study 2 (the more realistic setting with the influencers’ faces present in the sponsored postings), targeting low-follower influencers results in mean revenue per follower of .007, compared with .0001 when targeting high-follower influencers. Finally, in Study 3, in which we provided influencer-specific swipe-up links—but without a discount code—the mean revenue per follower amounts to .001 (low-follower influencers) versus .00006 (high-follower influencers). As a conclusion, we find across all field studies at least an order of magnitude difference.

Note that in these field studies, the revenue per follower is smaller than in the secondary data. A plausible explanation is that we collaborated with lesser-known brands compared with the globally known brand in the secondary data. Consistently, the results reveal a decreasing pattern from low- to high-follower influencers, that is, from .008 to .00007 in Study 1, from .007 to .0001 in Study 2, and from .001 to .00006 in Study 3. In fact, low-follower targeting is superior by a factor of 114 (Study 1), 70 (Study 2), and 17 (Study 3). From

this we learn that in our field study data, €1 invested in low-follower influencers leads to revenues per follower that are between 17 and 114 times higher than that generated through high-follower influencers.

A one-tailed Welch’s unequal variances t-test provides a *p*-value of less than .001 for all three field studies, and hence the differences in all three field studies are highly significant. To add further robustness to these findings, we determine the bias-corrected bootstrap confidence interval obtained by resampling the mean differences in revenue per follower for low- and high-follower influencers 1,000 times. For Study 1 the mean difference estimate for revenue per follower is .009 (bias-corrected 95% CI = [.004, .015]), for Study 2 the mean difference estimate for revenue per follower is .007 (95% CI = [.003, .011]), and for Study 3 the mean difference estimate for revenue per follower is .001 (95% CI = [.000, .002]).

In summary, in these field studies we held the following constant: (1) we did not allow for cross-posting on other social media channels; (2) we checked that the codes were not appearing on major third-party websites; (3) sponsored postings had to appear at the same time, where all the coupon codes had the same expiry date (the coupon codes were also just for a specific set of products); (4) content creation of image and text were gradually relaxed and in the hands of the influencer; and (5) the exact same product was in place to be advertised. To compare more or less stylized settings, in the first study we kept everything constant except for the number of followers. In the second study we allowed for some freedom in content creation to make it more realistic. Finally, in the third study we allowed for full freedom in content creation.

Reviewing these findings from the three field studies, we can conclude that consistently across different settings, the evidence leads to the same conclusion as the empirical evidence: low-follower targeting is superior (while keeping in mind that we had to pay the high-follower influencers at least three times more than the low-follower influencers in the three field studies).

Discussion

We contribute to the seeding literature by considering that follower levels and the level of engagement between the influencer and their followers matter for influencer marketing in the realm of DTC firms. Their main objective is revenue generation, namely direct consumer response. We find that such firms can achieve the highest ROI if they target low-follower influencers, or nano-influencers. In fact, our consistent result is that such nano-influencers provide a significantly better ROI than macro-influencers, by order of magnitude across empirical and field evidence.

Hence, when deliberating where to invest the first euro, it should be in the most profitable influencer type, which is nano-influencers. But this applies not just to the first euro; also the second and all further euros should be invested in nano-influencers until the budget is exhausted (see Web Appendix D).

To the best of our knowledge, we are the first to conduct a supply-side, full-fledged, field study comparison of seeding policies for paid influencer endorsements, in addition to analyzing secondary revenue data. This highly managerially relevant comparison helps resolve controversies about whether macro-influencers make use of their greater reach, and whether they are more persuasive when it comes to the purchasing decision.

The foundation for this comparison is influencer-level data, which marketers nowadays have access to: User-generated content networks such as Instagram make information available on influencers' follower characteristics. Specialized third-party service and data providers (i.e., influencer-marketing platforms) may also support marketers with more social-network information for further identifying the level of engagement between the influencer and their followers. These influencer-marketing platforms enable marketers to work with hundreds of low-follower influencers at the same time and efficiently leverage their potential at the labor cost of handling only one high-follower influencer. In addition, our survey among senior influencer-marketing managers at DTC firms reveals that it is not difficult to locate and collaborate with influencers (see Web Appendix A for details).

This new approach to influencer marketing requires both access to data and a conceptual foundation. When attempting to make the clean attribution to sales, marketers need to consider the whole influencer-marketing funnel, that is, from followers (e.g., on Instagram), to reached followers (via the sponsored posting), to engagement (with the sponsored posting), to actual revenue. We find that across ROI metrics, nano-influencers consistently outperform macro-influencers.

Specifically, ROIS, which considers both revenue and costs, is more than three times higher (18) for nano-influencers compared with macro-influencers (5) (see Table 2). Even though the revenue is 6 times higher for macro-influencers, the associated costs are 18 times higher than for nano-influencers (see Figure 2).

In contrast to our empirical evidence pointing out the monotonic negative relationship between number of followers and ROI, in our three field studies we were, due to cost constraints, only able to compare the extremes (particularly in Studies 1 and 2). Future research should evaluate follower levels in between those we studied and determine if at certain thresholds, the engagement plummets and hence impacts revenue generation. In addition, and given that we consider paid influencer endorsements, further research is needed, first to understand influencer incentives when offering product gifting, fixed fees, or performance-based compensation and second to determine the impact of influencer briefings on the influencer campaign effectiveness. It is important to mention the unobserved cost structure as a potential limitation as, in general, the influencer's fees (i.e., marketer's costs) may correlate with the strength of influence on their followers (e.g., loyalty, engagement). Moreover, a long-term consideration of influencers in terms of customer lifetime value is needed and can explain the initial interest in a firm, along with the behavior of returning customers. Importantly, when the primary focus of the influencer-marketing campaign is not to generate immediate

revenues, which is the primary goal in a DTC context, but to promote awareness, using high-follower influencers probably still makes sense given their broader reach. The dynamics of awareness and revenue goals should be further elaborated on, as that social influence may vary greatly depending on what kind of influence should be exerted. Finally, user-generated content networks (e.g., TikTok) increasingly enable influencers to reach an audience that is not even following the influencer. These networks work with algorithms favoring quick signs of popularity, and they mostly tend to favor low(er) follower levels in their boosts (Lee, Hosanagar, and Nair 2018). Along these lines, future research should look at indirect effects, namely when postings travel further and create cascades of influence.

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ORCID iDs

Andreas Bayerl  <https://orcid.org/0000-0002-7248-5444>
Andreas Lanz  <https://orcid.org/0000-0003-2643-1960>

Appendix A: Additional Generalizability Through Supportive Evidence

We were able to collect secondary data also in other contexts (entertainment and gaming) and on other user-generated content networks (YouTube and TikTok).

An entertainment company used 120 German influencers with the goal of advertising a TV day pass. We median-split influencers with respect to the followers they have and found that the smaller ones, with 105,959 followers on average, generated a revenue per reached follower of €0.0030, while the bigger influencers, with 1,477,290 followers on average, generated only €0.0018 with each reached user.

Another company wanted to advertise a voucher card in Europe. We found that 12 small influencers had on average 91,558 subscribers, reached 21% of them, and generated €0.016 in revenue for each reached subscriber. The 13 biggest YouTubers in the data, with 900,000 subscribers on average, reached only 12% of them and generated €0.006 in revenue for each reached subscriber.

A fashion company worked with 11 TikTok influencers from Germany between 2020 and 2021 to advertise discount codes valid for the brand's entire e-commerce store. The five small influencers had on average 197,977 followers and generated €0.042 in revenue for each follower. The six biggest influencers in the data, with 634,320 followers on average, generated €0.005 in revenue for each follower.

These results add robustness to our finding that when it comes to generating sales, smaller influencers achieve more relative to the number of followers or subscribers they have. And this holds across different contexts (e.g., fashion, beauty, entertainment, gaming), across different user-generated content networks (Instagram, YouTube, TikTok), and across different content formats (story posting, feed posting, video posting).

Appendix B. Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30						
1 Revenue per follower	1																																			
2 Followers	-.05	1																																		
3 Follower engagement	.09	-.13	1																																	
4 Influencer engagement	.05	-.14	.37	1																																
5 Following	-.02	-.12	-.09	.06	1																															
6 Media count	-.06	.34	-.35	-.17	.11	1																														
7 Days on platform	-.02	.07	-.25	-.13	.04	.48	1																													
8 Interest in focal brand	-.02	.04	-.19	-.03	-.04	.14	.09	1																												
9 Sponsored postings	-.06	.15	-.31	-.11	-.01	.33	.19	.37	1																											
10 Tone in previous postings	-.04	.03	-.11	.03	-.00	.05	-.04	.11	.28	1																										
11 Beauty score	.01	.02	-.01	.01	.02	.00	-.02	-.02	-.01	.07	1																									
12 Followers' age	-.07	.01	-.38	-.05	.12	.29	.07	.14	.24	.17	.01	1																								
13 Female followers	.03	.09	.07	.01	-.05	.08	-.01	-.04	.02	.01	.01	-.34	1																							
14 Caucasian followers	.06	-.11	.17	.09	-.02	-.05	.01	-.05	-.10	-.03	.05	-.11	.18	1																						
15 Fashion focus	.01	.08	.02	-.12	-.05	.05	.04	-.12	-.05	.08	.06	-.02	.13	.13	1																					
16 Home country focus	.03	-.06	.10	-.02	-.04	-.03	.02	.03	.02	.06	.04	-.07	.03	.26	-.02	1																				
17 Geographic/demographic overlap	.06	-.12	.24	.02	-.08	-.13	.03	-.15	-.14	-.05	.02	-.32	.14	.48	.18	.25	1																			
18 Sponsored/non-sponsored comparison	-.28	.08	.18	.01	-.05	.02	-.03	-.02	-.02	-.01	-.03	-.02	.03	.01	.04	.02	.02	1																		
19 Follower activity	.08	-.02	.38	.10	.01	-.13	-.06	-.18	-.26	-.12	.05	-.42	.51	.46	.27	.14	.48	.00	1																	
20 Likes	-.02	.65	.14	-.11	-.11	.09	-.03	-.03	-.01	-.02	.02	-.13	.11	-.05	.11	-.02	.02	-.02	.10	1																
21 Comments	-.01	.20	.10	.04	.02	-.02	-.06	-.00	.01	.05	-.01	-.02	.01	-.00	-.01	-.01	-.02	.01	-.40	.40	1															
22 Replies	-.02	-.05	.08	.57	.07	-.09	-.11	.03	.03	.08	-.01	.11	-.03	-.04	-.10	-.06	-.12	-.07	-.07	.05	.11	1														
23 Discount	-.06	.09	-.11	-.07	-.04	.08	.14	.24	.19	.00	-.02	.01	.03	-.01	-.00	.02	.01	-.01	-.01	.07	-.02	-.04	1													
24 Posting length	-.05	-.07	-.08	.08	.04	.04	-.05	.13	.27	.43	.06	.24	.00	-.02	.09	-.00	-.09	-.01	-.18	-.08	.04	.18	.01	1												
25 Tone of ad	-.04	.03	-.10	.01	.01	.05	-.03	.07	.21	.45	.06	.17	.00	-.00	.08	.06	-.06	-.03	-.08	.01	.04	.06	.00	.35	1											
26 Visual complexity	-.01	-.01	-.00	.02	.08	.04	-.02	.03	.06	.10	.05	.05	.00	-.01	-.00	.01	-.06	.01	-.07	-.01	.01	.02	-.07	.16	.08	1										
27 Visual balance	.03	.01	.02	-.03	-.03	-.01	-.03	.00	.01	.03	.04	-.01	.02	.00	.02	-.02	.03	.01	.00	.02	.02	-.03	-.01	.01	.02	.08	1									
28 Image clarity	-.01	-.04	-.03	.00	-.01	.03	.04	-.00	.03	.02	-.03	.04	.05	.02	.01	-.01	-.01	.01	.00	-.03	.01	-.01	.02	.02	-.00	-.16	-.04	1								
29 Image sharpness	-.01	.01	.02	.02	.05	.04	-.03	.04	.05	.10	.05	.07	.02	-.02	-.01	.02	-.09	.02	-.07	-.01	.01	.02	-.07	.14	.09	.66	.05	-.16	1							
30 Face shown	-.03	.03	.02	.02	-.02	-.03	-.002	.03	.01	.05	-.21	-.00	-.05	-.01	.03	.01	-.01	-.04	-.05	.03	.04	-.04	.02	.03	.08	.07	.02	-.00	-.04	1						

Notes: All variables here are not logged. The four nonnumerical variables (campaign focus area, time of day when posted, weekend, period of year) are not included here.

Appendix C. Model I: Mediation Model for Revenue per Follower

	Dependent Variable			
	Revenue per Follower (Step 1)	Follower Engagement (Step 2A)	Influencer Engagement (Step 2B)	Revenue per Follower (Step 3)
Followers	-.453*** (.028)	-.251*** (.011)	-.001*** (.000)	-.297*** (.031)
Follower engagement				.531*** (.050)
Influencer engagement				30.941** (12.355)
Influencer Characteristics				
Following	-.197*** (.037)	-.114*** (.014)	-.000 (.000)	-.136*** (.037)
Media count	-.067 (.046)	-.053*** (.018)	-.000 (.000)	-.038 (.045)
Days on platform	.000 (.000)	-.000 (.000)	-.000 (.000)	.000 (.000)
Interest in focal brand	.128*** (.028)	-.008 (.011)	.000 (.000)	.131*** (.028)
Sponsored postings	-.136*** (.031)	-.147*** (.012)	-.000 (.000)	-.057* (.031)
Tone in previous postings	.002 (.002)	-.001 (.001)	.000** (.000)	.002 (.002)
Beauty score	-.097 (.086)	-.020 (.033)	.000* (.000)	-.093 (.084)
Follower Characteristics				
Followers' age	.018 (.013)	-.045*** (.005)	-.000 (.000)	.042*** (.013)
Female followers	.922*** (.186)	-.142** (.070)	.000 (.000)	.989*** (.182)
Caucasian followers	.590 (.463)	.483*** (.175)	.002** (.001)	.286 (.454)
Fashion focus	-.053* (.029)	.012 (.011)	-.000*** (.000)	-.056* (.028)
Home country focus	.176 (.114)	.079* (.043)	-.001*** (.000)	.151 (.111)
Geographic/demographic overlap	1.161*** (.235)	.263*** (.089)	-.000 (.000)	1.023*** (.230)
Sponsored/nonsponsored comparison	-1.420*** (.411)	2.350*** (.155)	.004*** (.001)	-2.792*** (.419)
Follower activity	.800*** (.252)	1.097*** (.096)	.001*** (.000)	.185 (.253)
Posting Characteristics				
Comments	.143*** (.032)	.324*** (.012)	.000*** (.000)	-.042 (.036)
Replies	-.025 (.021)	-.039*** (.008)	.001*** (.000)	-.025 (.022)
Discount	-7.315*** (.641)	-.424* (.242)	-.001 (.001)	-7.074*** (.627)
Posting length	-.027 (.047)	.038** (.018)	.000 (.000)	-.049 (.046)
Tone of ad	-.001 (.001)	-.001** (.000)	-.000 (.000)	-.000 (.001)
Visual complexity	-5,066.844 (3,643.521)	-1,378.665 (1,378.565)	4.115 (5.557)	-4,461.505 (3,561.393)
Visual balance	.000 (.002)	.001 (.001)	-.000 (.000)	-.000 (.002)
Image clarity	-.083 (.118)	-.036 (.045)	.000 (.000)	-.066 (.115)
Image sharpness	.096* (.050)	.082*** (.019)	.000 (.000)	.053 (.049)
Face shown	.006 (.071)	-.030 (.027)	.000 (.000)	.019 (.070)
Campaign focus area (omitted base reference category: Benelux)				
DACH region	.260*** (.085)	.239*** (.032)	-.000* (.000)	.140* (.084)
Mediterranean	-.745*** (.117)	.040 (.044)	-.000 (.000)	-.764*** (.114)
Nordic	.567*** (.092)	.192*** (.035)	-.000 (.000)	.468*** (.090)
Others	-.602*** (.191)	.010 (.072)	-.000 (.000)	-.594*** (.186)
Time of day when posted (omitted base reference category: afternoon)				
Evening	-.062 (.064)	-.037 (.024)	-.000 (.000)	-.039 (.063)
Morning	.070 (.070)	-.042 (.027)	-.000 (.000)	.093 (.069)
Night	.577** (.265)	.048 (.100)	-.000 (.000)	.558** (.259)
Weekend	-.062 (.059)	-.005 (.022)	-.000 (.000)	-.058 (.058)
Period of year (omitted base reference category: fall)				
Spring	.022 (.071)	-.079*** (.027)	.000 (.000)	.064 (.070)
Summer	-.185** (.076)	-.044 (.029)	.000 (.000)	-.165** (.074)
Winter	-.254*** (.076)	-.053* (.029)	-.000 (.000)	-.222*** (.074)
Constant	.975 (.748)	-.364 (.283)	.004*** (.001)	1.041 (.733)

(continued)

(continued)

	Dependent Variable			
	Revenue per Follower (Step 1)	Follower Engagement (Step 2A)	Influencer Engagement (Step 2B)	Revenue per Follower (Step 3)
Observations	2,808	2,808	2,808	2,808
R ²	.319	.609	.350	.350
Adjusted R ²	.310	.604	.341	.341
Residual std. error	1.393 (d.f. = 2,770)	.527 (d.f. = 2,770)	.002 (d.f. = 2,770)	1.361 (d.f. = 2,768)
F-statistic	35.101*** (d.f. = 37; 2,771)	116.605*** (d.f. = 37; 2,771)	40.297*** (d.f. = 37; 2,771)	38.293*** (d.f. = 39; 2,769)

* $p < .1$,** $p < .05$,*** $p < .01$.

Notes: The steps refer to Baron and Kenny (1986): Step 1 is the total-effect model. Step 2A and Step 2B are a regression of both parallel mediators against the number of followers and all controls. Step 3 is the mediation model, which is the full model, with number of followers, both mediators, and the controls. The following variables went into the model after taking the log: revenue per follower, followers, follower engagement, influencer engagement, following, media count, interest in focal brand, sponsored postings, comments, replies, posting length, image sharpness. To avoid multicollinearity, we exclude the number of likes on the ad, as this would cause a variance inflation factor above 10.

Appendix D. Timeline and Details of Execution of Field Studies

	Study 1		Study 2		Study 3	
Country	Germany		Germany		United Kingdom	
Industry (campaign focus)	Fashion (sneaker)		Fashion (sneaker)		Beauty (makeup)	
User-generated content network	Instagram		Instagram		Instagram	
Time period	June 2020		October 2020		June 2021	
Point of sale	E-commerce store		E-commerce store		E-commerce store	
	Time of Contact					
	June 9, 2020		October 14, 2020		May 18, 2021	
	Low-Followers	High-Followers	Low-Followers	High-Followers	Low-Followers	High-Followers
Number of influencers	1,472	1,763	5,272	4,557	810	1,177
	Time of Acceptance					
	June 11, 2020		October 18, 2020		May 28, 2021	
	Low-Followers	High-Followers	Low-Followers	High-Followers	Low-Followers	High-Followers
Number of influencers	70	73	70	70	56	43
	Time of Posting					
	June 11-13, 2020		October 18-25, 2020		June 11-26, 2021	
	Low-Followers	High-Followers	Low-Followers	High-Followers	Low-Followers	High-Followers
Number of influencers	68	70	60	54	36	31
Mean number of followers	1,009	57,450	1,863	71,459	11,481	50,142
	Time of Insights Reported					
	Before June 28, 2020		Before October 31, 2020		Before July 14, 2021	
	Low-Followers	High-Followers	Low-Followers	High-Followers	Low-Followers	High-Followers
Number of influencers ^a	68	19	60	54	24	23
Compensation (vouchers)	10€/20€	30€/60€	20€	60€	250€ + 10% commission on generated revenue	850€ + 10% commission on generated revenue

^aInfluencers reported their actual views on sponsored content via screenshot from their "Insights" on Instagram. For an overview of field studies, see Web Appendix J.

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