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Climb or Jump: Status-Based Seeding in User-Generated Content Networks

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Abstract

This article addresses seeding policies in user-generated content networks by challenging the role of influencers in a setting of unpaid endorsements. On such platforms, the content is generated by individuals and firms interested in self-promotion. The authors use data from a worldwide leading music platform to study unknown music creators who aim to increase exposure of their content by expanding their follower base through directing outbound activities to other users. The authors find that the responsiveness of seeding targets strongly declines with status difference; thus, unknown music creators (the majority) do not generally benefit at all from seeding influencers. Instead, they should gradually build their status by targeting low-status users rather than attempt to "jump" by targeting high-status ones. This research extends the seeding literature by introducing the concept of risk to dissemination dynamics in online communications, showing that unknown music creators do not seed specific status levels but rather choose a portfolio of seeding targets while solving a risk versus return trade-off. The authors discuss various managerial implications for optimal seeding in user-generated content networks.

Keywords

influencer marketing, seeding, social networking, unpaid endorsements, user-generated content networks

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In the last decade, user-generated content networks such as YouTube, SoundCloud, and Instagram have become ubiquitous and now capture a substantial part of the social media sphere. On these platforms, the content is generated and offered by individuals and firms that are interested in promoting their own creations, their own network status, and, in some cases, their career (e.g., Goldenberg, Oestreicher-Singer, and Reichman 2012; Mayzlin and Yoganarasimhan 2012; Trusov, Bodapati, and Bucklin 2010). A well-known example is the Dutch electronic music artist San Holo, who focused all his self-promotion efforts on SoundCloud, a user-generated content network in the music domain with 175 million users (Pierce 2016). His efforts paid off, resulting in more than 2,000,000 plays and a growth in his follower base from 4,000 to over 40,000 SoundCloud users within a few months (Voogt 2015).

Considering an unknown creator of content (e.g., San Holo before his efforts) who wants to build and increase his or her follower base on a user-generated content network, what measures should be taken to reach this goal? What is the optimal policy to attract followers, and thus, whom on the social networking platform should a creator target?

By capitalizing on common outbound activities on user-generated content networks (i.e., follows, private messages, reposts, comments, and likes) creators can draw attention to their profile and content *without financial expenditure*. These activities with the objective of encouraging other users to follow back are, in fact, seeding programs (Haenlein and Libai 2017). In the specific case of such programs focusing on unpaid endorsements in user-generated content networks, a fairly common (albeit relatively new) ecosystem, the traditional influencer marketing approach is, in most cases, suboptimal. We show that for unknown creators relying on unpaid endorsements, it is not effective to gain status by trying to form ties with high-status individuals in the hope of a status transfer or endorsement. The predominant view on seeding is built on a strong (implicit) assumption that the responsiveness of individuals with a high status (i.e., the probability of them responding to targeted outbound activities) is (1) equal or similar to any other individual on the social networking platform, and (2) independent of status differences (e.g., Hinz et al. 2011;

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Yoganarasimhan 2012). In fact, in most seeding models, it is assumed that the response probability is 100% for any seeding target. For unpaid endorsements in user-generated content networks, it is not clear whether the assumption of equal response probabilities holds: Why should someone with high status treat endorsement requests by individuals with high and low status equally? We empirically show that the probability of responding to an endorsement request is dependent on status, and that it sharply declines with status difference. A model that takes into account both the reach of a targeted individual and the probability of an endorsement by this individual reveals that optimal seeding policies, in this case, are reversed: targeting ordinary, low-status individuals becomes more effective.

Using a rich data set of a worldwide leading music platform, we find that high-status seeding targets are associated with *very low responsiveness* (.03%), whereas low-status targets are associated with much higher responsiveness (7.41%). Similar to Van der Lans et al. (2010), we further analyze the creator's return on a targeted outbound activity and take into consideration the fact that the return scheme is composed of two sources: the direct return (the follow-back from the seeding target) and the indirect return (the number of followers from the seeding target's follower base). Naturally, high-status seeding targets are associated with high risks (due to their low responsiveness) but potentially high returns. Because there is a constraint in the form of a "budget" of outbound activities, creators must solve a risk versus return trade-off when deciding on a set of seeding targets. Along these lines, we find that once a creator gains followers and his or her status increases, the creator reallocates outbound activities from low- to high-status seeding targets, providing evidence that unknown creators who aim to build and increase their follower base indeed solve a risk versus return trade-off.

We strengthen the model-free evidence by regenerating the observed decreasing responsiveness and the tendency to target high-status individuals with increasing status using data-based simulations (in the spirit of Watts and Dodds 2007). More specifically, we simulate interactions on the music platform by assigning a utility function to each user that determines the individual allocation of outbound activities utilizing a Bayesian model of learning from experience.

In addition, we analyze the unknown creators' aversion to risk, which affects the individual portfolio choice of seeding targets. When factoring in the expected (total) return on a target, which is *lower* with increasing status, we find that their portfolio choices of seeding targets are predominantly risky. Instead of gradually building their status by slowly "climbing" in their follower counts through targeting low-status individuals, they attempt to "jump" by targeting high-status individuals—and thus keep failing to effectively accumulate followers to expand their fan communities.

Finally, we study the consequences of this risk-seeking behavior of unknown music creators compared with other seeding policies by means of a randomized dissemination process. We find that exclusively targeting low-status individuals outperforms not only the chosen seeding policy of these creators but also (and especially) the traditional influencer marketing approach by close to sixfold after not more than two years.

The remainder of this article is organized as follows. The next section presents an overview of the relevant literature, followed by the data description and empirical findings consisting of two parts. First, we provide evidence for the phenomenon—the decreasing responsiveness—and explore factors that play a role in it. Second, we investigate the consequences of this phenomenon on the unknown creator's decision-making process: the risk versus return trade-off. Following the empirical findings, we introduce a simulation study to compare the effectiveness of different seeding policies and discuss the gap between the optimal policy, the status quo, and the recommendation of prior literature. We conclude with a discussion of our findings and implications for marketing and online communications practice.

Background

A large body of literature exists on high-status individuals, or influencers, and it is widely agreed that they play a pivotal role due to their ability to either accelerate or block an information-dissemination process. In social network literature, the level of status is also referred to as rank, deference, or popularity (Wasserman and Faust 1994), with the most basic operationalization being indegree (e.g., Van den Bulte and Wuyts 2007), that is, the number of social ties an individual has. As a result, some researchers use the terms "status" and "indegree" interchangeably (e.g., Iyengar, Van den Bulte, and Valente 2011).

Social network literature suggests almost unanimously that marketing managers should try to seed individuals with a high status (e.g., Hanaki et al. 2007; Hinz et al. 2011; Iyengar, Van den Bulte, and Valente 2011; Van den Bulte and Joshi 2007; Yoganarasimhan 2012). In contrast, using an analytical model, Galeotti and Goyal (2009) propose low-status seeding, namely, when the content of social interaction is about information sharing and if the adoption probability increases with the amount of adopters in the proximity. Similarly, in a computer simulation, Watts and Dodds (2007) find that for most cases, high-status seeding does not have a major impact on cascades of influence, which is consistent with studies showing that high-status individuals are not influential per se (Aral and Walker 2012; Trusov, Bodapati, and Bucklin 2010).

Because marketing managers have to decide on a set of seeding targets for viral marketing campaigns (e.g., Libai, Muller, and Peres 2005), an assessment of the value of such high-status seeding targets is essential. In this context, Haenlein and Libai (2013) suggest shifting the focus toward the customer lifetime value of seeding targets. Alternatively, seeding effectiveness can be improved by following a multinetwork approach that takes into consideration relationship characteristics such as type, duration, and interaction intensity (Chen, Van der Lans, and Phan 2017). This weighting technique has been well investigated within the marketing domain (e.g., Ansari, Koenigsberg, and Stahl 2011; Iyengar, Van den Bulte, and Valente 2011). Its applicability for seeding, however, remains questionable because necessary information is generally private to the social networking platform itself or associated with great effort to fully uncover it, similar to the status assessment of seeding targets using sociometric measures such as closeness and betweenness centrality (Granovetter 1973). In effect, marketing managers and creators of content who are trying to build and increase their follower base usually make seeding decisions with very little information, the key factor being (network) status.

Closely related to our article is the work of Hinz et al. (2011), who compare three different seeding policies based on sociometric data. They show that high-status seeding outperforms two other policies focusing on fringes and bridges partially because well-connected individuals capitalize on their greater reach and not entirely because they exhibit a higher influence than others. In another study based on sociometric measures, Yoganarasimhan (2012) investigates the seed's follower base and its effect on macro-level dissemination using YouTube data. The conclusion from this study corresponds to Hinz et al. (2011) in that high-status seeding results in far more clicks on videos compared with random seeding.

The main implicit assumption in most of these articles is that the probability of buying a product or sharing information in response to a request or exposure is independent of status difference. However, in the case of unpaid endorsements in user-generated content networks, we argue (and empirically validate) that this assumption must be revisited. Whereas research usually places the focus on dissemination processes of products, our data concern the dissemination of unknown creators of content. Because such content creators aim to build and increase their follower base, they can capitalize on outbound activities to draw attention to their profile and their content. Following the seeding literature in marketing, these creators should direct outbound activities to individuals with a high status. These high-status seeding targets can then draw further attention to the creator's profile by reposting, or "rebroadcasting" (Zhang, Moe, and Schweidel 2017) the creator's content. Some of this attention then translates into additional followers and, thus, higher status for the creator. In this context, we argue that the effectiveness of these outbound activities—and, therefore, the return opportunities—depends jointly on the status of the sender and the receiver (i.e., the creator of content and the seeding target).

Another stream of related literature exists in the domain of social psychology, which investigates status and corresponding inter- and intragroup behaviors. In this domain, social identity theory (Tajfel and Turner 1979) reveals that high-status individuals are characterized by self-focused and self-serving behavior because they exhibit stronger in-group identification, as well as favoritism (Bettencourt et al. 2001), and they aim to preserve group boundaries and members (Ellemers et al. 1992; Terry, Carey, and Callan 2001). In contrast, low-status individuals wish to disconnect from the low-status category (Ellemers et al. 1988; Snyder, Lassegard, and Ford 1986) and aim to be associated with the high-status one (Tajfel 1974, 1975; Tajfel and Turner 1979). Indeed, individuals aim to form ties with high-status individuals due to status transfer, which has been studied in the context of academic researchers (Goode 1978; Latour 1987; Merton 1973) and can be interpreted as a form of endorsement (Stuart, Hoang, and Hybels 1999). Although low-status individuals benefit from such endorsement, high-status individuals exhibit a weaker attachment to low-status individuals than vice versa (Gould 2002) and risk devaluing their high status (Podolny 2001). This becomes apparent in the context of online dating, in which individuals take into consideration the status (or "market worth") of others, as well as their own (Heino, Ellison, and Gibbs 2010; Taylor et al. 2011). Studies reveal that individuals with a high value or physical attractiveness level are commonly targeted (Feingold 1990; Lee et al. 2008), whereas individuals with high physical attractiveness favor strong in-group preference (Buston and Emlen 2003; Little et al. 2001; Todd et al. 2007). These phenomena that (1) everyone tends to target high-status individuals and (2) they, in turn, respond preferably only to their own sort, serve as a starting point for the investigations we present.

In this article, we consider music creators who aim to build and increase their follower base utilizing user-generated content networks. Each creator engages in multiple outbound activities: follows, messages, comments, and likes. Outbound activities are directed to seeding targets—users who are not part of the creator's follower base at the time of sending. Prior research has shown that high-status seeding targets are bombarded with a large number of incoming actions (Feingold 1990; Lee et al. 2008), whereas low-status targets are not exposed to such competition for their attention. In addition, high-status seeding targets tend to respond only to other high-status individuals (Buston and Emlen 2003; Todd et al. 2007). Therefore, we expect that the greater the status difference[1] between the creator and the seeding target, the lower the responsiveness of the seeding target.

Data

We use data from one of the world's leading user-generated content networks in the domain of music. This platform consists of two types of user profiles: music creators and fans. Creators are individuals who have uploaded at least one song and use the network for self-promotion purposes. They engage with their fans and aim to expand their follower base.[2] Fans, in contrast, receive updates from their favorite creators and listen to their songs as well as connect with their peers on the platform. As with Twitter or Instagram, users of the platform can follow each other without being followed back (i.e., a directed graph). Users can listen to songs uploaded on the creators' profiles, "like" these songs, and leave comments about them.

[1] We define "status difference" as the indegree of the seeding target minus the indegree of the creator.

[2] A survey we conducted with 199 unknown music creators on the platform reveals that 48% aim to build a fan base (to get as many followers as possible), 13% aim to get as many song plays as possible, and 9% aim to find collaborators. Only 34% answered that they "don't take it too seriously."

If a user reposts a song, all followers of this user receive a notification in their news feed. As a result, song reposts have a considerable impact on song popularity and, for this reason, on the creators. Users can also contact each other by sending private messages. Consistent with Saboo, Kumar, and Ramani (2015), we focus on music creators who upload songs on their profiles that can be listened to by other network users. While fans usually browse the platform to discover new music, creators can grow their follower base by engaging in active promotion—as in the setting in Ansari et al. (2018). More precisely, unknown creators[3] who aim to build and increase their follower base (their brand communities) can reach out to users by following them or sending them private messages and, if the targets are creators themselves, reposting, commenting, or liking their songs.[4] Similar to Aral and Walker (2012), for example, by means of a personalized private message, unknown creators can draw user attention to their profiles containing their latest music. In line with Van der Lans et al. (2010), who describe a two-step response process in viral marketing campaigns, such an outbound activity directed to a seeding target can result in a follow-back (direct return) and/or a repost, which then might trigger additional follows from the follower base (indirect return). For both the direct and indirect returns, there is an explicit response needed by the seeding target because mere exposure does not result in any dissemination. Note that the platform does not allow users to post text messages such as tweets on Twitter. It only allows users to upload songs or collect them in the form of playlists, the two core features of the platform.

Within the scope of our research collaboration, we received two data samples from the platform. The first sample consists of 35,956 users (24,020 music creators and 11,936 fans) and their egocentric (local) networks. These users represent all sign-ups in the first quarter of 2009. This panel data set contains all information about the formation of the users' egocentric networks over a period of five years (January 2009 through March 2014), as well as all data on incoming and outgoing activities of each user including follows, messages, song plays, song comments, and song likes over the entire period. Moreover, we collected this information about their first-degree alters (followers). In late 2012, the music platform introduced the function and possibility for users to repost songs, which appear in followers' news feeds. As our first data sample does not include returns on song reposts (indirect returns), we utilize a second panel data set that consists of 35,000 users (4,978 music creators and 30,022 fans) who signed up in the first week of March 2013 and tracked them over a period of two years (until July 2015). Table 1 provides the descriptive statistics of both data samples used in our empirical analysis.

Overall, our two panel data sets consist of 70,956 users along with their alters (a total of 11,203,205 users). These data sets include complete information on (1) follows, (2) messages, (3) song plays, (4) song reposts, (5) song comments, and (6) song likes.

Empirical Findings

We first analyze the responsiveness of seeding targets by taking into consideration the status difference between the sender and receiver of outbound activities (i.e., follows, messages, comments, and likes). Following the literature review, we expect that the higher the status difference between the creator and the seeding target, the lower the responsiveness of the seeding target. To gain robustness, we complement the model-free evidence with a binary logistic regression while accounting for nonlinear effects involved in the estimation. In a second step, we then analyze the creator's allocation of outbound activities to high- and low-status seeding targets while associating the different levels of responsiveness with the respective returns. We strengthen the model-free evidence by regenerating the observed distributions using a data-based simulation. A study with a sample of unknown music creators enables us to finally connect revealed preferences from the data with the creators' actual beliefs.

Responsiveness Is Negatively Associated with Status Difference

Music creators on our platform of interest cannot influence the responsiveness of seeding targets, so they are, in fact, "probability-takers."[5] As part of their decision making, they assess the a priori probabilities of response, given the limited information at hand (i.e., the status difference between them and the available seeding targets). To study the dynamics of responsiveness of the seeding targets, we zoom in on the dyadic level and analyze all 4,964,174 outbound activities directed to users of the platform who were not part of the creators' follower base at the time of sending. These outbound activities—consisting of follows, messages, comments, and likes—were sent by 18,005 (out of 24,020) music creators over 1,959 days.[6] We focus on the responsiveness of seeding targets, a binary measure denoted as 1 if the seeding target followed the creator back and established a reciprocal tie within a week and 0 otherwise. We further take into

[3] We define unknown music creators as all users who have uploaded at least one song and whose indegree has not crossed a fan community of 100 followers.

[4] Regarding all creator sign-ups in the first quarter of 2009 with at least one follower, 95% did not cross the mark of 100 followers at the end of the year. This statistic dropped to 83% in the next year.

[5] We use this term in analogy to economics, in which consumers are referred to as "price-takers" when they cannot influence the price of a good or service due to rigid supply (typically due to an insufficiently competitive environment).

[6] Each promotional action is equally weighted, and we do not consider either the content of the private message/comment (and thus its effect on virality; Berger and Milkman 2012) or the motivation for why a seeding target reposts the creator's song (Toubia and Stephen 2013).

Table 1. Descriptive Statistics.

Descriptives		Sample 2009–2014[a]			Sample 2012–2015		
		Mean	Median	SD	Mean	Median	SD
Indegree	Aug. 2011	134.77	19.00	532.88	—	—	—
	Mar. 2014	1,254.81	59.00	31,730.52	53.07	5.00	12.10
	Jun. 2015	—	—	—	20.01	8.00	102.10
Follows	Sent	204.94	56.00	381.10	35.21	10.00	91.57
	Received	1,254.81	59.00	31,730.52	20.01	8.00	102.10
Song comments	Sent	69.12	12.00	290.67	5.52	2.00	19.84
	Received	132.31	14.00	711.46	12.33	3.00	97.49
Song likes	Sent	75.28	13.00	274.63	32.74	4.00	101.84
	Received	552.34	20.00	7,108.54	89.07	6.00	1,014.00
Messages	Sent	65.34	9.00	767.03	10.00	2.00	67.55
	Received	54.24	9.00	149.68	5.25	1.00	68.72
Song plays	Sent	1,703.26	390.00	3,876.24	771.25	37.00	2,885.87
	Received	14,378.87	380.00	222,609.50	4,785.35	176.00	59,770.22
Song reposts	Sent	—	—	—	.04	.00	.70
	Received	—	—	—	.02	.00	1.17
Songs	Uploaded	31.12	9.00	108.10	10.13	3.00	37.85
Weekly follows	Sent	.55	.00	10.18	.19	.00	4.37
	Received	4.12	.00	362.48	.10	.00	1.13
Weekly song comments	Sent	.14	.00	2.00	.01	.00	.28
	Received	.32	.00	4.84	.01	.00	.32
Weekly song likes	Sent	.17	.00	2.01	.12	.00	1.28
	Received	1.50	.00	49.93	.07	.00	3.19
Weekly messages	Sent	.13	.00	8.36	.003	.00	.21
	Received	.15	.00	1.01	.004	.00	.25
Weekly song plays	Sent	5.68	.00	84.37	5.20	.00	34.13
	Received	50.29	.00	1,658.29	5.98	.00	266.50
Weekly song reposts	Sent	—	—	—	.003	.00	.21
	Received	—	—	—	.004	.00	.25
Weekly songs	Uploaded	.12	.00	1.66	.01	.00	.35

[a]We consider only the 24,020 music creators and omit the 11,936 noncreators who signed up in the first quarter of 2009.

consideration the difference in indegree, the most common (and widely used) operationalization of network status (e.g., Van den Bulte and Wuyts 2007), between the sender and receiver of outbound activities. The period in which we consider reactions in the form of follow-backs was set to one week because this corresponds to the average login frequency of users of the platform. Panel A in Figure 1 exhibits the a priori response (follow-back) probabilities, given the order of magnitude of the seeding target to creator status ratio. Each bar captures 2.5% of the distribution whereby, for example, the bar with values between 2.5 and 2.9 includes each seeding target whose status is 2.5 to 2.9 times higher in order of magnitude than the status of the creator (the status of the seeding target is between $10^{2.5} \approx 300$ and $10^{2.9} \approx 800$ times greater than the status of the creator). From the monotonicity of the curve, we conclude that the higher the status difference is between the creator and the seeding target, the lower the a priori probability of response. When extending the reaction period to two or three weeks, the a priori probabilities increase by 13% and 20% on average, respectively. Yet, the monotonicity of the curve remains—this is true when the response is a song repost (Panel B in Figure 1) or a song play (Panel C in Figure 1) instead of a follow-back, or when we measure network status by the number of song plays instead of followers (Panel D in Figure 1).

Figure 1 exhibits a model-free representation of the probabilities. We do not measure the direct effect of status difference on the a priori response probabilities, nor do we claim that there are no other mediating factors. In this context, it may be that, for example, homophily (e.g., Aral, Muchnik, and Sundararajan 2009) contributes to the observed decreasing pattern of response probability with status difference and thus adds to the same qualitative conclusion: an unknown creator faces high risks when targeting high-status individuals (due to their low responsiveness), whereas targeting low-status individuals is associated with lower risk (due to their higher responsiveness). Although homophily may not explain the high responsiveness of low-status seeding targets to outbound activities from high-status creators, this observed phenomenon is in line with social identity theory: low-status individuals aim to be associated with high-status ones (Tajfel 1974, 1975; Tajfel and Turner 1979).

To extend the model-free evidence, we employ a binary logistic regression of responsiveness *on factors observable to the creators* and take into consideration nonlinear effects involved in the estimation because the order of magnitude of

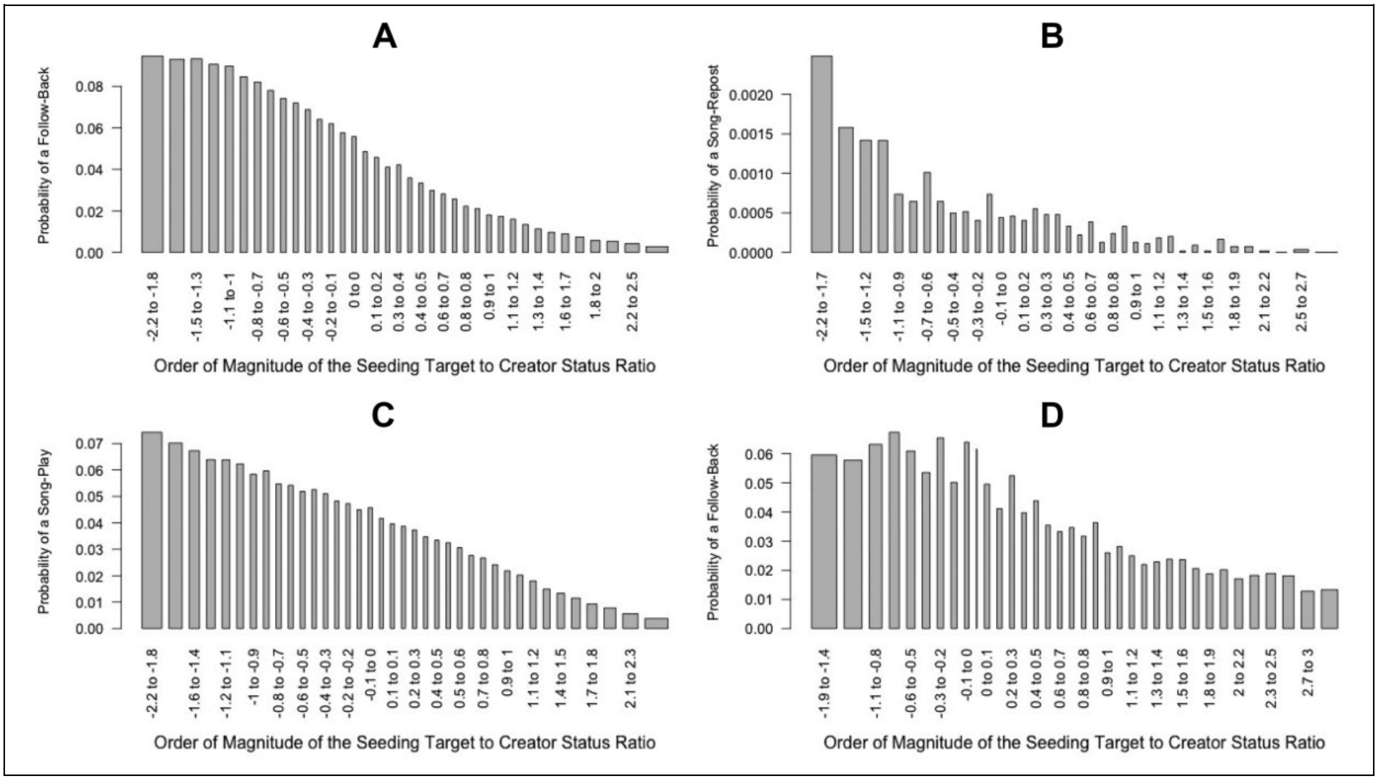

Figure 1. A priori response probabilities.

the interaction may deviate from the interaction term's marginal association—even featuring an opposite sign (Ai and Norton 2003). We validate the conclusions using bootstrapping. For the regression, we consider active creators,[7] which results in a sample of 9,010 creators and 4,792,309 outbound activities directed to users of the platform who were not part of the creators' follower base at the time of sending. Thus, we do not take retention efforts (i.e., outbound activities directed to the follower base) into consideration. In our sample of 9,010 music creators, only 4% of their outbound activities led to a response in the form of a follow-back (a binary measure denoted as 1 if the seeding target followed the creator back within a week, and 0 otherwise). The period in which we consider reactions in the form of follow-backs was again set to one week (as mentioned previously, one week corresponds to users' average login frequency).

Both creators and seeding targets vary greatly in their network status, ranging from unknown to extremely popular. We measure network status by the users' indegree. Status can be further measured by means of closeness and betweenness centrality, but, unlike indegree centrality, these status measures are not visible to the individuals in user-generated content networks. Thus, to investigate the association between the responsiveness of a seeding target and the status difference, we consider only factors that are observable to the creator (i.e., we focus on indegree as the core proxy of users' status). In addition, we incorporate other factors that are related to the creators such as type of the outbound activity, music genre, and the number of song uploads, as well as their interactions with status difference.

Let $\mathrm{statdiff}_{TS}$ denote the order of magnitude of the seeding target-to-creator status ratio: $\mathrm{statdiff}_{TS} = \log\left(\frac{\mathrm{status}_T}{\mathrm{status}_S}\right)$. The resulting binary logistic regression model is therefore

$$\mathrm{Prob} = \frac{e^{\Phi_{TS}}}{1 + e^{\Phi_{TS}}}\,, \tag{1}$$

where Prob is the probability of response (in the form of a follow-back), and Φ_{TS} is the score that includes the independent variables describing the interplay between the sender (creator) of outbound activities S and the receiver (seeding target) T, that is,

$$\Phi_{TS} = \beta_0 + \beta_1\,\mathrm{statdiff}_{TS} + \overrightarrow{\beta_2}\cdot\overrightarrow{\mathrm{outbound}_S} + \beta_3\,\mathrm{songs}_S + \overrightarrow{\beta_4}\cdot\overrightarrow{\mathrm{genre}_S} + \overrightarrow{\beta_{12}}\cdot\overrightarrow{\mathrm{outbound}_S}\times\mathrm{statdiff}_{TS} + \overrightarrow{\beta_{14}}\cdot\overrightarrow{\mathrm{genre}_S}\times\mathrm{statdiff}_{TS} + \epsilon\,, \tag{2}$$

where $\overrightarrow{\mathrm{outbound}_S}$ is the binary vector denoting the respective outbound activity (follow, message, comment, or like),[8] $\overrightarrow{\mathrm{genre}_S}$

[7] We define active music creators on the platform as all users who (1) have uploaded at least one song and (2) are among the top 50% of active creators (and thus carried out at least 69 outbound activities).

[8] Because there are four different outbound activities, the binary vector $\overrightarrow{\mathrm{outbound}_S}$ consists of three cells and thus excludes the fourth promotional action representing the baseline (for which all values in $\overrightarrow{\mathrm{outbound}_S}$ are zero).

is the binary vector denoting the creator's music genre (electronic, techno, house, or other),[9] $songs_S$ denotes the number of song uploads, and ϵ is assumed to be logistically distributed. (Note that $\cdot$ denotes a scalar product and $\times$ denotes a multiplication.)

Table 2 presents the results for four different models (Models I–IV) and with the baseline outbound activity "messages." In Model I, we take into account the order of magnitude of the seeding target-to-creator status ratio (i.e., $\mathrm{statdiff}_{TS}$), whereas in Model II, we segregate the status of the creator and the seeding target (i.e., $\log[\mathrm{status}_S]$ and $\log[\mathrm{status}_T]$). In Model III, as shown in Equation 2, we estimate a logit model with interactions, and in Model IV we incorporate creator-specific fixed effects. To gain robustness, for each model we measure status not only by the number of followers (Table 2, columns 1–4) but also by the number of song plays (Table 2, columns 5–8).

Focusing first on the former measurement, we find that Models I and II (Table 2, columns 1 and 2) fit significantly better than the null model with just the intercept (full vs. reduced likelihood ratio test gives $\Pr[>\chi^2] = 0$). Moreover, we find that the coefficient's sign of the order of magnitude of the seeding target-to-creator status ratio is highly significant and negative (Table 2, column 1). This holds true when estimating a logit model with interactions (Table 2, column 3) and when incorporating creator-specific fixed effects (Table, column 4), as we find that the full model fits significantly better than the null model without status difference ($\chi^2(1) = 98.64$, $p = 0$). As a result, the higher the status difference between the creator and the seeding target, the lower the responsiveness. This major insight is in line with the model segregating the status of the creator and the seeding target (Model II) because the coefficient's sign of the creator status is highly significant and positive, whereas the coefficient's sign of the seeding-target status is highly significant and negative. More precisely, when increasing the creator's status by one order of magnitude—while holding the seeding-target status constant—the odds ratio of getting a response increases $e^{.38} \approx 1.46$ times (by approximately 50%). In contrast, when directing outbound activities to seeding targets with a status that is one order of magnitude lower—while holding the creator status constant—the odds ratio of getting a response increases $e^{.73} \approx 2.08$ times (by approximately 100%). A decrease of the seeding-target status by one order of magnitude increases the odds ratio of a response about twice that of the increase in the odds ratio when increasing the creator status by one order of magnitude. Thus, changing the seeding-target status seems to be more effective, in terms of responsiveness. If we measure network status by the number of song plays instead of followers (Table 2, columns 5–8), the obtained results are robust: the coefficient's sign of the order of magnitude of the seeding target-to-creator status ratio is highly significant and negative for all models (Table 2, columns 5, 7, and 8). This holds true when segregating the status of the creator and the seeding target because the coefficient's sign of the creator status is highly significant and positive, whereas the coefficient's sign of the seeding-target status is highly significant and negative (Table 2, column 6).

From Table 2, we can also conclude that the most effective outbound activity to draw attention to one's profile is writing song comments, whereas sending private messages is the least effective (columns 1–3). Note that all coefficients for the different outbound activities also remain significant when changing the baseline outbound activities to follows, comments, and likes, which means that all the differences between the outbound activities are significant. Similarly, if we measure network status by the number of song plays instead of followers to gain robustness, the most effective outbound activity is writing song comments.

In line with Ai and Norton (2003), who demonstrate that for nonlinear models the order of magnitude of the interaction may deviate from the interaction term's marginal association, even featuring an opposite sign, we begin our analysis by examining the marginal association between the responsiveness of a seeding target and the status difference (the first derivative):

$$\frac{\partial \mathrm{Prob}}{\partial \mathrm{statdiff}_{TS}} = \left[\frac{e^{\Phi_{TS}}(1+e^{\Phi_{TS}}) - e^{2\Phi_{TS}}}{(1+e^{\Phi_{TS}})^2}\right]\left[\frac{\partial \Phi_{TS}}{\partial \mathrm{statdiff}_{TS}}\right]. \quad (3)$$

Then, we analyze the interaction between the status difference and the respective outbound activity (the cross-derivative approximation for discrete outbound activities):

$$\frac{\partial \mathrm{Prob}}{\partial \mathrm{statdiff}_{TS}}\bigg|_{\overrightarrow{\mathrm{outbound}_S}} - \frac{\partial \mathrm{Prob}}{\partial \mathrm{statdiff}_{TS}}\bigg|_{\overrightarrow{\mathrm{outbound}_S}=0}, \quad (4)$$

where the baseline outbound activity $\overrightarrow{\mathrm{outbound}_S} = 0$ is messages. To assess the statistical significance, we bootstrap 1,000 times on a panel of 500 creators, a representative sample of the 9,010 creators in our data set. Because the outbound activities by a creator cannot be considered creator-independent, we sample all outbound activities of a selected creator in a given iteration of the bootstrapping. Figure 2 presents for the binary logistic regression the marginal association of status difference as a function of the predicted probability (including the boundaries given by 95% confidence intervals) when the baseline outbound activity is messages. Because we find that there is a negative association (correlation), we conclude that the higher the status difference between the creator and the seeding target, the lower the responsiveness, complementing the model-free evidence presented in Figure 1.

For the binary logistic regression, Figure 3 presents the interaction between the status difference and the respective outbound activity as a function of the predicted probability (including the boundaries given by 95% confidence intervals) in the case where the baseline outbound activity is messages. Figure 3 allows us to rank-order the different outbound

Note that we replicate our results for all baseline actions, and we find that all coefficients for the different outbound activities remain significant.

[9] Because there are four different music genres, the binary vector $\overrightarrow{\mathrm{genre}_S}$ consists of three cells and thus excludes the fourth genre representing the baseline (i.e., "other," for which all values in $\overrightarrow{\mathrm{genre}_S}$ are zero).

Table 2. Binary Logit Model Results of Status Difference, Outbound Activities, Music Genre, and the Number of Song Uploads.

Status Measure	Status Measured by Number of Followers				Status Measured by Number of Song Plays			
Models	I	II	III	IV	I	II	III	IV
Intercept	−3.80 (.01)***	−3.00 (.01)***	−3.29 (.01)***	−3.15 (.01)***	−3.44 (.03)***	−2.35 (.04)***	−3.22 (.03)***	−3.29 (.04)***
Status difference	−.62 (.00)***		−.14 (.01)***	−.30 (.01)***	−.69 (.01)***		−.22 (.03)***	−.37 (.04)***
Status of the creator		.38 (.00)***				.03 (.01)**		
Status of the seeding target		−.73 (.00)***				−.34 (.01)***		
Outbound Activities								
Follows	.79 (.01)***	.72 (.01)***	.28 (.01)***	.15 (.01)***	.26 (.03)***	−.11 (.03)***	.04 (.03)	−.03 (.04)
Likes	.37 (.01)***	.43 (.01)***	−.21 (.01)***	−.37 (.01)***	−.16 (.05)***	−.24 (.05)***	.32 (.05)***	−.41 (.05)***
Comments	.90 (.01)***	.91 (.01)***	.37 (.01)***	.11 (.01)***	.50 (.04)***	.50 (.04)***	.26 (.04)***	.11 (.05)*
Music Genre								
Electronic	−.01 (.01)	.04 (.01)***	.02 (.01)*	−.06 (.01)	.05 (.04)	.15 (.04)***	.06 (.04)	−.02 (.05)
Techno	−.01 (.01)	.04 (.01)***	−.07 (.01)***	−.02 (.01)	−.22 (.05)***	−.16 (.05)**	−.24 (.06)***	−.18 (.07)*
House	−.25 (.01)***	−.20 (.01)***	−.21 (.01)***	−.10 (.01)***	.18 (.04)***	.21 (.04)***	.18 (.04)***	.14 (.06)*
Song uploads	.00 (.00)	.00 (.00)***	.00 (.00)***	.00 (.00)	.00 (.00)**	.00 (.00)***	.00 (.00)***	.00 (.00)
Interaction Terms								
Status difference × Follows			−.50 (.01)***	−.41 (.01)***			−.43 (.03)***	−.39 (.04)***
Status difference × Likes			−.77 (.01)***	−.42 (.01)***			−.91 (.05)***	−.87 (.06)***
Status difference × Comments			−.54 (.01)***	−.64 (.01)***			−.65 (.04)***	−.59 (.05)***
Status difference × Electronic			.02 (.01)*	−.02 (.01)**			−.11 (.04)**	−.13 (.05)**
Status difference × Techno			−.10 (.01)***	−.09 (.01)***			−.16 (.06)*	−.22 (.07)**
Status difference × House			.01 (.01)*	−.06 (.01)***			−.14 (.04)**	−.20 (.05)***
N	4,792,309	4,792,309	4,792,309	4,792,309	288,457	288,457	288,457	288,457
G^2	117,298	125,754	126,324		4,574	3,347	4,999	
$Pr(>\chi^2)$	.00	.00	.00	.00	.00	.00	.00	.00
AIC	1,569,972	1,561,518	1,560,958	86,737	80,515	81,744	80,103	77,201

*$p < .05$.
**$p < .01$.
***$p < .001$.
Notes: Standard errors are in parentheses. AIC = Akaike information criterion.

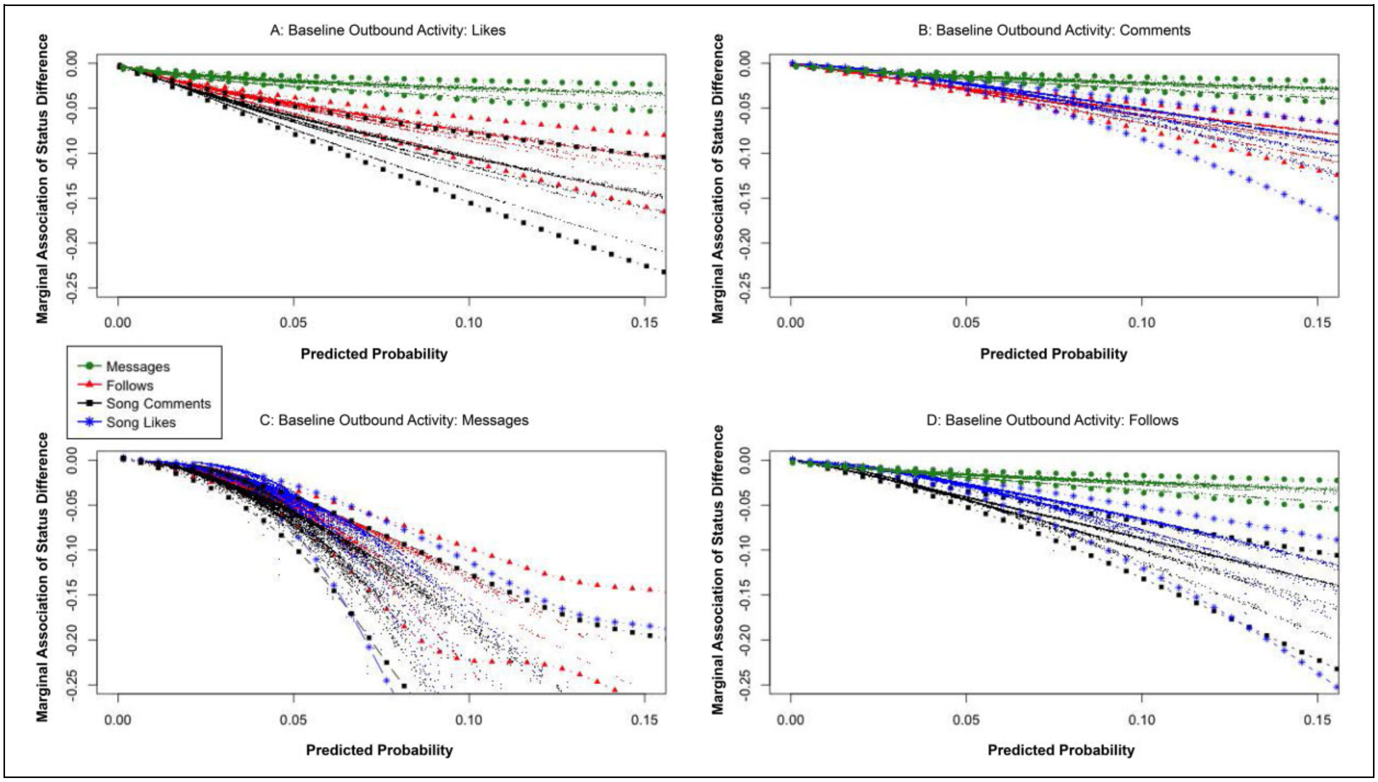

Figure 2. Marginal association of status difference as a function of the predicted probability.
Notes: The 95% confidence interval boundaries are included.

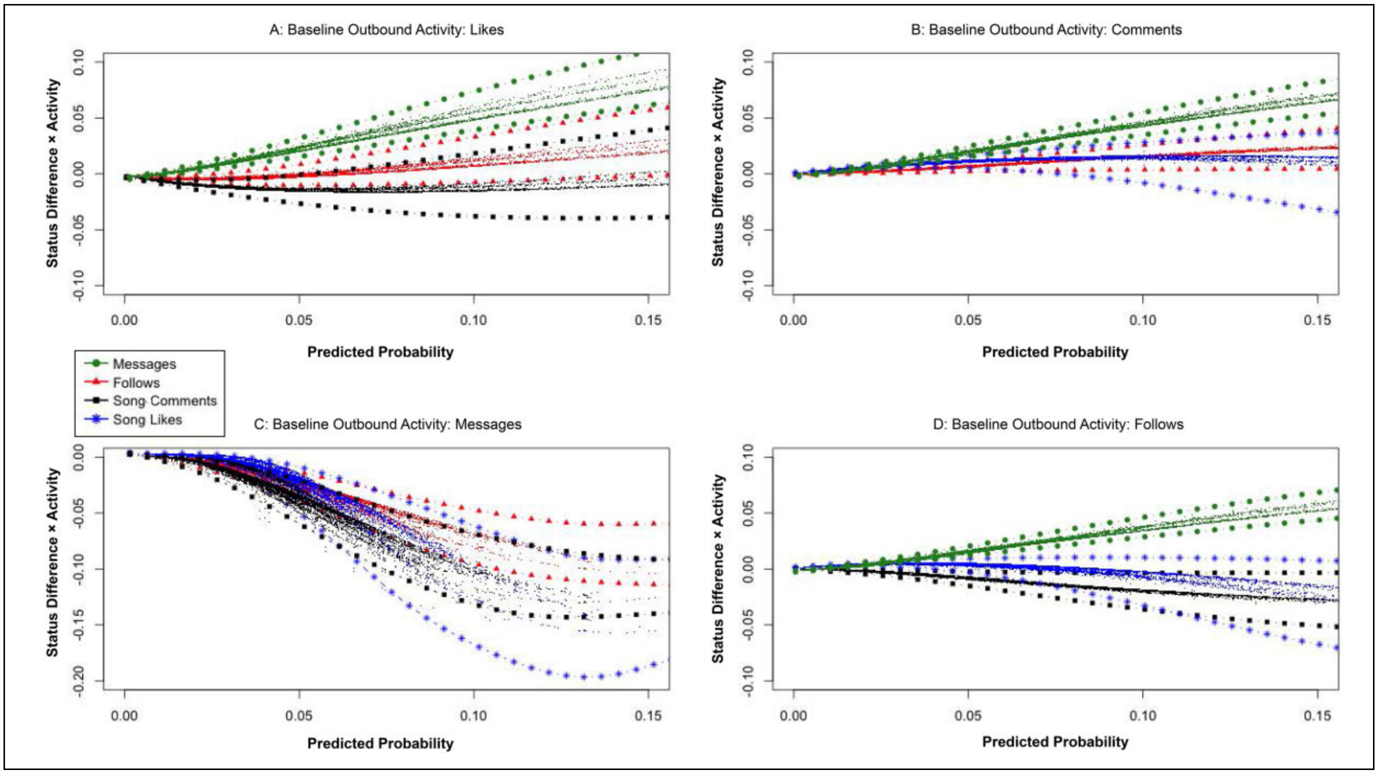

Figure 3. Interaction between the status difference and the respective outbound activity as a function of the predicted probability.
Notes: The 95% confidence interval boundaries are included.

activities according to the strength of their association with the responsiveness. We find that this association is not the same for all outbound activities. In particular, directing messages to seeding targets seems to be the least affected by status difference, as the marginal decrease in this difference is more strongly moderated than the other outbound activities. Yet, the curve is relatively steep considering that, in our regression model, we define status difference on a logarithmic scale, which flattens the curve.

The insights from the logistic regression are consistent with the model-free representation of the probabilities exhibited in Figure 1: taking into account the heterogeneity in genre and outbound activities, we see that the decreasing pattern of response probability with status difference holds. We may conclude that the higher the status difference is between the creator (sender) and the seeding target (receiver), the lower the a priori probability of response.

Risk Versus Return Trade-Offs

Considering relational mechanisms on a dyadic level, we expect different levels of returns at different levels of responsiveness, depending on status difference. The return scheme, which results from a seeding target who responds to a sender's outbound activity, is composed of two sources: (1) a direct return in the form of a follow-back from the seeding target, which depends on the responsiveness, and (2) an indirect return resulting from the seeding target's follower base, which depends on whether the seeding target further reposts songs from the creator. Song reposts may trigger additional follows as they disseminate into the seeding target's egocentric network (e.g., Everett and Borgatti 2005).

Creators vary in their expenditure of time for self-promotion and seeding efforts. Along these lines, we consider the number of outbound activities sent by a creator within a time period as budget. On average, low-status creators (those with fewer than 100 followers) have a weekly budget of 3.1 outbound activities (SD = 8.2). Due to the large size of user-generated content networks, including the platform in this research, creators cannot reach out to all users either at once or over their entire lifetime. Moreover, due to time constraints, search costs to find seeding targets, and strict antispam policies, the individual budget of outbound activities is not unlimited, as is often (mostly implicitly) assumed. Therefore, creators are forced to decide on a set of seeding targets and, thus, must create a portfolio of individuals.

According to common social network literature in marketing (e.g., Libai, Muller, and Peres 2013; Yoganarasimhan 2012), the optimal portfolio choice of seeding targets is to "invest" all outbound activities in high-status people (the optimal solution should exhibit a corner solution) because, in the case of a response, the increase in the creator's follower base will be higher compared with a response by a person with a low status. However, our analysis reveals that the probability of response by a seeding target (receiver) with a high status is associated with the status of the creator (sender). For unknown creators who aim to build and increase their follower base, investing in high-status seeding targets is associated with high risk (due to their low responsiveness), whereas investing in low-status seeding targets is associated with low risk (due to their higher responsiveness). The optimal composition of the portfolio of seeding targets with different status depends on the creator's aversion to risk. Consequently, we define the creator's seeding problem for the purpose of self-promotion in user-generated content networks as a risk versus return trade-off, depending on the individual aversion to risk.

To understand whether creators indeed solve a risk versus return trade-off, we cluster users by their status (i.e., their indegree) and separate them according to the order of magnitude. This classification is appropriate because it follows a logarithmic scale and, thus, lives up to the dispersion of indegrees in well-established user-generated content networks. As a result, we consider four groups of users: Type 1 users have fewer than or equal to 100 followers; Type 2 users have more than 100 but fewer than or equal to 1,000 followers; Type 3 users have more than 1,000 but fewer than or equal to 10,000 followers; and Type 4 users have more than 10,000 followers. In Figure 4, we compare the choices of seeding targets of (creator) Types 1, 2, 3, and 4. Along these lines, we define unknown creators as Type 1—all users who uploaded at least one song and whose status has not crossed two orders of magnitude (i.e., a fan community of 100 followers). Figure 4 illustrates that all creators of a specific type do not invest all outbound activities in a specific type of seeding target; a corner solution does not appear. This is also the case if status is measured by the number of song plays (Panel B) instead of followers (Panel A). In fact, creators spread their budget of outbound activities over several orders of magnitude in terms of seeding-target status. At the individual level, we find that the vast majority of unknown creators who are aiming to build and increase their follower base reach out to at least three different types of seeding targets. More specifically, out of all music creators with fewer than 100 followers who are actively[10] promoting their songs on the platform (8,846 creators in total), 390 invest in one status, 1,158 invest in two different levels of status, 2,600 invest in three different levels of status, and 4,698 invest in four different levels of status. Thus, also when taking heterogeneity at the creator level into account, we cannot find a corner solution in their portfolio choice of seeding targets either.

Could this allocation of outbound activities result from a random selection of seeding targets? We analyze and compare our findings with the seeding policy in which the creator of music randomly directs outbound activities to these targets. This random seeding policy is reflected by the status (indegree) distribution and serves as a benchmark. For this reason, we assess the status of all available users, which amounts to 394,262 music creators and fans in our sample. As we expect a right shift of the status distribution over time due to the

[10] Here, we define active music creators as those in the top 50th percentile in terms of active days.

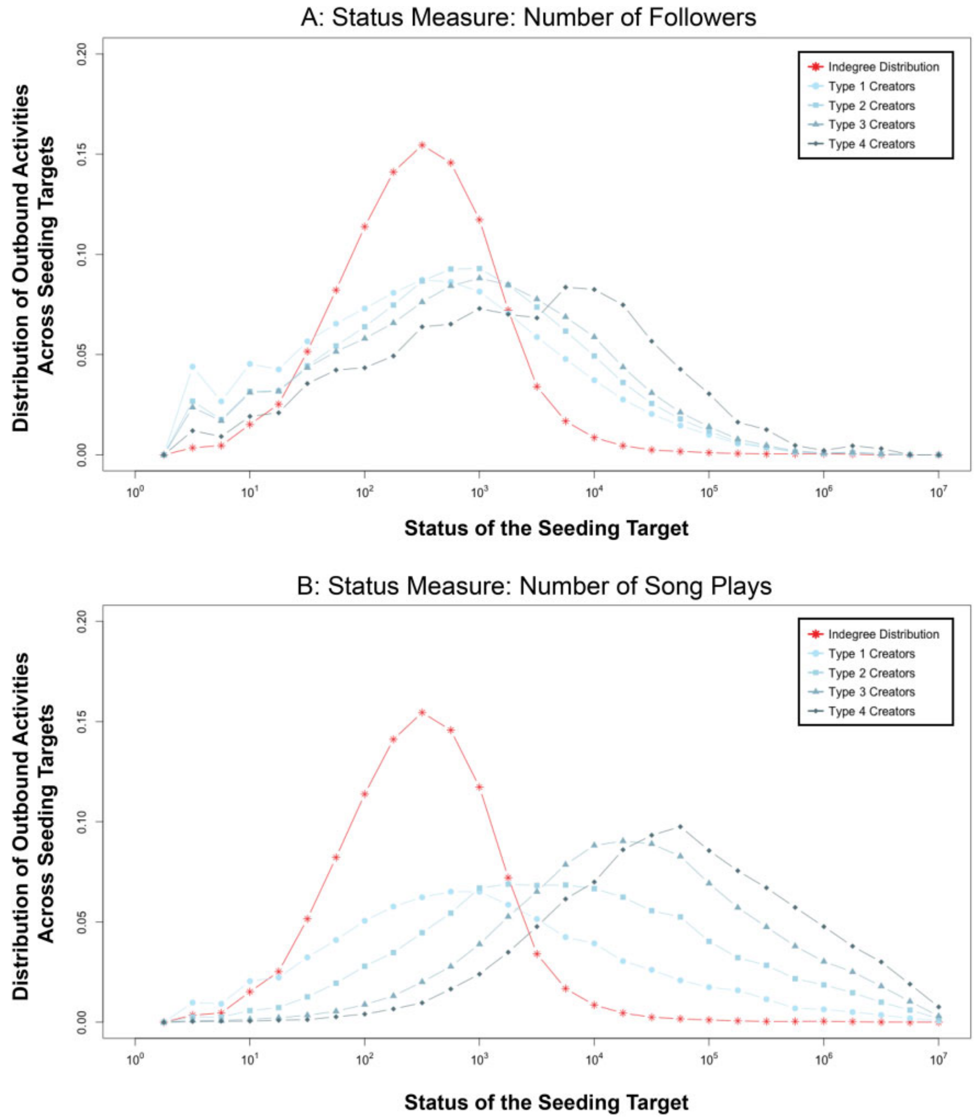

Figure 4. Creator portfolios under different status measures.

platform's growth, we calculate it at the end of the data sample's observation period in the first week of 2014. Because the different portfolios of seeding targets in the form of the four distribution curves are different from the status distribution, this implies that creators do not randomly distribute their outbound activities. Recall that creators are pressured to make seeding decisions with very little information, the key factor being status measured as indegree. Thus, the observation that creators do not engage in random seeding is evidence that they indeed consider the status of seeding targets.

If we assume that these creators are risk-neutral in their portfolio choice of seeding targets, then uncertainty does not influence their portfolio choice, and they would invest solely in seeding targets who yield the highest expected return.[11] However, Figure 4 reveals that music creators on the platform cannot be risk-neutral because they spread their budget of outbound activities over several orders of magnitude in terms of seeding-target status. Thus, it seems that they internalize the involved risks in their choice of seeding targets.

Figure 4 reveals that with creators' increasing status comes a stronger tendency to direct outbound activities to seeding targets with higher status, while all the distribution curves lie on the right side of the status distribution (i.e., the random seeding policy; for a detailed description of the statistical test, see Web Appendix A.1). Drawing on comparative statics (for supplementary elaborations, see Web Appendix A.2), we find that this tendency is stronger because the relative increase in responsiveness is higher.[12]

[11] The expected return on each seeding target is the expected value of the return given the distribution of returns.

[12] See Tables 4 and 5 in Web Appendix A.3—for example, an increase in the creator's status from Type 1 to Type 2 increases the a priori follow-back

Table 3. Expected Returns.

	Seeding Target Types			
	Type 1	Type 2	Type 3	Type 4
Type 1 creator	.0741 (.2619)	.0333 (.1828)	.0039 (.0721)	.0003 (.0446)
Type 2 creator	.0862 (.2807)	.0500 (.2199)	.0093 (.1401)	.0029 (.3757)
Type 3 creator	.0909 (.2876)	.0735 (.2629)	.0244 (.3421)	.0095 (.8038)
Type 4 creator	.1505 (.3576)	.1660 (.3749)	.0625 (.3443)	.0205 (.3390)

Notes: N = 4,964,174 follows, messages, comments, and likes for 18,005 music creators over 1,959 days. Reaction period = 1 week. Standard deviations appear in parentheses. Note that the standard deviations are not the standard deviations of the expected returns. According to the central limit theorem, the standard deviations of the means are given by the ratio of the standard deviations of the return to the square root of the sample size.

Aversion to Risk

The creator's choice of seeding a target with a specific status (i.e., the creator's allocation of budget to high- and low-status seeding targets) depends on the creator's aversion to risk. To develop deeper insights into creators' seeding policies and how these are influenced by their risk aversion, we now focus on the return scheme (for a detailed description, see Web Appendix A.3), which consists of the expected direct return (determined by the a priori response probabilities) and the expected indirect return (determined by the a priori song repost probabilities as well as the expected indirect returns given a song repost).

We find that from the perspective of unknown creators (Type 1; same definition of types as before), the a priori response probabilities range between 7.41% (Type 1 seeding target) and .03% (Type 4 seeding target), whereas the a priori song repost probabilities range between .109% (Type 1 seeding target) and .001% (Type 4 seeding target). We also find that the expected indirect return for a Type 1 creator within a week, given a song repost from a Type 4 user, amounts to 7.6 follows and 281.6 plays on average. Qualitatively, these results show that the a priori song repost probabilities, as well as the expected indirect returns given a song repost, are extremely low for an unknown creator who directs outbound activities to high-status seeding targets.

Taking into account the a priori response (follow-back) and song repost probabilities, as well as the expected indirect returns associated with a song repost, we are able to compute the expected (total) return on an outbound activity directed to a seeding target. Analyzing 4,964,174 outbound activities that include follows, messages, comments, and likes of 18,005 music creators over 1,959 days, Table 3 shows the expected returns for all combinations of creator and seeding-target types. Counterintuitively, the expected return on high-status seeding targets is *lower* than the expected return on low-status ones. In particular, an unknown creator who directs an outbound activity to a Type 1 seeding target gets on average .0741 follow-backs with a standard deviation of .2619. In contrast, directing an outbound activity to a Type 4 target yields almost no return with certainty because the expected return is as low as .0003 follow-backs, and the corresponding standard deviation amounts to .0446. Employing bootstrapping reveals that all the differences between the expected returns are significant. Thus, the lower the target's status, the higher the expected return, which implies that a creator of music on the platform should not direct outbound activities to high-status seeding targets.

Because revealed preferences do not shed light on these individual beliefs, we conducted a survey with the aim of understanding creators' expectations regarding returns from low- and high-status seeding targets (for a detailed description, see Web Appendix A.4). This survey of stated preferences reveals that 85% of the respondents believe that the expected return on high-status seeding targets is lower than the expected return on low-status ones. More specifically, 170 out of 199 respondents (85%) from a randomly selected sample of 5,000 unknown music creators on the platform are congruent with reality. Under these circumstances, risk-averse, utility-maximizing creators would never direct outbound activities to high-status seeding targets. Nevertheless, after retrieving the individual portfolio choice of the 199 respondents from the social network data before and after the study, we find that all respondents spread their budgets of outbound activities over several orders of magnitude in terms of seeding-target status. Consequently, these respondents reveal a behavior in the context of the platform we collaborate with that is associated with risk-seeking.

Despite the strong effect size (85%), an important limitation of this survey is the low response rate (4%), which may have a sample selection bias. However, we do not find a difference between the respondents' portfolio choices and the previously analyzed 8,846 music creators (all 199 respondents also spread their budget over several orders of magnitude in terms of seeding-target status, as observed in Figure 4). This provides supportive evidence that the respondents exhibit representative behavior. We also checked for differences between those who explicitly stated promotional goals in the survey versus those who did not and found no difference in how they allocate their budget, which better supports the prevailing assumption that music creators on the platform aim to build and increase their follower base.

Note that the average number of days since sign-up amounts to 1,006. Yet these respondents stayed active even though they were not able to become successful over this long time period, which rules out following-rate decay (e.g., due to reducing interest). Thus, a fully concave utility function cannot describe the risk aversion from their stated preferences. In effect, the respondents' utility function must have a threshold, below

probability of Type 1 seeding targets from 7.4% to 8.6%, which is equivalent to an increase of 16%, whereas the a priori follow-back probability of Type 4 seeding targets increases from .03% to .05%, which is equivalent to an increase of 67%.

which the returns are considered negligible, and the creator is generally risk-seeking (for supplementary elaborations, see Web Appendix A.2). However, if the return crosses this threshold, the (strictly increasing) utility function becomes concave, and the creator faces diminishing marginal returns.

Data-Based Simulations Using a Bayesian Model of Learning from Experience

To strengthen the empirical evidence, we simulate interactions on the platform by assigning such a utility function containing a threshold to each user that determines the individual allocation of outbound activities. Our data-based simulation includes 12,491 music creators that have between 1 and 50,137 followers (M = 329, SD = 1,137; taken from the data). In this sample, 11,628 creators are Type 1 and Type 2 users, which we consider to be low-status creators as they have fewer than or equal to 1,000 followers, while 863 creators are Type 3 and Type 4 users, which we consider to be high-status as they have more than 1,000 followers. In every month over the course of 24 months, each creator follows two steps: (1) action and (2) reaction.

First, the creator decides how to distribute his or her individual budget of outbound activities. The utility function determines the number of follows, messages, reposts, comments, and likes directed to the 11,628 low- and 863 high-status seeding targets (the creator has a budget of outbound activities).[13] Note that all creators have the same utility function containing a threshold, independent of their status and follower base (for a detailed description of the utility function, see Web Appendix A.5).

Second, if the creator received outbound activities from any of the other 12,490 creators in that month, (s)he then decides whom to follow back and repost (the creator also has a budget of follow-backs).[14] Note that we observe a "budget saturation effect" in the data: the more follow-backs and reposts have been carried out in the past, the lower the budget of another follow-back and repost in the present. Thus, we consider budget saturation in addition to the heterogeneity in the budget of low- and high-status creators. With the respective budget, the creator follows back and reposts along the decreasing status of the individuals from whom (s)he received outbound activities. This is in line with social identity theory: low-status creators aim to be associated with high-status ones (Tajfel 1974, 1975; Tajfel and Turner 1979) and, thus, preferably form ties with them because of the status transfer (Goode 1978; Latour 1987; Merton 1973).

[13] The monthly budget of outbound activities, which is observed in the data, differs by several orders of magnitude and varies between 4 and 4,244 (M = 29.13, SD = 70.55).

[14] The monthly budget of follow-backs varies between 0 and 5,955 (M = .99, SD = 14.28), whereas the monthly budget of reposts varies between 0 and 162 (M = .04, SD = .30). These monthly budgets, whose distributions are also observed in the data, depend on the creator's status, as well as on total number of follow-backs and reposts that the creator has engaged in previously.

All 12,491 creators start off with no information about the a priori response probabilities from low- and high-status seeding targets and are, thus, uniformly distributed. Starting from the second month, however, creators learn from experience. More precisely, depending on which seeding-target status followed back as a result of an outbound activity, they update the perceived probabilities through a Bayesian model of learning from experience (for a detailed description of the mechanism, see Web Appendix A.5). As a robustness check, we demonstrate in Figure 5, Panels A and B, that the proposed utility function is able to create an internal solution in which a high-status creator has a stronger tendency to direct outbound activities to high-status seeding targets if the a priori response (follow-back) probability from low- and high-status seeding targets is common knowledge.

Panels C and D of Figure 5 also illustrate that over the course of 24 months, the data-based simulation is able to regenerate the decreasing responsiveness: as a low-status creator (Panel C), the probability of getting a follow-back from a low-status seeding target is 4% and from a high-status target, .01%. As a high-status creator (Panel D), the probability of getting a follow-back from a low-status seeding target is 19% and from a high-status one, 3%. Along these lines, social identity theory can indeed explain the high responsiveness of low-status seeding targets to outbound activities from high-status creators.

Note that the data-based simulation is able to regenerate not only the monotonicity of the a priori probabilities but also their order of magnitude (compare with Table 4 in Web Appendix A.3, in which Types 1 and 2 are associated with low status and Types 3 and 4 are associated with high status). Panels E and F in Figure 5 that once a creator gains followers and, thus, his or her status increases, (s)he reallocates outbound activities from low- to high-status seeding targets. After learning over 24 months, low-status creators (Panel E) on average direct 64% of their budget to low-status seeding targets and 36% to high-status seeding targets. High-status creators (Panel F), in contrast, on average direct 44% of their budget to low-status seeding targets and 55% to high-status seeding targets. Thus, we find the same order of magnitude in terms of the tendency to direct outbound activities to seeding targets with higher status (compare with Figure 4).

As a result of updating the creators' perceived a priori probabilities in each month over the course of 24 months, and by incorporating a utility function containing a threshold to live up to the observed risk-seeking behavior, we were able to regenerate the model-free evidence in our data-based simulations. In the next section, we compare the effectiveness of seeding policies.

Comparing the Effectiveness of Seeding Policies

By means of a randomized dissemination process using the example of a creator who has just signed up on the platform, we contrast three seeding policies. In the first seeding policy,

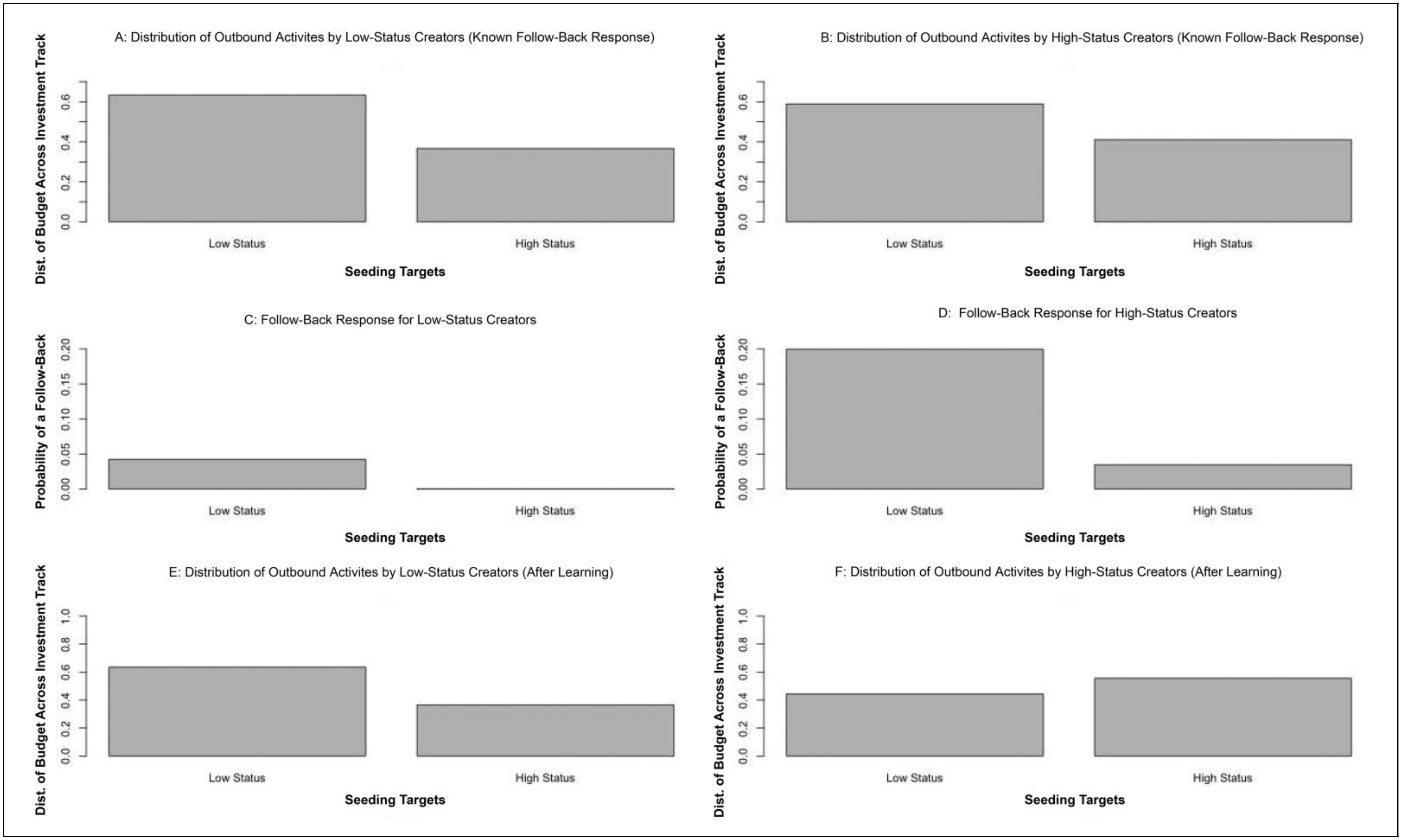

Figure 5. Data-based simulation results.

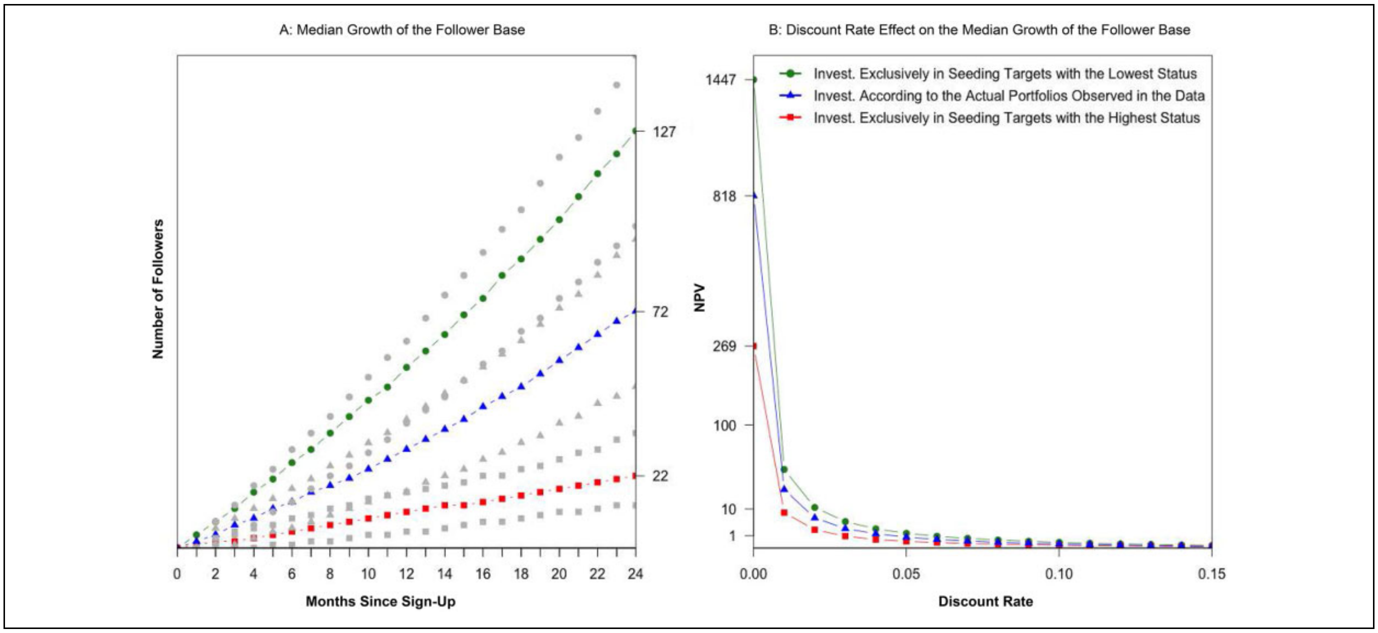

Figure 6. Randomized dissemination process results.
Notes: The 95% confidence interval boundaries are included in Panel A.

we simulate unknown creators, initially with zero followers, who invest their budgets of outbound activities in line with the status quo (i.e., according to the actual portfolios observed in the data). In the second policy, we simulate unknown creators who invest in line with common social network literature in marketing by exclusively seeding targets with the highest status. In the third policy, the simulation takes into account unknown creators following the seeding policy suggested in this article, who invest only in seeding targets with the lowest status.

Method

For each of the three seeding policies, we compute the median growth of a creator's follower base over a 24-month period. We focus on music creators who have just signed up and, thus, have zero initial followers. During each of the 24 months, the simulated creator invests 40 outbound activities, which corresponds to a weekly budget of 10 and an overall budget of 960 outbound activities. The simulated creator invests according to one of the three policies over the whole time period, for a total of 1,000 iterations. The mechanism is the same for any chosen policy: in each month, the creator's increase in follower base is determined by the status-dependent probability of a nonzero return on a seeding target and, further, on the status-dependent probability of either a direct and indirect return or only an indirect return. If the return in a given month for a given seeding target is nonzero, then there are two different scenarios. On the one hand, the investment in this seeding target can yield both a direct and indirect return—a follow-back from the seeding target and follows from subsequent song reposts. We consider the average number of song reposts from a seeding target over a year to account for the long-term indirect return on a follow-back. On the other hand, the investment in this seeding target can yield only an indirect return (i.e., follows from a single song repost). The monthly accumulation of baseline follows as well as returns on seeding targets increase the creator's status, which goes hand in hand with higher a priori probabilities and, thus, expected returns on each seeding target. Both the natural baseline follows and the a priori probabilities (and thus also the expected returns on each seeding target) are updated in multiples of 25 followers with regard to the growing follower base (i.e., after reaching a community size of 25 followers, 50 followers, etc.; for a detailed description of the randomized dissemination process, see Web Appendix A.6).

Results

Panel A in Figure 6 exhibits the median growth of a follower base of a creator endowed with zero followers when signing up and reveals that different seeding policies vary greatly in their outcomes. We find that investments in line with the current social network literature in marketing—high-status seeding—amount to a median of 22 followers over 24 months.[15] Such investments are not worthwhile, because an unknown creator who directs outbound activities to high-status seeding targets faces extremely low a priori song repost probabilities as well as very low expected indirect returns given a song repost. Even more striking, the expected return on individuals with a high status is lower than the expected return on individuals with a low status, as exhibited in Table 3. Thus, investments in high-

[15] After 24 months, the middle 50% have between 19 and 26 followers, where 95% of all observations lie between 13 and 35 followers.

status seeding targets result in the accumulation of natural baseline follows.

Furthermore, we found that investments according to the actual portfolios observed in the data result in a median of 72 followers.[16] This seeding policy, which reflects music creators' (status-dependent) status quo seeding policy, outperforms constant investments in high-status seeding targets by more than threefold. Therefore, the choice of seeding targets by music creators is more effective than the one suggested by current social network literature in marketing.

Finally, we find that investing only in seeding targets with the lowest status results in a median of 127 followers within 24 months.[17] As Table 3 shows, the expected return on high-status seeding targets is lower than the expected return on low-status seeding targets; therefore, low-status seeding manages to accumulate followers more effectively. By directing outbound activities to seeding targets with the lowest status, an unknown creator generates the highest possible continuous growth of his or her follower base, in addition to natural baseline follows. This, in turn, increases the creator's status, which goes hand in hand with higher a priori probabilities and expected returns on each seeding target, hence the slightly convex curve. Our results show that investments only in seeding targets with lowest status clearly dominate over the other two policies. The seeding policy suggested in this research outperforms not only the chosen seeding policy of music creators on the platform but also the one suggested by social network literature by close to sixfold within two years.

In Figure 6, Panel B, we demonstrate the effect of taking into account a discount rate on the ultimate number of followers (i.e., the median follower base after 24 months) by calculating its net present value (NPV). We find that the higher the discount rate—namely, the more myopic the creator is—the less the creator considers the ultimate number of followers. Furthermore, we find that with increasing discount rates, the lower the differences (in terms of NPV) among the three seeding policies. Therefore, a myopic creator might tend to direct outbound activities to high-status seeding targets because this is the only policy that could, in principle, immediately result in a large follower base (though with a very low probability) while all other policies result in a small follower base. If this creator has a utility function containing a threshold (i.e., getting just a few follow-backs from seeding targets is almost the same as getting no follow-backs at all), it strengthens the tendency to direct outbound activities to high-status seeding targets because only a return from such targets could push him or her above the respective threshold. In summary, patience pays off. Unknown creators who aim to build and increase their follower base should ignore predominant seeding policies and build their status gradually.

[16] After 24 months, the middle 50% have between 46 and 81 followers, where 95% of all observations lie between 49 and 94 followers.

[17] After 24 months, the middle 50% have between 116 and 139 followers, where 95% of all observations lie between 98 and 150 followers.

Discussion

Topical research has tended to assume that seeding a target in online social networks is simply a matter of choice and involves no constraints—such as time limitations, search costs to find seeding targets, or antispam policies—or risks in the form of differences in responsiveness (e.g., Hinz et al. 2011). For unpaid endorsements in the context of user-generated content networks, we relax this assumption and consider the risk of getting a return when seeding a specific target. Our research extends existing seeding literature by taking into consideration that, for unpaid endorsements in user-generated content networks, (1) the difference in network status between the creator and the seeding target matters, (2) the creator's budget of outbound activities is constrained, and (3) because different levels of returns are associated with different levels of responsiveness, creators of content solve a risk versus return trade-off when choosing a portfolio of seeding targets consisting of influencers (high status) and ordinary individuals (low status).

Our analyses reveal that music creators on one of the world's leading user-generated content networks in the domain of music do not direct outbound activities only to influencers (i.e., users with a high status measured as indegree). In fact, they spread their budgets of outbound activities and create a portfolio of seeding targets over several orders of magnitude in terms of their network status. Moreover, the higher the creator's status, the greater the number of outbound activities directed to seeding targets with higher status. When comparing the portfolios with the status (indegree) distribution of the platform, it becomes apparent that music creators also consider indirect returns in addition to direct ones, as they also direct outbound activities to high-status seeding targets or influencers. In the spirit of Watts and Dodds (2007), we strengthen the model-free evidence by regenerating the observed distributions using a data-based simulation. In conclusion, our analyses show that unknown creators who want to build and increase their follower base while relying on unpaid endorsements solve a risk versus return trade-off when deciding on a set of seeding targets. A fraction is "invested" in users with a high status difference compared with the music creator under consideration, which is associated with high risk (due to low responsiveness) but potentially high return. The remaining fraction of the portfolio is "invested" in users with a lower status difference, which is associated with lower risk (due to higher responsiveness), but relatively low return.

It is plausible to assume that the same monotonicity we discovered in this research exists in other cases and platforms, perhaps even in the context of paid endorsements. Trying to activate influencers who promote their products and services might be the appropriate policy for large corporations with a strong brand image. However, this seeding policy may not apply for small and medium-sized businesses. Nevertheless, with increasing size and, thus, status of such businesses, the probability of response when targeting influencers improves continuously. The insights for effective seeding policies may be of high importance because, according to recent analyses of federal statistical offices, most businesses are small and medium-sized (e.g., 99.7% in the United States), and they engage a large proportion of labor (e.g., 48.4% in the United States).

In the context of our platform of interest, our empirical analyses reveal that the expected return on influencers is lower than that on ordinary individuals. Influencers are associated not only with low responsiveness but also with surprisingly low return when relying on unpaid endorsements. As a result, an unknown creator of content who aims to build and increase his or her follower base should ignore predominant seeding policies and gradually build status—that is, slowly "climb" rather than attempt to "jump."

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