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

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Abstract

This paper addresses optimal seeding policies in user-generated content networks by challenging the role of influencers. Using data from SoundCloud, the world's leading user-generated content network in the music domain, we study creators of music who seek to build and increase their follower base by directing promotional actions to other users of the networking platform. Focusing on the network status of both creator and seeding targets, we find that, in particular, unknown creators of music do not benefit from seeding high-status users. In fact, it appears that unknown creators should ignore predominant seeding policies and slowly "climb" across status levels of seeding targets rather than attempt to "jump" towards those with the highest status. Our research extends the existing seeding literature by introducing the concept of risk to dissemination dynamics in online communications. We show evidence that unknown creators of music do not seed specific status levels but rather choose a portfolio of seeding targets while solving risk versus return trade-offs. We discuss managerial implications for information dissemination and optimal seeding in user-generated content networks.

Keywords: User-generated content networks, influencer marketing, seeding, information dissemination, social networking, online success.

INTRODUCTION

In the last decade, user-generated content networks and social networking platforms like 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, small groups, and firms that are interested in promoting their own creations as well as their own network status, and in some cases, their career (e.g., Goldenberg, Oestreicher-Singer, and Reichman 2012; Mayzlin and Yoganarasimhan 2012; Netzer et al. 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 growth in his follower base from 4,000 to over 40,000 SoundCloud users (Voogt 2015).

Considering an unknown creator of content (e.g., San Halo) who seeks 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, who on the social networking platform should a creator of content target in order to propagate relevant information or content into the network?

This problem generally belongs to influencer marketing, a topic currently attracting a great deal of attention in business practice (Maheshwari 2016). Influencer marketing and the academic literature on seeding share the common view that the higher the network status is of the target, the more effective the seeding or buzz program (Gladwell 2000; Iyengar, Van den Bulte, and Valente 2011; Katz and Lazarsfeld 1955; Rogers 1995; Valente 1995; Van den Bulte and Joshi 2007). Hence, a creator of content who seeks to build and increase his or her follower base on a user-generated content platform should direct promotional actions to individuals with a high indegree, a common yet basic operationalization of network status (Ball et al. 2001; Hu and Van den Bulte 2014; Sauder, Lynn, and Podolny 2012). However, in this paper, we show that high-indegree seeding is in fact often inefficient, and we demonstrate and recommend a more effective policy, which is somewhat counterintuitive: Optimal seeding in user-generated content networks is achieved by approaching users with low status.

The predominant view on dissemination dynamics is built on a strong assumption that the responsiveness of individuals with a high network status, i.e., the probability of responding to targeted promotional actions, is equal or similar to any other individual on the social networking platform (e.g., Hinz et al. 2011; Yoganarasimhan 2012). In user-generated content platforms, it is not clear whether this assumption holds: Why should someone with high status equally treat endorsement requests by individuals with high and low status? If we take into account that the probability of responding to an endorsement request is dependent on the network status, optimal seeding policies in user-generated content networks may completely change. Indeed, we show that (1) in almost all cases, responsiveness is a function of the status differences between the sender and receiver of endorsement requests, and (2) due to this difference, targeting high-status individuals is a significantly inferior seeding policy compared to targeting low-status individuals.

In this paper, we study commonly used endorsement requests in user-generated content networks – *promotional actions* including *follows*, *private messages*, *reposts*, *comments*, and *likes*. In the context of SoundCloud, we first analyze the responsiveness of seeding targets, namely, when creators of music send promotional actions to other users of SoundCloud in order to get *follow-backs*. We find that the higher the difference of network status between the creator and the seeding target, the lower is the a priori probability of a response. Furthermore, we analyze the creator's return on a targeted promotional action and find 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). Moreover, we find that the higher the network status of the seeding target, the higher the indirect return. Hence, the return on high-status individuals is higher than on low-status individuals, which is in line with common social network literature in marketing. However, the return scheme changes once we consider returns based on different levels of responsiveness. For unknown creators who seek to build and increase their follower base, high-status individuals are therefore associated with *very low responsiveness* but potentially high return, whereas low-status individuals are associated with *much higher responsiveness* but relatively low return.

In addition, we analyze how creators of music on SoundCloud distribute promotional actions over seeding targets with different network status by taking into account that the individual "budget" of promotional actions is constrained (first, the time during which creators consider and exert promotional actions to build and increase their follower base is limited; second, creators face search costs to find seeding targets as well as anti-spam policies, which limit their self-promotion efforts). In this sense, our research further extends existing seeding literature. Contrary to a common assumption that the limit on seeding resources is not confined, we account for this constraint and show how budget considerations affect the selection of seeding targets. Drawing on the von Neumann–Morgenstern utility function (e.g., Archak, Ghose, and Ipeirotis 2011; Eliashberg 1980; Von Neumann and Morgenstern 1947), we show evidence that creators of music on SoundCloud make their seeding decisions while taking into account a risk versus return trade-off. Considering their portfolios of seeding targets in a given time period, we find that a fraction is "invested" in SoundCloud users with a high status difference compared to the creator of music under consideration, which is associated with *high risks* (due to low responsiveness) but potentially high returns. The remaining fraction of the portfolio is "invested" in SoundCloud users with a lower status difference, which is associated with *lower risks* (due to higher responsiveness) but relatively low returns.

Finally, we analyze the creators' aversion to risk, which affects the individual portfolio choice of seeding targets. We find that creators' portfolio choices of seeding targets are predominantly risky: Instead of slowly "climbing" the ladder of status levels of seeding targets, they attempt to "jump" towards those with the highest status – and keep failing to effectively accumulate followers to build and increase their fan communities.

The remainder of the paper is organized as follows. An overview of the relevant literature is presented in the subsequent section followed by the data description, theoretical reasoning, and empirical findings, as well as a simulation study about optimal seeding policies. We conclude our paper with a discussion of our findings and implications for marketing and online communications practice.

BACKGROUND

This paper is related to three broad streams of literature. One stream focuses on information dissemination within social networking platforms. Another studies optimal seeding policies and their implications on viral marketing, and a third stream of literature concentrates on the domain of social psychology, which investigates status differences and the resulting inter- and intragroup behaviors. We discuss the related literature with a focus on user-generated content networks, which constitute a unique type of social networking platform.

Information Dissemination

User-generated content networks offer companies as well as individuals new opportunities to increase their follower base and, hence, brand awareness. On one hand, they can build and increase their follower base by means of paid advertisements. On the other hand, promotional actions in the form of follows, messages, comments, and likes allow companies and individuals to directly engage with targeted users in order to get a follow-back, i.e., to form a reciprocal tie (Wasserman and Faust 1994). A follow-back can further trigger cascades (Chae et al. 2016; Kozinets et al. 2010), which result in additional followers. Information dissemination and, therefore, the success of seeding decisions are dependent on the structure of the respective social networking platform, e.g., indegree distribution and density (for an overview see Jackson (2010)). It is possible to infer from the indegree distribution and, more specifically, the prevalence of users with a large follower base not only the speed but also the spread of the information dissemination (Goldenberg et al. 2009). The same applies to the density or degree of connectedness among users of a social networking platform (Katona, Zubcsek, and Sarvary 2011; Stephen and Toubia 2010).

We consider each creator in user-generated content networks to be a separate brand, also referred to as a *human brand* (Thomson 2006). Such human brands vary heavily in their network status, ranging from unknown to extremely popular. In social network literature, the level of status (Katz 1953; Moreno 1934) 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 a node has (Shaw 1954). Hence, some researchers use the terms status and indegree interchangeably (e.g., Iyengar, Van den Bulte, and Valente 2011). Status can be further measured by means of closeness and betweenness centrality (Freeman1978), but unlike indegree centrality, these are not clearly visible to all nodes in online social networks. The limited availability of information in user-generated content networks forces unknown creators to assess the status of seeding targets only by their indegrees. The closeness and betweenness centrality, on the other hand, can be observed exclusively by the social networking platform itself. This stands in contrast to various studies in which it is assumed that all network information is accessible (e.g., Katona, Zubcsek, and Sarvary 2011; Stephen and Toubia 2010). Nodes that are extremely popular and have a high indegree are referred to as hubs (Goldenberg et al. 2009), opinion leaders (e.g., Iyengar, Van den Bulte, and Valente 2011; Weimann 1991), connectors (Gladwell 2000), and influentials (e.g., Lionberger 1953; Merton 1968; Watts and Dodds 2007), with each term differing slightly in meaning.

Optimal Seeding

A large body of literature exists on high-status individuals, or influencers (Kirby and Marsden 2006; Rosen 2010), and it is widely agreed that they play a pivotal role due to their ability to either accelerate or block the dissemination process. The two-step flow model described by Katz and Lazarsfeld (1955) characterizes opinion leaders as disseminators of information and, therefore, as the link between mass media and the public. Hence, influencers are regarded as powerful seeding targets. Apart from high-indegree seeding, there are two other policies based on sociometric measures: low-indegree seeding (or fringes) and high-betweenness seeding (or bridges) (Granovetter 1973). Social network literature suggests almost entirely that self-promotion efforts should seek to seed individuals with a high indegree (e.g., Easley and Kleinberg 2010; Hanaki et al. 2007; Hinz et al. 2011; Iyengar, Van den Bulte, and Valente 2011; Van den Bulte and Joshi 2007; Yoganarasimhan 2012). On the contrary, in a computer simulation, Watts and Dodds (2007) find that for most cases, high-indegree seeding does not have a major impact on cascades of influence, which agrees with studies showing that high-status individuals are not influential per se (Aral and Walker 2012; Trusov, Bodapati, and Bucklin 2010).

Since marketing managers decide upon a set of seeding targets for viral marketing campaigns (e.g., Bampo et al. 2008; Libai, Muller, and Peres 2005), the assessment regarding the value of such influencers is essential. In this context, Haenlein and Libai (2013) suggest to shift the focus toward the customer lifetime value of seeding targets. However, marketing managers along with creators of content who seek to build and increase their follower base usually make seeding decisions with very little information, the key factors being the status and indegree. Hinz et al. (2011) compare three different policies based on sociometric data. They show that high-indegree seeding outperforms two other policies focusing on fringes and bridges, partially because well-connected nodes capitalize on their greater reach and not entirely due to the fact that 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 that emerges from this study corresponds to Hinz et al. (2011) because high-indegree seeding resulted in far more clicks on videos in comparison to random seeding.

The Role of Status

While research usually places the focus on dissemination processes of products, we move the emphasis to the dissemination of unknown creators of content, i.e., human brands. Since unknown creators of content seek to build and increase their follower base, all their efforts are considered to be promotional actions. In this context, we argue that the effectiveness of these promotional actions and, therefore, the return opportunities depend jointly on the status of the sender and the receiver, i.e., the creator of content and the seeding target. In a recent paper, Hu and Van den Bulte (2014) show that status matters not only in terms of one's susceptibility to adopt and the adoption time, but also in the way that one's behavior affects others in terms of adoption. The authors conclude that for commercial kits used in genetic engineering, optimal seeding targets are individuals with high and middle status due to inverse-U patterns regarding adoption susceptibility and time. However, a gap remains in our knowledge since the focus of Hu and Van den Bulte (2014) is mainly on the status of the seeding targets. We, on the other hand, take into account the status of both the seeding targets and the creators of content who seek to build and increase their follower base. Furthermore, we consider the confronted trade-offs in terms of risk versus return.

Risk (and hence the trade-off) occurs as a result of different responsiveness levels associated with different status levels of seeding targets. Status differences and the corresponding inter- and intragroup behaviors are investigated in the social psychology literature. In this domain, the social identity theory (Tajfel and Turner 1979, 1986) 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 aim to preserve group boundaries and members (Ellemers et al. 1992; Terry, Carey, and Callan 2001; Van Knippenberg and Ellemers 1993). In contrast, low-status individuals want 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). In fact, individuals aim to form ties with high-status individuals due to the status transfer, which has been studied in the context of 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, 2005). This becomes apparent in the context of online dating, where 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 (Buss and Barnes 1986; Feingold 1990; Lee et al. 2008; Walster et al. 1966), whereas individuals with high physical attractiveness favor strong in-group preference (Buston and Emlen 2003; Kowner 1995; Little et al. 2001; Todd et al. 2007). These phenomena that (1) everyone tends to reach out to high-status individuals, and that (2) they, in turn, respond preferably only to their own sort serve as a starting point for our paper.

We consider creators of music who seek to build and increase their follower base utilizing user-generated content networks. Each creator exerts a number of *promotional actions*: follows, messages, comments, and likes. Promotional actions are directed to *seeding targets* – users who are not part of the creator's follower base at the time of seeding. Hence, we do not take retention efforts into consideration, that is, promotional actions directed to the follower base. Prior research shows that high-status individuals are bombarded with a large number of incoming actions (Buss and Barnes 1986; Feingold 1990; Lee et al. 2008; Walster et al. 1966), whereas low-status individuals are not exposed to such competition for their attention. In addition, high-status individuals tend to respond only to other high-status individuals (Buston and Emlen 2003; Kowner 1995; Little et al. 2001; Todd et al. 2007). Therefore, we expect that *the higher the status difference*[1] *is between the creator of content and the seeding target, the lower the responsiveness of the seeding target will be.*

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

DATA

In our empirical analysis, we use data from SoundCloud, the world's leading user-generated content network in the domain of music. SoundCloud is home to 12 million creators of music and attracts 170 million monthly listeners (Pierce 2016). The social networking platform consists of two types of user profiles: creators of music 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 seek to expand their follower base. Fans, on the other hand, receive updates from their favorite creators and listen to their songs, as well as connect with their peers on the network. Hence, the social networking platform is composed of creators of music and their fan communities and offers users different possibilities to interact with each other. As with Twitter or Instagram, users of SoundCloud can follow each other without being followed back. Thus, the social networking platform at hand is directed. Users can further listen to songs uploaded on the artists' profiles; they can like these songs and leave comments about them. 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 the popularity of songs and, for this reason, on the creators of music. Finally, users can contact each other by sending private messages. Consistent with Saboo, Kumar, and Ramani (2015), we study creators of music who upload songs on their profiles that can be listened to by other network users. In this context, unknown creators[2] who seek to build and increase their follower base, i.e., their brand communities, can reach out to users of the social networking platform by following them, sending them private messages, reposting their songs, commenting on their songs, or liking their songs.[3]

Our first data sample consists of 35,956 users (24,020 creators of music and 11,936 fans) and their egocentric networks. These users represent all sign-ups in the first quarter of 2009.

[2] We define unknown creators of music as all users who have uploaded at least one song and whose indegree has not crossed two orders of magnitude, i.e., a fan community of 100 followers.

[3] Regarding all creators 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 drops to 83% in the consecutive year.

This dataset contains all information about the formation of the users' egocentric networks over a period of five years (January 2009–March 2014), as well as all data on all incoming and outgoing activities of each user including follows, messages, plays, comments and likes over the entire period. Moreover, we collected this information about their first degree alters, i.e., their followers. In late 2012, SoundCloud introduced the function and possibility for users to repost songs, which appears in followers' news feeds. As our first data sample does not include returns on song reposts (indirect returns), in our empirical analysis we incorporate a second data sample that consists of 35,000 users (4,978 creators of music and 30,022 fans) who signed up in the first week of March 2013, and we tracked them over a period of two years (until July 2015). The descriptive statistics of both data samples used in our empirical analysis are provided in Table 1.

— Insert Table 1 about here —

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

THEORETICAL REASONING AND EMPIRICAL FINDINGS

Status Difference Matters

To study the dynamics of reciprocity with the aim of investigating the responsiveness of seeding targets, we zoom in to the dyadic level and analyze all 4,964,174 promotional actions sent to users of SoundCloud who were not part of the creators' follower base at the time of sending. These promotional actions consisting of follows, messages, song comments, and song likes were sent by 18,005 creators of music over 1,959 days.[4] We focus on the responsiveness of

[4]Each promotional action is equally weighted, and we do not consider the content of the message or song comment (and thus its effect on virality; Berger and Milkman 2012).

seeding targets, a binary measure denoted as 1 if the seeding target followed the creator back within a week, and 0 otherwise. We further take into consideration the difference in indegree, the most basic operationalization of network status (e.g., Van den Bulte and Wuyts 2007), between the sender and receiver of promotional actions. 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 SoundCloud. 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 compared to 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). 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. Hence, Figure 1 exhibits a model-free representation of the probabilities. 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 a 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 curves remains.

— Insert Figure 1 about here —

To further investigate this phenomenon for low- and high-status creators, we segregate these two groups and define the former as creators with status less than two orders of magnitude, i.e., 100 followers, and the latter as creators with status more than three orders of magnitude, i.e., 1,000 followers. Figure 2 exhibits the a priori response probabilities as a result of promotional actions from low- and high-status creators. Since there is a clear right shift of a priori response probabilities from low- to high-status creators, status matters when directing promotional actions to seeding targets. Put differently, high-status creators have a higher a priori response probability in comparison to low-status creators for any status of a seeding target. The monotonicity of both curves is identical to Figure 1. This is also the case when allowing for longer reaction periods.

— Insert Figure 2 about here —

Both Figures 1 and 2 provide evidence that the higher the status difference between the creator and the seeding target, the lower is responsiveness. Whereas Figure 2 distinguishes between high- and low-status creators, Figure 1 generally exhibits the a priori response probability, given the status difference between the creator and the seeding target.

In a context where the probability to follow back varies, the optimal seed is not necessarily the influencer. However, our analyses do not reveal which seeding targets a creator *should* choose since different levels of responsiveness also correspond to different levels of return (an influencer can create a higher exposure relative to an ordinary individual). In the next subsection, we describe the individual portfolio of seeding targets, as well as associated returns.

Risk Versus Return Trade-Offs

Topical research assumes that seeding a target in online social networks is just a matter of choice and does not involve any risk, either in the form of time constraints, search costs to find seeding targets, anti-spam policies, or differences in responsiveness (e.g., Hinz et al. 2011; Yoganarasimhan 2012). Put differently, in current research, a chosen seeding target subsequently promotes the advertised product or service with certainty. We relax this assumption and consider the risk of getting a return when seeding a specific target. The previous subsection reveals that there is a difference in responsiveness when seeding an unconnected node compared to a highly connected one. Therefore, we again zoom into the relational mechanisms on a dyadic level (Rivera, Soderstrom, and Uzzi 2010) and associate different levels of responsiveness with different levels of *returns*. The return scheme, which results from a seeding target who responds to a promotional action, is composed of two sources: (1) a *direct return* – the follow-back from the seeding target, which depends on the responsiveness; and (2) an *indirect return* – one that results from the seeding target's follower base, which depends on whether the seeding target further reposts songs from the creator or not. Song reposts trigger additional follows as they disseminate into the seeding target's egocentric network (e.g., Everett and Borgatti 2005; Wasserman and Faust 1994). Therefore, creators make seeding decisions while accounting for the influence of status difference on the a priori probability of response, along with the associated potential returns.

Creators vary in their expenditure of time for self-promotion and seeding efforts. Along these lines, we consider the number of promotional actions sent by a creator within a time period as *budget*. On average, low-status creators (those with less than 100 followers) have a weekly budget of 2.3 promotional actions. Due to the large size of user-generated content networks such as SoundCloud, creators cannot reach out to all users, neither at once nor over the entire lifetime. Moreover, due to time constraints, search costs to find seeding targets, and anti-spam policies, the individual budget of promotional actions is not unlimited, as is often (mostly implicitly) assumed. In line with Facebook and Twitter, SoundCloud's Community Guidelines do not allow users to "post identical or almost identical comments or messages in large volumes; repeatedly follow large volumes of accounts in a short period of time; repeatedly contribute your tracks to large volumes of groups in a short period of time; repeatedly unfollow and refollow the same accounts, in order to draw attention to your own profile; repeatedly repost or like tracks that you have reposted or liked in the past" (SoundCloud 2016). Therefore, creators are forced to decide upon a set of seeding targets and, thus, have to create a *portfolio* of individuals, namely SoundCloud users they want to target with promotional actions to receive follow-backs.

According to common social network literature in marketing (e.g., Goldenberg et al. 2009; Libai, Muller, and Peres 2013), the optimal portfolio choice of seeding targets is a corner solution: to direct all promotional actions to individuals with a high indegree, because in the case of response, the increase in the creator's follower base is higher compared to a response by a person with a low indegree. However, our analysis reveals that the probability of response by a target with a high indegree depends on the status of the creator. For unknown creators who seek to build and increase their follower base, targeting influencers is associated with high risk (due to their low responsiveness), while targeting ordinary individuals is associated with lower risk (due to their higher responsiveness). The optimal composition of the portfolio of seeding targets with different indegrees 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*.

We define an optimal portfolio of seeding targets by drawing on the von Neumann–Morgenstern utility framework (see Archak, Ghose, and Ipeirotis 2011; Eliashberg 1980; Hauser and Urban 1977; Hauser 1978; Hauser and Urban 1979), which implies that the creator selects a portfolio that maximizes expected utility. We assume that the creator can choose between two investment tracks, namely influencers (individuals with a high status and indegree) and ordinary individuals. We further assume that the creator gains utility from the returns on a portfolio, where the utility is an increasing function of returns. Endowed with a budget B, the creator is confronted with a portfolio choice under uncertainty and has to invest a fraction X of budget B in low-status individuals and a fraction Y of budget B in high-status individuals, where $X + Y = B$. Investments in targets with a low status (ordinary individuals) are successful with probability p_L and, subsequently, yield a low return L. Investments in targets with a high status (influencers) are successful with probability p_H and yield a high return H. Following the risk versus return trade-off, the return on ordinary individuals is lower than on influencers, i.e., $L < H$; however, the probability of success when investing in low-status individuals is higher, i.e., $p_L > p_H$.[5]

[5] Although the response (follow-back) probability of high-status individuals is very low and the probability that they repost a song is marginal, it is possible that a series of follows from high-status individuals is triggered if one of them responds. In this case, the indirect return of the high-status individual that received the promotional action, i.e., H, would just be rescaled. Moreover, as the global clustering coefficient of SoundCloud is very low, low-status individuals are usually not interrelated. Based on the above, we thus assume independency of returns.

We consider a static model with one time period and incorporate in the magnitude of H all expected returns resulting from cascades initiated by a response from an influencer, as well as the status increase of the creator due to the additional number of followers. Formally, a creator directs a promotional action to seeding target R, where Z_R is the return that the creator gains as a result. Thus an investment in a low-status individual yields

$$Z_R = \begin{cases} L & \text{with probability } \ p_L \ , \\ 0 & \text{with probability } \ (1 - p_L) \ , \end{cases} \tag{1}$$

whereas an investment in a high-status individual yields

$$Z_R = \begin{cases} H & \text{with probability } \ p_H \ , \\ 0 & \text{with probability } \ (1 - p_H) \ . \end{cases} \tag{2}$$

Based on the above return scheme, the creator invests his or her budget in low- and high-status individuals, i.e., ordinary individuals and influencers. The expected utility of this portfolio choice is given by

$$EU = \sum_{x=0}^{X} \sum_{y=0}^{Y} \binom{X}{x} \binom{Y}{y} p_L^x \, p_H^y \, (1 - p_L)^{X-x} \, (1 - p_H)^{Y-y} \ U(xL + yH) \ . \tag{3}$$

While deciding upon a set of seeding targets, the creator solves the following optimization problem:

$$\operatorname*{Max}_{X,Y} \, EU(Z(X,Y)) \quad \text{s.t.} \quad X + Y = B \ , \tag{4}$$

where $Z(X,Y)$ is a random variable that expresses the return, given an investment X and Y in low- and high-status individuals, respectively, such that $Z(X,Y) = xL + yH$ with probability $\binom{X}{x}\binom{Y}{y} p_L^x \, p_H^y \, (1 - p_L)^{X-x} \, (1 - p_H)^{Y-y}$.

If we assume that the creator is risk neutral, then uncertainty does not influence the portfolio choice. Therefore, the creator solely chooses the investment track that yields the highest expected return.[6] In case the expected return on high-status individuals is higher

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

than on low-status individuals, the creator invests the whole budget in high-status individuals. Otherwise, the whole budget is invested in low-status individuals. Consequently, if the creator invests the budget in both investment tracks, then he or she cannot be risk neutral.

Proposition 1. *If a creator of content is risk neutral, then the whole budget is invested in high-status individuals, i.e.,* $Y^* = B$*, in case the expected return on high-status individuals is higher than on low-status individuals, i.e.,* $p_H H > p_L L$*. Otherwise, the whole budget is invested in low-status individuals, i.e.,* $X^* = B$ *(see Appendix A.1).*

Corollary 1. *If a creator of content invests in both low- and high-status individuals, i.e.* $X^* \neq 0$ *and* $Y^* \neq 0$*, then they cannot be risk neutral (see Appendix A.1).*

From Corollary 1, it follows that a creator of music on SoundCloud cannot be risk neutral if his or her individual portfolio choice of seeding targets includes both low- and high-status individuals. If we assume that the status difference between the creator and the seeding target does not influence the response (follow-back) probability of seeding targets, that is, if the creator believes that the response probability is the same across all status levels of seeding targets, then the optimal choice are high-status individuals and influencers, respectively.

Proposition 2. *If the response probability of high-status individuals equals the response probability of low-status individuals, i.e.,* $p = p_L = p_H$*, then the whole budget is invested in high-status individuals, i.e.,* $Y^* = B$ *(see Appendix A.1).*

From Proposition 2, it follows that if a creator of music on SoundCloud does not take different levels of responsiveness into account, then their individual portfolio choice of seeding targets includes only high-status individuals, as these yield the highest return. However, if we assume that high-status individuals are extremely unresponsive, namely, that their a priori response probability is close to zero, then the optimal choice of seeding targets would be low-status individuals. In this context, sending promotional actions to high-status individuals and influencers, respectively is a waste of resources.

Proposition 3. *If the response probability of high-status individuals is extremely low, then the whole budget is invested in low-status individuals, independent of the aversion to risk. More precisely, for any utility function U there exists a large number K such that for any $p_H < \frac{1}{K}$ the creator of content directs all promotional actions to low-status individuals, i.e. $X^* = B$ (see Appendix A.1).*

From Proposition 3, it follows that if a creator of music on SoundCloud takes into account different levels of responsiveness and assuming that high-status individuals are extremely unresponsive, then the creator's portfolio choice of seeding targets includes only ordinary (low-status) individuals. Propositions 2 and 3 represent two extreme choices of seeding targets and, hence, set the limits for all possible portfolio choices. In Proposition 2, the difference between the responsiveness of low- and high-status individuals is marginal. Therefore, the creator's tendency is to invest in high-status individuals and influencers, respectively. In proposition 3, however, the difference in responsiveness between the status levels is extremely high and, as a result, the creator tends to invest in ordinary (low-status) individuals. All portfolios with investments in both status levels exhibit a risk versus return trade-off. Moreover, if the creator directs promotional actions to low- and high-status individuals, then from Proposition 2, it follows that the creator cannot be risk neutral.

Along these lines, we assume that the higher the status of the creator, the higher the a priori response probabilities. Furthermore, with increasing status of the creator, the relative improvement of the a priori response probability regarding promotional actions directed to high-status individuals is higher compared to low-status individuals (see Tables 2 and 3). Thus, the higher the status of the creator, the more promotional actions are directed to seeding targets with higher status.

Proposition 4. *If the status of a creator of content, i.e. S, increases, then the more is invested in high-status individuals, i.e., $\frac{dX^*}{dS} < 0$ and $\frac{dY^*}{dS} > 0$ (see Appendix A.1).*

From Proposition 4, it follows that if a creator of music on SoundCloud gains followers and, hence, his or her status increases, then the creator reallocates promotional actions from low- to high-status individuals. The allocation of promotional actions is influenced not only by the creator's status, but also by the number of promotional actions sent within a time period, i.e., the budget size. If a creator is endowed with a low budget and few promotional actions, respectively, then with increasing budget, he or she will not necessarily reallocate promotional actions to seeding targets with higher status, as creators want to reach at least a certain baseline growth of follow-backs. If this baseline growth is achieved, then the creator is able to take higher risks and, consequently, can direct promotional actions to seeding targets with higher status, i.e., "first bread then butter".

Proposition 5. *Assuming that the response probability of high-status individuals is extremely low, i.e., $p_H \ll \frac{1}{B}$, and the resulting return (in case the high-status individual responds) is extremely high, i.e., $BL \ll H$, then the larger the budget of a creator of content, the more is invested in high-status individuals, i.e., $\frac{dY^*}{dB} > 0$ (see Appendix A.1).*

From Proposition 5, it follows that if a creator of music on SoundCloud increases the budget size, then the creator starts to reallocate promotional actions to seeding targets with higher status. Propositions 1 to 5 lay the foundation to examine if and how creators of music on SoundCloud are solving risk versus return trade-offs. For this purpose, we cluster SoundCloud users by their status, i.e., indegree, and separate them according to order of magnitude. This classification is appropriate as it follows a logarithmic scale and, thereby, lives up to the dispersion of indegrees in well-established online social 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 3, we contrast 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 indegree has not crossed two orders of magnitude, i.e., a fan community of 100 followers. Figure 3 illustrates that all creators of a specific type do not direct all promotional actions to a specific type of seeding target; a corner solution does not appear. In fact, they spread their budget of promotional actions over several orders of magnitude in terms of status of seeding targets. Moreover, in accordance with the insights provided by Propositions 2 and 3, creators choose a portfolio of seeding targets because they do not direct promotional actions just to low- or high-status individuals. These different portfolios, in the form of four bell-shaped distributions over several orders of magnitude in terms of status, are illustrated in Figure 3. Based on the insights from Proposition 1 and Corollary 1, creators are thus not risk neutral. They further consider the influence of status difference on the a priori probability of response; otherwise, they would, according to Proposition 2, simply direct promotional actions to individuals with high status, i.e., influencers with a high indegree. Therefore, we find supplementary evidence in support of our expectation regarding the effect of status difference on the a priori response probabilities. Furthermore, Figure 3 shows that the four bell-shaped distributions shift more to the right as the status of creators increases, providing evidence for Proposition 4, which states that the higher the creator's status, the higher the status of their seeding targets.

— Insert Figure 3 about here —

Could this allocation result from a random selection of targets? We analyze and compare our findings with the seeding policy in which the creator of music on SoundCloud randomly directs promotional actions to seeding targets. This random seeding policy is reflected by the indegree distribution of SoundCloud and serves as a benchmark. For this reason, we assess the status of all available users of SoundCloud, which amount to 394,262 creators of music and fans. As we expect a right shift of the indegree distribution over time due to SoundCloud's growth, we calculate it at the end of the observation period – in the first week of 2014. Since the different portfolios of seeding targets in the form of the four distribution curves are different from the indegree distribution, we conclude that creators do not randomly direct promotional actions to seeding targets. Moreover, Figure 3 reveals an increased tendency to direct promotional actions to seeding targets with higher status because the distribution curves lie on the right side of the indegree distribution, i.e., the random seeding policy. More specifically, in addition to direct returns, creators aim for indirect returns to get follow-backs from the followers of the seeding targets. To sum up, Figure 3 provides evidence for our expectation that unknown creators who seek to build and increase their follower base solve a risk versus return trade-off.

With Proposition 5 in mind, we study the effect of the number of promotional actions sent within a time period (considering the creator's budget size) on the choice of status levels of seeding targets. More precisely, there is heterogeneity among creators of the same type regarding their budget size: Some creators of music spend a larger fraction of their time on SoundCloud and, as a result, exert more promotional actions within the time period. Recall that our analyses focus on unknown creators who seek to build and increase their follower base. Figure 4 exhibits, given their weekly budget, a type-1 creator's relative investment in seeding targets of types 1, 2, 3, and 4. The weekly budget size is split into one to ten actions and more. For example, a type-1 creator with a budget of one promotional action per week allots 38% to type 1, 30% to type 2, 22% to type 3, and 10% to type 4. On average, a type-1 creator has a weekly budget of 2.3 promotional actions. Figure 4 suggests that these creators become less risk-averse with increasing budget. The probability to invest in type 1 seeding targets decreases with increasing budget, from 38% to 28%, which is found to be highly statistically significant, i.e., the Pearson's chi-squared test with Yates' continuity correction gives a p-value of < 0.0001.

— Insert Figure 4 about here —

So far, we have found evidence for both our expectations regarding the effect of status difference on the a priori response (follow-back) probabilities, as well as the risk versus return trade-offs. Due to the monotonicity of the curve in Figure 1, we conclude that the higher the status difference between the creator and seeding target, the lower the responsiveness. Furthermore, Figure 2 shows that for any status of a seeding target, high-status creators have a higher a priori probability of getting a response or direct return in comparison to low-status creators. In the absence of indirect returns – namely, follow-backs from the followers of the seeding targets – unknown (low-status) creators who seek to build and increase their follower base would only consider response probabilities. In this case, they would not include high-status individuals and influencers, respectively in their portfolio of seeding targets. However, Figure 3 shows that creators spread their budgets of promotional actions over several orders of magnitude in terms of status, meaning they choose a portfolio and do not send only to a certain status. More specifically, the higher their own status, the more promotional actions are sent to seeding targets with higher status. When comparing the portfolios with the indegree distribution of SoundCloud, it becomes apparent that creators of music also consider indirect returns in addition to direct returns, as they send promotional actions to high-status seeding targets too. These findings support our expectation regarding the risk versus return trade-offs. Thus, we conclude that unknown creators who seek to build and increase their follower base solve a risk versus return trade-off when choosing their portfolio. Furthermore, with increasing budget, they have a lower tendency to allocate promotional actions to low-status seeding targets, as Figure 4 shows.

Summing up, our empirical analysis of creators' revealed preferences on SoundCloud indicates that unknown creators of music are choosing a portfolio of seeding targets while solving a risk versus return trade-off. Hence, they do not reach out exclusively to those individuals with the highest status in the network in terms of centrality, as suggested by current social network literature in marketing. In the following section, we investigate expected total returns on seeding targets retrieved from the data and discuss these implications on the individual aversion to risk.

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 individuals, depends on the creator's aversion to risk. To develop deeper insights into creators' seeding policies and how these are influenced by their aversion to risk, we compute the expected total return on each seeding target (the expected value of the returns given their distribution), which accounts for (1) the expected direct returns and (2) the expected (indirect) returns associated with a song repost.

We first measure the a priori response (follow-back) and song repost probabilities before assessing the indirect return – the number of follows from the seeding target's follower base in the case of a song repost. Note that the direct return is a binary measure (equals 1 if the seeding target responds to the promotional action from the creator, or 0 otherwise). In our analysis, we classify users (creators and seeding targets) again by their indegree and separate them according to the order of magnitude, resulting in four groups of creators and seeding targets, respectively (same definition of types as before). Table 2 shows the a priori response probabilities for all combinations of creator and seeding target types, and whether the seeding target follows the creator back within a week after receiving a promotional action. Recall that our analyses focus on low-status (unknown) creators, type 1, who seek to build and increase their follower base. In the case of a type-1 creator, the a priori response probabilities range between 7.41% (type-1 seeding target) and 0.03% (type 4-seeding target). For a type-4 creator (with a fan community of more than 100,000 followers), these a priori response probabilities range as high as 15.03% (type-1 seeding target) and 0.75% (type-4 seeding target).

— Insert Table 2 about here —

To compute the expected (indirect) returns associated with a song repost, for all combinations of creator and seeding target types, we further analyze the a priori song repost probabilities – primarily, whether the seeding target reposts a song of the creator within a week after receiving a promotional action from the creator. Compared to the a priori response probabilities, as shown in Table 2, the a priori song repost probabilities are significantly lower. Table 3 shows that in the case of a type-1 creator, the a priori song repost probabilities range between 0.109% (type-1 seeding target) and 0.001% (type-4 seeding target). For a type-4 creator, these a priori song repost probabilities increase to 0.372% (type-1 seeding target) and 0.023% (type-4 seeding target).

— Insert Table 3 about here —

After measuring both the a priori response and song repost probabilities, we further compute the expected (indirect) return associated with a song repost to finally calculate the expected total return of a creator's promotional action and self-promotion effort. In our analysis, we consider 1,501,051 song reposts from 9,402 creators on SoundCloud over 424 days. For all combinations of creator and seeding target types, Table 4 exhibits the expected follows and song plays realized within a week after a song repost. The results reveal that the expected indirect return for an unknown creator within a week, given a song repost from a type-4 user, amounts to 7.6 follows and 281.6 plays on average. The reaction period was set to one week, as this time span corresponds to the average login frequency of users of SoundCloud and accounts for the short lifespan of published information in the user's news feed in which the song repost is shown. Doubling the reaction period to two weeks results in only a marginal increase: on average in a total of 8.1 new follows and 304.4 song plays, respectively. Both the conversion of plays to follows and the general level of the figures are low. Qualitatively, our results show that the a priori song repost probabilities, as shown in Table 3, as well as the expected indirect returns given a song repost, as shown in Table 4, are extremely low for an unknown creator who sends promotional actions to high-status individuals.

— Insert Table 4 about here —

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 analyze and compute the expected total return on a promotional action directed to a seeding target. The expected total return on a seeding target consists of the expected direct return, which is determined by the a priori response probabilities, and the expected indirect return, which is determined by the a priori song repost probabilities, as well as the expected indirect returns given a song repost (see Appendix A.2 for a detailed description).

Analyzing 4,964,174 promotional actions that include follows, messages, song comments, and song likes of 18,005 creators of music over 1,959 days, Table 5 shows the expected total returns for all combinations of creator and seeding target types. Surprisingly, the expected total return on high-status individuals is *lower* than the expected total return on low-status individuals. In particular, an unknown creator who directs a promotional action to a type-1 seeding target gets on average .0741 follow-backs with a standard deviation of .2619. In contrast, directing a promotional action to a type-4 seeding target yields almost no return with certainty because the expected total return is as low as .0003 follow-backs, and the corresponding standard deviation amounts to .0446. In other words, the lower the target's status, the higher the expected total return, which implies that a creator of music on SoundCloud should not direct promotional actions to high-status individuals and influencers, respectively.

— Insert Table 5 about here —

Our analysis shows that for unknown creators who seek to build and increase their follower base, influencers are associated not only with surprisingly low return but also with high risks (due to their low responsiveness), while ordinary individuals are associated with relatively lower return, but also lower risk (due to their higher responsiveness). However, we also find that creators spread their budgets of promotional actions over several orders of magnitude in terms of status, targeting even high-status individuals who feature a lower expected total return than ordinary (low-status) individuals. This indicates that utility-maximizing creators of music on SoundCloud are not completely risk-averse.

Proposition 6. *If the return on high-status individuals is much higher than on low-status individuals such that $H > BL$ but the expected return on high-status individuals is lower* *than on low-status individuals, i.e., $p_H H < p_L L$, and there is an optimal solution such that a creator invests in high-status individuals, i.e., $Y^* \neq 0$, then the creator cannot be risk averse (and the individual utility function U is not concave) (see Appendix A.1).*

If it is common knowledge among creators of music that the value of high-status individuals on SoundCloud in terms of expected total returns is questionable, it follows from Proposition 6 that high-indegree seeding indicates risk-seeking behavior: Risk-averse, utility-maximizing creators of music on SoundCloud would never direct promotional actions to high-status individuals based on this return scheme.

To conclude, our empirical analyses reveal that high-status individuals on SoundCloud are associated with surprisingly low returns, apart from the high risks due to their low responsiveness. Given that this return scheme is common knowledge, creators reveal a behavior in the context of SoundCloud that is associated with risk seeking because they spread their budgets of promotional actions over several orders of magnitude in terms of status. In the subsequent section, we investigate different seeding policies. In particular, we study the consequences of the observed risk-seeking policy of creators of music on SoundCloud.

COMPARING THE EFFECTIVENESS OF SEEDING POLICIES

The previous sections suggest that if an unknown (low-status) creator of content seeks to build and increase his or her follower base, then he or she should ignore predominant seeding policies and slowly "climb" the ladder of status levels of seeding targets rather than attempt to "jump" towards those with the highest status. More specifically, by directing promotional actions to seeding targets with the lowest status, an unknown creator can generate the highest possible continuous growth of his or her follower base, in addition to natural baseline follows. The accumulation of follows (baseline plus return on seeding targets) increases the creator's status, which goes hand in hand with higher a priori probabilities and, thus, expected total returns on each seeding target.

By means of a randomized dissemination process using the example of a creator who has just signed up on SoundCloud, we contrast three seeding policies. In the first, we simulate unknown creators, initially with zero followers, who invest their budgets of promotional actions in line with the *status quo*. More precisely, for each status we retrieve the average portfolio choice from the data and simulate unknown creators who exert promotional actions accordingly, where the return in the form of additional number of followers is drawn in correspondence with the probabilities 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 paper 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 time period. We focus on creators of music who have just signed up on SoundCloud and, thus, have zero followers in the beginning. During each of the 24 months, the simulated creator invests 40 promotional actions, which corresponds to a weekly budget of 10 and an overall budget of 960 promotional actions, respectively. 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 non-zero return on a seeding target and, further, on the status-dependent probability of either a direct or indirect return.

More specifically, if the return in a given month for a given seeding target is non-zero, then there are two different scenarios. On 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 increases the creator's status, which go hand in hand with higher a priori probabilities and, thus, expected total returns on each seeding target. Both the natural baseline follows and the a priori probabilities including the expected returns on each seeding target are updated in multiples of 25 followers with regard to the growing follower base, after a reaching a community size of ≥ 25 followers, ≥ 50 followers, and so forth. To sum up, the randomized dissemination process first takes into account the status-dependent probability of a non-zero return on a seeding target and, subsequently, considers whether the non-zero return is realized directly or indirectly (see Appendix A.3 for a detailed description of the simulation study).

Results

Figure 5 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-indegree seeding – amount to a median of 22 followers over 24 months.[7] Such investments are not worthwhile, since an unknown creator who directs promotional actions to high-status individuals faces extremely low a priori song repost probabilities, and also very low expected indirect returns given a song repost. Even more striking, the expected total return on individuals with a high indegree is lower than the expected total return on individuals with a low indegree, as exhibited in Table 5. Hence, investments in high-status individuals result in the accumulation of natural baseline follows.

Furthermore, we find that investments according to the actual portfolios observed in the data result in a median of 72 followers.[8] This seeding policy, which reflects the (status-

[7] After 24 months, the middle 50% have between 19 and 26 followers.
[8] After 24 months, the middle 50% have between 46 and 81 followers.

dependent) status quo seeding policy of creators of music on SoundCloud, outperforms constant investments in high-status individuals by more than threefold. Therefore, the choice of seeding targets by creators of music on SoundCloud 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.[9] As shown in Table 5, the expected total return on high-status individuals is lower than the expected total return on low-status individuals; therefore, low-indegree seeding manages to accumulate followers more effectively. Specifically, by directing promotional actions 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 the natural baseline follows. This, in turn, increases the creator's status, which goes hand in hand with higher a priori probabilities and expected total returns on each seeding target, hence the slightly convex curve. Our results show that investments only in seeding targets with lowest status clearly dominate the other two policies. The seeding policy suggested in this paper not only outperforms the chosen seeding policy of creators of music on SoundCloud, it is superior to the one suggested by the common social network literature, by close to sixfold after not more than two years.

— Insert Figure 5 about here —

In summary, patience pays off very well: Unknown creators who seek to build and increase their follower base should ignore predominant seeding policies and slowly "climb" across status levels of seeding targets rather than attempting to "jump" towards those with the highest status. Hence, unknown creators should invest in seeding targets with the lowest status, instead of chasing indirect returns by directing promotional actions to high-status individuals.

[9] After 24 months, the middle 50% have between 116 and 139 followers.

DISCUSSION

Topical research assumes that seeding a target on online social networking platforms is just a matter of choice and does not involve risk in the form of time constraints, search costs to find seeding targets, anti-spam policies, or differences in responsiveness (e.g., Goldenberg et al. 2009; Hinz et al. 2011; Libai, Muller, and Peres 2013; Yoganarasimhan 2012). In the context of user-generated content networks, which constitute a unique type of social networking platform (e.g., Goldenberg, Oestreicher-Singer, and Reichman 2012; Mayzlin and Yoganarasimhan 2012; Netzer et al. 2012; Trusov, Bodapati, and Bucklin 2010), 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 on user-generated content networks (1) the difference of network status between the creator and the seeding target matters, (2) the creator's budget of promotional actions is constrained, and (3) since different levels of returns are associated with different levels of responsiveness, creators of content solve a risk versus return trade-off when choosing their portfolios of seeding targets.

Our analyses reveal that creators of music on SoundCloud, the world's leading user-generated content network in the domain of music, do not direct promotional actions only to influencers, i.e., users with a high indegree. In fact, they spread their budgets of promotional actions 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 are the number of promotional actions sent to seeding targets with higher status. When comparing the portfolios with the indegree distribution of SoundCloud, it becomes apparent that creators of music also consider indirect returns in addition to direct returns, as they send promotional actions to high-status seeding targets too. Our analyses show that unknown creators who seek to build and increase their follower base solve a risk versus return trade-off when deciding upon a set of seeding targets: A fraction is "invested" in SoundCloud users with a high status difference compared to the creator of music 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 SoundCloud users with a lower status difference, which is associated with lower risk (due to higher responsiveness) but relatively low return.

We analyze data from a user-generated content network, which might limit our results to this type of platform. But let us revisit the assumption that the probability of an individual to endorse a person, small group, or firm that requested such an action is constant. This assumption is a very strong one and calls for new examination. It might be that the same monotonicity we discovered in this paper exists in other cases or platforms. In fact, any small- or medium-sized business faces a similar risk versus return trade-off when reaching out to seeding targets. Trying to activate high-status individuals might be the appropriate policy for large corporations with the financial power to compensate influencers who promote their products and services. However, this seeding policy may not apply for small- and medium-sized businesses. With increasing size and thus status of such businesses, the probability of response as well as the associated expected total return when reaching out to influencers improves continuously. The insights for effective seeding policies may be of high importance because, according to the recent analyses of federal statistical offices, most businesses are small- and medium-sized (e.g., 99.7% in the U.S. and 99.3% in Germany), and they engage a large proportion of labor (e.g., 48.4% in the U.S. and 60% in Germany).

In the context of SoundCloud, our empirical analyses reveal that the expected total return on individuals with a high indegree is lower than the expected total return on individuals with a low indegree. Put differently, high-status individuals are associated not only with low responsiveness but also with surprisingly low return. As a result, an unknown creator of content who seeks to build and increase his or her follower base should ignore predominant seeding policies and slowly “climb” in the ladder of status levels of seeding targets rather than attempt to “jump” towards those with the highest status. By directing promotional actions to seeding targets with lowest status, an unknown creator can generate the highest possible continuous growth of the follower base. Future research should investigate this phenomenon in other networks, e.g., in the context of telecommunication, and disentangle the underlying psychological processes, especially the individual aversion to risk, which is beyond the scope of this paper. We hope this paper encourages work in these and other related directions.

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Table 1: Descriptive Statistics

Descriptives		Sample 2009-2014[1] Mean	Sample 2009-2014[1] Median	Sample 2009-2014[1] Std	Sample 2012-2015 Mean	Sample 2012-2015 Median	Sample 2012-2015 Std
Indegree	Aug. 2011	134.77	19.00	532.88	-	-	-
	Mar. 2014	1254.81	59.00	31730.52	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	1254.81	59.00	31730.52	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	7108.54	89.07	6.00	1014.00
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	1703.26	390.00	3876.24	771.25	37.00	2885.87
	received	14378.87	380.00	222609.50	4785.35	176.00	59770.22
Song Reposts	sent	-	-	-	0.04	0.00	0.70
	received	-	-	-	0.02	0.00	1.17
Tracks	uploaded	31.12	9.00	108.10	10.13	3.00	37.85
Weekly Follows	sent	0.55	0.00	10.18	0.19	0.00	4.37
	received	4.12	0.00	362.48	0.10	0.00	1.13
Weekly Song Comments	sent	0.14	0.00	2.00	0.01	0.00	0.28
	received	0.32	0.00	4.84	0.01	0.00	0.32
Weekly Song Likes	sent	0.17	0.00	2.01	0.12	0.00	1.28
	received	1.50	0.00	49.93	0.07	0.00	3.19
Weekly Messages	sent	0.13	0.00	8.36	0.003	0.00	0.21
	received	0.15	0.00	1.01	0.004	0.00	0.25
Weekly Song Plays	sent	5.68	0.00	84.37	5.20	0.00	34.13
	received	50.29	0.00	1658.29	5.98	0.00	266.50
Weekly Song Reposts	sent	-	-	-	0.003	0.00	0.21
	received	-	-	-	0.004	0.00	0.25
Weekly Tracks	uploaded	0.12	0.00	1.66	0.01	0.00	0.35

[1] *We consider only the 24,020 creators of music and omit the 11,936 non-creators that signed up in the first quarter 2009.*

Table 2: Response Probabilities

	Seeding Target Types			
Creator Types	Type 1	Type 2	Type 3	Type 4
Type 1 Seeding Target	7.41%	3.31%	0.37%	0.03%
Type 2 Seeding Target	8.61%	4.97%	0.86%	0.05%
Type 3 Seeding Target	9.07%	7.30%	2.11%	0.22%
Type 4 Seeding Target	15.03%	16.46%	5.86%	0.75%

N = 4,964,174 follows, messages, song comments, and song likes of 18,005 creators of music over 1,959 days / Reaction period = 1 week

Table 3: Song Repost Probabilities

	Seeding Target Types			
Creator Types	Type 1	Type 2	Type 3	Type 4
Type 1 Seeding Target	0.109%	0.050%	0.007%	0.001%
Type 2 Seeding Target	0.174%	0.075%	0.025%	0.014%
Type 3 Seeding Target	0.457%	0.152%	0.078%	0.022%
Type 4 Seeding Target	0.372%	0.554%	0.123%	0.023%

N = 1,377,838 follows, messages, song comments, and song likes of 13,469 creators of music over 498 days / Reaction period = 1 week

Table 4: Expected Indirect Returns (and Standard Deviations) Given a Song Repost

	Follows	**Plays**
Type 1 Creator Reposted by		
Type 1 Seeding Target	0.01 (0.13)	0.48 (1.18)
Type 2 Seeding Target	0.41 (1.67)	6.51 (10.95)
Type 3 Seeding Target	2.22 (4.15)	43.19 (70.94)
Type 4 Seeding Target	7.60 (9.82)	281.60 (335.03)
Type 2 Creator Reposted by		
Type 1 Seeding Target	0.03 (0.19)	0.75 (1.55)
Type 2 Seeding Target	0.45 (1.14)	7.87 (12.68)
Type 3 Seeding Target	2.99 (5.95)	62.10 (112.72)
Type 4 Seeding Target	17.52 (26.94)	779.03 (1104.14)
Type 3 Creator Reposted by		
Type 1 Seeding Target	0.03 (0.20)	0.80 (1.55)
Type 2 Seeding Target	0.34 (0.91)	7.09 (12.96)
Type 3 Seeding Target	4.24 (10.32)	100.42 (194.90)
Type 4 Seeding Target	32.84 (42.81)	1144.18 (1719.02)
Type 4 Creator Reposted by		
Type 1 Seeding Target	0.03 (0.19)	1.13 (1.95)
Type 2 Seeding Target	0.26 (0.70)	7.66 (13.32)
Type 3 Seeding Target	3.15 (6.44)	113.13 (237.84)
Type 4 Seeding Target	55.86 (67.68)	2397.01 (3063.42)

N = 1,501,051 reposts of songs from 9,402 creators of music over 424 days / Reaction period = 1 week

Table 5: Expected Total Returns (and Standard Deviations)

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

N = 4,964,174 follows, messages, song comments, and song likes of 18,005 creators of music over 1,959 days / Reaction period = 1 week

Figure 1: A Priori Response Probabilities

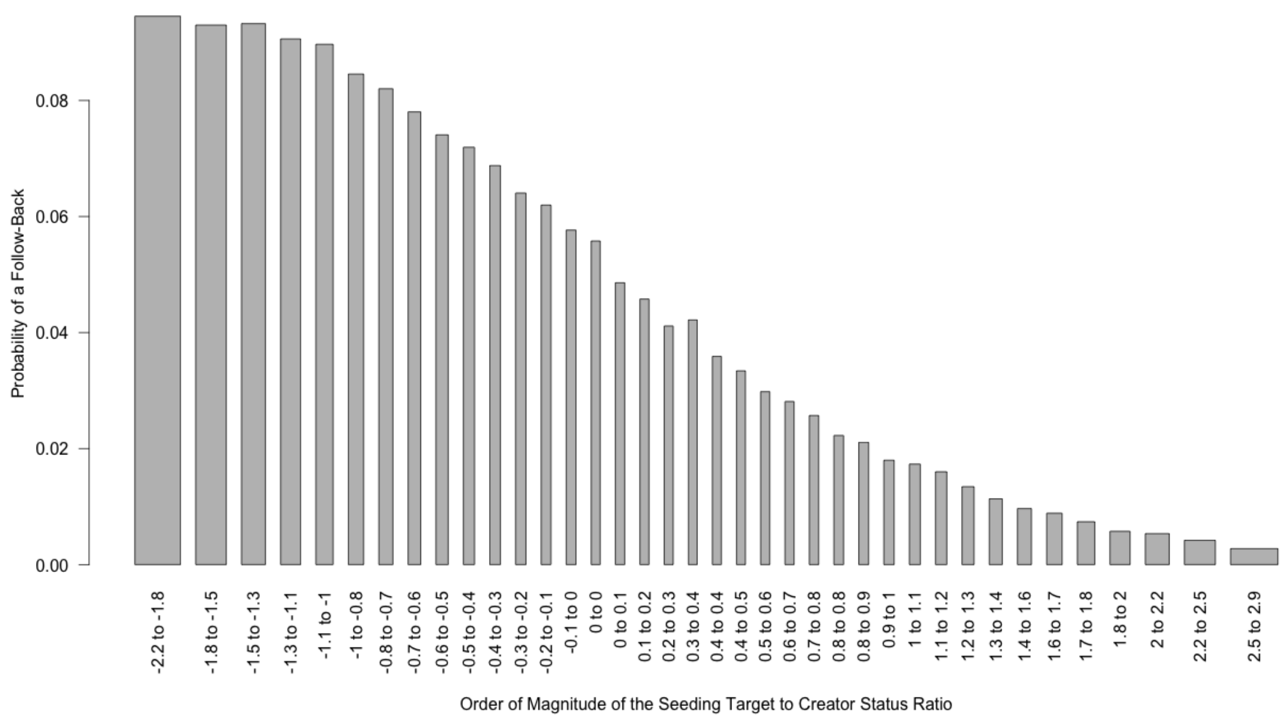


Figure 2: A Priori Response Probabilities: Low- and High-Status Creators

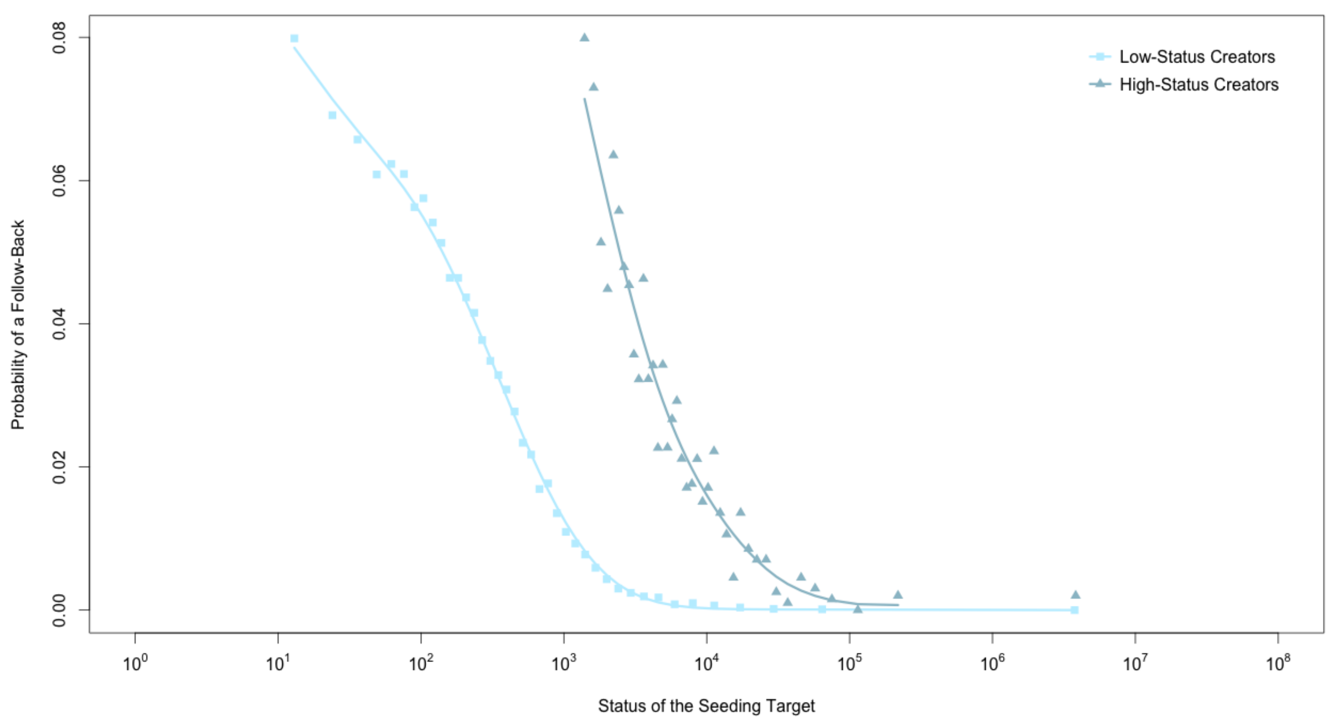


Figure 3: Portfolios of Creators

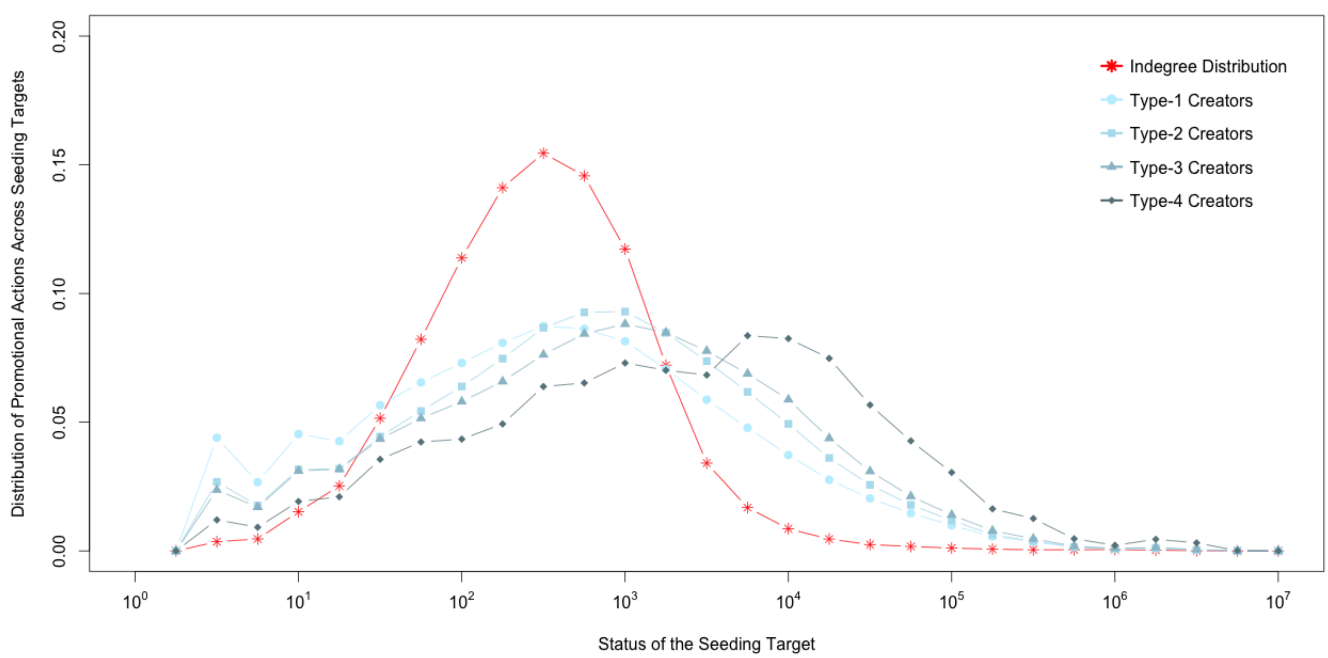


Figure 4: Portfolio of Type-1 Creators as a Function of the Budget

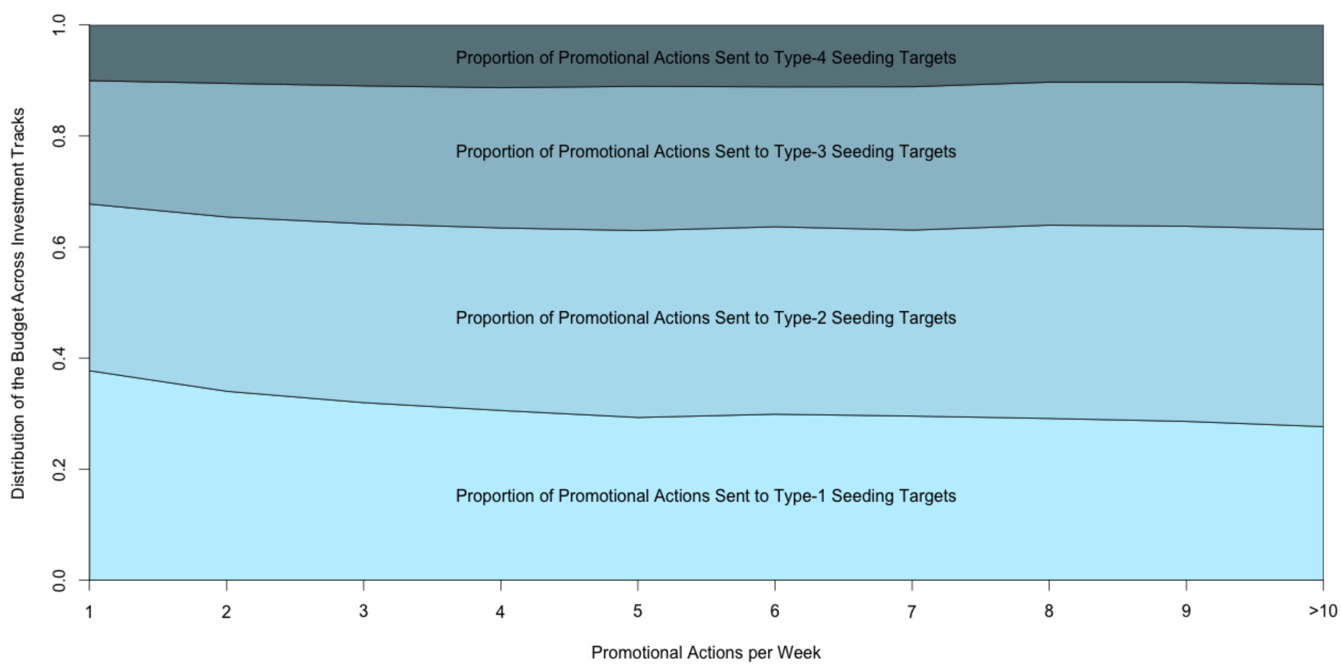
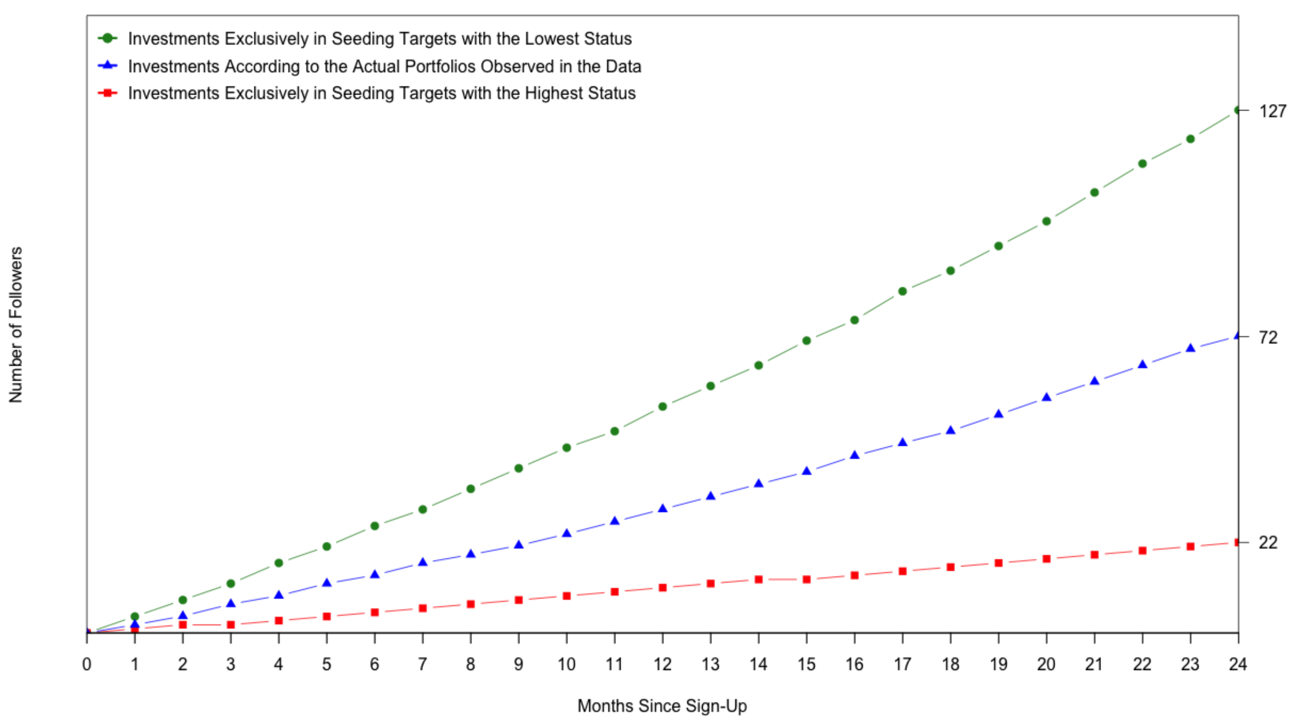


Figure 5: The Median Growth of the Follower Base: A Comparison of Three Seeding Policies



APPENDIX

A.1 Proofs

Proof of Proposition 1. We follow the expected utility given by (3), i.e.,

$$EU = \sum_{x=0}^{X} \sum_{y=0}^{Y} \binom{X}{x} \binom{Y}{y} p_L^x \, p_H^y \, (1-p_L)^{X-x} \, (1-p_H)^{Y-y} \; U(xL+yH) \, ,$$

and the optimization problem given by (4), i.e.,

$$\underset{X,Y}{\text{Max}} \; EU(X,Y) \quad \text{s.t.} \quad X+Y=B \, .$$

Since a risk neutral creator does not differentiate between the expected utility and the expected return, i.e., $U(xL+yH) = xL+yH$, the optimization problem is as a result given by

$$\begin{aligned} \underset{X,Y}{\text{Max}} \; EU &= \left(\sum_{x=0}^{X} \binom{X}{x} p_L^x \, (1-p_L)^{X-x} \, x \right) \left(\sum_{y=0}^{Y} \binom{Y}{y} p_H^y \, (1-p_H)^{Y-y} \right) L \\ &\quad + \left(\sum_{x=0}^{X} \binom{X}{x} p_L^x \, (1-p_L)^{X-x} \right) \left(\sum_{y=0}^{Y} \binom{Y}{y} p_H^y \, (1-p_H)^{Y-y} \, y \right) H \qquad \text{(A.1)} \\ &= X p_L + Y p_H \, . \qquad \text{(A.2)} \end{aligned}$$

Resolving the above optimization problem results in

$$\frac{\partial EU}{\partial X} = p_L L \, , \qquad \text{(A.3)}$$

$$\frac{\partial EU}{\partial Y} = p_H H \, . \qquad \text{(A.4)}$$

Therefore, the optimal solution is a corner solution, namely if $p_H H > p_L L$, then $\frac{\partial EU}{\partial Y} > \frac{\partial EU}{\partial X}$, hence $Y^* = B$ and $X^* = 0$; otherwise, if $p_H H < p_L L$, then $\frac{\partial EU}{\partial Y} < \frac{\partial EU}{\partial X}$, hence $Y^* = 0$ and $X^* = B$. We conclude that if a creator is risk neutral, then the whole budget is invested in high-status individuals in case $p_H H > p_L L$; otherwise (if $p_H H < p_L L$) the whole budget is invested in low-status individuals. □

Proof of Proposition 2. Since $p_L = p_H = p$, $B = X + Y$, and $z = x + y$ for each pair (x, y), we can rewrite the expected utility given by (3) as follows:

$$EU(X,Y) = \sum_{x=0}^{X} \sum_{y=0}^{Y} \binom{X}{x} \binom{Y}{y} p^z (1-p)^{B-z} U(xL + yH)\,, \tag{A.5}$$

where the optimization problem is given by (4), i.e.,

$$\underset{X,Y}{\text{Max}}\; EU(X,Y) \quad \text{s.t.} \quad X + Y = B\,. \tag{A.6}$$

To contrast the above case where the creator invests a fraction of her budget in low-status individuals and a fraction of her budget in high-status individuals, i.e., $X \neq 0$ an $Y \neq 0$, we now look at the case where the whole budget is invested in high-status individuals, i.e., $X = 0$ and $Y = B$. Then the expected utility is given by

$$EU_H = \sum_{z=0}^{B} \binom{B}{z} p^z (1-p)^{B-z}\; U(zH)\,, \tag{A.7}$$

where z is the number of cases, which yield a return H when investing B promotional actions in high-status individuals. Since $z = x + y$, $0 \leq z \leq B$, and $0 \leq x \leq z$, the expected utility can be rewritten as

$$EU_H = \sum_{z=0}^{B} \sum_{x=0}^{z} \binom{X}{x} \binom{Y}{y} p^z (1-p)^{B-z} U(zH)\,. \tag{A.8}$$

As $y = z - x$ and $B = X + Y$, according to Vandermonde's Convolution

$$\sum_{x=0}^{z} \binom{X}{x} \binom{Y}{y} = \sum_{x=0}^{z} \binom{X}{x} \binom{Y}{z-x} = \binom{X+Y}{z} = \binom{B}{z}\,. \tag{A.9}$$

Moreover, because the return on low-status individuals is lower than on high-status individuals, i.e., $L < H$, it follows that

$$U(xL + yH) \leq U(zH)\,, \tag{A.10}$$

Then, based on (A.5), (A.8), and (A.10), we conclude that the expected utility is lower when investing in both high- and low-status individuals, i.e.,

$$EU \leq EU_H. \tag{A.11}$$

To generalize (A.11), we look again at a creator who gets in x cases a return L when investing X promotional actions in low-status individuals and in y cases a return H when investing Y promotional actions in high-status individuals. In this context, the creator gains return $R(x, y)$ from her investment, i.e., $X \neq 0$ an $Y \neq 0$. However, if the creator directs promotional actions only to high-status individuals, i.e., $X = 0$ and $Y = B$, then she gains return $R(0, z)$ from her investment, where $z = x + y$. For any return r,

$$Prob(R(x, y) \leq r) \geq Prob(R(0, x + y) \leq r) \,, \tag{A.12}$$

where $Prob(R(x, y) \leq r)$ is the probability to get a return R less than r, given that there are x and y cases that yield a return from low- and high-status individuals, respectively. $Prob(R(0, z) \leq r)$ is the probability to get a return R less than r, given that there are no cases that yield a return from low-status individuals and z cases that yield a return from high-status individuals. Following Hadar and Russell (1969), $Prob(R(0, x + y) \leq r)$ has second-order stochastic dominance over $Prob(R(x, y) \leq r)$. Hence, for all nondecreasing and concave utility functions, the expected utility is lower when investing in both high- and low-status individuals, i.e.,

$$EU \leq EU_H \,. \tag{A.13}$$

Thus, we conclude that if the response probability of high-status individuals equals the response probability of low-status individuals, i.e., $p = p_L = p_H$, then the whole budget is invested in high-status individuals, i.e., $Y^* = B$. □

Proof of Proposition 3. We follow the expected utility given by (3), i.e.,

$$EU = \sum_{x=0}^{X} \sum_{y=0}^{Y} \binom{X}{x} \binom{Y}{y} p_L^x \, p_H^y \, (1 - p_L)^{X-x} \, (1 - p_H)^{Y-y} \; U(xL + yH) \,,$$

and the optimization problem given by (4), i.e.,

$$\operatorname*{Max}_{X,Y} EU(X,Y) \quad \text{s.t.} \quad X+Y=B\ .$$

Let us define K such that

$$K \gg max(B, \frac{1}{p_L \min\limits_{0\le x\le B}(\frac{U(x+1)L}{U(xL+H)})}) \ , \tag{A.14}$$

where $U(0)=0$. Thus, for any $p_H < \frac{1}{K}$ it holds that

$$p_H \ll \frac{1}{B} \ , \tag{A.15}$$

$$p_H \ll p_L \min\limits_{0\le x\le B}(\frac{U(x+1)L}{U(xL+H)}) \ . \tag{A.16}$$

Since $p_H \ll \frac{1}{B}$, an investment in high-status individuals behaves like a Bernoulli coin with probability Yp_H. Thus, the expected utility given by (3) has the following form:

$$EU = \sum_{x=0}^{X} \binom{X}{x} p_L^x (1-p_L)^{X-x}$$

$$\left\{ \binom{Y}{0} p_H^0 (1-Yp_H)U(xL) + \binom{Y}{1} p_H U(xL+H) + 0(p_H^2) \right\} \tag{A.17}$$

$$= \sum_{x=0}^{X} \binom{X}{x} p_L^x (1-p_L)^{X-x} \left((1-Yp_H)U(xL) + Yp_H U(xL+H)\right) \ . \tag{A.18}$$

To contrast the above case where the creator invests a fraction of her budget in low-status individuals and a fraction of her budget in high-status individuals, i.e., $X \neq 0$ and $Y \neq 0$, we now look at the case where the whole budget is invested in high-status individuals, i.e., $X = B$ and $Y = 0$. By applying Vandermonde's Convolution, the expected utility can be rewritten as

$$EU_L = \sum_{x=0}^{B} \binom{B}{x} p_L^x \left(1 - p_L\right)^{B-x} U(xL) \tag{A.19}$$

$$= \sum_{x=0}^{X} \binom{X}{x} p_L^x \left(1 - p_L\right)^{X-x} \sum_{y=0}^{Y} \binom{Y}{y} p_L^y \left(1 - p_L\right)^{Y-y} U((x+y)L) \tag{A.20}$$

$$> \sum_{x=0}^{X} \binom{X}{x} p_L^x \left(1 - p_L\right)^{X-x} \left(U(xL) + Y p_L U(xL+L)\right) . \tag{A.21}$$

As $p_H \ll p_L \underset{0 \leq x \leq B}{min} (\frac{U(x+1)L}{U(xL+H)})$, it follows that

$$p_H U(xL + H) < p_L U(xL + L) , \tag{A.22}$$

and therefore

$$\sum_{x=0}^{X} \binom{X}{x} p_L^x \left(1 - p_L\right)^{X-x} \left(U(xL) + Y p_L U(xL+L)\right)$$

$$\geq \sum_{x=0}^{X} \binom{X}{x} p_L^x \left(1 - p_L\right)^{X-x} \left(U(xL) + Y p_H U(xL+L)\right) \tag{A.23}$$

$$\geq \sum_{x=0}^{X} \binom{X}{x} p_L^x \left(1 - p_L\right)^{X-x} \left((1 - Y p_H) U(xL) + Y p_H U(xL+L)\right) . \tag{A.24}$$

Thus, we conclude that if the response probability of high-status individuals is extremely low, i.e., $p_H \ll \frac{1}{B}$, then the whole budget is invested in low-status individuals, i.e., $X^* = B$, independent of the individual aversion to risk. □

Proof of Proposition 4. We follow the expected utility given by (3), i.e.,

$$EU = \sum_{x=0}^{X} \sum_{y=0}^{Y} \binom{X}{x} \binom{Y}{y} p_L^x \, p_H^y \left(1 - p_L\right)^{X-x} \left(1 - p_H\right)^{Y-y} \, U(xL + yH) ,$$

and the optimization problem given by (4), i.e.,

$$\underset{X,Y}{\text{Max}} \, EU(X, Y) \quad \text{s.t.} \quad X + Y = B .$$

Since we assume that the response probability of high-status individuals is extremely low, i.e., $p_H \ll \frac{1}{B}$, an investment in high-status individuals behaves like a Bernoulli coin with probability Yp_H. Thus, the expected utility given by (3) has the following form:

$$EU = \sum_{x=0}^{X} \binom{X}{x} p_L^x \left(1 - p_L\right)^{X-x} \left((1 - Yp_H)U(xL) + Yp_H U(xL + H)\right) . \tag{A.25}$$

Let us assume that the return on low-status individuals is much lower than on high-status individuals such that $BL \ll H$. Since $\sum_{x=0}^{X} \binom{X}{x} p_L^x \left(1 - p_L\right)^{X-x} = 1$ and $U(xL+H) \approx U(H)$, the expected utility is thus given by

$$EU = V(X, p_L) + Yp_H(U(H) - V(X|p_L)) , \tag{A.26}$$

where $V(X, p_L) = \sum_{x=0}^{X} \binom{X}{x} p_L^x \left(1 - p_L\right)^{X-x} U(xL)$. Naturally, an increase in the status of the creator leads to an increase in the expected utility. Along these lines, we aim to show that the order of magnitude of the change in the expected utility due to an increase in the response probability of low-status individuals, i.e., $O(\Delta EU_{p_L})$, is lower than the order of magnitude of the change in the expected utility due to an increase in the response probability of high-status individuals, i.e., $O(\Delta EU_{p_H})$. We assume that the return on low-status individuals, i.e., L, is not changing much as it is typically close to 1 since the indirect return is marginal. The changes in the expected utility, i.e., ΔEU_{p_L} and ΔEU_{p_H}, have the following forms:

$$\Delta EU_{p_L} = \Delta V(X, p_L)(1 - Yp_H) , \tag{A.27}$$

$$\Delta EU_{p_H} = Yp_H(U(H) - V(X, p_L))\frac{\Delta p_H}{p_H} . \tag{A.28}$$

Let us look at the effect of an increase in the response probability of low-status individuals, i.e.,

$$p_L \to p_L + \Delta p_L , \tag{A.29}$$

$$V(X, p_L) \to V(X, p_L + \Delta p_L) . \tag{A.30}$$

We define $q_L = 1 - p_L$ and $\Delta q_L = -\Delta p_L$. Since $\frac{\Delta p_L}{p_L} \ll 1$ and further $(1 + \delta)^X \approx 1 + X\delta$ as well as $(1+\delta_1)(1+\delta_2) \approx 1+\delta_1+\delta_2$ if the δ's are small, then

$$V(X, p_L + \Delta p_L) = \sum_{x=0}^{X} \binom{X}{x} \left[p_L\left(1+\frac{\Delta p_L}{p_L}\right)\right]^X \left[q_L\left(1+\frac{\Delta q_L}{q_L}\right)\right]^{X-x} U(xL) \tag{A.31}$$

$$\approx \sum_{x=0}^{X} \binom{X}{x} p_L^x \left(1 + x\frac{\Delta p_L}{p_L}\right) q_L^{X-x}\left(1+(X-x)\frac{\Delta q_L}{q_L}\right) U(xL) \tag{A.32}$$

$$\approx \sum_{x=0}^{X} \binom{X}{x} p_L^x q_L^{X-x} U(xL) \left\{1 + \frac{x\Delta p_L}{p_L(1-p_L)} - X\frac{\Delta p_L}{1-p_L}\right\} \tag{A.33}$$

$$= V(X, p_L) + \frac{\Delta p_L}{p_L(1-p_L)} \sum_{x=0}^{X} \binom{X}{x} p_L^x q_L^{X-x} U(xL)(x - Xp_L)\,. \tag{A.34}$$

Recall that $\frac{\Delta p_L}{p_L} - \frac{\Delta q_L}{q_L} = \frac{\Delta p_L}{p_L} + \frac{\Delta p_L}{1-p_L} = \frac{\Delta p_L}{p_L(1-p_L)}$ and $\frac{\Delta q_L}{q_L} = -\frac{\Delta p_L}{1-p_L}$. To evaluate the order of magnitude of the change in the above component of the expected utility, i.e., $O(\Delta V(X, p_L))$, we approximate the binomial distribution $\binom{X}{x} p_L^x q_L^{X-x}$ by a rectangular, which is concentrated around the average, i.e., Xp_L, has a width of two standard deviations, i.e., 2σ, and is normalized:

$$O\left(\binom{X}{x} p_L^x q_L^{X-x}\right) \approx \begin{cases} \frac{1}{4\sigma} & -2\sigma < x < 2\sigma\,, \\ 0 & \text{otherwise}\,, \end{cases} \tag{A.35}$$

namely we rely on the fact that the distribution is centered around the average. It follows that

$$\sum_{x=0}^{X} \binom{X}{x} p_L^x q_L^{X-x} U(xL)(x - Xp_L) \tag{A.36}$$

$$= \sum_{x=Xp_L-2\sigma}^{Xp_L} \binom{X}{x} p_L^x q_L^{X-x} U(xL)(x - Xp_L) \tag{A.37}$$

$$+ \sum_{x=Xp_L}^{Xp_L+2\sigma} \binom{X}{x} p_L^x q_L^{X-x} U(xL)(x - Xp_L) \tag{A.38}$$

$$\approx 2\sigma\left\{\frac{1}{4\sigma}U((Xp_L-\sigma)L)(-\sigma)\right\}+2\sigma\left\{\frac{1}{4\sigma}U((Xp_L+\sigma)L)\sigma\right\} \tag{A.39}$$

$$=\frac{\sigma}{2}\left\{U((Xp_L+\sigma)L)-U((Xp_L-\sigma)L)\right\} \tag{A.40}$$

$$=\sigma^2 L\left\{\frac{U((Xp_L+\sigma)L)-U((Xp_L-\sigma)L)}{2\sigma L}\right\}\approx \sigma^2 L\left.\frac{\partial U}{\partial Z}\right|_{Z=Xp_L L}. \tag{A.41}$$

Note that $x - Xp_L = \pm O(\sigma)$. Hence, note that if $x \le Xp_L$, then $U(xL) = U((Xp_L - \sigma)L)$ and $(x - Xp_L) \approx -\sigma$. If $x \ge Xp_L$, then $U(xL) = U((Xp_L + \sigma)L)$ and $(x - Xp_L) \approx \sigma$. On the other hand, $V(X, p_L) = \sum_{x=0}^{X}\binom{X}{x}p_L^x q_L^{X-x}U(xL) \approx \sum_{x=Xp_L-2\sigma}^{Xp_L+2\sigma}\frac{1}{4\sigma}U(Xp_L L) = U(Xp_L L)$ and therefore $\frac{\partial V}{\partial X} \approx p_L L\left.\frac{\partial U}{\partial Z}\right|_{Z=Xp_L L}$. Thus,

$$O(\Delta V(X,p_L)) = \frac{\Delta p_L}{p_L(1-p_L)}\sum_{x=0}^{X}\binom{X}{x}p_L^x q_L^{X-x}U(xL)(x-Xp_L) \tag{A.42}$$

$$=\frac{\Delta p_L}{p_L(1-p_L)}\sigma^2\frac{1}{p_L}\frac{\partial V}{\partial X} \tag{A.43}$$

$$=X\frac{\Delta p_L}{p_L}\frac{\partial V}{\partial X}, \tag{A.44}$$

where we assume that $O(\sigma^2) = Xp_L(1 - p_L)$ as the distribution is approximately binomial. Hence, the order of magnitude of the change in the expected utility due to an increase in the response probability of low-status individuals, i.e., $O(\Delta EU_{p_L})$, and the order of magnitude of the change in the expected utility due to an increase in the response probability of high-status individuals, i.e., $O(\Delta EU_{p_H})$, are given by

$$O(\Delta EU_{p_L}) = \Delta p_L X\frac{\partial V}{\partial X}(1-Yp_H), \tag{A.45}$$

$$O(\Delta EU_{p_H}) = Yp_H(U(H)-V(X,p_L))\frac{\Delta p_H}{p_H}. \tag{A.46}$$

Following the expected utility given by (A.26), the marginal-rate-of-substitution-equation has the following form:

$$\frac{\partial EU}{\partial X} = \frac{\partial EU}{\partial Y} \tag{A.47}$$

$$\Rightarrow \frac{\partial V}{\partial X}(1 - Yp_H) = p_H(U(H) - V(X, p_L)) \tag{A.48}$$

$$\Rightarrow O\left(\frac{\partial V}{\partial X}(1 - Yp_H)\right) = O(p_H(U(H) - V(X, p_L))) \equiv M \tag{A.49}$$

Therefore, the order of magnitude of the change in the expected utility due to an increase in the response probability of low-status individuals, i.e., $O(\Delta EU_{p_L})$, and the order of magnitude of the change in the expected utility due to an increase in the response probability of high-status individuals, i.e., $O(\Delta EU_{p_H})$, given by (A.45) and (A.46), respectively, can be rewritten as

$$O(\Delta EU_{p_L}) = X\frac{\Delta p_L}{p_L}\frac{\partial V}{\partial X}(1 - Yp_H) = XM\frac{\Delta p_L}{p_L}\,, \tag{A.50}$$

$$O(\Delta EU_{p_H}) = Yp_H(U(H) - V(X, p_L))\frac{\Delta p_H}{p_H} = YM\frac{\Delta p_H}{p_H}\,, \tag{A.51}$$

and since $\frac{\Delta p_L}{p_L} \ll \frac{\Delta p_H}{p_H}$, it follows that

$$O(\Delta EU_{P_L}) \ll O(\Delta EU_{P_H})\,. \tag{A.52}$$

As a result, we assume that an increase in the status of the creator leads to an increase in the response probability of high-status individuals, i.e., p_H, whereas the response probability of low-status individuals, i.e., p_L, stays approximately constant. In the data we observe that an increase in the status of the creator increases both p_L and p_H but $\frac{\Delta p_L}{p_L} \ll \frac{\Delta p_H}{p_H}$, e.g., if the status of the creator increases from type 1 to type 2, then the increase in the response probability of a type 1 seeding target, i.e., $\frac{\Delta p_L}{p_L}$, is 16% and the increase in the response probability of a type 3 seeding target, i.e., $\frac{\Delta p_L}{p_L}$, is 132%.

Lemma 1. *If the response probability of high-status individuals and low-status individuals, i.e., p_H and p_L, increases such that $\frac{\Delta p_L}{p_L} \ll \frac{\Delta p_H}{p_H}$, then the expected utility increases in the manner that the order of magnitude of the increase in p_L, i.e., $O(\Delta EU_{P_L})$, is lower than the order of magnitude of the increase in p_H, i.e., $O(\Delta EU_{p_H})$.*

Corollary 2. *Based on the finding that* $\frac{\Delta p_L}{p_L} \ll \frac{\Delta p_H}{p_H}$*, if the status of a creator increases, then we can assure that the response probability of high-status individuals, i.e.,* p_H*, increases whereas the response probability of low-status individuals, i.e.,* p_L*, stays approximately constant.*

Thus, we conclude that if the status of a creator, i.e., S, increases, then the more is invested in high-status individuals, i.e., $\frac{dX^*}{dS} < 0$ and $\frac{dY^*}{dS} > 0$. □

Proof of Proposition 5. We follow the expected utility given by (3), i.e.,

$$EU = \sum_{x=0}^{X} \sum_{y=0}^{Y} \binom{X}{x} \binom{Y}{y} p_L^x \, p_H^y \, (1-p_L)^{X-x} \, (1-p_H)^{Y-y} \; U(xL + yH) \, ,$$

and the optimization problem given by (4), i.e.,

$$\underset{X,Y}{\text{Max}} \; EU(X,Y) \quad \text{s.t.} \quad X + Y = B \, .$$

Since we assume that the response probability of high-status individuals is extremely low, i.e., $p_H \ll \frac{1}{B}$, an investment in high-status individuals behaves like a Bernoulli coin with probability Yp_H. Thus, the expected utility given by (3) has the following form:

$$\begin{aligned} EU =& \sum_{x=0}^{X} \binom{X}{x} p_L^x \, (1-p_L)^{X-x} \\ & \left\{ \binom{Y}{0} p_H^0 (1 - Yp_H) U(xL) + \binom{Y}{1} p_H U(xL + H) + 0(p_H^2) \right\} && \text{(A.53)} \\ =& \sum_{x=0}^{X} \binom{X}{x} p_L^x \, (1-p_L)^{X-x} \left((1 - Yp_H) U(xL) + Yp_H U(xL + H) \right) \, . && \text{(A.54)} \end{aligned}$$

Let us assume that the return on low-status individuals is much lower than on high-status individuals such that $BL \ll H$. Since $\sum_{x=0}^{X} \binom{X}{x} p_L^x \, (1-p_L)^{X-x} = 1$ and $U(xL+H) \approx U(H)$, then

$$EU = V(X|p_L) + Yp_H(U(H) - V(X|p_L)) \, , \tag{A.55}$$

where $V(X|p_L) \equiv \sum_{x=0}^{X} \binom{X}{x} p_L^x \,(1-p_L)^{X-x}\, U(xL)$. The first-order condition is given by the marginal rate of substitution, i.e.,

$$\left.\frac{\partial EU}{\partial X}\right|_{X^*,Y^*} = \left.\frac{\partial EU}{\partial Y}\right|_{X^*,Y^*} \tag{A.56}$$

$$\Rightarrow \left.\frac{\partial V}{\partial X}\right|_{X^*}(1-Y^* p_H) = p_H(U(H) - V(X^*|p_H))\,. \tag{A.57}$$

Let us look at the effect of an increase in the budget, i.e., $B \to B + \Delta B$, and apply comparative statics. In case of an internal solution, (A.57) has the following form:

$$\begin{aligned} &\frac{\partial EU}{\partial X} + \frac{\partial^2 EU}{\partial X^2}\frac{dX^*}{dB}\Delta B + \frac{\partial^2 EU}{\partial X \partial Y}\frac{dY^*}{dB}\Delta B \\ =&\frac{\partial EU}{\partial Y} + \frac{\partial^2 EU}{\partial X \partial Y}\frac{dX^*}{dB}\Delta B + \frac{\partial^2 EU}{\partial Y^2}\frac{dY^*}{dB}\Delta B \end{aligned} \tag{A.58}$$

$$\Rightarrow \frac{\partial^2 EU}{\partial X^2}\frac{dX^*}{dB} + \frac{\partial^2 EU}{\partial X \partial Y}\frac{dY^2}{dB} = \frac{\partial^2 EU}{\partial X \partial Y}\frac{dX^*}{dB} + \frac{\partial^2 EU}{\partial Y^2}\frac{dY^*}{dB}\,, \tag{A.59}$$

and the budget constraint, i.e., $X + Y = B$, is given by

$$X^* + \frac{dX^*}{dB}\Delta B + Y^* + \frac{dY^*}{dB}\Delta B = B + \Delta B \tag{A.60}$$

$$\Rightarrow \frac{dX^*}{dB} + \frac{dY^*}{dB} = 1 \tag{A.61}$$

$$\Rightarrow p_H\frac{\partial V}{\partial X}\left(\frac{dX^*}{dB} + \frac{dY^*}{dB}\right) = p_H\frac{\partial V}{\partial X}\,. \tag{A.62}$$

On one hand, $\frac{\partial^2 EU}{\partial Y^2} = 0$ because

$$\frac{\partial EU}{\partial Y} = p_H(U(H) - V(X|p_L)) = \text{const. in } y\,, \tag{A.63}$$

and, on the other hand, $\frac{\partial^2 V}{\partial X \partial Y} < 0$ because

$$\frac{\partial^2 EU}{\partial X \partial Y} = \frac{\partial}{\partial Y}\left\{\frac{\partial EU}{\partial X}\right\} = \frac{\partial}{\partial Y}\left\{(1 - Y p_H)\frac{\partial V}{\partial X}\right\} = -p_H\frac{\partial V}{\partial X} < 0\,. \tag{A.64}$$

From (A.55) we further find that

$$\frac{\partial^2 EU}{\partial X^2} = \frac{\partial^2 V}{\partial X^2}(1 - Y p_H)\,, \tag{A.65}$$

and thus plugging (A.61) and (A.62) into (A.59) (recall that $\frac{\partial^2 EU}{\partial Y^2} = 0$) gives

$$(1 - Yp_H)\frac{\partial^2 V}{\partial X^2}\frac{dX^*}{dB} + p_H \frac{\partial V}{\partial X}\left(\frac{dX^*}{dB} - \frac{dY^*}{dB}\right) = 0\,. \tag{A.66}$$

From (A.62) it follows that

$$\begin{aligned}&(1 - Yp_H)\frac{\partial^2 V}{\partial X^2}\frac{dX^*}{dB} + p_H \frac{\partial V}{\partial X}\left(\frac{dX^*}{dB} - \frac{dY^*}{dB}\right)\\ &+ p_H \frac{\partial V}{\partial X}\left(\frac{dX^*}{dB} + \frac{dY^*}{dB}\right) = p_H \frac{\partial V}{\partial X}\end{aligned} \tag{A.67}$$

$$\Rightarrow\ (1 - Yp_H)\frac{\partial^2 V}{\partial X^2}\frac{dX^*}{dB} + 2p_H \frac{\partial V}{\partial X}\frac{dX^*}{dB} = p_H \frac{\partial V}{\partial X}\,, \tag{A.68}$$

and hence the change of investments in low- and high-status individuals, respectively, have the following forms:

$$\frac{dX^*}{dB} = \frac{p_H \frac{\partial V}{\partial X}}{(1 - Yp_H)\frac{\partial^2 V}{\partial X^2} + 2p_H \frac{\partial V}{\partial X}} \quad \xrightarrow[p_H \to 0]{<} \ 0\,, \tag{A.69}$$

$$\frac{dY^*}{dB} \to 1 > 0\,. \tag{A.70}$$

Note that if at the beginning $\frac{\partial EU}{\partial X} > \frac{\partial EU}{\partial Y}$ (since $\frac{dV}{dX}(1 - Yp_H) > p_H(V(H) - V(x))$ and as the response probability of high-status individuals, i.e., p_H, is very low), then there is a corner solution in which the whole budget is invested in low-status individuals, i.e., $X^* = B$ and $Y^* = 0$. An increase in the budget is followed by an increase of investments in low-status individuals, which in turn leads to a decrease in $\frac{\partial EU}{\partial X}$ (decreasing marginal returns) to the point where $\frac{\partial EU}{\partial X} = \frac{\partial EU}{\partial Y}$. From this point on, all additional budget is invested in high-status individuals, i.e., Y. Thus, we conclude that if a creator is endowed with a larger budget, then the more is invested in high-status individuals, i.e., $\frac{dY^*}{dB} > 0$. □

Proof of Proposition 6. We follow the expected utility given by (3), i.e.,

$$EU = \sum_{x=0}^{X}\sum_{y=0}^{Y}\binom{X}{x}\binom{Y}{y} p_L^x\, p_H^y\, (1 - p_L)^{X-x}\, (1 - p_H)^{Y-y}\ U(xL + yH)\,,$$

and the optimization problem given by (4), i.e.,

$$\operatorname*{Max}_{X,Y} EU(X,Y) \quad \text{s.t.} \quad X+Y=B\,.$$

To contrast the above case where the creator invests a fraction of her budget in low-status individuals and a fraction of her budget in high-status individuals, i.e., $X \neq 0$ an $Y \neq 0$, we now look at the case where the whole budget is invested in low-status individuals, i.e., $X = B$ and $Y = 0$. Then, according to Vandermonde's Convolution, the expected utility is given by

$$EU = \sum_{x=0}^{X} \binom{X}{x} p_L^x (1-p_L)^{X-x} \sum_{y=0}^{Y} \binom{Y}{y} p_L^y (1-p_L)^{Y-y} U(xL+yL) \tag{A.71}$$

$$= \sum_{z=0}^{B} \binom{B}{z} p_L^z (1-p_L^z)^{B-z} U(zL)\,, \tag{A.72}$$

where z is the number of cases, which yield a return L when investing B promotional actions in low-status individuals. Note that $z = x + y$. The entire budget, i.e., B, is invested in low-status individuals, if the expected return on high-status individuals is higher than on low-status individuals, i.e., $p_H H > p_L L$. Along these lines, we aim to show that for each portfolio, i.e., X and Y, it exists that

$$\sum_{z=0}^{B} \binom{B}{z} p_L^z (1-p_L^z)^{B-z} U(zL) \tag{A.73}$$

$$> \sum_{x=0}^{X} \sum_{y=0}^{Y} \binom{X}{x} \binom{Y}{y} p_L^z (1-p_L)^{X-x} p_H^y (1-p_H)^{Y-y} U(xL+yH) \tag{A.74}$$

$$= \sum_{x=0}^{X} \binom{X}{x} p_L^X (1-p_L)^{X-x} \sum_{y=0}^{Y} \binom{Y}{y} p_H^y (1-p_H)^{Y-y} U(xL+yH)\,. \tag{A.75}$$

More specifically, we aim to show that for any x (namely for each inequality separately) it exists that

$$\sum_{y=0}^{Y} \binom{Y}{y} p_L^y (1-p_L)^{Y-y} U(xL+yL) > \sum_{y=0}^{Y} \binom{Y}{y} p_H^y (1-p_H)^{Y-y} U(xL+yH)\,. \tag{A.76}$$

Let us assume that the creator gains with certainty at least the return of investments in low-status individuals, i.e., xL. As a result, the extra utility is given by

$$V(z) \equiv U(xL+z) - U(xL)\,, \tag{A.77}$$

where $U(xL)$ is constant and V is concave as U is invariant to translations. Hence, the inequality given by (A.76) can be rewritten as

$$\sum_{y=0}^{Y} \binom{Y}{y} p_L^y (1-p_L)^{Y-y} V(yL) > \sum_{y=0}^{Y} \binom{Y}{y} p_H^y (1-p_H)^{Y-y} V(yH)\,, \tag{A.78}$$

where $V(0) = 0$. By elimination, if we assume that V is concave, it holds that $\frac{V(z)}{z}$ is decreasing because $\frac{d}{dz}\frac{V(z)}{z} = \frac{zV'-V}{z^2} < 0$. Furthermore, since $z > 0$ it follows that $v' < \frac{V}{z}$. Moreover, let us assume that high-status individuals are more powerful than low-status individuals, i.e., $H > BL \geq YL$, and that $\frac{V(YL)}{YL} < \frac{V(yL)}{yL} < \frac{V(L)}{L}$. As $\frac{V(z)}{z}$ is decreasing and $yH > YL$, it follows that $\frac{V(yH)}{yH} < \frac{V(YL)}{YL}$ for any $1 \leq y \leq Y$. Since $V(0) = 0$ and $V\frac{V(YL)}{YL} < \frac{V(yL)}{yL}$ holds for any y, it follows that

$$\begin{aligned}
\sum_{y=0}^{Y} \binom{Y}{y} p_L^y (1-p_L)^{Y-y} V(yL) =& \sum_{y=1}^{Y} \binom{Y}{y} p_L^y (1-p_L)^{Y-y} \frac{V(yL)}{yL} yL && \text{(A.79)}\\
\geq& \frac{V(YL)}{YL} \sum_{y=1}^{Y} \binom{Y}{y} p_L^y (1-p_L)^{Y-y} yL && \text{(A.80)}\\
=& \frac{V(YL)}{YL} Y p_L L && \text{(A.81)}\\
>& \frac{V(YL)}{YL} Y p_H H && \text{(A.82)}\\
=& \frac{V(YL)}{YL} \sum_{y=1}^{Y} \binom{Y}{y} p_H^y (1-p_H)^{Y-y} yH\,. && \text{(A.83)}
\end{aligned}$$

As $p_H H < p_L L$ and since for any y it holds that $YL < yH$, and hence $\frac{V(YL)}{YL} > \frac{V(yH)}{yH}$, we conclude that

$$\frac{V(YL)}{YL} \sum_{y=1}^{Y} \binom{Y}{y} p_H^y (1-p_H)^{Y-y} yH > \sum_{y=1}^{Y} \binom{Y}{y} p_H^y (1-p_H)^{Y-y} V(yH)\,, \tag{A.84}$$

and further

$$\sum_{y=0}^{Y} \binom{Y}{y} p_L^y (1-p_L)^{Y-y} V(yL) > \sum_{y=0}^{Y} \binom{Y}{y} p_H^y (1-p_H)^{Y-y} V(yH) \,. \tag{A.85}$$

Thus, we conclude that if the return on high-status individuals is much higher than on low-status individuals such that $H > BL$ but the expected return on high-status individuals is lower than on low-status individuals, i.e., $p_H H < p_L L$, and there is an optimal solution such that a creator invests in high-status individuals, i.e., $Y^* \neq 0$, then the creator cannot be risk averse (and the individual utility function U is not concave). $\square$

A.2 Expected Total Return on a Seeding Target

On one hand, let P_{ST} be the a priori probability that the seeding target follows the creator within a week, where S stands for the creator type and T for the seeding target type. The creator and the seeding target can take any of the four different user types, i.e., $S = \{1, 2, 3, 4\}$ and $T = \{1, 2, 3, 4\}$. On the other hand, let R_{ST} be the a priori probability that the seeding target reposts a song of the creator within a week and $f_{TS}(z)$ be the a priori probability distribution that the creator gets as a result z followers within a week. Finally, we combine both the a priori response and song repost probabilities in order to calculate the expected total return on each seeding target, given the status of the creator. So let P_{zST} be the a priori probability that the creator gets z followers when choosing a certain type of seeding target. The a priori probabilities for all possible returns z are given by

$$P_{0ST} = (1 - P_{ST})\left[R_{ST} f_{TS}(0) + (1 - R_{ST})\right] \;, \quad \text{if } z = 0 \tag{A.86}$$

$$P_{1ST} = P_{ST}(1 - R_{ST}) + (1 - P_{ST}) R_{ST} f_{TS}(1) + P_{ST} R_{ST} f_{TS}(0) \;, \quad \text{if } z = 1 \tag{A.87}$$

$$P_{zST} = P_{ST} R_{ST} f_{TS}\,(z - 1) + (1 - P_{ST})\, R_{ST} f_{TS}(z) \;, \quad \text{if } z > 0 \tag{A.88}$$

where $\sum_z f_{TS}(z) = 1$ and $P_{0ST} + P_{1ST} + \sum_z P_{zST} = 1$. Then, the expected total return μ_{ST} and the standard deviation s_{ST} are given by

$$\mu_{ST} = \sum_z Z P_{zST} \;, \tag{A.89}$$

$$s_{ST} = \sqrt{\sum_z (z - \mu_{ST})^2 P_{zST}} \;. \tag{A.90}$$

A.3 Simulation Study: Comparing the Effectiveness of Seeding Policies

The randomized dissemination processes comparing the three seeding policies, i.e., investments (1) according to the actual portfolios observed in the data, (2) only in seeding targets with the highest status, and (3) only in seeding targets with the lowest status, are based on the status-dependent probability of a non-zero return on a seeding target and further on the status-dependent probability of either a direct or indirect return. For this reason, let us define the following probabilities:

- p_D is the probability of a direct return in the form of a follow-back from the seeding target,
- p_R is the probability of a song repost from the seeding target,
- $p_{D\&R}$ is the joint probability of a direct and indirect return,
- $p_{\bar{D}\&R}$ is the joint probability of no direct but an indirect return,
- $p_{R|D}$ is the probability of a song repost given a direct return,
- $p_{R|D} = \frac{p_{D\&R}}{P_D}$ is the probability of a song repost given a direct return,
- $p_{R|\bar{D}} = \frac{p_{\bar{D}\&R}}{p_{\bar{D}}}$ is the probability of a song repost given no direct return,
- $p_{I|R}$ is the probability of a non-zero indirect return in the form of follows from the seeding target's egocentric network given a song repost.

Hence, the probability of gaining only a *direct return* is $p_D(1 - p_{R|D}) + p_D\, p_{R|D}(1 - p_{I|R})$, whereas the probability of gaining only an *indirect return* is $(1 - p_D)p_{R|\bar{D}}\, p_{I|R}$. Finally, the probability to gain a *direct and indirect return* is $p_D\, p_{R|D}\, p_{I|R}$ and thus the probability of a *zero return* on a seeding target is

$$P_0 = (1 - p_D)\left[p_{R|\bar{D}}(1 - p_{I|R}) + (1 - p_{R|\bar{D}})\right] . \tag{A.91}$$

As a result, the probability of a *non-zero return* on a seeding target is

$$P = 1 - P_0 . \tag{A.92}$$

The status-dependent probability of a non-zero return, given by (A.92), is applied in every time step of the randomized dissemination process and on each target that is seeded using the monthly budget of promotional actions, i.e., 40 times in each of the 24 months. If the return in a given month for a given seeding target is non-zero, then there are two different scenarios. On one hand, the investment in this seeding target can yield both a direct and indirect return, i.e., a follow-back from the seeding target and follows from subsequent song reposts. On the other hand, the investment in this seeding target can yield only an indirect return, i.e., follows from a song repost.

Given a non-zero return, let $q_{D|P}$ be the probability of only a direct return and $q_{D\&I|P}$ be the joint probability of a direct and (non-zero) indirect return. Then, the *conditional probability that given a non-zero return on a seeding target there is also an indirect return* is

$$Q = q_{D|P} + q_{D\&I|P} \tag{A.93}$$

$$= \frac{p_D(1 - p_{R|D}) + p_D\, p_{R|D}(1 - p_{I|R})}{P} + \frac{p_D\, p_{R|D}\, p_{I|R}}{P} = \frac{p_D}{P} \ . \tag{A.94}$$

It follows that given a non-zero return, with probability Q the investment in a seeding target yields a direct return H_D in the form of a follow-back from this seeding target. As there might also be an additional indirect return associated with the direct return, we account for the follows resulting from subsequent song reposts. Therefore, let H be the average number of follows from the seeding target's egocentric network resulting from a single song repost. By further considering the average number of song reposts a over a time period τ, we allow for a longterm indirect return on a follow-back. Thus, the *direct and indirect return within a time period* τ is given by

$$H_D = 1 + a\tau H \ . \tag{A.95}$$

With probability $1 - Q$ the investment in a seeding target yields only an indirect return H, which is the average number of follows from the seeding target's egocentric network resulting from the single song repost. Hence, if an investment in a seeding target is successful, i.e., $c_i = 1$, then let the conditional probability to gain return z_i on a promotional action i be

$$Prob(z_i|c_i = 1) \begin{cases} Q & H_D = 1 + a\tau H \\ 1 - Q & H \end{cases} \tag{A.96}$$

Note that if an investment in a seeding target is not successful, i.e., $c_i = 0$, then the return is zero, i.e., $z_i = 0$.

To sum up, the status-dependent probability of a non-zero return, given by (A.92), is applied in every time step of the randomized dissemination process and on each target that is seeded using the monthly budget of promotional actions, i.e., 40 times in each of the 24 months. If the return in a given month for a given seeding target is non-zero, then there are two different scenarios. On one hand, the investment in this seeding target can yield both a direct and indirect return, i.e., H_D with probability Q. On the other hand, the investment in this seeding target can yield only an indirect return, i.e., H with probability $1-Q$. Note that we consider the average number of song reposts from a seeding target over a year, i.e., $\tau = 1$ year. This scheme overestimates the return on high status individuals, hence, overestimating the power of influencers.

Furthermore, we account for the status-dependent natural baseline follows, which is on average 0.93 follows per month for an unknown creator. This in turn increases the creator's status, which goes hand in hand with higher a priori probabilities and thus expected total returns on each seeding target. Both the natural baseline follows and the a priori probabilities including the expected returns on each seeding target are updated in multiples of 25 followers with regard to the growing follower base, i.e., after a reaching a community size of ≥ 25 followers, ≥ 50 followers, and so forth. To sum up, the randomized dissemination process first takes into account the status-dependent probability of a non-zero return on a seeding target and subsequently considers whether the non-zero return is realized directly or indirectly.