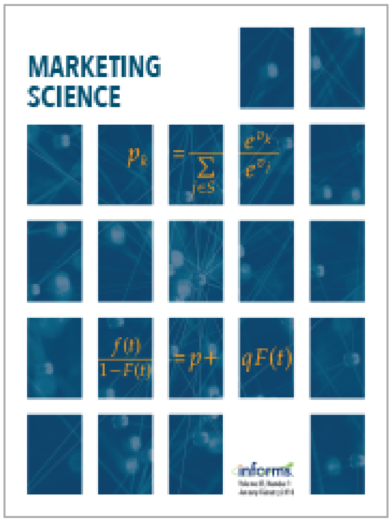

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Intrinsic vs. Image-Related Utility in Social Media: Why Do People Contribute Content to Twitter?

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We empirically study the motivations of users to contribute content to social media in the context of the popular microblogging site Twitter. We focus on noncommercial users who do not benefit financially from their contributions. Previous literature suggests that there are two main types of utility that motivate these users to post content: intrinsic utility and image-related utility. We leverage the fact that these two types of utility give rise to different predictions as to whether users should increase their contributions when their number of followers increases. To address the issue that the number of followers is endogenous, we conducted a field experiment in which we exogenously added followers (or follow requests, in the case of protected accounts) to a set of users over a period of time and compared their posting activities to those of a control group. We estimated each treated user's utility function using a dynamic discrete choice model. Although our results are consistent with both types of utility being at play, our model suggests that image-related utility is larger for most users. We discuss the implications of our findings for the evolution of Twitter and the type of value firms may derive from such platforms in the future.

Key words: social media; field experiments; dynamic discrete choice models
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1. Introduction

In recent years, social media have emerged as a major channel for broadcasting information. For instance, by late 2011, there were over 173 million public blogs,[1] and 250 million messages ("tweets") were sent each day through the popular microblogging platform Twitter (Bennett 2011). Although some contributors to social media are able to derive advertising revenue from their content (using, e.g., platforms such as Google's AdSense; see Sun and Zhu 2013), social media platforms rely predominantly on the benevolent contributions of millions of individuals as "content providers." Publishers' incentives in traditional media are well understood and are typically a function of the number of "eyeballs" reached by their content, but motivations to benevolently contribute content in social media are not well understood.

A social media platform may be utilized by a firm for different (nonexclusive) purposes. For example, it may be used as a media outlet (i.e., the firm broadcasts content to consumers), a viral marketing platform (i.e., the firm induces consumers to share information about its brands with other consumers and/or tracks naturally occurring word of mouth), or a customer insights platform (i.e., the firm monitors consumers' conversations). We argue that a firm cannot decide how to leverage social media and devise a fully efficient social media strategy unless it understands what motivates consumers to be active on such platforms in the first place. Moreover, for the platforms themselves, understanding what motivates their users to contribute is important because the viability of these platforms as businesses depends not only on how many users they have but also on how active their users are as content contributors. However, extant marketing research on social media and related phenomena such as online word of mouth has focused primarily on the *outcomes* of user activity and less on the *motivations* underlying user activity (e.g., Godes and Mayzlin 2004, Trusov et al. 2009, Katona et al. 2011, Stephen and Galak 2012).

In the absence of explicit economic incentives, the literature suggests two relevant types of utility that

[1] According to the Nielsen BlogPulse home page, available at http://www.blogpulse.com (last accessed October 7, 2011).

may motivate noncommercial social media users to contribute content: intrinsic utility and image-related utility. *Intrinsic utility* assumes that users receive direct utility from posting content and leads to "the doing of an activity for its inherent satisfactions rather than for some separable consequence" (Ryan and Deci 2000, p. 56). *Image-related utility*, on the other hand, assumes that users are motivated by the perceptions of others (see Fehr and Falk 2002 for a review of the psychological foundations of incentives).[2] Image-related utility is also related to status seeking or prestige motivation (e.g., Glazer and Konrad 1996; Harbaugh 1998a, b; Fershtman and Gandal 2007; Lampel and Bhalla 2007).

Intrinsic and image-related utility have been studied quite extensively in the domain of prosocial behavior (see, e.g., Glazer and Konrad 1996; Harbaugh 1998a, b; Bénabou and Tirole 2006; Ariely et al. 2009). In a domain closer to social media, Lerner and Tirole (2002, 2005) contrast the intrinsic pleasure open-source developers derive from working on "cool" projects with the (image-related) desire for peer recognition. See also Bitzer et al. (2007) or von Hippel and von Krogh (2003) for a theoretical discussion of the motivations to contribute to open-source projects, and see von Krogh and von Hippel (2006) for a review. Several papers have provided additional survey-based empirical evidence that intrinsic and image-related utility are indeed relevant in open-source development (e.g., Ghosh et al. 2002, Hars and Ou 2002, Lakhani and Wolf 2005, Roberts et al. 2006). Survey-based evidence for intrinsic and image-related utility has also been found in the context of electronic knowledge repositories (see, e.g., Kankanhalli et al. 2005, Wasko and Faraj 2005, Lampel and Bhalla 2007, Nov 2007). In the domain of social media specifically, Bughin (2007) surveys users of an online video-sharing site and finds that their primary motivations to upload videos are image-related (e.g., "I seek fame") and intrinsic (e.g., "It is fun"). Hennig-Thurau et al. (2004) survey the motivations of contributors to Web-based opinion platforms. Besides some motivations specific to their particular context, these authors found that motivations tend to be either intrinsic (e.g., "It is fun to communicate this way with other people in the community") or image-related (e.g., "My contributions show others that I am a clever consumer").

Therefore, based on the extant literature it appears that intrinsic utility and image-related utility are both plausible and realistic motivations for people to contribute content in social media. However, to the best of our knowledge, the empirical evidence to date is only survey-based. In this paper we compare these two types of utility using a different empirical approach that focuses specifically on the context of the popular microblogging platform Twitter.[3] Twitter is an ideal social media context in which to empirically study intrinsic and image-related utility because these two types of utility give rise to opposite predictions as to whether users should increase or decrease their posting activities when their number of followers increases. To address the issue that the number of followers is endogenous, we conducted a field experiment in which we exogenously added followers (or, follow requests, in the case of protected accounts) to a set of users (i.e., the treatment group) and then compared their posting activities to those of a control group.

We report two sets of analyses in this paper. An initial model-free analysis of our data shows that although our intervention did not have a statistically significant main effect, it did have a significant positive effect on posting activities for treated users with a moderately low initial number of followers and a significant negative effect for treated users with a moderately high initial number of followers. These findings are consistent with both intrinsic and image-related utilities being relevant, with the dominant motivation being different for users with different numbers of followers. Although it has the benefit of being free of any functional form assumption, this model-free analysis does not allow us to quantify the relative magnitudes of these two types of utility and how they vary across users based on observed and unobserved factors. Accordingly, we then analyze our data using a dynamic discrete choice model. This also allows us to make counterfactual predictions on the evolution of the Twitter platform as the network becomes stable.

Two recent papers related to our research are Kumar (2009) and Shriver et al. (2013). Kumar (2009) studies consumers' purchase of ringback tones for their mobile phones (a ringback tone is not consumed by the user purchasing it but rather by those who call that user). Kumar estimates the utility consumers derive from having a high status (i.e., more recently updated tones), from consuming the tones purchased by their peers, and from expressing themselves through the tones they purchase. Using a set of instrumental variables, Shriver et al. (2013) study the causal relations between content generation and the number of social ties in an online windsurfing community. However, neither paper studies specifically the utility derived from posting content in social media. Kumar (2009) uses a context slightly different

[2] Fehr and Falk (2002) also discuss reciprocity as a psychological source of motivation, which depends on whether an agent perceives the action of another agent as hostile versus kind. This is less relevant in our context.

[3] Whereas a blog is a website or part of a website that displays entries or elements of content (text, graphics, video, etc.) usually posted by an individual, a microblog is a type of blog that allows users to exchange smaller elements of content (e.g., short sentences, individual images, links).

from social media, and Shriver et al. (2013) do not study utility or motivation directly.

The remainder of this paper is organized as follows. In §2, we provide an overview of the Twitter platform, discuss how the concepts of intrinsic utility and image-related utility are operationalized in this context, and describe our empirical strategy. We describe our data in §3, provide some model-free analysis in §4, and analyze the data using a dynamic discrete choice model in §5. We conclude in §6.

2. Background

2.1. Twitter

Twitter is a very popular social media platform that allows registered users to share "tweets" (text messages up to 140 characters long) with their "followers" (other users who choose to subscribe to a user's feed of tweets). The ability to follow other users creates a directed social network (unlike other social networks such as Facebook or LinkedIn, which are undirected networks, user A following user B on Twitter does not automatically imply that B follows A). A user's home page (as seen by that user) contains a "timeline" that captures all the tweets posted by the users this user follows (in reverse chronological order), a text box labeled "What's happening" that allows the user to post a tweet, and a reminder of the number of users following the user and the number of users followed by the user.[4] Twitter users may be split into noncommercial and commercial users. Commercial users may be classified into celebrities, media and nonmedia organizations, and brands (Wu et al. 2011). In this paper we focus on noncommercial users for whom there exists no apparent financial incentive to contribute content.

Other features of Twitter include the ability for a user to "unfollow" another user (i.e., stop following a user whom he or she had been following), to "block" another user (i.e., prevent that other user from following him or her), and to make his or her own account "protected." Accounts that are not protected are called "public" (this is the default setting) and may be followed and accessed by any user. If a user elects to protect his or her account, then to follow that account, the user must approve any follow requests, and the text of his or her tweets may only be accessed by his or her followers. However, the number of users followed, the number of followers, and the cumulative number of tweets are public information for both public and protected accounts. According to Cha et al. (2010), approximately 8% of Twitter accounts are protected.

One final characteristic of Twitter that is critical to our analysis is that posting content is a way for users to attract new followers. This claim is supported by our data (i.e., the state transition probabilities reported in §5.1.4) and is consistent with Shriver et al. (2013) who find a positive causal effect of content generation on the number of social ties in an online windsurfing community. Note that unlike other directed social networks, reciprocity (i.e., user A follows user B, and vice versa) on Twitter is only moderate. Kwak et al. (2010) report that of all user pairs on Twitter with at least one link between them, only 22.1% have a reciprocal relationship (i.e., each user in the pair follows the other user). In other words, a user's number of followers is not simply a by-product of his or her following activities, and posting content in the form of tweets is one way for users to attract new followers.

Twitter usage has been steadily growing. The number of unique U.S. visitors to twitter.com in September 2011 was estimated at 35 million, up from 28 million in September 2010.[5] In March 2012, the number of active users throughout the world was reported to be 140 million (Twitter 2012). The average number of tweets per day was reported to be 250 million in October 2011 (Bennett 2011) and 340 million in March 2012 (Twitter 2012). Even if each tweet takes only a few seconds to write, with 340 million tweets written per day, the equivalent of multiple decades of one person's life are spent each day posting content on Twitter (340 million tweets $\times$ 5 seconds per tweet $=$ 53.9 years).

Given the scale and relevance of Twitter in society, it is not surprising that academic research on Twitter has started to emerge, mostly from computer science and information systems. Extant research has focused primarily on studying the structure and nature of the Twitter social network, as well as on issues related to influence and information diffusion on this network (see, e.g., Cha et al. 2010, Kwak et al. 2010, Weng et al. 2010, Bakshy et al. 2011, Romero et al. 2011, Wu et al. 2011, Goel et al. 2012). However, to the best of our knowledge, academic research on Twitter in marketing and other social sciences to date has been limited. Exceptions include Ghose et al. (2013), who compare user search costs in online versus mobile platforms using data from a microblogging site comparable to Twitter; and Stephen et al. (2012), who study how user activity on Twitter affects the extent to which URLs posted by users in tweets spread through the Twitter network.

[4] Besides typing a message in the "What's happening" window of their home pages, users may also post tweets as "replies" or "retweets." A *reply* to a previous tweet is a text message of up to 140 characters that will be seen by users who follow both the user who posted the initial tweet and the user replying to that tweet. A *retweet* forwards a previous tweet to a user's followers. In our data, *tweets* includes tweets, retweets, and replies.

[5] Based on http://siteanalytics.compete.com/twitter.com/ (accessed November 15, 2011).

2.2. Intrinsic vs. Image-Related Utility on Twitter

2.2.1. Intrinsic Utility. Twitter's initial positioning was as "a real-time information network powered by people all around the world that lets you share and discover what's happening now."[6] Twitter further states that "Twitter asks 'what's happening' and makes the answer spread across the globe to millions."[7] The public nature of Twitter and the claims that the information spreads "to millions across the globe" suggest that the intrinsic utility derived by a noncommercial user from posting content on Twitter should be monotonically nondecreasing in that user's number of followers. Put simply, a user should derive more intrinsic utility from broadcasting content as the size of his or her audience increases. This is similar to the case where content publishers receive explicit financial incentives, which are typically monotonically nondecreasing in the size of the publisher's audience. Although not critical to our argument, we also assume that intrinsic utility from posting content is concave in the number of followers.

2.2.2. Image-Related Utility. The definition of image-related utility on Twitter should *not* be limited to the management of the user's image (i.e., how the user is portrayed on the platform). Instead, image-related utility should be defined more broadly, to encompass the sense of self-worth and social acceptance provided by a user's activities on the platform.

In particular, there is some evidence suggesting that image-related utility on Twitter is related to a user's number of followers. Although any user is able to contribute as much content and follow as many users as he or she wants, followers need to be "earned," and a user's number of followers is an informative social signal. The number of followers has been used as a measure of influence by academics (Cha et al. 2010, Kwak et al. 2010) and is often associated with popularity by the general public (e.g., on sites such as Twitaholic.com and Wefollow.com; see also Beck 2009). There have been several press reports of Twitter users attaching a lot of importance to their number of followers. According to Poletti (2009), Twitter has become an avenue for self-promotion, and one's number of followers is becoming "the new barometer of how we gauge . . . our self worth." Leonhardt (2011) claims that the number of followers on Twitter is "just how people keep score on the site and compare themselves with friends and colleagues." Teitell (2011) reports on the social pressures to achieve high numbers of followers on Twitter and high scores on sites such as Klout.com and PeerIndex.net that rate all Twitter users based on their number of followers (as well as other metrics, by using proprietary scoring rules). The importance for many Twitter users of having a large number of followers is further revealed by the plethora of websites that offer advice on how to increase that number (a partial list may be obtained by typing "increase Twitter followers" in any search engine). Therefore it seems appropriate to measure the stature or prestige of a Twitter user by his or her number of followers.

It is reasonable to model utility from stature as a nondecreasing concave function of the number of followers. For example, Baumeister and Leary (1995) argue that humans have a fundamental need for a certain minimum number of social bonds but that "the formation of further social attachments beyond that minimal level should be subject to diminishing returns; that is, people should experience less satisfaction on formation of such extra relationships," (p. 500), and they review empirical evidence supporting this claim. Also consistent with image-related utility being concave, DeWall et al. (2008) provide experimental evidence that satiating the need for social acceptance leads to a reduction in the drive to satisfy that need.

In summary, both intrinsic utility from posting content and image-related utility from having many followers may be assumed to be monotonically nondecreasing and concave in the user's number of followers. However, one key difference is that whereas intrinsic utility is derived from *posting* content viewed by many followers, image-related utility is derived from *having* many followers. If a user does not post content on a given day, he or she will obviously not derive any intrinsic utility from posting content on that day. On the other hand, image-related utility from having many followers is a measure of stature that is independent of contemporaneous posting activities. We will next see how, as a result of this difference, the *motivation* to post content (i.e., the total expected incremental utility derived from posting content on a given day) takes a different form under intrinsic versus image-related utility.

2.3. Empirical Strategy

Twitter offers a unique opportunity to study and contrast intrinsic utility and image-related utility in social media for at least two reasons. First, by focusing on noncommercial users, we are able to study contributions to social media in a context in which financial or other extrinsic incentives are minimal, if at all present. Second, and more importantly, Twitter provides a context for empirically comparing intrinsic versus image-related utility, because both give rise to different predictions as to how users should react to an increase in their number of followers.

[6] From Twitter's About page, available at http://twitter.com/about (last accessed February 2010).

[7] *ibid.*

Table 1 Illustrative Model: Intrinsic Utility Case

	Action			
	Post in period 1		Doesn't post in period 1	
	Post in period 2	Does not post in period 2	Post in period 2	Does not post in period 2
Expected utility in period 2	$\delta U(n+1)+(1-\delta)U(n)$	0	$U(n)$	0
Total expected utility (period 1 + period 2)	$\delta U(n+1)+(2-\delta)U(n)$	$U(n)$	$U(n)$	0

Note. For period 1, the utility for posting is $U(n)$; for not posting, it is 0.

Throughout this section we illustrate the opposite predictions made by intrinsic versus image-related utility with a highly stylized and simplified model. This two-period model is presented only for illustration purposes and is not used anywhere else in the paper. We show in Appendix A that similar results are obtained with an infinite-horizon version of this model and illustrate the results graphically.

Let n denote a user's number of followers. Let $U(n)$ be the per-period utility derived from posting content to n followers in a given period (e.g., day). In the case of intrinsic utility, $U(n)$ is derived in a given period only if content is posted in that period; on the other hand, in the case of image-related utility, it is derived in a given period irrespective of whether content is posted in that period. We assume that $U(n)$ is monotonically increasing and concave in n. We further assume (for the purposes of this illustrative model only) that if a user posts content in period 1, his or her number of followers will increase to $n+1$ in the next period with probability δ and stay the same with probability $1-\delta$. If content is not posted in period 1, we assume that the number of followers will remain the same in the next period. (Note that in §5 we use empirical state transition probabilities instead of making these simplifying assumptions.) Table 1 lists the utility derived by the user in each period as a function of his or her action in each period for the case of intrinsic utility. Table 2 does the same for the case of image-related utility.

2.3.1. Intrinsic Utility: Implication When the Number of Followers Increases. If users contribute content to Twitter because of the intrinsic value they derive from broadcasting information to their followers, and if the utility derived from posting is monotonically nondecreasing and concave in a user's number of followers, then we should expect users to increase their posting activities as they receive additional followers. Quite simply, if the utility from posting content is increasing in the number of followers, having more followers should lead to more posting.

In terms of our illustrative model, we see in Table 1 that the user derives an additional utility $U(n)$ by posting in period 1, which, by assumption, is monotonically increasing in n. If the user also posts in period 2, then posting in period 1 increases the expected utility derived in period 2 from $U(n)$ to $\delta U(n+1)+(1-\delta)U(n)$ (because of the potential increase in the number of followers as a result of posting in period 1). In that case posting content in period 1 provides a total (over both periods) expected additional intrinsic utility of $U(n)+[\delta U(n+1)+(1-\delta)U(n)-U(n)]=\delta U(n+1)+(1-\delta)U(n)$. This quantity is also monotonically increasing in n, because $\delta \geq 0$, $1-\delta \geq 0$ and $U(n)$ is monotonically increasing in n. In other words, the total expected incremental utility from posting content in period 1 is increasing in n irrespective of whether the users posts content in period 2.

2.3.2. Image-Related Utility: Implication When the Number of Followers Increases. With image-related utility, posting content is not the direct source of utility but rather a means toward an end, i.e., a way to attract new followers. The utility comes from *having* many followers, not from broadcasting content to them. Posting content on a given day influences *future* expected image-related utility by increasing the expected number of followers the user will have in the future. Therefore, in contrast to intrinsic utility, the incremental image-related utility achieved by posting content on a given day will be derived in the *future* and is based on the *additional* followers the user will gain by posting that day. If there are diminishing returns to additional followers, this incremental future expected utility is decreasing in the current number of followers. Therefore the motivation to post content in order to attract new followers should be decreased as the current number of followers is increased.[8]

In terms of our illustrative model, if the user posts content in period 1, there is a probability δ that image-related utility in period 2 will be increased

[8] One may think that users who are motivated by image would feel compelled to actually post more as they amass more followers, in order to maintain their number of followers. However, our data suggest that the expected change in the number of followers when no posting occurs is not negative (see the state transition probabilities reported in §5.1.4), so this scenario seems unlikely. More generally, our model in §5 will enable us to take such scenarios into account by explicitly capturing and quantifying the impact of posting on a user's future number of followers.

Table 2 Illustrative Model: Image-Related Utility Case

	Action			
	Post in period 1		Does not post in period 1	
	Post in period 2	Does not post in period 2	Post in period 2	Does not post in period 2
Expected utility in period 2	$\delta U(n+1)+(1-\delta)U(n)$	$\delta U(n+1)+(1-\delta)U(n)$	$U(n)$	$U(n)$
Total expected utility (period 1 + period 2)	$\delta U(n+1)+(2-\delta)U(n)$	$\delta U(n+1)+(2-\delta)U(n)$	$2U(n)$	$2U(n)$

Note. For period 1, the utility for either posting or not positing is $U(n)$.

from $U(n)$ to $U(n+1)$. As shown in Table 2, posting content in period 1 provides an additional total expected image-related utility of $\delta(U(n+1)-U(n))$, which is realized in period 2 irrespective of whether the user posts content in period 2. This illustrates that under image-related utility, the incremental benefit from posting content on a given day is realized in the future and is a result of attracting new followers. Because $U(n)$ is concave in n, $U(n+1)-U(n)$ is decreasing in n; i.e., the incremental total expected image-related utility derived from posting content in period 1 is decreasing in the number of followers at the beginning of period 1.

Interestingly, under image-related utility, the incremental benefit from posting content on a given day is increasing in the likelihood that posting content will increase the number of followers (parameter δ in our illustrative model). Therefore, users motivated by image-related utility should also post less content as the structure of the network becomes stable (i.e., a nonevolving static structure of connections is achieved) and as posting activities become less likely to lead to additional followers. This raises questions on the longer-term sustainability of the Twitter platform and has implications for the type of value firms may be able to derive from social media in the future. This issue will be addressed using counterfactual analyses in §5.3.4.

In sum, the intrinsic utility from posting content and image-related utility from having many followers give rise to opposite predictions as to how users should react to an increase in their number of followers. If users are motivated by the intrinsic utility from broadcasting content to many followers, then having more followers should lead to an increase in posting activities. On the other hand, if users derive their utility from having many followers and post content to gain additional followers, then the motivation to post content should be diminished as the current number of followers is increased (as a result of additional followers having diminishing returns). In Appendix A, we show how the results of the simple two-period illustrative model used here generalize to an infinite horizon, and we also illustrate graphically how the incremental value from posting content in a given period varies with the number of followers under intrinsic and image-related utility.[9]

3. Data

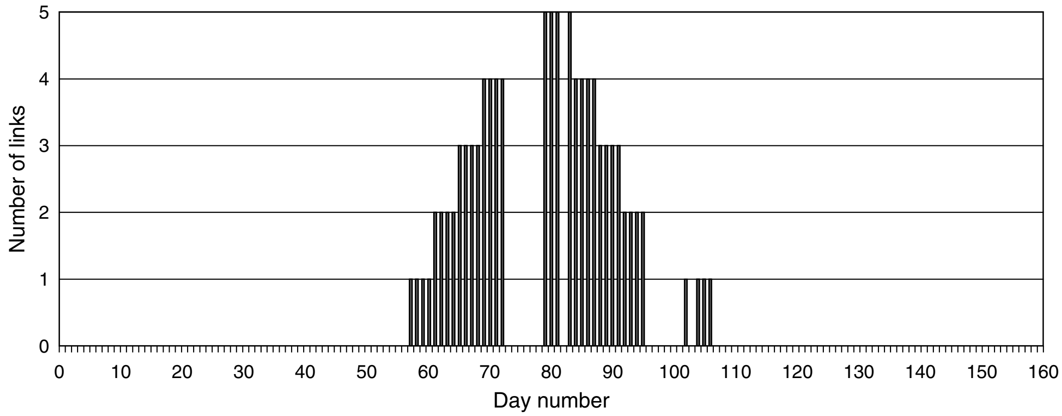
Our data were collected directly from Twitter using Twitter's application programming interface (API; see https://dev.twitter.com). We selected a random set of 2,493 noncommercial Twitter users from an initial database of approximately 3 million user accounts. We ensured that our users were noncommercial by checking account names and checking against lists and classifications on sites such as Wefollow.com and Twitaholic.com. The users in our data set are a mix of public and protected accounts. We collected data daily on the following variables for each user in our sample: (i) the number of followers, (ii) the number of users followed, and (iii) the cumulative number of tweets posted by that user since the account was created. Unfortunately, the structure of the social network to which these users belong was not available to us.

3.1. Initial Calibration Data Set

We first collected data daily for these 2,493 users for 52 days (between May 8, 2009 and June 28, 2009). This initial data set allowed us to identify active users among the set. We classified a user as "active" if he or she increased his or her cumulative number of tweets or number of users followed at least once during this screening observation window. Out of all users, 1,355 were classified as active.

[9] We note that there are conditions that are related to the way posting affects one's future number of followers under which intrinsic utility and image-related utility could in fact have the opposite effects to those just described. These conditions have low face validity and are discussed at the beginning of §5. Notwithstanding, our model in §5 enables us to quantify intrinsic versus image-related utility even under such conditions. In particular, the identification of our model does not rely on the assumption that intrinsic (image-related) utility always gives rise to an increase (decrease) in posting activity following an increase in the number of followers.

Figure 1 **Daily Number of Exogenous Links Created per Treated User Over the Main Observation Window**



3.2. Field Experiment

We collected daily data again from the same set of 2,493 users for 160 days (between September 14, 2009 and February 20, 2010), our main observation window. We selected 100 users randomly from the set of 1,355 active users as our treatment group. To introduce exogenous variations in the number of followers, we gradually added 100 followers to public accounts in the treatment group over a 50-day period (days 57–106). For protected accounts in the treatment group, we sent 100 follow requests over the same 50-day period.

To execute our treatment, we created and managed 100 synthetic Twitter users (50 males, 50 females) and created one link from each synthetic user to each treated user (i.e., followed or sent a follow request) between days 57 and 106. With the help of two undergraduate research assistants who were avid Twitter users, we attempted to make our synthetic users as realistic as possible (we will test the realism of these users experimentally in §4.3). The names of the synthetic users were generated using a name generator (http://www.fakenamegenerator.com). Before linking to the treated users, profile pictures were uploaded to the synthetic users' profiles, and each synthetic user followed an average of five other synthetic users as well as some celebrities and media organizations (as is typical for many Twitter users). The synthetic users also posted tweets on a regular basis. To increase the credibility of the exogenous links to the treated users from the synthetic users, we started by creating one link (i.e., adding one synthetic follower or sending one follow request in the case of protected accounts) per day to each treated user. After doing so each day for four days, we increased the daily number of exogenous links per treated user to two per day, and so on, until the rate increased to five per day for four days, after which it was decreased to four per day for four days, and so on. By day 106, each synthetic user had created one link to each treated user. Figure 1 shows the number of exogenous links created to each treated user on each of the 160 days in our main observation window.[10] Note that our experimental procedure respects Twitter's terms of service (available at http://twitter.com/tos).

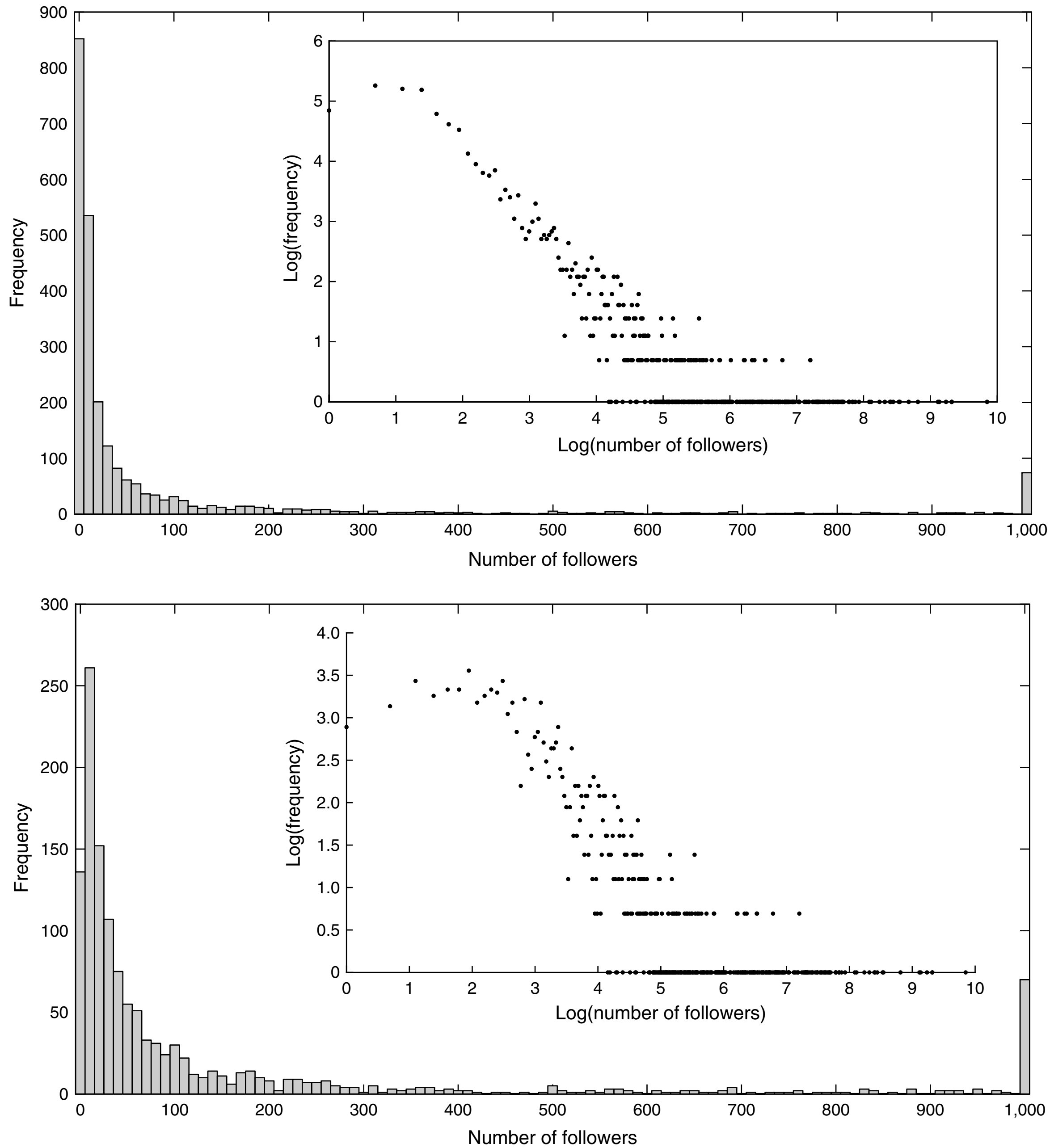
4. Model-Free Analysis

4.1. Descriptive Statistics

We first report some key descriptive statistics. Figure 2 shows histograms and log–log plots of the distribution of the number of followers on the first day of the main observation window for all 2,493 users and for all 1,355 users who were active during the screening period (i.e., the set of users from which our treated users were drawn). The distribution of the number of followers is close to a truncated power law (the log–log plots are close to linear), which is typical of social networks (e.g., de Solla Price 1965, Barabási and Albert 1999, Stephen and Toubia 2009). Figure 3 shows the distribution across all 1,355 active users of the average daily posting rate during the main observation window. The average daily posting rate is measured as the total number of posts during the window divided by the number of days. We see that the distribution is heavily skewed, with many users posting very little and few users posting heavily. Figure 4 shows the evolution of the median number of followers over time for treated versus control users. Figure 5 shows the distribution of the difference between the numbers of followers at the end versus the start of the intervention (day 107 minus day 57) for treated users only. We see that the control and treatment groups had very comparable median numbers of followers before the start of the intervention

[10] The gaps in Figure 1 are due to our research assistants needing to take breaks from this labor-intensive activity.

Figure 2 Histograms and Log–Log Plots of the Distribution of the Number of Followers on Day 1 for All Users (Top) and All Active Users (Bottom)



(days 1–57). We also see that the actual increase in number of followers for treated users may be larger than 100 (because of the addition of "organic" new followers) or smaller than 100 (because some treated users had protected accounts and did not accept all synthetic users' follow requests, and because all users have the ability to block any of their followers).[11] Nevertheless, by the end of the main observation window, the median number of followers for treated users was greater than the median number for nontreated users by a margin of 85.00.

To verify that the randomization between treatment and control groups was done appropriately, we conducted nonparametric rank sum tests comparing the number of followers on day 1, the number of users followed on day 1, and the average daily posting rate before treatment (days 1–56) for treated versus nontreated users. None of these test results were significant (all $p > 0.16$). Similar results were obtained with two-sample t-tests (all $p > 0.20$). We also compared

[11] The correlation coefficient between the number of followers on day 1 and the increase in number of followers is not significant ($\rho = 0.126$, p-value > 0.21).

Figure 3 **Distribution of Average Daily Posting Rate Among All Active Users**

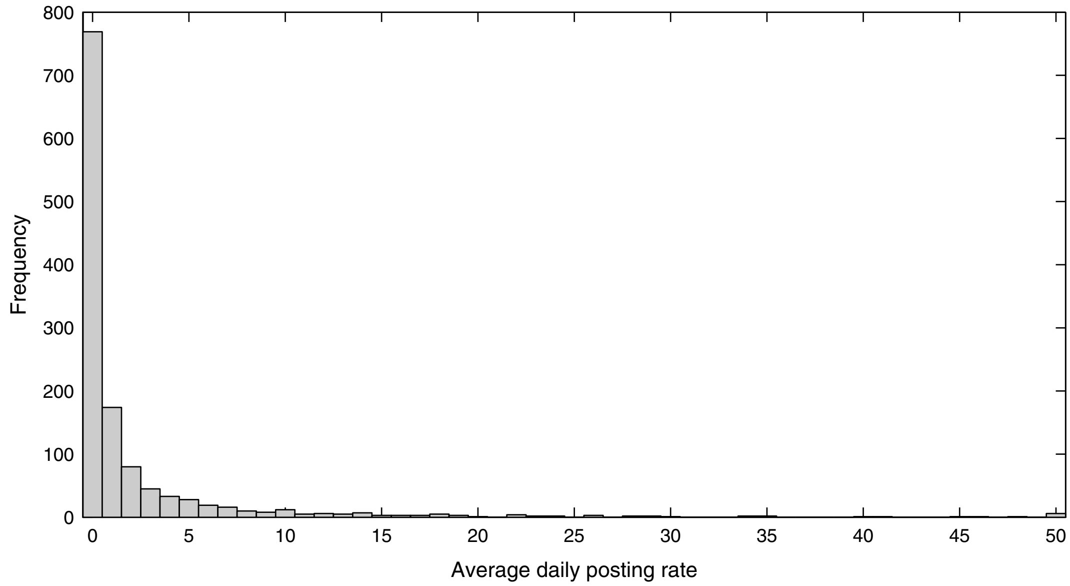
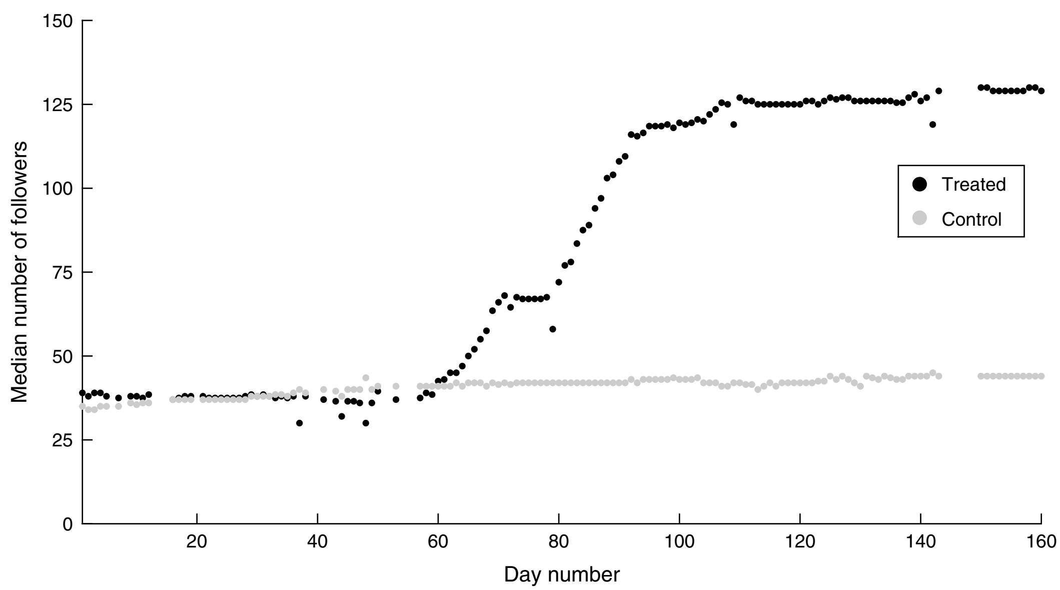


Figure 4 **Median Number of Followers as a Function of Time for Treated and Control Users**



the distributions of the number of followers on day 1 using the Kolmogorov–Smirnov (KS) statistic. The two distributions are not statistically significantly different ($p > 0.34$).[12]

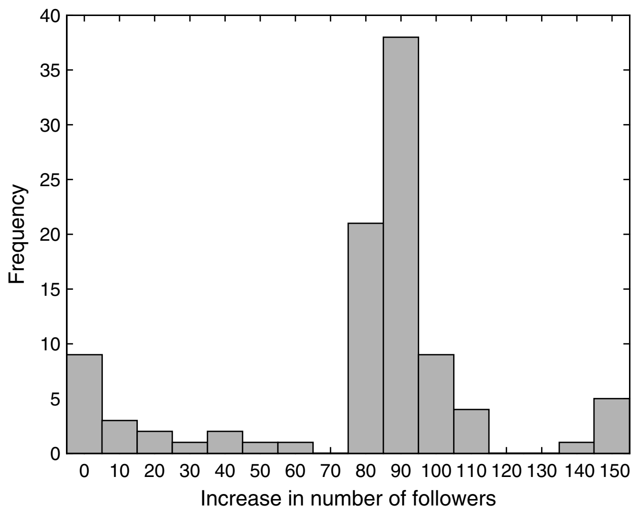
4.2. Impact of Intervention on Posting Activity

We now consider the posting behavior of treated versus control users. Studying how treated users reacted to our intervention is interesting and relevant in and of itself for Twitter and other social media platforms. Moreover, as we argued earlier, increasing (decreasing) posting activity following the addition of new followers is consistent with intrinsic utility (image-related utility). We note that we can only argue that each reaction is *consistent* with a different type of utility, not *equivalent* to it. As is often the case in social sciences, we do not observe or measure users' motivations directly; instead, we disentangle different sources of motivation by identifying a setting in which they make divergent predictions. However, we acknowledge that we cannot rule out all alternative explanations for the behavior of our treated users.

We compare each user's average daily posting rate after the intervention (days 107–160) to before the intervention (days 1–56). We find that the proportion of users for whom the average daily posting

[12] Because the KS test itself only applies to continuous distributions, we use bootstrapping to determine the correct p-value. A similar p-value is obtained using a standard KS test.

Figure 5 Distribution Among Treated Users of the Increase in the Number of Followers After vs. Before the Intervention (Day 107 − Day 57)



rate increased after the intervention is somewhat greater among treated users than it is among the control users. Specifically, 40.82% of treated users had a greater posting rate after the intervention than before, compared with 34.19% of control users. However, the difference between these two proportions is not statistically significant ($z = 1.32$, $p = 0.19$).[13] Therefore, our intervention did not have a significant main effect on posting activity.

We now explore whether our intervention had different effects based a user's initial number of followers. This is plausible for at least two reasons. First, we should expect intrinsic utility and image-related utility to vary differently as a function of a user's number of followers. Therefore, although the behavior of a user may be more consistent with one type of utility when that user has few followers, it may be more consistent with the other type as the number of followers increases. Second, there is likely heterogeneity across users in the relative importance of image-related versus intrinsic utility, and this heterogeneity may be reflected in the number of followers. For example, users for whom image-related utility is prevalent may be more likely to have made an effort to amass larger numbers of followers. Both of these factors would lead to users with different numbers of followers reacting differently to the treatment.

Figures 6 and 7 plot the probabilities that a user respectively increased and decreased his or her posting rate after versus before the intervention, as a function of the log of that user's initial number of followers (on day 1 of the main observation window), for treated and nontreated users. These figures were obtained by smoothing the raw data using a Gaussian kernel function (bandwidth = 1).[14] We see that treated users with lower initial numbers of followers tended to increase their posting rates relative to control users. However, treated users with higher initial numbers of followers tended to decrease their posting rates relative to control users.

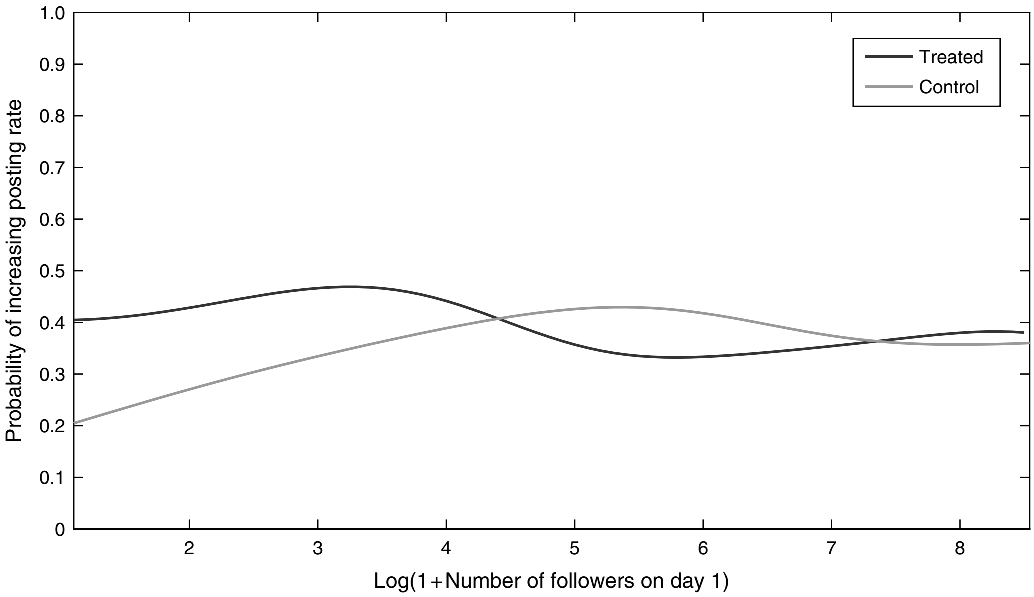
To statistically compare the impact of the treatment on posting behavior as a function of the initial number of followers, we split our treated users into quintiles based on their initial numbers of followers on day 1 of the main observation window. The five quintiles are described in Table 3. Table 4 reports the proportion of users with increased average daily posting rates and with decreased average daily posting rates (after versus before the intervention) in each quintile. Treated users in the second quintile were significantly more likely to increase their posting rates compared with users in the control group ($z = 2.42$, $p < 0.02$), and they were marginally significantly less likely to decrease their posting rates compared with users in the control group ($z = -1.85$, $p = 0.06$). Users in the fourth quintile, however, show the opposite result: treated users in that group were significantly less likely to increase their posting rates compared with users in the control group ($z = -2.18$, $p < 0.03$), and they were significantly more likely to decrease their posting rates compared with users in the control group ($z = 1.94$, $p = 0.05$). The differences in the other quintiles are not statistically significant. Therefore, our results suggest that exogenously adding followers (or, in the case of protected accounts, follow requests) made some users post more (users in the second quintile), made some users post less (users in the fourth quintile), and had little effect on the others.[15]

[13] Consistent with this result, the average daily posting rate after the treatment (days 107–160) is not statistically significantly different for treated versus nontreated users (Wilcoxon rank sum test, $z = 0.935$, $p > 0.35$; two-sample t-test, $t = 1.32$, $p > 0.18$).

[14] We also ran parametric logistic regressions where the dependent variable (DV) was whether users increased (respectively, decreased) their posting rates after versus before the intervention, and the independent variables (IVs) included a dummy for treatment, log(1 + number of followers on day 1), log(1 + number of followers on day 1)^2, the interaction between the treatment dummy and log(1 + number of followers on day 1), and the interaction between the treatment dummy and log (1 + number of followers on day 1)^2. Comparable figures were obtained, although these parametric regressions do not seem to capture the relationship between the number of followers and the impact of the intervention as well as the nonparametric regressions do. Details are available from the authors upon request.

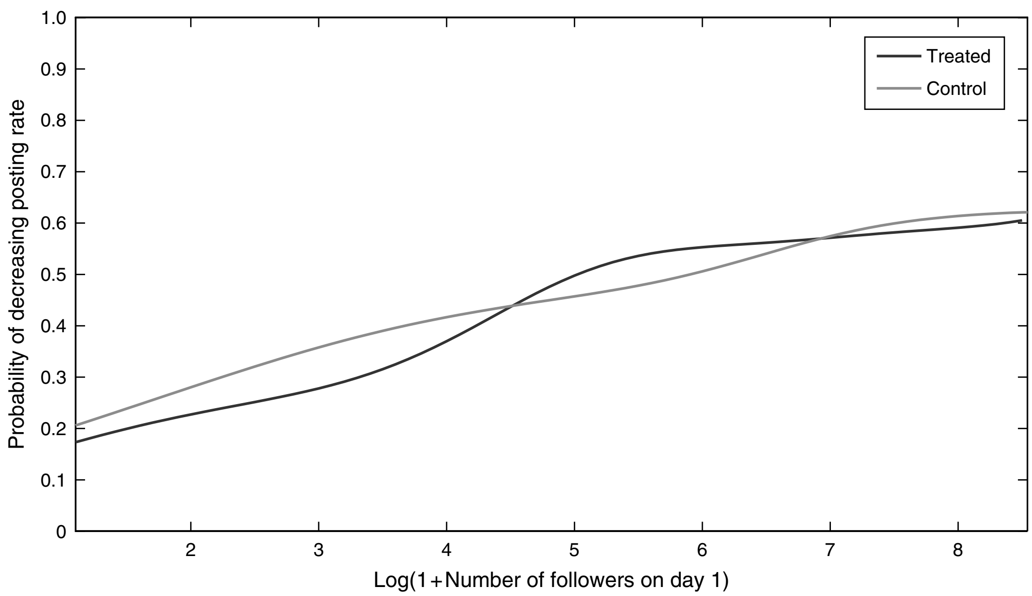
[15] Similar results were obtained when we ran a logistic regression where the DV was whether users increased (respectively, decreased) their posting rates after versus before the intervention, and the IVs included a dummy for treatment, dummies for the various quintiles, and interactions between the treatment and quintile dummies. Results are available from the authors upon request.

Figure 6 **Probability of Increasing Posting Rate After vs. Before the Intervention as a Function of the Log of the Number of Followers on Day 1**



Note. This figure is obtained by smoothing the raw data using a Gaussian kernel function (with a bandwidth of 1).

Figure 7 **Probability of Decreasing Posting Rate After vs. Before the Intervention as a Function of the Log of the Number of Followers on Day 1**



Note. This figure is obtained by smoothing the raw data using a Gaussian kernel function (with a bandwidth of 1).

The fact that the treatment had no effect on the first and fifth quintiles is not surprising. The first quintile is composed of users with very few followers who are only marginally active and may hardly visit the Twitter platform. The fifth quintile is composed of users with over 1,000 followers on average, for whom the addition of up to 100 followers over the 50-day window may have gone largely unnoticed. The results in the second quintile are consistent with intrinsic utility. As discussed above, intrinsic utility from posting content should lead users to post more content, on average, following our intervention. The results in the fourth quintile, however, are consistent with image-related utility. As argued above, if the benefits from posting come from attracting additional followers and if additional followers provide diminishing marginal utility, we should expect posting activity to be reduced, on average, following our intervention. The results in the third quintile are consistent with the effects of the two sources of utility canceling each other out, on average, for users with an initial number of followers within the corresponding range.

It is very common for companies to follow consumers on Twitter, partly in the hope that these

Table 3 Five Quintiles Based on Number of Followers on Day 1

Quintile	Range of number of followers	Median number of followers	Average number of followers
1	0–12	7	6.499
2	13–26	19	18.941
3	27–61	39.5	40.988
4	62–245	109	125.550
5	246–18,940	704	1,378.949

Notes. The quintiles (i.e., range of the number of followers) are determined based on the treated users to ensure an equal spread of these users across the five groups. The median and average numbers of followers reported are for the entire set of active users.

Table 4 Proportion of Users with Increased/Decreased Average Daily Posting Rate (After vs. Before Intervention)

	Increased average daily posting rate		Decreased average daily posting rate	
Quintile	Treated	Control	Treated	Control
1	0.286	0.205	0.238	0.185
2	0.632	0.350	0.158	0.370
3	0.556	0.370	0.278	0.426
4	0.200	0.451	0.700	0.474
5	0.400	0.375	0.500	0.574

Notes. Treated users in the second quintile were significantly more likely to increase their posting rates compared with users in the control group ($z = 2.42$, $p < 0.02$) and marginally significantly less likely to decrease their posting rates compared with users in the control group ($z = -1.85$, $p = 0.06$). Treated users in the fourth quintile were significantly less likely to increase their posting rates compared with users in the control group ($z = -2.18$, $p < 0.03$) and significantly more likely to decrease their posting rates compared with users in the control group ($z = 1.94$, $p = 0.05$). The differences in the other quintiles are not statistically significant.

consumers will become advocates and contribute content related to the companies' brands. Our model-free analysis has managerial implications related to this practice. Indeed, based on our results, it appears that following consumers on Twitter may have the counterintuitive effect of making them less active and therefore *less* likely to contribute content related to the companies' brands. This is particularly true for consumers with relatively large numbers of followers, who are precisely the ones typically targeted by companies for their ability to reach more people with brand-related messages (e.g., Goldenberg et al. 2009). In §5, we present a complementary model-based analysis that provides additional managerial insights by quantifying intrinsic utility and image-related utility and making counterfactual predictions regarding the evolution of Twitter.

4.3. Ecological Validity: Perceived Realism of Synthetic Followers

One potential concern with our results is that our synthetic followers may have been more likely to be perceived by treated users as being "fake," which may have led treated users in our experiment to react to the addition of followers (or follow requests, in the case of protected accounts) differently than they would have normally. To address this concern, in April 2012, we created a snapshot image for the profile of each synthetic user, each treated user, and one randomly selected follower of each treated user who did not have a protected account at that time (76 treated users were in that case).[16] The image was a screenshot from the profile summary publicly available on Twitter and contained the user's name, picture, number of tweets to date, number of users followed and following, and the three most recent tweets by the user (with the exception of protected accounts, for whom recent tweets are not publicly available).

Three hundred fifty-five members of the Amazon Mechanical Turk panel, who were prescreened as having Twitter accounts, assessed these profiles based on the snapshot images. Each respondent evaluated a random set of 20 profiles in exchange for \$1 and was asked to indicate whether each profile seemed fake (a *fake* profile was defined as one that "pretends to be another person or another entity in order to confuse or deceive other users"). By the end of the survey, each profile had received an average of 26.199 evaluations.

We computed the proportion of times each profile was judged to be fake. The mean (median) of this proportion was 0.199 (0.192) among synthetic users, 0.209 (0.192) among treated users, and 0.307 (0.241) among the followers of treated users. The mean and median proportions were not statistically significantly different between synthetic and treated users ($p > 0.46$). Followers of treated users, however, were significantly more likely to be evaluated as fake compared with synthetic and treated users (all $p < 0.01$). This is probably because these users included both commercial and noncommercial users.[17] In conclusion, this survey suggests that our synthetic users were not perceived as being more fake than other noncommercial users (our treated users) and were perceived as significantly less fake than a random subset of the followers of noncommercial users. This suggests that our treatment has good ecological validity.

[16] By the time we ran this study, five of our treated users did not exist anymore. Also, it was not possible for us to identify the followers of users with protected accounts.

[17] The statistical analysis reported here is based on the point estimates of the probability that each profile is judged to be fake. As an alternative approach, we used a parametric bootstrapping approach to construct confidence intervals around the mean and median probabilities reported in the text. We considered a model in which the posterior distribution of the probability that profile i will be judged to be fake is given by $p_i \sim \text{Beta}(0.01 + f_i, 0.01 + nf_i)$, where f_i (respectively, nf_i) is the number of times the profile was evaluated as fake (respectively, nonfake) in the data and where the beta distribution follows from an uninformative prior (Beta(0.01, 0.01)) and binomial likelihood. We constructed confidence intervals by drawing 10,000 values of p_i for each profile. Identical conclusions were reached.

4.4. Impact of Protected Accounts

As mentioned above, our intervention involved adding new followers to public accounts; for protected accounts, it involved sending follow requests that the treated users could either accept or reject. The fact that users with protected accounts could reject these requests may have reduced the impact of our intervention, which should make the significant treatment effects found in quintiles 2 and 4 more conservative, and it could artificially attenuate the effect of the treatment in the other quintiles. We recorded (manually) which treated users had protected accounts at the time of the intervention (unfortunately, we do not have this information for the nontreated users). Fifteen of our treated users had protected accounts at the time of the experiment. These users were equally spread across the first four quintiles reported in Table 3 (four, four, four, and three protected users in quintiles 1, 2, 3, and 4, respectively; none were in quintile 5). Therefore the null treatment effects in quintiles 1, 3, and 5 appear unlikely to have been driven by a larger proportion of protected accounts in these quintiles. Moreover, the results in Table 4 do not change qualitatively when limited to the public treated users. Details are available from the authors upon request.

4.5. Alternative Explanation

One alternative explanation for the effect of our treatment on the fourth quintile (those users who decreased their posting rate after the intervention) is that some users feel comfortable posting on Twitter when their followers are limited to immediate relations and when some level of intimacy is preserved, but they become less comfortable as their posts become more public. This would drive these users to contribute less content after receiving additional, unknown followers.

To investigate this issue, we were able to download, in April 2012, the text of all tweets posted by 44 of our treated users during the pre-treatment (days 1–56) and post-treatment (days 107–160) periods of our main observation window.[18] These 44 users posted 3,580 tweets in total during those periods. We asked 749 members of the Amazon Mechanical Turk panel (prescreened to be Twitter users) to classify these tweets in exchange for $2. Each respondent was shown the text of 60 tweets randomly selected from the full set (no information about each tweet other than its text was provided) and was asked to answer the following question about each tweet: "Is this tweet meant for the user's close friends and family members only?" The response categories were "Yes," "No," and "I do not know/I do not understand this tweet." Each tweet was classified by an average of 12.797 respondents.

We compute the proportion of occurrence of each response category for each tweet. Tables 5–7 report averages across users. We construct confidence intervals using a parametric bootstrapping approach.[19] Table 5 reports the average across treated users

Table 5 Average Categorization of Tweets Posted Before vs. After the Treatment

"*Is this tweet meant for the user's close friends and family members only?*"	Before treatment	After treatment
No	0.536 [0.519, 0.552]	0.536 [0.523, 0.548]
Yes	0.369 [0.353, 0.385]	0.354 [0.343, 0.367]

Note. In the interest of space, the third response category ("I do not know/I do not understand this tweet") is not reported; 95% credible intervals are reported in brackets.

Table 6 Average Categorization of Tweets Posted Before the Treatment by Users Who Increased vs. Decreased Their Posting Rate After the Treatment

"*Is this tweet meant for the user's close friends and family members only?*"	User increased posting rate	User decreased posting rate
No	0.572 [0.544,0.600]	0.507 [0.486,0.525]
Yes	0.364 [0.337,0.392]	0.373 [0.355,0.392]

Notes. In the interest of space, the third response category ("I do not know/I do not understand this tweet") is not reported; 95% credible intervals are reported in brackets.

Table 7 Average Categorization of Tweets Posted Before the Treatment by Users in Different Quintiles (as Defined in Table 3)

"*Is this tweet meant for the user's close friends and family members only?*"	Quintile to which user belongs		
	First three	Fourth	Fifth
No	0.486 [0.453, 0.518]	0.561 [0.538, 0.583]	0.602 [0.592, 0.611]
Yes	0.447 [0.415, 0.478]	0.328 [0.308, 0.349]	0.269 [0.260, 0.278]

Notes. In the interest of space, the third response category ("I do not know/I do not understand this tweet") is not reported; 95% credible intervals are reported in brackets.

[18] We were not able to retrieve these data for treated users who did not exist anymore as of April 2012, who had protected accounts, and who had posted more than 3,200 tweets since the end of our observation window (because of limits imposed by the Twitter API). The number of users for whom we have text data in each quintile (first to fifth) is 7, 8, 8, 10, and 11.

[19] We denote as p_{ijk} the multinomial probability that a random evaluation of tweet j by treated user i would fall into response category k. We draw 10,000 random sets of probabilities for each tweet, according to $\{p_{ij1}, p_{ij2}, p_{ij3}\} \sim \text{Dirichlet}(0.01 + n_{ij1}, 0.01 + n_{ij2}, 0.01 + n_{ij3})$, where n_{ijk} is the observed number of times tweet j by treated user i was classified in category k. This Dirichlet distribution results from an uninformative prior (Dirichlet(0.01, 0.01, 0.01)) combined with the multinomial likelihood function.

before and after the treatment. We see that the treatment decreased the proportion of "private" tweets slightly, although the 95% confidence intervals before and after the treatment overlap. Next, to investigate whether the treatment had a different effect on users who were posting more private tweets before the treatment, we report in Table 6 the average categorization across treated users before the treatment, for those users who increased their posting rate after the intervention versus those who decreased their posting rate. We see that, indeed, treated users who decreased their posting rate after the intervention tended to post tweets that were more private before the treatment. This is consistent with the hypothesis that some users decreased their posting rate after the treatment because their audience changed from being intimate to being more public.

However, for this phenomenon to explain why treated users in the fourth quintile posted less as a result of the intervention, it would need to be the case that the tweets posted by these users before the treatment were relatively more private. Table 7 reports the average categorization across treated users before the treatment for users in the first three quintiles versus the fourth quintile versus the fifth quintile (we group the first three quintiles to increase statistical power, and similar conclusions are reached if each of the five quintiles is considered separately). Users with more followers at the beginning of the observation window tended to post tweets that were *less* private before the treatment: the difference between the first three quintiles and the fourth quintile is statistically significant, as well as the difference between the fourth and the fifth quintiles. Therefore if the effect of the treatment was solely driven by privacy considerations, we should expect treated users in the lower quintiles—and not the fourth quintile—to be the ones decreasing their posting rate after the treatment; similarly, we should expect treated users in the higher quintiles—and not the second quintile—to be the ones increasing their posting rate.

In conclusion, although our analysis does provide support to the hypothesis that users who use Twitter more privately are more likely to decrease their posting rate after the addition of unknown followers, this phenomenon does not appear to drive our results.

5. Dynamic Discrete Choice Model

The results of the previous model-free analysis are consistent with the existence of both intrinsic utility and image-related utility among Twitter users, with each source of motivation being more or less predominant as a function of the user's number of followers. In this section we introduce and estimate a dynamic discrete choice model that attempts to address the following limitations of our model-free analysis.

First, our model-free analysis did not quantify the relative importance of intrinsic versus image-related utility. Instead, it simply provided patterns of results consistent with the existence of these two types of utility.

Second, our model-free analysis did not allow us to determine whether the different responses to the intervention were driven by heterogeneity in the preferences of the treated users versus heterogeneity in their initial number of followers. It could be the case that the same type of utility is always dominant for each user irrespective of his or her number of followers and that users for whom one versus the other type of utility is dominant happen to have different numbers of followers. However, it could also be the case that each user goes through different phases on Twitter, where one source of utility tends to be dominant initially and the other tends to become dominant as the user amasses more followers. Although we should expect some heterogeneity in preferences, it is not clear a priori whether the dominant source of utility may vary within a user over time.

Third, our model-free analysis did not allow us to make any counterfactual predictions on how users' motivations to post content on Twitter are likely to impact the platform in the future. Such predictions are valuable in light of the recent public debate on the sustainability and future growth of social media platforms such as Twitter (see, for example, Hagan 2011). and they have implications for the type of value firms may be able to derive from such platforms in the future.

Fourth, we have argued that intrinsic utility should lead to an increase in posting activities as the number of followers is increased and that image-related utility should lead to a decrease, but there exist conditions under which these theoretical predictions would be reversed. These conditions, which do not have high face validity, are related to the way posting affects one's future number of followers. For example, if attracting new followers became much harder as users acquired more followers, it might be possible that although a user motivated by image-related utility receives less marginal value from each additional follower as his or her number of followers increases, he or she has to post much more heavily in order to attract new followers. This could lead to a net increase in posting activities.[20] Conversely, it is possible that users driven by intrinsic motivation would

[20] This would go against the popular notion of preferential attachment, which is often believed to govern the evolution of "scale-free" social networks such as this one (Barabási and Albert 1999).

post less after having more followers, if, for example, their early posting activities were targeted toward building an audience to which they would broadcast later and if the only way to build such an audience was to post heavily early on. By capturing the effect of posting on the number of followers through the state transition probabilities, our model allows us to quantify intrinsic versus image-related utility irrespective of whether these conditions are satisfied. More generally, the identification of our model does not rely on the assumption that intrinsic (image-related) utility always gives rise to an increase (decrease) in posting activity following an increase in the number of followers.

5.1. Model

We index users by $i = 1, \ldots, I$. We index time (day) by $t = 1, \ldots, \infty$. In each time period, each user chooses one of four possible actions: (i) follow at least one new user and post content, (ii) follow at least one new user and post no content, (iii) follow no new users and post content, and (iv) follow no new users and post no content. We model each user's decision in each time period as a multinomial choice over these four possible actions. The utility derived by a user from each action in each time period is a function of the number of followers this user has at that time. The user's action will have an impact not only on his or her future number of followers but also on the utility offered by each possible action in the future. To capture these dynamic effects, we build a dynamic discrete choice model in which users take into account how their current actions will impact their future decisions. As with every dynamic discrete choice model, developing and estimating our model involves (i) defining the states, (ii) defining the actions, (iii) defining the utility function, (iv) modeling the state transition probabilities, and (v) specifying the likelihood function. We describe each of these steps next.

5.1.1. States. We define user i's state at time t by his or her number of followers on that day, s_{it}.

5.1.2. Actions. We denote the action taken by user i at time t by $a_{it} = \{n_{it}, p_{it}\}$, where n_{it} is a binary variable equal to 1 if user i followed at least one new user at time t, and p_{it} is a binary variable equal to 1 if user i posted content at time t.[21] As mentioned above, each user faces a choice between four possible actions in each period: $\{1, 1\}$, $\{1, 0\}$, $\{0, 1\}$, or $\{0, 0\}$. We next describe the costs and benefits associated with each action.

5.1.3. Utility Function. We model the utility derived by user i in period t as

$$u(s_{it}, a_{it} \mid \theta_i) = \theta_{i1}(1+s_{it})^{\theta_{i2}} + p_{it} \cdot \theta_{i3}(1+s_{it})^{\theta_{i4}} + \theta_{i5} n_{it} + \theta_{i6} p_{it}, \quad (1)$$

where $\theta_i = \{\theta_{i1}, \theta_{i2}, \theta_{i3}, \theta_{i4}, \theta_{i5}, \theta_{i6}\}$, and the following constraints are imposed: θ_{i1}, $\theta_{i3} \geq 0$; $\{\theta_{i2}, \theta_{i4}\} \in [0, 1]^2$; and θ_{i5}, $\theta_{i6} \leq 0$ (when estimating the model, we further constrain θ_i to a compact set Θ).

The specification of our utility function is driven by the discussion in §2.2. The first term, $\theta_{i1}(1+s_{it})^{\theta_{i2}}$, captures image-related utility from having many followers. As discussed above, the stature or prestige of a Twitter user may be measured as a monotonically nondecreasing and concave function of that user's number of followers. This term does not depend on the action chosen in period t, but it does depend on the current state, which is the result of past actions. The next term, $p_{it} \cdot \theta_{i3}(1+s_{it})^{\theta_{i4}}$, captures intrinsic utility from posting content. This term is positive only if the user posts content in period t and is equal to 0 otherwise. When positive, this term is also monotonically nondecreasing and concave in the number of followers. Finally, the last two terms capture the costs of following a new user and of posting, respectively.

5.1.4. State Transition Probabilities. We denote the state transition probabilities by $f(s' \mid s, a)$, the probability of reaching state s' in the next period given a state s and an action a in the current period. Because we have access to a substantial amount of data (daily states and actions of 2,493 users over 160 days) and because our action space includes only four possible actions, we are able to use the observed transition frequencies as state transition probabilities instead of estimating them parametrically (see, e.g., Bajari et al. 2007). These empirical state transition probabilities are based on all observations from all 2,493 users in our main observation window. Each observation consists of a triplet $\{s_{it}, a_{it}, s_{i(t+1)}\}$, i.e., a starting state, an action, and a resulting next state. The empirical transition probability $f(s' \mid s, a)$ is simply the proportion of times state s' was observed among all the observations where action a was taken in state s.[22]

[21] An alternative formulation would consider the *number* of posts and the *number* of new users followed. However, this would make the action space unbounded and would pose significant computational challenges. Therefore, we treat these actions as binary. Note, however, that this is different from assuming that users may only follow one new user (or any other fixed number of new users) or post only one tweet on each day. Indeed, our empirical state transition probabilities are based on the actual observations; i.e., they are based on the true numbers of posts and new followers.

[22] Using observed transition frequencies implies that we need to limit our analysis to the largest set of states in which all four actions were observed and in which these actions always led to states in that same set of states. This results in a state space containing 539 states with the numbers of followers ranging from 0 to 1,618, which covers 93.36% of the initial observations (only 2.08% of the initial observations involve states with more than 1,618 followers).

Across all states and observations, we find that the actions {*follow*, *post*}, {*follow*, *don't post*}, {*don't follow*, *post*}, and {*don't follow*, *don't post*} give rise to expected changes in the number of followers $E(s' - s \mid a)$ of 1.209, 0.487, 0.197, and 0.022, respectively, and that the probability of an increase in the number of followers, $\text{Prob}(s' - s > 0 \mid a)$, is 0.511, 0.335, 0.257, and 0.075, respectively. This confirms that both posting content and following new users are ways to attract new followers.

5.1.5. Likelihood Function. Following Rust (1987), we assume an unobservable shock ε_{it} to utility for consumer i at time t, which follows a double-exponential distribution. The value function for user i in state $\{s, \varepsilon\}$ is the solution to the following Bellman equation:

$$V(s, \varepsilon \mid \theta_i) = \max_{a \in A} \left[u(s, a \mid \theta_i) + \varepsilon(a) + \beta \sum_{s'} f(s' \mid s, a) \cdot V(s' \mid \theta_i) \right], \quad (2)$$

where β is a discount factor, A is the action space, and $V(s \mid \theta_i) = E_\varepsilon(V(s, \varepsilon \mid \theta_i))$. Note that we make the standard assumption that all users have correct beliefs regarding the state transition probabilities. We define action-specific value functions as

$$V_a(s \mid \theta_i) = u(s, a \mid \theta_i) + \beta \cdot \sum_{s'} f(s' \mid s, a) \cdot V(s' \mid \theta_i). \quad (3)$$

Rust (1987) showed that

$$V(s \mid \theta_i) = \log\left(\sum_{a \in A} \exp(V_a(s \mid \theta_i)) \right) \quad (4)$$

and that the probability that user i chooses action a_{it} at time t in state s_{it} is given by

$$P(a_{it} \mid s_{it}, \theta_i) = \frac{\exp(V_{a_{it}}(s_{it} \mid \theta_i))}{\sum_{a' \in A} \exp(V_{a'}(s_{it} \mid \theta_i))}. \quad (5)$$

Equation (5) defines our likelihood function. Maximizing this likelihood function poses great computational challenges because the likelihood involves the solution to Bellman's equation. We use a method recently proposed by Norets (2009a) to estimate the set of parameters $\{\theta_i\}$. We describe our estimation procedure next.

5.2. Estimation

Although we use the full set of users to estimate the state transition probabilities, we estimate the parameters of the model $\{\theta_i\}$ for treated users only, mainly for tractability and identification purposes. In particular, we estimate the model on the set of treated users over the main observation window ($t = 1, \ldots, 160$) and remove from the analysis users with fewer than 10 usable observations. The estimation method proposed by Norets (2009a) is closely related to the method proposed by Imai et al. (2009), and it uses a Bayesian approach to simulate the posterior distribution of the parameters conditional on the data. Given our particular data set and model, we specifically adapt the approach proposed in Corollary 2 of Norets (2009a). This method offers the combined benefits of being computationally tractable, of being based on the full solution of the dynamic program, and of allowing us to capture heterogeneity in the estimated parameters.

Our estimation algorithm relies on a hierarchical Bayes model that consists of a likelihood, a first-stage prior, and a second-stage prior. As mentioned above, our likelihood function is given by Equation (5). We then impose a first-stage prior on the parameters, according to which θ_i comes from a truncated normal distribution with mean θ_0 and covariance matrix D_θ; the truncation ensures that θ_i remains in a compact set Θ: $\theta_i \sim \text{TN}(\theta_0, D_\theta)$. The arrays θ_0 and D_θ are themselves parameters of the model on which we impose a second-stage prior. Following standard practice (Allenby and Rossi 1998), we use a noninformative second-stage prior to let these parameters be driven by the data. We fix $\beta = 0.995$. We draw values of all the parameters using a Gibbs sampler. Details are provided in Appendix B.

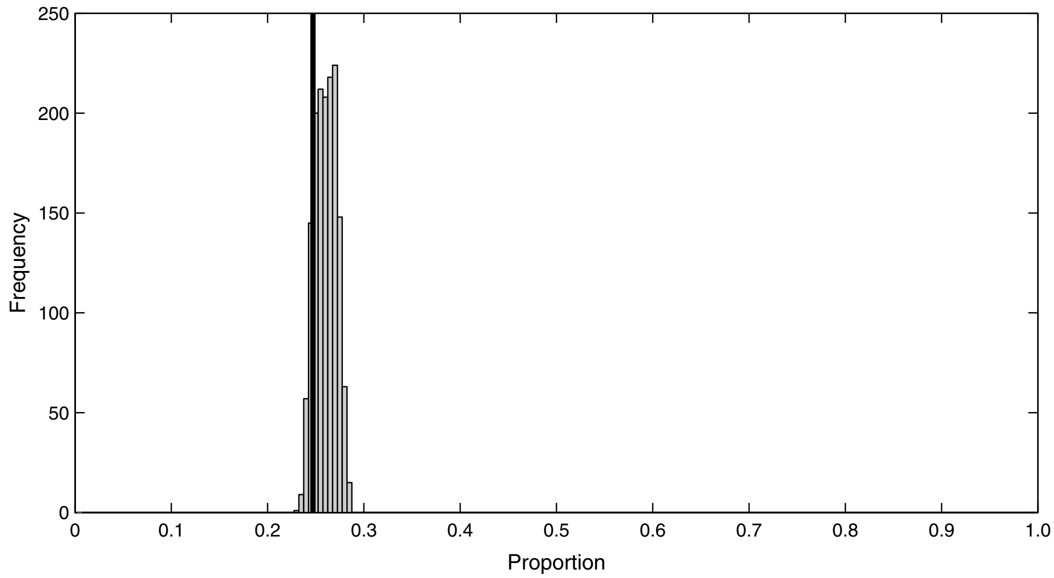
5.3. Results

5.3.1. Model Fit. A common measure of model fit in Bayesian statistics is the marginal density of the data according to the model, defined as

$$LMD = \int_{\Theta^I} P(data \mid \{\theta_i\}) P(\{\theta_i\})\, d\theta,$$
$$\text{where} \quad P(data \mid \{\theta_i\}) = \prod_{i=1}^{I} \prod_{t=1}^{T} P(a_{it} \mid s_{it}, \theta_i),$$

and $P(\{\theta_i\})$ is the prior distribution on the parameters. The log marginal density is approximated by the harmonic mean across the Gibbs sampler iterations of the likelihood of the data (see, e.g., Sorensen and Gianola 2002). To make the results more intuitive, we report the marginal density to the power of the inverse of the total number of observations; i.e., we report the geometric mean of the marginal density per observation. We obtain a value of 0.4726. For comparison, a null model that assumes that all four actions are equally likely would achieve a per-observation marginal density of 0.2500. We also assess the fit of the model using posterior predictive checks (Gelman et al. 1996). Posterior predictive checks assess how well the model fits key aggregate statistics of the data by comparing the posterior distribution of these statistics based on the model with the observed values. We consider the proportion of observations in our data in which posting was observed (i.e., $a_{it} = \{0, 1\}$ or $\{1, 1\}$). The observed proportion is 0.2470. The predicted value of this quantity is computed at each

Figure 8 Posterior Check of Proportion of Observations That Include Posting



Notes. The histogram plots the posterior distribution of the proportion of observations in which users post content, as predicted by the model. The solid line represents the observed proportion.

iteration of the Gibbs sampler as

$$\sum_{i=1}^{I}\sum_{t=1}^{T} P(a_{it} = \{1, 1\} \mid s_{it}, \theta_i) + P(a_{it} = \{0, 1\} \mid s_{it}, \theta_i).$$

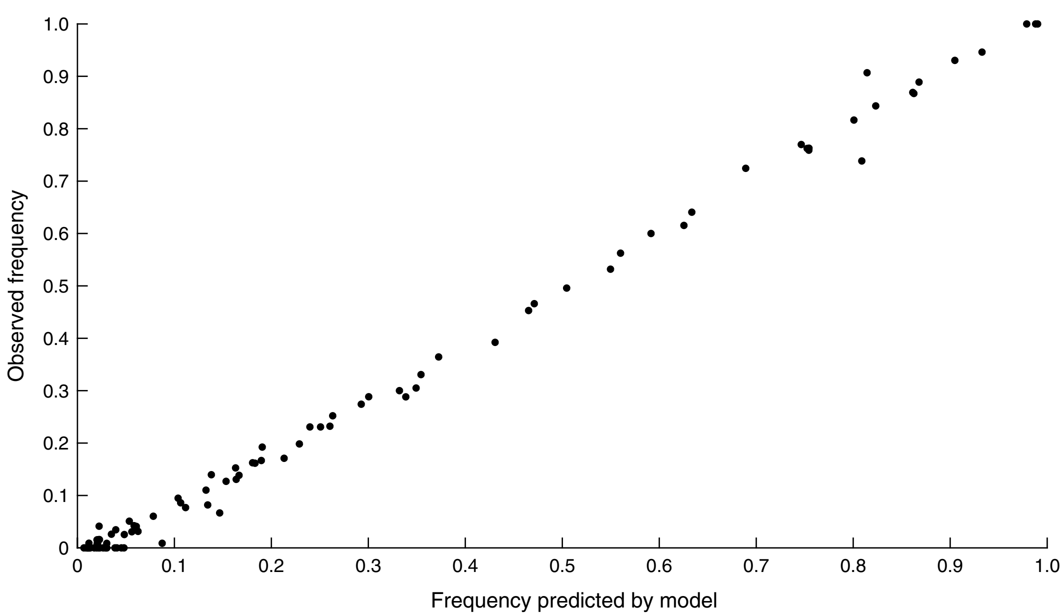
The posterior distribution (across iterations of the Gibbs sampler) of the predicted value of this quantity is shown in Figure 8. The mean of the posterior distribution is 0.2604, and the 95% credible interval ([0.2405; 0.2797]) contains the observed value of 0.2470.

We also consider the distribution (across users) of the proportion of observations in which posting was observed. We compute a point estimate of the posting frequency for each user; this point estimate for user i is the average across posterior draws of

$$\sum_{t=1}^{T} P(a_{it} = \{1, 1\} \mid s_{it}, \theta_i) + P(a_{it} = \{0, 1\} \mid s_{it}, \theta_i).$$

Figure 9 provides a scatterplot of the posting frequency as predicted by the model versus that

Figure 9 Posting Frequency as Predicted by the Model vs. Observed (Across Users)



Notes. The x axis corresponds to the posting frequency (proportion of observations that involve posting) as predicted by the model; the y axis corresponds to the observed frequency. Each dot corresponds to one user.

Table 8 **Point Estimates and 95% Credible Intervals of the Average Parameters Across Users**

Parameter	Point estimate	Credible interval
θ_1	0.309	[0.170; 0.497]
θ_2	0.329	[0.241; 0.388]
θ_3	0.690	[0.586; 0.791]
θ_4	0.265	[0.226; 0.309]
θ_5	−5.008	[−5.301; −4.648]
θ_6	−5.075	[−5.380; −4.775]

Notes. The utility derived by user i at period t is $u(s_{it}, a_{it} \mid \theta_i) = \theta_{i1}(1+s_{it})^{\theta_{i2}} + p_{it}\theta_{i3}(1+s_{it})^{\theta_{i4}} + \theta_{i5}n_{it} + \theta_{i6}p_{it}$, where s_{it} is user i's number of followers in period t, p_{it} is a binary variable equal to 1 if user i posts content in period t, and n_{it} is a binary variable equal to 1 if user i follows at least one new user in period t. We fix $\beta = 0.995$.

observed across users. We see that the model is able to recover these frequencies very well at the individual level.

5.3.2. Parameter Estimates. Table 8 reports the point estimates and 95% credible intervals of the average parameters across users, and Figure 10 plots the distribution across users of the point estimates of the parameters.

We use the parameter estimates to explore the distinction between heterogeneity in preferences versus heterogeneity in the number of followers. In our model, both image-related utility and intrinsic utility from posting are monotonically increasing and

Figure 10 **Distribution of the Parameters Across Users**

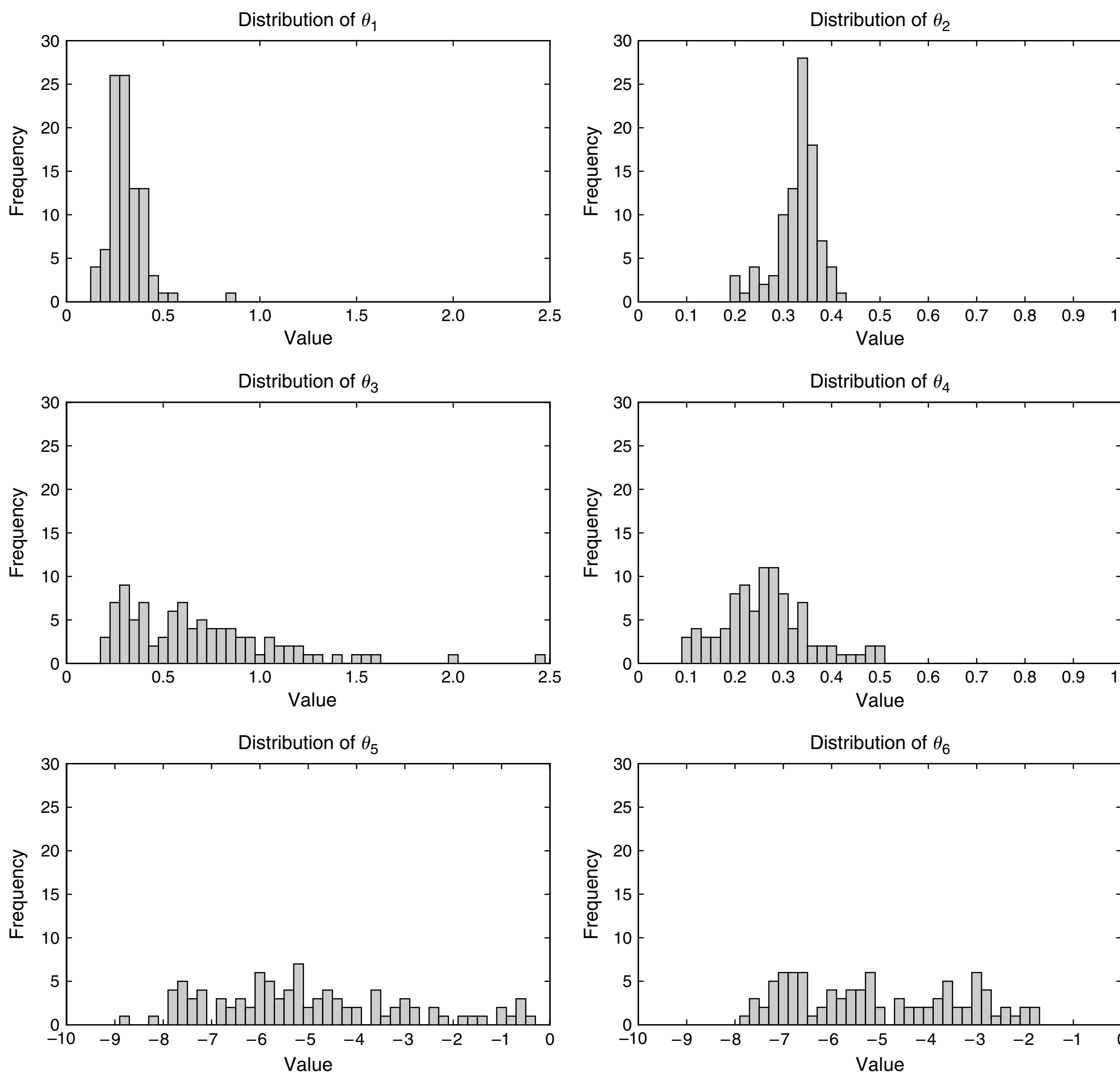


Table 9 User Segmentation Based on Parameter Estimates

	Image-related utility > Intrinsic utility when $s_i \to \infty$ ($\theta_{i2} > \theta_{i4}$)	Intrinsic utility > Image-related utility when $s_i \to \infty$ ($\theta_{i2} < \theta_{i4}$)
Image-related utility > Intrinsic utility when $s_i \to 0$ ($\theta_{i1} > \theta_{i3}$)	0.106	0.011
Intrinsic utility > Image-related utility when $s_i \to 0$ ($\theta_{i1} < \theta_{i3}$)	0.649	0.234

Note. Based on the proportion of treated users in each segment.

concave in the number of followers. The parameters θ_{i2} and θ_{i4} capture the curvature of these utility curves, and the parameters θ_{i1} and θ_{i3} influence their scale. It is easy to show that the two curves cross exactly once in the $[0, \infty)$ range if $(\theta_{i2} - \theta_{i4})(\theta_{i1} - \theta_{i3}) < 0$; they do not cross otherwise. Moreover, as s_{it} goes to 0, image-related utility is larger if $\theta_{i1} > \theta_{i3}$, and the reverse is true if $\theta_{i1} < \theta_{i3}$. As s_{it} goes to ∞, image-related utility is larger if $\theta_{i2} > \theta_{i4}$, and the reverse is true if $\theta_{i2} < \theta_{i4}$. This gives rise to four possible segments of treated users based on which source of utility is larger for lower versus higher values of s_{it}.

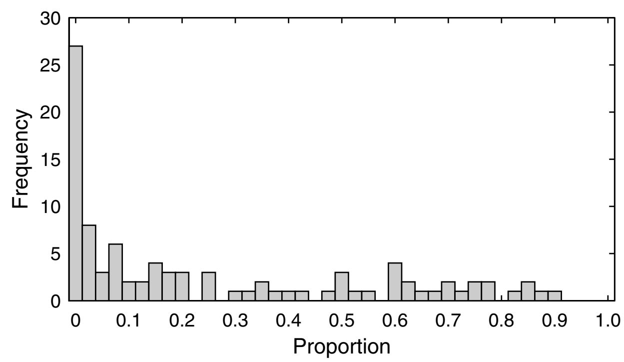
The proportion of treated users in each segment according to our parameter estimates is reported in Table 9. For 34.0% of the treated users, the same type of utility is larger irrespective of the number of followers (image-related utility is always larger for 10.6% of the treated users and intrinsic utility for 23.4% of the users). However, and perhaps more interesting, there is a large proportion of treated users—64.9%—for whom the larger source of utility varies within user as the number of followers increases. We also see a large asymmetry: in almost all cases (64.9% out of 66.0%), the evolution is such that intrinsic utility is initially larger when the number of followers is smaller, and image-related utility eventually becomes the larger one as the number of followers grows.

This analysis suggests that the differences in the behavior of treated users in our experiment were not only driven by heterogeneity in preferences across users but also by the fact that for the majority of the users, intrinsic utility is larger when the number of followers is smaller, and image-related utility takes over as the number of followers grows.

5.3.3. Intrinsic vs. Image-Related Utility Derived by Users. The previous analysis was based on the parameter estimates and did not take into account the users' actions. We now estimate the proportion of intrinsic versus image-related utility *derived* by each user, according to the model. We define the total image-related utility and total intrinsic utility, respectively, for user i as

$$u_{\text{image}_i} = \sum_{t=1}^{T} u_{\text{image}_{i,t}} \quad \text{and} \quad u_{\text{intrinsic}_i} = \sum_{t=1}^{T} u_{\text{intrinsic}_{i,t}},$$

Figure 11 Distribution Across Users of the Proportion of Intrinsic Utility Derived During the Main Observation Window (Intrinsic/(Intrinsic + Image-Related))



where

$$u_{\text{image}_{i,t}} = \theta_{i1}(1+s_{it})^{\theta_{i2}} \quad \text{and} \quad u_{\text{intrinsic}_{i,t}} = p_{it} \cdot \theta_{i3}(1+s_{it})^{\theta_{i4}}.$$

We estimate the proportion of intrinsic utility for user i as $proportion_i = u_{\text{intrinsic}_i}/(u_{\text{intrinsic}_i} + u_{\text{image}_i})$.

Figure 11 plots the distribution across users of the estimate of this proportion. The average across users is 0.2533 and the median is 0.1313. Therefore, according to the model, most treated users derived more image-related utility from Twitter than they did intrinsic utility during our main observation window.[23]

5.3.4. Counterfactual Analysis: Change in Posting Activity If the Network's Structure Were Stable. Finally, we consider the question of how posting frequency would be affected if the network's structure were stable, i.e., if a user's actions did not influence his or her future states. If actions did not influence future states, actions would be chosen according to the utility derived in the current period only. For each observation in our data, we estimate the probability of

[23] One may argue that our treatment affected the proportion of intrinsic versus image-related utility derived by users. However, computing this proportion on the pre-treatment period gives rise to similar conclusions (the average proportion across users is 0.2184 and the median is 0.0580).

each of the four actions based only on the immediate utility provided by that action:

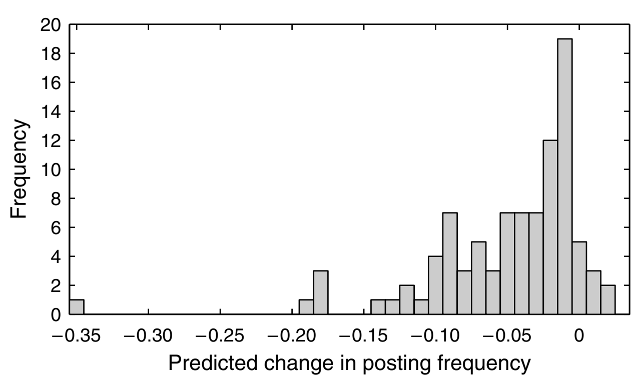
$$P^{\text{stable}}(a_{it} \mid s_{it}, \theta_i) = \frac{\exp(u(s_{it}, a_{it} \mid \theta_i))}{\sum_{a' \in A} \exp(u(s_{it}, a' \mid \theta_i))}.$$

For each user we estimate the posting frequency under these probabilities and compare these frequencies with those obtained under the initial model (used to construct the scatterplots in Figure 9). Figure 12 plots the distribution across users of the change in posting frequency that results from the assumption that actions do not influence future states. The average predicted change across users is -0.0502 (with a 95% credible interval of $[-0.0617; -0.0384]$), the median is -0.0347, and the predicted change is negative for 94.68% of the users. In other words, this counterfactual analysis suggests that if users' posting activities did not influence their future number of followers, posting frequency would decrease by an average of approximately 5%.

This analysis suggests that as Twitter matures and the network's structure becomes stable, content is likely to be contributed more prominently by commercial users. In that case the value derived from Twitter by noncommercial users is likely to shift somewhat from the *production* of content to the *consumption* of content. Therefore our analysis is consistent with the prediction that Twitter is likely to shift from a platform where noncommercial users share content with each other toward a more traditional media platform where noncommercial users consume content contributed primarily by commercial users. This is consistent with recent research by Goel et al. (2012), who find that the diffusion of popular content on Twitter operates through users with very large numbers of followers (e.g., Justin Bieber) rather than through peer-to-peer social influence.

This prediction is also consistent with recent changes in Twitter's positioning. As mentioned previously, Twitter's initial positioning was as "a real-time information network powered by people all around the world that lets you share and discover what's happening now" (from Twitter's About page, last accessed February 2010). As of April 2012, Twitter's positioning had shifted to "a real-time information network that connects you to the latest stories, ideas, opinions and news about what you find interesting."[24] Twitter advises users to "simply find the accounts you find most compelling and follow the conversations" and clearly states that "you don't have to tweet to get value from Twitter."[25]

Figure 12 Distribution Across Users of the Predicted Change in Posting Frequency If the Network's Structure Were Stable



In a managerial sense, this shift implies that in the future, firms are likely to derive more value from social media platforms such as Twitter by using them as media channels where they broadcast content to consumers, rather than as viral marketing platforms where they create or track word of mouth or customer insights platforms where they monitor consumers' conversations.

6. Discussion and Conclusion

Whereas publishers' incentives in traditional media are well understood, individuals' motivations for contributing content in social media platforms such as Twitter are still underresearched and have been explored so far only using surveys (e.g., Hennig-Thurau et al. 2004, Bughin 2007).

Previous literature suggests that the two primary types of utility that motivate noncommercial users to contribute content to social media are intrinsic and image-related. These two sources of utility may be identified empirically on Twitter because they give rise to opposite predictions as to whether users should increase or decrease their posting activities when their number of followers increases. To address the issue that the number of followers is endogenous, we conducted a field experiment in which we exogenously added followers (or made follow requests, in the case of protected accounts) for a set of users (treatment group), and we compared their posting activities to those of a control group. We then estimated a dynamic discrete choice model that quantified intrinsic versus image-related utility for each treated user.

6.1. Summary of Substantive Findings and Predictions

Our key substantive findings and predictions may be summarized as follows.

- Some noncommercial users respond to the addition of new followers (or new follow requests, in the case of protected accounts) by increasing their posting activities, whereas others respond by posting less content.

[24] From Twitter's About page, available at http://twitter.com/about (last accessed April 2012).

[25] *ibid*.

- The majority of noncommercial users go through two phases, where intrinsic utility from posting is larger than image-related utility when they have fewer followers, but image-related utility becomes larger than intrinsic utility as they amass more followers.
- Most noncommercial users on Twitter appear to derive more image-related utility from their posting activities than they do intrinsic utility.
- Noncommercial user contributions to Twitter are likely to decrease as the platform matures and the network's structure becomes stable. Twitter is likely to become more of a platform where noncommercial users consume content posted by commercial users, rather than a platform where noncommercial users share content with each other.

6.2. Managerial Implications

Our findings are relevant not only theoretically but also managerially. Understanding what motivates consumers to be active on social media platforms such as Twitter is a prerequisite for marketers interested in devising efficient social media strategies and optimizing the ways they engage with consumers on these platforms. We hope that our research will provide specific guidelines to marketers interested in leveraging Twitter. Two examples are as follows.

- It is standard for firms to follow consumers on Twitter, partly in the hope that these consumers will become advocates for their brands. According to our results, this practice may have the counterintuitive effect of making consumers less active and therefore *less* likely to contribute content related to a brand. Firms and other commercial accounts may need to exert greater caution when deciding whether to follow noncommercial users.
- If noncommercial users reduce their contributions as Twitter matures, then firms in the future may benefit more from using Twitter as a media channel where they broadcast content to consumers, rather than a platform for creating or tracking word of mouth or a platform for gathering consumer insights.

6.3. Future Research

Our research also offers several areas for future research. First, future research may enrich our findings by using data that would include the structure of the users' social network and also include the text of the tweets in a more systematic manner. Second, beyond the context of the present paper, future research may explore further the use of field experiments as a way to address endogeneity issues in social networks (Manski 1993, Moffitt 2001, Hartmann et al. 2008). Given that social media platforms such as Twitter exist in the public domain, future research on social media and social interactions may adopt identification strategies similar to ours. Finally, future research may study motivations in other social media contexts. Intrinsic and image-related utility are fundamental concepts that have been shown to be relevant across many domains; therefore our results may be expected to generalize to at least some degree. However, the relative importance of these two types of utility may vary, for example, based on the type of content posted by users (e.g., short messages versus videos versus pictures) or the structure of the social network (e.g., directed versus undirected).

Acknowledgments

The authors are grateful for the comments and suggestions made on this paper by Jean-Pierre Dubé, Avi Goldfarb, Christophe Van Den Bulte, as well as seminar participants at Cornell University, Emory University, ESMT European School of Management and Technology, the Hong Kong University of Science and Technology, Tilburg University, the University of Miami, and Yale University.

Appendix A. Illustration of Opposite Predictions of Intrinsic vs. Image-Related Utility

We extend the two-period model used in §3 to an infinite horizon with a discount factor of $\beta < 1$. We denote by $V(n)$ the value function. In the case of intrinsic utility, the Bellman equation takes the following form: $V(n) = \max\{U(n)+\beta[\delta V(n+1)+(1-\delta)V(n)], \beta V(n)\}$. In the case of image-related utility, the Bellman equation takes the following form (the only difference is that the per-period utility $U(n)$ is derived irrespective of whether content is posted in that period): $V(n) = \max\{U(n)+\beta[\delta V(n+1)+(1-\delta)V(n)], U(n)+\beta V(n)\}$. We solve for the value function in closed form.

Lemma 1. *The value function is as follows*:

$$V(n) = \sum_{m=n}^{+\infty} \frac{U(m)}{1-\beta(1-\delta)} \left(\frac{\beta\delta}{1-\beta(1-\delta)}\right)^{m-n}.$$

Proof. To focus on the *benefits* obtained from posting content, we have assumed that posting content is costless such that it is optimal to post content in each period under both types of utility. (In §5, we estimate a cost of posting content instead of making this assumption.) Because the utility derived when content is posted takes the same form under intrinsic and image-related utility, the Bellman equation takes the following form under both types of utility: $V(n) = U(n)+\beta[\delta V(n+1)+(1-\delta)V(n)]$. If $V(n)$ is as specified in Lemma 1, then

$$\begin{aligned}
&U(n)+\beta[\delta V(n+1)+(1-\delta)V(n)]\\
&\quad = U(n)+\beta\delta \sum_{m=n+1}^{+\infty} \frac{U(m)}{1-\beta(1-\delta)} \left(\frac{\beta\delta}{1-\beta(1-\delta)}\right)^{m-n-1}\\
&\qquad +\beta(1-\delta) \sum_{m=n}^{+\infty} \frac{U(m)}{1-\beta(1-\delta)} \left(\frac{\beta\delta}{1-\beta(1-\delta)}\right)^{m-n}\\
&\quad = U(n)\left(1+\frac{\beta(1-\delta)}{1-\beta(1-\delta)}\right) + \left[\beta\delta\frac{1-\beta(1-\delta)}{\beta\delta} + \beta(1-\delta)\right]
\end{aligned}$$

$$\cdot \sum_{m=n+1}^{+\infty} \frac{U(m)}{1-\beta(1-\delta)}\left(\frac{\beta\delta}{1-\beta(1-\delta)}\right)^{m-n}$$

$$= \frac{U(n)}{1-\beta(1-\delta)} + \sum_{m=n+1}^{+\infty} \frac{U(m)}{1-\beta(1-\delta)}\left(\frac{\beta\delta}{1-\beta(1-\delta)}\right)^{m-n}$$

$$= \sum_{m=n}^{+\infty} \frac{U(m)}{1-\beta(1-\delta)}\left(\frac{\beta\delta}{1-\beta(1-\delta)}\right)^{m-n} = V(n). \quad \text{Q.E.D.}$$

In addition, we show that the value function itself is concave in n.

Lemma 2. *The value function is concave in n.*

Proof. Based on the Bellman equation, we have

$$V(n) = U(n) + \beta[\delta V(n+1) + (1-\delta)V(n)],$$
$$V(n+1) = U(n+1) + \beta[\delta V(n+2) + (1-\delta)V(n+1)].$$

Taking the difference between these two equalities yields

$$\beta\delta[(V(n+2)-V(n+1)) - (V(n+1)-V(n))]$$
$$= (V(n+1)-V(n))(1-\beta) - (U(n+1)-U(n)).$$

We show that $V(n)$ is concave by showing that for all n, $V(n+2) - V(n+1) < V(n+1) - V(n)$, which, based on the above-mentioned equality, is equivalent to showing that $(V(n+1)-V(n))(1-\beta) < (U(n+1)-U(n))$.

Based on Lemma 1, we have

$$V(n+1) - V(n) = \sum_{m=n+1}^{+\infty} \frac{U(m)}{1-\beta(1-\delta)}\left(\frac{\beta\delta}{1-\beta(1-\delta)}\right)^{m-n-1}$$
$$- \sum_{m=n}^{+\infty} \frac{U(m)}{1-\beta(1-\delta)}\left(\frac{\beta\delta}{1-\beta(1-\delta)}\right)^{m-n}$$
$$= \sum_{m'=n}^{+\infty} \frac{U(m'+1)}{1-\beta(1-\delta)}\left(\frac{\beta\delta}{1-\beta(1-\delta)}\right)^{m'-n}$$
$$- \sum_{m=n}^{+\infty} \frac{U(m)}{1-\beta(1-\delta)}\left(\frac{\beta\delta}{1-\beta(1-\delta)}\right)^{m-n}$$

(where we replaced $m-1$ with m' in the first expression)

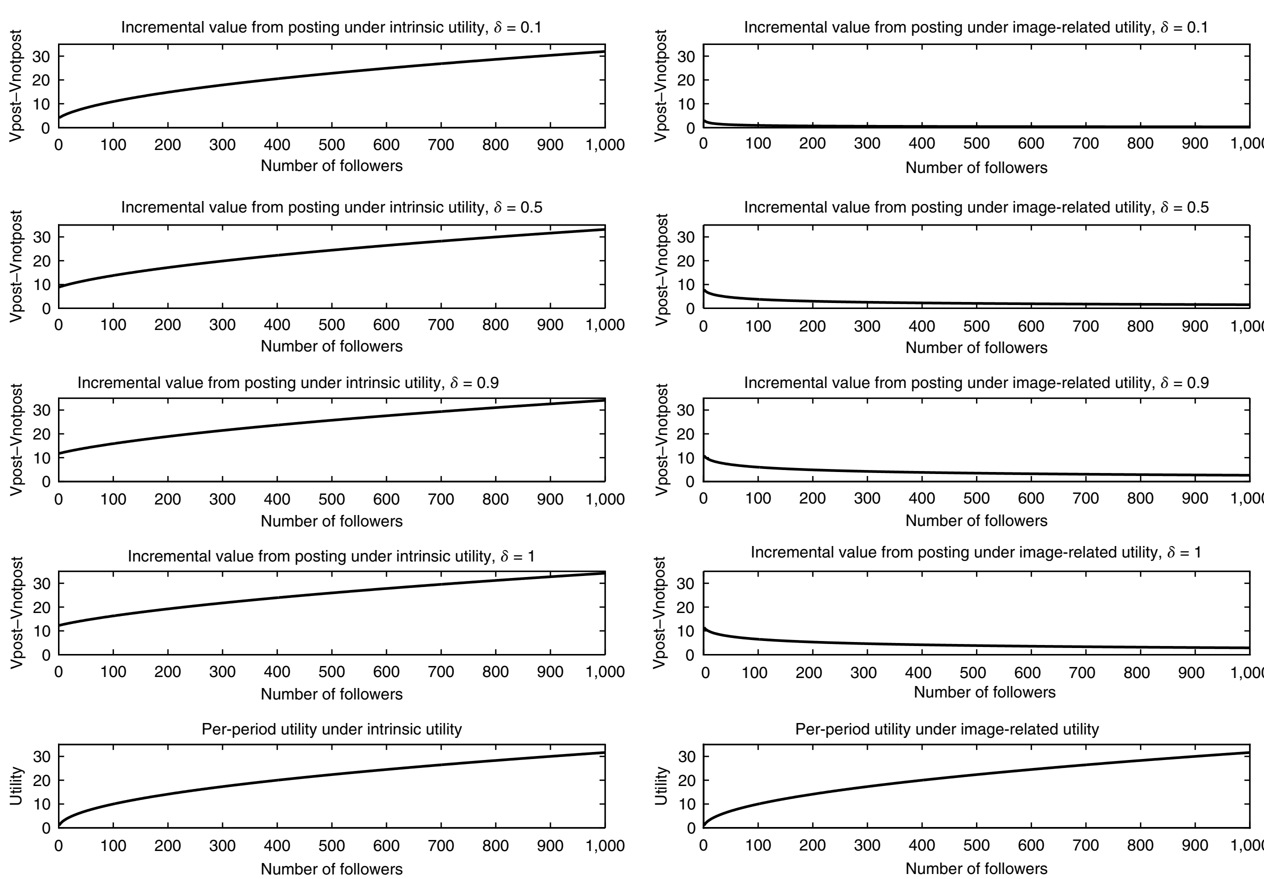
$$= \sum_{m=n}^{+\infty} \frac{U(m+1)-U(m)}{1-\beta(1-\delta)}\left(\frac{\beta\delta}{1-\beta(1-\delta)}\right)^{m-n}$$
$$< \frac{U(n+1)-U(n)}{1-\beta(1-\delta)} \sum_{m=n}^{+\infty}\left(\frac{\beta\delta}{1-\beta(1-\delta)}\right)^{m-n}$$

(because $U(n)$ is concave)

$$= \frac{U(n+1)-U(n)}{1-\beta(1-\delta)} \frac{1}{1-(\beta\delta)/(1-\beta(1-\delta))}$$
$$= \frac{U(n+1)-U(n)}{1-\beta}. \quad \text{Q.E.D.}$$

We now show the following two propositions.

Figure A.1 Incremental Value for Posting Content in a Given Period and Per-Period Utility, Under Intrinsic Utility and Image-Related Utility



Notes. We assume $U(n) = \sqrt{n}$ and set $\beta = 0.995$. V_{post} (V_{nonpost}) is the action-specific value function when posting (not posting) in a given period.

Proposition 1. *In the case of intrinsic utility, the benefit from posting content in a given period is monotonically increasing in the number of followers in that period.*

Proof. Given Lemma 1, $V(n)$ is increasing in n. If a user posts content in a given period, he or she derives an action-specific value function of $V(n)$. On the other hand, if the user decides not to post content, he or she derives no utility in that period and will derive $V(n)$ starting from the next period, giving rise to an action-specific value function of $\beta V(n)$. The benefit from posting in the current period is $V(n)(1-\beta)$, which is monotonically increasing in n because $\beta < 1$ and $V(n)$ is monotonically increasing in n. Q.E.D.

Proposition 2. *In the case of image-related utility, the benefit from posting content in a given period is monotonically decreasing in the number of followers in that period.*

Proof. Under image-related utility, the action-specific value function when posting content is $V(n) = U(n) + \beta[\delta V(n+1) + (1-\delta)V(n)]$, and the action-specific value function when content is not posted is $U(n) + \beta V(n)$. The difference is equal to $\beta\delta(V(n+1) - V(n))$, which is decreasing in n because $V(n)$ is concave (Lemma 2). Q.E.D.

Finally, we illustrate Propositions 1 and 2 graphically.[26] We assume $U(n) = \sqrt{n}$, set $\beta = 0.995$, and compute the value function for $n = 1, \ldots, 1{,}000$, for $\delta = 0.1, 0.5, 0.9$, and 1. Note that we approximate the value function by

$$\sum_{m=n}^{n+1{,}000} \frac{U(m)}{1-\beta(1-\delta)} \left(\frac{\beta\delta}{1-\beta(1-\delta)}\right)^{m-n}$$

instead of

$$\sum_{m=n}^{+\infty} \frac{U(m)}{1-\beta(1-\delta)} \left(\frac{\beta\delta}{1-\beta(1-\delta)}\right)^{m-n}.$$

Figure A.1 shows the incremental value for posting content in a given period as a function of n and δ together with $U(n)$ as a function of n.

Appendix B. Details of the Estimation Procedure

The estimation algorithm proposed by Norets (2009a) relies on an approximation of the value function. Let m index the iterations of the Gibbs sampler. The approximation of the value function at iteration m leverages the value function approximations from previous iterations. Let $\{\theta_i^{*(1)}, \ldots, \theta_i^{*(m-1)}\}_{i=1,\ldots,I}$ be the parameter draws from the first $m-1$ iterations. For each user i, the approximation at iteration m uses only the past $N(m)$ iterations, where $N(m) = [m^{\gamma 1}]$ (we set $\gamma_1 = 0.6$). Among these iterations, the approximation relies on the ones at which the draws of the parameters were the closest to the current draw of θ_i. In particular, the $\widetilde{N}(m)$ closest neighbors are considered, where $\widetilde{N}(m) = [m^{\gamma 1}]$ (we set $\gamma_2 = 0.4$). At iteration m, we consider the following approximation of V_a for user i:

$$\widetilde{V}_a^{(m)}(s \mid \theta_i) = u(s, a \mid \theta_i) + \beta \cdot \frac{1}{\widetilde{N}(m)} \sum_{l=1}^{\widetilde{N}(m)} \sum_{s'} \widetilde{V}^{(k_l)}(s' \mid \theta_i^{*(k_l)}) \cdot f(s' \mid s, a),$$

where $\{k_l\}_{l\in\{1,\ldots,\tilde{N}(m)\}}$ index the closest neighbors to θ_i among the $N(m)$ past draws, and $\widetilde{V}^{(k_l)}$ refers to value function approximations computed in previous iterations. Norets proves theoretically that these approximations converge uniformly and completely to the exact values (see Norets 2009a, Theorem 1, p. 1677). We run the Gibbs sampler for 2,000 iterations, using the first 500 as burn-in. Convergence was assessed visually using plots of the parameters.

At each iteration m of the Gibbs sampler,

1. A proposed value of θ_i, $\theta_i^{*(m)}$, is drawn for each user. Let $\theta_i^{(m-1)}$ denote the value retained at iteration $m-1$. For each i, the new proposed value is drawn such that $\theta_i^{*(m)} = \theta_i^{(m-1)} + d_i$, where $d_i \sim \mathrm{N}(0, \gamma D_\theta)$ and γ is adjusted such that the acceptance rate is around 30%. Using rejection sampling (see, e.g., Allenby et al. 1995), we constrain $\theta_i^{*(m)}$ to a compact set $\Theta = [0, 10] \times [0, 0.6] \times [0, 10] \times [0, 0.6] \times [-10, 0]^2$ (Note that we use 0.6 instead of 1 as an upper bound for $\theta_{i,2}$ and $\theta_{i,4}$ for numerical stability issues—this constraint does not appear to be binding). The new value is retained (i.e., $\theta_i^{(m)} = \theta_i^{*(m)}$) with probability:

$$\min\left\{\frac{P(\theta_i^{*(m)} \mid \theta_0, D_\theta) \cdot \tilde{L}^{(m)}(\{a_{it}\}_{t=1,\ldots,T} \mid \theta_i^{*(m)})}{P(\theta_i^{(m-1)} \mid \theta_0, D_\theta) \cdot \tilde{L}^{(m)}(\{a_{it}\}_{t=1,\ldots,T} \mid \theta_i^{(m-1)})}, 1\right\},$$

$$\text{where} \quad \tilde{L}^{(m)}(\{a_{it}\}_{t=1,\ldots,T} \mid \theta_i) = \prod_{t=1}^{T} \tilde{P}^{(m)}(a_{it} \mid s_{it}, \theta_i)$$

and where

$$\tilde{P}^{(m)}(a_{it} \mid s_{it}, \theta_i) = \frac{\exp(\widetilde{V}_{a_{it}}^{(m)}(s_{it} \mid \theta_i))}{\sum_{a' \in A} \exp(\widetilde{V}_{a'}^{(m)}(s_{it} \mid \theta_i))}.$$

Otherwise, we set $\theta_i^m = \theta_i^{(m-1)}$.

2. A new set of value function approximations are generated to be used in future iterations. These new approximations are obtained by applying the Bellman operator:

$$\widetilde{V}^{(m)}(s \mid \theta_i^{*(m)}) = \log\left(\sum_{a\in A} \exp\left(\widetilde{V}_a^{(m)}(s \mid \theta_i^{*(m)})\right)\right).$$

As recommended by Norets (2009b), we apply the Bellman operator more than once. In our implementation we apply the Bellman operator until the new values are close enough to the previous ones (maximum absolute deviation less than 1), with a minimum of 10 iterations.

3. The first-stage prior parameters θ_0 and D_θ are updated. Our second-stage prior on θ_0 is uniform on the compact set Θ, and our second-stage prior on D_θ follows an inverse Wishart distribution: $D_\theta^{-1} \sim \mathrm{W}(v_0, V_0)$, where $v_0 = k + 3$ (where k is the number of elements in θ_i) and $V_0 = 0.001I$ (where I is the identity matrix). These second-stage priors have the attractive property of being conjugate with the likelihood for the first-stage prior parameters, which allows us to draw the parameters directly from their respective conditional posterior distributions:

$$\theta_0 \sim \mathrm{TN}\left(\frac{\sum_{i=1}^{I} \theta_i}{I}, \frac{D_\theta}{I}\right),$$

$$D_\theta^{-1} \sim \mathrm{W}\left(v_0 + I, V_0 + \frac{\sum_{i=1}^{I} (\theta_i - \theta_0)(\theta_i - \theta_0)^T}{I}\right).$$

[26] We are indebted to an anonymous reviewer for suggesting this illustration.

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