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The Positive Effect of Not Following Others on Social Media

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Abstract

Marketers commonly seed information about products and brands through individuals believed to be influential on social media, which often involves enlisting micro influencers, users who have accumulated thousands as opposed to millions of followers (i.e., other users who have subscribed to see that individual's posts). Given an abundance of micro influencers to choose from, cues that help distinguish more versus less effective influencers on social media are of increasing interest to marketers. The authors identify one such cue: the number of users the prospective influencer is following. Using a combination of real-world data analysis and controlled lab experiments, they show that following fewer others, conditional on having a substantial number of followers, has a positive effect on a social media user's perceived influence. Further, the authors find greater perceived influence impacts engagement with the content shared in terms of other users exhibiting more favorable attitudes toward it (i.e., likes) and a greater propensity to spread it (i.e., retweets). They identify a theoretically important mechanism underlying the effect: following fewer others conveys greater autonomy, a signal of influence in the eyes of others.

Keywords

autonomy, following, opinion leader, micro influencer, social media

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The commercial use of social media influencers is a rapidly growing phenomenon, with marketers increasingly seeding information about their brands through select individuals on social media (Libai, Muller, and Peres 2013). Motivating the market is the longstanding belief that a small subset of consumers is extraordinarily influential, those considered opinion leaders (Brown and Hayes 2008; Rogers 1962). A common social media marketing strategy thus involves identifying an initial set of influencers and incentivizing them to share specific content, thereby initiating a viral marketing campaign in which their posts generate engagement—likes, comments, and reposts—widely believed to be indicators of the audience's future consumption behavior. The development of practical approaches to identifying who is truly influential online, however, is still in its infancy (Probst, Grosswiele, and Pfleger 2013).

One widely used social media seeding strategy is selecting individuals who can reach a large number of users. This often involves enlisting celebrities with millions of followers. For example, singer Selena Gomez, with 167 million followers on Instagram and 59.9 million followers on Twitter (as of February 2020), has taken part in social media campaigns for Coach, Coca-Cola, Verizon, and Pantene (Friedman 2017).[1] With her massive reach, Gomez is a highly sought after—albeit extremely expensive—social media influencer, reportedly reaping hundreds of thousands of dollars for a single sponsored post (Heine 2016). Given this kind of reach comes at such a high cost, marketers have begun looking for more efficient ways to spread their message on social media networks.

An alternative strategy has been for marketers to direct budgets toward "micro" influencers, social media users with anywhere between 1,000 and 100,000 followers who charge hundreds rather than hundreds of thousands of dollars per post

[1] Social media platforms such as Instagram, Twitter, Snapchat, and Musical.ly allow asymmetric following, which lets users follow an individual or account without that individual or account needing to follow them back. Other platforms, including Facebook and LinkedIn, require symmetric following, in which connected users must follow each other.

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(Barker 2017). Micro influencers share content daily about everything from bass fishing to bass guitars and are considered an effective way to reach a specific target market. Consider, for example, competitive bass fisherman Randy Howell (@theRandyHowell) who, as of February 2020, had 33,606 followers on Twitter. With an audience presumably composed of fishing aficionados, at that time he promoted brands such as Lowrance 3D fish finders, Power-Pole boats, and Pelican marine coolers. Another competitive bass fisherman, Mark Zona (@MarkZonaFishing), had 36,276 followers at that time and promoted Strike King fishing lures, Daiwal reels, and Bass Mafia bait boxes. Zona had approximately the same "reach" as Howell. What distinguishes the two?

This question is of growing concern to marketers wrestling with the question of who among an ever-expanding assortment of candidate social media influencers to sponsor (Momtaz, Aghaie, and Alizadeh 2011; Nejad, Sherrell, and Babakus 2014). Pragmatically speaking, a survey of marketing practitioners finds that selecting the "right" influencer is the biggest challenge in working with influencers online (Simpson 2016). Returning to the aforementioned fishermen, one obvious distinction stands out; in February 2020, Howell was following 11,513 users on Twitter, while Zona was following a mere 155. This comparison introduces the central question addressed in this research: Is there value in considering the number of other social media platform users someone is following (henceforth referred to simply as following)? In other words, does following tell us anything about how influential a social media user might be?

The premise of this work is that a substantial number of social media users will attend to these numbers and that this can have meaningful downstream consequences. We show that the number of people a user is following on social media affects how other users respond to the content the user shares. More specifically, we observe that social media users are more engaged (in terms of likes and retweets) with content shared by those who follow fewer others. This phenomenon is due, at least in part, to the fact that people interpret following fewer others as a signal that the user is less susceptible to outside influence and thus more autonomous. Given that one's own influence is often negatively correlated with one's susceptibility to the influence of others (Aral and Walker 2012; Iyengar, Van den Bulte, and Valente 2011), it stands to reason that someone perceived as more autonomous would also be perceived as more influential. In turn, being perceived as influential matters for engagement because, as Rogers and Cartano (1962, p. 439) note, people's perception of someone's influence is in large part "actually what affects behavior."

By documenting how following serves as a cue of influence, this research contributes to the literature in four important ways. First, theoretically, we answer the call for further research on the causal mechanisms of social influence online (Aral 2011) as well as add to the literature examining characteristics of influentials (Kopller 1984; Rogers and Shoemaker 1971). We do so by identifying a previously unstudied characteristic driving perceptions and behavioral responses to influencers: perceptions of autonomy. We leverage the idea of a "two-step flow of communication" (Katz and Lazarsfeld 1955) that implies communication flows from a source to opinion leaders, who then pass it on to others in the social system. In an age with unlimited sources of information online, we find that having too many sources in step one is associated with less perceived influence—and thus less engagement—in step two. Importantly, in doing so, we bridge two related yet distinct approaches used to study influence: an individual-based approach of identifying personal characteristics of influentials (i.e., autonomy) with a network-based approach of identifying sociometric measures of influence (following, or out-degree centrality).

Second, we contribute to an emerging literature on informative cues and inference making in digital environments (Berger and Barasch 2018; Grewal and Stephen 2019; Li, Chan, and Kim 2018; Ranganathan 2012). Digital environments often present significant ambiguity, which drives the use of contextual cues in online decision making and opinion formation (Ranganathan 2012). As social media is absorbing an increasing amount of social interaction, it is important to understand how what individuals do online signals aspects of the self to others. We find that following fewer others on a social media platform is an effective cue of an individual's autonomy and, thus, influence.

A third contribution of this research is to add to a nascent body of work investigating the positive signaling effects associated with being viewed as autonomous, or acting according to one's own inclinations (Bellezza, Gino, and Keinan 2014; Warren and Campbell 2014). Lacking direct access to the internal states of others, observation is the primary way in which people make inferences about others' autonomy (Ryan and Connell 1989). Following, an easily observable characteristic of social media users, signals autonomy and drives important downstream consequences.[2]

Finally, this work documents the value of incorporating following as a useful criterion for screening influencers, and micro influencers in particular. Given the latter are defined in part by their limited reach (i.e., number of followers), identifying additional indicators of influence is especially important and makes a substantive contribution to the field.[3] A review of 40 recognized influencer identification platforms revealed that only three included following as a criterion they publicize to prospective clients to compare micro influencers (see details in the Web Appendix). If following is useful in assessing social media influencers (henceforth referred to as "influencers"), it does not appear to be widely known or endorsed by practitioners.

[2] Table A1 in the Web Appendix provides a brief summary of related research on identifying influentials, informative cues in inference making in digital environments, and the positive signal effects of autonomy.

[3] Table A2 in the Web Appendix provides a brief summary of related research on social media influencers drawn from marketing's top journals.

Relevant Literature

Influentials

Influentials, or opinion leaders, are people who exert an extraordinary amount of influence on the attitudes and behaviors of others (Katz and Lazarsfeld 1955; Merton 1968). Marketing researchers have directed a great deal of attention toward studying these individuals partly because they believe that what influencers have to say affects what others purchase (Rogers and Cartano 1962) and ultimately a product's success or failure (Rogers 1962). While the literature on peer-to-peer influence and opinion leadership is vast and dates back more than a half century, two broad streams of research are of particular interest here: studies investigating (1) characteristics of influentials and (2) how to identify who is in fact influential.

First, an important characteristic of influentials is what type of information they transmit and in what domain their influence is exerted. Some literature suggests that opinion leaders focus on specific topics, thereby being "monomorphic" (Engel, Kollat, and Blackwell 1968; Jacoby 1974). However, other literature shows that opinion leaders' influence can extend to a variety of (sometimes unrelated) topics, which is characteristic of being "polymorphic" (King and Summers 1970; Marcus and Bauer 1964; Myers and Roberston 1972). By their nature, micro influencers typically start out being monomorphic and later evolve into being polymorphic as their popularity grows (e.g., sharing makeup advice initially and then branching out to fashion advice as well).

In addition to identifying the boundaries of their influence, extensive research has examined the personal characteristics that make someone an opinion leader (see Keller and Berry 2003 for a review). Considering demographic characteristics, according to Weimann et al. (2007), influentials can be found at every social level, across the sexes, and in all professions and age groups. This heterogeneity is consistent with what one might expect for micro influencers online. Research has also shown expertise is often an antecedent of opinion leadership (Grewal, Mehta, and Kardes 2000) and that innovative consumers are more likely to be opinion leaders than consumers with conservative characteristics (Ruvio and Shoham 2007). Importantly, we show that following fewer others affects perceptions of autonomy, but neither perceived expertise nor innovativeness.

A second broad stream of research has focused less on understanding characteristics of an opinion leader and more on how to identify influential consumers. The literature documents a number of approaches (see Weimann et al. 2007). One popular method historically has been self-designation, which has contributed to the development of various opinion leadership scales (Childers 1986; Flynn, Goldsmith, and Eastman 1996; King and Summers 1970; Rogers and Cartano 1962). More recently, as consumers have become progressively more interconnected on social media, a different approach has increased in prominence, one that focuses on analyzing the structure of a network.

Social Networks and Influence

One way to identify influentials within a network is to apply sociometric techniques to capture relationships between members of the social system. Conventional wisdom suggests that highly connected nodes within a network should disproportionally contribute to the spread of information and thus promote product adoption. Consequently, researchers have proposed a variety of measures of network centrality (see Muller and Peres 2019 for a review), and studies show that influence is often more strongly associated with network centrality than commonly used self-reports of opinion leadership (Iyengar, Van den Bulte, and Valente 2011).

Work comparing seeding strategies based on centrality supports seeding well-connected people. For example, using controlled field experiments, Hinz et al. (2011) compare different seeding strategies and find that seeding "hubs," individuals connected with many others (i.e., high degree centrality), is the most successful strategy; however, the authors note this is because of hubs' extensive reach rather than because these individuals are more persuasive. What this suggests, and the opening example involving Selena Gomez illustrates, is that relying on expansive reach (i.e., number of followers) alone can be inefficient and considering which well-connected people are more or less influential is important. This led us to investigate an additional, alternative cue for influence within a social network—following. In doing so, we distinguish between two network characteristics, the number of inbound links (followers, or in-degree centrality) and outbound links (following, or out-degree centrality), as separate indicators of influence, each informative in its own right.

Following Others as a Cue of Autonomy and Influence

In the absence of complete information, consumers often rely on signals, or cues, to make inferences that allow them to form opinions and make decisions (Huber and McCann 1982). We propose the number of other users someone is following is one such cue, one that signals autonomy. Autonomy refers to the extent to which people act in alignment with their values, unaffected by others' influence (Brehm 1993; Deci and Ryan 1985, 2000; Ng 1980; Schwartz 1992). In the marketing literature, autonomy has been defined as "a willingness to pursue one's own course irrespective of the norms, beliefs, and expectations of others" (Warren and Campbell 2014, p. 544).

Past research supports the idea that individuals care a great deal about being perceived as autonomous, to the point that "people are more concerned with managing the impression of autonomy than they are with actually maintaining autonomy" (Baer et al. 1980, p. 416). Moreover, it is particularly important to influentials that they are viewed as formulating their own opinions unadulterated by the influence of others (Dworkin 1988). This is consistent with findings that influence is often negatively correlated with one's susceptibility to the influence of others (Aral and Walker 2012; Iyengar, Van den Bulte, and Valente 2011) and may help explain why, in the United States, the idea of being autonomous is aspirational (Markus and Schwartz 2010) while being easily influenced by others is not (Jetten, Hornsey, and Adarves-Yorno 2006). In this work, we propose that following others on social media affects the extent to which someone is perceived to be autonomous, which in turn affects perceptions of being influential.

The Current Research

To summarize our theorizing, we propose that following can be an important cue that helps distinguish more versus less effective influencers on a social media platform, at least partly because individuals view those following fewer others as more autonomous. Given the naturally occurring negative correlation between one's own influence and one's susceptibility to the influence of others, we propose that other users infer more autonomous individuals are also more influential. Importantly, we propose this inferential process has important implications for marketers in that following fewer others can have significant downstream consequences in terms of social media engagement. By viewing certain users as more influential at the onset, consistent with theories of social influence (Salganik, Dodds, and Watts 2006), we propose other users are more likely to engage with content they post in terms of both likes and retweets (as well as click-throughs when a link is available). A schematic of our conceptual model along with how each study supports the model is illustrated in Figure 1. Table 1 features an overview of our five laboratory studies and main findings.

We begin our empirical process by analyzing real-world social media data drawn from Twitter. In Study 1, we observe a negative correlation between the number of likes and retweets received by a particular Twitter post and the number of users the source of the post is following at the time, ceteris paribus. Next, we present four lab studies aimed at clarifying and explaining the role of following in influencing how people respond to social media users. Study 2 demonstrates that following fewer others increases perceptions of an individual's influence, conditional on the individual having a substantial number of followers. In Study 3, we show that autonomy mediates the relationship between following and perceptions of influence. We also show downstream consequences in terms of respondents' engagement, replicating the effects observed in Study 1. In Study 4, we again replicate the effect observed in Study 1 and provide additional evidence of process through moderation, while in Study 5 we test the effect of following on a more consequential behavioral indicator of engagement, namely, click-through.

Study 1

In Study 1, we use data obtained from Twitter to test the effect of following on how others respond to a user's post, ceteris paribus. We predict that the fewer users an individual is following, controlling for other factors, the greater the engagement his/her tweets will get in terms of both likes and retweets. Our focal independent variable is Following while our dependent variables include two different measures of engagement: how positive followers are toward the content (Likes) and how many times the content is shared (Retweets).

Data

The data utilized in the analysis include all tweets written in English on September 16, 2016, in the Los Angeles metropolitan area.[4] We collected all of the data directly from twitter.com over a three-day period (September 20–22, 2016). Twitter allows anyone to collect data about real-time tweets and past tweets (up to a week old) as well as user profiles through its public API. The data include 1,581,522 tweets from 784,170 distinct users as well as a wide-ranging set of features of the tweet and the user provided by the API, described next.

Tweet features. For every tweet in our data set, we know the number of Likes it received and the number of Retweets. Moreover, we have additional information about its content, including the number of links to websites (URLs), videos, photos, financial symbols (e.g., "$," "TSLA"), user mentions, and hashtags. Further, we collected the timestamp of publication and whether the tweet is an original posting, a retweet, or a reply to someone else's tweet. Of the 1,581,522 tweets we collected, 447,793 are original tweets, 969,488 are retweets, and 164,241 are replies. Given our interest is in how others respond to original content, we focus on original tweets and remove replies and retweets from the data.[5] The 447,793 original tweets were produced by 146,444 users.

User profile features. For each tweet, we collected information regarding the user who posted the tweet, including our focal independent variable of interest, the number of fellow Twitter users s/he follows (Following). We also collected several control variables, including the user's ID and screen name, a timestamp for the creation of the user's account (measuring the time the user had been on Twitter), the number of users who follow him or her (Followers), the total number of tweets ever written, the total number of likes ever given, and whether the account is "verified" (a verification badge assures other users an account is authentic). We also collected the length of the user's profile bio, whether it contained a URL, and whether the user has chosen to personalize his or her profile and image.

Given that our focus is on micro influencers, we restricted the data set to users with at most 100,000 followers, resulting in the exclusion of 8,742 tweets by 1,325 users.[6] The final data set

[4] In the Web Appendix, we show that the results replicate using alternative data sets, one comprising tweets from all over the United States and one comprising tweets from the Tokyo (Japan) metropolitan area.

[5] In the robustness checks section, we show that our results hold even using the full sample of tweets (see column 5 of Tables 4 and 5).

[6] In the robustness checks section, we show that our results hold using alternative thresholds to identify micro-influencers, as well as analyzing the full sample (see columns 1–4 of Tables 4 and 5).

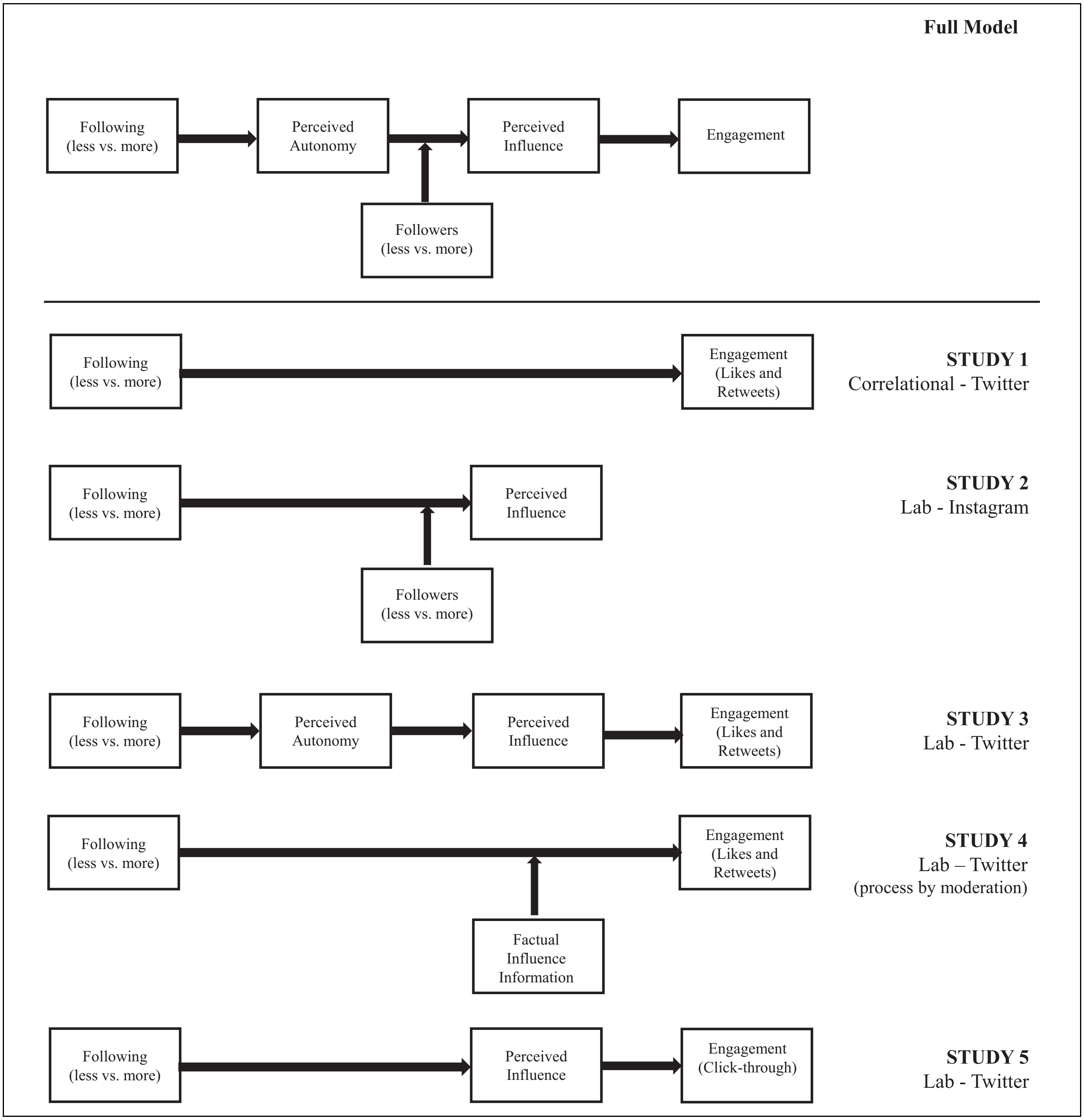

Figure 1. Conceptual model with associated studies and context.

includes 439,051 original tweets by 145,119 Twitter users with fewer than 100,000 followers.

Content features. We computed linguistic features of the text of each tweet using Linguistic Inquiry and Word Count (LIWC; Pennebaker et al. 2015), a program used for automated text analysis. This program categorizes words along several dimensions, including emotions, thinking styles, social concerns, and parts of speech. Among the standard variables in LIWC's default dictionary are social and psychological states such as positive and negative emotions, anxiety, anger, and sadness. The standard output includes the percentage of words in the text pertaining to that variable. Past literature has shown that how individuals react to content shared online by others is often a function of identifiable linguistic features of the content (Berger and Milkman 2012). In particular, this literature has

Table 1. Summary of Experimental Results.

	Study 2 (N = 276, 49.6% female, M_{age} = 20.5 years)					
	High Followers			Low Followers		
	High Following (N = 70)	Low Following (N = 65)		High Following (N = 70)	Low Following (N = 71)	
Influence	4.80 [4.40, 5.20]	6.09 [5.67, 6.51]	$p < .001$	2.16 [1.71, 2.61]	2.07 [1.69, 2.45]	$p = .765$
Opinion Leadership	4.71 [4.43, 5.00]	5.46 [5.17, 5.74]	$p = .003$	3.05 [2.63, 3.46]	3.08 [2.71, 3.45]	$p = .894$
Main Findings: Following fewer others increases perceptions of an individual's influence, conditional on the individual having a substantial number of followers.						
	Study 3 (N = 315, 50.8% female, M_{age} = 20.4 years)					
	High Following (N = 159)	Low Following (N = 156)				
Autonomy	5.48 [5.23, 5.73]	5.90 [5.68, 5.13]	$p = .015$			
Influence	4.13 [3.85, 4.42]	5.33 [5.04, 5.61]	$p < .001$			
Likes	2.44 [2.16, 2.72]	3.14 [2.81, 3.47]	$p = .001$			
Retweets	1.89 [1.67, 2.11]	2.40 [2.11, 2.69]	$p = .006$			
Main Findings: Perceived autonomy mediates the relationship between following and perceptions of influence; perceptions of influence, in turn, affect engagement intentions.						
	Study 4 (N = 703, 47.8% female, M_{age} = 20.5 years)					
	Control			Influence Info		
	High Following (N = 176)	Low Following (N = 176)		High Following (N = 175)	Low Following (N = 176)	
Likes	3.31 [3.02, 3.61]	4.30 [3.95, 4.65]	$p < .001$	5.21 [4.85, 5.58]	5.32 [4.95, 5.70]	$p = .651$
Retweets	2.70 [2.44, 2.97]	3.61 [3.28, 3.95]	$p < .001$	4.40 [4.02, 4.78]	4.26 [3.86, 4.65]	$p = .564$
Main Findings: Following drives engagement intentions only when it serves as a cue of influence.						
	Study 5 (N = 256, 47.7% female, M_{age} = 20.0 years)					
	High Following (N = 128)	Low Following (N = 128)				
Influence	4.53 [4.22, 4.84]	5.77 [5.46, 6.07]	$p < .001$			
Click	40.6%	53.9%	$p = .033$			
Main Findings: Following drives actual engagement by affecting perceptions of influence.						

identified Positivity, Anxiety, Anger, Sadness, and Arousal as relevant text characteristics that result in content being shared more often (i.e., virality).[7] Given Retweets is one of our dependent variables, we compute these metrics for each tweet to include as covariates. We use the standard LIWC dictionary for the first four variables and the dictionary and word values provided by Warriner, Kuperman, and Brysbaert (2013) to compute Arousal scores.[8]

[7] The Positivity index is calculated as the difference between the scores (percentages) for positive and negative emotion words and is computed on a scale from 1 to 100.

[8] Unlike with LIWC, the Arousal metric is not a percentage. Every word in the dictionary is associated with an arousal value ranging from 1 to 10, and a tweet's arousal is calculated as the average arousal value for all of the words in that tweet.

Descriptive Statistics

The average number of tweets per user in our data set is 3 (SD = 10.2). The average number of Followers per tweet is 3,224 (SD = 9,604), and the average number of other users someone is Following per tweet is 1,362 (SD = 4,643). The average number of Likes per tweet is 2.80 (SD = 36.8), and the average number of Retweets is 1.1 (SD = 43.8). The relative size of the standard deviations suggests the distributions of these four variables are extremely skewed.

Looking at the content of the tweets (see summary statistics in Table 2), we observe that hashtags and URLs are included more often than videos and photos and that financial symbols are rarely used. Moreover, the LIWC analysis reveals the emotional content of our tweets is, on average, relatively neutral. Finally, the accounts in our data set are approximately four years old, on average, and only 2% of

Table 2. Summary Statistics.

Variable	Mean	SD
User Following	1,362.30	4,643.62
User Followers	3,224.21	9,604.13
Tweet Likes	2.80	36.83
Tweet Retweets	1.10	42.79
Tweet Controls		
User Mentions	.21	.62
Hashtags	.55	1.25
URLs	.54	.52
Photos	.15	.35
Videos	.01	.08
Financial Symbols	.00	.13
Length	15.22	6.70
Tone (Positivity)	45.37	37.22
Arousal	1.24	.69
Anger	.98	4.17
Anxiety	.23	1.89
Sadness	.39	2.49
Scrape Timestamp − Tweet Timestamp (mins)	7,658.48	899.67
User Controls		
User Age (months)	51.08	30.23
User Tweets	36,241.92	104,226.96
Total Likes	5,793.32	15,563.68
Is Verified	.02	.15
Bio Length	75.73	53.62
Bio Has URL	.53	.50
Default User Profile	.33	.47
Default User Image	.01	.08

Notes: Statistics computed at the tweet level.

tweets come from verified accounts. We present the correlation matrix between all of the variables in Table A3 of the Web Appendix.

The Effect of Following on Likes/Retweets

To estimate the effect of Following on Likes as well as Retweets, we use negative binomial regression for two reasons. First, the dependent variables are counts (number of Likes, Retweets). Second, both outcome variables are overdispersed (i.e., the variance for each is much larger than the mean). The base model takes the following form:

$$Y_{ijt} = \beta_1 \log \text{Following}_{jt} + \beta_2 \log \text{Followers}_{jt} + X_{ijt}^{'}\gamma + \epsilon_{ijt}, \quad (1)$$

in which the dependent variable is the number of either Likes or Retweets received by tweet i written by user j at time t. The focal independent variable is log Following_{jt}, the (log) number of others that user j is following at time t. In addition to Following, in the model, we include log Followers_{jt}, the (log) number of users that follow user j. Thus, the coefficient of interest, β_1, measures the effect of Following on Likes holding constant Followers. Further, we include a number of additional covariates, X_{jt}, in our regression, as described in the following section.

Tweet Controls

The first set of control variables included relates to features of the tweet, namely the number of user mentions, URLs, images, videos, financial symbols, and hashtags present in the tweet.[9] We also include the tweet length (word count), and measures of Positivity, Anxiety, Anger, Sadness, and Arousal derived from the LIWC analysis. Finally, recall the tweets in our data set were all posted on September 16, 2016, but our data collection spanned three days (September 20–22, 2016). The difference between posting time and collection time can affect Following and, importantly, the number of Likes/Retweets a tweet receives. Thus, we include the (log) time difference (in minutes) between the time the tweet was posted and when we collected the data (i.e., difference between the two timestamps) in our regression.

User Profile Controls

We also include a set of controls related to characteristics of the Twitter user. One important factor is the user's experience within the social network, because a more experienced user might be able to write tweets that receive more Likes and Retweets. While experience is unobserved and generally difficult to measure, we utilize three separate measures as proxies. First, we include (log) User Age, which corresponds to the number of months between the tweet's publication and the date of the creation of the user's account. Second, we include the (log) total number of tweets written by the user prior to the focal tweet (User Tweets). Third, we include the total number of Likes the user has given (User Total Likes).

Another user control variable we incorporate in the model is an indicator of whether the user has a verified account (User is Verified). Verified Twitter accounts have a blue check mark next to the username, making verified users easily recognizable to other users. Because these accounts are associated with public or popular figures (e.g., businesses, celebrities), verified users may be more likely to receive Likes and/or Retweets. Finally, we control for the length of the user bio, whether the user bio contains URLs, and whether the user has kept the default profile and default profile image versus having customized these elements.

Results

We estimate Equation 1 with standard errors clustered at the user level to account for potential correlation across tweets written by the same user. We report the results for Likes in Table 3 and Retweets in Table 4. In column 1, we report the coefficients obtained with the simplest model, which controls

[9] We do not log these variables because they are relatively small and not very skewed, but results hold even if logged.

Table 3. The Effect of Following on Likes.

	(1)	(2)	(3)	(4)
log Following	−.237*** (.028)	−.238*** (.020)	−.240*** (.019)	−.066 (.070)
log Followers	.634*** (.015)	.784*** (.021)	.777*** (.018)	.916*** (.069)
log Followers × log Following				−.023* (.010)
Tweet User Mentions		.148*** (.014)	.117*** (.014)	.115*** (.014)
Tweet Hashtags		−.082*** (.021)	−.094*** (.018)	−.093*** (.018)
Tweet URLs		−.693*** (.042)	−.794*** (.033)	−.800*** (.032)
Tweet Photos		.662*** (.076)	.604*** (.073)	.607*** (.073)
Tweet Videos		1.557*** (.220)	1.532*** (.233)	1.527*** (.233)
Tweet Financial Symbols		−.256** (.091)	−.289*** (.087)	−.284*** (.083)
lag Scrape Timestamp − Tweet Timestamp (mins)		−.062 (.112)	.001 (.097)	−.003 (.097)
log User Age (months)		−.206 (.126)	−.180 (.093)	−.189* (.096)
log User Tweets		−.304*** (.050)	−.317*** (.038)	−.321*** (.036)
log User Total Likes		.157*** (.030)	.174*** (.023)	.170*** (.024)
User Is Verified		.784*** (.076)	.789*** (.075)	.820*** (.074)
log User Bio Length		.017 (.029)	−.014 (.021)	−.016 (.020)
User Bio Has URL		−.353*** (.089)	−.343*** (.071)	−.335*** (.067)
Default User Profile		.149** (.047)	.154*** (.042)	.149*** (.040)
Default User Image		−1.125*** (.237)	−1.214*** (.223)	−1.148*** (.216)
log Tweet Length			.542*** (.072)	.541*** (.071)
Tweet Positivity			.014 (.021)	.015 (.020)
Tweet Arousal			−.005 (.011)	−.005 (.011)
Tweet Anger			.063 (.038)	.060 (.036)
Tweet Anxiety			−.008 (.005)	−.007 (.004)
Tweet Sadness			.076 (.041)	.073 (.039)
N	439051	439051	439051	439051
Pseudo R^2	.066	.12	.13	.13

Notes: The dependent variable is the number of likes of tweet i of user j at time t. Cluster-robust standard errors at the individual user level are shown in parentheses.
* $p < .05$, ** $p < .01$, *** $p < .001$.

for the number of Followers exclusively. As predicted, β_1, the coefficient of (log) Following for Likes is negative and statistically significant ($-.24$, $p < .001$). This estimate suggests a 1% increase in the number of users the person is Following decreases the number of Likes a tweet receives by approximately .24%. For Retweets, the coefficient of (log) Following is also negative and statistically significant ($-.25$, $p < .001$).

These results are in line with our predictions. Not surprisingly, we also find that β_2, the coefficient of log Followers, is positive and statistically significant (.63, $p < .001$ for Likes; .73, $p < .001$ for Retweets). This suggests that the number of Followers a user has positively affects the number of likes and retweets a tweet receives. Someone with more Followers is expected to have more people reading their tweets and consequently liking/retweeting their posts.

In columns 2 and 3, we report the results of the model incorporating the control variables described previously. The estimates for β_1 remain negative, statistically significant, and similar in magnitude to those presented in column 1, suggesting the results are robust to the inclusion of several characteristics of the tweets and the users who posted them.

These results are consistent with the prediction that following fewer (vs. more) others on a social media platform affects how others respond to content shared. All else being equal, tweets from Twitter users following fewer others are more prone to be liked and retweeted.

The Moderating Effect of Number of Followers

It stands to reason that for following to matter, the user must first have a substantial number of followers, implying a significant number of people want to hear what that person has to say. The assumption is that they accumulated many of these followers due to tweets that included interesting and valuable content, and Followers itself serves as an important cue for influence. While identifying the exact magnitude of a "substantial number of followers" is beyond the scope of this research, we can use our data set to test whether the number of Followers matters. An intuitive way to do so is to add the interaction $\log \text{Following} \times \log \text{Followers}$ to our main model. We present the results of this specification in column 4 of Tables 3 and 4. The interaction coefficient is negative for both dependent variables of interest and statistically significant when the dependent variable is Likes, suggesting a moderating effect of number of Followers (at least in the case of Likes). We acknowledge, however, several difficulties in interpreting the interaction between two continuous variables (Jaccard, Wan, and Turrisi 1990).

Table 4. The Effect of Following on Retweets.

	(1)	(2)	(3)	(4)
log Following	−.250*** (.042)	−.214*** (.030)	−.217*** (.029)	−.178* (.077)
log Followers	.730*** (.029)	.891*** (.034)	.880*** (.031)	.911*** (.080)
log Followers × log Following				−.005 (.010)
Tweet User Mentions		.216*** (.022)	.196*** (.022)	.195*** (.022)
Tweet Hashtags		−.048 (.030)	−.052 (.029)	−.052 (.028)
Tweet URLs		−.450*** (.064)	−.531*** (.054)	−.532*** (.053)
Tweet Photos		.752*** (.137)	.703*** (.142)	.704*** (.142)
Tweet Videos		1.920*** (.235)	1.912*** (.252)	1.909*** (.252)
Tweet Financial Symbols		−.295 (.171)	−.284 (.172)	−.282 (.171)
lag Scrape Timestamp − Tweet Timestamp (mins)		.030 (.221)	.096 (.200)	.094 (.200)
log User Age (months)		−.371** (.119)	−.333*** (.092)	−.335*** (.096)
log User Tweets		−.163*** (.044)	−.177*** (.037)	−.177*** (.036)
log User Total Likes		.081* (.033)	.097*** (.029)	.096** (.030)
User Is Verified		.483*** (.100)	.473*** (.099)	.480*** (.099)
log User Bio Length		−.012 (.031)	−.045* (.023)	−.046* (.022)
User Bio Has URL		−.523*** (.105)	−.500*** (.093)	−.498*** (.092)
Default User Profile		.218** (.074)	.219** (.067)	.218*** (.066)
Default User Image		−1.054*** (.289)	−1.109*** (.285)	−1.093*** (.281)
log Tweet Length			.435*** (.080)	.435*** (.080)
Tweet Positivity			.026 (.038)	.026 (.038)
Tweet Arousal			.024 (.017)	.024 (.017)
Tweet Anger			.082* (.035)	.082* (.034)
Tweet Anxiety			.003 (.007)	.003 (.007)
Tweet Sadness			.078* (.035)	.077* (.034)
N	439,051	439,051	439,051	439,051
Pseudo R^2	.072	.10	.11	.11

Notes: The dependent variable is the number of retweets of tweet i of user j at time t. Cluster-robust standard errors at the individual user level are shown in parentheses.
Significance levels: * $p < .05$, ** $p < .01$, *** $p < .001$.

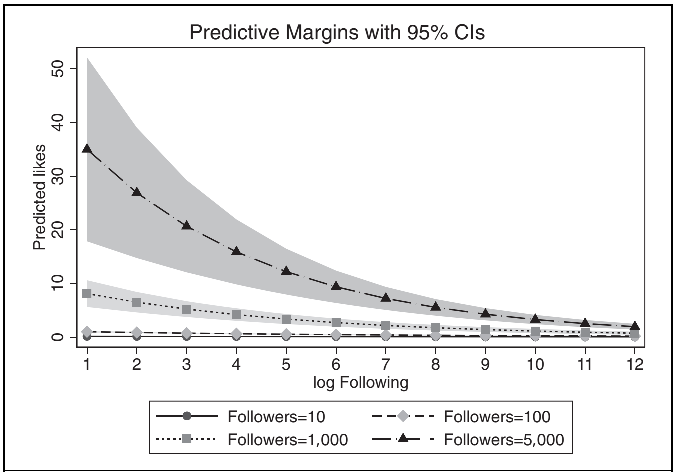

Figure 2. The influence of Followers on Following (Likes).

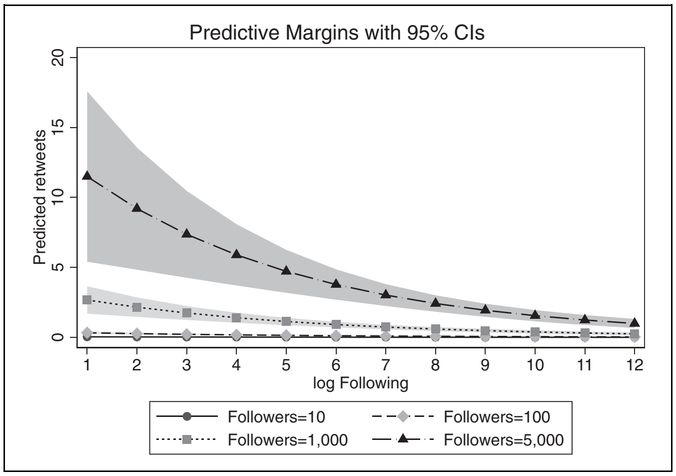

Figure 3. The influence of Followers on Following (Retweets).

An alternative way to analyze the interaction that is easier to interpret is to estimate the model and then compute simple slopes (i.e., the slopes of the independent variable Following on the dependent variables Likes/Retweets when the moderator variable Followers is held constant at different values). We provide a series of plots of these slopes in Figures 2 and 3. In line with our expectations, we observe that the negative effect of Following on Likes and Retweets becomes easily discernible at roughly 1,000–5,000 Followers; it does not take tens of thousands, or hundreds of thousands, of Followers before Following fewer others appears to matter.

Robustness Checks

In this section, we discuss several tests of the robustness of our results, including using different subsamples of data, a

Table 5. Robustness Checks: Alternative Data Sample (DV = Likes).

	(1) Followers ≤ 10 k	(2) Followers ≤ 50k	(3) Followers ≤ 150k	(4) Followers ≤ 200k	(5) All Users and Tweets
log Following	−.233*** (.023)	−.239*** (.020)	−.229*** (.020)	−.230*** (.019)	−.216*** (.016)
log Followers	.760*** (.032)	.770*** (.021)	.772*** (.018)	.768*** (.018)	.723*** (.015)
Controls	Yes	Yes	Yes	Yes	Yes
N	406006	433414	441735	443629	1581522
Pseudo R2	.098	.12	.14	.14	.32

Note: The dependent variable is the number of likes of tweet i of user j at time t. Cluster-robust standard errors at the individual user level are shown in parentheses. In column 1, we report the results for a sample of original tweets written by users with 10,000 followers or fewer; in column 2, we report the results for a sample of original tweets written by users with 50,000 followers or fewer; in column 3, we report the results for a sample of original tweets written by users with 150,000 followers or fewer; in column 4, we report the results for a sample of original tweets written by users with 200,000 followers or fewer; in column 5, we use the full sample, that is, all users and tweets.
$^{*} p < .05$, $^{**} p < .01$, $^{***} p < .001$.

Table 6. Robustness Checks: Alternative Data Sample (DV = Retweets).

	(1) Followers ≤ 10 k	(2) Followers ≤ 50k	(3) Followers ≤ 150k	(4) Followers ≤ 200k	(5) All Users and Tweets
log Following	−.224*** (.036)	−.215*** (.030)	−.208*** (.029)	−.205*** (.029)	−.170*** (.017)
log Followers	.894*** (.046)	.870*** (.034)	.872*** (.031)	.866*** (.031)	.576*** (.021)
Controls	Yes	Yes	Yes	Yes	Yes
N	406006	433414	441735	443629	1581522
Pseudo R2	.075	.093	.11	.12	.083

Notes: The dependent variable is the number of retweets of tweet i of user j at time t. Cluster-robust standard errors at the individual user level are shown in parentheses. In column 1, we report the results for a sample of original tweets written by users with 10,000 followers or fewer; in column 2, we report the results for a sample of original tweets written by users with 50,000 followers or fewer; in column 3, we report the results for a sample of original tweets written by users with 150,000 followers or fewer; in column 4, we report the results for a sample of original tweets written by users with 200,000 followers or fewer; in column 5, we use the full sample, that is, all users and tweets.
$^{*} p < .05$, $^{**} p < .01$, $^{***} p < .001$.

different modeling approach, and data sets collected from alternative geographical areas. First, recall our original analysis included users with 100,000 Followers or fewer and focused only on original tweets. In columns 1–4 of Table 5 (Likes) and Table 6 (Retweets), we show results are robust to different thresholds of Followers (10,000, 50,000, 150,000, and 200,000). In column 5 of Table 5 (Likes) and Table 6 (Retweets), we show they are robust to the inclusion of all users and all tweets (original, retweets, and replies).

Second, we test whether our results are robust to a different modeling approach. Our main analysis uses a negative binomial regression, and we replicate the results using ordinary least squares regression (see Tables A4 and A5 in the Web Appendix). In addition, because our dependent variables are correlated, we replicate the results using a bivariate negative binomial regression model (see Table A6 in the Appendix).

Finally, we replicate the results using alternative data sets scraped from different geographical areas and different points in time. These include a sample of tweets from all over the United States written on February 18, 2019, and a sample of tweets from the Tokyo (Japan) metropolitan area written between March 9 and March 11, 2019 (see Tables A7–A10 in the Web Appendix).

Discussion

Taken together, the results presented in Study 1 provide compelling correlational evidence from real-world data that, ceteris paribus, content shared by a social media user following fewer others garners greater engagement in terms of more likes and retweets. In the lab studies that follow, we replicate these findings in a controlled setting while investigating an important contributory explanation as to why this occurs.

Study 2

In Study 2, we begin by testing the principal hypothesis that following affects perceptions of an individual's influence. We also test a proposed moderator for the effect discussed in our secondary data analysis, namely that for following to operate effectively as a signal of influence, the user must have a substantial number of followers. Simply put, a person needs to be seen as someone worth listening to (i.e., one with a significant number of followers) before the number of people they listen to (i.e., following) matters.

Method

Respondents were 276 undergraduate students (49.6% female, $M_{age} = 20.5$ years) who completed the study for partial course

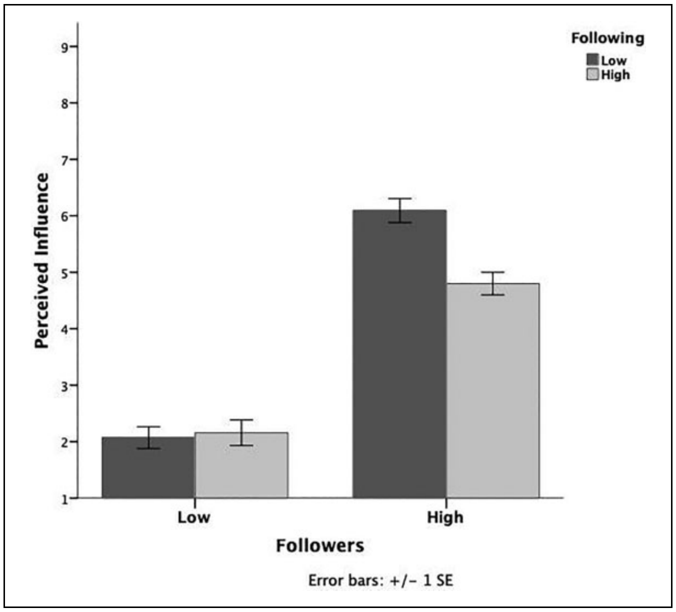

Figure 4. The moderating effect of followers (Influence).

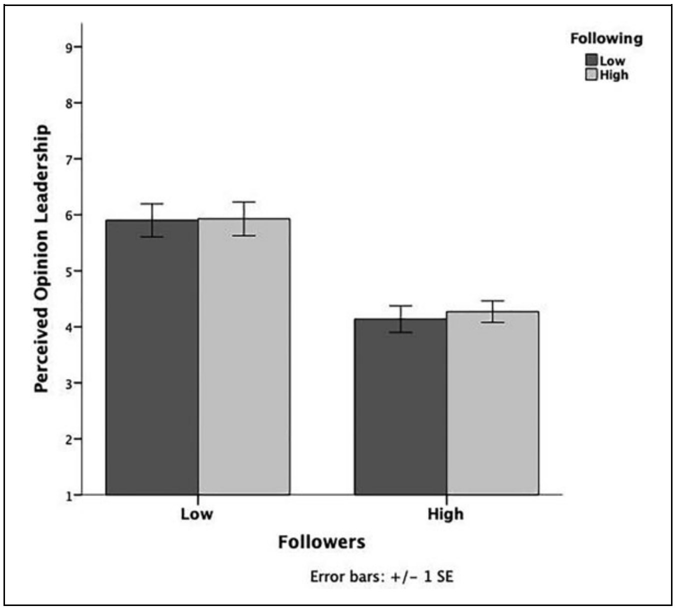

Figure 5. The moderating effect of followers (Opinion Leadership).

credit. The study employed a 2 (Following: High vs. Low) × 2 (Followers: High vs. Low) between-subjects design. Respondents were asked to evaluate a social media user based on the individual's profile page (see the Web Appendix for all experimental stimuli). To enhance generalizability, we use Instagram as the domain in this study. The stimuli replicated the features of a real Instagram page, including the user's Instagram name, picture, and number of photos posted (309).[10] Across conditions, we varied the number of Followers (58 or 15,457) and Following (49 or 21,530). We selected these numbers based on the distribution of the data collected in Study 1 such that in the Low condition they would fall around the 10th percentile and in the High condition would fall between the 90th and 95th percentile.[11] The number of Followers was below the threshold we identified for detecting an effect of Following in Study 1 in the Low condition and above that threshold in the High condition.

To assess how Following affects Perceived Influence, respondents were asked "To what extent do you think this user is influential on Instagram?" (1 = "not at all influential," and 9 = "very influential"). Further, we also asked respondents to rate the user on six domain-specific items adapted from the Opinion Leadership scale by Flynn, Goldsmith, and Eastman (1996, see the Web Appendix). We included this measure to assess the robustness of our effect across a polymorphic measure of influence (the former) and a monomorphic measure, specific to the domain of travel (the latter).[12] These dependent variables are highly correlated (r = .72) and present similar findings. Thus, in subsequent studies, we focus exclusively on the concept of perceived influence. In this and all subsequent studies, before exiting the study, respondents were asked their age and gender as well as to recall the number of users followed by the user they just evaluated (see measures in the Web Appendix).[13]

Results

A between-subjects analysis of variance (ANOVA) with Perceived Influence as the dependent variable reveals a significant main effect of both Following and Followers. The number of Followers has a significant effect on perceived Influence ($F(1, 272) = 257.45, p < .001$), as does Following ($F(1, 272) = 8.42, p = .004$). More importantly, consistent with our theorizing, these effects are qualified by a significant interaction ($F_{\text{Interaction}}(1, 272) = 11.02, p = .001$). Simple contrasts reveal that Following has a significant effect on Perceived Influence in the High Followers condition ($M_{\text{Low Following}} = 6.09$, 95% CI = [5.67, 6.51] vs. $M_{\text{High Following}} = 4.80$, 95% CI = [4.40, 5.20], $F(1, 272) = 18.93, p < .001$) but not in the Low Followers condition ($M_{\text{Low Following}} = 2.07$, 95% CI = [1.69, 2.45] vs. $M_{\text{High Following}} = 2.16$, 95% CI = [1.71, 2.61], $F(1, 272) = .09, p = .765$). These results are plotted in Figure 4.

As expected, we observed a similar pattern of results when Opinion Leadership ($\alpha = .88$) is the dependent variable (see Figure 5). Both Following ($F(1, 272) = 5.03, p = .026$) and Followers ($F(1, 272) = 137.13, p < .001$) predict Opinion

[10] The average number of Instagram posts in a sample of 20 million Instagram users (see Jang, Han, and Lee 2015).

[11] A separate study presented in the Web Appendix shows the effect is not sensitive to the choice of these specific values and the negative relationship between following and perceived influence holds across a wide range of Following.

[12] The name of the Instagram user indicated this person posted about travel.

[13] Across studies, the number of individuals who failed to recall the number of Following accurately varied between 9% and 16%. For simplicity in reporting, we did not exclude these respondents from any of our analyses. Importantly, however, the results are substantively the same if we exclude those who failed to recall the number of Following correctly.

Leadership. Again, these effects are qualified by a significant interaction ($F_{Interaction}(1, 272) = 4.23$, $p = .041$). Simple contrasts reveal that Following affects perceived Opinion Leadership significantly in the High Followers condition ($M_{Low\ Following} = 5.46$, 95% CI = [5.17, 5.74] vs. $M_{High\ Following} = 4.71$, 95% CI = [4.43, 5.00], $F(1, 272) = 9.04$, $p = .003$), but not in the Low Followers condition ($M_{Low\ Following} = 3.08$, 95% CI = [2.71, 3.45] vs. $M_{High\ Following} = 3.05$, 95% CI = [2.63, 3.46], $F(1, 272) = .02$, $p = .894$).

Discussion

Results from Study 2 provide initial evidence in support of our conceptual model by demonstrating how following fewer others can affect a social media user's perceived influence (opinion leadership). These results are noteworthy given practitioners' desire for cues other than followers to assess an influencer's potential. Moreover, we show that the impact of following is contingent on having accumulated a substantial number of followers. Next, we investigate a key mechanism underlying the effect: we demonstrate that following fewer others affects perceptions of an individual's autonomy, which in turn drives perceptions of influence.

Study 3 Pretest

We first designed a pretest to explore the basic proposition that following affects perceptions of the user's autonomy, our proposed mediator, along with two potential alternative explanations for our effect, namely, that someone following fewer others is perceived (1) as more of an expert and/or (2) as more innovative in general. Previous literature has established that expertise (Grewal, Mehta, and Kardes 2000) and innovativeness (Ruvio and Shoham 2007) are both viewed as characteristics of an opinion leader. It is thus possible that following could serve as a cue of expertise and/or innovativeness, which could, in turn, affect perceptions of influence.

Participants included 598 Twitter users (45.7% female, $M_{age} = 36.0$ years) enlisted via Amazon's Mechanical Turk (mTurk) in exchange for a US$.50 payment. We divided participants into three groups, 198 of whom evaluated a Twitter user's autonomy, 200 of whom evaluated a Twitter user's expertise, and 200 of whom evaluated a Twitter user's innovativeness. As in earlier studies, respondents evaluated a Twitter user based on a snapshot of the person's profile page. The number of Followers (15,457), Tweets (7,835), and the number of Likes (916) remained constant across conditions. The number of Followers corresponded to our High Followers condition in Study 2, and Tweets and Likes reflected averages in the data set used in Study 1. We varied Following to be either Low (49) or High (21,530). Respondents evaluated the Twitter user in terms of Autonomy, Expertise, or Innovativeness (each respondent provided only one type of evaluation to avoid common method bias). We adapted the Deci and Ryan (2001) autonomy scale to measure autonomy, the Ohanian (1990) expertise scale to measure expertise, and the Goldsmith and Hofacker (1991) consumer innovativeness scale to measure innovativeness (see the Web Appendix).

Results

Autonomy ($\alpha = .89$). Respondents perceived the user to be significantly more autonomous when Following was Low as opposed to High ($M_{Low\text{-}Following} = 6.07$, 95% CI = [5.73, 6.41] vs. $M_{High\text{-}Following} = 5.35$, 95% CI = [5.02, 5.68], $F(1, 196) = 9.23$, $p = .003$).

Expertise ($\alpha = .97$). Respondents did not perceive the Twitter user to be significantly more expert when Following was Low as opposed to High ($M_{Low\text{-}Following} = 5.77$, 95% CI = [5.34, 6.19] vs. $M_{High\text{-}Following} = 5.70$, 95% CI = [5.28, 6.11], $F(1, 198) = .05$, $p = .824$).

Innovativeness ($\alpha = .87$). Respondents did not perceive the Twitter user to be significantly more innovative when Following was Low as opposed to High ($M_{Low\text{-}Following} = 6.98$, 95% CI = [6.73, 7.22] vs. $M_{High\text{-}Following} = 7.03$, 95% CI = [6.78, 7.28], $F(1, 198) = .09$, $p = .766$).

Discussion

Taken together, these results suggest that while following fewer others on social media does not appear to signal expertise or innovativeness, it does signal autonomy. Turning back to our real-world data, we also observe that users who follow fewer others on Twitter are more inclined to use the first-person pronoun "I" and less inclined to use second- or third-person pronouns in their tweets (the analysis and results are reported in Table A11 of the Web Appendix). This suggests those who follow fewer others on Twitter may in fact be more autonomous with respect to the content they post; thus, following may serve as an accurate and reliable cue of autonomy.

Study 3

In Study 3, we directly test whether autonomy mediates the relationship between following fewer others and perceptions of influence. Additionally, while in Study 2 respondents evaluated users in the absence of any content, Study 3 increases external validity by including content along with the user profile. This is important as it allows us to measure respondents' engagement with the content shared (tweet) in terms of providing Likes and Retweets.

Method

Respondents were 315 undergraduate students (50.8% female, $M_{age} = 20.4$ years) who completed the study for partial course credit. As in earlier studies, respondents evaluated a Twitter user based on a snapshot of the person's profile page. The number of Followers (15,457), Tweets (7,835), and Likes (916) remained constant as in previous studies. We varied

Following to be either Low (49) or High (21,530). The profile included the latest tweet shared by the user that read: "Top ten songs of all times" accompanied by a URL link. After viewing the profile, respondents evaluated the Perceived Influence and Autonomy of the user using the same measures employed in previous studies. Importantly, in this study, they were also asked to evaluate the content of the tweet by reporting how likely they would be to Like and Retweet it ($1 =$ "not at all likely," and $9 =$ "very likely").

Results

Autonomy ($\alpha = .85$). Respondents perceived the Twitter user to be significantly more autonomous when Following was Low as opposed to High ($M_{Low\text{-}Following} = 5.90$, 95% CI = [5.68, 6.13] vs. $M_{High\text{-}Following} = 5.48$, 95% CI = [5.23, 5.73], $F(1, 313) = 6.01$, $p = .015$).

Influence. A between-subjects ANOVA with Influence as the dependent variable reveals a significant main effect of Following such that those following fewer others were perceived as more influential ($M_{Low\text{-}Following} = 5.33$, 95% CI = [5.04, 5.61] vs. $M_{High\text{-}Following} = 4.13$, 95% CI = [3.85, 4.42], $F(1, 313) = 34.61$ $p < .001$).

Likes. With respect to the content, respondents were more prone to Like the post when Following was Low as opposed to High ($M_{Low\text{-}Following} = 3.14$, 95% CI = [2.81, 3.47] vs. $M_{High\text{-}Following} = 2.44$, 95% CI = [2.16, 2.72], $F(1, 313) = 10.31$, $p = .001$).

Retweets. Respondents were also more prone to Retweet the post when Following was Low as opposed to High ($M_{Low\text{-}Following} = 2.40$, 95% CI = [2.11, 2.69] vs. $M_{High\text{-}Following} = 1.89$, 95% CI = [1.67, 2.11], $F(1, 313) = 7.72$, $p = .006$).

Mediation. We ran the sequential mediation model Following → Autonomy → Influence → Likes using a bootstrap estimation approach with 5,000 bias corrected samples (Hayes 2013, model 6). In line with our conceptual model, we observe a significant indirect ($b_{indirect} = -.03$, 95% CI = [−.084, −.006]) effect. Substituting Retweets as our dependent variable, we observe similar results ($b_{indirect} = -.02$, 95% CI = [−.068, −.004]).

Discussion

Taken together, the results from Study 3 show that following fewer other users on social media leads to greater perceptions of autonomy and thus influence. This leads to greater engagement manifested as a more positive attitude (likes) toward shared content and a greater propensity to share (retweets) the content. Thus, we replicate the results of Study 1 in a controlled setting in which we also test the proposed underlying mechanism, being seen as more autonomous and thus more influential.

Study 4

Whereas Study 3 provides evidence of process through mediation, Study 4 provides additional evidence of process through moderation. We also identify an important boundary condition for the effect. Specifically, if outside information is available that confirms a person is indeed influential, consumers should no longer rely on heuristic processing as an effort-reducing mechanism (Shah and Oppenheimer 2008); thus, following is less likely to serve as a useful cue. Its effect on engagement will therefore be attenuated.

Method

Respondents were 703 undergraduate students (47.8% female, $M_{age} = 20.5$ years) who completed the study for partial course credit. This study followed a 2 (Following: High vs. Low) × 2 (Influence Information: Yes vs. No) between-subjects design. As in previous studies, respondents evaluated a Twitter user based on a snapshot of the person's profile page. The stimuli used were the same as Study 3. We varied Following to be either Low (49) or High (21,530). In this study, we also manipulated whether additional information about the user's influence was provided. In the Yes condition, respondents read a brief introduction of the Twitter user: "Robert Diaz is an influential and well respected music journalist" and saw a screenshot of a magazine referring to Robert Diaz as one of the top influential music writers. In the No condition, no such information was provided, mirroring what we did in earlier studies. We pretested this manipulation to ensure that providing such information would increase the perceived influence of a social media user in the absence of information regarding the user's followers and following (see the Web Appendix).

Respondents subsequently reported how likely they would be to Like and Retweet the accompanying tweet ($1 =$ "not at all likely," and $9 =$ "very likely"). A priori, we expected following fewer others would impact engagement only when respondents were not informed the user was an influential and well-respected journalist.

Results

Likes. We ran an ANOVA predicting Likes with Following and Influence Information. Both the main effect of Following ($F(1,699) = 9.81$, $p = .002$) and that of Influence Information ($F(1, 699) = 69.09$, $p < .001$) reached statistical significance. Most importantly, as expected these main effects were qualified by a significant interaction ($F(1, 699) = 6.21$, $p = .013$). When no Influence Information was provided, respondents were more prone to Like the post when Following was Low as opposed to High ($M_{Low\text{-}Following} = 4.30$, 95% CI = [3.95, 4.65] vs. $M_{High\text{-}Following} = 3.31$, 95% CI = [3.02, 3.61], $F(1, 669) = 15.84$, $p < .001$). However, this was not the case when outside Influence Information was available ($M_{Low\text{-}Following} = 5.32$, 95% CI = [4.95, 5.70] vs. $M_{High\text{-}Following} = 5.21$, 95% CI = [4.85, 5.58], $F(1, 669) = .20$, $p = .651$).

Retweets. We observed similar results with Retweet as the dependent variable. Again, the main effects of Following ($F(1, 699) = 4.68$, $p = .031$) and that of Influence Information ($F(1, 699) = 43.75$, $p < .001$) were qualified by a significant interaction ($F(1, 699) = 8.88$, $p = .003$). When no Influence Information was provided, respondents were more prone to Retweet the post when Following was Low as opposed to High ($M_{Low\text{-}Following} = 3.61$, 95% CI = [3.28, 3.95] vs. $M_{High\text{-}Following} = 2.70$, 95% CI = [2.44, 2.97], $F(1, 699) = 13.25$, $p < .001$). This was not the case when Influence Information was available ($M_{Low\text{-}Following} = 4.26$, 95% CI = [3.86, 4.65] vs. $M_{High\text{-}Following} = 4.40$, 95% CI = [4.02, 4.78], $F(1,699) = .33$, $p = .564$).

Discussion

The results of Study 4 provide evidence that engagement is higher for social media users who follow fewer others, but only when following serves as a cue for influence. They are also consistent with the opinion of Rogers and Cartano (1962), who point out that the perception of being influential can affects others' behavioral responses, thus resulting in actual influence.

Study 5

We designed Study 5 to test the effect of following on other users' engagement in a more behaviorally consequential manner. In this study, we focus on a different measure of engagement: click-through. We gave respondents the opportunity to actually click on a link posted by a social media user and spend time exploring a list of personally recommended restaurants. We thus tested whether click-through rates vary as a function of following.

Method

Respondents were 256 undergraduate students (47.7% female, $M_{age} = 20.0$ years) who completed the study for partial course credit. As in earlier studies, respondents evaluated a Twitter user based on a snapshot of the person's profile page. The number of Followers (15,457), Tweets (7,835), and Likes (916) remained constant across conditions. We varied Following to be either Low (49) or High (21,530). The profile included the following content, displayed as the latest tweet shared by the user: "This is my list of 10 new restaurants to try in LA" together with a URL link. We expected this content to have the potential to elicit participants' interest because it was relevant to the city they lived in (and many had recently just moved to).

Respondents first rated the perceived Influence of the Twitter user. Next, they were asked whether they wanted to click on the link provided in the tweet to review the restaurants recommended by the user or move to an unrelated task. Those who clicked the link were redirected to a list of ten (actual) new restaurants drawn from a popular food magazine. We expected respondents in the Low condition to show a greater interest in the restaurant recommendation made by the Twitter user (perceived as more influential) and therefore be more likely to click on the link.

Results

Influence. A between-subjects ANOVA with perceived Influence as the dependent variable reveals a significant main effect of Following ($M_{Low\text{-}Following} = 5.77$, 95% CI = [5.46, 6.07] vs. $M_{High\text{-}Following} = 4.53$, 95% CI = [4.22, 4.84], $F(1, 254) = 31.56$, $p < .001$).

Click. As anticipated, significantly more respondents chose to click on the link in the Low Following condition than in the High Following condition (53.9% vs. 40.6%, respectively, χ^2 (1, 255) = 4.53, $p = .033$).

Mediation. We ran the mediation model Following → Influence → Click using a bootstrap estimation approach with 5,000 bias corrected samples (Hayes 2013, model 4) and observed a significant indirect effect ($b_{indirect} = -.23$, 95% CI = [−.475, −.049]).

Discussion

Study 5 replicates previous findings that following on social media can affect how others perceive someone and, in turn, impact engagement with the content they share. Importantly, this study reinforces the external validity of our findings and extends Study 1 by showing in a well-controlled laboratory setting that this simple cue of influence can affect consequential behavior, namely clicking on a link to view additional content suggested by the focal user. Intuitively, one might expect someone following more users to be able to draw information from more sources, leading them to be viewed as more knowledgeable and making it more worthwhile to attend to their posts. Study 5 suggests this is not necessarily the case.

General Discussion

Marketers are increasingly seeding information about their products and brands through individuals deemed to be influential on social media (i.e., influencers). Thus, practitioners and researchers alike have expressed interest in identifying what makes a social media user more (or less) influential (Van den Bulte 2010). This question is especially relevant as marketers shift from relying on internationally known celebrities, those with millions of followers, to micro influencers, online personalities with fewer, but presumably more loyal, followers (Main 2017). Choosing among the myriad of micro influencers available is not easy, and a key question remains: What makes an influencer more or less likely to affect the behavior of his/her followers? We find that, holding a user's number of followers constant, an important indicator of this individual's online influence is the number of individuals this person chooses to follow.

Worth noting is that, in general, there is a correlation between the number of people a user follows and the number who follow that user. Reciprocity is a well-worn method of accumulating followers, so much so that Twitter has identified the practice of users following others solely to be followed in return and then employing algorithms to unfollow those followers. This practice offers anecdotal support for the central idea here that following fewer others is viewed more positively by others; otherwise, why go to such lengths to reduce the number one is following? Twitter has put a halt to the practice of bulk following, which has restored following few others as a more reliable (less corrupted) signal on that platform.

We acknowledge some limitations to this work worth mentioning, as they could provide interesting directions for future research. First, we varied followers and following without offering precise guidance regarding what constitutes a substantial enough number of followers for following to be impactful. In our studies, we tried to use numbers that reflect actual numbers from real-world data. The "right" numbers, we believe, are context dependent (e.g., depend on platform, topic category, influencer) and difficult to specify a priori with any degree of certainty. One can imagine, however, researchers in information systems attempting to address the question of the "right" numbers in various contexts using big data.

Moreover, by limiting our focus to following, we intentionally did not consider other potential drivers of perceptions of an influencer online. For instance, we did not explore the nature of the connections between users on a social network. We do not study whether the accounts one follows and the accounts that follow a user matter at the time of inferring one's influence, or whether disclosing the identity of these accounts would affect one's perceptions. While two social media users may have the same number of followers, who those followers are, or who those users are choosing to follow (i.e., their network structures) may differ. This information is not transparent on a user's profile (it requires clicking on additional pages and scrolling) and is therefore less salient to others than simply the number of following and followers. Yet, we believe this information might also affect how a social media user is perceived and could be interesting to study in further research.

Randy Howell from our opening example is a veteran of the Bassmaster Tour and the 2014 Bassmaster Classic Champion, and specializes in shallow-water fishing. Mark Zona is cohost of the Bassmaster Elite Series on ESPN2. Each presumably has his own writing style and other idiosyncratic characteristics that differentiate him. How much weight do followers give to their accolades and other information? These factors are specific to the context of bass fishing, and our goal was to instead try to identify a cue that applies more generally. However, a richer model using language analysis and machine learning may one day incorporate all of this information.

Looking at the downstream consequence of influence perceptions studied in this work, we should also stress that perceived influence is only one factor expected to affect engagement. While we find following affects perceived autonomy and in turn perceived influence, we consider the mechanism we unveiled as contributing to the effect of following on engagement and not necessarily explaining it completely. It is possible following can work as a cue for other user characteristics not ruled out in this work, which might be worth exploring in future research.

Abstracting away from following and followers, one might reframe our investigation in terms of numbers of sources and receivers of information. One can judge a person by the number of receivers who subscribe to the information they provide as well as by the number of sources they rely on for their information. We believe more work could be done examining the effect of number of sources on receivers' responses outside of social media per se. The broader question of how many sources an information provider should draw from—and the impact that number has on the perceptions of those who receive information from the provider—is much broader than what we have done here and worthy of more investigation. While one could argue more sources are better, our results suggest that this intuition does not always hold true.

Author Contributions

The authors contributed equally and are listed in reverse alphabetical order.

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