The Impact of Viral Posts on Visibility and Behavior of Professionals: A Longitudinal Study of Scientists on Twitter

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Abstract

On social media, due to complex interactions between users' attention and recommendation algorithms, the visibility of users' posts can be unpredictable and vary wildly, sometimes creating unexpected viral events for 'ordinary' users. How do such events affect users', particularly those who use such platforms to enhance their professional reputation, subsequent behaviors and long-term visibility on the platform? For almost 3 years, we collected activities and changes in follower graphs of 17,157 scientists on Twitter, and identified those who experienced 'unusual' virality for the first time in their profile lifespan. Using a matching strategy, we investigated how viral events influence behavioral patterns and follower counts of those who experienced virality ('viral' group) vs. those who didn't. After virality, the viral group increased tweeting frequency, their tweets became more objective and focused on fewer topics, and expressed more positive sentiment relative to their pre-virality tweets. Also, their post-virality tweets were more aligned with their professional expertise and similar to the viral tweet compared to past tweets. Finally, the viral group gained more followers in short and long terms than their matched counterparts.

Introduction

Online platforms for professional networking (e.g., LinkedIn) have seen tremendous growth in the last decade. Despite the availability of such professional networking channels, general-purpose social media services, such as Facebook and Twitter, where the boundary between professional and social communications is often blurred, are still being used as major channels for professional communication across science (Meishar-Tal and Pieterse 2017; Ke, Ahn, and Sugimoto 2017), business (Sivarajah et al. 2020), and politics (Buccoliero et al. 2020). Scientists, who serve multiple audiences: their peers, their institutions' administration, the public, and others (Kozinets 2017), and face pressures to develop an online presence and digital personae (Duffy and Pooley 2017), may benefit from participating in an open network such as Twitter.

As social media platforms facilitate interactions among vast numbers of people from diverse backgrounds, they have given rise to viral events that stem from complex interactions. Going 'viral' may have life-changing impacts on individuals, both favorable and adverse. For example, individuals gained internet fame (Stampler 2014) and career opportunities (Arató 2019) after memes featuring them went viral. On the other hand, people have lost their jobs and faced social embarrassment after their tweets were judged as inappropriate and retweeted by millions and caught the attention of the news media (Ronson 2015; Strehlke 2015). Although such massive events are rare for ordinary people, smaller-scale viral events, which are still extraordinary for normal users, occur more frequently. We term such events as 'micro-viral events'. How does experiencing such micro-viral events for the first time affect social media users, particularly those who use the platform for professional purposes? Do the users alter their behaviors, e.g., by increasing platform engagement? Do such events help users to gain more visibility in the long-term?

In this paper, we examine these questions using a longitudinal dataset of scientists on Twitter and a matching-based inference method. Specifically, we study how *anomalous* micro-viral tweets – tweets with a large number of retweets that are 'unusual' for the particular user, but that would not necessarily be considered viral in the traditional sense – influence their behaviors. We examined how scholars reacted to such exposures and whether they used this *sudden* popularity to promote their professional self, such as by adopting specific strategies to get additional viral events. We further examine if these events help in accumulating followers, which is 'social capital' in the virtual world. We focus on Twitter because of its increasing popularity among scholars for professional purposes and its general-purpose nature; indeed, past research has found that the primary motivation for a majority of scholars to use Twitter was to fulfill professional goals (Yu et al. 2019). Scholars use Twitter to attract potential employers (Radford et al. 2020), advertise academic positions (Guzman, Alkadhi, and Seyff 2016), build an 'expert' identity (Han 2020; Dauenhauer 2020), and connect with peer scientists and related associations to build a community (Mohammadi et al. 2018; Haustein et al. 2014). Additionally, the public nature of Twitter facilitates complex and unexpected interactions, which increases the chance of viral events, thereby making Twitter an appropriate and attractive platform to study our research questions. Specifically, we study the following research questions:

1. Do micro-viral events influence people's behaviors on the platform (e.g., changing tweeting frequency, sentiment, objectivity, and topics of tweets, and posting tweets that are more similar to the viral tweets and relevant to the users' professional expertise)?
2. Do micro-viral events influence short- and long-term follower gain (or loss) on Twitter?

We study the impacts of micro-viral events using a matching-based inference framework—by obtaining a control group that is matched with the treatment group using *Mahalanobis distance metric* (Stuart 2010)—on a longitudinal Twitter dataset. For more than two years and eight months, the Tweeting activities and changes in the follower networks of 17,157 Twitter users, who were identified as scholars (Ke, Ahn, and Sugimoto 2017), were continuously monitored using the Twitter API. From this data, those who experienced micro-viral events (the 'viral group'; for simplicity, in the rest of the paper we will omit the designation 'micro' unless we want to highlight the features of our definition; the formal definition of micro-viral events is provided below) *for the first time* since they started using Twitter were identified. Using a matching procedure, we also identified a comparable 'non-viral group' that includes users who never had any viral event, but whose profile and tweeting activities were similar to the users in the viral group up to the time of the viral event. We compared these two groups to assess how micro-viral events might have affected the behavior of viral users and if they subsequently gained (or lost) followers.

Our findings suggest that micro-viral events changed scholars' tweeting behaviors. After a micro-viral event, viral scholars tweeted and retweeted more frequently compared to their matched non-viral counterparts. Comparing with their pre-virality tweets, they also posted tweets i) with more positive sentiment, ii) containing more factual information, iii) focused on fewer topics, and iv) similar to their first tweet that went viral. Additionally, experiencing micro-viral events had a positive impact on accumulating followers in both the short- and long-run and broadening one's reach to the general public. These findings add to the understanding of the usage of social media to promote professional reputation by scholars and people in other professions where reputation helps to advance their careers.

Background and Related Work

Scholars' Use of Twitter

Jordan and Weller identified four reasons for using social media platforms by academics: maintaining a personal learning network, promoting the professional self, promoting and seeking research publications, and advancing one's career (Jordan and Weller 2018). Maintaining presence in online platforms (including Twitter) was regarded as creating a 'digital self', where academics promote themselves in a competitive environment (Shah and Cox 2017; Radford et al. 2020; Haustein et al. 2014; Mohammadi et al. 2018; Lemon, McPherson, and Budge 2015). Twitter provides a unique opportunity for scholars to communicate science to the public (Côté and Darling 2018; Dudo and Besley 2016; Mohammadi et al. 2018) by virtue of being a platform open to all and the *by-default-public* nature of tweets. Scholars use Twitter to share research ideas (Dauenhauer 2020) and build collaborations (Mohammadi et al. 2018) that may have direct positive impact on professional success. Twitter is used as a channel to continue discussion and collaboration during academic conferences (Li and Greenhow 2015; Kimmons and Veletsianos 2016). In this paper, we go beyond understanding *why* and *how* scholars use twitter and focus on how unexpected, but perhaps desired, events, such as viral tweets, help them achieve their identified goals, such as getting attention from other scholars, and if and how impacted scholars capitalize on such events.

Defining and Identifying Micro-viral Events

Previous research has characterized 'viral' events from several different perspectives. Jenders et al. indicated a tweet as viral when the number of retweets it had received exceeded some threshold (such as 50) (Jenders, Kasneci, and Naumann 2013). Subbian et al. considered a tweet as a viral tweet when it received a higher number of retweets compared to other tweets (e.g., 90th percentile) (Subbian, Prakash, and Adamic 2017). More complex measures of virality have also been proposed that considered the structural properties of the diffusion, such as the depth of the cascades (Dow, Adamic, and Friggeri 2013) and the average distance between all pairs of nodes in a diffusion tree (Goel et al. 2015). By contrast, we characterized a tweet as a micro-viral tweet if it had received a higher number of retweets compared to other tweets of the *same* user, as our goal is to measure the impact of viral events that are rare and unusual for the person who experienced them, even if they would be unremarkable for highly popular users, which is why we call them micro-viral events.

Impact of Viral Events and Strategic Behaviors

Prior research has shown that viral events often cause accumulation of followers (Myers and Leskovec 2014). For scholars, such events may help to reach to the people who are outside of specific research fields or even scientific professions (Côté and Darling 2018). On the other hand, such unusual but desired attention from peers may cause scholars to be more engaged to the platform and change their tweeting behaviors (Adelani et al. 2020). In particular, we are interested in detecting if scholars change their tweeting behaviors in a way that might increase the probability of receiving more attention (e.g., subsequent viral tweets) and accumulate more followers. Prior research has shown that tweeting more frequently helps to get more followers (Schnitzler et al. 2016). Regarding content, Berger and Milkman found that content expressing positive sentiment were more likely to go viral (Berger and Milkman 2012). Schnitzler et al. advocated scientists to maintain objectivity in tweet content (i.e., free from personal bias), and engage in professional conversations with fellow scientists (Schnitzler et al. 2016). In this work, we investigated whether scholars demonstrate more of these behaviors, and several others, after achieving virality, even if it is a small degree of virality.

Method

Establishing causal effects with observational data is challenging, as it is difficult to eliminate all non-causal explanations (Shalizi and Thomas 2011). Here, we employ a matching method with a longitudinal database of tweeting activities and follower accumulation to compare outcomes experienced by viral and non-viral users after viral events. To create this dataset, we followed 17,157 scholars on Twitter for two years and eight months and collected their tweets, retweets, and changes in followers over time. Using this dataset, we identified users who experienced micro-viral events (we call them 'viral users') for the first time in their profile's lifespan. Although viral events may influence future interactions and follower gains/losses on Twitter, simply comparing tweeting behaviors and the number of followers of viral users before and after viral events would lack a counterfactual. Thus, to isolate the impact of viral events, each of the viral users was matched with a user who had a similar number of followers and tweeting behaviors up to the point of the viral event, but who never experienced any viral event. This matching procedure approximates controlled experiments (Ho et al. 2007) and allows for stronger inference from observational data. Although it is impossible to rule out possible influences of unobserved confounders, by comparing how the tweeting behaviors and number of followers of viral vs. non-viral users diverge after a viral event, we provide a stronger argument for a causal relationship between the viral event and the observed changes.

Data collection procedure

Selecting the initial set of users. Our dataset builds on a previous research on the use of Twitter by scientists (Ke, Ahn, and Sugimoto 2017). Their dataset comprised of 45,867 Twitter users, a majority being scientists or researchers. Since Twitter API has rate limitations (Twitter 2020), we selected a subset of the users for continuous data collection as follows. First, we identified the "novel tweets" (i.e., not a retweet, but can be a reply to another tweet) of each user in the initial dataset with the highest number of retweets to date (the 'peak tweet'). Then, the difference between the average number of retweets for tweets posted *before* and *after* the 'peak tweet' was calculated. After sorting users based on these values, the top 3,000 and bottom 3,000 users were selected for continuous monitoring. This set therefore contains users with the maximum 'ups' and 'downs' during their profile lifespan. We extended and diversified this set in two ways: A) users who had at least one tweet with 50 or more retweets were included, resulting in a set of 8,157 users and, B) a random sample of 9,000 users who never had a tweet with 50 or more retweets were included, totaling to 17,157 users. From July 1, 2017 to February 21, 2020, we continuously collected tweets posted by these users and changes in their follower graphs. This data collection procedure was approved by our institute's ethics board.

Selecting the final set of users. We monitored 17,157 users, but data from many of these users were discarded for various reasons that we describe in this section. We aimed to detect 'anomalous' viral events that were experienced by the users for the first time. The Twitter API provides a maximum of 3,200 past tweets of a user. Thus, we discarded 5,573 users who had posted more than 3,200 tweets before we started monitoring them. Next, users who either deleted their profiles or made them 'protected' (N=3,113), or did not post any tweets (N=762) during the data collection period were removed. From the remaining users, 753 (9.7%) were identified as bots by the Botometer (Varol et al. 2017) (using a classification threshold of 0.49 as suggested by the authors of Botometer (Varol et al. 2017)). After this step, 6,956 users remained in the final set.

Defining and detecting micro-viral tweets

We consider a tweet as a *micro-viral tweet* only if it was both *popular* (in 'absolute' terms, although using a relatively low bar) and *unusual* (in 'relative' terms). These criteria exclude some of the hugely popular tweets (e.g., by celebrities or politicians) because people with larger followings may regularly garner large numbers of retweets. Therefore, in our definition we use both the absolute number of retweets and how anomalous it is for a given user, which is estimated by the z-score of the number of retweets. We chose 50 as the absolute threshold for retweets based on a previous study (Jenders, Kasneci, and Naumann 2013), which shows that retweets follow a Pareto distribution and only 4% of tweets get 50 or more retweets. [1] Thus, at first, we identified all tweets of a user with at least 50 retweets and included them in the set of 'potential viral tweets', T, for that user. Then, for each tweet $t \in T$, the z-score was calculated using the mean and standard deviation of retweets for tweets posted within the 10 weeks before t. If the z-score of a tweet was above eight, it was classified as a 'viral tweet'.

We chose 10 weeks as the window for calculating the z-score based on the auto-correlation of the users' weekly tweeting frequency as follows. First, for each user, a time series was created by calculating the weekly tweeting frequency during the data collection period. Then, the auto-correlation coefficients of that time series was calculated for lags ranging from 1 to 20 weeks. For each time lag, we computed the mean, standard deviation, and 95% confidence intervals of the auto-correlation coefficients across all users (Figure 1). We selected 10 weeks because this is the longest time duration with mean correlation coefficient greater than 0.1, indicating that the users' tweeting behavior had some consistency over this time interval.

The threshold for z-score was selected with the goal of maximizing the number of users who had only one viral event. This selection criterion would maximize the extraordinary aspect of the event for an user, and minimize the number of users with subsequent viral events so that the effect of the first viral event on the outcomes could be isolated. To do

[1] We experimented with other threshold values: 75, 100, and 150. But using higher values simply resulted in a smaller set of viral users, without any qualitative change. For example, using 100 as the threshold yielded in a *proper* subset of the set of viral users who were identified using 50 as the threshold. This was true for other higher thresholds as well.

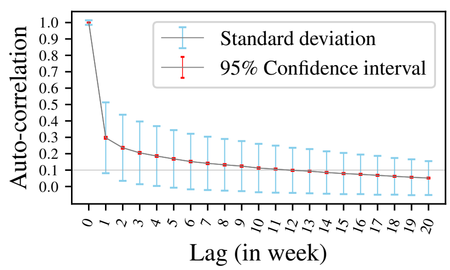


Figure 1: Auto-correlation of tweeting frequency per week.

that, we computed the percentage of users with a single viral event for different thresholds of z-score (ranging from two to 30) and chose eight since this maximized the number of such users.

Using these thresholds, we identified 1,610 tweets from 758 users as 'viral' events. Of them, 409 (54%) had only one viral event and 68 (8.9%) had 5 or more viral events.

Matching Procedure to Create the Control Group

To isolate the influence of viral events on users' behaviors and follower gain, we created a control group to compare with the viral group. For a 'fair' comparison, people in the control group should have similar follower networks and tweeting behaviors as those who experienced virality (Stuart 2010), until the viral event (after which the groups might diverge). Thus, each user in the *viral group* was paired with the most 'similar' user from the 'non-viral group', and these matched non-viral users formed the control group.

Selecting covariates for measuring 'similarity' between a viral and a non-viral user. The similarity was measured based on the following variables: number of followers, number of *novel* tweets (i.e., not a retweet, reply, or quoted tweet), number of retweets per tweet, and number of URLs and hashtags used per tweet. These covariates were selected based on relevant literature. Prior research has shown that tweeting frequency, number of followers, and including URLs and hashtags in tweets were associated with obtaining large retweets (Suh et al. 2010; Schnitzler et al. 2016). We included *average number of retweets per tweet* to pair users whose tweets usually receive similar attention. Although the age of the account may influence retweets (Suh et al. 2010), we omitted it since many Twitter users remain inactive after creating their profiles (Ruhela et al. 2016; Kwak et al. 2010). We also omitted sentiment and emotion of tweets, as many viral and non-viral users had posted only a few tweets and thus estimations of affective properties may be unreliable. Including these variables would also increase the large number of covariates and may result in a poor similarity measure in the Euclidean space (Stuart 2010).

Estimating covariates. The identified covariates were estimated as follows. For viral users, the number of followers was equal to how many followers they had immediately before their respective first viral events. Covariates whose value depended on tweets (e.g., the average number of URLs) were computed using tweets posted by viral users within 10 weeks prior to their respective first viral event. For non-viral users, the covariates were computed based on the viral users with whom they are being compared to measure similarity. Thus, while computing the similarity between a *non-viral* user and a *viral* user, tweets posted by the *non-viral* user within 10 weeks before the first viral event of the *viral* user was used to calculating the covariates, and the number of followers was equal to how many followers the non-viral user had immediately before the same viral event. Measuring similarity based on covariates computed prior to the viral events ensures that no covariate was affected by the treatment (the viral events in our case) (Stuart 2010). The 10 week period was selected by observing the consistency of users' behavior within this interval. Table 1 shows covariate estimates for the two groups before and after the first viral events (the number of followers is not shown as they were computed just before the viral events).

Matching with the Nearest Neighbor in an Euclidean space. Each viral user was paired with the closest user in the non-viral group based on the z-scores of values of the covariates using *k-nearest neighbor (KNN)* matching. We used z-scores of covariates instead of using raw values (i.e., used Mahalanobis (Stuart 2010) distance instead of Euclidean distance) in the matching procedure since the covariates have widely different ranges. For example, number of followers varies in the order of thousands, while the average number of hashtags per tweet has a range of zero to one. Thus, if these raw values were used, covariates with smaller ranges of values would have been ignored while computing the distance between two users in the Euclidean space.

Our goal was to find unique matches; one way to achieve this was to matching without replacement: once a non-viral user had been matched with a viral user, discard them from the pool of potential matches for subsequent viral users. But the result from this procedure would depend on the order in which non-viral users were considered for matching, and may not result in the best possible matched pairs. We avoided this by considering all non-viral users as potential matches for all viral users, paring two users when they had the smallest distance among all potential pairs. This resulted in duplicate matches, which we resolved with an iterative algorithm that is outlined in Algorithm 1 and as explained in the following section.

At first, this algorithm finds N non-viral users who are nearest to a viral user (N was set experimentally, see below). Then, it matches the closest (non-viral) neighbor with the viral user. But that non-viral user may be nearest to more than one viral user, creating duplicate matches. It then finds and removes duplicate matches iteratively. In each iteration, if one non-viral user was matched with multiple viral users, then the match with the lowest distance was retained and the non-viral user was removed from other pairs. The viral users in those pairs were re-matched with the next nearest neighbor (from the initial set of N neighbors). This process continues until there are no duplicate matches anymore, or it is not possible to find a unique match for every viral user. The latter can happen when N is too low and it becomes

	Viral users		Non-viral users	
	Before	**After**	**Before**	**After**
Tweets	34.36 (51.68)	38.94 (115.58)	27.97 (47.22)	24.32 (38.30)
Retweets	5.14 (7.70)	9.93 (21.68)	4.20 (6.29)	3.94 (12.63)
URLs	0.75 (0.25)	0.81 (0.24)	0.76 (0.25)	0.78 (0.30)
Hashtags	0.37 (0.47)	0.33 (0.44)	0.38 (0.52)	0.39 (0.52)

Table 1: Mean (SD) number of tweets and retweets, URLs, and hashtags per tweet in 10 weeks before and after viral events.

impossible to re-match a viral user after detecting a duplicate match. We experimented with different values of N, and found that setting $N = 10$, i.e. initially identifying 10 nearest neighbors for each viral user was sufficient to obtain unique matches. This procedure thus identifies the best possible unique matched pairs regardless of the order of matching.

We further enhanced the comparability between matched pairs by removing pairs that had distances larger than one standard deviation, resulting in 670 matched pairs.

Evaluating the quality of the matching procedure. To assess the balance in the *observed* covariance in our matched sample, we compared the standardized mean differences (SMD) of the covariates for the matched pairs using our algorithm with SMDs for randomly matched pairs (Zhang et al. 2019). We conducted 100 trials of the random matching, computed the mean SMDs of the covariates across these trails, and compared them with the SMDs for the pairs matched by our algorithm. As Fig. 2 shows, all covariates except the number of followers had much smaller differences when matching was performed using our algorithm compared to random matching. We followed up this analysis with significance tests to examine whether differences in means are negligible for the matched pairs (see Table 2). The significant differences between covariates disappeared after matching, which indicates that the paired viral and non-viral users had comparable follower networks and tweeting behaviors before viral events.

To assess the balance in the *unobserved* covariates, we conducted sensitivity analysis for three outcomes: change in followers after 10 weeks, change in followers at the end of data collection period, and change in the proportion of 'scientist' followers (see below for details on outcome variables). Note that, the other outcome variables (e.g., tweeting frequency) are inappropriate to be used for sensitivity analysis, since they were not compared between the viral and non-viral group, rather they were compared before and after viral events only for the viral group. Figure 3) shows the results from sensitivity analysis using Rosenbaum bounds (Rosenbaum 2014), where the grey horizontal line indicates $p = 0.05$. We hypothesized that viral events would positively impact follower-gain; thus, for changes in the followernumber, we plotted the upper bound of p-values (Rosenbaum 2014). The plot shows that for both outcomes related to change in followers, there are significant effects of viral events in the expected direction, which change only after bias due to unobserved confounders reach (i.e., $gamma$) to greater than 4.5 and 3.5, respectively. This shows that our findings are

Data: Set of 'viral users' and set of 'non-viral users'
Result: Returns subset of users from 'non-viral user' group each of who was matched against one of the users in 'viral group'
N=10
foreach $u_1 \in$ *'viral group'* **do**
    find the set V of the closest N users of u_1 from 'non-viral users' in terms of the co-variates using nearest neighbor search;
    Sort these N neighbors in V according to their distance from u_1 in the ascending order and match u_1 with its closest neighbor v;
    set $V = V - \{v\}$;
end
while *not all users in 'viral group' have unique match* **do**
    foreach $u_2 \in$ *'non-viral group' who were matched with more than one users in the 'viral group'* **do**
        let U is the set of users who were matched with u_2;
        find the user $u \in U$ who has the minimum distance with u_2;
        foreach $u_1 \in U - \{u\}$ **do**
            remove u_2 from the neighbors of u_1, (i.e. set $V = V - \{u_2\}$)
            if V *is empty* **then**
                Error('Failed to find unique match for all users in viral group');
                Exit();
            end
            else
                match $v \in V$ with u_1 where v has the minimum distance with u_1;
            end
        end
    end
end

Algorithm 1: Procedure for finding unique matched pairs.

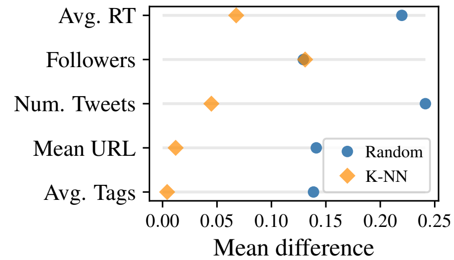


Figure 2: Standard mean differences of covariates for matching randomly and using our algorithm.

	Before matching		**After matching**	
Covariate	***t-statistic***	***p***	***t-statistic***	***p***
Mean hashtags	-1.1	0.27	0.41	0.68
Mean URLs	3.1	0.002	-0.4	0.7
Num. of tweets	2.5	0.01	1.2	0.23
Followers	2.8	0.006	0.83	0.41
Retweet per tweet	4.6	0.0001	1.44	0.15

Table 2: Results of significance tests to assess the differences in means among covariates before and after matching.

robust against strong bias from hidden confounders (Rosenbaum 2014). For the change in the proportion of 'scientist' followers, we plotted the lower bound of p-values, as we hypothesized that experiencing viral events would expand one's reach outside of the scientist community, leaving the proportion of 'scientist' followers lower than before. [2] According to Fig. 3, the expected effect of virality on this outcome only diminishes when $gamma$ reaches to around 1.7, indicating moderate sensitivity to unobserved confounding factors (Rosenbaum 2014).

Pre-processing tweets

Computations involving tweet content (e.g., sentiment) were preceded by a pre-processing step using the TweetTokenize library.[3] This step removed white-spaces and punctuation, and replaced usernames, URLs, phone numbers, and time with *USER*, *URL*, *PHONE*, and *TIME* tokens, respectively. Only tweets in English language were used for these analyses.

Evaluating the Effects of Viral Events on Outcome Variables

Below, we list the outcome variables (related to scholars' behaviors and follower gains) we examined, detail the procedures for estimating them, and explain how the effects of viral events on them were computed and compared. Although we report findings involving all the users who had (one or more) viral events, these computations were repeated considering only users with a single viral event and we found comparable results.

[2] In the Findings section, we show that results were in accordance to our expectation.

[3] https://github.com/jaredks/tweetokenize/

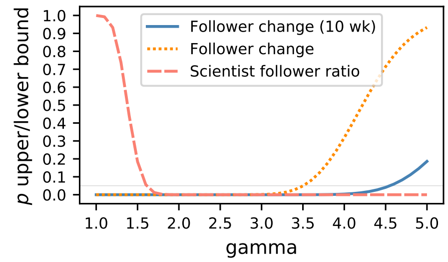


Figure 3: Results from sensitivity analysis. The horizontal axis shows odds of being treated (i.e., bias due to unobserved variables) and the vertical axis shows the upper/lower bounds of the probability of significant outcomes. The points where the curves cross the horizontal line (representing $p = 0.05$) indicate when the outcome becomes non-significant from significant (and vice versa). The large values of $gamma$ at these points indicates that there has to be large amount of bias for that switch to occur, demonstrating robustness of our findings against unobserved confounders (Rosenbaum 2014).

Behavioral Changes

We studied if virality influences behavioral changes focusing on behaviors that were identified to be helpful in building scholarly reputation by prior research: tweeting frequency, sentiment, objectivity, and engaging *professionally* with other scholars (i.e., posting tweets that are aligned with the posters area of expertise) (Mueller and Stumme 2017; Schnitzler et al. 2016). We also examined if viral users posted tweets that were more similar to the viral tweets, presumably, as a way to re-create the cascading phenomenon, and if they tweeted on more (or less) diverse topics after the viral events, than before. Similar computations were performed for the non-viral group. All computations were performed on tweets posted in a 20-weeks time period (within 10 weeks before or after the first viral event). Below, we describe the behavioral measures we examined and how they were computed using these tweets.

Change in tweeting frequency. The average number of tweets per day for 10 weeks (≈ 75 days) *before* the first viral event was computed that indicates the *baseline* tweeting frequency of each user. Then, the average number of tweets per day within 7, 15, 30, 60, and 75 periods *after* the same event was computed and compared to the baseline frequency to detect any changes over time.

Change in sentiment. After pre-processing the tweets, sentiment scores were estimated as follows. First, the sentiment scores of the English words according to the NRC Word-Emotion Association Lexicon (Mohammad and Turney 2010) dataset were summed. Then, the emoticon sentiment lexicon dataset (Hogenboom et al. 2013) and the emoji lexicon dataset (Kralj Novak et al. 2015) were used to obtain sentiment scores for emoticons and emojis, respectively. Finally, the three scores were summed and averaged to get the final sentiment score of a tweet. The average sentiment scores of the tweets that were posted within 75 days before viral events represent the 'baseline' score. As before, the average sentiment scores across the tweets posted within different time intervals after viral events were computed and compared with the baseline to detect changes in tweet sentiment.

Objectivity of tweets. Following the pre-processing step, a tweet's objectivity score was estimated using the SentiWordNet dataset (Baccianella, Esuli, and Sebastiani 2010). Each lexicon in this dataset has both positive (P) and negative (N) *subjectivity* ratings. The objectivity of a lexicon was calculated using the equation: $objectivity = 1 - (P + N)$, and then average across all tokens in a tweet, which represents to what extent the tweet was free from positive/negative subjectivity of the author. Change in objectivity was compared in a similar way as the sentiment estimates.

Similarity of tweets with users' professional expertise. To measure if users posted tweets that are more (or less) aligned with their professional expertise after experiencing virality than before, first, we estimated users' areas of professional expertise using list membership (Ghosh et al. 2012). Using TF-IDF, the top five keywords were identified from the titles and descriptions of all lists that a user created or subscribed to. The keywords were then embedded in a vector space using Gensim (Rehurek and Sojka 2010) library and a FastText (Bojanowski et al. 2016) model for vector embedding that was trained with 400 million tweets (Godin 2019). Next, we computed the *World Mover's Distance* (WMD) (Kusner et al. 2015) between the keywords and a tweet (after embedding it in the same vector space). WMD between two text sequences is the sum of the distances from each word of one sequence to the nearest word (in a vector space) of the other sequence. WMD allows one to compute a 'meaningful distance' between two text documents even when they share no common words and has been shown to outperform other state-of-the-art methods (Kusner et al. 2015).We treat WMD as the similarity measure of a tweet with the tweeter's professional expertise where smaller WMDs indicate more similarity.

Similarity of tweets with the viral tweet. To asses whether viral users post tweets that are more (or less) similar to the viral tweet after experiencing virality than before, for each viral user, the average similarity of tweets posted within 75 days *before* the first viral event with the viral tweet was computed (representing the 'baseline' similarity). Then, the average similarity of the viral tweet with the tweets posted within different intervals (7, 15, 30, 60, and 75 days) *after* the viral event was computed and compared to the baseline similarity. Similar computation was repeated for tweets posted within those intervals *before* the first viral event to verify whether any observed change in similarity was due to the experienced virality or simply a function of time (e.g., people may post similar tweets for a specific amount of time regardless of the tweets' popularity). The similarity between two tweets was computed by first embedding them in a vector space and then finding the Word Movers' Distance (WMD) between them, where a lower WMD indicates higher similarity between two tweets.

Diversity in tweet topics. We examined if tweeters diversify the tweet topics after experiencing virality compared to the non-viral group. We trained an LDA (Latent Dirichlet Allocation (LDA) (Blei, Ng, and Jordan 2003)) model using all tweets posted by users in both viral and non-viral groups. To improve model accuracy, we identified and extracted unigrams, bi-grams, and tri-grams in tweets using Gensim's 'Phraser' module (Rehurek and Sojka 2010) and used them to train several LDA models. The number of topics was set as a hyper parameter, which varied from 50 to 500 with a step size of 50. The models were evaluated based on the coherence score, which is an widely used metric to evaluate topic models (Röder, Both, and Hinneburg 2015). We picked the model with 100 topics as it had the highest coherence value. Then, tweets posted within 75 days before the viral events were combined and the top five topics (based on probability) were identified using the trained LDA model. Next, for each topic, the top five words/phrases were extracted from the model and pairwise similarities among these 25 phrases were computed and summed that indicated how similar the tweets' topics were. The difference in similarity score for tweets posted after viral events and tweets posted before viral events was computed. A significant positive value would indicate that viral users posted more similar tweets after virality and thus the topics were less diverse than before. Similar computations were done for non-viral users. The differences in similarity scores were then compared to assess whether viral events impact the topic distributions of tweets.

Changes in Number and Composition of Followers

Change in the number of followers. To measure viral events' influence in follower gain, the changes in followers of viral and non-viral groups after 10 weeks of the respective first viral events were compared. To assess the long-term impact, the same comparison was made at the end of the data collection period.

Change in the proportion of 'scientist' followers. For both viral and non-viral groups, their followers who are also scientists were identified using scientist titles compiled by Ke et al. (Ke, Ahn, and Sugimoto 2017): if at least one title was found in the profile description of the followers, they were considered as scientists. The change in the proportions of scientist followers between two time points—immediately before the first viral event and at the end of data collection period—were compared using t-tests for both viral and non-viral groups.

Findings

Descriptive Statistics

We identified 1426 viral tweets that were posted by 670 users. Most of these tweets received less than three hundred retweets: $mean = 515$, $sd = 2721$, $min = 50$, $Q1 = 72$,

$Q2 = 113$, $Q3 = 243$, and $max = 63695$. There were 147 (10.3%) non-English tweets from 69 users. The number of viral events per user ranged from 1 to 18: majority of the viral users (54%, $N = 366$) had only one viral event, 132 (20%) and 65 (9%) had two and three viral events, respectively, and 63 (9.4%) had five or more viral events. During the 20-week period (10 weeks before and after viral events), the viral users posted 239,459 novel tweets where 214,330 (89.5%) of them were in English. Within the same time period, non-viral users posted 150,796 novel tweets; 121,445 (80.5%) of them were in English.

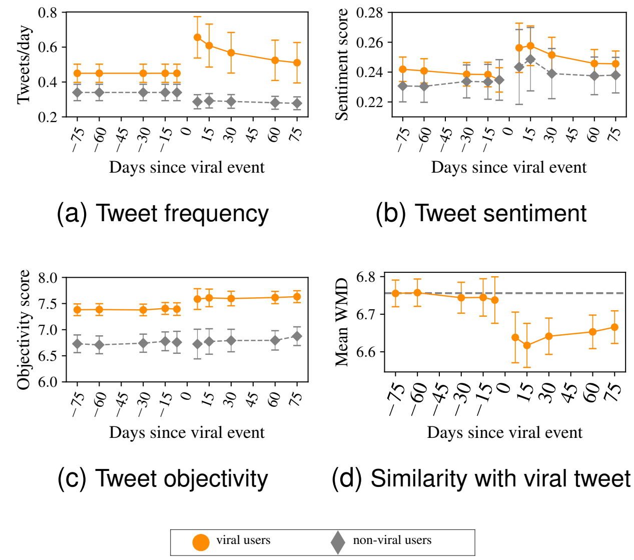
Influence of Viral Events on Behaviors

Tweet frequency. Fig. 4a shows the number of tweets per day for different time intervals before and after viral events. Immediately after experiencing virality, users increased engagement with Twitter and then tweeting frequency gradually starts to drop off. Viral users posted significantly more tweets within 7, 15, and 30 days after the viral event compared to the baseline frequency ($t = 4, 2.92, 2.3$, $d = 0.17, 0.13, 0.10$ and $p < 0.01, 0.01, 0.05$). Differences for more than the 30 day interval were not significant. In contrast, non-viral users reduced tweeting activities over time; they posted significantly lower number of tweets in all intervals compared to their baseline frequency ($t = -3.13, -2.57, -3.10, -3.06, -3.12$, $d = 0.10, 0.10, 0.10, 0.11, 0.11$ and $p < 0.05$ in all cases).

Change in tweet-sentiment. Fig. 4b shows the changes in sentiment of tweets posted within different time intervals after the first viral event date compared to the mean sentiment scores of tweets posted within 75 days before the viral events. Tweets posted by viral users within 7 and 15 days of experiencing viral events had significantly higher (positive) sentiment ($t = 2.66, 2.87$, $d = 0.15, 0.14$, and $p < .01$ in both cases) than the baseline; but after this interval it went back to the baseline level. No significant difference was found for the non-viral group.

Change in objectivity. Viral users posted tweets that were more factual and contained less subjective opinions compared to the non-viral users (Fig. 4c). The objectivity scores of their tweets went even higher after the viral events: for all intervals, the tweets had significantly higher objectivity scores compared to the tweets they posted over 75 days before the viral events ($t = 2, 2.51$, $d = 0.9, 0.9$ and $p < .05$ for 7 and 15 days; $t = 3.42, 3.91, 4.28$, $d = 0.10, 0.11, 0.12$, and $p < .001$ for 30, 60, and 75 days intervals, respectively). No difference in the objectivity score was found for the non-viral group.

Similarity of tweets with users' professional expertise. The mean Word Movers' Distance (WMD) between professional expertise and tweets posted within 75 days before viral events was 7.65 and 7.68 for viral and non-viral users, respectively. This indicates that both groups acted similarly regarding posting tweets that were related to their professional expertise. Further, for both groups, this behavior remained consistent over time after viral events and no significant change was found.



(a) Tweet frequency (b) Tweet sentiment

(c) Tweet objectivity (d) Similarity with viral tweet

Figure 4: Tweeting frequency, sentiment and objectivity of the tweets, and similarity of tweets with the viral tweet; they were measured using tweets posted within 7, 15, 30, 60, and 75 days intervals before and after the viral events. The similarity of tweets with the viral tweet was measured only for viral users, as shown in Fig. 4d where the dotted line represents the 'baseline similarity' score. Note that, in Fig. 4b and 4c, measurements (sentiment and objectivity) before the viral event (the 'baseline' measurements) are not parallel to the x-axis. This is because the comparisons were pairwise, i.e., measurements for a specific time interval after viral events for each user were compared to the baseline measurements of the same user. But not all users tweeted within a given interval (e.g., 7 days) after the viral event, and they were not considered when the means of sentiment and objectivity were computed. Thus these baseline measurements varied across the time intervals.

Similarity of tweets with viral tweet. Tweets that were posted during the surrounding days of viral events were more similar to the viral tweets (i.e., lower WMD) where the most similar tweets were posted immediately following viral events (Fig. 4d). The tweets posted within 7, 15, 30, 60, and 75 days *after* the viral event were more similar to the viral tweet compared to the baseline similarity (i.e., average similarity of tweets posted within 75 days before viral event with the viral tweet, indicated by the dotted line in the plot) ($t = -3.23, -3.89, -3.39, -3.08, -2.75$, $d = 0.20, 0.23, 0.19, 0.17, 0.15$, and $p < 0.001$ in all cases). But tweets posted within the same intervals *before* the viral events were not more similar to the viral tweet compared to the baseline similarity (all $p > 0.05$). These results suggest that similarity among tweets posted by the same user may not vary as a function of time; instead, the users may have deliberately posted tweets that were more similar to the tweet that went viral.

Diversity in tweet topics. For viral users, the average similarity in tweet topics before and after viral events were 144.37 (SD= 27.30) and 140.53 (SD=36.04), respectively. For non-viral users, the average similarity in tweet topics before and after viral events was 137.41 (SD=38.38) and 117.90 (SD=59.19), respectively. Thus, both groups had diversified tweets over time, but non-viral users did that at a significantly larger scale ($t = 6.1$, $d = 0.32$, and $p < .0001$). In other words, experiencing virality resulted in more focused tweeting in terms of topic distribution.

Impact of Viral Events on Gaining Followers

Gaining followers. After 10 weeks of the first viral event, both groups gained followers: mean = 322.9, SD = 1196, median = 133 for the viral group, and mean=66.8, SD= 162.5, median= 34, for the non-viral group. The changes in followers had log-normal distributions, as verified by conducting Kolmogorov-Smirnov tests of goodness of fit (ks = .041, .046 for viral and non-viral groups, respectively, $p > .2$ in both cases). The difference between the viral and non-viral two groups were compared using a *Mann-Whitney U* test: $u = 70339.0$, $p < 0.0001$, with a large effect-size (r=0.62) (Cohen 1988), indicating that virality indeed helps to gain more followers.

At the end of our data collection period, the average follower gain was 2,793.7 (SD = 9356.4, median = 998) for the viral group and 652.14 (SD = 2515.9, median = 283) for the non-viral group. By comparing the log-normal distributions of follower gains (ks = .036 and .035, $p > .4$ in both cases), we detected a medium to large effect (r=0.49) of virality in increasing followers ($u = 113686$, $p < 0.0001$) in the long-term.

Change in the proportion of 'scientist' followers. Before the first viral event, on average, 11.2% followers of the viral users were scientists, and at the end of the data collection period, this proportion became 10.9%. The difference between these proportions was negative and significant ($t = -2.84$, $d = 0.04$, $p < 0.001$). For non-viral users, the proportions were 9.2% and 9.3% during the same time points, but the difference was not significant ($p > 0.05$).

Robustness of the findings

To demonstrate that our findings represent true differences between the viral and non-viral groups, we conducted random-split analyses. To do this, we randomly assigned treatment and control conditions to users and again compared the three outcomes (change in followers after 10 weeks, change in followers at the end of data collection period, and change in the proportion of scientist followers) between these two groups using Mann-Whitney U test. In all cases, the effect size was negligible (0.00008, 0.01, and 0.03), and there was no significant difference between the groups (all $p > 0.1$). These results further corroborate our results.

Discussion

Developing an online-presence is becoming increasingly important for scientists and researchers. While there are many studies of how celebrities use social media and behave online, the goals of scientists are different. Celebrities engage with social media to seek publicity for their already famous public personae, and thus their actions are oriented towards projecting an intimate and relatable image while maintaining fan's expectations (Marwick and Boyd 2011). The goal of scholars are probably closer to micro-celebrities, who use social media to develop a self-brand and personally engage with their followers (Abidin 2018; Senft 2008). However, there are still big differences in the goals of micro-celebrities and scholars, and thus it is not obvious how scientists behave online. Scientists serve multiple audiences, and their professional success is tied to scientific contributions and recognition through academic citations (Kozinets 2017). In this paper we examined how scientists adjust their Twitter behavior after their first surges in visibility, which we called micro-viral events. We employed a longitudinal dataset of scientists on Twitter that captures both tweet activities and their follower network structure in time. Differently from prior studies, our definition of virality is determined in relative terms, as we seek to identify the impact of events that are 'exceptional' relative to the users' usual experiences on Twitter, and investigated how such events influenced the users' subsequent engagement with and their popularity on the platform.

Our results suggest that scientists modify their behaviors after experiencing micro-virality. We observed increased engagement with the platform: both tweeting and re-tweeting frequency surged immediately after viral events. For a short period after the viral event, we also observed that tweets expressed more positive sentiments, but reverted to normal after a few weeks. These patterns concur with our expectations. Also, the duration of these behavioral changes is consistent with our expectation that viral events are unlikely to change users' behaviors permanently as they are rather short-lived experiences.

Our results also suggest that viral users consistently posted tweets with more objective content compared to the non-viral group, which was further enhanced after experiencing a viral event. Moreover, following the event, users posted tweets that were more similar to viral tweets and focused on fewer topics. None of these behavioral changes were observed for the non-viral users who had similar profiles and tweeting patterns as the viral users until the later group experienced viral events. Since we analyzed our data using a matching-framework, these group differences may be attributable to the viral events.

These behavioral changes agree with the previously identified behaviors that are beneficial for building online reputation (Suh et al. 2010; Schnitzler et al. 2016). However, our data did not allow us to examine whether the users strategically changed their behaviors to get additional viral events and/or followers, which is an interesting direction for future research.

Finally, our analysis shows that scholars on Twitter accrued significantly more followers in the long term after experiencing micro-viral events relative to comparable non-viral scholars. While prior work has established correlations between large-scale viral events and follower-gain (Myers and Leskovec 2014), we define virality relative to the users' past experiences, and we established causal relationships between virality and the observed outcomes.

Limitations

This work has several limitations. While we collect a novel longitudinal dataset that allows us to study the evolution of users' followers and behaviors, our data is limited to a small subset of Twitter users (scientists). Personal reputation and broad impact of one's work is particularly important for career outcomes in the academia. Thus, it might have been easier to observe behaviors related to advancing one's reputation, visibility, and diffusion of work in this group of users. But, other professions may behave in a very different way that makes our results less relevant to them. Thus, the results of our work must be carefully interpreted as they may not generalize to the whole population of Twitter users.

One of our key motivations for engaging in this research was to understand how Twitter users may leverage the platform to enhance their professional reputation. In practice, we analyzed how viral events lead to an increase in the number of followers and influence users' engagement with the platform. Although the number of followers indicates 'popularity' on Twitter, and being followed and discussed by fellow scholars may result in increased scholarly reputation, we did not directly measure how one's *professional reputation* increased due to virality. Furthermore, we approximated virality as random exogenous events; but they could be the result of a deliberate strategy to increase visibility on the platform or confounded by unobserved characteristics of the users that may lead to large follower accumulations. For instance, those who provide more 'useful' information on Twitter, which would be difficult to measure, may be more likely to get more retweets and/or followers.

Finally, our analysis was limited to Twitter; but other external, unobserved factors might have influenced virality and change in behaviors and followers (e.g., popularity on other platforms or research findings being discussed in the news).

Conclusions

Online virality can have major impacts on people's lives, both positive and negative. Such events may cause significant behavioral changes, particularly if experienced for the first time. However, detecting such events is challenging as they almost always involve online platform users who are not already 'popular,' and isolating the effect of virality requires carefully controlling for other covariates. To advance in this direction, in this study, we monitored a population of scientists (N=17,157), who are known to leverage Twitter to increase professional reputation, for nearly three years. We identified 670 scientists who experienced micro-viral events for the first time in their profile's lifespan. Our definition of micro-virality purposely focuses on smaller-scale viral events that can be observed by an ordinary user (and may be insignificant for popular users), but still is an 'extraordinary' experience for the same user. We then examined how micro-viral events influenced viral users' subsequent behaviors on Twitter, and its long-term effect on their followers size and composition. To analyze the relationships between viral events and our variables of interest, we compared the evolution of users who experienced viral events to the evolution of users who did not and were (up to the point of the viral event) comparable according to our matching procedure. We found that after a viral event, users increased tweeting and retweeting frequency, posted tweets that are more objective and similar to their viral tweets, expressed a higher positive sentiment, and focused on fewer topics. Finally, viral users gained and retained followers at a higher rate than non-viral users, and virality helped scientists to reach Twitter users outside of the scientific community. Although our strategy is not without limitations, these findings may advance our understanding of how 'common' Twitter users react to 'unusual' visibility at a scale they had never experienced before. Additionally, our methodology may be leveraged by platform developers to detect viral events and increase the associated users' engagement with the platform and motivate them to improve the quality of user-generated content.

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