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Tweeting as a Marketing Tool – Field Experiment in the TV Industry

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Tweeting as a Marketing Tool – Field Experiment in the TV Industry

Abstract

Many businesses today adopt tweeting as a new form of product marketing. However, whether and how tweeting affects product demand remains inconclusive. The authors explore this question using a randomized field experiment on Sina Weibo, the top tweeting website in China. The authors collaborate with a major global media company and examine how the viewing of its TV shows is affected by (1) the media company's tweets about its shows, and (2) recruited Weibo influentials' retweets of the company tweets. The authors find that both company tweets and influential retweets increase show viewing, but in different ways. Company tweets directly boost viewing, whereas influential retweets increase viewing if the show tweet is informative. Meanwhile, influential retweets are more effective than company tweets in bringing new Weibo followers to the company, which indirectly increases viewing. The authors discuss recommendations on how to manage tweeting as a marketing tool.

Keywords: tweet; microblog; Weibo; Twitter; social media marketing; social media ROI; field experiment; television

1. INTRODUCTION

Microblogging platforms, such as Twitter in the U.S. and Weibo in China, have gained remarkable popularity. The central feature of microblogging is called "tweets", which are short posts disseminated from registered users to their followers. In 2013, the year of its initial public offering, Twitter's users posted approximately 500 million tweets a day, and Weibo users posted more than 100 million. Drawn to this high traffic, many companies are adopting tweeting as a new marketing tool. In 2015, 78% of Fortune 500 companies had active presence on Twitter,[1] while 960,000 business accounts were operating on Weibo.[2]

It remains unclear, however, whether tweeting indeed helps companies increase the demand for their products. We explore this question in this paper. In particular, we focus on two common types of tweeting activities relevant to product demand. First, a company may tweet about its own product to its followers. Second, some users exposed to the company tweet may forward – or "retweet" – this message to their own follower network. We investigate how company tweets and user retweets influence product demand.

It is challenging to answer this question using naturally occurring data. There are often multiple explanations for the correlation between tweets and demand. For example, a positive correlation between company tweets and demand may be driven by the company's increased attention to product promotion. A positive correlation between user retweets and demand may arise if the product is a much anticipated new release that consumers are eager to experience and tweet about. These alternative explanations confound the causal effect of tweets on demand.

In this study, we aim to identify the causal effect of tweets on product demand using the controlled field experiment approach.[3] We conduct a field experiment on Weibo with a major global media company that produces documentary television (TV) shows. The media company

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[1] Source: http://www.umassd.edu/cmr/socialmediaresearch/2015fortune500/.
[2] Source: 2015 Weibo Business White Paper.
[3] See List and Reiley (2008) and Simester (2017) for reviews of the field experiment approach.

broadcasts one show on seven local channels each day, and uses Weibo as the main promotional platform. Our primary experimental design involves random allocation of TV shows into three experimental conditions. In the control condition, the media company posts no tweets about the show and, naturally, no user retweets. In the "Tweet" condition, the company posts a tweet about the show of the day. In the "Tweet & Retweet" condition, the company posts a tweet about the show; in addition, an active and impactful Weibo user, also known as a "Weibo influential," is recruited to retweet the company's message. We track the percentage of local audiences viewing each show as a measure of show demand.

We find that both company tweets and influential retweets effectively increase show viewing. On average, if the media company tweets about a show, viewing of the show increases by 77%; if an influential retweets the company tweet, viewing increases by an additional 33%. The effect of influential retweeting is especially strong (a boost of viewing by 57% as opposed to 33%) if the original company tweet contains detailed broadcast information of the show. Furthermore, influential retweets help grow the company's base of followers on Weibo, which in turn amplifies the effect of company tweets on show viewing. These findings suggest the following behavioral mechanism: company tweets increase show viewing by influencing its own followers; an influential's retweet increases show viewing by informing his/her followers about the show, and by bringing new followers to the company. Influentials who are actively retweeted by their own followers are especially effective in this process.

The finding that tweeting increases product demand, at least in the context of TV viewing, is encouraging news to businesses who have turned to tweeting as a new marketing tool. We identify two effective tweeting strategies: tweet about a company's own product, and hire influential users to retweet. The former strategy parallels the classic marketing activity of firm-generated advertising. The latter strategy, less conventional as it sounds, echoes another familiar marketing activity – celebrity endorsement. Our results suggest that, to use this latter strategy effectively, businesses should make their product tweets informative and make purchase easy for new customers. Meanwhile, businesses should consider collaborating with influentials who are actively retweeted in their follower network.

Our results are also relevant to microblogging platforms, for which the question of optimal revenue model has attracted much attention. For example, Twitter's major revenue source has been paid advertising (Koh 2016). The sustainability of this model has raised concerns. Forbes, for instance, identifies the problem with Twitter's business model as "the best interests of the users (i.e. quick, easy access to the content of their choosing) are not aligned with the best interests of advertisers (i.e. getting more attention of users not necessarily looking for them)" (Trainer 2016). Our findings suggest that charging a fee for businesses to open accounts on Twitter could be another revenue model. By following a business account, users are opting to let the business send promotional tweets to them, as opposed to receiving third-party advertisements they did not sign up for. The fact that businesses can effectively grow demand through tweeting, in turn, provides the economic rationale for the platform to require a transfer payment.

The rise of microblogging has spurred active research in computer science, information systems, operations management, statistics, and economics. A range of topics have been examined, including the effect of mobile technologies (Ghose et al. 2012), structure of diffusion networks (Goel et al. 2012), influence of Twitter word of mouth (Rui et al. 2013), drivers of tweeting (Shi et al. 2014), prediction of tweet popularity (Zaman et al. 2014), and impact of Twitter presence on political outcomes (Petrova et al. 2016).[4] Marketing researchers are also paying increasing attention to the microblogging phenomenon, exploring issues such as noncommercial users' motivation to tweet (Toubia and Stephen 2013), drivers of content transmission (Stephen et al. 2014), targeting of promoted tweets (Lambrecht et al. 2015), customer-firm interaction on Twitter (Ma et al. 2015), brand image mining using Twitter data (Culotta and Cutler 2016), social TV activity (Fossen and Schweidel 2016), effect of company tweeting on word of mouth (Kuppuswamy and Barry 2016), demand forecasting using cloud computing of Twitter data (Liu

[4] See http://www.danah.org/researchBibs/twitter.php for a bibliography of research on microblogging.

et al. 2016), paid, earned, vs. owned media (Lovett and Staelin 2016), and effects of content, content-user fit, and influence on retweeting (Zhang et al. 2016). In a recent paper, Seiler et al. (2016) leverage a natural experiment, the temporary shut-down of Weibo, to study the effect of online word of mouth on the demand for TV shows. Our paper differs from and contributes to this literature by explicitly studying the impact of commercial tweets on product demand.

There is a vast literature on social media. However, companies are still struggling to understand the effect of various social media marketing strategies on tangible performance metrics such as product demand (Cespedes 2015). A burgeoning line of research explores this question.[5] Findings to date include: firm-created word of mouth influences sales (Godes and Mayzlin 2009), viral product design facilitates diffusion (Aral and Walker 2011), viral marketing boosts customer acquisition (Hinz et al. 2011), pre-launch advertising and blogging synergistically influence movie sales (Onishi and Manchanda 2012), traditional and social earned media interact to affect microlending (Stephen and Galak 2012), firm-generated social media content encourages customer spending and cross-buying (Kumar et al. 2016), and firm-solicited Facebook "likes" influences customer involvement offline (Mochon et al. 2016). We contribute to this literature by showing that tweeting can be a productive social media marketing strategy to increases product demand and by offering recommendations on how to use this strategy effectively.

2. FIELD EXPERIMENT

2.1. Background

To examine the causal effect of tweets on product demand, we collaborate with a major global

[5] A related stream of research studies the effect of digital marketing, which not necessarily involves social media, on tangible performance metrics. Findings include: banner ads affect online repurchase (Manchanda et al. 2006), advertising the size of the user base influences user participation (Tucker and Zhang 2010), retargeted and generic ads affect purchase differently (Lambrecht and Tucker 2013), online ads grow the offline channel (Dinner et al. 2014), online display ads increase offline sales (Lewis and Reiley 2014), paid search ads increase infrequent buyers' purchases (Blake et al. 2015), online display ads influence various stages of the purchase funnel (Hoban and Bucklin 2015), targeted mobile ads generate purchases especially in crowded environments (Andrews et al. 2016), and emailed discount offers boost customer expenditure through price discrimination and advertising (Sahni et al. 2016).

media company to conduct a field experiment on the leading Chinese microblogging website Weibo.com. In this section, we provide background information about Weibo and the media company, and discuss features of the experiment setting that help answer our research question.

Weibo.com is a Chinese microblogging website owned by Sina Corporation. It provides a set of user functions akin to Twitter. A key function is "tweet", which allows users to send a text message within 140 characters and multimedia elements such as image, music, and video. A second function is "retweet", which allows users to forward and optionally comment on other users' tweets. Another key function is "follow", which allows users to subscribe to other users' tweets. The subscribers are called "followers" and the tweets of their followees would automatically appear on their home pages.

Launched in August 2009, Weibo rapidly gained nationwide popularity in China. In 2012, the year of the experiment, the number of registered users and monthly active users increased by approximately 150 million and 16 million, respectively (See Table W1 of the Web Appendix for an overview). By the end of 2012, there were more than 500 million registered users and approximately 46 million monthly active users. About 130 million tweets were generated each day on Weibo. At an Alexa rank of 17, Weibo began public trading in April 2014.

The rise of Weibo has attracted many businesses to explore it as a marketing platform. The company we collaborate with is one of the pioneers.[6] This company is a major global media company that produces documentary TV shows for worldwide audiences. In China, the company's shows are translated into Chinese and mainly broadcast on seven local channels: Shanghai, Tianjin, Wuhan, Guangzhou, Hangzhou, Chongqing, and Fuzhou. One show is broadcast each day and the show is identical for all channels. Audiences of the TV shows in these markets are 60% male, 40% female, and typically 25 to 54 years old.

The company created a business account on Weibo in October 2010. Since then, each day the

[6] The name of the media company and its products are kept anonymous based on a confidentiality agreement.

company had been posting one tweet about the show of that day and several noncommercial tweets. These noncommercial tweets, usually including interesting stories and pictures about science, technology, nature, history, etc., were aimed to engage the company's existing followers and attract new followers without explicitly advertising a particular show (see Figure W1 of the Web Appendix for an example). Right before the field experiment, the media company had posted 2,268 tweets and attracted 125,056 Weibo followers.

The experiment setting has several desirable features. First, the effect of marketing on tangible market outcomes is measurable. For the media company, the key outcome measure is show viewing, which we are able to track. Second, the company uses Weibo as its primary marketing platform in China, which helps attribute changes in demand to tweets. Third, shows are broadcast on the same day of company tweets and influential retweets (if any). This helps us investigate the immediate effect of social media marketing on firm performance. Finally, the contractual arrangement between the media company and the local channels facilitates natural separation of show demand across channels. For example, the audience in Shanghai can only watch the company's shows on the Shanghai channel. This feature allows us to implement further between-subject design across channels (details to follow).

2.2. Experimental Design

Our experimental design consists of two levels. The primary design is across TV shows, aiming to measure the main effects of company tweets and influential retweets on show viewing. The secondary design is across TV channels, aiming to provide a falsification test of the main results and explore the underlying behavioral mechanism.

2.2.1. Primary Design: TV Show Level

The primary design of the experiment involves assigning TV shows into three conditions. Below we describe the conditions, the randomization strategy, and the recruitment of influentials.

TV shows are randomly assigned into three conditions: control, Tweet, and Tweet & Retweet. Shows assigned to the control condition are neither tweeted by the company nor retweeted by an influential. Shows in the Tweet condition are tweeted by the company. The company tweet follows a fixed format including three parts (see Figure W2 of the Web Appendix for an example): a short text that contains a brief introduction of the show and a reminder for the audience to watch the show, a show relevant picture, and broadcast information of three TV channels (details to follow). In the Tweet & Retweet condition, a show is not only tweeted by the company but also retweeted by a recruited influential. The influential retweet includes a forwarded copy of the original company tweet and some comments on the show (see Figure W3 of the Web Appendix for an example). The comments are pre-designed to include a brief personal description of the show and a short recommendation such as "Don't miss the show today" or "Check out this show today."

During the experiment, a total of 98 TV shows are randomly assigned into the three experimental conditions. Table 1 summarizes the conditions and the number of shows assigned to each condition. The number of shows assigned to the control condition is determined in discussion with the media company; the goal is to build a control group of sufficient size while maintaining an active level of Weibo promotion for the TV shows.[7]

[Insert Table 1 about here.]

We implement a two-step randomization strategy to assign the shows into the three conditions. In the first step, we randomly select 14 shows for the control condition. Specifically, we use a Latin square design to make sure that shows in the control condition are dispersed evenly across week and day of week. In the second step, we randomly select 42 shows for the Tweet condition and assign the remaining 42 shows into the Tweet & Retweet condition. We verify that each condition is present in each week and on each day of week during the experiment. This allows us

[7] Limiting the size of the control group should not bias our results and should only make the test more conservative because the comparison between the treatment and the control conditions has less statistical power.

to subsequently control for unobservable week effects and day-of-the-week effects. Figure W4 of the Web Appendix presents more details of the randomization strategy.

We need to recruit Weibo users to retweet the company's show tweets in the Tweet & Retweet condition. We could in theory involve average users. In fact, the literature has shown that ordinary peers can be influential (e.g., BenYishay and Mobarak 2015). However, because the company's tweets tend to be retweeted by many, recruiting another average user to retweet is unlikely to generate a detectable exogenous shock in our experiment. Logistically, the media company also wants to target a few "key opinion leaders" as opposed to many average users. Hence we focus on impactful Weibo users. Some of these users are actual celebrities. We deliberatively avoid recruiting actual celebrities for two reasons. First, any effect of their tweets on show viewing may be attributed to their celebrity status outside of Weibo. Second, their tweets often attract the attention of other media outlets. If these media outlets in turn feature a celebrity's retweet of a show, they essentially engage in secondary promotion of the show, which confounds the treatment effects. Therefore, we choose to recruit "grass root influentials," who are ordinary people but who have gained impact on Weibo through tweeting. To operationalize Weibo impact, we draw on previous research (e.g., Goldenberg et al. 2009; Trusov et al. 2010; Stephen et al. 2014) and require qualified influentials to: (1) have many followers, (2) tweet actively, and (3) be retweeted actively by their followers.

We collaborate with a Weibo advertising agency to identify influentials who meet our criteria. A total of 42,000 CNY (6,790 USD) is spent to recruit 42 influentials, or 1,000 CNY (162 USD) each. We randomly assign different influentials to different shows. This allows us to examine the effect of influential characteristics on retweeting efficacy. It also allows the company to reach a broader audience through influential retweeting. Table 2 presents the summary statistics of the influentials recruited for our experiment. On average, these influentials each have over 2 million followers, post 45 tweets per day, and each tweet is retweeted 729 times by their followers.

[Insert Table 2 about here.]

2.2.2. Secondary Design: TV Channel Level

As mentioned earlier, the geographical separation of show viewing across TV channels provides us an opportunity to implement a second layer of design at the channel level.

The first important feature we exploit is that the same TV show is broadcast at different times for different channels. We set the timing of company tweets and influential retweets before the shows' broadcasting time on five channels and after their broadcasting time on the other two channels.[8] Specifically, Shanghai, Tianjin, Wuhan, Guangzhou, and Hangzhou are "treated channels," because treatments occur before the shows' broadcasting, so that show viewing on these channels is expected to be affected by company tweets and influential retweets. On the contrary, Chongqing and Fuzhou are "untreated channels," because treatments occur after broadcasting, so that show viewing should not be affected by company tweets or influential retweets. This fact allows us to perform a falsification test of the treatment effects.

The separation of show viewing across channels also allows us to explore the effect of tweet content. Although the company posts the same show tweet for all channels, we are able to vary the informativeness of the company tweet across channels by selectively displaying broadcast information of three channels (see bottom of Figure W2 of the Web Appendix). For example, if we display broadcast information of the Shanghai channel, the same company tweet will be more informative to the Shanghai audience. One issue is that we need to create within-channel variation in tweet informativeness in order to include channel fixed effects in subsequent analysis. Therefore, we divide the experiment window into two halves. During weeks 1-7, we display broadcast information of Shanghai, Tianjin and Wuhan in company tweets. During weeks 8-14, we switch Guangzhou and Hangzhou from the not-display group with Tianjin and Wuhan from the display group, so that all permutations of display and not-display are implemented. Table 3 summarizes the design at the TV channel level.

[8] Company tweets are posted at 11:00 am and influential retweets are posted at noon.

[Insert Table 3 about here.]

2.3. Procedure and Data

The field experiment ran for 14 weeks, from August 20 to December 2, 2012.[9] During this period, we ensured that the media company's other Weibo activities remained constant and balanced across conditions, that the media company engaged in no marketing activities outside Weibo, and that Weibo implemented no feature changes. Two datasets were collected during the experiment: a show viewing dataset, and a tweet diffusion dataset.

Show viewing data. From the media company's perspective, the key performance measure is show viewing. We obtained show viewing data from CSM Media Research, a joint venture between CTR Market Research and Kantar Media. Beginning its service in 1996, CSM has become a leading TV viewing data supplier that offers reliable and uninterrupted TV viewing information in the China market. As of December 2012, CSM has built one of the world's largest TV audience measurement networks, representing 1.27 billion TV household members in mainland China and 6.4 million in Hong Kong. Using the People Meter Method, the measurement network provides TV household members' daily TV viewing data by channel, covering almost all primary cities in China. We provide more details about this data in the Web Appendix.

Our sample includes 98 shows from the media company broadcast on the seven local channels. CSM provided data on the percentage of the audience of each channel who watched a particular show on a given day (also known as "ratings point" of a show on a channel in the TV industry). Table 4 summarizes viewing percentage by experimental condition. Figures W5, W6, and W7 of the Web Appendix plot viewing percentage by experimental condition, by channel, and over time. Altogether, the show viewing data contain $98 \times 7 = 686$ observations where each observation is a show-channel combination. Of these observations, 490 are from treated channels and 196 from

[9] We suspended the experiment during the Chinese National Holiday (October 1 through 7) because most of the shows were replaced by other holiday-related programs.

untreated channels. On average, .0966% of the audience of a local channel watched a show during the experiment period. A comparison across conditions reveals the raw treatment effects. The average percentage of the audience watching a show is .0599% in the control condition, which increases to .0971% in the Tweet condition and .1083% in the Tweet & Retweet condition. Both increases are statistically significant (p-values being .002 and .000, respectively). These increases are even more pronounced if we look at treated channels where we expect to see the treatment effects (p-values being .001 and .000, respectively), but are insignificant over untreated channels (p-values being .302 and .708, respectively). These patterns provide the first evidence that company tweets and influential retweets increase show viewing.

[Insert Table 4 about here.]

Tweet diffusion data. Using Weibo application program interface (API), we developed a software package to track the diffusion of each show tweet and its retweets, as well as the media company's noncommercial tweets and number of followers each day of the experiment.

Table 5 presents summary statistics of the diffusion of show tweets in each condition. The number of retweets measures the total number of times a show tweet is retweeted on Weibo. These retweets include recruited influentials' retweets of show tweets (if any), further retweets of these influential retweets, and organic user retweets without involvement of recruited influentials. The number of impressions measures the number of users exposed to a show tweet either directly or indirectly through retweeting. Diffusion depth measures the maximum number of layers of follower networks a show tweet reaches. All these measures equal zero in the control condition by design, and are remarkably different between the two treatment conditions. The average number of retweets, number of impressions, and diffusion depth in the Tweet & Retweet condition are approximately 5 times, 20 times, and 1.5 times their counterparts in the Tweet condition. All these differences are highly significant (all p-values being .000). The difference in the number of retweets seems to be mainly driven by retweets of influential retweets. In fact, the number of organic retweets does not differ significantly between the two treatment conditions

(t=1.09, p=.279), which is expected given the random assignment of shows across conditions. These initial statistics reveal that the participation of influentials plays an important role in the process of show tweet diffusion, which is consistent with findings from previous research (e.g., Goldenberg et al. 2009). Whether these effects translate into show viewing needs further study, a question we explore in subsequent analysis.

[Insert Table 5 about here.]

Besides the diffusion of show tweets, we collected data on the number of noncommercial tweets posted by the company each day to control for the company's other Weibo activities. The company posted an average of 2.8 noncommercial tweets a day during the experiment, with a standard deviation of 1.78. The number of noncommercial tweets per day does not differ significantly across conditions (p=.689) and is consistent with the level before the experiment.

Finally, we tracked the number of company followers to measure the size of the audience directly exposed to company tweets. Figure W8 of the Web Appendix shows that the number of company followers increased from around 125,000 to around 153,000 over the span of the experiment. The figure also plots the daily change in the number of company followers across experimental conditions. Table 6 summarizes the corresponding statistics. In the control group, on average the company gains 259 followers each day. Compared with this baseline level, the daily increase is only 237 in the Tweet condition although the difference is insignificant (p=.662), and is 335 in the Tweet & Retweet condition, which significantly exceeds the baseline value (p=.012). These results suggest that influential retweets are likely more effective in growing company followers than company tweets. We will further assess this argument in the next section.

[Insert Table 6 about here.]

3. ANALYSES AND RESULTS

In this section, we analyze whether and how company tweets and influential retweets affect show viewing. We begin by identifying the effect of tweeting on show viewing. We explore the mechanism using variations in the informativeness of company tweets and the number of company followers. We then check the robustness of the results with respect to other dependent variables and prior TV viewership, and corroborate the findings using difference-in-differences analysis. We conclude by assessing the magnitude of the tweeting effect, calculating the company's return on tweeting, and discussing possible reasons and boundaries of the findings.

3.1. Does Tweeting Affect Show Viewing?

Our main question is whether company tweets and influential retweets affect show viewing. To answer this question, we rely on the following identification strategies. First, we exploit the random assignment of shows into the three experimental conditions to assess the treatment effects of company tweets and influential retweets. Second, to address the possibility that show characteristics are not fully balanced across conditions, we include a rich set of show control variables into the regression analysis. Finally, to address the possibility that unobserved show characteristics are not fully balanced across conditions, we conduct a falsification test using a unique feature of the experimental setting – that only a strict subset of channels are treated.

To measure the treatment effects, we begin with regression analysis using data from the five treated channels. An observation is a show-channel combination. The dependent variable is the percentage of a channel's audience viewing a show. The key independent variables are *Tweet*, and *Tweet & Retweet* dummy variables indicating whether the show is in the Tweet condition, or the Tweet & Retweet condition, respectively. In addition, we include as control variables the number of noncommercial tweets posted by the company on the day of the show, as well as a series of dummy variables to capture the effects of channel, time, and show characteristics.[10]

Table 7 reports the results. Column (1) presents the result when the two treatment dummies are the only independent variables. Columns (2)-(5) in a stepwise fashion introduce control variables

[10] Note that show fixed effects cannot be estimated separately from the condition dummies.

that may influence show viewing. Specifically, column (2) controls for the company's other Weibo activities using its number of noncommercial tweets on the day of the show; column (3) in addition controls for cross-channel variations with channel dummies; column (4) adds week and day-of-week dummies to capture unobserved time effects; and column (5) further includes a dummy variable indicating whether a show is a serial show, as well as episode and genre dummies. For all columns, we report OLS estimates with robust standard errors clustered at the show level to account for heteroskedasticity and dependence within a show.

[Insert Table 7 about here.]

The specification reported in column (5) with all control variables included is our "main model," but the qualitative and quantitative results are comparable across all five columns. The coefficients of *Tweet* and of *Tweet & Retweet* are both positive and significant at the $p<.01$ level for all specifications, suggesting that shows in both treatment conditions are associated with higher viewing compared with shows in the control condition. In addition, the coefficient of *Tweet & Retweet* is significantly higher than that of *Tweet* ($p=.039$ in the main model), which shows that influential retweeting has a significant incremental effect on show viewing.[11]

Despite our best efforts to randomly assign shows into conditions, show quality may not be perfectly balanced across conditions – the sample includes 98 shows and 98 is certainly not infinity. We have controlled for potential differences in observed show characteristics by including a rich set of control variables (Table 7). However, there may be unobserved differences in show quality. If a show with unobserved high quality were included in a treatment condition, we would have spuriously attributed its active viewing to the treatment. Fortunately, we can test this competing explanation with a falsification check. Recall that there are two untreated channels that broadcast the shows before the time of both treatments. If the unobserved-show-quality explanation were true, the spurious treatment effects would have

[11] We report p-values based on one-tailed tests because the hypothesis that influential retweets increase show viewing in addition to company tweets is unidirectional.

appeared on these two untreated channels as well. We therefore re-estimate the models in Table 7 using viewing data from the two untreated channels only. Table 8 reports the results. The coefficients of *Tweet* and *Tweet & Retweet* are both small and insignificant in all specifications, thus ruling out the alternative explanation that unobserved show quality drives show viewing.

[Insert Table 8 about here.]

To further rule out the possibility that the insignificant estimates in Table 8 are driven by the smaller sample size of the untreated channels, we re-estimate the models in Table 7 based on the combined sample of treated and untreated channels. We add a dummy variable *Treated* to indicate whether an observation comes from treated channels. Table W2 of the Web Appendix presents the results. The interaction terms, *Tweet* × *Treated* and *Tweet & Retweet* × *Treated*, are both positive and significant, and their difference is significant at the $p<.05$ level. Meanwhile, the effects of *Tweet* and *Tweet & Retweet* remain small and insignificant. These results confirm our finding that company tweets and influential retweets significantly increase show viewing, but only on treated channels.[12]

3.2. How Does Tweeting Affect Show Viewing?

3.2.1. Tweeting as Informative Advertising

In this section, we explore the mechanism by which company tweets and influential retweets affect show viewing. As discussed before, cross-channel variation in the informativeness of tweets provides a first test. Specifically, for each show, the company tweet only contains broadcast information for a strict subset of channels, which makes the same company tweet and its retweet by an influential more informative to audiences of these channels than others.

To examine the effect of tweet informativeness, we re-estimate the main model except that we add the following independent variables: a *Display* dummy indicating whether a channel is

[12] To facilitate presentation, we retain our focus on treated channels in subsequent analysis.

selected to display broadcast information in the company tweet, and two interaction terms, *Tweet* × *Display* and *Tweet & Retweet* × *Display*, to capture the moderating effects of displaying broadcast information on the treatment effects.[13]

The results appear in columns (1) and (2) of Table 9. The main effect of *Display* is insignificant, which suggests that displaying broadcast information on average does not affect show viewing. The interaction term *Tweet* × *Display* is insignificant, meaning that displaying broadcast information does not affect show viewing when shows are only tweeted by the company. However, the interaction term *Tweet & Retweet* × *Display* is positive and significant at the p<.05 level, suggesting that, when shows are both tweeted by the company and retweeted by an influential, displaying broadcast information increases show viewing.

[Insert Table 9 about here.]

To see this effect from another perspective, we stratify the sample based on whether the company tweet displays a channel's broadcast information. We re-estimate the main model for these two subsamples and present the results in columns (3) and (4) of Table 9. Both treatment effects are positive and significant for both subsamples. Moreover, the incremental effect of influential retweets, as captured by the difference between these two treatment effects, is significant (p=.043) for the subsample with broadcast information and insignificant (p=.189) for the subsample without. This result again suggests that displaying broadcast information amplifies the incremental effect of influential retweets on show viewing.

The effect of displaying broadcast information can be understood as follows. The audience of a company tweet consists of the company's Weibo followers. By choosing to follow the company, these users presumably are familiar with the company's shows or have watched them in the past. Providing broadcast information to these users is thus unlikely to drastically increase their tendency to watch a show. On the other hand, the audience of an influential retweet consists of

[13] The *Display* dummy and its interactions with the treatment dummies are empirically identified because, as shown in Table 3, *Display* is defined at the channel-time level, while the treatment dummies are defined at the show level.

followers of the influential. Some of them may be new to the show, but become interested after seeing the influential retweet. For these users, broadcast information facilitates viewing, thus bridging the gap between intention and action. These findings suggest that tweets and retweets serve, at least in part, as informative advertising, and the information is particularly helpful in attracting audiences less familiar with the company to watch the show. This result complements early research on the role of informative advertising in the TV industry (e.g., Anand and Shachar 2011) and on the benefit of targeting uninformed users with informative advertising (e.g., Blake et al. 2015). It also extends past studies on influentials as information disseminators by showing that their effectiveness depends on the informativeness of the contents being disseminated (e.g., Watts and Dodds 2007; Goldenberg et al. 2009; Hinz et al. 2011).

3.2.2. Company Followers

We have seen that the effect of tweeting depends on the audience. In this section, we focus on the audience of company tweets – the company's followers. We ask how the number of company followers moderates the effect of company tweets, and what drives users to follow the company.

To measure the moderating effect of company followers on company tweets, first we transform the main model to separate out the effects of company tweets and influential retweets. In place of the treatment dummies *Tweet* and *Tweet & Retweet*, we include a *Company tweet* dummy which equals 1 if the show is tweeted by the company (which holds for shows in both treatment conditions), and an *Influential retweet* dummy which equals 1 if the show is in addition retweeted by an influential. We then introduce two interaction terms: *Company tweet × Lag Followers* and *Company tweet × Lag ΔFollowers*, where *Lag Followers* is the cumulative number of company followers by the end of the previous day and *Lag ΔFollowers* is the change in the number of company followers on the previous day, both in thousands.[14] Strictly speaking,

[14] Because company tweets and influential retweets occur early in the day, both *Lag Followers* and *Lag ΔFollowers* are measured with a one-day lag. We thus exclude data on the first day of the experiment from the regressions. We should in theory include *Lag Followers* and *Lag ΔFollowers* in the regressions. However, these variables are highly correlated with their corresponding interaction terms. The variance inflation factors (VIFs) are greater than 25, exceeding the conventional cutoff value of 10 (Hair et al. 2010). If we introduce the terms one by one, the main

the number of followers is endogenous, hence its effect should be interpreted as correlational. However, we mitigate this concern by using lagged values to rule out the possibility that contemporaneous shocks affect both the number of followers and show viewing on the same day.

Table 10 presents the results. Column (1) is essentially the same as the main model, which is expected because the recoding of the treatment dummies should not change the results. In columns (2)-(4), the interaction term *Company tweet × Lag Followers* is insignificant, suggesting that the effect of company tweets on show viewing is not significantly moderated by the cumulative number of company followers. This is true even if we divide the sample based on whether the company tweet displays broadcast information of the show. Column (5) on the other hand reveals a new pattern. The interaction term *Company tweet ×Lag ΔFollowers* is significant at the p<.10 level, implying that the number of newly subscribed company followers does moderate the effect of company tweets on show viewing. Columns (6) and (7) further indicate that *Company tweet ×Lag ΔFollowers* is significant only if the company tweet contains broadcast information of the show. This result echoes our earlier finding: informative company tweets are disproportionately effective in attracting newly subscribed company followers, who are more likely to need broadcast information, to watch a show.

[Insert Table 10 about here.]

The results above suggest that newly subscribed company followers play an important role in increasing show viewing. A natural question then is what affects the number of company followers. Summary statistics in Table 6 suggest that influential retweets are effective. We turn to regression analysis to explore the question in greater detail. Table 11 presents the results. The dependent variable is the change in the number of company followers each day. For column (1), the independent variables are the *Company tweet* and *Influential retweet* dummies. Column (2) adds the company's number of noncommercial tweets of the day. Column (3) further includes the

effects are insignificant. Therefore, Table 10 reports the results with only the interaction terms included. We have also expanded the specification to include the change in the number of company followers two days before the show, and its effect is insignificant.

viewing percentage of the show averaged across channels.[15] The idea is that popular shows may spur more discussions on Weibo and attract other Weibo users to follow the company. Across all specifications, company show tweets have a negative but insignificant effect on the number of company followers, whereas influential retweets have a positive and significant effect. Although show popularity does not seem to significantly increase the number of company followers, the company's noncommercial tweets do, a result consistent with the company's goal to engage users by posting entertaining tweets that are not specifically related to its shows.

[Insert Table 11 about here.]

3.2.3. Heterogeneous Effects of Influential Retweets

The fact that influential retweets bring new followers is good news to businesses, who can recruit influentials to grow their follower base. But what type of influentials should companies target? We have data on the attributes of the recruited influentials to help answer this question. Specifically, for each influential we recruited, we collected data on the number of followers, the daily number of tweets, and the number of follower retweets prior to the start of the experiment. Because of the large disparity in scale across these attributes (Table 2), in subsequent regressions we use median split to transform these variables into dummy variables to facilitate interpretation of the results. We create three dummy variables: *Has many followers*, *Tweets actively*, *Retweeted actively*. Each variable equals 1 if the corresponding value is above its median level.

To see how these attributes moderate the impact of influential retweets on company followers, we expand specification (3) of Table 11 by interacting attribute dummies with *Influential retweet*.[16] One potential problem is that some attribute variables are highly correlated (e.g. the correlation between *Has many followers* and *Retweeted actively* is .82). Reassuringly, however,

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[15] To circumvent the possibility that contemporaneous shocks drive both company following and show viewing, we run a regression using the average viewing percentage of the show on the previous day instead. We also run a regression using average show viewing percentage across channels weighted by each channel's TV population. The results are similar to column (3) and the coefficient of show viewing percentage remains insignificant.

[16] The main effects of influential attributes cannot be separately estimated because their effects are only activated if *Influential retweet*=1.

we compute the variance inflation factors (VIFs) and find that all VIFs are below the conventional cutoff value of 10 (Hair et al. 2010), with the highest being 3.43 on *Influential retweets* × *Has many followers*. Nevertheless, to mitigate multicollinearity concerns, we also introduce the interaction terms to the regression one by one.

Table 12 presents the results. The qualitative insight remains the same across specifications. Retweets by influentials who have more followers and who are retweeted more actively are more effective in bringing new followers to the company. Retweets by influentials who tweet actively are less effective. These results are intuitive. That fact that an influential is enthusiastically followed and retweeted suggests impact in his/her follower network. Meanwhile, if an influential posts a large volume of tweets each day, this dilutes the "tweet share" allocated to the company.

[Insert Table 12 about here.]

Finally, for completeness, we examine the heterogeneous effects of influential retweets on show viewing. We include a fourth influential attribute *Local*, a dummy variable that indicates whether the influential is located in the same city as the channel.[17] Table W3 of the Web Appendix presents the results. Among the interaction terms, *Influential retweets* × *Retweeted actively* is positive and significant (p<.01) especially in the subsample where broadcast information is displayed. In addition, *Influential retweets* × *Local* is positive and significant (p<.10) for the displayed subsample. Intuitively, influential retweets are more effective at increasing show viewing if the influential's tweets are more actively shared in his/her follower network, if broadcast information is displayed such that interested users know how to watch a show, and if the influential is local which plausibly makes his/her retweet more relevant.[18] These results corroborate and complement findings reported earlier in this paper.

3.3. Robustness Checks

[17] We do not study the relationship between *Local* and company followers. *Local* is measured at the show-channel level whereas the number of company followers is constant across channels.

[18] The effect of influentials' location is consistent with findings from the literature that the impact of the internet often depends on the offline setting (see Goldfarb 2012 for a review).

In this section, we verify that the effects of tweeting on show viewing are robust with respect to a number of alternative specifications. In the interest of space, we will focus on reporting robustness checks of the main model presented in column (5) of Table 7.

3.3.1. Addressing the Truncated Nature of the Dependent Variable

One technical issue is that the dependent variable, the percentage of a channel's audience viewing a show, is truncated below zero. In other words, even if a consumer has a strong dislike for a show, her show consumption cannot be negative. We address this issue by performing a Tobit transformation of the dependent variable (Tobin 1958). The idea is to specify a linear relationship between the independent variables and an unobservable latent variable – same way we specify a linear relationship between the independent and dependent variable in the analysis so far – but allow this latent variable to equal the observed dependent variable only if it is nonnegative; if it is negative, the observed dependent variable equals zero.[19] Column (1) of Table 13 reports the Tobit estimation results of the main model. Reassuringly, compared with their OLS counterparts, all independent variables in the Tobit model retain the same sign and remain close in both significance and magnitude. We keep the OLS specification for most of the paper because it allows for more direct presentation of effect magnitude.

[Insert Table 13 about here.]

3.3.2. Number of Viewers as Dependent Variable

Although viewing percentage is the key performance index for the media company, it does not reflect the variation of audience population across channels. To check whether this affects our conclusions, we transform show viewing percentage into the number of viewers. To do so, we obtain data on the total number of TV household members (i.e., "TV population") for each of the

[19] Theoretically speaking, viewing percentage is also bounded above by 100%. Empirically, however, viewing percentage in our sample tends to be small, with the maximum value being .73% (Table 4). Indeed, a model that allows observed viewing percentage to be bounded between 0 and 100% yields the same result as the Tobit model.

seven channels in our sample.[20] We then multiply TV population with viewing percentage, the dependent variable used in the main analysis, for each show on each channel. Table W4 of the Web Appendix presents the summary statistics of TV population, viewing percentage, and the number of viewers per show by channel and by condition. Figure W9 of the Web Appendix presents the distribution of the number of viewers per show.

We re-estimate the main model using the number of viewers as the dependent variable. In addition, we estimate a fixed effects Poisson model to accommodate the "count data" nature of the number of viewers (Wooldridge 1999). Columns (2) and (3) of Table 13 report the estimation results. For both specifications, our main conclusion continues to hold – both tweeting and retweeting significantly increase the number of show viewers.

Translating viewing percentage into the number of viewers also allows us to calculate the "conversion rate" of the tweeting campaign. Across the five treated channels, the average number of viewers per show is 43,038 in the control condition, 71,279 in the Tweet condition, and 82,094 in the Tweet & Retweet condition (Table W4). The average number of impressions is 0, 160,522, and 3,238,494 for the three conditions, respectively (Table 5). Using the value in the control condition as the common benchmark, the impression-to-view conversion rate is 17.59% for the Tweet condition, and 1.21% for the Tweet & Retweet condition. This result is consistent with our finding that exposure to show tweets has a strong effect on the company's existing followers. Influential retweets effectively facilitate the diffusion of show tweets, but these newly exposed users have more diluted interest – only a fraction of them end up watching a show.

3.3.3. Controlling for Prior Viewership

Previous studies on the TV industry find that people's TV viewing decisions depend on their past choices (Shachar and Emerson 2000; Goettler and Shachar 2001; Moshkin and Shachar 2002; Wilbur 2008). We examine the robustness of our findings with respect to this carryover effect.

[20] Source: http://en.csm.com.cn/index.php/Tv/tvnetwork.

We construct four measures of prior viewership. First, because the company airs new shows on a daily basis, we use the viewing percentage of the show broadcast on the same channel the day before to measure the company-level carryover effect. Second, research finds that consumers' TV viewing choices depend on the day of the week and that firms take the day-of-the-week effect into account when scheduling TV shows (Wilbur 2008; Yeo 2014). Hence, we use the viewing percentage of the show broadcast exactly a week before on the same channel to capture this day-of-the-week carryover effect. Third, for serial shows, prior experience with an episode may influence the decision to watch another. Therefore, for the subsample of serial shows, we use the viewing percentage of the previous show on the same channel to capture the series-level carryover effect. To the extent that this effect may be cumulative throughout the series, we also measure the average viewing percentage across all previous shows in the same series on the same channel. The direction of these carryover effects is ambiguous *a priori*. For example, it could be positive because of addiction, or negative due to variety seeking.[21]

We re-estimate the main model by introducing each of the four measures of prior viewership as an independent variable. Note that the resulting specification becomes one with lagged dependent variable and (channel) fixed effects. To avoid the dynamic panel bias (Nickell 1981), we use the Feasible Generalized Least Squares (FGLS) estimator. We allow for channel-specific AR(1) autocorrelation and heteroskedastic errors with cross-channel correlation. Table 14 presents the estimation results. The net impact of prior viewership is weak except for a negative effect from the show the day before and from the previous show in the same series, which may indicate variety seeking. Meanwhile, the conclusions from the main model remain valid.[22]

[Insert Table 14 about here.]

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[21] We do not have data on other TV programs broadcast right before the shows in our study. As a result, we cannot control for the immediate lead-in effect. However, given the random assignment of shows into experimental conditions, we expect the lead-in effect, if any, to be independent of the experimental treatment.

[22] Another correction of the dynamic panel bias is the generalized method of moments (GMM) of Arellano and Bond (1991). This GMM approach is not ideal in our empirical setting because there are few cross-sectional units (channels) but many time periods (days/shows). Nevertheless, we obtain similar estimation results using GMM and FGLS.

3.3.4. Difference-in-Differences Analysis

As discussed earlier, a potential threat to identification is that unobserved show attributes might differ systematically across experimental conditions. The falsification check using data from the untreated channels addresses this concern. Another solution, commonly used in the literature, is difference-in-differences analysis. The idea is to track the difference in show viewing before vs. after the experiment, and identify a treatment effect by comparing the difference in a treatment condition with that in the control condition. We use this approach to corroborate our conclusions.

There is a challenge. All shows in our sample were broadcast on a channel only once and thus have no pre-experiment viewing data. To circumvent this problem, for each show we need to find a corresponding "benchmark" show aired before the experiment that is otherwise similar to the focal show. To do so, we draw on the fact that the media company tends to schedule shows of similar "types" on the same day of the week. (Conversation with company management confirmed this practice.) We construct a pre-experiment panel spanning the 98 days immediately before the experiment. Like the experiment panel, this pre-experiment panel consists of 14 weeks, with 7 daily shows aired per week. For a show broadcast on the d^{th} day of the w^{th} week during the experiment, we define its benchmark show as the one broadcast on the d^{th} day of the w^{th} week of the pre-experiment panel. In this way, we exploit the day-of-the-week effect behind show similarity, and maintain a constant time lag between shows in the experiment and their benchmark shows. Each benchmark show is assigned to the same condition as its corresponding show in the experiment. Even if the assignment of shows across conditions is not perfectly random, as long as the difference between a show and its benchmark is uncorrelated with condition assignment, the difference-in-differences approach continues to apply.

We pool the pre-experiment and experiment panels to run the difference-in-differences estimation. We define a new dummy variable, *After*, which equals 1 for shows in the experiment and 0 for benchmark shows in the pre-experiment panel. The coefficients of the interaction terms, *Tweet* × *After* and *Tweet & Retweet* × *After*, provide the difference-in-differences estimators of the treatment effects of company tweets and influential retweets on show viewing.[23]

Table 15 reports the estimation results using data from the five treated channels. Similar to Table 7, we add show control variables progressively. We focus on column (5), the counterpart of the previous main model. Both condition dummies, *Tweet* and *Tweet & Retweet*, are largely insignificant. This reassures us that benchmark shows in the treatment conditions are not inherently more popular than those in the control condition. The coefficient of *After* is negative and significant, which means that shows, absent the experimental treatments, are overall less watched during the experiment period than before. One possible explanation is seasonality – the pre-experiment panel includes the summer vacation in China when students have more time to watch TV. Another explanation has to do with the "removal-design" nature of the experiment – the company had been positing a show tweet per day prior to the experiment but ceased to do so in the control condition of the experiment. This possibly caused a decline in viewing for shows in the control group compared with their benchmark shows. Turning to the key variables of interest, *Tweet* × *After* and *Tweet & Retweet* × *After*, are both positive and significant at the p<.01 level. Moreover, the coefficient of *Tweet & Retweet* × *After* is significantly higher than that of *Tweet* × *After* (p=.022 for the main specification). These findings lend further confidence to the conclusion that company tweets and influential retweets both increase show viewing.

[Insert Table 15 about here.]

3.4. Effect Magnitude and Return on Tweeting

So far we have shown that (1) company tweets significantly increase show viewing, (2) influential retweets significantly increase show viewing especially if broadcast information is displayed, (3) influential retweets significantly increase the number of company followers, which in turn amplifies the effect of company tweets on show viewing, and (4) influential retweets are particularly effective if the influential is actively retweeted. We derive the magnitude of these

[23] A week dummy indicates the w^{th} week of both the experiment period and the pre-experimental period. Therefore, week dummies are separately identified from the *After* dummy.

effects and assess the company's return on its tweeting campaign.

3.4.1. Effect Magnitude

The top panel of Table 16 presents the effect magnitude by condition, where the bold values are significant at the $p<.10$ level. Consider a show that is broadcast on one of the five treated channels during the experiment. First, imagine that the company engages in no Weibo promotion for this show. In this control condition, the show will achieve an average viewing percentage of .0749 across the five channels, and the company will attract 259 new followers on that day. Now, suppose the same show is tweeted by the company, and three channels are randomly selected to display their broadcast information in the show tweet. The viewing percentage of this show will increase to .1325, which represents a 77% increase compared with the level in the control condition.[24] Meanwhile, the company will gain 244 new followers on that day, which is less than the control level although the difference is insignificant. In addition, the company could also recruit an influential to retweet the original show tweet. Doing so will increase viewing percentage to .1573, which is a 110% increase compared with the control level, or an additional increase of 33% beyond what the company can achieve by tweeting the show itself. The effect of influential retweeting is especially pronounced if the company tweet displays broadcast information of the show. In that case, viewing percentage will rise to .1755, which is a 134% increase over the control level, or an additional increase of 57% beyond the level with company tweets alone. At the same time, if the company both tweets and recruits an influential to retweet, it will attract 349 new followers, a 35% increase from the control level.

[Insert Table 16 about here.]

Recall that retweeting has carryover effects on show viewing, as the influx of new company

[24] To predict the viewing percentages in the treatment conditions, we use the parameter estimates of the main model in column (5) of Table 7. This approach captures the effects of other control variables, which may not be perfectly balanced out across conditions. In contrast, if we ignore other control variables and base the prediction on column (1) of Table 7, the predicted viewing percentages in each condition will simply reflect the actual average viewing percentage as reported in Table 4. The same idea applies to the rest of the effect magnitude analysis.

followers amplifies the effect of company tweets on the next day. The bottom panel of Table 16 presents the magnitude of these carryover effects. Suppose the company tweeted a show and had an influential retweet it on the previous day. Now, if the company tweets today's show, the viewing percentage will be .1497, among which .0172 is associated with the newly subscribed company followers. If the company in addition recruits an influential to retweet today's show, the viewing percentage will reach .1745 on average and .1927 if broadcast information is shown.

For a further look into the effect of influential retweets, we report the effect magnitude by influential attribute in Table 17. Influentials who are retweeted actively by their followers are the most effective in both increasing show viewing directly and bringing new followers to the company. Consider one of these actively retweeted influentials. Recall that, if the company tweets alone, it will on average achieve a viewing percentage of .1325 and attract 244 new followers each day. If the company in addition recruits this influential to retweet, it will increase show viewing by .0796, or 60%. If the show tweet displays broadcast information, the increase will be .1086, or 82%. Meanwhile, by having this influential retweet, the company will generate another 140 new followers each day, which is 57% more than if the company tweets alone. These results suggest that companies interested in influential retweeting may consider targeting influentials who are retweeted actively by their followers. They should also make the company tweet informative to help new customers navigate the purchase funnel – even a simple sentence providing purchase instructions can make a difference.

[Insert Table 17 about here.]

3.4.2. Return on the Tweeting Campaign

The experiment results allow us to assess the media company's return on this tweeting campaign. To gauge the return, we first interviewed personnel at China Central Television regarding the financial structure of the TV industry in China. Typically, to broadcast a certain TV program, a TV channel pays the content producer a program license fee. The license fee depends on the viewing percentage of the program as agreed upon between both parties. Other things being equal, license fees tend to increase with viewing percentage which, naturally, motivates the content producer to grow the viewership of its programs.[25]

Without access to the media company's private data on its license fees, we resort to the Research Report on China's Documentary TV Industry for 2012, the year of the experiment. We approximate the media company's license fee per show by multiplying the length of each show with the average license fee per minute of documentary TV shows in China in 2012. This yields a license fee of 2,625 CNY per show. For back-of-the-envelope calculation, we assume that the license fee is proportional to viewing percentage. Given an average viewing percentage of .0966% for shows in our study (Table 4), we obtain 27,174 CNY per percentage point of show viewing for this sample. Based on estimation results of the main model, compared with the control condition, the company gains a license fee increase of 1,565 CNY per show in the Tweet condition, and 2,239 CNY per show in the Tweet & Retweet condition.

On the cost side, the total operating cost of the media company's Weibo account is about 5,000 CNY per week. Over the 14 weeks of the experiment, the company posted 358 tweets, including 42 show tweets in each of the treatment conditions and 274 noncommercial tweets. For a conservative ROI estimate, we assume zero overhead, and compute the average cost per company tweet as $5{,}000 \times 14/358 \approx 196$ CNY. In addition, to recruit a Weibo influential to retweet a show tweet, the company paid an average cost of 1,000 CNY.

Combining the gain and cost figures, our rough estimates of the company's return on tweeting are 698% in the Tweet condition and 87% in the Tweet & Retweet condition. The return rates would be even higher if we consider the carryover effects of tweeting.

3.5. Additional Studies and Discussion

[25] In China's TV industry, the norm is for each TV channel to determine its advertising schedule and advertising fees without the involvement of the content producer.

Our findings suggest that the media company's use of tweeting to grow viewership is a remarkable success. We reflect on the possible reasons and discuss the plausibility of this result.

The aggregate nature of the data limits our ability to form a detailed portrait of the behavioral mechanism other than showing that company tweets contain an element of informative advertising to new followers of the company. Therefore, we conducted two additional studies to better understand the findings from the experiment.

One possible reason behind the large effect of tweeting on show viewing is that shows included in the study are documentaries and there can be substantial information in the show title regarding the content of a show. If this is the case, show tweets serve as informative advertising beyond conveying broadcast information. To evaluate this possibility, we recruited five independent evaluators to rate the informativeness of the title of each of the 98 shows in the study. On a scale from 1 ("extremely uninformative") to 5 ("extremely informative"), these 98 shows' average title informativeness scores across evaluators have a mean value of 3.34 and standard deviation of .65. We further introduce each show's average title informativeness score into the main model. Both the main effect of this variable and its interaction terms with the two treatment dummies are insignificant. Therefore, although there is some information value in the show title, it does not seem to affect show viewing or moderate the effect of tweeting.

Another possible reason behind the large effect of tweeting on show viewing is social diffusion. Not only do show tweets diffuse on Weibo, their influence may go beyond Weibo through channels such as friend recommendations. To assess the extent of social diffusion, we conducted a survey on TV viewing behaviors among Chinese consumers. The survey was distributed in March, 2016 on www.sojump.com, a leading survey website in China similar to Qualtrics. A total of 285 individuals across the nation responded to the survey, including 132 from the seven provinces affected by the field experiment. We present the full questionnaire and responses in the Web Appendix and highlight the key results below.

Across all respondents, watching TV shows is a regular activity. On a scale from 1 ("Never") to 5 ("Very often"), average TV watching tendency is 3.428, significantly higher than the neutral level of 3 (t=6.233, p<.001). Among sources of TV show information, social media such as Weibo influence 62.46% of consumers, and friend recommendations influence 48.42%. In 2012, 70.88% of respondents were registered Weibo users. On a scale from 1 ("Never") to 5 ("Very often"), the average answer to the question, "how often do you watch TV shows recommended by your friends," is 3.193, significantly higher than the neutral level (t=3.077, p<.01). The average answer to "how often do you watch TV shows retweeted by your friends on Weibo" is 2.905, not significantly different from the neutral level (t=1.520, p=.130). This means show viewing choices are influenced by friends although the effect of friend retweets on Weibo is not as strong. Hence we ask whether friend commendations go beyond the boundary of Weibo. The answer is yes. On a scale from 1 ("Definitely not") to 5 ("Definitely yes"), the average responses are 3.728 to "if you learn about an interesting TV show on Weibo, would you recommend it to your friends who are not Weibo users," and 3.602 to "if your friends learn about an interesting TV show on Weibo, would they recommend it to you." Both average responses significantly exceed the neutral value (t=10.368, p<.001, and t=5.426, p<.001, respectively). Survey responses from the subsample of participants in the seven provinces influenced by the experiment exhibit similar patterns. These results suggest that social diffusion may have existed to some extent to amplify the effect of tweeting beyond Weibo.

Some final comments on the plausibility of the estimated tweeting effects are in order. First, TV viewing is a relatively low-stake and quick decision, making it potentially susceptible to tweeting and marketing activities in general. In fact, through a mobile ad campaign, HBO was also able to increase the viewership of the season-three premiere of "True Blood" by 38% over the previous season (Butcher 2010). The effect of tweeting on demand in bigger-ticket categories, such as cars, is likely smaller. Second, as mentioned earlier, the media company did not pursue other marketing activities besides tweeting during the experiment. The marginal effect of tweeting may be smaller when it coexists with other marketing campaigns. For example, in the movie industry known for heavy pre-launch advertising, tweeting may not generate as strong effects on viewing. Third, the media company was one of the first to adopt tweeting as a marketing tool in its industry. The return to tweeting may be diluted when competitors join the race to tweet. Nevertheless, the findings of the paper suggest that, at least as an existence proof, tweeting can effectively grow demand, and that the effect of tweeting is worth exploring in other contexts.

4. CONCLUDING REMARKS

Tweeting is now commonly used as a marketing tool. We ask whether tweeting indeed tangibly improves business performance. The good news is that, at least in the market of TV shows, company tweets about its own product increase demand. At the same time, involving influential users, especially those retweeted actively by their own followers, to retweet company tweets can further boost product demand. A caveat is that the retweeted content should be informative to the expanded audience who may not be familiar with the product. Finally, influential retweets help bring new followers to the company, and these newly subscribed company followers partly contribute to the increase in product demand. This last result is also encouraging news to businesses because many of today's social media marketing campaigns focus on cultivating follower communities, an effort that we show to be constructive to the bottom line.

There are several directions for future research. A natural follow-up is to study the design of tweet content. We find that even simple tweets are effective, but companies may be able to do better. It will also be interesting to analyze the market of influentials. For example, as this market evolves, what would be the price for influentials to engage in social media promotions? How does this price affect the influence of influentials? Similar to advertising expenditure, the price to recruit influentials may signal product quality (Milgrom and Roberts 1986) or moderate consumers' attribution of market performance to product quality (Miklós-Thal and Zhang 2013). Finally, data permitting, it will be informative to study the impact of tweeting on TV viewership (and more generally, the impact of social media activities on demand) at an individual level.[26]

[26] To our best knowledge, there is currently no database that reliably connects TV viewership to internet usage. In

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Table 1 Summary of Experimental Conditions

Condition	Description	Number of TV Shows
Control	Each show is neither tweeted by the company nor retweeted by an influential	14
Tweet	Each show is tweeted by the company	42
Tweet & Retweet	Each show is tweeted by the company and retweeted by an influential	42

Notes. The company tweets at 11:00 am of the day of the show. Influentials retweet company tweets at noon.

Table 2 Summary Statistics of Weibo Influentials Recruited to Retweet

	Mean	S.D.	Min	Median	Max
Number of followers	2,111,873	1,798,811	321,644	1,403,684	9,574,535
Number of tweets per day	45	38	1	44	179
Average number of follower retweets	729	528	60	642	3,049

Notes. The sample includes 42 influentials. For each influential, the average number of follower retweets measures, on average, how many times each of his/her tweets is retweeted by his/her followers.

Table 3 Summary of Experimental Design at the TV Channel Level

TV Channel	Broadcast Time	Weeks 1-7	Weeks 8-14
Shanghai	After Treatment	Display	Display
Tianjin	After Treatment	Display	Not display
Wuhan	After Treatment	Display	Not display
Guangzhou	After Treatment	Not display	Display
Hangzhou	After Treatment	Not display	Display
Chongqing	Before Treatment	Not display	Not display
Fuzhou	Before Treatment	Not display	Not display

Notes. Display means the broadcast information of the channel is displayed in the company tweet.

Table 4 Summary Statistics of Show Viewing Percentage by Experimental Condition

	#Observations	Mean	S.D.	Min	Median	Max
Entire sample						
Control	98	.0599	.0748	0	.04	.43
Tweet	294	.0971	.1158	0	.05	.65
Tweet & Retweet	294	.1083	.1284	0	.06	.73
All	686	.0966	.1176	0	.05	.73
Shows on treated channels (i.e., channels that broadcast the shows after the treatments)						
Control	70	.0749	.0811	0	.05	.43
Tweet	210	.1249	.1234	0	.09	.65
Tweet & Retweet	210	.1443	.1345	0	.11	.73
All	490	.1261	.1252	0	.09	.73
Shows on untreated channels (i.e., channels that broadcast the shows before the treatments)						
Control	28	.0225	.0362	0	0	.13
Tweet	84	.0275	.0462	0	.01	.26
Tweet & Retweet	84	.0185	.0331	0	0	.17
All	196	.0229	.0396	0	0	.26

Notes. An observation is a show-channel combination.

Table 5 Summary Statistics of Tweet Diffusion by Experimental Condition

	#Obs.	Mean	S.D.	Min	Median	Max
Control condition						
Number of retweets	14	0	0	0	0	0
Influential retweets	14	0	0	0	0	0
Retweets of influential retweets	14	0	0	0	0	0
Organic retweets	14	0	0	0	0	0
Number of impressions	14	0	0	0	0	0
Diffusion depth	14	0	0	0	0	0
Tweet condition						
Number of retweets	42	27	25	2	20	149
Influential retweets	42	0	0	0	0	0
Retweets of influential retweets	42	0	0	0	0	0
Organic retweets	42	27	25	2	20	149
Number of impressions	42	160,522	37,765	130,848	151,073	344,549
Diffusion depth	42	2	.99	1	2	5
Tweet & Retweet condition						
Number of retweets	42	127	117	10	86	512
Influential retweets	42	1	0	1	1	1
Retweets of influential retweets	42	92	87	4	58	388
Organic retweets	42	34	34	2	25	134
Number of impressions	42	3,238,494	6,610,906	470,074	1,618,676	43,461,666
Diffusion depth	42	3	1.07	2	3	7

Notes. An observation is a show. The number of retweets measures the total number of times a show tweet is retweeted. Organic retweets refer to user retweets without involvement of recruited influentials. The number of impressions measures the number of users exposed to a show tweet either directly or indirectly through retweeting. Diffusion depth measures the maximum number of layers of follower networks a show tweet reaches.

Table 6 Summary Statistics of the Daily Change in Company Followers by Experimental Condition

	#Observations	Mean	S.D.	Min	Median	Max
Control	14	259	85	110	242	392
Tweet	42	237	188	73	201	1046
Tweet & Retweet	42	335	199	87	288	1240

Notes. An observation is a day. The variable is the daily change in the number of company followers during the experiment.

Table 7 Main Results – Effect of Tweeting on Show Viewing (Treated Channels)

	(1)	(2)	(3)	(4)	**(5)** **"Main Model"**
Tweet (α_1)	.0500	.0514	.0514	.0492	**.0576**
	(.0133)***	(.0138)***	(.0138)***	(.0145)***	**(.0161)*****
Tweet & Retweet (α_2)	.0694	.0698	.0698	.0707	**.0824**
	(.0144)***	(.0148)***	(.0149)***	(.0156)***	**(.0169)*****
#Noncommercial tweets		.0035	.0035	.0007	**-.0022**
		(.0030)	(.0031)	(.0050)	**(.0056)**
Channel dummies	No	No	Yes	Yes	**Yes**
Week dummies	No	No	No	Yes	**Yes**
Day-of-week dummies	No	No	No	Yes	**Yes**
Series dummies	No	No	No	No	**Yes**
Episode dummies	No	No	No	No	**Yes**
Genre dummies	No	No	No	No	**Yes**
$\alpha_2 - \alpha_1$	.0194	.0184	.0184	.0215	**.0248**
p-value of $\alpha_2 - \alpha_1$	.069	.080	.081	.052	**.039**
#Observations	490	490	490	490	**490**
R-squared	.033	.035	.347	.372	**.389**

Notes. An observation is a show-channel combination. The dependent variable is the percentage of a channel's audience viewing a show. The sample consists of all 98 shows on the five treated channels (i.e., channels that broadcast the shows after the time of company tweets and influential retweets). The *p*-values for the difference between α_2 and α_1 are based on one-tailed tests. OLS estimates with robust standard errors clustered at the show level. * $p<.10$, ** $p<.05$, *** $p<.01$.

Table 8 Falsification Check – Effect of Tweeting on Show Viewing (Untreated Channels)

	(1)	(2)	(3)	(4)	(5)
Tweet (α_1)	.0050	.0058	.0058	.0052	.0075
	(.0086)	(.0089)	(.0090)	(.0087)	(.0088)
Tweet & Retweet (α_2)	-.0040	-.0038	-.0038	-.0039	-.0044
	(.0079)	(.0082)	(.0082)	(.0082)	(.0078)
#Noncommercial tweets		.0021	.0021	.0008	.0022
		(.0013)	(.0013)	(.0026)	(.0026)
Channel dummies	No	No	Yes	Yes	Yes
Week dummies	No	No	No	Yes	Yes
Day-of-week dummies	No	No	No	Yes	Yes
Series dummies	No	No	No	No	Yes
Episode dummies	No	No	No	No	Yes
Genre dummies	No	No	No	No	Yes
$\alpha_2 - \alpha_1$	-.0090	-.0096	-.0096	-.0091	-.0119
p-value of $\alpha_2 - \alpha_1$	.930	.940	.940	.924	.944
#Observations	196	196	196	196	196
R-squared	.011	.020	.030	.132	.177

Notes. An observation is a show-channel combination. The dependent variable is the percentage of a channel's audience viewing a show. The sample consists of all 98 shows on the five untreated channels (i.e., channels that broadcast the shows before the time of company tweets and influential retweets). The *p*-values for the difference between α_2 and α_1 are based on one-tailed tests. OLS estimates with robust standard errors clustered at the show level. * $p<.10$, ** $p<.05$, *** $p<.01$.

Table 9 Effect of Displaying Broadcast Information on Show Viewing

	(1) All	(2) All	(3) Display	(4) Not Display
Tweet (α_1)	.0576	.0462	.0691	.0402
	(.0161)***	(.0161)***	(.0213)***	(.0182)**
Tweet & Retweet (α_2)	.0824	.0551	.1007	.0550
	(.0169)***	(.0169)***	(.0177)***	(.0184)***
Display	.0052	-.0224		
	(.0078)	(.0154)		
Tweet × Display		.0189		
		(.0210)		
Tweet & Retweet × Display		.0455		
		(.0194)**		
#Noncommercial tweets	-.0022	-.0022	-.0004	-.0048
	(.0056)	(.0056)	(.0070)	(.0073)
Channel dummies	Yes	Yes	Yes	Yes
Week dummies	Yes	Yes	Yes	Yes
Day-of-week dummies	Yes	Yes	Yes	Yes
Series dummies	Yes	Yes	Yes	Yes
Episode dummies	Yes	Yes	Yes	Yes
Genre dummies	Yes	Yes	Yes	Yes
$\alpha_2 - \alpha_1$	.0248	.0089	.0316	.0148
p-value of $\alpha_2 - \alpha_1$	.039	.291	.043	.189
#Observations	490	490	294	196
R-squared	.390	.394	.442	.236

Notes. An observation is a show-channel combination. The dependent variable is the percentage of a channel's audience viewing a show. Columns (1) and (2) include all 98 shows on the five treated channels. Columns (3) and (4) split this sample based on whether the show tweet displays broadcast information for a channel. The *p*-values for the difference between α_2 and α_1 are based on one-tailed tests. OLS estimates with robust standard errors clustered at the show level. * $p<.10$, ** $p<.05$, *** $p<.01$.

Table 10 Effect of Company Followers on Show Viewing

	(1) All	(2) All	(3) Display	(4) Not Display	(5) All	(6) Display	(7) Not Display
Company tweet	.0576	-.2280	-.1578	-.3331	.0387	.0422	.0334
	(.0161)***	(.2297)	(.3225)	(.2286)	(.0181)**	(.0250)*	(.0233)
Company tweet × Lag Followers		.0020	.0016	.0027			
		(.0016)	(.0023)	(.0016)			
Company tweet × Lag ΔFollowers					.0493	.0747	.0112
					(.0290)*	(.0381)*	(.0473)
Influential retweet	.0248	.0289	.0362	.0180	.0312	.0398	.0183
	(.0139)*	(.0137)**	(.0183)*	(.0165)	(.0132)**	(.0180)**	(.0166)
#Noncommercial tweets	-.0022	-.0048	-.0033	-.0071	-.0022	.0003	-.0061
	(.0056)	(.0059)	(.0074)	(.0074)	(.0062)	(.0076)	(.0076)
Channel dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Series dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Episode dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Genre dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	485	485	291	194	485	291	194
R-squared	.389	.400	.454	.246	.402	.460	.242

Notes. An observation is a show-channel combination. The dependent variable is the percentage of a channel's audience viewing a show. Columns (1), (2) and (5) include the 97 shows aired from day 2 through day 98 of the experiment on the five treated channels. Columns (3)-(4) and (6)-(7) split this sample based on whether the show tweet displays broadcast information for a channel. *Lag Followers* and *Lag ΔFollowers* are in thousands. OLS estimates with robust standard errors clustered at the show level. * p<.10, ** p<.05, *** p<.01.

Table 11 Effect of Tweeting on Company Followers

	(1)	(2)	(3)
Company tweet	-21.95	-13.48	-20.74
	(56.36)	(55.44)	(58.11)
Influential retweet	97.21	90.86	88.26
	(39.85)**	(39.21)**	(39.83)**
#Noncommercial tweets		22.24	21.75
		(10.29)**	(10.39)**
Average show viewing percentage			141.28
			(323.99)
#Observations	98	98	98
R-squared	.061	.106	.108

Notes. An observation is a day. The dependent variable is the change in the number of company followers on a day. The sample consists of all 98 shows on the five treated channels. OLS estimates. * p<.10, ** p<.05, *** p<.01.

Table 12 Heterogeneous Effects of Influential Retweets on Company Followers

	(1)	(2)	(3)	(4)
Company tweet	-2.04	-14.18	-.12.21	-7.19
	(57.07)	(57.32)	(57.52)	(57.28)
Influential retweet	78.17	35.62	146.33	29.07
	(59.12)	(47.36)	(49.99)***	(47.40)
Influential retweet × Has many followers	52.44	111.52		
	(77.61)	(24.06)**		
Influential retweet × Tweets actively	-94.13		-108.23	
	(57.35)		(57.58)*	
Influential retweet × Retweeted actively	79.34			131.00
	(82.95)			(59.50)**
#Noncommercial tweets	18.32	20.40	20.24	19.30
	(10.20)*	(10.25)**	(10.28)*	(10.24)*
Average show viewing percentage	-258.40	.07	-40.49	-147.98
	(351.62)	(326.86)	(333.97)	(343.60)
#Observations	98	98	98	98
R-squared	.181	.144	.141	.152

Notes. An observation is a day. The dependent variable is the change in the number of company followers on a day. The sample consists of all 98 shows on the five treated channels. OLS estimates. * p<.10, ** p<.05, *** p<.01.

Table 13 Robustness Checks – Alternative Dependent Variables

	(1)	(2)	(3)
	Truncated DV	Number of Viewers as DV	Number of Viewers as DV
	Tobit Model	OLS	Fixed Effects Poisson
Tweet (α_1)	.0609	6,306.41	.5449
	(.0165)***	(1,761.70)***	(.1642)***
Tweet & Retweet (α_2)	.0847	8,977.80	.7180
	(.0172)***	(1,867.22)***	(.1658)***
#Noncommercial tweets	-.0029	-75.72	-.0074
	(.0057)	(613.73)	(.0410)
Channel dummies	Yes	Yes	Yes
Week dummies	Yes	Yes	Yes
Day-of-week dummies	Yes	Yes	Yes
Series dummies	Yes	Yes	Yes
Episode dummies	Yes	Yes	Yes
Genre dummies	Yes	Yes	Yes
$\alpha_2 - \alpha_1$	.0238	2,671.39	.1731
p-value of $\alpha_2 - \alpha_1$	.091	.084	.064
#Observations	490	490	490
(Pseudo) R-squared	.460	.600	.628

Notes. An observation is a show-channel combination. For column (1), the dependent variable is the percentage of a channel's audience viewing a show. For columns (2) and (3), the dependent variable is the number of individuals in a channel's audience viewing a show. The sample consists of all 98 shows on the five treated channels. The *p*-values for the difference between α_2 and α_1 are based on one-tailed tests. Column (3) reports the marginal effects. Robust standard errors clustered at the show level. * $p<.10$, ** $p<.05$, *** $p<.01$.

Table 14 Robustness Checks – Controlling for Prior Viewership

	(1)	(2)	(3)	(4)
Tweet (α_1)	.0452	.0436	.0838	.0874
	(.0132)***	(.0145)***	(.0192)***	(.0198)***
Tweet & Retweet (α_2)	.0650	.0704	.1251	.1265
	(.0128)***	(.0137)***	(.0199)***	(.0206)***
Viewing pct. of the show the day before	-.1108			
	(.0443)**			
Viewing pct. of the show a week before		.0203		
		(.0457)		
Viewing pct. of last show in series			-.1055	
			(.0547)*	
Avg. viewing pct. of prior shows in series				.0686
				(.0692)
#Noncommercial tweets	-.0043	-.0082	-.0134	-.0105
	(.0049)	(.0052)	(.0071)*	(.0073)
Channel dummies	Yes	Yes	Yes	Yes
Week dummies	Yes	Yes	Yes	Yes
Day-of-week dummies	Yes	Yes	Yes	Yes
Series dummies	Yes	Yes	No	No
Episode dummies	Yes	Yes	Yes	Yes
Genre dummies	Yes	Yes	Yes	Yes
$\alpha_2 - \alpha_1$	.0198	.0268	.0414	.0392
p-value of $\alpha_2 - \alpha_1$	.023	.007	.000	.001
#Observations	485	455	275	275
R-squared	.403	.404	.510	.499

Notes. The samples for the columns are: (1) shows on days 2-98 of the experiment, (2) shows on days 8-98, (3)-(4) serial shows except the first one in the observation window. FGLS estimates. Otherwise, see Table 7 notes.

Table 15 Robustness Checks – Difference-in-Differences Analysis

	(1)	(2)	(3)	(4)	(5)
Tweet	-.0067	-.0076	-.0076	-.0085	-.0088
	(.0211)	(.0210)	(.0210)	(.0184)	(.0175)
Tweet & Retweet	-.0266	-.0266	-.0266	-.0257	-.0277
	(.0201)	(.0199)	(.0149)	(.0170)	(.0163)*
After	-.0987	-.1005	-.1004	-.1004	-.1058
	(.0204)***	(.0203)***	(.0203)***	(.0207)***	(.0217)***
Tweet × After (α_1)	.0567	.0594	.0594	.0595	.0645
	(.0237)**	(.0236)**	(.0236)**	(.0242)**	(.0242)***
Tweet & Retweet × After (α_2)	.0960	.0965	.0965	.0965	.0978
	(.0238)***	(.0236)***	(.0236)***	(.0238)***	(.0238)***
#Noncommercial tweets		.0047	.0048	.0048	.0050
		(.0024)*	(.0024)*	(.0037)	(.0036)
Channel dummies	No	No	Yes	Yes	Yes
Week dummies	No	No	No	Yes	Yes
Day-of-week dummies	No	No	No	Yes	Yes
Series dummies	No	No	No	No	Yes
Episode dummies	No	No	No	No	Yes
Genre dummies	No	No	No	No	Yes
$\alpha_2 - \alpha_1$	.0393	.0371	.0371	.0370	.0334
p-value of $\alpha_2 - \alpha_1$	.012	.016	.016	.019	.022
#Observations	980	980	980	980	980
R-squared	.034	.037	.348	.360	.369

Notes. An observation is a show-channel combination. The dependent variable is the percentage of a channel's audience viewing a show. The sample consists of all 98 shows in the experiment and their 98 benchmark shows before the start of the experiment on the five treated channels. The *p*-values for the difference between α_2 and α_1 are based on one-tailed tests. OLS estimates with robust standard errors clustered at the show level. * $p<.10$, ** $p<.05$, *** $p<.01$.

Table 16 Effect Magnitude by Experimental Condition

	Show Viewing Percentage		Daily Growth in Company followers	
	Mean	Change	Mean	Change
Current effects				
Control	.0749	0%	259	0%
Tweet	**.1325**	**77%**	244	-6%
Tweet & Retweet	**.1573**	**110%**	**349**	**35%**
Display	**.1755**	**134%**	N/A	N/A
Not display	.1300	74%	N/A	N/A
Current + carryover effects (assuming Tweet & Retweet on the previous day)				
Control	.0749	0%		
Tweet	**.1497**	**100%**		
Tweet & Retweet	**.1745**	**133%**		
Display	**.1927**	**157%**		
Not display	.1472	97%		

Notes. The sample consists of all 98 shows on the five treated channels for the "Show Viewing Percentage" columns, and all 98 days/shows for the "Daily Growth in Company Follower" columns. Changes are calculated using the value in the control condition as the common benchmark. Bold indicates significance at the p<.10 level.

Table 17 Effect Magnitude of Influential Retweets by Influential Type

	Show Viewing Percentage (Relative to Company Tweeting Alone)			Daily Growth in Company Followers (Relative to Company Tweeting Alone)
	All	Display	Not Display	
Has many followers	-.0208	-.0364	-.0036	**132**
Tweets actively	-.0249	-.0397	-.0253	**-10**
Retweeted actively	**.0796**	**.1086**	-.0212	**140**
Local	.0018	**.0386**	-.0212	N/A

Notes. The sample consists of all 98 shows on the five treated channels for the "Show Viewing Percentage" columns, and all 98 days/shows for the "Daily Growth in Company Follower" columns. Changes are calculated using the value in the Tweet condition as the benchmark. Bold indicates significance at the p<.10 level.

Tweeting as a Marketing Tool – Field Experiment in the TV Industry

Web Appendix

Shiyang Gong, Juanjuan Zhang, Ping Zhao, Xuping Jiang

Detailed Information about the Show Viewing Data

CSM Media Research collects TV viewing data using the following procedure.[1] First, CSM conducts an Establishment Survey to characterize the TV population of a market. The survey collects detailed information on demographical variables of individuals in this market and factors that may influence their TV viewing decisions, such as TV channel reception capability and ownership of TV-related equipment. An Establishment Survey is usually conducted in the initial stage of building a TV viewership measurement system, and is thereafter repeated at a regular basis (typically annually) to incorporate evolutions of the TV market.

Second, CSM samples the TV population to create a TV audience panel. CSM uses stratified multi-stage PPS random sampling to ensure that the panel is representative of the population from which it is chosen. A panel tracks a given sample of individuals over time. The sample remains relatively stable except for periodic turnovers of fractions of the panel. As of February, 2016, CSM owns 163 panels, including one national panel, 25 provincial panels, and 137 city panels. Containing more than 61 thousand TV households and 1,138 TV channels, CSM panels are the world's largest TV audience measurement panel network.

Across the seven channels covered in our study, the TV audience panel contains 7,601 TV household members, including 1,246 in Shanghai, 1,031 in Tianjin, 1,072 in Wuhan, 1,044 in Guangzhou, 1,100 in Hangzhou, 1,265 in Chongqing, and 843 in Fuzhou. Interview with CSM management indicates that the typical standard error is 3% for CSM panel data and is less than 3% for major cities (all seven cities in our study are classified as major cities).

[1] Source: http://en.csm.com.cn.

Third, for each TV audience panel, CSM measures each individual's TV viewing choices 24 hours a day, 365 days a year. The data we obtained from CSM was collected using the People Meter Method. This method relies on people meter devices to track TV viewing information for all panel household members ages 4 and above. The people meter device automatically records every use of every TV set in the panel, including the turning on and off of the TV set and channel switching, on a second-by-second basis. Each household member presses a remote control handset to indicate his/her presence, which allows CSM to track TV viewing at the individual (as opposed to household) level. Viewership data stored in the people meter device is transferred to the CSM server overnight and made available to clients by the following morning.

A typical format of TV viewership data reported by CSM is the "ratings point" of a TV program. Ratings point measures the percentage of TV household members in a given market watching a TV program in a given minute, aggregated over the duration of the program. This metric is commonly used in the TV industry and in academic research of the TV industry (e.g., Wilbur 2008). For example, ratings point is also one of the most commonly cited metrics produced by Nielsen.[2] We use ratings point as the dependent variable for most of the paper and label it "viewing percentage" for readers less familiar with terminologies used in the TV industry.

Another standard metric in the media industry is "gross rating point." Primarily used to measure the exposure to TV advertising campaigns, gross rating point is calculated as the sum of ratings points across all commercial spots within the campaign. In other words, the gross rating point of a campaign equals the percentage of an audience who saw the campaign multiplied by the average number of commercial spots they saw.[3] We do not use gross rating point as the dependent variable of this paper because the TV programs in our data are shows instead of advertising campaigns and because each show is aired only once on each channel, which means viewing frequency per individual is not a focal variable of interest in this context.

[2] Source: https://en.wikipedia.org/wiki/Nielsen_ratings#cite_ref-3.
[3] Source: https://en.wikipedia.org/wiki/Gross_rating_point.

Chinese TV Audience Survey

We conducted a survey to understand TV viewing behaviors among Chinese consumers and, in particular, the impact of Weibo on their TV viewing choices. The survey was distributed in March, 2016 on www.sojump.com, a leading survey website in China similar to Qualtrics. A total of 285 individuals across the nation responded to the survey, including 132 from the seven provinces that participated in the field experiment. Below is the questionnaire we used together with the distribution of answers from all 285 respondents. Answers from the subsample of respondents in the seven participating provinces exhibit similar patterns.

1. How often do you watch TV shows?

   a. Never (3.51%)
   b. Not often (23.16%)
   c. Sometimes (21.4%)
   d. Often (30.88%)
   e. Very Often (21.05%)

2. From which sources do you usually obtain information about TV shows? (You can choose more than one answer.)

   a. TV (81.75%)
   b. Newspapers (33.33%)
   c. Social media (such as Weibo) (62.46%)
   d. Magazines (19.65%)
   e. Radio (17.89%)
   f. Billboard advertisements (21.05%)
   g. Friends' recommendations (48.42%)
   h. Other (1.75%)

3. How often do you watch TV shows recommended by your friends?

   a. Never (3.51%)
   b. Not often (25.61%)
   c. Sometimes (30.88%)
   d. Often (28.07%)
   e. Very Often (11.93%)

4. How often do you watch TV shows retweeted by your friends on Weibo?

a. Never (7.02%)
b. Not often (29.82%)
c. Sometimes (38.25%)
d. Often (15.44%)
e. Very Often (9.47%)

5. Were you a registered Weibo user in 2012? (If the answer is "Yes", go to question 6; if the answer is "No", go to question 7.)

a. Yes (70.88%)
b. No (29.12%)

6. If you learn about an interesting TV show on Weibo, would you recommend it to your friends who are not Weibo users?

a. Definitely not (3.47%)
b. Probably not (9.41%)
c. Not sure (17.82%)
d. Probably yes (49.5%)
e. Definitely yes (19.8%)

7. If your friends learn about an interesting TV show on Weibo, would they recommend it to you?

a. Definitely not (4.82%)
b. Probably not (8.43%)
c. Not sure (24.1%)
d. Probably yes (46.99%)
e. Definitely yes (15.66%)

8. Your gender：

a. Male (52.98%)
b. Female (47.02%)

9. Your age：

a. Under 18 (.35%)
b. 18~25 (23.86%)
c. 26~30 (27.37%)
d. 31~40 (31.93%)
e. 41~50 (14.04%)
f. 51~60 (2.11%)

g. Above 60 (.35%)

10. Your highest education:

a. Middle school (1.05%)
b. High school (9.12%)
c. Three-year college (21.4%)
d. Four-year college (60.35%)
e. Master’s and above (8.07%)

11. Your province/region：

1) Anhui (1.75%) 2) Beijing (8.77%) 3) Chongqing (14.39%) 4) Fujian (2.46%)
5) Gansu (0%) 6) Guangdong (13.33%) 7) Guangxi (2.11%) 8) Guizhou (.35%)
9) Hainan (0%) 10) Hebei (3.86%) 11) Heilongjiang (2.46%) 12) Henan (3.51%)
13) Hong Kong (0%) 14) Hubei (2.46%) 15) Hunan (1.4%) 16) Jiangsu (7.02%)
17) Jiangxi (1.05%) 18) Jilin (.7%) 19) Liaoning (3.51%) 20) Macau (0%)
21) Neimenggu (.35%) 22) Ningxia (.7%) 23) Qinghai (0%)
24) Shandong (7.02%) 25) Shanghai (7.37%) 26) Shanxi (1.05%)
27) Shaanxi (3.86%) 28) Sichuan (3.86%) 29) Taiwan (0%) 30) Tianjin (2.11%)
31) Xinjiang (0%) 32) Xizang (0%) 33) Yunnan (.35%) 34) Zhejiang (4.21%)
35) Overseas (0%)

12. Your current occupation:

1) Full-time student (6.32%) 2) Manufacturing (5.26%) 3) Sales (17.19%)
4) Marketing/PR (3.16%) 5) Customer service (.7%)
6) Administrative/support (11.58%) 7) Human resources (3.16%)
8) Finance/auditing (5.96%) 9) Secretary (8.42%) 10) Technical/R&D (12.28%)
11) Management (9.12%) 12) Education (7.37%) 13) Consulting (.7%)
14) Other professions (e.g. accounting, law, architecture, healthcare, journalism) (5.61%)
15) Other (3.16%)

13. Your income level:

a. Less than 2,000 CNY per month (7.02%)
b. 2,000~5,000 CNY per month (36.14%)
c. 5,001~10,000 CNY per month (42.46%)
d. 10,001~20,000 CNY per month (10.88%)
e. More than 20,000 CNY per month (3.51%)

Table W1 Overview of Weibo Compared with Twitter

	Weibo	Twitter
Registered users	Over 500 million	Over 500 million
Growth of registered users in 2012	Over 150 million	Over 100 million
Monthly active users	46 million	200 million
Growth of active users in 2012	16 million	60 million
Daily tweets	130 million	340 million
Business accounts	130,565	Unknown
Fortune 500 accounts	143	365

Notes. Statistics as of December 2012, the year of the field experiment. Source: 2012 Weibo Business White Paper.

Table W2   Effect of Tweeting on Show Viewing (Treated and Untreated Channels)

	(1)	(2)	(3)	(4)	**(5)**
Tweet	.0050	.0062	.0062	.0044	.0111
	(.0085)	(.0090)	(.0090)	(.0096)	(.0110)
Tweet & Retweet	-.0040	-.0038	-.0038	-.0031	.0051
	(.0078)	(.0084)	(.0084)	(.0090)	(.0102)
Tweet × Treated (α_1)	.0450	.0450	.0450	.0450	.0450
	(.0116)***	(.0116)***	(.0117)***	(.0118)***	(.0119)***
Tweet & Retweet × Treated (α_2)	.0735	.0735	.0735	.0735	.0735
	(.0127)***	(.0127)***	(.0128)***	(.0129)***	(.0130)***
#Noncommercial tweets		.0031	.0031	.0008	-.0009
		(.0022)	(.0022)	(.0038)	(.0042)
Treated	.0524	.0524			
	(.0068)***	(.0068)***			
Channel dummies	No	No	Yes	Yes	Yes
Week dummies	No	No	No	Yes	Yes
Day-of-week dummies	No	No	No	Yes	Yes
Series dummies	No	No	No	No	Yes
Episode dummies	No	No	No	No	Yes
Genre dummies	No	No	No	No	Yes
$\alpha_2 - \alpha_1$	.0284	.0284	.0284	.0284	.0284
p-value of $\alpha_2 - \alpha_1$	.025	.025	.025	.027	.028
#Observations	686	686	686	686	686
R-squared	.185	.187	.439	.455	.464

Notes. An observation is a show-channel combination. The dependent variable is the percentage of a channel's audience viewing a show. The sample consists of all 98 shows on the five treated channels and the two untreated channels (i.e., channels that broadcast the shows after, and before, the time of company tweets and influential retweets, respectively). The p-values for the difference between α_2 and α_1 are based on one-tailed tests. OLS estimates with robust standard errors clustered at the show level. * p<.10, ** p<.05, *** p<.01.

Table W3 Heterogeneous Effects of Influential Retweets on Show Viewing

	(1) All	(2) Display	(3) Not Display
Company tweet	.0532	.0647	.0364
	(.0150)***	(.0195)***	(.0177)**
Influential retweet	-.0049	-.0048	-.0168
	(.0205)	(.0234)	(.0226)
Influential retweet × Has many followers	-.0159	-.0316	.0132
	(.0184)	(.0241)	(.0265)
Influential retweet × Tweets actively	-.0200	-.0349	-.0085
	(.0180)	(.0227)	(.0249)
Influential retweet × Retweeted actively	.0845	.1134	-.0044
	(.0206)***	(.0298)***	(.0253)
Influential retweet × Local	.0067	.0434	-.0044
	(.0165)	(.0235)*	(.0253)
#Noncommercial tweets	-.0036	-.0006	-.0079
	(.0058)	(.0070)	(.0081)
Channel dummies	Yes	Yes	Yes
Week dummies	Yes	Yes	Yes
Day-of-week dummies	Yes	Yes	Yes
Series dummies	Yes	Yes	Yes
Episode dummies	Yes	Yes	Yes
Genre dummies	Yes	Yes	Yes
#Observations	490	294	196
R-squared	.418	.486	.259

Notes. An observation is a show-channel combination. The dependent variable is the percentage of a channel's audience viewing a show. Column (1) includes shows on the five treated channels. Columns (2) and (3) split these shows based on whether the broadcast information was displayed. OLS estimates with robust standard errors clustered at the show level. * p<.10, ** p<.05, *** p<.01.

Table W4 Viewership per Show by Channel and by Experimental Condition

Channel	#Obs	TV Population	Avg. Viewing Pct.	Avg. #Viewers
Control condition				
Shanghai	14	15,945,000	.1700	27,107
Tianjin	14	9,932,000	.0457	4,540
Wuhan	14	9,209,000	.0414	3,815
Guangzhou	14	8,223,000	.0286	2,349
Hangzhou	14	5,902,000	.0886	5,227
Chongqing	14	14,528,000	.0229	3,321
Fuzhou	14	2,784,000	.0221	616
Tweet condition				
Shanghai	42	15,945,000	.2576	41,077
Tianjin	42	9,932,000	.0962	9,553
Wuhan	42	9,209,000	.0967	8,902
Guangzhou	42	8,223,000	.0636	5,227
Hangzhou	42	5,902,000	.1105	6,520
Chongqing	42	14,528,000	.0224	3,252
Fuzhou	42	2,784,000	.0326	908
Tweet & Retweet condition				
Shanghai	42	15,945,000	.2957	47,151
Tianjin	42	9,932,000	.1198	11,849
Wuhan	42	9,209,000	.0995	9,165
Guangzhou	42	8,223,000	.0752	6,186
Hangzhou	42	5,902,000	.1312	7,743
Chongqing	42	14,528,000	.0143	2,075
Fuzhou	42	2,784,000	.0226	630
Entire sample				
Shanghai	98	15,945,000	.2614	41,680
Tianjin	98	9,932,000	.0991	9,843
Wuhan	98	9,209,000	.0900	8,288
Guangzhou	98	8,223,000	.0636	5,230
Hangzhou	98	5,902,000	.1162	6,858
Chongqing	98	14,528,000	.0190	2,760
Fuzhou	98	2,784,000	.0268	746

Notes. An obs. is a show-channel combination. TV population data source: http://en.csm.com.cn/index.php/Tv/tvnetwork.

Figure W1 Example of Noncommercial Tweets Posted by the Company

Figure W2 Example of A Company Tweet

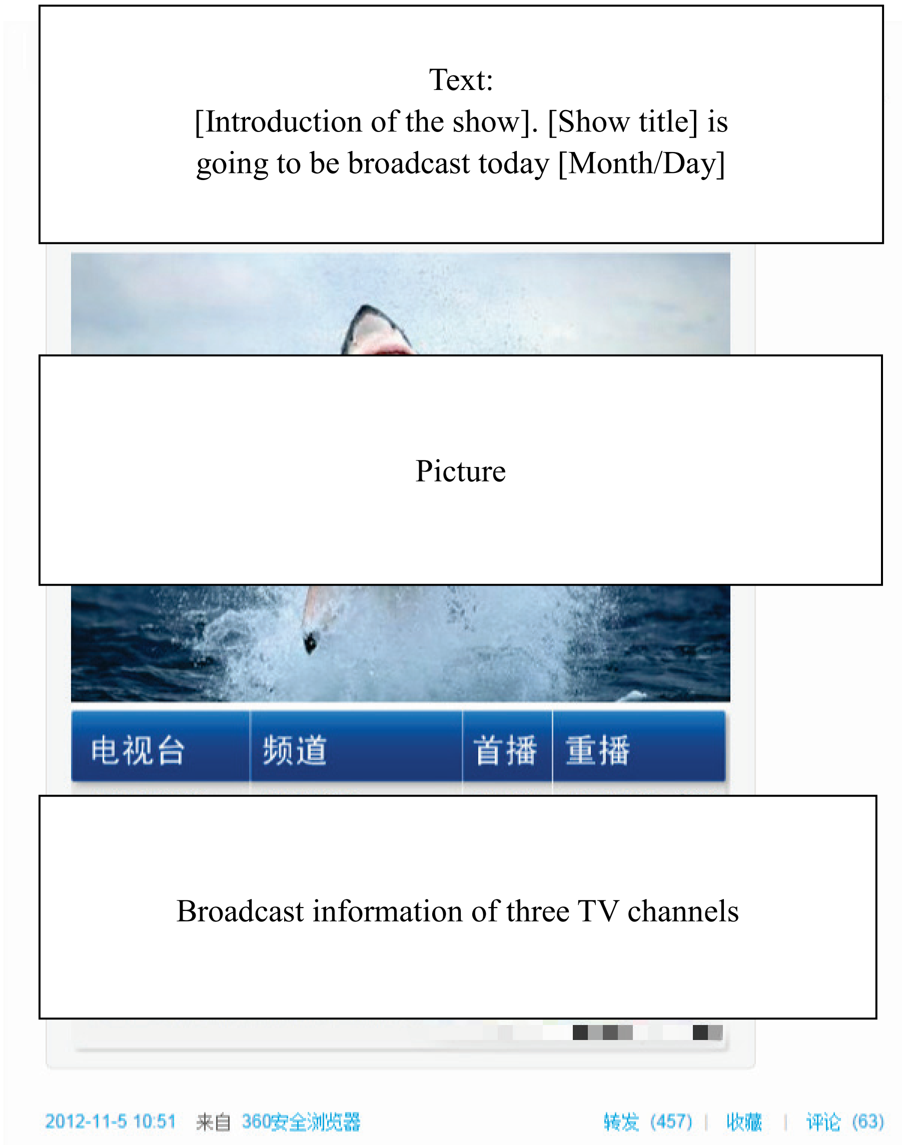
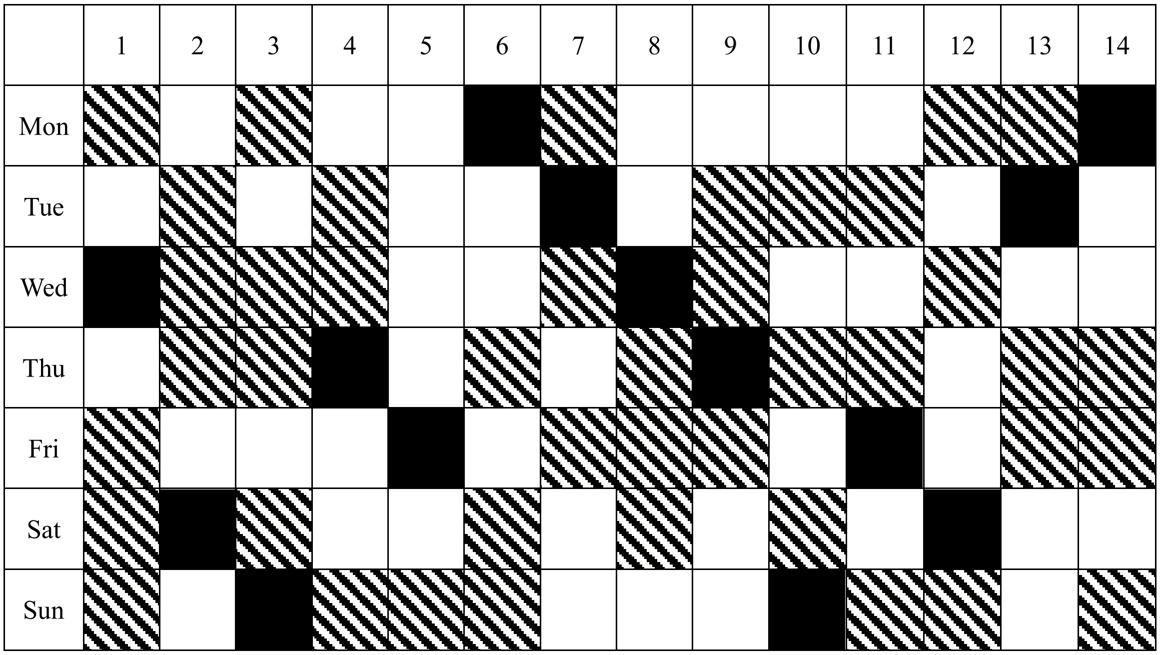


Figure W3 Example of An Influential Retweet

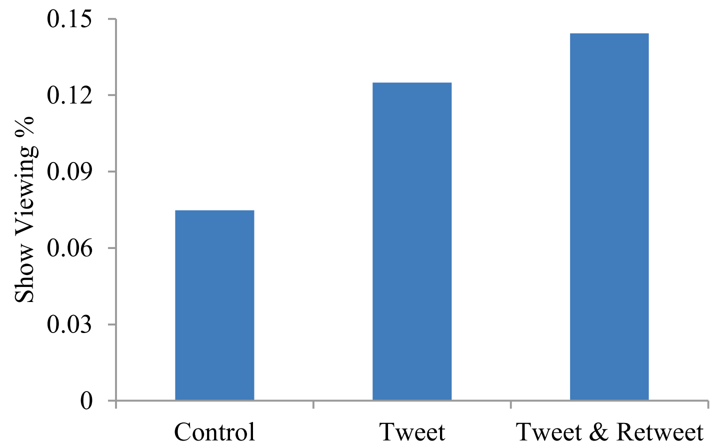
Figure W4 Random Allocation of TV Shows into the Three Experimental Conditions



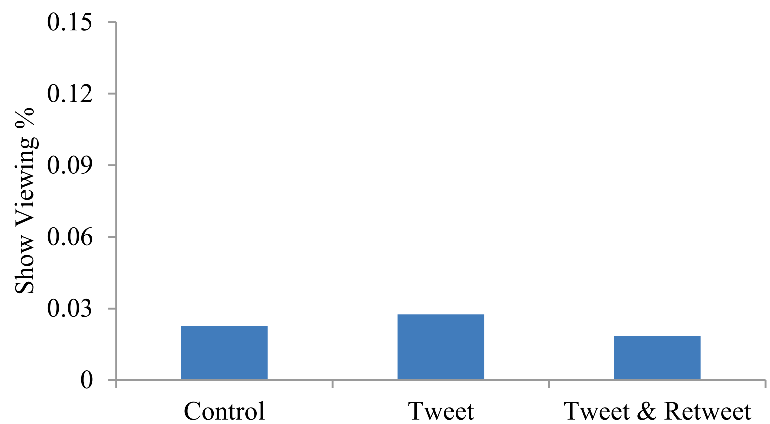
Notes. This figure presents the random allocation of the 98 TV shows selected for the experiment into the three experimental conditions. We use a Latin square design to control variations across weeks (week 1 through week 14) and across days of the week (Monday through Sunday). The columns and rows represent the week and the day of the week, respectively. Each cell corresponds to a show. The black cells represent the 14 shows in the control condition, the gray cells represent the 42 shows in the Tweet condition, and the white cells represent the remaining 42 shows in the Tweet & Retweet condition.

Figure W5 Show Viewing Percentage by Experimental Condition

a. Treated Channels



b. Untreated Channels



Notes. Treated channels are channels that broadcast the shows after the time of company tweets and influential retweets (Shanghai, Tianjin, Wuhan, Guangzhou, and Hangzhou). Untreated channels are channels that broadcast the shows before the time of company tweets and influential retweets (Chongqing and Fuzhou).

Figure W6 Show Viewing Percentage by Experimental Condition and by Channel

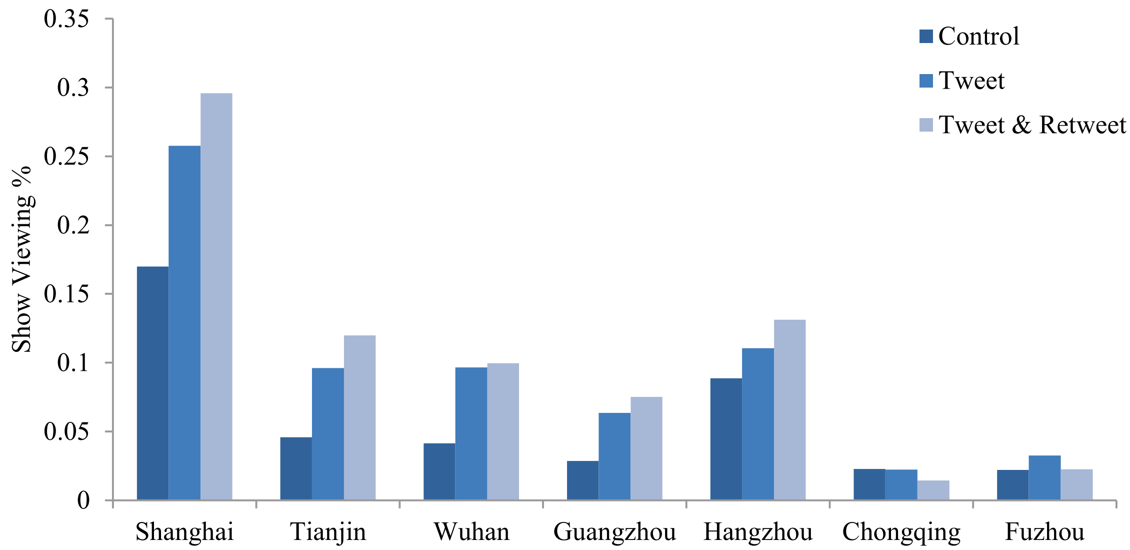
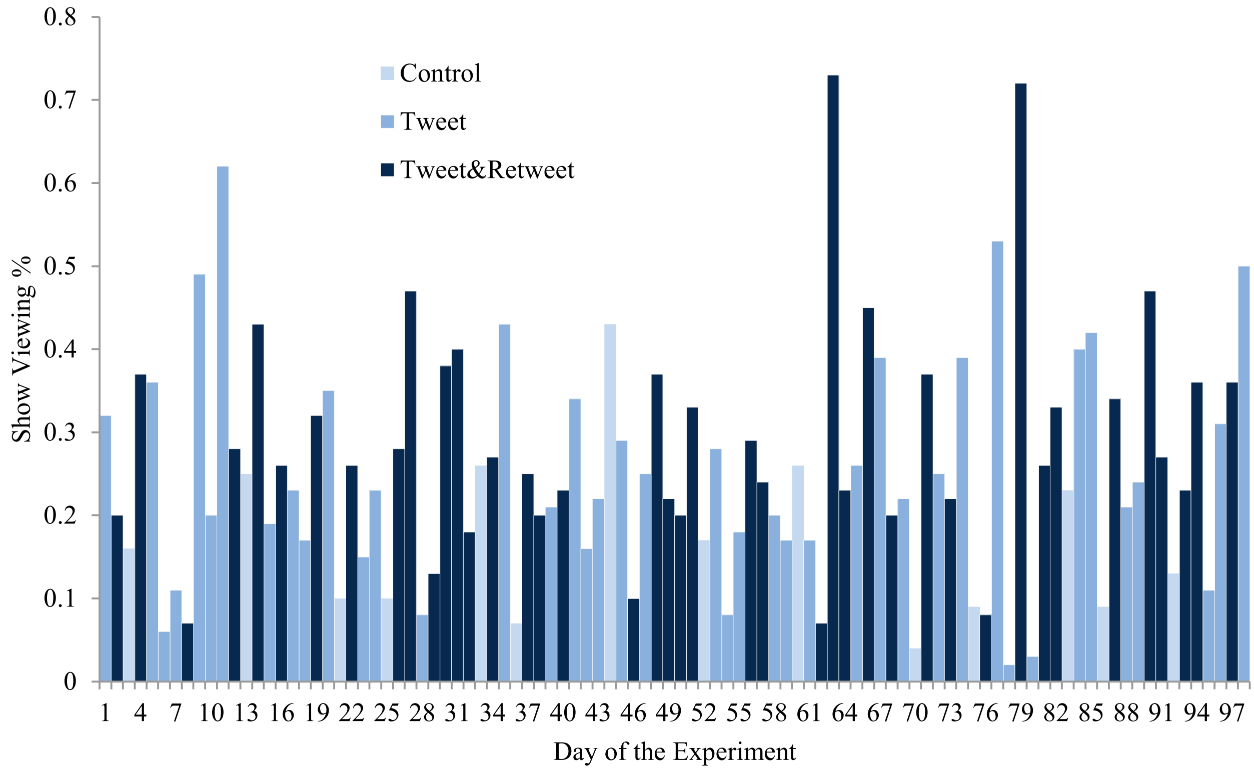
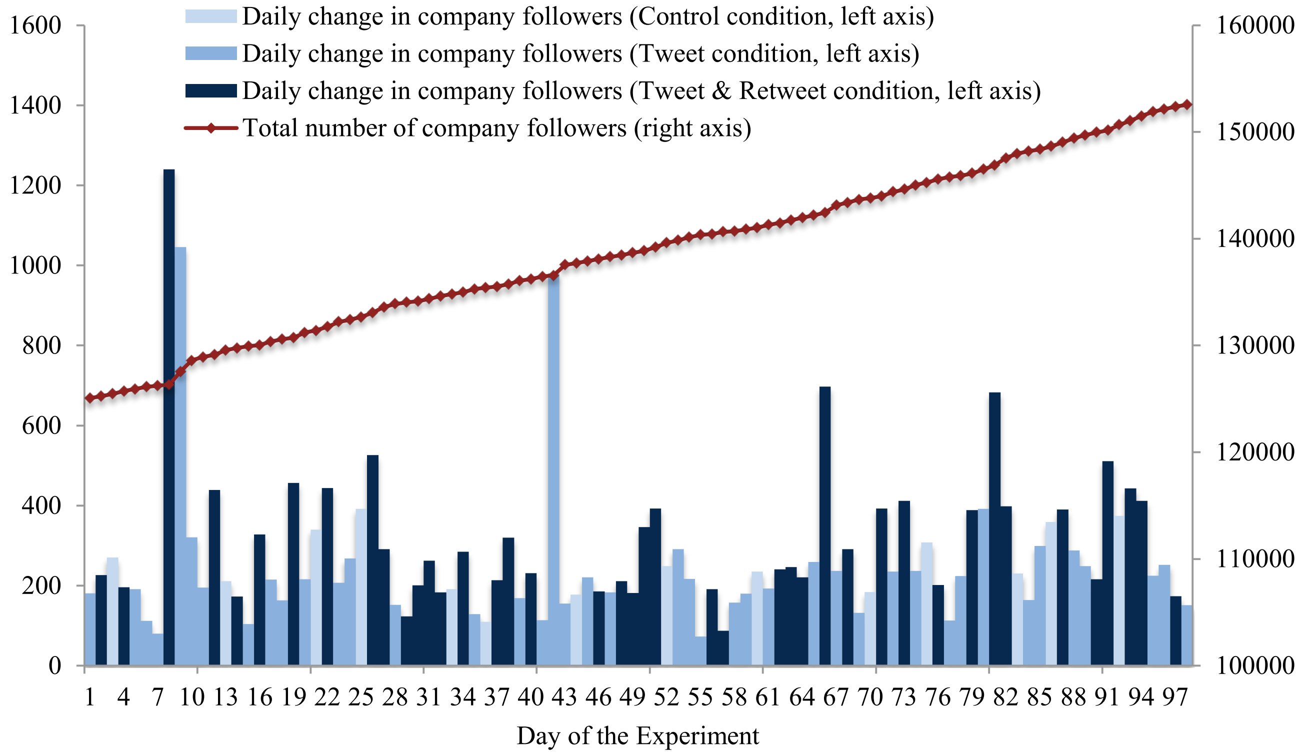


Figure W7 Show Viewing Percentage by Experimental Condition and Over Time



Notes. The horizontal axis indexes the day of the experiment, from day 1 through day 98.

Figure W8 Evolution of Company Followers over Time



Notes. The horizontal axis indexes the day of the experiment, from day 1 through day 98.

Figure W9 Distribution of the Number of Viewers per Show