Check for updates

SHIYANG GONG, JUANJUAN ZHANG, PING ZHAO, and XUPING JIANG*

Many businesses today have adopted 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, social media marketing, social media return on investment, field experiment, television

Online Supplement: http://dx.doi.org/10.1509/jmr.14.0348

Tweeting as a Marketing Tool: A Field Experiment in the TV Industry

*Shiyang Gong is Assistant Professor of Marketing, University of International Business and Economics (email: gongshiyang@uibe.edu.cn). Juanjuan Zhang is Epoch Foundation Professor of International Management and Professor of Marketing, Sloan School of Management, Massachusetts Institute of Technology (email: jjzhang@mit.edu). Ping Zhao is Professor of Marketing, School of Economics and Management, Tsinghua University (email: zhaop@sem.tsinghua.edu.cn). Xuping Jiang is Professor of Marketing, School of Economics and Management, Tsinghua University (email: jiangxp@sem.tsinghua.edu.cn). The authors are indebted to Yubo Chen for his tremendous help throughout this study. They also thank the *JMR* review team for excellent suggestions. The authors have received helpful comments from Martin Peitz, David Reiley, Ken Wilbur, and Nathan Yang; seminar participants at Beihang University, Boston University, China Europe International Business School, Columbia University, Cornell University, Erasmus University Rotterdam, Hong Kong University of Science and Technology, Interdisciplinary Center Herzliya, Johns Hopkins University, Lehigh University, Microsoft Research in New York City, Nankai University, Renmin University, Shanghai University of Finance and Economics, Temple University, Tsinghua University, University of Alberta, University of Chicago, University of International Business and Economics, University of Maryland, and University of North Carolina at Chapel Hill; attendees of the American Marketing Association Conference, Beijing Humboldt Forum, China India Insights Conference, Conference on Digital Experimentation, Marketing Science China Conference, Workshop on Social and Business Analytics, Yale Customer Insights Conference, and ZEW Conference on the Economics of Information and Communication Technologies. The authors thank Boosen Social Marketing Company and the anonymous media company for their enthusiastic cooperation in the field experiment, as well as the National Natural Science Foundation of China (grant nos. 71372045 and 71602033) for financial support. Coeditor: Randolph Bucklin; Associate Editor: Avi Goldfarb.

Microblogging platforms, such as Twitter in the United States and Weibo in China, have gained remarkable popularity. The central feature of microblogging is "tweets," short posts disseminated from registered users to their followers. In 2013, the year of Twitter's initial public offering, Twitter 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 article. 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

[1]Source: http://www.umassd.edu/cmr/socialmediaresearch/2015fortune500/.

[2]Source: 2015 Weibo Business White Paper (in Chinese; http://weibo.com/ttarticle/p/show?id=2309403935560250078246).

© 2017, American Marketing Association

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 TV shows. The media company 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, of course, there are 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 about 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 that 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, suggests a problem with Twitter's business model: "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 would be 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 has been examined, including the effect of mobile technologies (Ghose, Goldfarb, and Han 2012), the structure of diffusion networks (Goel, Watts, and Goldstein 2012), the influence of Twitter word of mouth (Rui, Liu, and Whinston 2013), drivers of tweeting (Shi, Rui, and Whinston 2014), prediction of tweet popularity (Zaman, Fox, and Bradlow 2014), and the impact of Twitter presence on political outcomes (Petrova, Sen, and Yildirim 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); customer–firm interaction on Twitter (Ma, Sun, and Kekre 2015); brand image mining using Twitter data (Culotta and Cutler 2016); the effect of company tweeting on word of mouth (Kuppuswamy and Bayus 2016); demand forecasting using cloud computing of Twitter data (Liu, Singh, and Srinivasan 2016); differences between paid, earned, and owned media (Lovett and Staelin 2016); social TV activity (Fossen and Schweidel 2017); targeting of promoted tweets (Lambrecht, Tucker, and Wiertz (2017) and effects of content, content–user fit, and influence on retweeting (Zhang, Moe, and Schweidel 2017). In a recent study, Seiler, Yao, and Wang (2017) leverage a natural experiment, the temporary shutdown of Weibo, to study the effect of online word of mouth on the demand for TV shows. Our study 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 the following: firm-created word of mouth influences sales (Godes and Mayzlin 2009), viral product

[3]For reviews of the field experiment approach, see List and Reiley (2008) and Simester (2017).

[4]For a bibliography of research on microblogging, see http://www.danah.org/researchBibs/twitter.php.

[5]A related stream of research studies the effect of digital marketing, which does not necessarily involve social media, on tangible performance metrics. Findings include the following: 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, Van Heerde, and Neslin 2014); online display ads increase offline sales (Lewis and Reiley 2014); paid search ads increase infrequent buyers' purchases (Blake, Nosko, and Tadelis 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, Zou, and Chintagunta 2017).

design facilitates diffusion (Aral and Walker 2011), viral marketing boosts customer acquisition (Hinz et al. 2011), prelaunch 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" influence customer involvement offline (Mochon et al. 2017). We contribute to this literature by showing that tweeting can be a productive social media marketing strategy to increase product demand and by offering recommendations on how to use this strategy effectively.

FIELD EXPERIMENT

Background

To examine the causal effect of tweets on product demand, we collaborate with a major global 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 of up to 140 characters and multimedia elements such as images, 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 followed users automatically appear on their home pages.

Launched in August 2009, Weibo rapidly gained nationwide popularity in China. In 2012, the year of our experiment, the number of registered users and monthly active users increased by approximately 150 million and 16 million, respectively (for an overview, see Table W1 in the Web Appendix). 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 across all channels. Audiences of the TV shows in these markets are 60% male, 40% female, and typically 25–54 years old.

The company created a business account on Weibo in October 2010. Since then, each day the company has posted one tweet about that day's show, as well as several noncommercial tweets. These noncommercial tweets, usually including interesting stories and pictures about science, technology, nature, history, and so on, were aimed to engage the company's existing followers and attract new followers without explicitly advertising a particular show (for an example, see Figure W1 in the Web Appendix). At the start of 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 can 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 as 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-subjects design across channels (see "Secondary design: TV channel level").

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.

Primary design: TV show level. The primary design of the experiment involves assigning TV shows into three conditions. Next, we describe the conditions, the randomization strategy, and the recruitment of influentials.

Each TV show is randomly assigned into one of 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 (for an example, see Figure W2 in the Web Appendix): 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 (see "Secondary design: TV channel level"). 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 (for an example, see Figure W3 in the Web Appendix). The comments are predesigned 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]

We implement a two-step randomization strategy to assign the shows into the three conditions. In the first step, we randomly

[6]The name of the media company and its products are kept anonymous in accordance with a confidentiality agreement.

[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.

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 A.M. on the day of the show. Influentials retweet company tweets at noon on the same day.

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 to the tweet & retweet condition. We verify that each condition is present in each week and on each day of the week during the experiment. This allows us to subsequently control for unobservable week effects and day-of-the-week effects. Figure W4 in 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 users, 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. Therefore, 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 "grassroots influentials," ordinary people who have gained impact on Weibo through tweeting. To operationalize Weibo impact, we draw on previous research (e.g., Goldenberg et al. 2009; Stephen et al. 2014; Trusov, Bodapati, and Bucklin 2010) 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 Chinese yuan (CNY), or 6,790 U.S. dollars (USD), is spent to recruit 42 influentials; that is, CNY 1,000 (USD 162) is spent per influential. We randomly assign influentials to 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 have 729 retweets by their followers for each tweet posted.

Secondary design: TV channel level. As mentioned previously, the geographical separation of show viewing across TV

Table 2
SUMMARY STATISTICS OF WEIBO INFLUENTIALS RECRUITED TO RETWEET

	M	*SD*	*Min*	*Mdn*	*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.

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' broadcast time on five channels and after their broadcast time on the other two channels.[8] Specifically, Shanghai, Tianjin, Wuhan, Guangzhou, and Hangzhou are "treated channels," because treatments occur before the shows' broadcast, 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 broadcast. 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 can vary the informativeness of the company tweet across channels by selectively displaying broadcast information for three channels (see bottom portion of Figure W2 in the Web Appendix). For example, if we display broadcast information for the Shanghai channel, the company tweet will be more informative to the Shanghai audience than to the other channel audiences. 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 for Shanghai, Tianjin, and Wuhan in company tweets. During weeks 8–14, we display information for Shanghai, Guangzhou, and Hangzhou. Thus, all possible combinations of display condition in the two halves (i.e., displayed in both halves, displayed in first half but not second half, displayed in second half but not first half, and not displayed in either half) are implemented for at least one channel. Table 3 summarizes the design at the TV channel level.

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

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

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

Table 3
SUMMARY OF EXPERIMENTAL DESIGN AT THE TV CHANNEL LEVEL

		Broadcast Information	
TV Channel	*Broadcast Time*	*Weeks 1–7*	*Weeks 8–14*
Shanghai	After treatment	Displayed	Displayed
Tianjin	After treatment	Displayed	Not displayed
Wuhan	After treatment	Displayed	Not displayed
Guangzhou	After treatment	Not displayed	Displayed
Hangzhou	After treatment	Not displayed	Displayed
Chongqing	Before treatment	Not displayed	Not displayed
Fuzhou	Before treatment	Not displayed	Not displayed

Notes: "Displayed" means the broadcast information for the channel is displayed in the company tweet.

and balanced across conditions, that the media company engaged in no marketing activities outside Weibo, and that Weibo implemented no feature changes. Two data sets were collected during the experiment: a show viewing data set and a tweet diffusion data set.

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 had 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 these 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 in 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 wherein each observation is a show–channel combination. Of these observations, 490 are from treated channels and 196 from untreated channels. On average, .0966% of the audience of a local channel watched any given 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 = .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 = .001 and .000, respectively), but are insignificant over untreated channels (p = .302 and .708, respectively). These patterns provide the first evidence that company tweets and influential retweets increase show viewing.

Tweet diffusion data. Using the Weibo application program interface, 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 they 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, respectively. All these differences are highly significant (all p = .000). The difference in the number of retweets seems to be mainly driven by retweets of influentials' 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.

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 in 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 335 in the tweet & retweet condition, which significantly exceeds the baseline value (p = .012). These results suggest that influential retweets are more effective in growing company followers than company tweets. We further assess this argument in the next section.

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

Table 4
SUMMARY STATISTICS OF SHOW VIEWING PERCENTAGE BY EXPERIMENTAL CONDITION

Condition	Number of Observations	M	SD	Min	Mdn	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						
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						
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: Treated channels are channels that broadcast the shows after the treatments. Untreated channels are channels that broadcast the shows before the treatments. An observation is a show–channel combination.

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 for and boundaries of the findings.

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 in 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: the fact 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

Table 5
SUMMARY STATISTICS OF TWEET DIFFUSION BY EXPERIMENTAL CONDITION

	M	SD	Min	Mdn	Max
Control Condition (N = 14)					
Number of retweets	0	0	0	0	0
Influential retweets	0	0	0	0	0
Retweets of influential retweets	0	0	0	0	0
Organic retweets	0	0	0	0	0
Number of impressions	0	0	0	0	0
Diffusion depth	0	0	0	0	0
Tweet Condition (N = 42)					
Number of retweets	27	25	2	20	149
Influential retweets	0	0	0	0	0
Retweets of influential retweets	0	0	0	0	0
Organic retweets	27	25	2	20	149
Number of impressions	160,522	37,765	130,848	151,073	344,549
Diffusion depth	2	.99	1	2	5
Tweet & Retweet Condition (N = 42)					
Number of retweets	127	117	10	86	512
Influential retweets	1	0	1	1	1
Retweets of influential retweets	92	87	4	58	388
Organic retweets	34	34	2	25	134
Number of impressions	3,238,494	6,610,906	470,074	1,618,676	43,461,666
Diffusion depth	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

Condition	*Number of Observations*	*M*	*SD*	*Min*	*Mdn*	*Max*
Control	14	259	85	110	242	392
Tweet	42	237	188	73	201	1,046
Tweet & retweet	42	335	199	87	288	1,240

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

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 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-the-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 ordinary least squares (OLS) estimates with robust standard errors clustered at the show level to account for heteroskedasticity and dependence within a show.

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 (i.e., channels that broadcast the shows before both treatment periods). If the explanation based on unobserved show quality were true, the spurious treatment effects would have 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.

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 in 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]

How Does Tweeting Affect Show Viewing?

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 with the following independent variables added: a Display dummy indicating whether a channel is 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.

To see this effect from another perspective, we stratify the sample according to 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

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

[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.

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

[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, whereas the treatment dummies are defined at the show level.

Table 7

MAIN RESULTS: EFFECT OF TWEETING ON SHOW VIEWING (TREATED CHANNELS)

	Model Specifications				
	1	*2*	*3*	*4*	*5 (Main Model)*
Tweet (α_1)	.0500 (.0133)***	.0514 (.0138)***	.0514 (.0138)***	.0492 (.0145)***	.0576 (.0161)***
Tweet & Retweet (α_2)	.0694 (.0144)***	.0698 (.0148)***	.0698 (.0149)***	.0707 (.0156)***	.0824 (.0169)***
Number of noncommercial tweets		.0035 (.0030)	.0035 (.0031)	.0007 (.0050)	−.0022 (.0056)
Channel dummies	No	No	Yes	Yes	Yes
Week dummies	No	No	No	Yes	Yes
Day-of-the-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
Number of observations	490	490	490	490	490
R^2	.033	.035	.347	.372	.389

****p* < .01.

Notes: For details of the various model specifications, see the main text. 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.

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. Because they chose 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. In contrast, the audience of an influential retweet consists of followers of the influential. Some of them may be new to the show but may 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, Nosko, and Tadelis 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., Goldenberg et al. 2009; Hinz et al. 2011; Watts and Dodds 2007).

Table 8

FALSIFICATION CHECK: EFFECT OF TWEETING ON SHOW VIEWING (UNTREATED CHANNELS)

	Model Specifications				
	1	*2*	*3*	*4*	*5*
Tweet (α_1)	.0050 (.0086)	.0058 (.0089)	.0058 (.0090)	.0052 (.0087)	.0075 (.0088)
Tweet & Retweet (α_2)	−.0040 (.0079)	−.0038 (.0082)	−.0038 (.0082)	−.0039 (.0082)	−.0044 (.0078)
Number of noncommercial tweets		.0021 (.0013)	.0021 (.0013)	.0008 (.0026)	.0022 (.0026)
Channel dummies	No	No	Yes	Yes	Yes
Week dummies	No	No	No	Yes	Yes
Day-of-the-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
Number of observations	196	196	196	196	196
R^2	.011	.020	.030	.132	.177

Notes: For details of the various model specifications, see the main text. 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.

Table 9
EFFECT OF DISPLAYING BROADCAST INFORMATION ON SHOW VIEWING

	Model Specifications			
	1	*2*	*3*	*4*
Broadcast information condition	*All*	*All*	*Displayed*	*Not Displayed*
Tweet (α_1)	.0576 (.0161)***	.0462 (.0161)***	.0691 (.0213)***	.0402 (.0182)**
Tweet & Retweet (α_2)	.0824 (.0169)***	.0551 (.0169)***	.1007 (.0177)***	.0550 (.0184)***
Display	.0052 (.0078)	−.0224 (.0154)		
Tweet × Display		.0189 (.0210)		
Tweet & Retweet × Display		.0455 (.0194)**		
Number of noncommercial tweets	−.0022 (.0056)	−.0022 (.0056)	−.0004 (.0070)	−.0048 (.0073)
Channel dummies	Yes	Yes	Yes	Yes
Week dummies	Yes	Yes	Yes	Yes
Day-of-the-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
Number of observations	490	490	294	196
R^2	.390	.394	.442	.236

**$p < .05$.
***$p < .01$.
Notes: For details of the various model specifications, see the main text. An observation is a show–channel combination. The dependent variable is the percentage of a channel's audience viewing a show. The models in columns 1 and 2 include all 98 shows on the five treated channels. Those in columns 3 and 4 split this sample according to 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.

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, the number of followers is endogenous, so 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. The specification in 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 according to whether the company tweet displays broadcast information of the show. Column 5, however, 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 for the show. This result echoes our prior 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.

These results 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, and column 3 further includes the viewing percentage of

[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 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.

Table 10
EFFECT OF COMPANY FOLLOWERS ON SHOW VIEWING

Broadcast information condition	*Model Specifications*						
	1	*2*	*3*	*4*	*5*	*6*	*7*
	All	*All*	*Displayed*	*Not Displayed*	*All*	*Displayed*	*Not Displayed*
Company Tweet	.0576 (.0161)***	−.2280 (.2297)	−.1578 (.3225)	−.3331 (.2286)	.0387 (.0181)**	.0422 (.0250)*	.0334 (.0233)
Company Tweet × Lag Followers		.0020 (.0016)	.0016 (.0023)	.0027 (.0016)			
Company Tweet × Lag ΔFollowers					.0493 (.0290)*	.0747 (.0381)*	.0112 (.0473)
Influential Retweet	.0248 (.0139)*	.0289 (.0137)**	.0362 (.0183)*	.0180 (.0165)	.0312 (.0132)**	.0398 (.0180)**	.0183 (.0166)
Number of noncommercial tweets	−.0022 (.0056)	−.0048 (.0059)	−.0033 (.0074)	−.0071 (.0074)	−.0022 (.0062)	.0003 (.0076)	−.0061 (.0076)
Channel dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-the-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
Number of observations	485	485	291	194	485	291	194
R^2	.389	.400	.454	.246	.402	.460	.242

**p* < .10.
***p* < .05.
****p* < .01.
Notes: For details of the various model specifications, see the main text. 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, 6, and 7 split this sample according to 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.

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.

Heterogeneous effects of influential retweets. The fact that influential retweets bring new followers is good news to businesses, which can recruit influentials to grow their follower base. But what type of influentials should companies target? We gathered 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, and 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 the specification in column 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, 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 for Influential Retweet × 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. The 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.

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 in the same city as the channel.[17] Table W3 of the Web Appendix presents the results. Among the interaction terms, Influential Retweet × Retweets

[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 those in column 3 of Table 6, 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.

[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.

Table 11
EFFECT OF TWEETING ON COMPANY FOLLOWERS

	Model Specifications		
	1	*2*	*3*
Company Tweet	−21.95 (56.36)	−13.48 (55.44)	−20.74 (58.11)
Influential Retweet	97.21 (39.85)**	90.86 (39.21)**	88.26 (39.83)**
Number of noncommercial tweets		22.24 (10.29)**	21.75 (10.39)**
Average show viewing percentage			141.28 (323.99)
Number of observations	98	98	98
R^2	.061	.106	.108

**$p < .05$.

Notes: For details of the various model specifications, see the main text. 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.

Actively is positive and significant ($p < .01$) especially in the subsample where broadcast information is displayed. In addition, Influential Retweet × 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 previously in this paper.

Robustness Checks

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.

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, his/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—the same way we have specified a linear relationship between the independent and dependent variables in the analysis so far—but allow this latent variable to be equal to 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 article because it allows for more direct presentation of effect magnitude.

[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 (for a review, see Goldfarb 2012).

[19]Theoretically, 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.

Number of viewers as dependent variable. Although viewing percentage is the key performance index for the media company, it does not reflect the variation in audience populations across channels. To check whether this affects our conclusions, we transform show viewing percentage into 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 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 in 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 in the Web Appendix presents the distribution of the number of viewers per show.

We re-estimate the main model using 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 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.

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

We construct four measures of prior viewership. First, because the company airs new shows daily, we use the viewing

[20]Source: http://www.csm.com.cn/en/cpfw/ds/wldc.html.

Table 12

HETEROGENEOUS EFFECTS OF INFLUENTIAL RETWEETS ON COMPANY FOLLOWERS

	Model Specifications			
	1	*2*	*3*	*4*
Company Tweet	−2.04 (57.07)	−14.18 (57.32)	−.12.21 (57.52)	−7.19 (57.28)
Influential Retweet	78.17 (59.12)	35.62 (47.36)	146.33 (49.99)***	29.07 (47.40)
Influential Retweet × Has Many Followers	52.44 (77.61)	111.52 (24.06)**		
Influential Retweet × Tweets Actively	−94.13 (57.35)		−108.23 (57.58)*	
Influential Retweet × Retweeted Actively	79.34 (82.95)			131.00 (59.50)**
Number of noncommercial tweets	18.32 (10.20)*	20.40 (10.25)**	20.24 (10.28)*	19.30 (10.24)*
Average show viewing percentage	−258.40 (351.62)	.07 (326.86)	−40.49 (333.97)	−147.98 (343.60)
Number of observations	98	98	98	98
R^2	.181	.144	.141	.152

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: For details of the various model specifications, see the main text. 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.

percentage of the show broadcast on the same channel the day before to measure the company-level carryover effect. Second, research has found 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). Therefore, 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 most recent show in the target series 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 first-order autoregressive 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]

Difference-in-differences analysis. As discussed previously, 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 versus 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 seven 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]

[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.

[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.

Table 13
ROBUSTNESS CHECKS: ALTERNATIVE DEPENDENT VARIABLES

	Model Specifications		
	1 (Tobit Model for Truncated DV)	*2 (OLS with Number of Viewers as DV)*	*3 (Fixed-Effects Poisson with Number of Viewers as DV)*
Tweet (α_1)	.0609 (.0165)***	6,306.41 (1,761.70)***	.5449 (.1642)***
Tweet & Retweet (α_2)	.0847 (.0172)***	8,977.80 (1,867.22)***	.7180 (.1658)***
Number of noncommercial tweets	−.0029 (.0057)	−75.72 (613.73)	−.0074 (.0410)
Channel dummies	Yes	Yes	Yes
Week dummies	Yes	Yes	Yes
Day-of-the-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
Number of observations	490	490	490
(Pseudo) R^2	.460	.600	.628

***$p < .01$.

Notes: For details of the various model specifications, see the main text. 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.

Table 15 reports the estimation results using data from the five treated channels. As in 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 it. 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 relates to the "removal-design" nature of the experiment: the company had been posting a show tweet each day prior to the experiment but ceased to do so in the control condition of the experiment. This may have caused a decline in viewing for shows in the control group compared with their benchmark shows. 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.

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

Effect magnitude. 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 have their broadcast information displayed in the show tweet. The viewing percentage of this show will increase to .1325, which represents a 77% increase over the level in the control condition.[24] Meanwhile, the company will gain 244 new followers on that day—less than in the control level, although the difference is insignificant. In addition, the company may also recruit an influential to retweet the original show tweet. Doing so will increase viewing percentage to .1573, a 110% increase over the control level, and an 33% increase 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 for the show. In that case, viewing percentage will rise to .1755, a 134% increase over the control level and 57% beyond the level achieved by company tweets alone. Furthermore, if the company both tweets and recruits an influential to retweet, it will attract 349 new followers, a 35% increase over the control level.

Recall that retweeting has carryover effects on show viewing, as the influx of new company followers amplifies the effect of company tweets the next day. Table 16 presents the magnitude of these carryover effects. Suppose that yesterday, the company tweeted a show and had an influential retweet it. Now, if the company tweets today's show, the viewing percentage will

[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 percentages as reported in Table 4. The same idea applies to the rest of the effect magnitude analysis.

Table 14
ROBUSTNESS CHECKS – CONTROLLING FOR PRIOR VIEWERSHIP

	Model Specifications			
	1	*2*	*3*	*4*
Tweet (α_1)	.0452 (.0132)***	.0436 (.0145)***	.0838 (.0192)***	.0874 (.0198)***
Tweet & Retweet (α_2)	.0650 (.0128)***	.0704 (.0137)***	.1251 (.0199)***	.1265 (.0206)***
Viewing percentage of the show the day before	−.1108 (.0443)**			
Viewing percentage of the show a week before		.0203 (.0457)		
Viewing percentage of last show in series			−.1055 (.0547)*	
Average viewing percentage of prior shows in series				.0686 (.0692)
Number of noncommercial tweets	−.0043 (.0049)	−.0082 (.0052)	−.0134 (.0071)*	−.0105 (.0073)
Channel dummies	Yes	Yes	Yes	Yes
Week dummies	Yes	Yes	Yes	Yes
Day-of-the-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
Number of observations	485	455	275	275
R^2	.403	.404	.510	.499

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: For details of the various model specifications, see the main text. The samples are as follows: column 1, shows on days 2–98 of the experiment; column 2, shows on days 8–98; columns 3–4, serial shows except the first one in the observation window. FGLS estimates. For further details, see Table 7 notes.

be .1497, out of which .0172 is associated with the newly subscribed company followers. If the company also 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 at 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 also 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 tweets informative to help new customers navigate the purchase funnel—even a simple sentence providing purchase instructions can make a difference.

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 by 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 Zhang and Hu's (2013) "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 by the average license fee per minute for documentary TV shows in China in 2012. This yields a license fee of CNY 2,625 per show. For a 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 CNY 27,174 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 CNY 1,565 per show in the tweet condition and CNY 2,239 per show in the tweet & retweet condition.

On the cost side, the total operating cost of the media company's Weibo account is about CNY 5,000 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 estimate of return on investment, we assume zero overhead and compute the average cost per company tweet as $5{,}000 \times 14/358 \approx$ CNY 196. In addition, to recruit a Weibo influential to retweet a show tweet, the company paid an average of CNY 1,000.

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 considered the carryover effects of tweeting.

[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.

Table 15
ROBUSTNESS CHECKS: DIFFERENCE-IN-DIFFERENCES ANALYSIS

	Model Specifications				
	1	*2*	*3*	*4*	*5*
Tweet	−.0067 (.0211)	−.0076 (.0210)	−.0076 (.0210)	−.0085 (.0184)	−.0088 (.0175)
Tweet & Retweet	−.0266 (.0201)	−.0266 (.0199)	−.0266 (.0149)	−.0257 (.0170)	−.0277 (.0163)*
After	−.0987 (.0204)***	−.1005 (.0203)***	−.1004 (.0203)***	−.1004 (.0207)***	−.1058 (.0217)***
Tweet × After (α_1)	.0567 (.0237)**	.0594 (.0236)**	.0594 (.0236)**	.0595 (.0242)**	.0645 (.0242)***
Tweet & Retweet × After (α_2)	.0960 (.0238)***	.0965 (.0236)***	.0965 (.0236)***	.0965 (.0238)***	.0978 (.0238)***
Number of noncommercial tweets		.0047 (.0024)*	.0048 (.0024)*	.0048 (.0037)	.0050 (.0036)
Channel dummies	No	No	Yes	Yes	Yes
Week dummies	No	No	No	Yes	Yes
Day-of-the-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
Number of observations	980	980	980	980	980
R^2	.034	.037	.348	.360	.369

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: For details of the various model specifications, see the main text. 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.

Additional Studies and Discussion

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 there is, then 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

Table 16
EFFECT MAGNITUDE BY EXPERIMENTAL CONDITION

	Current Effects				*Current + Carryover Effects*[a]	
	Show Viewing Percentage		*Daily Growth in Company Followers*		*Show Viewing Percentage*	
Condition	*M*	*Change*	*M*	*Change*	*M*	*Change*
Control	.0749	0%	259	0%	.0749	0%
Tweet	.1325***	77%***	244	−6%	.1497***	100%***
Tweet & retweet	.1573***	110%***	349**	35%**	.1745***	133%***
Displayed	.1755***	134%***	N.A.	N.A.	.1927***	157%***
Not displayed	.1300	74%	N.A.	N.A.	.1472	97%

**$p < .05$.
***$p < .01$.
[a]Assuming tweet and retweet on the previous day.
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 Followers" columns. Changes are calculated using the value in the control condition as the common benchmark. N.A. = not applicable.

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	*Displayed*	*Not Displayed*	
Has Many Followers	−.0208	−.0364	−.0036	132**
Tweets Actively	−.0249	−.0397	−.0253	−10*
Retweets Actively	.0796***	.1086***	−.0212	140**
Local	.0018	.0386*	−.0212	N.A.

*$p < .10$.
**$p < .05$.
***$p < .01$.
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 Followers" column. Changes are calculated using the value in the tweet condition as the benchmark. N.A. = not applicable.

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 next.

Across all respondents, watching TV shows is a regular activity. On a scale from 1 ("never") to 5 ("very often"), average TV watching frequency is 3.428, significantly higher than the neutral level of 3 ($t = 6.233$, $p < .001$). Among sources of TV show information, social media sites 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 response 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 response 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. Thus, we ask whether friend recommendations 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 for "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 for "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, to some extent, amplified the effect of tweeting beyond Weibo.

Some final comments on the plausibility of the estimated tweeting effects are in order. First, choices about TV viewing are relatively low-stakes and quick decisions, making them potentially susceptible to tweeting and marketing activities in general. In fact, through a mobile ad campaign, HBO was 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 previously, the media company did not pursue other marketing activities besides tweeting during the experiment, and the marginal effect of tweeting may be smaller when it coexists with other marketing campaigns. For example, in the movie industry, known for heavy prelaunch advertising, tweeting may not generate such strong effects on viewing. Third, the media company was one of the first to adopt tweeting as a marketing tool in its industry; the returns to tweeting may be diluted when competitors join the race to tweet. Nevertheless, our findings 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.

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 to retweet company tweets—especially users who are retweeted actively by their own followers—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 will be the price for influentials to engage in social media promotions? How does this price affect the influence of influentials? Like 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 related efforts, Joo et al. (2014) investigate the impact of TV advertising on online search; Liaukonyte, Teixeira, and Wilbur (2015) study the effect of TV advertising on online shopping; and Bluefin Labs, a subsidiary of Twitter, uses social media commentary data to measure viewer engagement with TV contents (Shontell 2013).

REFERENCES

Anand, Bharat N., and Ron Shachar (2011), "Advertising, the Matchmaker," *RAND Journal of Economics*, 42 (2), 205–45.

Andrews, Michelle, Xueming Luo, Zheng Fang, and Anindya Ghose (2016), "Mobile Ad Effectiveness: Hyper-Contextual Targeting with Crowdedness," *Marketing Science*, 35 (2), 218–33.

Aral, Sinan, and Dylan Walker (2011), "Creating Social Contagion Through Viral Product Design: A Randomized Trial of Peer Influence in Networks," *Management Science*, 57 (9), 1623–39.

Arellano, Manuel, and Stephen Bond (1991), "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *Review of Economic Studies*, 58 (2), 277–97.

BenYishay, Ariel, and A. Mushfiq Mobarak (2015), "Social Learning and Incentives for Experimentation and Communication,"working paper, College of William & Mary.

Blake, Thomas, Chris Nosko, and Steven Tadelis (2015), "Consumer Heterogeneity and Paid Search Effectiveness: A Large-Scale Field Experiment," *Econometrica*, 83 (1), 155–74.

Butcher, Dan (2010), "HBO True Blood Mobile Ad Campaign Increases Viewership 38pc," Mobile Marketer (accessed July 20, 2010), http://www.mobilemarketer.com/cms/news/advertising/6855.html.

Cespedes, Frank V. (2015), "Is Social Media Actually Helping Your Company's Bottom Line?" *Harvard Business Review* (March 3), https://hbr.org/2015/03/is-social-media-actually-helping-your-companys-bottom-line.

Culotta, Aron, and Jennifer Cutler (2016), "Mining Brand Perceptions from Twitter Social Networks," *Marketing Science*, 35 (3), 343–62.

Dinner, Isaac M., Harald J. Van Heerde, and Scott A. Neslin (2014), "Driving Online and Offline Sales: The Cross-Channel Effects of Traditional, Online Display, and Paid Search Advertising," *Journal of Marketing Research*, 51 (5), 527–45.

Fossen, Beth L., and David A. Schweidel (2017), "Television Advertising and Online Word-of-Mouth: An Empirical Investigation of Social TV Activity," *Marketing Science*, 36 (1), 105–23.

Ghose, Anindya, Avi Goldfarb, and Sang Pil Han (2012), "How Is the Mobile Internet Different? Search Costs and Local Activities," *Information Systems Research*, 24 (3), 613–31.

Godes, David, and Dina Mayzlin (2009), "Firm-Created Word-of-Mouth Communication: Evidence from a Field Test," *Marketing Science*, 28 (4), 721–39.

Goel, Sharad, Duncan J. Watts, and Daniel G. Goldstein (2012), "The Structure of Online Diffusion Networks," in *Proceedings of the 13th ACM Conference on Electronic Commerce*. New York: Association for Computing Machinery, 623–38.

Goettler, Ronald L., and Ron Shachar (2001), "Spatial Competition in the Network Television Industry," *RAND Journal of Economics*, 32 (4), 624–56.

Goldenberg, Jacob, Sangman Han, Donald R. Lehmann, and Jae Weon Hong (2009), "The Role of Hubs in the Adoption Process," *Journal of Marketing*, 73 (2), 1–13.

Goldfarb, Avi (2012), "Internet and the Offline World," in *New Palgrave Dictionary of Economics*, online ed., Steven N. Durlauf and Lawrence E. Blume, eds. London: Palgrave Macmillan, http://www.dictionaryofeconomics.com/article?id=pde2012_I000313.

Hair, Joseph F., Jr., William C. Black, Barry J. Babin, and Rolph E. Anderson (2010), *Multivariate Data Analysis*, 7th ed. Upper Saddle River, NJ: Prentice Hall.

Hinz, Oliver, Bernd Skiera, Christian Barrot, and Jan U. Becker (2011), "Seeding Strategies for Viral Marketing: An Empirical Comparison," *Journal of Marketing*, 75 (6), 55–71.

Hoban, Paul R., and Randolph E. Bucklin (2015), "Effects of Internet Display Advertising in the Purchase Funnel: Model-Based Insights from a Randomized Field Experiment," *Journal of Marketing Research*, 52 (3), 375–93.

Joo, Mingyu, Kenneth C. Wilbur, Bo Cowgill, and Yi Zhu (2014), "Television Advertising and Online Search," *Management Science*, 60 (1), 56–73.

Koh, Yoree (2016), "Twitter Revenue Growth Dwindles; Outlook Disappoints," *Wall Street Journal* (July 26), http://www.wsj.com/articles/twitter-revenue-growth-dwindles-outlook-disappoints-1469564731.

Kumar, Ashish, Ram Bezawada, Rishika Rishika, Ramkumar Janakiraman, and P.K. Kannan (2016), "From Social to Sale: The Effects of Firm-Generated Content in Social Media on Customer Behavior," *Journal of Marketing*, 80 (1), 7–25.

Kuppuswamy, Venkat, and Barry Bayus (2016), "Using Tweets to Generate Electronic Word of Mouth: An Analysis of the Kickstarter Crowdfunding Community," working paper, University of North Carolina.

Lambrecht, Anja, and Catherine Tucker (2013), "When Does Retargeting Work? Information Specificity in Online Advertising," *Journal of Marketing Research*, 50 (5), 561–76.

Lambrecht, Anja, Catherine Tucker, and Caroline Wiertz (2017), "Advertising to Early Trend Propagators: Evidence from Twitter," *Marketing Science*, forthcoming.

Lewis, Randall A., and David H. Reiley (2014), "Online Ads and Offline Sales: Measuring the Effects of Retail Advertising via a Controlled Experiment on Yahoo!" *Quantitative Marketing and Economics*, 12 (3), 235–66.

Liaukonyte, Jura, Thales Teixeira, and Kenneth C. Wilbur (2015), "Television Advertising and Online Shopping," *Marketing Science*, 34 (3), 311–30.

List, John A., and David H. Reiley (2008), "Field Experiments," in *New Palgrave Dictionary of Economics*, online ed., Steven N. Durlauf and Lawrence E. Blume, eds. London: Palgrave Macmillan, http://www.dictionaryofeconomics.com/article?id=pde2008_F000305.

Liu, Xiao, Param Vir Singh, and Kannan Srinivasan (2016), "A Structured Analysis of Unstructured Big Data by Leveraging Cloud Computing," *Marketing Science*, 35 (3), 363–88.

Lovett, Mitchell J., and Richard Staelin (2016), "The Role of Paid, Earned, and Owned Media in Building Entertainment Brands: Reminding, Informing, and Enhancing Enjoyment," *Marketing Science*, 35 (1), 142–57.

Ma, Liye, Baohong Sun, and Sunder Kekre (2015), "The Squeaky Wheel Gets the Grease: An Empirical Analysis of Customer Voice and Firm Intervention on Twitter," *Marketing Science*, 34 (5), 627–45.

Manchanda, Puneet, Jean-Pierre Dubé, Khim Yong Goh, and Pradeep K. Chintagunta (2006), "The Effect of Banner Advertising on Internet Purchasing," *Journal of Marketing Research*, 43 (1), 98–108.

Miklós-Thal, Jeanine, and Juanjuan Zhang (2013), "(De)marketing to Manage Consumer Quality Inferences," *Journal of Marketing Research*, 50 (1), 55–69.

Milgrom, Paul, and John Roberts (1986), "Price and Advertising as Signals of Product Quality," *Journal of Political Economy*, 94 (4), 796–821.

Mochon, Daniel, Karen Johnson, Janet Schwartz, and Dan Ariely (2017), "What Are Likes Worth? A Facebook Page Field Experiment," *Journal of Marketing Research*, 54 (2), 306–17.

Moshkin, Nickolay V., and Ron Shachar (2002), "The Asymmetric Information Model of State Dependence," *Marketing Science*, 21 (4), 435–54.

Nickell, Stephen (1981), "Biases in Dynamic Models with Fixed Effects," *Econometrica*, 49 (6), 1417–26.

Onishi, Hiroshi, and Puneet Manchanda (2012), "Marketing Activity, Blogging, and Sales," *International Journal of Research in Marketing*, 29 (3), 221–34.

Petrova, Maria, Ananya Sen, and Pinar Yildirim (2016), "Social Media and Political Donations: Evidence from Twitter," working paper, Barcelona Institute for Political Economy and Governance.

Rui, Huaxia, Yizao Liu, and Andrew Whinston (2013), "Whose and What Chatter Matters? The Effect of Tweets on Movie Sales," *Decision Support Systems*, 55 (4), 863–70.

Sahni, Navdeep S., Dan Zou, and Pradeep K. Chintagunta (2017), "Do Targeted Discount Offers Serve as Advertising? Evidence from 70 Field Experiments," *Management Science*, 63 (8), 2688–705.

Seiler, Stephan, Song Yao, and Wenbo Wang (2017), "Does Online Word-of-Mouth Increase Demand? (and How?) Evidence from a Natural Experiment," *Marketing Science*, forthcoming.

Shachar, Ron, and John W. Emerson (2000), "Cast Demographics, Unobserved Segments, and Heterogeneous Switching Costs in a Television Viewing Choice Model," *Journal of Marketing Research*, 37 (2), 173–86.

Shi, Zhan, Huaxia Rui, and Andrew B. Whinston (2014), "Content Sharing in a Social Broadcasting Environment: Evidence from Twitter," *Management Information Systems Quarterly*, 38 (1), 123–42.

Shontell, Alyson (2013), "Twitter Makes Big Acquisition, Buys Social TV Analytics Company Bluefin Labs," *Business Insider* (February 4), http://www.businessinsider.com/twitter-bluefin-labs-2013-2.

Simester, Duncan (2017), "Field Experiments in Marketing," in *Handbook of Economic Field Experiments*, Esther Duflo and Abhijit Vinayak Banerjee, eds. Amsterdam: North-Holland, 465–98.

Stephen, Andrew T., Yaniv Dover, Lev Muchnik, and Jacob Goldenberg (2014), "The Effect of Source Activity on the Decision to Retransmit Content in Social Media," working paper, University of Oxford.

Stephen, Andrew T., and Jeff Galak (2012), "The Effects of Traditional and Social Earned Media on Sales: A Study of a Microlending Marketplace," *Journal of Marketing Research*, 49 (5), 624–39.

Tobin, James (1958), "Estimation of Relationships for Limited Dependent Variables," *Econometrica*, 26 (1), 24–36.

Toubia, Olivier, and Andrew T. Stephen (2013), "Intrinsic vs. Image-Related Utility in Social Media: Why Do People Contribute Content to Twitter?" *Marketing Science*, 32 (3), 368–92.

Trainer, David (2016), "Twitter's Business Model Remains Broken, Stock Price Too High," *Forbes* (February 12), http://www.forbes.com/sites/greatspeculations/2016/02/12/twitters-business-model-remains-broken-stock-price-too-high/#43bce5415900.

Trusov, Michael, Anand V. Bodapati, and Randolph E. Bucklin (2010), "Determining Influential Users in Internet Social Networks," *Journal of Marketing Research*, 47 (4), 643–58.

Tucker, Catherine, and Juanjuan Zhang (2010), "Growing Two-Sided Networks by Advertising the User Base: A Field Experiment," *Marketing Science*, 29 (5), 805–14.

Watts, Duncan J., and Peter Sheridan Dodds (2007), "Influentials, Networks, and Public Opinion Formation," *Journal of Consumer Research*, 34 (4), 441–58.

Wilbur, Kenneth C. (2008), "A Two-Sided, Empirical Model of Television Advertising and Viewing Markets," *Marketing Science*, 27 (3), 356–78.

Wooldridge, Jeffrey M. (1999), "Distribution-Free Estimation of Some Nonlinear Panel Data Models," *Journal of Econometrics*, 90 (1), 77–97.

Yeo, Jungwon (2014), "The Day of the Week Effects in Television Viewership and Primetime Television Scheduling," working paper, Singapore Management University.

Zaman, Tauhid, Emily B. Fox, and Eric T. Bradlow (2014), "A Bayesian Approach for Predicting the Popularity of Tweets," *Annals of Applied Statistics*, 8 (3), 1583–611.

Zhang, Tongdao, and Zhifeng Hu (2013), " 2012 Research Report on China's Documentary TV Industry," *Modern Communication*, 201 (4), 81–89.

Zhang, Yuchi, Wendy W. Moe, and David A. Schweidel (2017), "Modeling the Role of Message Content and Influencers in Social Media Rebroadcasting," *International Journal of Research in Marketing*, 34 (1), 100–19.