Information Systems Research
Vol. 24, No. 1, March 2013, pp. 52–70
ISSN 1047-7047 (print) | ISSN 1526-5536 (online)
http://dx.doi.org/10.1287/isre.1120.0466

Active Social Media Management: The Case of Health Care

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Given the demand for authentic personal interactions over social media, it is unclear how much firms should actively manage their social media presence. We study this question empirically in a health care setting. We show that active social media management drives more user-generated content. However, we find that this is due to an incremental increase in user postings from an organization's employees rather than from its clients. This result holds when we explore exogenous variation in social media policies, employees, and clients that are explained by medical marketing laws, medical malpractice laws, and distortions in Medicare incentives. Further examination suggests that content being generated mainly by employees can be avoided if a firm's postings are entirely client focused. However, most firm postings seem not to be specifically targeted to clients' interests, instead highlighting more general observations or achievements of the firm itself. We show that untargeted postings like these provoke activity by employees rather than clients. This may not be a bad thing because employee-generated content may help with employee motivation, recruitment, or retention, but it does suggest that social media should not be funded or managed exclusively as a marketing function of the firm.

Key words: business value of IT; computer-mediated communication and collaboration; social media
History: Chris Dellarocas, Senior Editor; Pei-Yu Chen, Associate Editor. This paper was received on January 13, 2012, and was with the authors 5 months for 2 revisions.

1. Introduction

The arrival of social media has led many organizations to question the extent to which they should actively guide, promote, and shape online conversations about their organization. In the past, firms have made considerable investments in controlling the offline conversations surrounding their brands and also in controlling direct forms of consumer feedback such as online reviews (Godes et al. 2005, Chen et al. 2011). However, it is not clear that such a hands-on approach is an optimal strategy on social media platforms. Much of the emphasis so far on marketing in social media has been on the achievement of "earned reach," whereby a brand builds its subscriber base organically without direct intervention (Corcoran 2009). By actively trying to shape and direct their social media presence, firms might risk undermining this organic form of expansion.

This paper asks what incremental social media activity organizations can expect to generate from actively managing their social media presence. We look at the universe of hospitals in the United States and collect data on whether the hospital is actively managing its social media presence by customizing its Facebook page and posting messages to it. We study Facebook partly because it is the most visited media site in the United States, accounting for 20% of all time spent on the Internet (comScore 2011) and partly because the Facebook Places initiative meant that Facebook created a page for every single hospital in the United States, which each hospital then chose whether to actively manage.

Empirically, we find that actively managing a Facebook page increases the amount of recent user-generated content by Facebook users. This user-generated content spans both "liking" and checking in at the organization as well as posting to the hospital's page or mentioning the organization name in a posting.

We then investigate the source of this incremental user-generated content. We find evidence that for hospitals that do not actively manage their Facebook presence, user-generated content is a function of their number of clients. However, when hospitals do actively manage their Facebook presence, user-generated content no longer increases in the number of clients. Instead, it becomes a function of the number of their employees. We show that this result is robust to multiple specifications and alternative definitions of both the dependent and explanatory variables. The results are also robust when we look at exogenous variation in social media policies, clients, and employees that derives from state laws governing the use of patient testimonials, federal and state laws governing Medicare reimbursement, and laws governing medical malpractice lawsuits.

We interpret this evidence as indicating that when an organization actively manages its social media presence, it predominantly succeeds in increasing user-generated content from users of that social media platform who are internal to the organization rather than external to the organization.

When we look at the content of the typical postings made by hospitals, we see further support for this interpretation. We find that if a hospital devotes its postings toward client-specific communications, then active social media management can still lead to incremental user-generated content that is a function of the number of clients. However, most hospitals do not do this. Instead, more of their postings are devoted to either generic observations or to employee-related issues and achievements. Such content appears to inspire primarily the employees at the organization to respond, rather than clients.

The managerial implications of these findings are threefold. First, it is not necessarily a bad thing if the increase in user-generated content that stems from active social media management represents an increase in interactivity between a firm and its employees. Strengthening communication channels with employees is important for any organization's performance (Pincus 1986). However, as of yet we know of no measurement of the efficacy of social media communications at inspiring and motivating employees compared to more traditional methods of internal firm communication such as email. Furthermore, the industry-based research that exists generally suggests creating separate groups and collaboration spaces (such as wikis) for employees (Cook 2008, Harrill 2011). Therefore, the efficacy of using the firm's major social media presence for internal communications remains unproven. The results of this study emphasize that if firms pursue a strategy of active social media management, they need to invest in ways of measuring the return on investment of doing it both on the client side and the employee side.

Second, it is possible that firms, when adopting active social media management, do not intend for it to mainly lead to more employee rather than client social media activity. Indeed, most firms, including those in health care, cite improved communications with clients as their aim when they start to participate actively over social media (Hawn 2009, Orsini 2010). This is because the management of social media is traditionally viewed as a marketing responsibility. Firms spent 7.4% of their marketing budget on social media in 2012 (Moorman 2012). Much of this cost is manpower devoted to the active management of social media—on average in 2012, large firms employed nine people to manage their social media "in house" and four people from outside vendors. This suggests that active promotion of social media is eclipsing more traditional marketing channels, even though the findings of this paper suggest the benefits of this active management of social media may not be derived primarily from marketing. Moorman's (2012) data stems from a survey of 239 chief marketing officers, which highlights that currently the cost of social media management is borne by the marketing function in the firm. This is understandable given that the majority of popular literature on social media investments is marketing based (Chase and Knebl 2011, Wollan et al. 2011, Blanchard 2011). However, if the benefits of active social media management lie primarily in increased interactions between employees and their organizations, it would be appropriate for firms to specifically incorporate human resources into the management and funding of social media activity.

Third, our results concerning the effects of the content of hospital postings suggest that much of this empirical phenomenon is because firms tend to post content that is not exclusively client focused but instead is more generic, for example, highlighting recent organizational achievements or referring to recent events. It appears that this more generic content is more effective at inspiring further activity from employees rather than from clients. Speculatively, this may be because employees already have closer ties to the organization than do the firm's clients and so are better able to engage with content that is not focused exclusively on their needs. In our sample, client-focused postings constituted around only one fourth of all postings. Our paper highlights that if firms wish to use social media primarily for client-facing reasons, their efforts may be more effective if social media content posted is specifically focused around their clients' needs and interests rather than being of broader organizational interest.

2. Contribution to Literature

This paper builds on an existing literature that tries to measure the usefulness to firms of user-generated content, often in social media settings.[1]

One obvious use of such online content posted to Facebook is that a firm can use it to explicitly promote a product or service to others. Godes and Mayzlin

[1] A full discussion of the topic of how social media conversations can be used to enhance the product development process is beyond the scope of this paper. See Sawhney et al. (2005) for a summary.

(2004), in their study of the use of online conversations as a metric for measuring word of mouth, cite two early studies (Katz and Lazarsfeld 1955, Slack 1999) that document how important word-of-mouth recommendations are for driving purchases. Since this early work, a literature has burgeoned studying how online user-generated content on social websites can promote product adoption by that user's contacts (Trusov et al. 2009) and also how, when featured in advertising, such content can drive sales (Tucker 2012). There is also the possibility of using aggregate user-generated content for marketing purposes (Tucker and Zhang 2011, Oestreicher-Singer and Sundararajan 2012). Ghose (2008) argues that user-generated content on social networking sites can improve search quality.

As of yet, there is little academic research directly studying the effect of participating in an online social media page by either liking the organization or posting on the organization's webpage and the subsequent actions of current clients. However, there is research on online communities that suggests that firms instigating conversations among their customers is helpful for promoting brand loyalty and trust (Algesheimer et al. 2005, Thompson and Sinha 2008).

In general, there is a heavy marketing emphasis when studying the return on investment of social media activity. We could find no research that investigates how to improve internal communications within the firm by means of using external social media websites rather than internal blogs or wikis. This lack of research contrasts with the major finding of the paper, which is that active social media management leads user-generated content to become a function of employee numbers rather than client numbers.

This paper joins a small literature that questions the extent to which commercial purposes are served through firms participating actively in social media. Recent research by Bakshy et al. (2011) that examined 1.6 million Twitter users and 74 million instances of their sharing messages suggested that the organic sharing of content relating to business and finance was the second most unlikely form of content to be shared or exhibit a cascade and was only one third as likely to be shared as content related to the user's lifestyle. Aral and Walker (2011) examine the diffusion of an app on Facebook and show that integrating an automated message broadcasting adoption by users has a larger effect on new adoption than the effect of giving users the opportunity to post their own messages publicizing their adoption. In the sphere of online advertising, Tucker (2011a) shows that video advertising designed for websites, such as YouTube, may have to sacrifice the commercial appeal of its message to be spread virally.

The question of whether or not a firm should actively participate in the conversations about it was first raised as a question of managerial strategy in Godes et al. (2005). Such work has led to theoretical analysis such as Zubcsek and Sarvary (2011), which lays out the advantages to firms of seeding messages. However, work on whether firms should promote themselves via social media has been largely theoretical. Dellarocas (2005) shows the theoretical implications of firms manipulating online forums such as Facebook. Mayzlin (2006) shows that firm-directed social media in a competitive setting can lead to promotion of inferior products. Earlier empirical studies such as Godes and Mayzlin (2009) have focused on measuring the effectiveness of firm participation in offline consumer conversations. However, no empirical work to our knowledge has investigated the incremental effect on social media activity attributable to whether a firm decides to actively participate or not in social media.

3. Data

To establish the identity of all hospitals in the United States, we use data from the American Hospital Association's most recent survey. This survey was conducted in 2009, and the data were released in 2011. The American Hospital Association survey provides an annual census of all hospitals in the United States and their characteristics, such as the number of patients they see and operations they perform. Table 1 provides summary statistics for the data. The depth and breadth of these descriptive data is an attractive feature of studying the use of social media in the health care industry from an academic perspective. This means we can advance existing research on the use of social media, such as Culnan et al. (2010), which is based on individual case studies.

Table 1 Summary Statistics

	Mean	Std dev	Min	Max
	Dependent variables			
UGC	24.4	77.9	0	3,666
Likes	488.1	10,047.1	0	686,899
Visited	934.7	1,988.4	0	38,333
	Explanatory variables			
Active social media	0.19	0.39	0	1
Inpatient days (000)	40.1	52.6	0.0060	679.9
Total operations (000)	5.12	7.19	0	104.2
Total outpatient visits (000)	112.6	174.4	0	2,543.3
No. doctors	16.3	70.9	0	2,067
No. nurses	225.9	349.3	0	4,347
No. trainees	18.5	89.9	0	1,839
Nonmedical staff	397.4	614.4	0	9,025
Group practice association	0.019	0.14	0	1
Integrated salary model	0.25	0.44	0	1
Nonprofit hospital	0.54	0.50	0	1
Speciality hospital	0.17	0.38	0	1
StandAlone	0.46	0.50	0	1
Observations	5,033			

We then collected data on the extent of active management of social media on Facebook by these hospitals. We focused on Facebook for two reasons. First, Facebook is, as of 2012, the major social media website as well as the most visited website in the United States (comScore 2011). Second, since October 2011, Facebook has released novel data that allow measurement of more general forms of user interactions with an organization by Facebook users.

We had to identify each hospital's Facebook page manually because there was no central directory. The pages were created automatically from a database of companies as part of Facebook's Places strategy, where it automatically created social media websites for U.S. local businesses to facilitate Facebook users' ability to interact with geographical locations using mobile devices. Hospitals were then able to claim these automatically generated pages through a simple process and start posting to them. For example, for the Stanford Hospital and Clinics, we identified the Facebook page depicted in Figure 1. This is an example of an actively managed Facebook page for a hospital; it has been claimed and Stanford Hospitals is actively posting to it.

For the handful of hospitals where there was more than one Facebook page (this happened occasionally if Facebook had erroneously inserted duplicate listings), we picked the Facebook page where there was more activity. Our analysis is robust to the exclusion of these observations. We were able to identify Facebook pages for 5,035 out of the 5,759 hospitals listed in the American Hospital Association data. We check robustness to the missing observations in subsequent empirical analysis.[2]

We then collected data on client interactions with the organization. For each website, we collected data on the number of Facebook users who had "talked about the hospital," who had liked the hospital, and who had recorded on Facebook that they had been near the hospital. Figure 1, for example, suggests that 327 people had talked about the organization in the past week, 4,805 people had liked the Stanford hospital page, and 13,715 had at some point in time visited that location.[3] Because these data have been available only since October 2011, and there has been no new data on hospital characteristics released since then, we use cross-sectional data for our analysis.

Figure 1 **Sample Facebook Page for a Hospital**

These data were reasonably time consuming to collect. Early attempts at using screenscraping techniques proved unviable because of inconsistencies in webpage format. This means we had to manually identify Facebook hospital websites and record the actual data. For each hospital, three researchers were told to identify webpages, and we cross-referenced their inputs to ensure data accuracy. If there was disagreement, one of the authors verified the page.

We next discuss the precise definitions of these three measures of social media activity.

The talking about it metric (which appears second on the panel of numbers displayed in Figure 1) is a newly introduced measure of social media activity surrounding a Facebook page. A Facebook user is counted as talking about a page if in the past week they have liked a page; posted to a wall; commented, liked, or shared content on a page; answered a posted question; RSVPed to an event, mentioned a page in a post; phototagged a page; or checked in at a page. In our regression analysis, we label this as *UGC*, for user-generated content. This will be our major dependent variable of interest because this measures the broadest category of ways a user can interact using social media with an organization. Also, because it is

[2] This discrepancy may be because Facebook gives business owners the option of deleting their Facebook page.

[3] Sometimes, hospitals set up separate pages for their foundations. For example, Crozer-Chester hospital system, though not having a Facebook page for its individual hospitals, did have a Facebook page for the Crozer-Chester and Delco Memorial Foundations. In cases like this, where the foundations are detached from the individual hospitals we study, we exclude the pages.

a weekly measure, it has the advantage of being measured for the same time period for all organizations. Given that it was a weekly measure, we made sure that all observations were collected within a 48-hour period.

When a Facebook user likes a page, this means that he or she signs up for the news feed, so he or she receives posted communications from the organization. Further, now that the Facebook advertising system allows social targeting, it is possible for companies to use this liking data to target people who are affiliated to their brand *and* to their social networks. Unlike the talking about it metric, this is a stock variable that records the stock of all people in the past who have liked the page rather than a set window measuring recent activity. Though we show robustness to this as a dependent variable, it is not our major dependent variable because it reflects passive consumption of news from the organization rather than active social media activity (Gossieaux and Moran 2010).

The "were here" measure tracks how many people used a GPS-enabled device to check in at the location or tagged a location in a posting, status update, or photo.[4] Again this is a stock variable, which records all people who have checked in over time at that location. We show robustness to this as a dependent measure, but because it is a narrower measure of social media activity than talking about it, it is not the main focus of our analysis.[5]

Table 1 reports summary statistics for these measures of social media activity.

We then went on to identify whether the hospital was engaged in actively managing its Facebook page. To qualify as actively managing the page, the hospital had to have both claimed the page as its own and posted to it. As shown in Table 1, 19% of hospitals actively managed their Facebook page. This is in line with studies such as Thaker et al. (2011) that show that 20% of hospitals actively use social media.[6] We supplemented this binary metric with data we collected seven months later that measured how many times in the past two weeks the hospital had posted to its page, to allow analysis of the effects of the intensity of active social media management.

Appendix Table A.1 splits the summary statistics from Table 1 by whether or not the hospital has adopted active social media management. It is clear that larger hospitals are more likely to actively manage their Facebook page.[7]

4. Results

In our econometric specification, we start with a simple specification to explore the main effect of active social media management on the level of social media activity surrounding the organization.

In this simple specification, for hospital i in health referral region j, we model the level of social media activity surrounding the hospital as a function of

$$\begin{aligned} UGC_i &= \beta_1 Admissions_i + \beta_2 Employees_i + \beta_3 Active_i \\ &\quad \cdot \beta_4 Admissions_i \times Active_i + \beta_5 Employees_i \times Active_i \\ &\quad \beta_6 Orgtype_i + \beta_7 PropMedicare_i + \gamma_j + \epsilon_i \end{aligned} \tag{1}$$

UGC_i is the amount of user-generated content surrounding the organization in the past week based on the talking about it metric described in §3. We argue that the ability of a firm to generate this content is a function of its relationships with individuals. We distinguish between two types of relationship that a firm can have with an individual: a relationship that is largely external to the firm's organization because it takes place with a client and a relationship that is internal to the firm's organization because it is with an employee.

The number of admissions $Admissions_i$ and number of employees $Employees_i$ measure how the scope of existing internal and external relationships affects the hospital's ability to generate user responses.[8] $Active_i$ is a indicator variable for whether the hospital actively manages its social media. We allow the influence of the measures of internal and external organizational scope to depend on whether or not the organization is actively managing its social media.

We also include various controls. $PropMedicare_i$ is a measure of the proportion of Medicare patients that a hospital treats, which controls for differences across the patient demographic mix that might drive online user-generated content. Specifically, because Medicare patients are older, it controls for the age of clients at the hospital. This is important because

[4] In some retail situations, for example, when Facebook users check in at a Starbucks, they may be offered a location-specific deal as a result of checking in. However, there have been no cases of check-in deals being offered by hospitals that the authors can identify, perhaps because of the payments and pricing system in health care.

[5] Though Facebook makes tracking the differences between these measures hard, by manually tracking a subset of hospitals for four weeks we obtained a very rough estimate that around 82% of the talking about it metric comprised likes and visits.

[6] Later in the paper, we follow Berger and Milkman (2011) and analyze the nature of the content posted.

[7] However, the split slightly overstates the mean-difference because it is driven by a few outliers. If we ignore the bottom and top size deciles then, though different, the size of the difference is far less, as is shown in Table A.2.

[8] Figure A.1 in Appendix A plots out their joint distribution. As expected, they are positively related, but, crucially for this research, they are not perfectly collinear.

Table 2 Active Social Media Management Increases User-Generated Content Mainly by Employees

	All data (1)	(2)	Active (3)	Inactive (4)	Active (5)	Inactive (6)	All data (7)
Active social media	56.94***	38.82***					36.38***
	(2.711)	(2.764)					(3.699)
Employees		0.0294***	0.0294***	0.0114***	0.0606***	−0.00856***	−0.00911***
		(0.00204)	(0.00305)	(0.000442)	(0.00623)	(0.00109)	(0.00279)
Admissions (000)		−1.704***			−6.336***	2.820***	2.813***
		(0.280)			(0.933)	(0.141)	(0.362)
Active social media × *Admissions*							−9.145***
							(0.540)
Active social media × *Employees*							0.0743***
							(0.00382)
Managed care		12.94***			58.69***	0.465	13.27***
		(3.515)			(16.01)	(1.479)	(3.389)
Proportion Medicare patients		−20.15***			−205.6***	−4.298**	−26.66***
		(4.865)			(31.33)	(1.933)	(4.702)
Health region controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,033	5,033	932	4,101	932	4,101	5,033
R-squared	0.0806	0.191	0.145	0.186	0.245	0.260	0.248

Notes. OLS Estimates. Dependent variable is the number of people generating content about the organization via social media. Robust standard errors.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Chou et al. (2009) found that youth was a significant predictor of health-related blogging and social networking site participation. $ManagedCare_i$ is an indicator variable for whether the hospital has links with managed care contractors such as a health maintenance organization (HMO). We include such insurance arrangements because they may affect the depth of a hospital's relationship with its clients. As both an insurer and as a provider of primary care, the HMO had more points of contact with a patient than a non-HMO hospital. γ_j is a vector of fixed effects for each of the 306 health referral regions.[9]

Table 2 explores this initial specification and incrementally builds up to the final specification indicated by Equation (1) in column (7). In columns (1) and (2) we estimate an specification that allows $Active_i$ to enter simply as a main effect rather than as a moderating variable. The positive and significant coefficient estimate for $Active_i$ indicates that active management of social media increases the level of user-generated content. The additional controls for hospital characteristics in column (2) noticeably depress the size of the estimate for the effects of $Active_i$, suggesting it may have been conflating other hospital characteristics with the adoption of active social media management. Table A.3 in Appendix A investigates the drivers of adoption of active management of social media and finds that hospitals that were significantly more likely to use social media were large, urban, or part of a health system; were run by nonprofit or nongovernmental organizations; were involved in graduate medical education; or primarily treated children. The coefficients suggest that hospitals that are part of a managed care health system and have fewer Medicare patients are more likely to have more user-generated content.

The result that $Active_i$ has a positive effect on user-generated content is not unexpected. Even social media specialists who advocate a hands-off organic approach to social media still believe that firms need to actively manage their social media (Gossieaux and Moran 2010). The more interesting question, which is the major focus of this paper, is where this increase in user-generated content comes from. In particular, does it come from encouraging activity from social media users outside or inside the firm's boundaries?

To investigate this, we estimate Equation (1) separately for hospitals that actively manage their social media presence and those that do not. Columns (3) and (4) of Table 2 report the results of a simple specification that states the relationship between employees and user-generated content for hospitals that actively manage their social media and those that do not. It is striking that the effect of incremental employees on the total amount of user-generated content is far larger for hospitals that actively manage their social media than for those that do not. This is the first empirical finding that suggests that much of the power of active social media management is to

[9] Many of these health referral regions cross state borders. This lack of collinearity with state regulation is crucial for our identification strategy, which will exploit differences in state-level regulations to identify the effect. Our results are also robust to the exclusion of these fixed effects.

encourage employees to start interacting with the firm's social media presence.

In columns (5) and (6) we estimate a full stratified specification that parallels Equation (1). What is striking is the extent to which the effects of *Employeees* and *Admissions* vary for hospitals that do actively manage their social media versus hospitals that do not. Conditional on the other controls, hospitals that do actively manage their social media have user-generated content levels that are an increasing function of their number of employees but a decreasing function of their number of admissions. In contrast, conditional on these same controls, hospitals that do not actively manage their social media have user-generated content levels that are a decreasing function of their number of employees but an increasing function of their number of admissions. We emphasize that because employees and admissions are of course somewhat collinear, the correct interpretation is not necessarily that admissions depress user-generated content under active management or that full-time employees depress user-generated content under inactive management. Instead, the interpretation should be that hospitals with a high staff:patient ratio generate more user-generated content under active social media management, but hospitals with a low staff:patient ratio generate more user-generated content under inactive social media management.[10]

To check the statistical significance of the difference observed in the coefficients in columns (5) and (6), in column (7) of Table 2 we estimate the full Equation (1). The results confirm our previous findings. Active management of social media appears to lead to an increase in user-generated content that is a function of the number of internal employees rather than the number of clients that the hospital has. To aid interpretation, we provide estimates of the total effect of active social media management on user-generated content for hospitals that have above and below average employees and admissions in Table 3. This effect is positive for three of the four groups of hospitals but negative for hospitals with the combination of low staffing and high admissions. The magnitude of the largest of these effects shows that active management can have a substantial impact on user-generated social media content for hospitals with high staffing and low admissions: an increase of 127 items, or 1.6 standard deviations (see Table 1).

This is a notable finding because there is little evidence that this increase in employee-generated

Table 3 Total Effects of Active Social Media Management by Hospital Size

	Below average employees	Above average employees
Below average patients	34.25	126.64
Above average patients	−48.77	43.61

Notes. Below and above average are calculated at 0.5 standard deviations below or above the mean. Based on coefficient estimates from column (7) of Table 2.

content is hospitals' objective when pursuing an active social media campaign. For example, Thaker et al. (2011) in a survey of hospital practices found that hospitals used social media to target a general audience (97%), provide content about the entire organization (93%), announce news and events (91%), further public relations (89%), and promote health (90%). All of these appear to be more client-facing objectives than employee-facing objectives. Commentators have also emphasized client-facing objectives. Hawn (2009) emphasizes the importance of social media for health care of patients exchanging information and of medical professionals exchanging information with their patients. Similarly, Orsini (2010) emphasizes the adoption of social media by health care organizations to communicate with their clients.

There are many potential explanations of this finding. One is that organizations are able to exert pressure on their employees to interact with their social media page but cannot easily exert the same pressure on clients.[11] This pressure may not be overt. For example, in the Stanford Hospital example, an employee named Angie posts her appreciation for Stanford Hospital's provision of a caregivers' support network and concludes by saying "I love Stanford." It is probable that although her enthusiasm may be noted and appreciated by management, there are no direct incentives for her to post in this manner.

Another possibility is that because the employer is already often part of an employee's Facebook profile, interaction with that organization over Facebook will not raise new privacy concerns or highlight a new facet of that Facebook user's life to his or her friends.

4.1. Robustness Checks

This finding that active management of social media leads user-generated content to be a function of the number of employees rather than clients is unexpected, so in this section we report a battery of robustness checks for the results in Table 2. The first set of checks presented in Table 4 focuses on establishing robustness to different definitions of the sample.

[10] We confirm this pattern in a separate specification that looks at the ratio directly. Controlling for hospital size, the estimated effect of staffing ratio (staff:patients) on user-generated content is positive for hospitals that actively manage their social media but negative for those that do not.

[11] For example, an organization that one of the authors works for regularly sends emails to its employees exhorting them to like and engage with their Facebook page.

Table 4 Robustness Checks: Sample

	More controls (1)	Within-system (2)	Speciality hosp (3)	No outliers (4)	All unmatched (5)
Employees	−0.0100***	−0.00926***	−0.00345	0.000297	−0.00907***
	(0.00283)	(0.00241)	(0.0102)	(0.00328)	(0.00269)
Admissions (000)	2.974***	2.757***	1.818	2.610***	2.820***
	(0.377)	(0.312)	(2.515)	(0.391)	(0.350)
Active social media × *Admissions*	−9.108***	−3.366***	−8.917*	−6.107***	−5.817***
	(0.542)	(0.475)	(5.259)	(0.771)	(0.477)
Active social media × *Employees*	0.0742***	0.0299***	0.119***	0.0899***	0.0555***
	(0.00382)	(0.00344)	(0.0170)	(0.00514)	(0.00346)
Active social media	35.75***	24.94***	−23.87	−3.002	6.169**
	(3.723)	(3.368)	(21.17)	(3.403)	(2.469)
Managed care	13.33***		61.57***	2.587	11.62***
	(3.389)		(17.38)	(2.326)	(3.073)
Proportion Medicare patients	−24.10***	−16.39***	−15.18	−12.75***	−21.54***
	(4.861)	(4.831)	(14.84)	(3.079)	(4.172)
Group practice association	−5.454				
	(6.970)				
Integrated salary model	−2.650				
	(2.359)				
Nonprofit hospital	8.397***				
	(2.223)				
Speciality hospital	10.70***				
	(2.875)				
StandAlone	1.333				
	(2.026)				
Health region controls	Yes	Yes	Yes	Yes	Yes
System fixed effects	No	Yes	No	No	No
Observations	5,033	2,729	860	3,523	5,756
R-squared	0.252	0.320	0.478	0.272	0.197

Notes. OLS Estimates. Dependent variable is the number of people generating content about the organization via social media. Robust standard errors.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

In Column (1) of Table 4, we add more controls for hospital type and organization. This is to address the concern that there may be certain types of hospitals that have more employees and fewer clients, for example, hospitals that specialize in a medical speciality that has fewer patients but requires a lot of caregivers, that are also successful at mobilizing social media. Both nonprofit status and a speciality appear to mobilize user-generated content. The key result remains robust, suggesting that it is not the case that unobserved heterogeneity in hospital structure is driving the result.

In column (2), we look purely at *within*-system variation. Many hospitals are not standalone institutions but instead are part of a system of hospitals, such as Good Samaritan. There are 2,735 such hospitals in our data. We use hospital-system fixed effects. This means we only look at the effect of variation in employee numbers and admissions for hospitals that enjoy the same larger organizational structure. Even using within-system variation, the result is robust and similar to previous estimates.

In column (3), we show that our results hold when we look only at speciality hospitals. These hospitals are more likely to adopt active social media management (as is clear in Table A.1) but also may be systematically different in their ability to provoke user-generated content from regular hospitals. However, our results also hold when we look only at variation for these hospitals.

In column (4), we check robustness to excluding potential outliers—that is, hospitals in the top or bottom decile of admissions or number of employees. The results are robust to their exclusion. This is important because, as shown in Table A.1, many of the outliers in the top decile have active social media management.

In column (5), we check robustness to our identifying only 5,035 out of 5,759 total hospitals. In these regressions, we treat the missing observations as not actively managing their Facebook page because they did not have one. Our results are robust, though less precisely measured, as might be expected.

The second set of checks is presented in Table 5 and focuses on establishing robustness to different ways of defining the dependent and explanatory variables.

In columns (1) and (2), we explore whether our results are robust to different definitions of

Table 5 Robustness Checks: Variables

	Alt DV (1) Likes	(2) Visited	Cts X (3) UGC	Log–Log (4) UGC (Log)	Poisson (5) UGC
Employees	−0.0981	−0.441***	0.00871***		−0.000353***
	(0.399)	(0.0703)	(0.00243)		(0.00000578)
Admissions (000)	17.10	140.5***	1.091***		0.0917***
	(51.79)	(9.127)	(0.321)		(0.000725)
Active social media × *Admissions*	−818.1***	−111.0***			−0.116***
	(77.29)	(13.62)			(0.000869)
Active social media × *Employees*	6.539***	0.726***			0.000655***
	(0.546)	(0.0963)			(0.00000627)
# postings × *Admissions*			−0.621***		
			(0.0408)		
# postings × *Employees*			0.00409***		
			(0.000277)		
Active social media × *Admissions* (log)				−0.757***	
				(0.119)	
Active social media × *Employees* (log)				0.499***	
				(0.103)	
Employees (log)				0.171***	
				(0.0413)	
Admissions (log)				0.663***	
				(0.0480)	
Active social media	1,614.5***	1,066.6***		−0.866*	1.640***
	(529.2)	(93.26)		(0.481)	(0.00821)
Managed care	1,450.2***	179.4**	14.36***	−0.00993	0.417***
	(484.9)	(85.45)	(3.446)	(0.0577)	(0.00839)
Proportion Medicare patients	−1,671.0**	−629.3***	−23.52***	0.00133	−1.366***
	(672.8)	(118.6)	(4.776)	(0.0832)	(0.0157)
Number of comments in last week			4.501***		
			(0.361)		
Health region controls	Yes	Yes	Yes	Yes	Yes
Observations	5,033	5,033	5,033	5,033	5,033
R-squared	0.0748	0.266	0.223	0.448	

Notes. OLS Estimates in columns (1) to (4). Poisson model estimates in column (5). Dependent variable is the number of people generating content about the organization via social media in columns (3) and (5) and its logged value in column (4). Dependent variable is the total number of likes in column (1) and the total number of visits in column (2). Robust standard errors.

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

the dependent variable. For example, one potential critique is that our dependent measure may not be representative because it only covers user-generated content in the past week. To check that this was not driving our results, we checked robustness to the total stock of number of likes that a hospital has attracted and the number of people who had publicly stated they had physically visited the facility. Our results are robust to these two alternative measures of user-generated content.

So far we have taken active social media management as being a binary decision. However, hospitals can also make decisions regarding the intensity of postings they make on their Facebook page. In column (3), we explore whether using this more nuanced measure of active social media management alters our results. Our results turn out to be similar. The more a hospital posts on its Facebook page, the more likely that user-generated content is a function of the number of employees rather than the number of clients.

In column (4), we check robustness to a log–log functional form specification. The result is robust to this specification, suggesting that extreme values do not drive our results.

In column (5), we show that our results are robust to a poisson specification that takes into account that the dependent variable cannot be negative. The results remain robust.[12] We report the marginal effects for this specification in Table A.5 in Appendix A. The marginal effects for the key interaction term,

[12] We replicate Table 2 for this count-model specification in Table A.4 in Appendix A.

calculated at the mean, suggest that when a hospital adopts social media management, the marginal effect of admissions switches from 1.46 to −1.34, and the marginal effect of employees switches from −0.005 to 0.016. This is directionally consistent with the estimates so far.

4.2. Identification Through Instrumental Variables

As with any research that seeks to interpret relationships in historical data, it is important to both consider and rule out alternative explanations for the phenomenon observed in the data.

4.2.1. The Employees:Admissions Ratio Is Not Random. The first set of alternative explanations that need to be ruled out is that there are unobserved differences in the nature of hospitals that have more employees or more admissions that explain the way that Facebook users respond to active social media management. For example, a hospital with a higher employee:admission ratio may give its patients more attentive care. This could in turn affect response to active social media management because clients harbor more positive feelings toward the hospitals and are more likely to respond positively to a hospital posting. This is an alternative explanation of the observed moderating relationships. Alternatively, a hospital with a smaller employee:admission ratio may treat more trivial conditions, which would also fit in with the data pattern we have observed if the triviality of the conditions it treats was less likely to inspire a client response to its postings.

To rule out these and similar alternative explanations of our results, we introduce two instrumental variables that offer plausibly exogenous shifts in staff:patient ratios that are not related to the hospital's unobserved ability to provoke a positive response from its clients to its postings.

A suitable instrument for a hospital's number of employees is something that exogenously led a hospital to change its number of employees but did not affect the likelihood of a Facebook user engaging with their Facebook page directly. We find such an instrument in the work of Acemoglu and Finkelstein (2008), who show that in earlier decades distortions inherent in the Medicare system meant that hospitals substituted away from labor inputs to capital inputs. They show that the change from full to partial cost reimbursement under the Medicare Prospective Payment System reform increased the relative price of labor faced by U.S. hospitals in the 1980s. If a hospital saw more Medicare patients during that decade, then it is likely now to have fewer employees and instead to employ more labor-replacing capital investments.

We argue that the proportion of Medicare patients two decades ago will still be predictive of employee levels in the present day because a switch to

Table 6 **First-Stage Regressions for Instruments**

	(1) *Employees*	(2) *Admissions* (000)	(3) *Admissions* (000)	(4) *Active social media*
Proportion Medicare patients (1990)	−436.0*** (88.89)			
Cap punitive damages		−0.656** (0.270)	−0.270 (0.285)	
Cap damages		−2.519*** (0.432)	−2.468*** (0.445)	
Managed care × Cap punitive damages			−3.256*** (0.895)	
Managed care × Cap damages			−0.666 (1.802)	
Managed care			3.693*** (0.666)	
No testimonials				−0.0475*** (0.0152)
Constant	1,087.1*** (44.99)	7.372*** (0.213)	6.948*** (0.225)	0.180*** (0.00728)
Observations	4,367	5,033	5,033	5,033
R-squared	0.00548	0.00926	0.0154	0.00280

Notes. OLS estimates. Dependent variables as shown. Only observations of hospitals where we have data on the pattern of 1980s Medicare patients are included in Column (1). Robust standard errors.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

labor-replacing capital investment tends to be sticky; labor-replacing capital investments are generally hard to reverse because costs are typically sunk. To explore the predictive power of this instrument, in Table 6 column (1) we present the raw correlation between the number of employees and the proportion of Medicare patients to total patients. The relationship is strongly negative, suggesting that the distortions documented by Acemoglu and Finkelstein (2008) persist even today.

Of course, an instrument does not need simply to be predictive of the endogenous variable to be valid. It also has to meet the exclusion restriction, which is that the proportion of Medicare patients in 1990 should not affect total social media activity surrounding a hospital on Facebook in 2011 through any direct channel that is independent of the number of hospital employees. One obvious issue is that if there is state dependence in the number of Medicare patients over the last two decades, then the historic instrument may be related to the number of older patients that a hospital sees. As seen earlier, having fewer Medicare patients is associated with higher social media activity. To address this concern, we control for the current proportion of Medicare patients in our IV specification. Therefore, we generate exogenous variation solely from variation in hospitals' Medicare patient levels two decades ago relative to the present day.

To place a causal interpretation on the "admissions" variable, we also need an appropriate instrument. We found such an instrument in the literature on defensive medicine. The underlying theme of this literature is that medical providers have an incentive to "overtreat" patients because of liability risk. Therefore, the number of admissions to a hospital is a function of the medical malpractice environment. There has been empirical research, such as Kessler and McClellan (1996) that has documented the association of these laws with medical activity and procedures. Therefore, the instrument is correlated with the endogenous variable. It also seems likely that this instrument meets the exclusion restriction because it is difficult to think of a direct channel by which whether or not there are caps on the damages that can be awarded to a patient in a medical malpractice suit could affect the number of postings on a Facebook page. However, we should note that identification may be weaker relative to other research that uses these instruments because we only use cross-sectional variation rather than the within-state panel variation in legal environment that other researchers have exploited.

We use data from Avraham (2011) on state tort law reforms governing medical malpractice. The results of a single correlation between admissions levels and these medical malpractice reforms are reported in column (2) of Table 6. As expected, both a cap on the amount of punitive damages that can be awarded and total damages that can be awarded reduce the total number of admissions because medical professionals face lower malpractice liability risk and so are less likely to practice defensive medicine and treat marginal patients.

As shown by Hall (1991) and Kessler and McClellan (2002) there are important interactions between the efficacy of tort reform law and reducing defensive medicine and whether an organization is a managed care provider because they are both cost-containment measures. Therefore, we allow our instrument's power to vary by hospital managed care status in column (3) of Table 6.

4.2.2. The Decision to Adopt Active Social Media Management May Be Endogenous. It is also likely that the decision to adopt social media management may be endogenous. For example, it could be that what we observe in the data is simply reverse causality—hospitals adopt active social media management because user-generated content surrounding the hospital is mainly generated by employees, and the hospital's historical relationship with patients is such that they are not posting organically. Therefore, what we are measuring by the active social media management indicator may not be the cause of the problem but simply the response to the problem.

Therefore, we need to find an exogenous source of variation that is related to whether or not hospitals actively manage their social media but is unrelated to the amount of user-generated content they generate. We find such an instrument in the form of state-level regulations that limit the use of patient testimonials in marketing communications by physicians and health care providers.[13] For example, Cal. Bus. and Prof. Code Section 651 forbids the inclusion of "any statement, endorsement, or testimonial that is likely to mislead or deceive because of a failure to disclose material facts." Similarly, Illinois 225 *ILCS* 60/26, 68 *IL ADC* 1285.245 states that it is unlawful "under this Act to use testimonials or claims of superior quality of care to entice the public."

Such prohibitions are relevant for the decisions of hospitals to actively manage their social media Web presence for two reasons. First, if a Facebook page is eventually judged by courts to be an explicit "advertising" channel, then it would be covered by this prohibition. At the moment, the extent to which the promotion of user-generated content by organizations outside of health should be considered advertising or something else is ambiguous and under discussion in court (for an example, see *Fraley et al. v. Facebook, Inc.* 2012 Case No.: 11-CV-01726-LHK). This might lead to potential legal liability if a hospital's Facebook page were found to be illegally centered around testimonials from happy patients that did not have appropriate disclaimers about the lack of representativeness of that patient's experience (Becker 2011, Becker and Callard 2012). Second, even if the appearance of testimonials in a hospital-managed communications vehicle were judged legal, such laws would still restrict a hospital's ability to use such positive user-generated content in their marketing materials.

These statutes were generally written and promulgated in earlier decades and were designed to control print and yellow pages advertising. Therefore, they are unlikely to be related to the digital sophistication of the local state. However, the way they are written means that they apply equally to print and electronic media. Therefore, for hospitals that are in such states, there is an exogenous reason why it may be preferable for the hospital to not actively manage any social media presence. And importantly this is not related directly to the level of social media activity in that state.

To explore the predictive power of this instrument, in Table 6 column (4) we report the simple correlation between this variable and the adoption of active social media management. It is both negative and significant, suggesting that such legal considerations

[13] This is in a similar spirit to the use of state regulations governing the flow of medical data for identification in Miller and Tucker (2009; 2011; 2013).

are driving decisions about the extent to which hospitals can embrace social media. It is worth noting that the relationship between the instrumental variable and the endogenous outcome of interest, although highly statistically significant, is somewhat modest in magnitude. The presence of a statute is associated about a five percentage point decline in active social media management and the *R*-squared of the regression is less than 1%. Although the low power of this instrument is a potential limitation of this part of the analysis, the Stock and Wright (2000) *S*-statistic, which is robust to weak instruments, does support the significance of the endogenous variables.

Because we have multiple endogenous variables that are in turn instrumented by multiple instrumental variables and their interactions, we report our results incrementally. We report in Table 7 in columns (1) and (2) results for a two-stage least squares specification where we use this historic Medicare instrument to predict the exogenously explained level of employees. We have fewer observations than before because the American Hospital Association data for two decades ago obviously do not cover many recently built hospitals or hospitals that have changed their name or merged. However, a comparison of the results in columns (1) and (2) suggest that even when using exogenous variation in the number of employees as an explanatory variable, our key result holds that user-generated content levels when hospitals actively manage their social media are a function of number of employees, not number of clients. Similarly, when hospitals do not actively manage their social media, social media activity is a positive function of number of clients and not number of employees.

We estimate a specification that uses these defensive medicine instruments and report the results in columns (3) and (4) of Table 7. Again the main results hold, though as to be expected with instrumental variables and two endogenous variables our estimates are less precise than with simple ordinary least squares (OLS). Once again, user-generated content is a function of number of employees not number of clients when hospitals actively manage their social media and is a function of number of clients and not number of employees when hospitals do not actively manage their social media.

In column (5), we present the full specification (from column (7) of Table 2), where we instrument for all three endogenous variables and their interactions simultaneously with the instruments and their appropriate interactions. The results confirm the insights from Table 2. Again, the amount of conversations generated by active social media management are increasing in number of employees but decreasing in the number of patients. Table 8 presents the total predicted effects of active social media management for hospitals with above and below average numbers of

Table 7 Instrumental Variable Specification

	IV for *Emp*		IV for *Adm* + *Emp*		IV for *Adm* + *Emp* + Active	
	(1) Active	(2) Inactive	(3) Active	(4) Inactive	(5) All	(6) All: Poisson
Employees	0.212***	0.000420	0.192**	0.00703	−0.0463	−0.000477
	(0.0805)	(0.00760)	(0.0753)	(0.0103)	(0.0470)	(0.000721)
Admissions (000)	−26.53**	1.907**	−22.40*	2.236*	6.197	0.316**
	(10.84)	(0.882)	(13.10)	(1.296)	(5.003)	(0.132)
Proportion Medicare patients	−1.267	−0.498	−16.78	1.565	6.514	−0.540***
	(86.00)	(2.876)	(147.3)	(4.440)	(9.199)	(0.0118)
Managed care	91.16**	1.054	81.98**	−0.608	3.243	−0.0451
	(41.59)	(1.804)	(41.54)	(1.765)	(5.435)	(0.0428)
Active social media × *Admissions*					−29.36*	−0.328*
					(15.50)	(0.184)
Active social media × *Employees*					0.293**	0.00114**
					(0.125)	(0.000454)
Active social media					45.41	1.285
					(132.9)	(1.352)
Health region controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	832	3,535	832	3,535	4,367	4,367
R-squared	—	0.312	—	0.203	—	

Notes. Instrumental variable estimates from two-stage least squares in columns (1)–(5). Estimates in column (6) are from generalized method of moments estimator of a poisson specification that allows for instrumental variables. Dependent variable is the number of people generating content about the organization via social media. Robust standard errors. Only observations of hospitals where we have data on the pattern of 1980s Medicare patients are included.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8 IV Estimates of Total Effects of Active Social Media Management by Hospital Size

	Below average employees	Above average employees
Below average patients	51.49	415.82
Above average patients	−215.06	149.27

Notes. Below and above average are calculated at 0.5 standard deviations below or above the mean. Based on IV coefficient estimates from column (5) of Table 7.

employees and patients in our sample. The pattern is identical to that in Table 3 for the OLS estimates, but the magnitudes are larger.

In column (6), we repeat the specification from column (5) but this time use a poisson functional form to take account of the fact that the dependent variable is a count variable. We estimate the specification using generalized method of moments. The results are similar to those in column (5), suggesting that the OLS specification does not drive the results.

5. Analyzing the Content of the Hospital Postings

The next question is how the content (as well as the intensity) of Facebook postings contributes to the empirical regularities established so far. To investigate this, we did a partial content analysis of the three most recent postings by all hospitals that were actively managing their Facebook page. This analysis involved 2,565 postings.[14] Because this required subjective ratings, we followed the procedure laid out by Bakshy et al. (2011) and used workers from Amazon Mechanical Turk to independently categorize the postings' content into postings that were targeted at staff, patients, or both. For each comment, we had multiple ratings to ensure the reliability of this rating procedure. Table 9 lays out a random subsample of the postings that were analyzed and the categories they were allocated to. Staff-targeted postings appear to mainly consist of employee benefits, awards, and employee activities announcements. Patient-targeted communications mainly concerned hospital initiatives to promote health. The communications that were ambiguous in whether they were targeted at staff or patients were those that made observations either about non-hospital matters such as the weather or about hospital achievements. Figure 2 summarizes the proportion of types of targeted content for the hospitals in the sample. What is striking is the small relative proportion of postings that were exclusively directed at patients.

Table 10 uses this data to further refine our analysis in Table 5 where we examined how the intensity of posting activity affected our estimates. To this specification we now add the proportion of times that the hospital posted content that was targeted at different groups. Column (1) presents results where we examine the extent to which content that is targeted toward patients affects our earlier results. Strikingly, when hospitals have a larger proportion of postings targeted toward patients, this acts to reduce the extent to which active social media management makes user-generated content a function of employee numbers rather than client numbers. In other words, hospitals are able to avoid this outcome if they consciously and exclusively gear their communications toward patients.

Column (2) of Table 10 examines how the proportion of staff-targeted postings affects the results. Strikingly, the more content that hospitals target at staff, the larger is the previously documented effect. That is, hospitals with a higher proportion of staff-targeted postings are more likely to see their user-generated content become a function of their number of employees than number of clients. This result emphasizes that the results presented before need not necessarily be considered to be detrimental to all hospital aims. Presumably there is a subset of hospitals that have, for various strategic reasons, decided to use their social media presence to engage with employees rather than clients. The earlier results suggest that their strategy of active management is successful at increasing employee social media activity.

Column (3) Table 10 examines how the proportion of nontargeted postings affects the results. As is clear in Figure 2, this is the majority of postings analyzed. As shown in Table 9, these tend to be rather generic postings that could potentially be appreciated by both insiders and outsiders. What is interesting is that the effect of a high proportion of these postings follows a similar pattern to that of staff-targeted postings in column (2) rather the patient-targeted postings in column (1). In other words, such undirected content appears better at provoking user-generated content from staff rather than patients. Speculatively, because the content is often organization-centric, it is easier to engage employees who are close to the organizational mission than outsiders with such postings.[15]

We present these regressions as suggestive rather than conclusive. This is because there are many unobserved reasons why a hospital may choose to focus

[14] Though 932 hospitals actively managed their social media page, some had not posted recently enough for us to be easily able to analyze their postings.

[15] These results also accord with further specifications where we divide employee responses into whether or not the employee is part of medical personnel and show that non-medical personnel often appear more likely to respond than do medical personnel. This analysis is reported in Table B.1 in Appendix B.

Table 9 Sample Postings and Categorizations

Target audience	Comment
Staff	We're wearing red tomorrow. Are you? Employees at CHSB who wear red tomorrow will get a free red apple. National Wear Red Day 2012
Staff	We rolled out the red carpet this morning for Betty Jones, the first employee to ever reach an amazing 50 years of service at Glens Falls Hospital! In the photo, George Moxham, Director of Housekeeping and Laundry, presents Betty with a dozen roses.
Staff	The Wellness Center at Windom Area Hospital has NEW staff hours for the summer. Staff will be available from 8:30 A.M. to 5:00 P.M. Monday–Wednesday, and from 9:30 A.M. to 5:00 P.M. Thursday and Fridays. Call 831-0672 for more information.
Staff	The TRMC Employee Engagement Committee is pleased to announce the July Employee of the Month Award winner is Alison Hanna of Volunteer Services. Alison was nominated by Sarah Marsh. Congratulations, Alison!
Staff	Reminder for all associates! If you haven't enrolled for your 2012–2013 benefits, the deadline to enroll or make changes to your plan is this Friday, May 25, 2012 at noon.
Staff	To our employees, docs, and volunteers: Don't forget the annual PUSMC picnic is this Saturday Turtle Run Golf and Banquet Center/Snapper's Bar and Grill!!
Staff	American Idol contestant, Jeremy Rosado, performed at our Employee Picnic. Thanks for coming, Jeremy!
Both	The EJ Noble Guild members have been hard at work constructing a butterfly garden in front of the new addition to the EJ Noble Building in Canton. Beautiful!
Both	Thought of the day: Believe you can and you are halfway there. Theodore Roosevelt Hope everyone is having a great week!
Both	Severe thunderstorms are approaching from the northwest that will affect most of northern Vermont until about 9 P.M. tonight. Heavy rain, damaging winds, and large hail are forecast. Stay safe everyone.
Both	For all the babies born at our hospital today, how cool it will be to have their birthday on 11/11/11!
Both	We heard president Obama will be in the area next week … we'd love to have him stop in!
Both	Today Duke University Health System started a massive, system-wide transformation of its electronic health record. It's a really big deal that will benefit patients in many ways.
Both	Our history is written on the wall … literally. Visit our Heritage Wall and learn our amazing history!
Patients	It's Meditation Monday at 5:30 P.M.! Each week this introductory meditation class guides cancer patients and survivors through reflections and guided imagery. Meditation can help decrease stress and assist in improving concentration.
Patients	Stop by the Skagit Valley Hospital main lobby on Monday, July 23rd from 9 A.M. to noon to have your child's stroller, car seat or toy tested for heavy metals or toxins. Registered nurses will be onsite to provide information about health hazards.
Patients	Are you ready for some football?! Football season is right around the corner, and RWJ and UMDNJ-Robert Wood Johnson Medical School (RWJMS) are teaming up to offer free physicals to New Brunswick Pop Warner football players and cheerleaders
Patients	Looking for a Cardiac Rehabilitation and Lifestyle Program? Established in 1979, the Cardiac Rehabilitation and Lifestyle Program was the first of its kind in the Central Valley. Hear Cardiac Rehab Nurse Lori Waddell …
Patients	Many people avoid going to the doctor for lower back pain because they think they will need surgery. However, most people with lower back pain can find relief through other treatment options. The Pain Center at St. Marys Medical Center
Patients	Get a $10 Speedway gas card just for attending a FREE Bariatric Surgery Seminar. Make your reservation online by phone, print up the attached coupon and redeem at the seminar. What are you waiting for?
Patients	We want to see you as quickly as possible in the ER. Check out how we re doing by viewing our average wait times online. http://aventurahospital.com/our-services/er-wait-time.dot

Note. Random subsample of content posted by hospitals on their Facebook page and the categories to which the posting was allocated by the raters.

its social media messaging to either patients or staff or have more generically targeted content. Unlike in §4.2, we do not have obvious instruments that could be plausibly exogenous shifters for the kind of content that a hospital decides to post. Therefore, we view these regressions primarily as a complement to our previous analysis.[16]

We also looked at the comments that were made in response to typical postings on the Facebook page. Specifically, we analyzed the content and implied origin of the content of comments that were made in response to the most recent posting made on the hospital's webpage for a 10% subsample of hospitals in our data. We again followed the procedure laid out by Bakshy et al. (2011) and used workers from Amazon

[16] The aim is, in the spirit of "big data" analysis, to directly measure the phenomenon rather than inferring a phenomenon from natural experiments in the data.

Figure 2 Proportion of Each Type of Posting

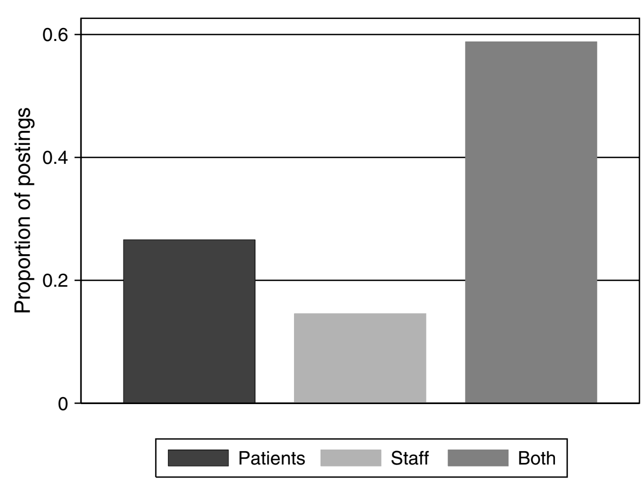

Table 10 **Content Analysis: Only Hospitals Who Orientated Their Social Media Postings Directly at Clients Can Avoid This Effect**

	(1)	(2)	(3)
Employees	0.0105***	−0.00851***	−0.00738***
	(0.00246)	(0.00254)	(0.00263)
Admissions (000)	0.795**	2.900***	2.746***
	(0.326)	(0.332)	(0.343)
# postings × *Admissions*	−0.702***	−0.222***	−0.261***
	(0.0453)	(0.0472)	(0.0492)
# postings × *Employees*	0.00464***	0.00122***	0.00148***
	(0.000310)	(0.000315)	(0.000331)
Prop patient-targeted postings × *Admissions*	5.813***		
	(1.373)		
Prop patient-targeted postings × *Employees*	−0.0376***		
	(0.00951)		
Prop staff-targeted postings × *Admissions*		−11.73***	
		(0.847)	
Prop staff-targeted postings × *Employees*		0.0960***	
		(0.00556)	
Prop nontargeted postings × *Admissions*			−8.852***
			(0.786)
Prop nontargeted postings × *Employees*			0.0744***
			(0.00536)
Prop. patient-targeted postings	3.886		
	(11.28)		
Prop. staff-targeted postings		31.84***	
		(6.758)	
Prop. nontargeted postings			24.22***
			(5.764)
Number of comments in last week	4.334***	2.854***	2.935***
	(0.419)	(0.423)	(0.430)
Managed care	13.98***	13.46***	13.51***
	(3.440)	(3.325)	(3.362)
Proportion Medicare patients	−23.07***	−24.93***	−25.82***
	(4.769)	(4.607)	(4.661)
Health region controls	Yes	Yes	Yes
Observations	5,033	5,033	5,033
R-squared	0.227	0.278	0.261

Notes. OLS estimates. Dependent variable is the number of people generating content about the organization via social media. Robust standard errors.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Mechanical Turk to independently categorize content into comments that clearly originated with staff members rather than patients. For each comment, we had multiple ratings to ensure the reliability of this rating procedure. We found that for webpages that had inactive management, only 2% of comments could be clearly attributed to staff, whereas 43% of all comments could be clearly attributed to staff members for hospitals that actively managed their webpage. This difference was highly significant with a *t*-statistic of 11.88. Though comments in response to postings represent a small proportion of possible user-generated content that occurs on a platform such as Facebook, this represents a reasonably convincing direct test of the proposed mechanism behind our results.

6. Conclusion

Firms are increasingly having to make strategic decisions about whether they actively manage their social media presence. The tension arises because most social media experts advocate that social media campaigns need to be perceived as organic and consumer-led to be successful (Gossieaux and Moran 2010). However, active firm promotion of word of mouth has also been found to be effective offline (Godes and Mayzlin 2009).

We investigate this using the empirical setting of hospitals. We use comprehensive data on active management of social media and the level of user-generated social media content surrounding the hospital for each hospital in the United States, which we then relate back to that hospital's characteristics. We find that active management of social media is effective at boosting the amount of user-generated content. However, this boost appears to be driven by the hospital's employees rather than the hospital's clients. This finding is robust to multiple specifications and to the use of instrumental variables for the organizational structure of the hospital and its decision to adopt active social media. Further, content analysis of the postings made by these hospitals suggests that the blame may lie in that they are not client-centric enough but instead are often generic or focused around the organization.

The result is important because it suggests that active management of social media does not lead to the client-side benefits that firms put forward when they explain why they are adopting social media strategies (Thaker et al. 2011). Instead such strategies seem mainly to improve internal employee communications. This may not be undesirable, but at the moment the social media literature has focused almost exclusively on the marketing benefits of social media for firms, so the effectiveness of using external social media websites for improving employee communications remains unproven. Further, in most firms social media is funded by the marketing function, even though empirically it may not be deriving the primary benefit from it. This suggests that one response for firms to our findings is to think about diffusing the control and funding of social media efforts across the firm including the human resources function. Last, if firms want active social media management to primarily drive marketing efforts, our results suggest they may be successful if postings are focused around the clients rather than the organization.

The most obvious limitation of this paper is that we focus on the use of social media in health care. There are two features of health care that might make it unrepresentative of social media in other industries. First, consumer choice of hospitals in the United

States is often limited by insurance arrangements that are determined by consumers' workplace. Further, these insurance arrangements complicate competition between hospitals. Second, health care is an unusual industry sector in terms of the privacy concerns it generates (Goldfarb and Tucker 2012). Social networks are very sensitive to privacy concerns (Tucker 2011b, Gross and Acquisti 2005). This may mean that social media activity surrounding health care organizations is depressed by privacy concerns relative to other sectors online. Despite this, the comparison between active and inactive management of social media may still hold. Other limitations of the research include that we do not have clean experimental variation in the use of active media strategies and consequently have to rely on quasi-experimental variation generated by instrumental variables for identification. Given the ease with which firms can purposely experiment with social media in a controlled manner, this is an obvious direction for future research. Another avenue for future research is measuring the effects of social media management on other outcomes, such as recruitment and retention of employees and perceptions of customers regarding the quality or legitimacy of the firm.

These limitations notwithstanding, we believe that this paper, by documenting that actively managing social media is more successful at engaging those inside the firm than outside it, makes an important contribution to our understanding of social media and the appropriate strategies firms should employ toward it.

Acknowledgments
All errors are the authors' own. The authors thank workshop participants at the *ISR* Special Issue Workshop on "Social Media and Business Transformation" for their helpful comments.

Appendix A. Further Data Analysis

Figure A.1 Joint Distribution of Admissions and Employees

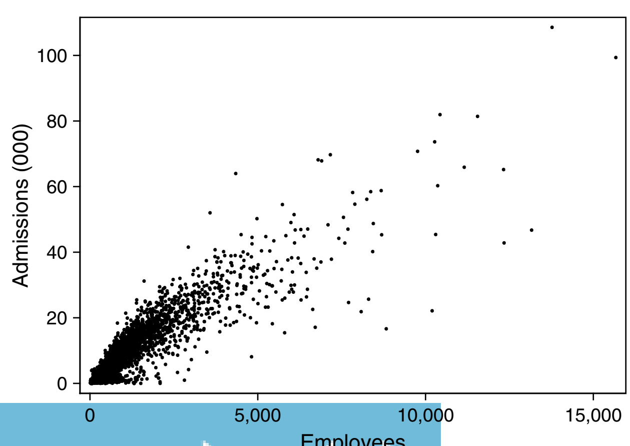

Table A.1 Summary Statistics: Split

	Mean (not active)	SD (not active)
Inpatient days (000)	33.6	47.9
Total operations (000)	4.00	6.04
Total outpatient visits (000)	90.4	148.7
No. doctors	12.0	49.2
No. nurses	171.9	285.0
No. trainees	11.5	68.1
Nonmedical staff	307.8	502.3
Group practice association	0.020	0.14
Integrated salary model	0.24	0.43
Nonprofit hospital	0.50	0.50
Speciality hospital	0.19	0.39
StandAlone	0.47	0.50
Observations	4,101	
	Mean (active)	**SD (active)**
Inpatient days (000)	68.9	61.9
Total operations (000)	10.0	9.45
Total outpatient visits (000)	210.4	234.9
No. doctors	35.1	126.9
No. nurses	463.4	482.0
No. trainees	49.3	148.5
Nonmedical staff	791.5	859.4
Group practice association	0.019	0.14
Integrated salary model	0.33	0.47
Nonprofit hospital	0.71	0.45
Speciality hospital	0.086	0.28
StandAlone	0.42	0.49
Observations	932	

Table A.2 Summary Statistics: Split, No Outliers

	Mean (not active)	Mean (active)
Admissions (000)	3.15	5.33
Employees	422.1	724.9
Managed care	0.079	0.084
Proportion Medicare patients	0.48	0.48
Inpatient days (000)	22.9	29.7
Total operations (000)	2.66	4.80
Total outpatient visits (000)	63.6	113.8
No. doctors	6.35	11.9
No. nurses	99.6	180.5
No. trainees	2.33	4.89
Nonmedical staff	191.2	340.1
Group practice association	0.020	0.010
Integrated salary model	0.22	0.28
Nonprofit hospital	0.48	0.67
Speciality hospital	0.20	0.12
StandAlone	0.47	0.47
Observations	3,523	

Note. This sample excludes hospitals in the top or bottom decile of admissions or number of employees.

Table A.3 Drivers of Active Management of Social Media

	(1) *Active social media*	(2) *Active social media*	(3) *Active social media*	(4) *Prop. patient-targeted postings*	(5) *Prop. patient-targeted postings*
Admissions (000)	0.0398***	0.0362***	0.0273***	0.00361***	0.000412
	(0.00592)	(0.00605)	(0.00849)	(0.000864)	(0.00124)
Employees	0.0000422	0.0000644	0.0000743	0.000000117	0.0000211**
	(0.0000459)	(0.0000466)	(0.0000711)	(0.00000649)	(0.0000102)
Managed care	0.0496	0.0642	−0.0585	0.0124	−0.00728
	(0.0731)	(0.0760)	(0.112)	(0.00888)	(0.0116)
Proportion Medicare patients	−0.0937	−0.0347	−0.0655	0.00701	0.0138
	(0.0972)	(0.105)	(0.176)	(0.00756)	(0.0121)
Health region controls	No	Yes	Yes	Yes	Yes
System fixed effects	No	No	Yes	No	Yes
Observations	5,033	4,991	2,347	5,033	2,729
Log-likehood	−2,174.0	−2,079.0	−1,010.9	2,353.2	1,193.2

Notes. Probit estimates. Dependent variable is whether or not the hospital actively manages its social media page by posting itself. Robust standard errors.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.4 Poisson Specification: Active Social Media Management Increases User-Generated Content Mainly by Employees

	Active (1)	*Inactive* (2)	All data (3)
Active social media			1.640***
			(0.00821)
Employees	0.000253***	−0.000305***	−0.000353***
	(0.00000287)	(0.00000593)	(0.00000578)
Admissions (000)	−0.0173***	0.0885***	0.0917***
	(0.000519)	(0.000749)	(0.000725)
Active social media × Admissions			−0.116***
			(0.000869)
Active social media × Employees			0.000655***
			(0.00000627)
Managed care	0.595***	0.0740***	0.417***
	(0.0111)	(0.0140)	(0.00839)
Proportion Medicare patients	−2.637***	−0.0735***	−1.366***
	(0.0229)	(0.0232)	(0.0157)
Health region controls	Yes	Yes	Yes
Observations	932	4,101	5,033
R-squared			

Notes. Dependent variable is the number of people generating content about the organization via social media. Robust standard errors.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.5 Marginal Effects for Poisson Specification in Column (5) of Table 5

Measurement	Delta-method dy/dx	Std. err
	Main effects	
Active social media	40.13687	0.27020
Admissions (000)	0.72322	0.01143
Employees	−0.00003	0.00008
Managed care	10.17771	0.20686
Proportion Medicare patients	−33.36340	0.39480
Interactions with active social media management (*ASM*)		
× *Admissions* (000)		
ASM = 0	1.465137	0.0135678
ASM = 1	−1.340185	0.0294347
× *Employees*		
ASM = 0	−0.0056419	0.0000948
ASM = 1	0.0169581	0.0001587

Appendix B. Analysis by Employee and Client Type

In supplementary analysis, we break down the number of employees and number of admissions into more finely graded buckets such as doctors, nurses, medical trainees, and nonmedical staff. Table B.1 reports the results. It is noticeable that under active social media management, nonmedical employees are the major driver of user-generated content, though that is not the case under nonactive media management.

Table B.1 Major Driver of User-Generated Content Under Active Social Media Management Is Non-Medical Staff

	(1) *Active*	(2) *Inactive*	(3) *Active*	(4) *Inactive*
Admissions (000)	−6.733**	2.497***		
	(3.021)	(0.353)		
No. doctors	−0.0987	0.0104	−0.0748	0.0118
	(0.0965)	(0.0310)	(0.0496)	(0.0112)
No. nurses	0.0549	0.00606	0.0379	0.0506***
	(0.0387)	(0.0121)	(0.0320)	(0.00498)
No. trainees	−0.0558	−0.0283	−0.000567	−0.0436***
	(0.0579)	(0.0267)	(0.0482)	(0.00889)
Nonmedical staff	0.114**	−0.0144***	0.123***	−0.0139***
	(0.0515)	(0.00484)	(0.0152)	(0.00257)
Managed care	54.05*	0.523	54.98***	1.137
	(29.49)	(1.651)	(15.85)	(1.509)
Proportion Medicare patients	−192.2***	−4.223***	−247.5***	−2.409
	(45.33)	(1.543)	(31.17)	(2.085)
Inpatient days (000)			−1.302***	0.0128
			(0.192)	(0.0185)
Total operations (000)			1.386	0.947***
			(0.938)	(0.143)
Total outpatient visits (000)			−0.0964***	0.00486
			(0.0319)	(0.00478)
Health region controls	Yes	Yes	Yes	Yes
Observations	932	4,101	932	4,101
R-squared	0.263	0.264	0.271	0.232

Notes. OLS estimates. Dependent variable is the number of people generating content about the organization via social media. Robust standard errors.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

There are several potential explanations for this pattern which are all nonexclusive and speculative. First, it could be that nonmedical employees have more leisure time to engage with social media. Second, it could be that because the people managing the social media are not from a medical background, the content they produce is more effective at engaging nonmedical personnel. Third, if there is internal organizational pressure for employees to engage with their organization's active social media presence, then such pressure is more keenly felt by the nonmedical personnel.

Of course there is the potential that the proportion of staff of each type is reflective of the kind of procedures and medical care they provide. Therefore, in columns (3) and (4) of Table B.1, we report specifications that break up admissions into different categories such as inpatient stays, outpatients, and operations. The result holds that the major difference between what drives user-generated content under active and nonactive social media management is the number of nonmedical staff, and the coefficient is estimated more precisely.

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