Active Social Media Management: The Case of Health Care

Amalia R. Miller* and Catherine Tucker†‡

October 12, 2012

Abstract

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 healthcare setting. We show empirically that active social media management drives more user-generated content. However, we find that this is due to an increase in incremental 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, empirically the majority of 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 this provoke activity by employees rather than clients. This may not be a bad thing, as 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.

*Economics Department, University of Virginia, Charlottesville, VA and RAND Corporation

†MIT Sloan School of Management, MIT, Cambridge, MA and NBER

‡All errors are our own.

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 on marketing in social media so far 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 US and collect data on whether the hospital is actively managing its social media presence by customizing its Facebook page and posting messages to their page. We study Facebook partly because it is the most visited media site in the US, 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 US, which each hospital then had a choice about 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 their number of 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 towards client-specific communications, then active social media management can still lead to incremental user-generated content which 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 three-fold. 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 healthcare, 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 (2012)'s 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 can be attributed to the fact that firms tend to post content which 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 clients. Speculatively, this may be because employees already have closer ties to the organization than the firm's clients, and so are better able to engage with content which is not focused exclusively on their needs. In our sample, client-focused postings constituted around only one-fourth of all postings. Therefore, a major implication of our paper is to highlight that if firms wish to use social media primarily for client-facing reasons, their efforts may be more effective if they ensure that any 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 which 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 (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) which document how important word-of-mouth recommendations are for driving purchases. Since this early work, there has developed a burgeoning literature 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

[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.

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 which 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 ROI 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), in their study of users of an application on a social media website, show that integrating an automated message to their contacts has a larger effect on new adoption than the incremental effect of also giving users the opportunity to post their own messages. In the sphere of online advertising, Tucker (2011a) shows that video advertising that is designed for websites such as YouTube may have to sacrifice the commercial appeal of its message in order 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 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 was released in 2011. The American Hospital Association survey provides an annual census of all hospitals in the US 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 this 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.

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 US (Comscore 2011). Second, since October 2011, Facebook has released novel data which allows measurement of more general forms of user interactions with an organization by Facebook users.

We had to identify each hospital's Facebook page manually as there was no central directory of such pages. The pages were created automatically from a database of companies as part of Facebook's 'Places' strategy, where they automatically create social media websites for US 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, as 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] Since this data has been available only since October 2011, and there has been no new data on hospital characteristics released in the intervening

[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.

months, we use cross-sectional data for our analysis.

This data was reasonably time-consuming to collect. Early attempts at using screen-scraping 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 went and actually verified what was indeed the case.

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, since this measures the broadest category of ways a user can interact using social media with an organization. Also, since it is 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 they sign up for the news feed, meaning that they received 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 which 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 since it reflects passive consumption of news from the organization rather than active social media activity(Gossieaux and Moran 2010).

The 'were here' is a measure of 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 since 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 their own and posted to it. As shown in Table 1, we found that 18 percent of hospitals actively managed their Facebook page. This is in line with studies such as Thaker et al. (2011) that show that 20 percent of hospitals actively use social media.[6] We supplemented this binary metric with data we collected seven months later, which 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.

Table A-11 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]In some retail situations, for example when a Facebook user checks 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 due to the payments and pricing system in healthcare.

[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 were comprised of 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 since 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-12.

Figure 1: Sample Facebook Page for a Hospital

Table 1: Summary Statistics

Dependent Variables				
	Mean	Std Dev	Min	Max
UGC	24.4	77.9	0	3666
Likes	488.1	10047.1	0	686899
Visited	934.7	1988.4	0	38333
Explanatory Variables				
	Mean	Std Dev	Min	Max
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	2543.3
No. Doctors	16.3	70.9	0	2067
No. Nurses	225.9	349.3	0	4347
No. Trainees	18.5	89.9	0	1839
Non-Medical Staff	397.4	614.4	0	9025
Group Practice Association	0.019	0.14	0	1
Integrated Salary Model	0.25	0.44	0	1
Non-Profit Hospital	0.54	0.50	0	1
Speciality Hospital	0.17	0.38	0	1
StandAlone	0.46	0.50	0	1
Observations	5033			

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:

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

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 Section 3. We argue that the ability of a firm to generate this content is a function of their 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 since 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

[8]Figure A-3 in the appendix plots out their joint distribution. As expected, they are positively related, but, crucially for this research, they are not perfectly collinear.

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 which might drive online user-generated content. Specifically, since Medicare patients are older, it controls for the age of clients at the hospital. This is important because 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 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-13 in the appendix 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

[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.

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 of or inside of 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 size of the estimate for the effect of incremental employees on the total amount of user-generated content is far higher for hospitals that actively manage their social media than for those that do not. This is the first empirical finding which suggests that much of the power of active social media management is to 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 and 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 since 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 that hospitals with a high staff:patient ratio generate more user-generated content under active social media management, but that 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 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-

[10]We confirm this pattern in a separate specification that looks at the ratio directly. Controlling for hospitals 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.

facing objectives. Commentators have also emphasized client-facing objectives. Hawn (2009) emphasizes the importance of social media for healthcare 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, while 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 since 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 their friends.

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

	All Data		Active	Inactive	Active	Inactive	All Data
	(1)	(2)	(3)	(4)	(5)	(6)	(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	5033	5033	932	4101	932	4101	5033
R-Squared	0.0806	0.191	0.145	0.186	0.245	0.260	0.248

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

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

Note: 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.

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.

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 which have more employees and fewer clients, for example hospitals that specialize in a medical speciality that has fewer patients but requires a lot of carers, that also are successful at mobilizing social media. Both non-profit 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 stand-alone 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-11), 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-11 many of the outliers in the top decile have active social media management.

In Column (5), we check robustness to the fact that we were only able to identify 5,035 out of 5,759 total hospitals. In these regressions, we treat the missing observations as not actively managing their Facebook page since 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 the dependent variable. For example, one potential critique is that our dependent measure may not be representative, since 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 the fact that the dependent variable cannot be negative. The results remain robust. [12] We report the marginal effects for this specification in Table A-15 in the appendix. The marginal effects for the key interaction term, 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.

[12] We replicate Table 2 for this count-model specification in Table A-14 in the appendix.

Table 4: Robustness Checks: Sample

	More Controls	Within-System	Speciality Hosp	No Outliers	All Unmatched
	(1)	(2)	(3)	(4)	(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)				
Non-Profit 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	5033	2729	860	3523	5756
R-Squared	0.252	0.320	0.478	0.272	0.197

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

Table 5: Robustness Checks: Variables

	Alt DV		Cts X	Log-Log	Poisson
	(1)	(2)	(3)	(4)	(5)
	Likes	Visited	UGC	UGC (Log)	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	1614.5***	1066.6***		-0.866*	1.640***
	(529.2)	(93.26)		(0.481)	(0.00821)
Managed Care	1450.2***	179.4**	14.36***	-0.00993	0.417***
	(484.9)	(85.45)	(3.446)	(0.0577)	(0.00839)
Proportion Medicare Patients	-1671.0**	-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	5033	5033	5033	5033	5033
R-Squared	0.0748	0.266	0.223	0.448	

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) the total number of visits in Column (2). Robust standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 admissions:employee ratio is not random

The first set of alternative explanations which need to be ruled out is that the 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 their patients more attentive care. This could in turn affect response to active social media management as clients harbor more positive feelings towards 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 they treat were less likely to inspire a client response to their postings.

To rule out these and similar alternative explanations of our results, we introduce two instrumental variables which 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 their number of employees but did not affect the likelihood of a Facebook user engaging with their Facebook page directly. We find such as 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 cost 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 they are 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 labor-replacing capital investment tends to be sticky; labor-replacing capital investments are generally hard to reverse since 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 to simply 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 directly 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 which has documented the association of these laws with medical activity and procedures such as Kessler and McClellan (1996). Therefore, the instrument is correlated with the endogenous variable. It also seems likely that this instrument meets the exclusion restriction, as 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 which uses these instruments as 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, as 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), 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, since 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 too

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 is not 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 which limit the use of patient testimonials in marketing communications by physicians and healthcare providers.[13] For example, Cal. Bus. & Prof. Code Section 651 states 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 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.:

[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, 2011a,b).

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 were in such states there is an exogenous reason why it may be preferable to not actively manage any social media presence that is not related directly to the extent to 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 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, while highly statistically significant, is somewhat modest in magnitude. The presence of a statute is associated about a 5 percentage point decline in active social media management and the R-squared of the regression is less than 1 percent. 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.

As we have multiple endogenous variables which are in turn instrumented by multiple instrumental variables and their interactions, we report our results incrementally. We report in Table 7 in Column (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, as the American Hospital Association data for two decades ago obviously does 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 which 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 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 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 as those in Column (5), suggesting that the OLS specification does not drive the results.

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***	-2.468***	
		(0.432)	(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	1087.1***	7.372***	6.948***	0.180***
	(44.99)	(0.213)	(0.225)	(0.00728)
Observations	4367	5033	5033	5033
R-Squared	0.00548	0.00926	0.0154	0.00280

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

Table 7: Instrumental Variable Specification

	IV for Emp		IV for Adm+Emp		IV for Adm+Emp+Active	
	(1)	(2)	(3)	(4)	(5)	(6)
	Active	Inactive	Active	Inactive	All	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	3535	832	3535	4367	4367
R-Squared	.	0.312	.	0.203	.	

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

Note: 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.

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] Since 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 either made observations about non-hospital matters such as the weather or about hospital achievements. Figure 2 summarizes the proportion of types of target 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 towards patients moderates our earlier results. Strikingly, when hospitals have a larger proportion of postings targeted towards patients, this acts to reduce the extent to which active social media management transforms user-generated content to be a function

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

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 & Banquet Center/Snapper's Bar & 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 PM 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 pm! 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. Mary s 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

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

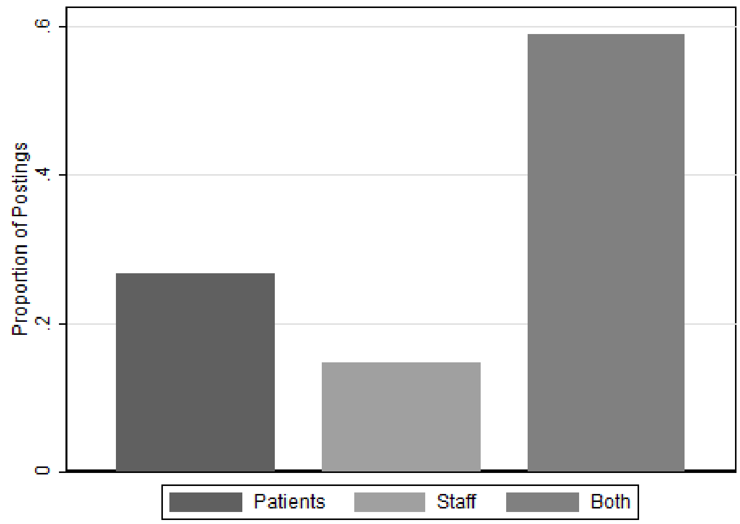

Figure 2: Proportion of Each Type of Posting

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 are a subset of hospitals who 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 non-targeted 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 follow 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 its social media messaging to either patients or staff or have more generically targeted content. Unlike in Section 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 a 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 Mechanical Turk to independently categorize the postings 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, while 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

[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 medical personnel. This analysis is reported in Table A-16 in the appendix.

[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.

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 Non-Targeted Postings × Admissions			-8.852***
			(0.786)
Prop Non-Targeted Postings × Employees			0.0744***
			(0.00536)
Prop. Patient-Targeted Postings	3.886		
	(11.28)		
Prop. Staff-Targeted Postings		31.84***	
		(6.758)	
Prop. Non-Targeted 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	5033	5033	5033
R-Squared	0.227	0.278	0.261

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

to postings represent a small proportion of possible user generated content that occurs on a platform such as a 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 from the fact that 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 US, 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 the 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 will be more successful if they ensure that all postings are focused entirely around the clients' needs and interests rather than the organization's interests.

The most obvious limitation of this paper is that we focus on the use of social media in healthcare. There are two features of healthcare in that might make it unrepresentative of social media in other industries. First, consumer choice of hospitals in the US is often limited by insurance arrangements which are determined by their workplace. Further, these insurance arrangements complicate competition between hospitals. Second, healthcare 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 healthcare 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 the fact 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 recruiting 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 towards it.

References

Acemoglu, D. and A. Finkelstein (2008, October). Input and technology choices in regulated industries: Evidence from the health care sector.

Algesheimer, R., U. M. Dholakia, and A. Herrmann (2005). The Social Influence of Brand Community: Evidence from European Car Clubs. *Journal of Marketing 69*(3).

Aral, S. and D. Walker (September 2011). Creating social contagion through viral product design: A randomized trial of peer influence in networks. *Management Science 57*(9), 1623–1639.

Avraham, R. (2011). Database of State Tort Law Reforms (DSTLR 4th). *U of Texas Law, Law and Econ Research Paper No. 184*.

Bakshy, E., J. M. Hofman, W. A. Mason, and D. J. Watts (2011). Everyone's an influencer: quantifying influence on Twitter. In *Proceedings of the fourth ACM international conference on Web search and data mining*, WSDM '11, New York, NY, USA, pp. 65–74. ACM.

Becker, S. (2011, June 15). As medical specialists race into consumer-direct marketing, watch for legal tripwires. *Healthcare Success Strategies*.

Becker, S. and A. Callard (2012, Feb 10). 3 core legal issues for hospital marketing programs. *Becker's Hospital Review*.

Berger, J. and K. L. Milkman (2011). What makes online content viral? *Journal of Marketing Research, Forthcoming*.

Blanchard, O. (2011). *Social Media ROI: Managing and Measuring Social Media Efforts in Your Organization*. Que Biz-Tech. Que.

Chase, L. and K. Knebl (2011). *The Social Media Sales Revolution: The New Rules for*

Finding Customers, Building Relationships, and Closing More Sales Through Online Networking. McGraw-Hill Companies.

Chen, Y., S. Fay, and Q. Wang (2011). The role of marketing in social media: How online consumer reviews evolve. *Journal of Interactive Marketing 25*(2), 85 – 94.

Chou, S. W.-y., M. Y. Hunt, B. E. Beckjord, P. R. Moser, and W. B. Hesse (2009, Nov). Social media use in the united states: Implications for health communication. *J Med Internet Res 11*(4), e48.

Comscore (2011). Comscore's 2011 social report: Facebook leading, microblogging growing, world connecting. *White Paper*.

Cook, N. (2008). *Enterprise 2.0: How Social Software Will Change the Future of Work.* Gower.

Corcoran, S. (2009, December 16). Defining earned, owned and paid media. *Forrester Research*.

Culnan, M. J., P. J. McHugh, and J. I. Zubillaga (2010). How large U.S. companies can use twitter and other social media to gain business value. *MIS Quarterly Executive 9*(4).

Dellarocas, C. (2005). Strategic manipulation of internet opinion forums: Implications for consumers and firms. *Management Science*.

Ghose, A. (2008). *The Economic Impact of User-Generated and Firm-Generated Online Content: Directions for Advancing the Frontiers in Electronic Commerce Research*, pp. 35–58. John Wiley & Sons, Inc.

Godes, D. and D. Mayzlin (2004, September). Using online conversations to study word-of-mouth communication. *Marketing Science 23*(4), 545–560.

Godes, D. and D. Mayzlin (2009). Firm-Created Word-of-Mouth Communication: Evidence from a Field Test. *Marketing Science 28*(4), 721–739.

Godes, D., D. Mayzlin, Y. Chen, S. Das, C. Dellarocas, B. Pfeiffer, B. Libai, S. Sen, M. Shi, and P. Verlegh (2005). The firm's management of social interactions. *Marketing Letters 16*, 415–428. 10.1007/s11002-005-5902-4.

Goldfarb, A. and C. Tucker (2012). Privacy and innovation. In *Innovation Policy and the Economy, Volume 12*, NBER Chapters. National Bureau of Economic Research, Inc.

Gossieaux, F. and E. Moran (2010). *2010.* McGraw-Hill.

Gross, R. and A. Acquisti (2005). Information revelation and privacy in online social networks. In *Proceedings of the 2005 ACM workshop on Privacy in the electronic society*, WPES '05, New York, NY, USA, pp. 71–80. ACM.

Hall, M. A. (1991). The defensive effect of medical practice policies in malpractice litigation. *Law and Contemporary Problems 54*(2), 119–145.

Harrill, H. (2011, Sep 7). How to use Facebook groups for internal communication. *Ragan's HR Communication*.

Hawn, C. (March/April 2009). Take two aspirin and tweet me in the morning: How Twitter, Facebook, and other social media are reshaping health care. *Health Affairs 28*(2), 361–368.

Katz, E. and P. F. Lazarsfeld (1955). *Personal influence.* Glencoe, IL: Free Press.

Kessler, D. and M. McClellan (1996). Do doctors practice defensive medicine? *The Quarterly Journal of Economics 111*(2), pp. 353–390.

Kessler, D. and M. McClellan (2002, May). Malpractice law and health care reform: optimal liability policy in an era of managed care. *Journal of Public Economics 84*(2), 175–197.

Mayzlin, D. (2006). Promotional chat on the internet. *Marketing Science*.

Miller, A. and C. Tucker (2011a). Encryption and the loss of patient data. *Journal of Policy Analysis and Management 30*(4), 534–56.

Miller, A. R. and C. Tucker (2009). Privacy Protection and Technology Diffusion: The Case of Electronic Medical Records. *Management Science 55*(7), 1077–1093.

Miller, A. R. and C. Tucker (2011b). Electronic Discovery and the Adoption of Information Technology. *conditionally accepted, Journal of Law, Economics and Organizations*.

Moorman, C. (2012). CMO survey. *Mimeo, Duke University*.

Oestreicher-Singer, G. and A. Sundararajan (2012). The visible hand? Demand effects of recommendation networks in electronic markets. *Management Science*.

Orsini, M. (2010). Social media: How home health care agencies can join the chorus of empowered voices. *Home Health Care Management and Practice 22*(3), 213–217.

Pincus, J. D. (1986). Communication satisfaction, job satisfaction, and job performance. *Human Communication Research 12*(3), 395–419.

Sawhney, M., G. Verona, and E. Prandelli (2005). Collaborating to create: The internet as a platform for customer engagement in product innovation. *Journal of Interactive Marketing 19*(4), 4–17.

Slack, M. (1999). Guerilla marketing breaking through the clutter with word-of-mouth. *Jupiter Research. Darien, CT.*.

Stock, J. H. and J. H. Wright (2000, September). Gmm with weak identification. *Econometrica 68*(5), 1055–1096.

Thaker, S. I., A. S. Nowacki, N. B. Mehta, and A. R. Edwards (2011). How U.S. hospitals use social media. *Annals of Internal Medicine 154*(10), 707–708.

Thompson, S. A. and R. K. Sinha (2008, Nov). Brand communities and new product adoption: the influence and limits of oppositional loyalty. *Journal of Marketing 72*(6), 65–80.

Trusov, M., R. E. Bucklin, and K. Pauwels (2009, September). Effects of word-of-mouth versus traditional marketing: Findings from an internet social networking site. *Journal* *of Marketing 73*, 90–102.

Tucker, C. (2011a). Ad virality and ad persuasiveness. *Mimeo, MIT*.

Tucker, C. (2011b). Social Networks, Personalized Advertising, and Privacy Controls. *Mimeo, MIT*.

Tucker, C. (2012). Social advertising. *Mimeo, MIT*.

Tucker, C. and J. Zhang (2011). How does popularity information affect choices? a field experiment. *Management Science 57*(5), 828–842.

Wollan, R., N. Smith, and C. Zhou (2011). *The Social Media Management Handbook: Everything You Need To Know To Get Social Media Working In Your Business*. John Wiley & Sons.

Zubcsek, P. and M. Sarvary (2011). Advertising to a social network. *Quantitative Marketing and Economics 9*, 71–107.

A Further Data Analysis

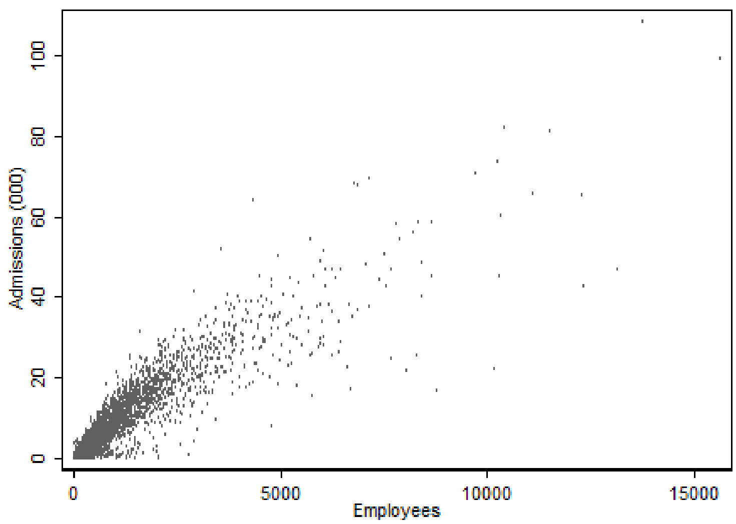

Figure A-3: Joint Distribution of Admissions and Employees

Table A-11: 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
Non-Medical Staff	307.8	502.3
Group Practice Association	0.020	0.14
Integrated Salary Model	0.24	0.43
Non-Profit Hospital	0.50	0.50
Speciality Hospital	0.19	0.39
StandAlone	0.47	0.50
Observations	4101	

	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
Non-Medical Staff	791.5	859.4
Group Practice Association	0.019	0.14
Integrated Salary Model	0.33	0.47
Non-Profit Hospital	0.71	0.45
Speciality Hospital	0.086	0.28
StandAlone	0.42	0.49
Observations	932	

Table A-12: 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
Non-Medical Staff	191.2	340.1
Group Practice Association	0.020	0.010
Integrated Salary Model	0.22	0.28
Non-Profit Hospital	0.48	0.67
Speciality Hospital	0.20	0.12
StandAlone	0.47	0.47
Observations	3523	

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

Table A-13: 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	5033	4991	2347	5033	2729
Log-likehood	-2174.0	-2079.0	-1010.9	2353.2	1193.2

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-14: 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	4101	5033
R-Squared			

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-15: Marginal Effects for Poisson Specification in Column (5) of Table 5

Measurement	Delta-Method $\frac{dy}{dx}$	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)		
$\times$ Admissions (000)		
$ASM = 0$	1.465137	.0135678
$ASM = 1$	-1.340185	.0294347
$\times$ Employees		
$ASM = 0$	-.0056419	.0000948
$ASM = 1$	.0169581	.0001587

B Analysis by Employee and Client Type

In supplementary analysis, we break down the number of employees and number of admissions into more finely gradated buckets such as doctors, nurses, medical trainees, and non-medical staff. Table A-16 reports the results. It is noticeable that under active social media management, non-medical employees are the major driver of user-generated content, though that is not the case under non-active media management.

There are several potential explanations for this pattern which are all non-exclusive and speculative. First, it could be that non-medical employees have more leisure time to engage with social media. Second, it could be that since the people managing the social media are not from a medical background, the content they produce is more effective at engaging non-medical 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 non-medical 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 A-16, we report specifications which 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 non-active social media management is the number of non-medical staff, and the coefficient is estimated more precisely.

Table A-16: 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)
Non-Medical 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	4101	932	4101
R-Squared	0.263	0.264	0.271	0.232

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