Active Social Media Management: The Case of Health Care

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Abstract

Given the demand for authentic personal interactions over social media, it is unclear how much firms should actively try and engage with consumers using social media. We investigate empirically what drives the degree of engagement that healthcare organizations generate by actively managing their social media presence. We find that active management of social media is more likely to generate incremental engagement from an organization's employees than its clients. In other words, active management of social media by an organization seems more successful at boosting internal engagement than external engagement. This result holds when we explore exogenous variation in a firm's relationships with its employees and clients that are explained by medical malpractice laws and distortions in Medicare incentives.

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1 Introduction

The arrival of social media has led many organizations to question the extent to which they should actively guide, promote and shape the 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 new 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 the creation of this organic form of influence.

This paper asks what kind of incremental engagement organizations 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 this 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 Facebook has just starting releasing new data that measures the 'engagement' of Facebook users. Engagement captures the extent to which a user interacts with an organization on Facebook.

Empirically, we find that actively managing a Facebook page increases engagement by Facebook users. Our paper focuses on the question of where this incremental engagement comes from. We find evidence that for hospitals that do not actively manage their Facebook presence, engagement is a function of their number of clients. However, when hospitals do actively manage their Facebook presence, engagement 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. The results are also robust when we look at exogenous variation in clients and employees that derives from federal and state laws governing Medicare reimbursement and laws governing medical malpractice lawsuits.

We interpret this evidence as suggesting that when an organization actively manages its social media presence, it predominantly succeeds in increasing its engagement with users of that social media platform who are internal to the organization rather than external to the organization. Since strengthening communication channels with employees is important for any organization's performance (Pincus 1986), this may be a desirable outcome. However, it differs from the marketing aims or client communications aims that many organizations, in particular healthcare organizations, have when they start to participate actively over social media (Hawn 2009, Orsini 2010).

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) has emphasized that the organic sharing of commercial messages across social media is far rarer than previously supposed. They found very few empirical examples of a commercial message being consistently transmitted across social networks. Aral and Walker (2011) show that a passive rather than interactive method of engagement is more effective over social media. In the sphere of online advertising, Tucker (2011a, 2012) shows that advertising that is designed for social media may have to sacrifice the commercial nature of its message to be effective. Theoretical models such as Zubcsek and Sarvary (2011) share this perspective since they explicitly do not allow the organization to control word-of-mouth.

The question of whether or not a firm should actively participate in the conversations about it was first raised as a question facing managerial strategy in Godes et al. (2005). However, the work on this question has been largely theoretical. Dellarocas (2006) 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 engagement of whether a firm decides to actively participate or not in social media.

2 Data

To establish the identity of all hospitals in the United States, we use data from the American Hospital Association from their most recent survey. This survey was conducted in 2009, and the data 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 emphasizes that an attractive feature of studying the use of social media in the health care industry from an academic perspective is the existence of data on the universe of organizations and their characteristics. 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 2011, 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 engagement with Facebook 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.

We then collected data on engagement. 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.[1] Since this data has been available only since October 2011, and there has been no new data on hospital characteristics released in the intervening months, we use cross-sectional data for our analysis.

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 engagement 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

[1]Sometimes, hospitals set up separate pages for their foundations. For example, Crozer-Chester hospital system, though not having a Facebook 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.

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, 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 is necessarily a measure of passive consumption of news from the organization rather than the kind of active engagement emphasized as being desirable by social media experts (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.[2] 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 engagement than 'talking about it,' it is not the main focus of our analysis. 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

[2]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.

Figure 1: Sample Facebook Page for a Hospital

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.[3]

[3]We do not have data on the kind of content that the hospital posts, meaning that unlike Berger and Milkman (2011), we do not relate content to engagement.

Table 1: Summary Statistics

Dependent Variables				
	Mean	Std Dev	Min	Max
Engagement	24.0	77.7	0	3666
Likes	485.2	10067.0	0	686899
Visited	911.3	1946.2	0	38333
Explanatory Variables				
	Mean	Std Dev	Min	Max
Active Social Media	0.18	0.39	0	1
Admissions (000)	6.68	9.08	0.0040	108.6
Employees	857.7	1244.5	14	15672
Managed Care	0.092	0.29	0	1
Proportion Medicare Patients	0.48	0.21	0	1.02
Inpatient Days (000)	40.1	52.6	0.0060	679.9
Total Operations (000)	5.11	7.19	0	104.2
Total Outpatient Visits (000)	112.6	174.7	0	2543.3
No. Doctors	16.3	71.1	0	2067
No. Nurses	225.5	349.4	0	4347
No. Trainees	18.5	90.0	0	1839
Non-Medical Staff	396.8	614.8	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	5013			

3 Results

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

In this simple specification, for hospital i in health referral region j, we model their social media engagement as a function of:

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

$Engagement_i$ is the level of engagement based on the 'talking about it' metric described in Section 2. We argue that the ability of a firm to generate engagement 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 engagement. $Active_i$ 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 which might drive online engagement. Specifically, since Medicare patients are older, it controls for the age of customers at the hospital. This is important because Chou et al. (2009) found that younger age 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. γ_j is a vector of fixed effects for each of the 306 health referral regions. The hospital region fixed effects help to control for differences in legal climates, such as state-level variation in privacy and security regimes (Miller and Tucker 2009, 2011a) and electronic discovery regimes (Miller and Tucker 2011b) that may affect a hospital's move towards digitization.

Table 2 explore this initial specification, incrementally building 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 engagement. The additional controls for hospital characteristics in Column (2) noticeably depress the size of the estimate for the effects of $Active_i$. This suggests that larger hospitals, who are also more likely to engage people because of their size, are more likely to adopt active social media management. This is not surprising, given earlier evidence of the drivers of new information technologies by hospitals.[4] The coefficients suggest that hospitals that are part of a managed care health system and have fewer Medicare patients are more likely to experience engagement in social media.

[4]Table A-1 in the appendix investigates the drivers of adoption of active management of social media. This is in line with earlier research such as Thaker et al. (2011) that suggests that hospitals that were statistically significantly more likely to use social media were large, urban, or part of a health system; were run by nonprofit, nongovernmental organizations; were involved in graduate medical education; or primarily treated children. They also appear similar to those reported for other healthcare IT such as studied in (Kim and Michelman 1990, Miller and Tucker 2011c).

The result that $Active_i$ has a positive effect on engagement is not unexpected. Even social media specialists who advocate a hands-off organic approach to social media do 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 social engagement comes from. In particular, does it come from engaging 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 reports the results of a simple specification that simply reports the relationship between employees and engagement 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 engagement 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 engage employees.

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. Hospitals that do actively manage their social media have engagement levels that are an increasing function of their number of employees but a decreasing function of their number of admissions. Hospitals that do not actively manage their social media have engagement 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 engagement under active management or that full-time employees depress engagement under inactive management. Instead the interpretation should be that that hospitals with a high staff:patient ratio generate more engagement under active social media management, but that hospitals with a low staff:patient ratio generate more engagement under inactive social media management.

To check the statistical significance of 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 engagement that is a function of the number of internal employees, rather than the number of clients that the hospital has.

This is a notable finding, because there is little evidence that this increase in employee engagement 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 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 consumers.[5] 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 is noted and appreciated by management, there

[5]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.

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, then interaction with that organization over Facebook would not raise new privacy concerns, or highlight a new facet of that Facebook user's life to their friends.

Table 2: Active Social Media Management Increases Engagement by Employees Primarily

	All Data		Active	Inactive	Active	Inactive	All Data
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Active Social Media	55.58***	37.29***					34.55***
	(2.734)	(2.786)					(3.727)
Employees		0.0296***	0.0296***	0.0114***	0.0607***	-0.00856***	-0.00916***
		(0.00204)	(0.00309)	(0.000442)	(0.00632)	(0.00109)	(0.00278)
Admissions (000)		-1.727***			-6.338***	2.820***	2.817***
		(0.281)			(0.947)	(0.141)	(0.362)
Active Social Media× Admissions							-9.232***
							(0.542)
Active Social Media× Employees							0.0751***
							(0.00382)
Managed Care		12.39***			57.70***	0.465	12.56***
		(3.530)			(16.52)	(1.479)	(3.401)
Proportion Medicare Patients		-19.86***			-209.0***	-4.298**	-26.41***
		(4.869)			(31.94)	(1.933)	(4.702)
Health Region Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5013	5013	912	4101	912	4101	5013
R-Squared	0.0762	0.187	0.145	0.186	0.246	0.260	0.246

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

3.1 Robustness Checks

This finding that active management of social media promotes engagement by employees rather than clients is unexpected, so Table 3 reports a battery of robustness checks for the results in Table 2.

In Columns (1) and (2) of Table 3, we add more controls for hospital type and organization. This is to address the concern that there may be certain types of hospitals who 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. Column (1) reports a series of controls for different types of organizational forms and specialities that a hospital might engage in. Both non-profit status and a speciality appear to mobilize engagement. 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 Columns (3) and (4), 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 social media engagement 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 social media engagement.

In Column (5), we check robustness to a log-log functional form specification. The result is robust to this specification, suggesting that it is not extreme values driving our results.

In Column (6), 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.

Table 3: Robustness Checks

	Hospital Controls	Within-System	Alt DV		Log-Log	Including Unmatched
	(1)	(2)	(3)	(4)	(5)	(6)
	Engagement	Engagement	Likes	Visited	Engagement (Log)	Engagement
Employees	-0.0101***	-0.00923***	-0.0996	-0.442***		-0.00911***
	(0.00283)	(0.00238)	(0.400)	(0.0690)		(0.00269)
Admissions (000)	2.992***	2.741***	17.49	140.5***		2.822***
	(0.376)	(0.309)	(51.90)	(8.955)		(0.349)
Active Social Media × Admissions	-9.202***	-3.407***	-824.5***	-112.8***		-5.919***
	(0.543)	(0.472)	(77.77)	(13.42)		(0.477)
Active Social Media × Employees	0.0750***	0.0304***	6.576***	0.756***		0.0561***
	(0.00382)	(0.00342)	(0.549)	(0.0947)		(0.00346)
Active Social Media × Employees (log)					0.506***	
					(0.104)	
Active Social Media × Admissions (log)					-0.744***	
					(0.119)	
Employees (Log)					0.168***	
					(0.0412)	
Admissions (Log)					0.665***	
					(0.0479)	
Active Social Media	33.96***	22.29***	1622.3***	942.2***	-0.971**	5.238**
	(3.750)	(3.367)	(535.1)	(92.33)	(0.482)	(2.470)
Managed Care	12.63***		1448.5***	133.0	-0.0190	10.97***
	(3.401)		(488.2)	(84.24)	(0.0579)	(3.078)
Proportion Medicare Patients	-23.75***	-15.73***	-1668.2**	-608.3***	0.00178	-21.31***
	(4.862)	(4.785)	(675.0)	(116.5)	(0.0832)	(4.167)
Group Practice Association	-5.201					
	(6.995)					
Integrated Salary Model	-2.941					
	(2.362)					
Non-Profit Hospital	8.320***					
	(2.223)					
Speciality Hospital	10.92***					
	(2.872)					
StandAlone	1.545					
	(2.026)					
Health Region Controls	Yes	Yes	Yes	Yes	Yes	Yes
System Fixed Effects	No	Yes	No	No	No	No
Observations	5013	2717	5013	5013	5013	5736
R-Squared	0.250	0.316	0.0750	0.263	0.444	0.196

OLS Estimates. Dependent variable is the number of people engaged via social media in the organization in Columns (1)-(2) and (5). Dependent variable is the total number of likes in Column (3) the total number of visits in Column (6). Robust standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.2 Identification through Instrumental Variables

The results of Table 3 are reassuring but, as with any study that attempts to relate network activity to an installed base, they still fall short of establishing causality (Manski 2007). To address this, we turn to instrumental variables.

A suitable instrument for the scope of the number of employees that a hospital has relationships with would be 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. 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 medical patients who were covered by Medicare during that decade, then they are likely now to have fewer employees and instead 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 4 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 engagement with a hospital on Facebook in 2011. 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 increased social media engagement. 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.

We report in Table 5 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 engagement levels when hospitals actively manage their social media are a function of employees not clients. Similarly, when hospitals do not actively manage their social media, engagement is a positive function of clients and not employee levels.

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). It 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 4. 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 4. This is advantageous for estimating our main specification, as it means that our instruments generate sufficient variation at the hospital level to include our health region fixed effects which would otherwise be potentially collinear with the state laws.

We estimate a specification which uses these defensive medicine instruments and report the results in Columns (3) and (4) of Table 5. 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, engagement is a function of employees not clients when hospitals actively manage their social media, and is a function of clients and not employees when hospitals do not actively manage their social media.

Table 4: First Stage Regressions for Instruments

	(1) Employees	(2) Admissions (000)	(3) Admissions (000)
Proportion Medicare Patients (1990)	-434.0***		
	(89.14)		
Cap Punative Damages		-0.660**	-0.278
		(0.271)	(0.285)
Cap Damages		-2.506***	-2.468***
		(0.433)	(0.446)
Managed Care × Cap Punative Damages			-3.301***
			(0.900)
Managed Care × Cap Damages			-0.533
			(1.803)
Managed Care			3.604***
			(0.670)
Constant	1084.7***	7.356***	6.948***
	(45.11)	(0.213)	(0.225)
Observations	4348	5013	5013
R-Squared	0.00542	0.00924	0.0150

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 5: Instrumental Variable Specification

	IV for Employees		IV for Admissions+Employees	
	(1)	(2)	(3)	(4)
	Active	Inactive	Active	Inactive
Employees	0.213***	0.000420	0.206***	0.00703
	(0.0770)	(0.00760)	(0.0758)	(0.0103)
Admissions (000)	-26.78***	1.907**	-22.74*	2.236*
	(10.39)	(0.882)	(12.69)	(1.296)
Proportion Medicare Patients	2.830	-0.498	17.60	1.565
	(83.66)	(2.876)	(157.0)	(4.440)
Managed Care	88.13**	1.054	76.60*	-0.608
	(41.12)	(1.804)	(39.64)	(1.765)
Health Region Controls	Yes	Yes	Yes	Yes
Observations	813	3535	813	3535
R-Squared	0.242	0.312	0.173	0.203

Instrumental Variable Estimates from Two-Stage Least Squares. Dependent variable is the number of people engaged via social media in the organization. Robust standard errors. Only observations of hospitals where we have data on the pattern of 1980s Medicare patients are included.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.3 Analysis by Employee and Client Type

In our final 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 6 reports the results. It is noticeable that under active social media management, non-medical employees are the major driver of engagement, 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 6, 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 engagement under active and non-active social media management is the number of non-medical staff, and the result is estimated more precisely.

Table 6: Major Driver of Engagement with Active Social Media Management is Non-Medical Staff.

	(1) Active	(2) Inactive	(3) Active	(4) Inactive
Admissions (000)	-6.725**	2.497***		
	(3.022)	(0.353)		
No. Doctors	-0.0994	0.0104	-0.0754	0.0118
	(0.0968)	(0.0310)	(0.0500)	(0.0112)
No. Nurses	0.0549	0.00606	0.0395	0.0506***
	(0.0390)	(0.0121)	(0.0324)	(0.00498)
No. Trainees	-0.0565	-0.0283	-0.00159	-0.0436***
	(0.0584)	(0.0267)	(0.0486)	(0.00889)
Non-Medical Staff	0.114**	-0.0144***	0.123***	-0.0139***
	(0.0520)	(0.00484)	(0.0154)	(0.00257)
Managed Care	53.69*	0.523	54.80***	1.137
	(30.94)	(1.651)	(16.34)	(1.509)
Proportion Medicare Patients	-195.3***	-4.223***	-251.4***	-2.409
	(45.94)	(1.543)	(31.73)	(2.085)
Inpatient Days (000)			-1.319***	0.0128
			(0.195)	(0.0185)
Total Operations (000)			1.429	0.947***
			(0.949)	(0.143)
Total Outpatient Visits (000)			-0.0957***	0.00486
			(0.0322)	(0.00478)
Health Region Controls	Yes	Yes	Yes	Yes
Observations	912	4101	912	4101
R-Squared	0.264	0.264	0.273	0.232

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

4 Implications

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 settings of hospitals. We use comprehensive data on active management of social media and user engagement with the hospital through social media 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 engagement. 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.

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 engagement with healthcare organizations is depressed by privacy concerns relative to other sectors online. However, though privacy concerns likely depress engagement in the sector, 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.

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, makes an important contribution to our understanding of social media and the appropriate strategies firms should employ towards it.

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Table A-1: Drivers of Active Management of Social Media

	(1) Active Social Media	(2) Active Social Media	(3) Active Social Media
Admissions (000)	0.0390***	0.0353***	0.0261***
	(0.00594)	(0.00605)	(0.00850)
Employees	0.0000484	0.0000701	0.0000807
	(0.0000460)	(0.0000467)	(0.0000713)
Managed Care	0.0278	0.0429	-0.0871
	(0.0745)	(0.0773)	(0.115)
Proportion Medicare Patients	-0.0927	-0.0352	-0.0582
	(0.0977)	(0.106)	(0.177)
Health Region Controls	No	Yes	Yes
System Fixed Effects	No	No	Yes
Observations	5013	4971	2335
Log-likehood	-2142.4	-2049.1	-995.3

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