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Blog, Blogger, and the Firm: Can Negative Employee Posts Lead to Positive Outcomes?

Rohit Aggarwal
Department of Operations and Information Systems, David Eccles School of Business, University of Utah, Salt Lake City, Utah 84112, rohit.aggarwal@busienss.utah.edu

Ram Gopal, Ramesh Sankaranarayanan
Department of Operations and information Management, School of Business, University of Connecticut, Storrs, Connecticut 06269 {ram.gopal@business.uconn.edu, rsankaran@business.uconn.edu}

Param Vir Singh
David A. Tepper School of Business, Carnegie Mellon University, Pittsburgh, Pennsylvania 15213, psidhu@cmu.edu

Consumer-generated media, particularly blogs, can help companies increase the visibility of their products without spending millions of dollars in advertising. Although a number of companies realize the potential of blogs and encourage their employees to blog, a good chunk of them are skeptical about losing control over this new media. Companies fear that employees may write negative things about them and that this may bring significant reputation loss. Overall, companies show mixed response toward negative posts on employee blogs—some companies show complete aversion; others allow some negative posts. Such mixed reactions toward negative posts motivated us to probe for any positive aspects of negative posts. In particular, we investigate the relationship between negative posts and readership of an employee blog.

In contrast to the popular perception, our results reveal a potential positive aspect of negative posts. Our analysis suggests that negative posts act as catalyst and can exponentially increase the readership of employee blogs, suggesting that companies should permit employees to make negative posts. Because employees typically write few negative posts and largely write positive posts, the increase in readership of employee blogs generally should be enough to offset the negative effect of few negative posts. Therefore, not restraining negative posts to increase readership should be a good strategy. This raises a logical question: what should a firm's policy be regarding employee blogging? For exposition, we suggest an analytical framework using our empirical model.

Key words: blog; employee blogs; bloggers; attribution theory; nonlinear models; negative posts; influence
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1. Introduction

Companies spend billions of dollars reaching out to their stakeholders—customers, investors, employees, and so forth through advertisements, event sponsorships, and other means. A recent Nielsen Global Survey suggests that blogs are considered a reliable source of information by North Americans and Asians and are trusted more than all types of advertisements except those in newspapers (Nielsen 2007). Because blogs are trusted more, they can influence customers and other stakeholders in a cost-effective manner (Edelmen and Intelliseek 2005). For instance, on March 18, 2006, the Yankee Group/Sunbelt's survey found Windows to be more reliable than Linux (Eckelberry 2006). However, this finding went unnoticed until Microsoft's employee Robert Scoble wrote about it on June 6, 2006 (Scoble 2006), after which it generated significant interest[1]—without Microsoft having to pay for the coverage.

Realizing the potential of blogs, many companies encourage their employees to maintain blogs. A CEO at a Fortune 500 firm expresses the importance of employee blogs in these words: "If you want to lead, blog.... We talk about our successes—and our mistakes. That may seem risky. But it's riskier not to have a blog" (Schwartz 2005, p. 2). IBM and Microsoft, for example, have more than 2,000 employee blogs (Byron and Broback 2006), and about 10 percent of the workforce at Sun Microsystems maintains blogs (Oliver 2006).

[1] After posting the results on March 18, 2006, this Yankee Group finding received no citations in blogs for two and half months. But after Robert Scoble's posting, the survey received more than 37 citations in less than two weeks.

Companies recognize the importance of employee blogs, but they also recognize the pitfalls. Employees may not always write positively about their employing companies. Employees may criticize the firm or its products, say embarrassing things about coworkers, or promote competitors. For instance, Michael Hanscom, who used to work at a printshop on Microsoft's main campus, was fired after he shot some pictures of Macintosh G5 computers being delivered to the campus and posted them on his blog. Mark Jen, a Google employee, compared Google's health policies unfavorably to those of Microsoft and suggested that Google provides extensive campus facilities such as free food, car service, dentist, etc. to allow employees to work for as many hours a day as possible. He was fired after just 17 days on the job. These firings attracted even more criticism for the involved companies (Crawford 2005).

Companies are understandably concerned that negative blog postings by employees may adversely impact the companies' reputation. A typical reaction may therefore be to completely forbid blogging by employees or to forbid any negative posting whatsoever. But there is an alternative view about negative posts on employee blogs, as explained by Michael Wiley, Director of Communications GM, in an interview with the Wall Street Journal:

> A lot of what blogging is about is authenticity, getting beyond corporate speak and PR, and really creating a conversation. Not being thin skinned and accepting the negatives, that's key. (Brian 2005).

Conventional wisdom and the business press suggest that if readers only see positive posts on employee blogs, then they may ignore the blog, thinking it another marketing outlet deployed by the company. But if an employee candidly discusses flaws in his/her company, then readers may consider him an honest and helpful person. This perception could lead to increased visibility and credibility of the blog, which could result in greater exposure to the positive posts as well, the net effect of which may well be an increase in the overall positive influence of the blog on readers (Halley 2003, Scoble and Israel 2006).

In this context, we now explore three questions: (i) Do negative posts help attract more readers to a blog? (ii) If so, why? What might be some of the theoretical underpinnings for this phenomenon? (iii) Finally, how can companies use this knowledge to optimize their employee blogging policies? We next explore each question in more detail, while emphasizing that the main focus and contribution of the paper is with respect to question (i).

For a blog to have any impact, in addition to being perceived as an honest source of information, it must be read by a significant number of people. Do negative posts attract more readers? To the best of our knowledge, there is no prior work that empirically examines this question. This critical question needs to be answered for firms that are contemplating letting their employees blog. Although negative posts may make the blog look more interesting, they may hurt the firm. If negative posts do not attract more readers, then they may not provide any real benefit to the firm. But if negative posts do attract more readers, then there is a chance that the readers could be exposed to the positive posts on the blog as well, which could result in a net overall benefit to the firm. Having a wide readership of employee blogs will thus help the firm use such blogs as a channel for disseminate credible and timely information.

Using a unique longitudinal sample of employee blogs of a Fortune 500 information technology (IT) firm, we derive empirical insights into the impact of negative posts on blog readership. We find that with an increase in negative posts, readership increases exponentially up to a certain level and then stabilizes. This finding is a key contribution of our paper.

This raises another question—why do negative posts increase readership? Our data set does not have the requisite granularity to provide a robust answer to this question. However, we draw on attribution theory from research in social psychology to present a plausible explanation of why letting an employee post negative entries may result in increased credibility for that employee's blog and why that could translate to increased readership.

We then present an analytical framework that helps identify conditions under which the presence of negative posts could generate greater net positive influence or create more positive views of a firm. For illustration, we apply this analytical framework to data from the Fortune 500 IT firm and calculate the net positive influence of a sample of employee blogs at the company. Our framework helps identify conditions for this company wherein more negative posts by bloggers may result in an increase in the overall positive influence on readers regarding toward the company.

Our model is of significant interest to firms interested in exploring employee blogging. First, by providing rigorous evidence that negative posts do indeed increase blog readership, our model serves to caution firms that controlling their employees' blogging behavior may be counterproductive. Second, our model provides a framework for firms to collect and analyze data from their employee blogs, so that the firms can identify what type of blogging activity is most effective in their context, and thereby fine-tune their blogging policies. Our results are of significant interest to information systems researchers and social psychologists interested in exploring this emerging phenomenon further.

The rest of the paper is organized as follows. In §2, we briefly discuss the related literature. In §3, we lay the groundwork for the empirical analysis by discussing the data, definitions, and measures. In §4, we derive an empirical model to test the link between negative posts and blog readership using econometric analysis. In §5, we use attribution theory to explore why negative posts on an employee's blog might result in increased readership and credibility for the blog. In §6, we incorporate the empirical relationship derived in §3 into a framework for companies to evaluate the conditions under which negative posts could increase the overall positive influence of a blog on readers, and we apply this framework to the specific case of the Fortune 500 firm. Finally, in §7, we conclude with the limitations of this study and suggest future research directions.

2. Literature Review

Our research builds on and adds to the emerging literature on blogs. Extant literature has studied different facets of blogs. The earliest questions deal with understanding why individuals blog in the absence of any direct incentives (Nardi et al. 2004, Miura and Yamashita 2007, Pedersen and Macafee 2007, Furukawa et al. 2007, Huang et al. 2010). These studies find that individuals are driven to document their ideas, provide commentary and opinions, and express deeply felt emotions. Another stream of literature on blogs primarily focuses on the volume of posts written on a topic in the blogosphere and how this volume affects their respective variables of interest such as product sales (Goldstone 2006, Onishi and Manchanda 2009, Mishne and Glance 2006), stock trading volume (Fotak 2008), and political event outcome (Adamic and Glance 2005, Farrell and Drezner 2008). That literature has largely ignored the affiliations of individuals writing blogs. Blogger affiliation is an important attribute to consider in blog studies, because this can radically change expectations of readers and in turn the readership of a blog (Scoble and Israel 2006).

Blogs maintained by employees are of particular interest to employing companies because the business press suggests that employee blogs provide a human face for companies and act as free advertising instruments (Brian 2005, Wright 2005, Halley 2003, Weil 2010, Kirkpatrick 2005). Marketing literature states that any form of advertising (be it single advertisement, campaign of advertisements, or a medium of advertising) has two attributes at its core—how many customers you reach and how strongly you influence them (Coffin 1963). Companies traditionally focus predominantly on the former core attribute of advertising—audience size (Headen et al. 1977); in the context of employee blogs, this connotes readership. Thus, companies that appreciate the potential of employee blogs as an advertising avenue understandably want to increase the readership of employee blogs.

There is a general paucity of research investigating the readership of employee blogs. The reason for this gap is that the readership data are proprietary and hence not easily accessible. Besides a company's willingness to share data, another challenge is that such data are only available from companies that provide dedicated space on company servers to their employees for blogging. These factors pose a formidable challenge for researchers studying research questions in the employee blog domain. Our research has only been made possible through a successful data sharing agreement with a Fortune 500 IT firm. Other than our work, very few studies have empirically investigated blogs within an enterprise context (e.g., Yardi et al. 2009, Singh et al. 2010). Yardi et al. (2009) find that when employees blog, they expect to receive attention from others. If their expectations go unmet, they express frustration and stop blogging. This suggests that firms should help employees with increased readership for continued blogging. Both these studies emphasize the importance that a firm lays on the readership of its employees' blogs. In comparison to our study, where employee blogs are accessible to outside individuals, the blogs in the above studies are only accessible to the employees. Blogs not accessible outside a company completely lose the chance of acting as advertising instruments for a company. It is the blogs with open access that make a firm more interested in blog readership because negative posts by employees may harm it significantly.

Our research is also related to the broader area of user-generated content. Specifically, it adds to the literature that studies how textual characteristics of a post may affect its readership. Recently, Ghose and Ipeirotis (2010) found that readers find helpful reviews that are objective, readable, and free of grammatical errors. Lu et al. (2010) found that individuals are more likely to trust reviewers whose reviews are moderately objective, comprehensive, and readable. Ghose et al. (2009) studied how the feedback posted by buyers affects a seller's reputation and pricing power. In the same vein, our study sheds light on a new aspect, that is, the sentiment of the post, and explores its relationship with its readership.

3. Data, Definitions, and Measures

3.1. Data

Data for this study come from three archival sources.

The first source is the blog posting and readership data from a Fortune 500 IT firm. This firm is one of the early adopters of Web 2.0 technologies. It provides a platform for its employees to host their blogs. Given that the workforce is primarily technical, blogging as an activity has been widely adopted by its employees. This firm has more than 1,000 employees who write blogs on a regular basis. We have access to the time-stamped blog posting data along with the post content and the readership data at a blog-week level.

The second source is the post citation data from a blog search engine, Technorati.com. Every post has a unique URL (called its "permalink") that other sites can cite or link to. Search engines such as Technorati provide a count of the number of such citations to each permalink. We collected post citation information for all posts in our data set.

The third source is the daily XML feed subscription data for each of the bloggers from Bloglines.com. Ask.com also uses the same subscription data set to rank bloggers according to their popularity (Massie and Kurapati 2006). These data were also collected for all bloggers in our data set.

3.2. Definitions and Measures

3.2.1. Blog Readership. As discussed earlier the firm would be interested in increasing the readership of its employees' posts. The firm collects the readership data in the form of web server access logs. The firm provided the readership data of a blog to us on a weekly level. We define, $P_{i,t}$, as the number of readers (page-views) who read blog i during week t.

3.2.2. Post Classification. Our key explanatory variable of interest deals with post sentiment. We employed 10 graduate students to help us categorize the posts into three categories: positive, negative, and neutral. A post was classified as positive if it promoted the firm (employer)—either the company or any of its products—or if it was critical of a competitor or its products. Conversely, a post was classified as negative if it criticized the firm or its products, or if it promoted competitors or their products. Posts that did neither of the above were categorized as neutral. Every post was categorized by two graduate students, and in case of a tie, the third student's decision was sought. The interstudent reliability for the categorization of posts was 0.91, which suggests a high level of agreement about the category of a post.

3.2.3. Blog Importance. In a blogosphere, a post's importance is measured by the number of other blogs citing it (Leskovec et al. 2007, Adamic and Glance 2005, Drezner and Farrell 2004).[2] The use of citations as a measure of importance is based on the premise that authors cite what they consider important in the development of their work/arguments. A citation captures a considerable amount of latent human judgment and indicates that the citer is influenced by the citing work and finds it worthy of discussion. Therefore, frequently cited posts are likely to exert a greater influence on readers than those less frequently cited. Therefore, our study assumes that when comparing two posts, the one with greater importance is the one being cited more.

Scholars have criticized the assumption that every citation has equal importance (Posner 2000, Pinski and Narin 1976).[3] Indeed, it makes little intuitive sense to treat every post as equally important, because a citation from Yahoo cannot be put on a par with citation by a site that gets few visitors. To account for this difference, we assign weights to each citation based on the number of citations to the citing site. Therefore, to measure the weighted citations to a post ($W_{p,t}$), we consider the citations and weigh them with their second-level citations (please see Online Appendix A to this paper for an example calculation[4]). This weighted citation of a post represents its importance in our study.

So far we have defined the importance of a post and how to measure it. A blog can have more than one type of post: positive posts will cast the company in a positive light, and negative posts will leave the reader with a negative impression of the company. We define $W^+_{i,t}$, $W^-_{i,t}$, and $W^0_{i,t}$ as weighted citations received by positive, negative, and neutral posts, respectively. Each of these measures is calculated by summing the weighted citations of the posts of its type displayed on the blog during period t. We also construct the measure of weighted citations to a blog as the sum of weighted citations of posts on a blog ($W_{i,t} = W^+_{i,t} + W^-_{i,t} + W^0_{i,t}$), without regard to whether the posts are

[2] Citations have been used as a measure of importance in varied settings ranging from scholarly publications (Culnan 1986, 1987; Stigler and Friedland 1975; Medoff 1996; Gittelman and Kogut 2003; Tahai and Meyer 1999; Alexander and Mabry 1994; Ramos-Rodríguez and Ruíz-Navarro 2004), to judicial decisions (Landes et al. 1998, Fred 1992, Kosma 1998), to patents (Trajtenberg 1990, Hall et al. 2005, Harhoff et al. 1999, Gittelman and Kogut 2003), to Web pages (Brin and Page 1998).

[3] Some studies point out, not all citations of an entity may reflect the importance of the entity. Sometimes, entities may be cited because of perfunctory mention and negation (Baumgartner and Pieters 2003). A blogger may cite an article for strategic reasons, as in the case of an article written by his or her senior colleague or supervisor, or may cite a post in order to disagree with it. Nevertheless, when a blogger cites another blog post to disagree with it, this is also a gauge of the importance of the post, since the blogger could have ignored the post as unimportant instead of explaining why it is inaccurate or why he takes an opposite stance. In any event, critical citations do not pose a problem in our data set, where they amount to less than 5.1% of citations. Although these limitations are important, using citations as a measure of influence is less prone to systematic biases than other measures.

[4] An electronic companion to this paper is available as part of the online version at http://dx.doi.org/10.1287/isre.1110.0360.

positive, negative, or neutral. The weighted citations capture two effects—traffic driven to a blog purely because of higher visibility brought by links and traffic driven to a blog because of the quality and the importance of the blog in the blogosphere.

3.2.4. Ratio of Negativity. To measure the extent of negative posts on each blog, we define the ratio of negativity as the ratio of negative content to positive content and measure it as ($R_{i,t} = W^{-}_{i,t}/W^{+}_{i,t}$). The ratio of negativity indicates the extent to which the negative posts on the blog are considered important in the blogosphere, compared with positive posts on the same blog. As ratio of negativity increases, it implies that the blogger is posting more influential negative posts or equally influential but more negative posts. The effect of the ratio of negativity on readership is of key interest to us. A positive relationship between ratio of negativity and blog readership would indicate that negative posts lead to higher readership.

3.2.5. Blog Popularity. The readership of a blog can be affected by the popularity of the blog. To control for a blog's popularity, we use two blog-level variables to measure the popularity of the blog during past periods: page-view lag (Battelle 2005) and XML feed subscription data (Massie and Kurapati 2006). The rationale for using page-view lag is that a more popular blog should have more page views during past periods. Page-view lag can also serve as a proxy for the blog quality and employee-specific latent variables that make some blogs more popular than others (Wooldridge 2001). XML feed subscribers refers to the number of people who subscribe to a blogger's posts. Whenever a blogger publishes a post, the headline of the post is sent to the subscriber automatically. The number of people subscribing to a blog is likely to be proportional to the popularity of a blog, so we use XML feed subscribers as a measure of popularity of the blog (Massie and Kurapati 2006). The variable definitions are provided in Table 1.

We randomly selected 211 employees and collected data for 13 weeks starting from January 2007, which resulted in a total of 2,743 employee-week observations. We split the data set into two subsets: the first 11 weeks' data (2,321 observations) were used as the training data set, to estimate the model parameters; the last 2 week's data (422 observations) were used as a test data set to illustrate the fit and compare our model with alternate specifications. Table 2 provides the descriptive statistics for key variables. Our unit

Table 1 Definitions and Interpretations of Variables

Variable	Definition	Interpretation
Page views ($P_{i,t}$)	Number of views of blog i in period t	High page views indicates higher number of readers.
Page-view lag ($P_{i,t-1}$)	Number of views of blog i in period $t-1$	High page-view lag indicates higher popularity of a blog.
Weighted citation of a blog ($W_{i,t}$)	Number of weighted citations received by blog i for posts displayed in period t	Higher weighted citations indicate that the blog posts are considered important by the blogging community.
Weighted citation of positive posts of a blog ($W_{i,t}$)	Number of weighted citations received by blog i for positive posts displayed in period t	Higher weighted citations indicate that the blog posts that say positive things about the blogger's firm are considered important by the blogging community.
Weighted citation of negative posts of a blog ($W_{i,t}$)	Number of weighted citations received by blog i for negative posts displayed in period t	Higher weighted citations indicate that the blog posts that say negative things about the blogger's firm are considered important by the blogging community.
Influence of a blog on a reader ($I_{i,t}$)	Extent to which blog i affects views of a reader in period t	High influence of a blog indicates that a blog affects a reader's views more.
Positive influence of a blog on a reader ($I^{+}_{i,t}$)	Total positive effect of blog i on the views of a reader in period t towards the employer of the blogger	High positive influence of a blog indicates that a blog has a high total positive effect on a reader's views toward the employer of the blogger.
Negative influence of a blog on a reader ($I^{-}_{i,t}$)	Total negative effect of blog i on the views of a reader in period t towards the employer of the blogger	High negative influence of a blog indicates that a blog has a high total negative effect on a reader's views toward the employer of the blogger.
Net positive influence of a blog on a reader ($I^{+}_{i,t} - I^{-}_{i,t}$)	Total overall positive effect of blog i on the views of a reader in period t towards the employer of the blogger	High net positive influence of a blog on a reader indicates that a blog has a high overall positive effect on a reader's views toward the employer of the blogger.
Net positive influence of a blog on readers ($NPI^{-+}_{i,t}$)	Total overall positive effect of blog i on the views of readers in period t towards the employer of the blogger	High net positive influence of a blog on readers indicates that a blog has a high overall positive effect on readers' views toward the employer of the blogger.
Ratio of negativity ($R_{i,t}$)	Sum of weighted citations of negative posts/sum of weighted citations of positive posts of blog i in period t	High ratio of negativity indicates higher proportion of negative content on a blog.
Subscribers ($S_{i,t}$)	XML feed subscribers of blog i in period t	More subscribers indicate higher popularity of a blog.

Table 2 Descriptive Statistics

Variable	Mean	Min.	Max.	Std. dev.
Page views ($P_{i,t}$)	2,402.77	96	4,587	820.34
Citations received by blog ($W_{i,t}$)	84.21	0	130.23	55.74
Citations received by positive posts ($W^+_{i,t}$)	56.56	0	98.66	36.53
Citations received by negative posts ($W^-_{i,t}$)	12.31	0	85.74	39.31
Citations received by neutral posts ($W^0_{i,t}$)	2.34	0	26.52	9.46
Ratio of negativity ($R_{i,t}$)	0.15	0	1.5	0.39
No. of positive posts	7.24	4	15	3.14
No. of negative posts	0.97	0	6	1.08
No. of neutral posts	6.79	0	10	2.46
No. of subscriber ($S_{i,t}$)	97.11	16	295	89.94

of observation for average, 2,402.77 visitors visited a blog in our sample. On average, a blogger posted once every two and a half days. A post was archived when 15 subsequent posts had been made on the blog. Bloggers on average posted less than one negative post in every set of 15 posts. Therefore, once a negative post was made, it stayed on the blog page for about 40 days. As a result, there were many days during the testing period when the blogs displayed negative posts. From the descriptive statistics, one can make the following insightful observations:

- The total number of weighted citations received by positive posts is higher than the weighted citations received by negative posts. The number of weighted citations received by the positive posts on average is 59.36 and that by negative posts is 12.31. Note that weighted citation of a type of post is calculated as the sum of the weighted citations of all posts of that type that are displayed during the focal week.
- Negative posts receive disproportionate citations from others. We found that the extent of weighted citations received by a negative post is, on average, approximately double the extent of weighted citations received by a positive post (see Table 2). Note that the weighted citation is calculated at a week level. In a given week on average, a blog displays 0.97 negative and 7.24 positive posts. Hence, per post the numbers of weighted citations for negative and positive posts are ($12.31/0.97 = 12.69$) and ($56.56/7.24 = 7.81$), respectively.

4. Econometric Specifications

4.1. Blog Readership Model

We now address the task of empirically examining whether negative posts increase blog readership. We start with a simple linear specification, where page views ($P_{i,t}$) are affected by blog popularity ($P_{i,t-1}$, and $S_{i,t}$), blog importance ($W_{i,t}$), ratio of negativity ($R_{i,t}$), and the interaction of blog importance with the ratio of negativity. Consider the following linear model specification:

$$P_{i,t} = \alpha_0 + \alpha_1 P_{i,t-1} + \alpha_2 W_{i,t} + \alpha_3 W_{i,t} R_{i,t} + \alpha_4 R_{i,t} + \alpha_5 S_{i,t} + \varepsilon_{i,t}. \quad (1)$$

If this specification is appropriate, pooled ordinary least squares (OLS) will give consistent and efficient estimates. This specification includes an interaction term that has the potential to cause multicollinearity problems. We tested for the presence of multicollinearity in our data. The maximum variance inflation factor in specification (1) is 1.9, which is much less than 10, indicating that multicollinearity is not a problem. Furthermore, if a specification has an interaction term and there is a multicollinearity problem between the independent variables and the interaction term, then typically the interaction term is nonsignificant (Jaccard and Turrisi 2003). However, in this case, it comes out to be strongly significant; hence this serves as another check for the conclusion that multicollinearity is not a problem here. Table 3 presents the estimated results (pooled OLS) from the training data set and reports that other than XML feed subscription and ratio of negativity, all other variables significantly influence a blog's readership.

The above analysis tells us that

- The ratio of negativity does not directly affect the blog readership but moderates the effect of importance of a blog on readership.
- The XML feed subscription is nonsignificant. After controlling for the popularity of a blog through page-view lag, XML feed subscription does not significantly increase the explanatory power of the model.

Another possible specification (2) is to decompose the weighted citation of a blog on a reader into the citations to the positive, negative, and neutral posts

Table 3 Effect of Negative Posts on Readership

Parameter	Pooled OLS estimates
$P_{i,t-1}$	0.165*** (0.05)
$W_{i,t}$	18.467*** (7.64)
$R_{i,t}$	15.526 (15.35)
$W_{i,t}R_{i,t}$	15.757*** (4.93)
$S_{i,t}$	3.757 (4.98)
Constant	32.291*** (14.21)
Adj. R^2	46.149%
N	2,321
Pr > F	0.000
RMSE	796.139

Note. Standard errors in parentheses.
$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4 **Effect of Negative Posts on Readership**

Parameter	Pooled OLS estimates
$P_{i,t-1}$	0.167*** (0.04)
$W^{+}_{i,t}$	18.491*** (5.35)
$W^{-}_{i,t}$	34.457*** (9.61)
$W^{0}_{i,t}$	15.478*** (4.33)
$R_{i,t}$	15.264 (16.35)
$W^{0}_{i,t}R_{i,t}$	14.567*** (3.93)
$W^{-}_{i,t}R_{i,t}$	31.526*** (4.67)
$S_{i,t}$	3.691 (5.02)
Constant	31.163*** (12.25)
Adj. R^2	51.312%
N	2,321
Pr > F	0.000
RMSE	836.195

Notes. Standard errors in parenthesis. Posts separated by type.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

of a blog, and their interaction with the ratio of negativity.

$$P_{i,t} = \alpha_1 P_{i,t-1} + \alpha_2 W^{+}_{i,t} + \alpha_3 W^{-}_{i,t} + \alpha_4 W^{0}_{i,t} + \alpha_5 W^{-}_{i,t} R_{i,t} + \alpha_6 W^{0}_{i,t} R_{i,t} + \alpha_7 R_{i,t} + \alpha_8 S_{i,t} + \varepsilon_{i,t}. \quad (2)$$

Results for specification 2 (estimated as pooled OLS) are presented in Table 4. The results are consistent with those from specification 1. Additionally, these results tell us that:

- For all three types of posts, the coefficient corresponding to weighted citations is positive and significant. This confirms our belief that the more important posts receive higher readership.
- Further, both interaction term coefficients are positive and significant, indicating that important posts receive more readership when displayed on a blog with negative posts than otherwise.

Although specifications (1) and (2) are very simple and hence preferable, additional analysis reveals that they fail on several econometric issues. Neither of the two specifications capture nonlinearity in the data. Using Ramsey's RESET test, we reject the null hypothesis ($p < 0.009$) that all nonlinearity patterns are captured in the specification. Note that the interaction term in specification (1) is linear. To illustrate that there is a need for non linear interaction term, we present Figure 1.

Figure 1 is a plot between the rate at which readership increases per citation and the ratio of negativity. It shows that there is a nonlinear pattern (initial exponential increase followed by stability) instead of a straight line. This nonlinearity is the reason Ramsey's RESET test failed. We find that such curves are best modeled using the Michaelis-Menten model of the kinetics of chemical reactions (Seber and Wild 2003, Bates and Watts 1988, Michaelis and Menten 1913). The influence of negative posts on the readership for a blog appears to share some similarities with the chemical reaction in a presence of catalyst,[5] for which a nonlinear model such as the Michaelis-Menten model is appropriate. Negative posts appear to be most effective when present in small quantities: readership increases with the ratio of negativity exponentially at first, then at a rapidly declining rate, and finally stabilizes after a point.

Based on this observation, we changed our model specification to the following:

$$P_{i,t} = \beta_1 P_{i,t-1} + \beta_2 W_{i,t} + \beta_3 W_{i,t} \frac{R_{i,t}}{R_{i,t} + \beta_4} + \beta_5 R_{i,t} + \beta_6 S_{i,t} + \varepsilon_{i,t}. \quad (3)$$

Using Ramsey's RESET test, this time we failed to reject the null hypothesis ($p > 0.37$), which indicates that all the nonlinearity in the data is captured. Results are given in Table 5 (estimated as pooled OLS). Even after accounting for the nonlinearity in the data, XML feed subscriptions does not significantly affect readership. Although the ratio of negativity does not have a significant direct effect on the readership, it has a nonlinear significant effect on readership, whereby readership increases with the ratio of negativity exponentially at first, then at a rapidly declining rate, and finally stabilizes after a point.

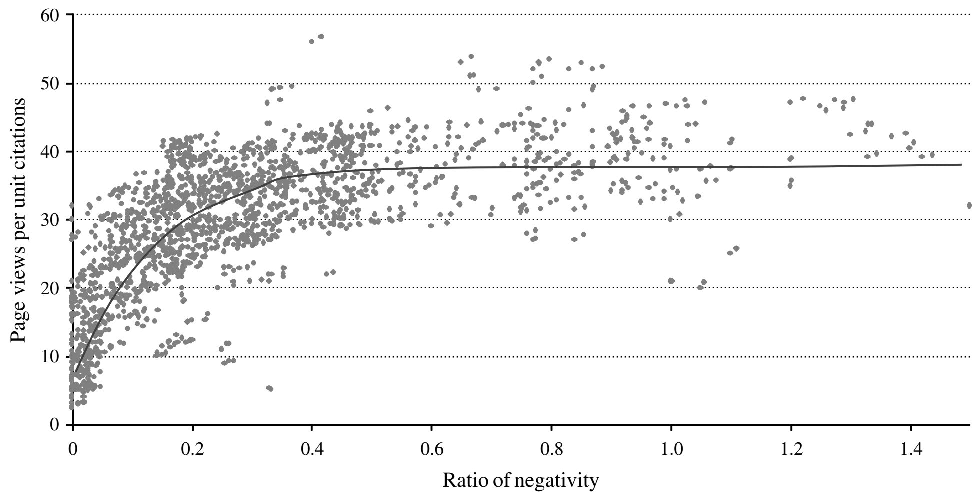
The results from specification (3) clearly indicate that negative posts may not always have a negative impact on blog readership, but several other econometric issues need to be addressed to gain more confidence in our results. To account for other econometric issues, we modify specification (3) in several ways. First we incorporate blog-specific unobserved effects in the specification. Second, we allow first-order serial correlation among errors in the specification. We test for higher-order serial correlation also and find that the first-order serial correlation is appropriate.

$$\begin{aligned} P_{i,t} &= \beta_1 P_{i,t-1} + \beta_2 W^{+}_{i,t} + \beta_3 W^{-}_{i,t} + \beta_4 W^{0}_{i,t} \\ &\quad + (\beta_5 W^{+}_{i,t} + \beta_6 W^{-}_{i,t} + \beta_7 W^{0}_{i,t}) \frac{R_{it}}{R_{i,t} + \beta_8} \\ &\quad + \beta_9 R_{i,t} + \beta_{10} S_{i,t} + \beta_{11i} + \gamma_{i,t} \\ \gamma_{i,t} &= \eta \gamma_{i,t-1} + \varepsilon_{i,t}, \quad \varepsilon_{i,t} \sim N(0, \sigma^2). \end{aligned} \quad (4)$$

Finally, we note that there could be a possible simultaneity in readership and importance of a blog for the same period: if readership for a post increases

[5] Negative posts appear to play a role similar to that of a substrate in the presence of catalyst in a chemical reaction: page views (reaction rate) increase with increasing proportion of negative posts (substrate concentration), asymptotically.

Figure 1 Page Views per Unit Citations vs. Ratio of Negativity



during a period, then that post is likely to get more citations, which increases its importance. We require an instrument variable that is correlated with the importance of a blog but not with sudden changes ("shock") in readership that would reflect idiosyncratic errors. A lag in the weighted citation of a blog can be a valid instrument if the model is dynamically complete or sequentially exogenous (Wooldridge 2001), i.e., if the shock in readership during a given period does not change the weighted citations of a blog in past periods. The econometrics literature has shown that if the dynamic completeness condition is violated, there will be autocorrelation in idiosyncratic errors. We tested for autocorrelation after accounting for first-order serial correlation (Wooldridge 2001) but failed to reject the null hypothesis ($p > 0.71$),

Table 5 Effect of Negative Posts on Readership—Michaelis-Menten Model

Parameter	Maximum likelihood estimates
$P_{i,t-1}$	0.129*** (0.01)
$W^{+}_{i,t}$	14.334** (2.99)
$W^{-}_{i,t}$	29.718*** (4.47)
$W^{0}_{i,t}$	11.371*** (1.06)
$W^{+}_{i,t}R_{i,t}/(R_{i,t}+\beta_4)$	13.546*** (2.08)
$W^{-}_{i,t}R_{i,t}/(R_{i,t}+\beta_4)$	33.293*** (3.37)
$W^{0}_{i,t}R_{i,t}/(R_{i,t}+\beta_4)$	9.952* (4.89)
β_4	0.307*** (0.02)
$R_{i,t}$	12.116 (13.95)
$S_{i,t}$	3.054 (4.12)
Constant	34.009*** (8.22)
N	2,321
Log likelihood	−291,109.32

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$; std. errors in parentheses.

suggesting that the assumption of dynamic completeness in our model is justified. Therefore, we can use lags of weighted citations of a blog as valid instruments for the blog's importance. We choose a two-period lag and a two-period lagged first difference of weighted citations of a blog as two instruments. The two instruments provide us the latitude to perform additional weak instrument tests. On the surface, both the instruments appear to satisfy both the conditions for being a good instrument. First, two-period lag and lagged first difference are correlated with the present weighted citations of a blog because both periods share many posts in common. Secondly, the lags may not be correlated with the shock in readership because that shock occurs in the present period.

We performed a two-stage regression estimation. In the first stage, the importance of a blog is estimated as a function of a two-period lagged weighted citation, the lagged first difference weighted citation, and other exogenous variables. Note that this corresponds to three first-stage equations, one each for positive, negative, and neutral importance. Predicted values of the importance of a blog are calculated from the estimates of this regression. In the second stage, the readership is estimated as a function of the predicted importance and other exogenous variables as specified in specification (4). The standard deviation of the parameters is adjusted appropriately. The second stage is estimated as a maximum likelihood estimation (Davidson and MacKinnon 1993). The blog specific unobserved term is estimated nonparametrically to avoid the bias which may result if one specifies a wrong parametric functional form for them (Heckman and Singer 1984). As a first indicator of instrument strength, the F-statistic of the three first stage regressions are 47.59 for positive posts, 37.15 for negative posts, and 29.31 for neutral posts; these numbers indicate that the

Table 6 Effect of Negative Posts on Readership

Parameter	Blog random effects AR1 (IV) estimates	Blog random effects AR1 (IV) estimates	Blog first difference AR1 (IV) estimates
$P_{i,t-1}$	0.119*** (0.01)	0.122*** (0.01)	0.127*** (0.05)
$W_{i,t}^{+}$	16.212*** (2.19)	16.917*** (2.18)	15.879*** (3.94)
$W_{i,t}^{-}$	36.011*** (3.72)	34.259*** (3.74)	38.191*** (5.35)
$W_{i,t}^{0}$	7.207*** (1.97)	7.618*** (1.97)	7.494*** (2.29)
$W_{i,t}^{+}R_{i,t}/(R_{i,t}+\beta_4)$	10.463*** (3.11)	9.441*** (3.13)	10.415*** (4.01)
$W_{i,t}^{-}R_{i,t}/(R_{i,t}+\beta_4)$	28.134*** (4.72)	28.834*** (4.61)	27.356*** (6.98)
$W_{i,t}^{0}R_{i,t}/(R_{i,t}+\beta_4)$	5.151** (2.19)	5.104** (2.11)	7.159** (3.49)
β_4	0.497*** (0.02)	0.489*** (0.03)	0.479*** (0.07)
$R_{i,t}$	12.121 (14.02)	15.935 (18.87)	18.291 (24.54)
$S_{i,t}$	3.031 (4.07)	3.919 (4.76)	5.068 (5.13)
Constant	35.699*** (8.36)	35.385*** (8.22)	—
	0.07*** (0.001)	0.07*** (0.001)	0.07*** (0.001)
Control variables	—	Time	—
N	2,321	2,321	2,321
Log likelihood	−284,619.52	−284,614.92	−246,106.48

Notes. Robust standard errors in parenthesis; likelihood ratio test results (time dummies are insignificant). Because a constant term is estimated, the mean for blog random effects is set to zero. Blog random effects are estimated by a nonparametric estimation (Heckman and Singer 1984).
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

instruments are not weak (Davidson and MacKinnon 1993). The assumption that instruments are not correlated with the error terms cannot be directly tested, but can be tested indirectly if the model is overidentified—that is, if the number of instruments is more than the number of endogenous variables (Stock et al. 2002). Because our model is overidentified, we perform two tests to check if the instruments are truly exogenous. First, we perform the Sargan test (Arellano and Bond 1991, Stock et al. 2002). The Sargan test involves regressing the second stage IV residuals $\hat{u}_i^{\mathrm{IV}}$ on all instruments and exogenous variables. An R^2 from this regression is obtained. The test statistic is then $S = nR^2$, where n is the number of observations. Under the null hypothesis that all instruments are exogenous, S is distributed as χ_1^2. We fail to reject the null that the instruments are exogenous: (positive) $p = 0.37$; (negative) $p = 0.55$; (neutral) $p = 0.31$. The second test that we employ is a J-test (Stock et al. 2002). In the J-test, IV residuals are regressed on the instruments and other control variables; an F-statistic is calculated from this regression and the test statistic (F) is distributed as χ_1^2 under the null of exogenous instruments (Stock et al. 2002). We again fail to reject the null hypothesis of all instruments being exogenous at (positive) $p = 0.36$, (negative) $p = 0.56$, (neutral) $p = 0.31$.

We have assumed the blog-specific unobserved effects to be uncorrelated with other explanatory variables. Under this assumption it is appropriate to treat these effects as random. However, if these blog-specific unobserved effects are correlated with other explanatory variables, our results would be biased. To address this issue, we estimate another regression, where we treat the blog-specific unobserved effects as fixed effects. The second-stage regression is transformed by rho differencing followed by first differencing to get rid of serial correlation in errors and the unobserved fixed effects. The resulting data set is estimated through a maximum likelihood estimation. The estimates obtained from this fixed-effects regression are tested against the estimates from the random effects estimation by a Hausman test (Hausman 1978). We fail to reject the null that both the estimates are consistent at $p = 0.49$. Hence, the results with random effects are consistent as well as efficient. Further, we find that although the inclusion of time dummies improves the log likelihood of the model, the specification without time dummies has a better Bayesian information criterion and Akaike information criterion (Davidson and MacKinnon 1993, Wooldridge 2001). Table 6 presents the three sets of results (1) specification (4) with blog random effects and autoregressive model of order 1 (AR1) error structure (2) specification (4) with blog random effects, AR1 error structure, and time dummies, (3) specification (4) with blog fixed effects and AR1 error structure.

The results from Table 6 clearly highlight the way in which the ratio of negativity affects blog readership. It shows that the readership of a blog would increase exponentially initially with the ratio of negativity, then at a declining rate, after which it stabilizes. From these results it is obvious that a moderate amount of negative posts would be beneficial for a blog.

4.2. Model Comparison

We consider the following three model forms and contrast the results:

• An initial exponential increase followed by stability—This is the case when, *ceteris paribus*, the

Table 7 Models Used for Comparison

(1) $P_{i,t} = \beta_1 P_{i,t-1} + \beta_2 W^+_{i,t} + \beta_3 W^-_{i,t} + \beta_4 W^0_{i,t} + (\beta_5 W^+_{i,t} + \beta_6 W^-_{i,t} + \beta_7 W^0_{i,t}) \dfrac{R_{it}}{R_{i,t} + \beta_8} + \beta_9 R_{i,t} + \beta_{10} S_{i,t} + \beta_{11i} + \gamma_{i,t}$

(2) $P_{i,t} = \beta_1 P_{i,t-1} + \beta_2 W^+_{i,t} + \beta_3 W^-_{i,t} + \beta_4 W^0_{i,t} + (\beta_5 W^+_{i,t} + \beta_6 W^-_{i,t} + \beta_7 W^0_{i,t}) \exp(\beta_8 R_{it}) + \beta_9 R_{i,t} + \beta_{10} S_{i,t} + \beta_{11i} + \gamma_{i,t}$

(3) $P_{i,t} = \beta_1 P_{i,t-1} + \beta_2 W^+_{i,t} + \beta_3 W^-_{i,t} + \beta_4 W^0_{i,t} + (\beta_5 W^+_{i,t} + \beta_6 W^-_{i,t} + \beta_7 W^0_{i,t}) \dfrac{R_{it}}{R_{i,t} + \beta_8 + \beta_{12} R^2_{i,t}} + \beta_9 R_{i,t} + \beta_{10} S_{i,t} + \beta_{11i} + \gamma_{i,t}$

(4) $P_{i,t} = \beta_1 P_{i,t-1} + \beta_2 W^+_{i,t} + \beta_3 W^-_{i,t} + \beta_4 W^0_{i,t} + \beta_6 W^-_{i,t} R_{i,t} + \beta_7 W^0_{i,t} R_{i,t} + \beta_{13} W^-_{i,t} R^2_{i,t} + \beta_{14} W^0_{i,t} R^2_{i,t} + \beta_9 R_{i,t} + \beta_{10} S_{i,t} + \beta_{11i} + \gamma_{i,t}$

(5) $P_{i,t} = \beta_1 P_{i,t-1} + \beta_2 W^+_{i,t} + \beta_3 W^-_{i,t} + \beta_4 W^0_{i,t} + \beta_6 W^-_{i,t} R_{i,t} + \beta_7 W^0_{i,t} R_{i,t} + \beta_9 R_{i,t} + \beta_{10} S_{i,t} + \beta_{11i} + \gamma_{i,t}$

Notes. In all models: $\gamma_{i,t} = \eta\gamma_{i,t-1} + \varepsilon_{i,t}$, $\varepsilon_{i,t} \sim N(0, \sigma^2)$ (*ceteris paribus*). In all the models with the increase in negative influence, readership initially increased.

increase in the ratio of negativity initially leads to an exponential increase in readership, after which readership does not change. We take two model specifications for this case: a base model that uses the Michaelis-Menten formulation and a model that uses the exponential function (Seber and Wild 2003, Bates and Watts 1988).

- An initial exponential increase followed by a decrease—This is the case when, *ceteris paribus*, the increase in the ratio of negativity on a reader leads initially to an exponential increase in readership, after which readership starts decreasing as the ratio of negativity increases. We consider two model specifications for this case: a refinement of the base model that uses the Michaelis-Menten formulation and the quadratic growth model (Seber and Wild 2003, Bates and Watts 1988).
- Linear increase—This will be the case when, *ceteris paribus*, the increase in the ratio of negativity leads to a linear increase in readership.

We also tested for logarithmic specification, but it performed the worst of all the approaches considered. For brevity's sake, we do not report the model based on logarithmic specification. The model selection is based on two widely accepted model selection criteria: Bayesian and Akaika information criteria (Davidson and MacKinnon 1993, Wooldridge 2001). Models are shown in Table 7 and the empirical comparisons are shown in Table 8. Results indicate that our base model, specification (4), based on the Michaelis-Menten model of chemical kinetics, offers the best fit.

4.3. Blog Citation Model

We have shown that the blogs with negative posts have higher readership than blogs with positive posts only. We now focus our attention on whether negative posts also get more citations than positive posts. Our citation specification is given here:

$$C_{i,p,t} = \beta_1 P_{i,t-1} + \beta_2 Post^+_{i,p,t} + \beta_3 Post^-_{i,p,t} + \beta_4 R_{i,t} + \beta_5 S_{i,t} + \beta_{6i} + \gamma_{i,t}. \quad (5)$$

In this specification, C_{it} is the number of citations received by a post p (posted at time t) by blogger i within three weeks of the posting time t. $P_{i,t-1}$ is as before the lagged readership of the blog; $Post^+_{i,p,t}$ is an indicator variable that equals 1 if the post is positive and zero otherwise; and $Post^-_{i,p,t}$ is an indicator variable that equals 1 if the post is negative and zero otherwise. Specification (5) is at post level. Because $C_{i,p,t}$ is a count variable, specification (5) is estimated as a negative binomial random effects model. Maximum likelihood estimation is used and blog-specific unobserved random effects are accounted through a non-parametric distribution. Results for specification (5) are provided in Table 9.

Results reveal several interesting insights. Negative posts receive significantly higher number of citations than positive and neutral posts. Differences between the number of citations received between the positive and neutral posts is insignificant. Posts on blogs with a higher ratio of negativity receive more citations. These results indicate that negative posts not only increase the readership of a blog, but they also increase the citations of its other posts. To test this result more rigorously, we estimate the specification (6), which allows interactions of post type with ratio of negativity:

$$\begin{aligned} C_{i,p,t} = {} & \beta_1 P_{i,t-1} + \beta_2 Post^+_{i,p,t} + \beta_3 Post^-_{i,p,t} + \beta_4 R_{i,t} \\ & + \beta_5 Post^+_{i,p,t} R_{i,t} + \beta_6 Post^-_{i,p,t} R_{i,t} \\ & + \beta_7 S_{i,t} + \beta_{8i} + \gamma_{i,t}. \end{aligned} \quad (6)$$

Results for specification (6) are shown in Table 9. They reveal that the interaction terms are significant. This confirms the earlier finding from specification (5) that negative posts increase citations for future posts. Interestingly, the coefficient for interaction between positive post dummy and ratio of negativity is significantly higher than the interaction between negative post dummy and ratio of negativity ($p < 0.01$). However, on average, the citations received by the positive post are still fewer than the citations received by a negative post. Hence, a negative post on the blog helps a positive post receive much more citations than other type of posts. Positive posts typically receive fewer citations than the negative posts, but

Table 8 Comparison of Potential Models

IV estimates; AR1 correlation in errors; blog random effects					
	Exponential and after a point stabilize		Exponentially and after a point fall		Linearly
Models	1	2	3	4	5
β_1	0.119*** (0.01)	0.125*** (0.03)	0.125*** (0.02)	0.145*** (0.05)	0.147*** (0.04)
β_2	16.212*** (2.19)	18.925*** (3.26)	15.927*** (2.23)	18.991*** (2.19)	18.473*** (3.31)
β_3	36.011*** (3.72)	39.997*** (4.82)	34.819*** (3.69)	32.457*** (3.72)	34.457*** (4.61)
β_4	7.207*** (1.97)	9.975*** (2.38)	7.288*** (2.08)	15.478*** (1.97)	15.478*** (1.33)
β_5	10.463*** (3.11)	−1.383* (0.68)	9.743*** (3.19)		
β_6	28.134*** (4.72)	−2.918*** (1.39)	26.988*** (5.24)	32.526*** (4.72)	14.567*** (1.93)
β_7	5.151** (2.19)	−0.592 (1.14)	5.216** (2.11)	15.567** (2.19)	31.526*** (3.67)
β_8	0.497*** (0.02)	−6.105*** (1.22)	0.423*** (0.03)		
β_9	12.121 (14.02)	15.947 (14.25)	12.983 (13.99)	13.046 (14.28)	15.264 (11.15)
β_{11}	35.699*** (8.36)	39.982*** (8.89)	35.074*** (8.42)	37.504*** (8.31)	32.032*** (8.21)
β_{10}	3.031 (4.07)	3.913 (4.37)	3.246 (4.18)	3.231 (4.11)	3.691 (3.41)
β_{12}			0.098 (1.21)		
β_{13}				−13.8115*** (1.74)	
β_{14}				−7.187* (2.32)	
ρ	0.07*** (0.001)	0.07*** (0.002)	0.07*** (0.001)	0.07*** (0.001)	0.07*** (0.002)
Log likelihood	−284,619.52	−292,170.35	−284,618.93	−294,029.70	−297,818.54
Training BIC	569,378.54	584,480.20	579,287.11	58,8198.90	595,761.08
Training MAD	614.324	645.601	635.081	704.189	754.098
Testing MAD	819.209	856.39	855.35	890.36	899.19

Notes. Robust std. errors in parenthesis; Because a constant term is estimated, the mean for blog random effects is set to 0. Blog random effects are estimated by a nonparametric estimation (Heckman and Singer 1984). Note that main effect of ratio of negativity is insignificant in all models ($p < 0.25$).

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

their citations increase significantly if they are posted by a blogger who posts negative posts also. We also tested specifications (5) and (6) by replacing citations by weighted citations, and the results are consistent.

5. Theoretical Discussion

Whereas the discussion in §§3 and 4 focused on establishing the relationship between negative posts and readership, the present section focuses on the possible reasons for this relationship. Visitors to a blog can be classified as new visitors or loyal readers. There are certain characteristics of a blog that may affect the likelihood that an individual who has never visited the blog would visit it. A highly visible blog would receive a greater amount of new visitors. Negative posts affect the visibility of a blog. As shown earlier, negative posts receive higher number of citations from others, increasing their visibility in the blogosphere. Negative posts also increase the citations received by other types of posts, which increases the visibility of the overall blog in the blogosphere. This increased visibility of a blog helps attract new readers. Note that the traffic that is driven to the blog through visibility is appropriately captured through the blog importance in specification (4). This also

Table 9 Effect of Negative Posts on Citations

Parameters	Blog random effects negative binomial model	Blog random effects negative binomial model with interactions
$P_{i,t-1}$	2.441*** (1.14)	2.362** (1.16)
$Post^{+}$	2.893** (1.41)	2.325* (1.19)
$Post^{-}$	45.271*** (8.49)	43.983*** (8.78)
$R_{i,t}$	6.13*** (1.32)	2.896*** (1.091)
$S_{i,t}$	0.21 (0.29)	0.17 (0.31)
$Post^{-}XR_{i,t}$		2.562*** (0.97)
$Post^{0}XR_{i,t}$		3.727** (1.87)
$Post^{+}XR_{i,t}$		7.81*** (2.50)
Constant	−1.41*** (0.43)	−1.76*** (0.38)
Dispersion	0.009*** (0.001)	0.009*** (0.001)
N	2,743	2,743
Log likelihood	−18,905.32	−18,605.43

Notes. Robust standard errors in parenthesis; because a constant term is estimated, the mean for blog random effects is set to zero. Blog random effects are estimated by a non parametric estimation (Heckman and Singer 1984).

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

highlights that negative posts have an effect on readership above and beyond the visibility effect, as even after controlling for the weighted citations, the ratio of negativity has a significant effect on blog readership. Therefore, another major effect of negative posts on readership is through converting new visitors to loyal visitors.

To explain how negative posts help convert some of the new visitors to loyal visitors, we view the phenomenon through the lens of attribution theory. Before we proceed further, we want to emphasize that the limitations imposed by our data do not permit us to empirically test the applicability of attribution theory, which we leave for future research.

In a social influence situation, attribution theory helps explain how people attribute a cause to somebody's behavior and what the results of those inferences are (Jones et al. 1987). People use the perceiver's belief about what others would do in the same situation to make attributions (Kelley and Michela 1980). Many studies on blogs suggest that readers expect employee bloggers to promote their firms (Scoble and Israel 2006, Edelmen and Intelliseek 2005, Byron and Broback 2006, Halley 2003, Brian 2005). But if employees blog about the failures of their employer or promote positive aspects of competitors, this may contradict a reader's preconceived belief. Kelly's augmentation principle states that a perceiver observing an action contradicting her belief will attribute that action more to the actor's disposition than to situational pressures (Kelley 1972). Consider the following example: Yoda is a GM employee who blogs at gmblog.com and declares his affiliation on his blog. He chooses to declare the problems in GM's hybrid models, along with pointing out how GM has the best cars in other segments (positive posts) and writing about his trip to Switzerland (neutral posts) on his blog. A negative post contradicts a reader's—say Cindy's—prior belief about an employee blog. She expects a company spokesperson to write in favor of his company (Folkes 1988), but the contradiction to this expectation leads her to attribute the blog primarily to factual evidence. The more she attributes the blog to factual evidence rather than to Yoda's affiliation, the more she attributes Yoda's action to his honesty (Wood and Eagly 1981). Although some amount of negative posts can increase credibility, a large number of negative posts on a blog may have an adverse effect. Readers may disregard the blogger, considering him a disgruntled employee.

We now consider the other side of the causal coin, namely, the consequences of the attributions made by a reader about the blogger on the reader's subsequent actions. Consumer research studies explain that when a perceiver who ascribes a helpful act to the actor's disposition rather than to environmental factors feels gratitude toward the actor, this instills "person loyalty" (Weiner 2000). Continuing with our example from the above discussion, Cindy is more likely to make attributions of honesty and a helping nature about the personal disposition of Yoda in the light of his choice and to perceive that Yoda helped her by providing full information even at the risk of upsetting his employer; therefore, she is likely to convert to a loyal reader as well as to recommend Yoda's blog to others, increasing his readership.

6. Analysis of Firm Policies for Employee Blogging

Any form of advertising (be it a single advertisement, a campaign of advertisements, or a medium of advertising) has two attributes at its core—how many customers are reached (in this context readership) and how strongly they were influenced (Coffin 1963). Next, we provide a framework focusing on the second core attribute of advertising—how negative posts influence readers.

In this section, we model how the functional form suggested by the Michaelis-Menten specification can help a firm decide when employees should be allowed to write negative posts. As discussed earlier, one way that employee blogs may affect a firm is through influencing a reader's perception about the firm. A firm typically faces a tradeoff, where allowing negative posts may influence the reader's perception negatively, but negative posts also increase blog readership overall and the citations received by positive posts. Faced with such a problem, a firm can completely forbid its employees to post anything negative or leave it to their discretion but impose an upper bar on the level of negativity allowed. If a firm allows employees to post anything, the net positive influence of a blog i at time t on readers is given by

$$\textit{Net positive influence on readers} = NPI_n = (I^+_{i,t,n} - I^-_{i,t,n}) * P_{i,t,n}. \tag{7}$$

The subscript n indicates that negative posts are allowed. In this equation, $P_{i,t,n}$ is given by specification 4. $I^+_{i,t,n}(I^-_{i,t,n})$ is the influence of positive (negative) posts. Based on the literature on social influence, we define influence of a post as measured by a function of its weighted citations[6] (Burt 1997). The influence I of a post can be expressed as $I = W^v$, where v is the power law coefficient and W represents the weighted citations for the post. A value of v close to 1 indicates that the post is only as influential as its weighted citation. A value much lower than 1 implies that each post is equally influential, irrespective of its weighted citations; a value much higher than 1 implies that as the number of weighted citations increases, the influence of a post increases exponentially. As one may observe, this relationship is quite flexible. The power law coefficient can be allowed to vary for different types of posts (positive, negative, neutral). For example, in the analysis, we have allowed it to differ for negative (vn) and positive (vm) posts.

In the Michaelis-Menten-based formulation, each variable applies to an individual blogger on a weekly basis. However, for simplicity, we now replace each variable in specification (4) and (7) with its average value across bloggers and across time to yield the average net positive influence on readers for a firm not imposing any restrictions on posting. This averaging of variables is justified, considering that bloggers who are allowed to post negative entries will periodically overshoot and undershoot the optimal level of negative posts. As long as the average level of negative posts across bloggers and across several periods is close to the optimal level, the decision is served. Therefore, we have net positive influence on readers when negative posts are allowed:

$$\overline{NPI}_n = (\bar{I}^+_{i,t,n} - \bar{I}^-_{i,t,n}) * \bar{P}_n \tag{8}$$

where

$$\bar{P}_n = \frac{1}{1-\beta_1}\left(\beta_9 + \beta_2\bar{W}^+_n + \beta_3\bar{W}^-_n + \beta_4\bar{W}^0_n + (\beta_5\bar{W}^+_n + \beta_6\bar{W}^-_n + \beta_7\bar{W}^0_n)\left(\frac{\bar{W}^-_n}{\bar{W}^-_n + \beta_8\bar{W}^+_n}\right)\right). \tag{9}$$

[6] The firm can also measure the influence of a post using sales data.

Simplifying from Equations (8) and (9) gives the average net positive influence on readers for a firm allowing negative posts in terms of publicly available data.

$$\overline{NPI}_n = \left(\frac{\bar{W}^{+vm}_n \bar{W}^{-vn}_n}{1-\beta_1}\right)\left(\beta_9 + \beta_2\bar{W}^+_n + \beta_3\bar{W}^-_n + \beta_4\bar{W}^0_n + (\beta_5\bar{W}^+_n + \beta_6\bar{W}^-_n + \beta_7\bar{W}^0_n)\left(\frac{\bar{W}^-_n}{\bar{W}^-_n + \beta_8\bar{W}^+_n}\right)\right) \tag{10}$$

Note that in this equation, we have allowed the power law coefficient to differ for positive (vm) and negative (vn) posts. If a firm doesn't allow its bloggers to post anything negative, then the average net positive influence on readers can be calculated as

$$\overline{NPI}_p = \frac{(\bar{W}^{+vm}_p)}{1-\beta_1}(\beta_9 + \beta_2\bar{W}^+_p + \beta_4\bar{W}^0_p). \tag{11}$$

Subscript p indicates that negative posts are not allowed.

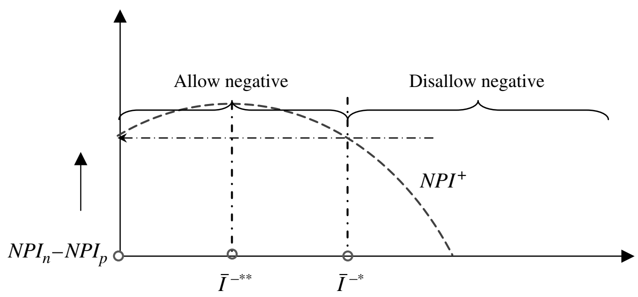
The firm can compare the two options and choose to allow negative posts when $\overline{NPI}_n > \overline{NPI}_p$.

Proposition. *There exists a cutoff value of the average negative influence* $\bar{I}^{-*}$ *such that* (i) *for all values of the average negative influence on a reader* $\bar{I}^-\varepsilon(0, \bar{I}^{-*})$, *the decision to allow negative posts creates more average net positive influence on readers than the decision to not allow negative posting, whereas* (ii) *for* $\bar{I}^- > \bar{I}^{-*}$, *the decision of no negative posting offers a higher average net positive influence on readers than the decision to allow negative posts.*

This proposition suggests that prohibiting negative posts is not always the best strategy. The basic intuition is that when a blog has a small number of negative posts, it attracts more readers, who are also exposed to the (more numerous) positive posts on the blog. As more negative posts are added, more readers are attracted at a decreasing rate (as shown empirically in the earlier section), and each of these readers is exposed to a smaller proportion of positive posts. At some point, the benefit of having negative posts to increase net positive influence on readers starts to disappear. Eventually, a sufficiently large number of negative posts leads to a worse net positive influence on readers than having no negative posts at all, making the decision of no negative posting better. Please note that a sufficient condition for the above proposition to hold is provided in the online appendix to this paper. Figure 2 shows a comparison of the net positive influence on readers generated by the decision to allow negative posts and to prohibit negative posts.

Diverse Reader Types. It is possible that readers who visit the blog through a citation only read that post

Figure 2 Decisions Corresponding to Average Negative Influence on a Reader



and no other post. In such scenarios, the reader would form an impression of the firm that is displayed by that one post. To account for such behavior, let us assume a fraction $f_1(f_2)$ of readers coming through a citation and reading only the cited positive (negative) post. For simplification, further assume that all other readers read all posts displayed on the blog during their visit. Then the fractions of readers who read all displayed posts on the blog are $(1 - f_1 - f_2)$. Under these assumptions, the net positive influence from allowing negative posts is

$$\overline{NPI}_n = [\alpha_p \bar{W}_n^{+vm} f_1 - \alpha_n \bar{W}_n^{-vn} + f_2(\bar{W}_n^{+vm} - \bar{W}_n^{-vn})(1 - f_1 - f_2)] * \bar{P}_n, \quad (12)$$

where $0 \le \alpha_p \le 1$ and $0 \le \alpha_n \le 1$ are constants that account for the fact that only one post is read by the reader and adjust the influence appropriately. Note that there are 15 posts displayed on a blog at any time, and W_n corresponds to the sum of the weighted citations of those 15 posts. For example, of these posts, on average, in our data only 7.24 posts are positive, leading to $\alpha_p = 1/7.24$. α accounts for the fact that the reader is reading only one of those posts and hence allows influence from only that post. Similarly, the net positive influence from forbidding negative posts is

$$\overline{NPI}_p = [\alpha_p \bar{W}_p^{+vm} f_1 + (\bar{W}_p^{+vm})(1 - f_1) * \bar{P}_p]. \quad (13)$$

A firm can compare both these strategies and choose to allow negative posts if $\overline{NPI}_n > \overline{NPI}_p$. Certain interesting insights can be revealed by comparing Equations (12) and (13) to Equations (10) and (11). First, as the fraction f_2 increases, the cutoff point under which allowing negative posts is optimal (I^{-*}) shifts toward 0. A simple explanation of this phenomenon is that as f_2 increases, a large fraction of readers who are visiting the blog are reading only the negative post and hence are exposed to negative influence. And there would be a smaller fraction of readers coming through links to negative posts and being exposed to positive posts also displayed on the blog. Second, for $\alpha_p > 1 - \bar{W}_n^{-vn} / \bar{W}_n^{+vm}$, an increase in fraction f_1 shifts the cutoff point, under which allowing negative posts is optimal, away from 0. Below this limit, an increase in fraction f_1 shifts I^{-*} toward 0. To better understand it, let us restate the condition as $\bar{W}_n^{-vm} > (1 - \alpha_p)\bar{W}_n^{+vm}$. The left-hand side of this condition represents the influence from negative posts. The right-hand side represents the influence from positive posts that readers who read only the cited positive post are not exposed to (belong to fraction f_1). When α_p satisfies this condition, it implies that there are very few positive posts on the blog. The additional influence to which the reader could be exposed by reading all positive posts is less than the influence from negative posts.

6.1. Application of the Framework to the Case of Our Research Setting

Firms that encourage blogging by their employees can easily access (and are accessing) the kind of data required for the above analysis. We now apply our analysis to data from the Fortune 500 company and illustrate how it can provide suitable recommendations for optimal blogging policy. Using specifications (10) and (11), we calculate the upper limit of average negative influence, $\bar{I}^{-*} = 46$ ($R = 0.81$) (for $vn = vm = 1$). Beyond this point, employee blogs may still generate net positive influence on readers under the decision of allowing negative posts, but can generate more net positive influence on readers if employees refrain from any further negative posts about the firm. In our data set, we find that the actual average negative influence on a reader is $\bar{I}^{-} = 12.31$ ($R = 0.22$) (for $vn = vm = 1$), which is less than the calculated upper value. Furthermore, the optimal average negative influence on a reader for the whole data set, $\bar{I}^{-**} = 15.1$, is ($R = 0.27$) (for $vn = vm = 1$), which is more than the present average negative influence on a reader. Figure 3(a) plots how $\bar{I}^{-*}$ and $\bar{I}^{-**}$ change as vn and vm vary. As discussed earlier, at $vm(vn)$ fixed as $vn(vm)$ increases, both $\bar{I}^{-*}$ and $\bar{I}^{-**}$ decrease (increase). Similarly, using specifications (12) and (13), we plot $\bar{I}^{-*}$ and $\bar{I}^{-**}$ for varing f_1 and f_2 (constant $vn = vm = 1$). Results are presented in Figure 3(b). For a given f_1 as f_2 increases, the optimal weighted citations of negative posts decrease. It is important to note that $\bar{I}^{-*}$ and $\bar{I}^{-**}$ vary widely as vn, vm, f_1, or f_2 vary. Hence, a firm should pay attention in estimating these parameters. A firm can estimate these parameters by combining the blog data with the sales data.

Therefore, the sample data set and the results based on our suggested framework suggest that the concerned firm's decision of allowing its employees to write negative posts is good only if the true values of vn, vm, f_1, and f_2 lie in certain ranges, as illustrated by Figures 3(a) and 3(b). In summary, to determine whether to relax or tighten its blogging policy, the firm needs to know how far removed its employee blogs may be from the optimum.

Figure 3(a) **Optimal Weighted Citations of Negative Posts vs. vn**

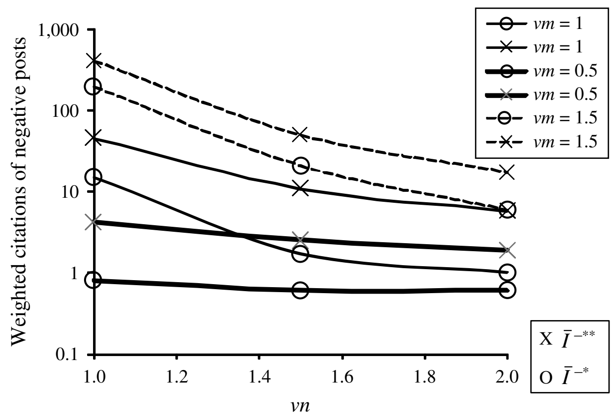
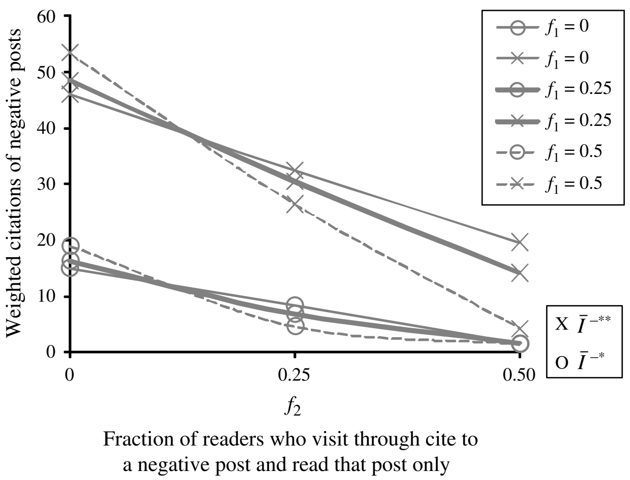


Figure 3(b) **Optimal Weighted Citations of Negative Posts vs. f_2**



Note. f_1 is the fraction of readers who visited the blog through cite to a positive post and read that post only.

We realize that although a firm can decide on the extent of negative posts to be allowed, exactly how a firm implements its desired blogging policy is beyond the scope of this paper. We are not advocating, for instance, that a firm should actively encourage its employees to post negative comments on their blogs. Firms may not choose to restrict certain types of negative posts, which is different from actually encouraging negative posts. Examples of actual blogging policies of firms suggest that some firms set broad guidelines that do not forbid critical posts by employees, as long as those posts are written carefully—posts that are not rude or insulting, that do not reveal company secrets, and that do not violate the law.

7. Conclusions and Future Research Directions

One of our main empirical findings is that, *ceteris paribus*, negative posts exponentially increase the readership initially, and after a point the page views do not increase. We also present some theoretical grounding for the idea that negative posts do not always harm a firm and under some conditions could create more net positive influence. Firms should therefore be careful when discouraging or prohibiting negative posts by their employees. Firms can decide whether to allow or prohibit negative posts using our suggested framework. However, the exact process by which a company should regulate its employee blogs is beyond the scope of this paper. Here we have considered only the case of a uniform decision of allowing or prohibiting negative posts for all employees; nevertheless, our suggested framework is fairly general and the decision can be customized for bloggers in specific firms. For example, bloggers may be heterogeneous in their influence, owing to several factors such as job title and experience. This can be allowed by having a blogger-specific influence coefficient.

Our analysis has a few limitations. One limitation is that net positive influence on readers, i.e., overall positive effect of a blog on readers toward the blogger's employing firm, may not directly map to monetary profits or losses for the firm. It would be difficult to map the effect of employee posts on blogs to product sales, because such a study would need to control for all the other plausible causes, such as the firm's advertising, competitors' advertising, press releases, public statements, media coverage, stage of product life cycle, price, competing and substitutable prices, seasonality effect, and product's previous sales. Besides controlling for such factors, such a study would need to control for selection bias, because a blogger may choose to write about a product for all the other plausible reasons mentioned. Therefore, establishing causality between posts and product sales would be challenging. Likewise, it may be difficult to tease out the effect of employee blogging on the price of the company's stock. Though a lot of market measures are easily available for public companies, adding variables in a model may add variability in the model parameters, and such a comprehensive study would need to work with many more variables. It would therefore be difficult to detect the slight effect of employee blogs on company stock price.

In this study, we have access to aggregate readership of a blog at week level. Hence, we cannot identify the readers. If one could identify the readers, it would be interesting to see how negative posts attract new readers and retain old readers. It would also be interesting to see how the context in which blog posts are cited affects its readership. Further, our study needs to be replicated on other data sets to ensure generalizability of the findings. We have reported the results for a technology firm's blogs. Future research can study if the results are similar across industries.

For future research, it will be interesting to see how company-specific characteristics affect our framework, but such analysis will require readership data of employee blogs of different companies during the same time period. Another interesting direction would be to study how different textual characteristics of a post or blogger demographics affect the readership as well as the influence of a post. Such a study would help firms move closer to the optimal solution for their employees' blogs. For example, if the outcome of the study is that promoting a product of a firm's competitor has much higher influence on average than criticizing the firm's own product, and if the firm wants to encourage slight negative content on employee blogs, it may ask its employees not to promote competitors' products but instead encourage them to discuss drawbacks of the firm's products.

Electronic Companion

An electronic companion to this paper is available as part of the online version at http://dx.doi.org/10.1287/isre.1110.0360.

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