No Comment?!

The Drivers of Reactions to Online Posts in Professional Groups

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ABSTRACT

Social media has moved beyond personal friendships to professional interactions in high-knowledge industries. In particular, online discussion forums are sponsored by firms aiming to position themselves as thought-leaders, to gain more insight in their customer base and to generate sales leads. However, while firms can seed discussion by posts, they depend on the forum members to continue the discussion in the form of reactions to these posts. The goal of the current study is to investigate what features and characteristics drive the number of comments that a post receives on an online discussion forum. The empirical setting involves a global manufacturer connecting with health care professionals through a LinkedIn discussion forum. We project that (i) content characteristics, (ii) post characteristics, (iii) author characteristics, and (iv) timing characteristics jointly determine the number of comments a post receives. We show that the readability of the post, the controversiality of the content and the status of the post author have the highest elasticity on the number of comments. These results provide valuable insights for firms on how to build and maintain an attractive online forum through ongoing discussions.

Keywords: Social media, Online discussion forum, Count data, Content analysis, B2B.

Introduction

Over the last decade, the Internet has evolved to a dynamic network where people can easily and constantly connect with each other (Cheung et al. 2008; Stephen and Lehmann 2009a). Social media websites allow consumers from around the world to interact and inform each other on products and services (Stephen and Toubia 2010). Increasingly, B2B firms embrace social media as a way to connect with their professional clients. Often their initiatives take the shape of establishing online communities. Firm goals include the (i) positioning as thought-leader in knowledge-intensive industries, (ii) gaining insights used for product innovation, (iii) developing meaningful relationships with the customer base and (iv) increasing brand preference resulting in sales leads (LinkedIn 2010a-c, 2011a-b). Currently, B2B firms selling products[1] spend on average 8.3% of their marketing budget on social media (The CMO Survey 2015). They plan on increasing this to 10.4% (18.9%) in the next (five) year(s). However, B2B firms struggle with the measurement of content marketing, specifically regarding how to generate engaging content and to measure its effectiveness (Content Marketing Institute 2015).

To build and maintain attractive forums it is crucial for firms to stimulate discussion appealing to the forum members. Wiertz and De Ruyter (2007) argue that the success of firm-hosted commercial online communities entirely depends on the willingness of the users of the platform to spend time and effort responding to each other. Online discussion forums share this need for member investment with other social media, such as microblogging (e.g. Twitter) and social networks (e.g. Facebook) (Hoffman and Fodor 2010). However, under-contribution is a problem for many online communities (Ling et al. 2005), as encouraging participation has proved to be one of the greatest challenges for any online community provider (Bishop 2007).

[1] Our empirical setting deals with a global manufacturer selling healthcare products to organizations such as hospitals.

Recent research has shed light on the motivations for consumers to engage in social media (Hoffman and Fodor 2010; Stephen and Lehmann 2009a, 2009b), and the consequences of social media use by consumers (Chen and Xie 2008; Chevalier and Mayzlin 2006; Dellarocas 2003; Godes and Mayzlin 2004, 2009). Other studies analyzed the value of online word-of-mouth (Libai et al. 2009; Trusov et al. 2009, 2010) and the best metrics to evaluate social media effectiveness (Peters et al. 2013). However, no study examined which specific posts generate most participation, with the exception of De Vries et al. (2012), who focus on the characteristics of the content (what was said) and the post (how it was said). Based on work in innovation though, post *author* characteristics (who said it) should matter as well (Bayus 2013), especially if commenters are motivated to establish a relation with the author (e.g. Hoffman and Fodor 2010). And in a cost-benefit framework (e.g. Johnson and Payne 1985), posts that cost more effort to comment on (e.g. because of inconvenient timing) should receive fewer comments (Johnson and Payne 1985). We bring these factors together in a conceptual framework that includes content, post, author and timing characteristics. In contrast to the past focus on consumer environments (Bayus 2013; De Vries et al. 2012; Goh et al. 2013), we contribute to the academic literature by investigating the importance of these content, post, authors and timing characteristics in a business-to-business setting of online forum participation.

Interesting to researchers, our findings also lead to actionable recommendations for firms running a forum by (i) identifying several categories of content-induced comment drivers, (ii) suggesting and operationalizing measurement for these drivers, and (iii) assessing the (relative) influence of the identified characteristics in driving post comments. First, firms can highlight the content, post, author, and timing[2] characteristics most likely to get comments. Second, many firms hire communication agencies to keep the discussion on their online discussion forum going. Optimizing the design and content of the topics that are inserted in the forum should lead to more discussion in the form of comments. Finally, the newfound knowledge might also be used in future social media activities (i.e. corporate blogs). In sum, our results can help firms to grow their online discussion groups.

Research Background: Social Media and Online Discussion Forums

In this section we review different types of social media and zoom in on social network sites and online discussion forums. These two types are blended in our empirical setting, an online discussion forum for healthcare professionals managed within social network site LinkedIn.

Social Media Characteristics and Classification

Social media can be briefly defined as a group of Internet-based applications that allow the creation and exchange of user-generated content (Kaplan and Haenlein 2010). These applications differ on several characteristics, leading to the classification in Table 1.

[INSERT TABLE 1 ABOUT HERE]

Social media platforms differ in the level of self-disclosure, their primary use (informative or entertaining), the requirement to create a personal page or account, the typically expected posting frequency and their media richness. We focus on social media network sites and online discussion forums, of which our empirical setting is a hybrid form.

[2] The timing of a post may not directly affect the amount of comments, but rather be a proxy for audience size and interest level. In our work, the implications for when to posts will stay the same, regardless of the underlying process. Still, we encourage future research to disentangle these effects with the appropriate data.

Social Network Sites and Online Discussion Forums

Social network sites are web-based services that allow individuals to construct a public or semi-public profile within a bounded system, articulate a list of other users with whom they are connected and view a list of connections of others (Boyd and Ellison 2007). Popular sites include Facebook, LinkedIn, and Pinterest. *Discussion groups* refer to Internet-based forums and computer-mediated social gatherings. Online discussion groups or forums are defined as 'places in which consumers often partake in discussions whose goals include attempt to inform and influence fellow consumers about products and brands' (Kozinets 2002). Brown, Broderick and Lee (2007) argue that consumption-related online communities are representations of word-of-mouth networks, where individuals with a shared interest regarding a certain product category interact. These online communities offer an increasingly prominent environment for interpersonal exchange, as it allows members to continuously share opinions (Miller, Fabian, and Lin 2009). Steyer, Garcia-Bardidia, and Quester (2006) highlight that online discussion groups have the potential to be great sources for data collection, as the discussions can be recorded in real time and information is available regarding the source and the sequence of the messages.

Online Discussion Forum on LinkedIn for Healthcare Professionals

Many companies use the LinkedIn environment to start discussion groups[3]. Examples include British Gas for Business, Cisco, Hewlett-Packard, Philips, and Sage. Using the LinkedIn environment allows firms to benefit from the readily available IT infrastructure and from a large and still expanding global audience. Currently, LinkedIn operates the world's largest

[3] A recent survey by the Content Marketing Institute (2015) showed that 94% of the B2B marketers in North America use LinkedIn to distribute content, making it the most popular social media outlet for content distribution. In addition, they indicate that it is the most effective channel.

professional network on the Internet with more than 300 million members in over 200 countries and territories (LinkedIn 2015a).

LinkedIn facilitates members to start groups on specific topics. Online discussion groups on LinkedIn enable the firms to connect with (potential) customers in a relatively inexpensive way. Following Table 1 these groups can be classified as hybrids between a discussion group and a social networking site. In fact, they can be seen as discussion group within a social network domain. More specifically, members have a relatively high level of self-disclosure with a personal page on a platform that is mostly informative with low media richness. However, the post frequency of members can be seen as relatively low, medium at best, especially compared to e.g. microblogging (see Table 1). As implied in its name, a key threat to the viability of a discussion group is the lack of *discussion*.

In our empirical application we focus on a LinkedIn discussion group for healthcare professionals. The group, carrying the name "*Innovations* in Health", is established and maintained by Philips. This company is a global manufacturer of, among others, advanced healthcare products such as fMRI machinery. Philips established the group to build thought leadership, engage with the target audience, facilitate peer-to-peer discussions, gain customer insights, and detect product issues early on (LinkedIn 2011b). The level of online discussion is key to achieving these goals (personal conversation with the managers thanked in the acknowledgments). The company decided to use the LinkedIn environment for its discussion group as the target audience was widely represented on this social media platform. Leveraging of the LinkedIn expertise and tools allowed Philips to jump start their own social media initiatives. Figure 1 depicts a screenshot of the "*Innovations* in Health" group.

[INSERT FIGURE 1 ABOUT HERE]

The "*Innovations* in Health" group provides healthcare professionals a platform, hosted by Philips, to connect with their peers. At the time of data collection the group had 16,000 subscribers[4]. Members included doctors (generalists and specialists), technicians and hospital administrators. Nearly 90% of all members originated from the US, UK, The Netherlands and India, with the latter making up less than 5% of the population. When asked what they like best about the group (Philips 2011), members answered:

> "Meaningful/interesting discussion about future trends – offshoring of healthcare, applicability of mobile medicine, etc. Unlike other healthcare related groups, they're not just interested in references and job offers."
>
> "Some discussions are really about hot topics and provide interesting contacts."
>
> "Good ideas are generated. Engaged group. Always something to learn about."

The discussion forum is made up of content created by the group members. As concepts such as threads, posts, comments and topics are sometimes used interchangeably, it is useful to define them as they will be used in this study. A *post* is an opening article written by someone who wants to start a discussion with other members of the group. Other members reply with their *comments*, which are their written reactions to the opening post. The collection of the opening post and comments together make up a *thread*. A *topic* is defined here as the subject of interest in a thread.

A key goal of the global manufacturer sponsoring the forum (Philips) is to be seen as the thought leader in healthcare (LinkedIn 2011b). It perceives the online discussion group as instrumental in reaching this goal. To this end, the company believes that it is crucial to have a lot of discussion between its members. This can be achieved by members posting a discussion topic with other members responding to it. Whereas there is a steady increase in the number of

[4] Currently, it has more than 105,000 subscribers (LinkedIn 2015b).

posts, the majority of posts do not evoke a single comment. Consequently, it is an interesting question what factors determine the number of comments a certain post evokes.

Conceptual Development: Drivers of Conversation in an Online Discussion Forum for Healthcare Professionals

Most research on what drives people to participate in online discussion forums has focused on the *individual motivations* people have to engage in such activity (i.e. Ardichvili et al. 2003; Dholakia et al. 2004; Hennig-Thurau et al. 2004; Wasko and Faraj 2005). Motivations such as concern for others and self-enhancement were found to determine member participation. More generally, Hoffman and Fodor (2010) discuss connection, creation, consumption and control as drivers of a consumer's use of social media. Also, Wiertz and De Ruyter (2007) argue that certain people have a higher intrinsic propensity to engage in online interaction than others. But these findings do not explain why certain *posts* lead to lengthy discussions, while others languish. The current research wishes to address this issue by exploring the differences between posts in the discussion group and investigating the number of comments they evoke.

Our main conceptual inspiration is Grice's (1975) influential theory of conversation. The theory specifies four maxims: (1) Quantity ("be informative"), (2) Quality ("be true"), (3) Relation ("be relevant") and (4) Manner ("be perspicuous"). In our context, this theory implies that we should consider not just *what* is said, but also *how* it was said and *who* says it. Within those maxims, Grice (1975, p. 45) implies benefit and costs tradeoffs, for instance refining 'Quantity' as

1. Make your contribution as informative as possible (for the current purposes of the exchange)
2. Do not make your contribution more informative than is required,

and "Manner" as being brief, being orderly, avoiding obscurity of expression and ambiguity.

Applied to online posts, these maxims imply that readers make a cost-benefit tradeoff in their decision whether or not to comment on a post. This rationale is similar to the cost-benefit tradeoffs faced by word-of-mouth transmitters (e.g. Stephen and Lehmann 2009b) and online review posters (e.g. Moe and Schweidel 2012) and by decision makers in general (Johnson and Payne 1985). In our context, perceived costs and benefits could be related to the *What* of post content (e.g. topic ambiguity versus practical utility), the *How* of post characteristics (e.g. post length versus asking a question), the *Who* of post author characteristics (the higher the status, the higher potential benefits from reacting to the post) and the *When* of post timing (inconvenient timing yields a higher cost). Derived from this framework, our hypotheses are shown in Table 2.

[INSERT TABLE 2 ABOUT HERE]

Characteristics of the Content (What?)

Consistent with Grice (1975), an intuitively appealing starting point is the actual content of the post. In our context of a discussion forum, we hypothesize content benefits include practical utility and controversiality, and content costs include self-centeredness and topic ambiguity. *Practical utility* has been shown to increase the virality of newspaper articles (Berger and Milkman 2012) and should also appeal to professionals in the healthcare industry (hypothesis H_1), who joined the LinkedIn group to discuss job-related matters and obtain information that is useful to them in practice.[5] *Controversiality* should increase post comments (H_2) because the discovery of dissonance starts interaction (Gunawardena et al. 1997) as it motivates people to reduce that dissonance (Festinger 1957).

[5] Practical utility differs from the broader concept of relevance. A post is only argued to be practically useful when it has the potential to influence and alter actual behavior of the reader (Berger and Milkman 2012). Relevance can also pertain to issues that are theoretically relevant, but do not have any potential to modify behavior. In our setting the practical utility is judged from the perspective of the healthcare professional.

On the cost side, some posts violate conversational norms that people should aspire to spur conversations that are informative to others (Grice 1975) but instead are *self-centered* (Stephen and Berger 2010), which should yield fewer comments (*H_3*). Also, *topic ambiguity* induces uncertainty for the post recipients in what exactly the topic starter is talking about. This violates Grice (1975)'s "Manner" norms of "avoiding obscurity of expression and avoiding ambiguity" and should therefore evoke fewer comments (*H_4*).

Characteristics of the Post (How?)

Next to the content of the post, the way in which it is said ('Quantity' in Grice 1975) and its valence (Stephen and Lehmann 2009b) also affect the costs and benefits of responding. We expect that costs increase with post length, sentence length, negativity and the inclusion of a hyperlink. We expect that benefits increase with readability, positivity, encouragement, and posing a question in the title.

As to *post length,* Grice's (1975) conversational norms hold that contributions to a conversation should only be as informative as required. Consistent with effort minimization (Johnson and Payne 1985), individuals should prefer and respond more to shorter posts (*H_5*). Likewise, *long sentences* take more effort to read, evoking less responses (*H_6*). The *inclusion of hyperlink(s)* also requires more effort from the reader, which should reduce the likelihood of commenting (*H_7*) (Johnson and Payne 1985). Moreover, such hyperlinks may distract the reader, who can get sidetracked and does not return to the forum to comment. In contrast, posts with better *readability* reduce effort and should therefore evoke more comments (*H_8*) (Johnson and Payne 1985).

Expected benefits of commenting on a post should increase with a clear *question in the topic title* (*H_9*). Scrolling through posts, readers easily see the topic starter's problem and thus can judge whether they can be of help or show their expertise, which were found to be core motivations for discussion forum participation (Ardichvili et al. 2003; Hennig-Thurau et al. 2004). In their B2C context, De Vries et al. (2012) also find that posing a question enhances the number of comments a post receives. Likewise, some posts contain an active *encouragement to reply* (H_{10}). This should lead to more comments because the reader is more likely to perceive the topic poster as genuinely interested in reaction (Grice 1975).

Emotion valence. Because people strive to be happy, they tend to look for information that is positive, which would highlight positive associations and induce a positive mood (Fiske 2004). Contrarily, most people aim to avoid negative information, which could decrease their mood. For instance, Berger and Milkman (2012) find that positive news is more likely to go viral than negative news. Therefore, relative to neutral posts, *positivity* should evoke more comments (H_{11}), while *negativity* should evoke fewer comments (H_{12}).

Finally, posts differ in the *degree of jargon* (in our case, vocabulary specific to the healthcare industry) that is used. When relatively much jargon is used, only experts on the matter can properly understand and consequently comment on it. The effect on comments can go either way. On the one hand, the use of jargon narrows the population that feels comfortable to comment. On the other hand, jargon may increase the individual likelihood for an expert to respond, either for altruistic reasons ('few can respond, so if I don't, who will?') or for self-enhancement purposes, i.e. to show off their knowledge (Wojnicki and Godes 2008). Consequently, we will include the degree of jargon as one of the post characteristics in our model but will not formulate a corresponding hypothesis.

Characteristics of the Author (Who)

The relevance of the conversation (Grice 1975) to forum members likely depends on who is the conversation starter. People are selective transmitters, meaning that they purposely choose to whom they convey information and to whom they do not (Stephen and Lehmann 2009b). Because people like to associate with successful others (Cialdini et al. 1976), a person with more *connections* (which is clearly visible in platforms such as LinkedIn) is more likely to be closely tied to others in the community and should therefore receive more feedback on topics (s)he started (H_{13}). Likewise, the higher the author's *social/expert status (SES)*, the higher the anticipated social benefits they expect to receive from forming a relation with that person (Stephen and Lehmann 2009a) and thus the higher the comments a post should evoke (H_{14}).

Timing (When)

Timing matters for the opportunity costs of reading and commenting on posts. Such costs likely depend on the type of forum: social discussion forums may get more comments in the weekend, while profession-related discussion forums should get more comments during the work week. *Weekend posts* are likely read only on Monday, at which time they have to compete for attention with Monday posts and thus should evoke fewer comments (H_{15}).

Control Variables

Next to the explanatory variables we include the author's gender as a control variable. Schler, Koppel, Argamon, and Pennebaker (2006) found significant differences in writing style between male and female bloggers. Nowson, Oberlander, and Gill (2005) argue that gender differences are projected in the language used in weblogs, with women writing more contextual than men. We do not have a clear expectation about these effects on the number of comments a post generates. Therefore, we include author gender as a control variable. In addition, we include a monthly trend to capture the general tendency of commenting more or less in the forum.

Methodology

Our methodology needs to account for the characteristics of our data, which consists of a collection of threads, i.e. a post and the comments that follow it. First, the number of comments evoked by a posts is a non-negative integer number (count data). Second, the number of comments across different posts displays overdispersion (i.e. high variability, long tails). We allow for overdispersion by adopting a count data model that assumes the distribution of the underlying data to be Negative-Binomial. In addition, we explicitly test for overdispersion by also estimating a model that assumes the underlying data to follow an equidispersion Poisson distribution.

Model Formulation

We assume that the number of comments to post i, Y_i, obeys the following Negative-Binomial process:

$$P(Y_i = k) = \frac{\Gamma(\lambda_i/\theta + k)}{\Gamma(\lambda_i/\theta)\Gamma(k+1)}\left(\frac{1}{1+\theta}\right)^{\frac{\lambda_i}{\theta}}\left(\frac{\theta}{1+\theta}\right)^{k},\ \lambda_i > 0,\ \theta > 0, \tag{1}$$

where

Y_i = the number of comments evoked by post i (=1,…,N), with N the number of posts,

$\Gamma(\cdot)$ = the gamma distribution.

The Negative Binomial distribution is a two-parameter distribution. The two parameters are respectively the λ_i and θ. The expected number of comments of post i, E(Y_i) is equal to λ_i. The corresponding variance, Var(Y_i), is equal to $\lambda_i(1+\theta)$. The theta parameter is often referred to as the overdispersion parameter. Larger values for theta represent more overdispersion of the underlying data. When theta approaches zero the negative binomial distribution converges to a Poisson distribution which has equidispersion, meaning that mean and variance are equal (to λ_i). We will also estimate the single-parameter Poisson distribution and compare the models based on fit and complexity.

Next, we relate the lambda parameters to the explanatory variables:

$$\begin{aligned}\log(\lambda_i) = {} & \beta_0 + \beta_1 \cdot PRACT_i + \beta_2 \cdot CONTR_i + \beta_3 \cdot SELF_i + \beta_4 \cdot AMBIG_i + \beta_5 \cdot POST\_LENGTH_i + \\ & + \beta_6 \cdot SENT\_LENGTH_i + \beta_7 \cdot HYPER_i + \beta_8 \cdot READ_i + \beta_9 \cdot QUESTION_i + \\ & + \beta_{10} \cdot ENCOUR_i + \beta_{11} \cdot POS_i + \beta_{12} \cdot NEG_i + \beta_{13} \cdot JARGON_i + \beta_{14} \cdot NUM\_CONNECT_i + \\ & + \beta_{15} \cdot SES_i + \beta_{16} \cdot WEEKEND_i + \beta_{17} \cdot FEMALE_i + \beta_{18} \cdot TREND_i \end{aligned} \tag{2}$$

Table 3 provides the definitions of the explanatory variables.

[INSERT TABLE 3 ABOUT HERE]

Elasticities

Comparing the effect sizes across variables can best be done by comparing the marginal effect of each variable. To this end we compute the elasticities. For a continuous variable the elasticity is given by (Washington et al. 2003)[6]:

$$\eta_{x_{ij}}^{\lambda_i} = \frac{\partial \lambda_i}{\partial x_{ij}} \cdot \frac{x_{ij}}{\lambda_i} = \beta_j x_{ij}, \tag{3}$$

where x_{ij} is the j^{th} variable in the vector of explanatory variables for post i, and β_j is the corresponding coefficient for the j^{th} variable. In case of a dummy variable we compute the pseudo-elasticity as an approximate elasticity of this variable (Washington et al. 2003):

[6] The metric variables are included in the model in their standardized form. Appendix A shows how the formula in Equation (3) can be adjusted to obtain the elasticity with respect to the unstandardized variable while using the coefficient corresponding to the standardized variable.

$$\eta_{x_{ij}}^{\lambda_i} = \frac{\exp(\beta_j) - 1}{\exp(\beta_j)}. \qquad (4)$$

Next, we describe the empirical setting to which we apply our model.

Empirical Application

In this section we first describe the data followed by the estimation results.

Data Description.

Sample. LinkedIn was contacted by Philips to obtain the necessary data. During a period of 9 months (October 2009 – June 2010), we observe 316 relevant posts[7] on threads finished before the end of the data period. On average, the number of days until the last comment was inserted was 11.52 days, with the longest thread (i.e., post + corresponding comments) being active for 85 days (i.e. less than 3 months). Therefore posts that were inserted in the last three months were excluded from the dataset to deal with the issue of right truncation of the number of comments.

Measurement. For a lot of the variables, such as post length or presence of a hyperlink, measurement is straightforward. However, some of the independent variables cannot be observed directly, they have to be judged by a human rater. To increase objectivity, multiple human raters were asked to judge the same data. Two human raters were found with sufficient expertise in the corresponding domain and in command of the English language. They were unaware of the goals of the study. Moreover, they did not know how many comments the posts generated. Both coders were asked to rate the content characteristics for each post independently of each other. Clear

[7] Our data do not contain any posts that were initiated by the company or anyone hired by the company. We started off with a corpus of 381 posts but had to remove post from the analyses due to missing data with respect to one or multiple of the following characteristics: (i) gender of the author (missing for 53 posts), (ii) number of connections (4 posts), and (iii) date of the posts (2). Moreover, for 24 posts our judges did not have enough information to rate the social/expert status of the author. In total 65 posts (17.1%) were left out from further consideration.

coding instructions were provided. The different subjective dimensions (*practical utility*, *controversy, self-centeredness*, *topic ambiguity*, *readability, degree of jargon*) are rated on a seven-point Likert scale (1 = not at all, 7 = extremely) for each post. The *sentiment* of a post, the *positivity* and *negativity*, is determined using the Linguistic Inquiry and Word Count (LIWC) software. This package performs a content analysis and classifies each word as positive, neutral, or negative. Measures for both *positivity* (% of words that are positive) and *negativity* (% of words that are negative) are part of the LIWC output. *Author popularity* is captured by the number of connections the author had for his LinkedIn profile. This information was not displayed directly next to the post. However, the information is just one click away and checking other members' profiles is common in LinkedIn, especially for people who use the discussion group for networking. The *author's social/expert status* (SES) is coded by human raters on a seven-point Likert scale based on the author's job title. One would expect the perceived SES of a technician at a hospital with little reputation to be lower than that of a brain specialist from a reputable hospital. We use a dummy variable to indicate if the post was placed over the weekend. In addition, we use a trend variable at the monthly level to allow for long-term trends in the level of commenting based on the growth of the discussion forum.

Inter-rater reliability. We compute the level of inter-rater reliability at the variable-level using Spearman's rho (correlation) on the ordinal (Likert-type) data. A correlation of .1 to .29 should be considered small, .3 to .49 should be considered medium and .5 to .1 should be considered large inter-rater reliability (Cohen 1988). The correlations for all variables, except for readability, fall within the large inter-rater reliability category. Readability falls into the medium category with a rho of .49. However, it is on the border with the large category. Hence, we believe that the agreement between the judges is sufficiently high. Consequently, we take the averages of their scores to measure the constructs. Table 4 provides the descriptive statistics for the resulting dataset. Table 5 shows the correlations among the variables in the model.

[INSERT TABLES 4 & 5 AND FIGURE 2 ABOUT HERE]

Distribution of the number of comments. Figure 2 represents the distribution of the number of comments across all posts in a histogram. Besides overdispersion, the distribution also reveals that more than 60% of the posts do not evoke a single comment. This observation inspired this paper's title and highlights the relevance of our research, but also suggests that the data may be zero-inflated; i.e. the fraction of zeros is too high to be compatible with a standard underlying count data model (Winkelmann 2008, p. 173). Theoretically, the process generating the zeros might depend on other factors than the process for strictly positive outcomes. In our study, posts may raise no comments because of some apparent factors (e.g., being extremely lengthy) that may have no or differential impact on a given positive number of comments. To allow for this to occur in our data we also estimate *zero-inflated versions of the Negative-Binomial and Poisson models*. The idea behind these models is that the excess zeros are modeled separately. With a given probability an observation is a zero. With one minus that probability it is an observation with a positive number. The probability of the zero typically follows a binary logit model using the explanatory variables present in the rest of the model. For more details we refer to Chapter 6 of Winkelmann (2008).

[INSERT TABLE 6 ABOUT HERE]

Before we move on to model estimation we first present model free evidence for the differences between the posts without comments and those with comments. Table 6 compares both groups on all of our explanatory variables. Besides the averages per group the table also provides the test statistic and p-value corresponding to an independent samples t-test on the difference in means between the two groups. Many of the differences are significant. At a significance level of 5% posts without any comments score lower on practical utility and controversiality, while scoring higher on self-centeredness and topic ambiguity. This seems to provide some model free evidence for hypotheses 1-4. Moreover, posts without any comments are significantly longer (consistent with H_5), more frequently contain a hyperlink (H_7), a question in the title (H_9), and encouragement to answer (H_{10}). Posts without comments are less readable (H_8), contain less negative words (inconsistent with H_{12}), and contain less jargon (hinting at a positive effect of jargon). Finally, authors of posts that result in zero comments have more connections (inconsistent with H_{13}), lower SES (H_{14}), and are more often female. We now move on to model estimation to see if we find the same kind of support for our hypotheses when modeling the full variation in the number of comments. Based on fit statistics we can also see if the posts with zero comments warrant special attention (i.e., if the factors that explain the differences between posts with and without comments are any different from those that explain the variation in the positive number of comments). Before we do so, however, we need to discuss potential multicollinearity between our variables.

Multicollinearity. Some of the correlations between our independent variables are substantial. Topic ambiguity and post readability are responsible for the largest correlation in absolute sense of -.53. To investigate whether multicollinearity is a potential problem we have computed Variance Inflation Factors (VIFs). The largest of these is only 2.13, well below the critical cut-off value of 5. Hence, our results seem not to suffer from multicollinearity. As an additional check, we have also re-estimated the best-fitting model without some of the variables that are involved in high bivariate correlations. Whereas the fit statistics showed a decrease in model fit vis-à-vis the full model, the size of the remaining effect sizes and corresponding significances hardly changed. In sum, we believe that multicollinearity is not a severe concern.

Model Estimation

In total we estimated four models that differ on the underlying statistical distribution (Negative-Binomial versus Poisson) and whether they allow for zero-inflation or not. All of the models were estimated in STATA 11.0. Table 6 summarizes model fit for all four models.

[INSERT TABLE 7 ABOUT HERE]

The models are compared based on the log-likelihood, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The AIC and BIC statistics balance model fit and complexity. For these measures, lower values are more preferred. The Negative-Binomial model without zero-inflation fits the data best. It is interesting to see how accounting for zero-inflation greatly improves fit under the Poisson distribution but does not lead to any improvements under the Negative-Binomial distribution. Apparently, the large amount of zeros is sufficiently captured by the overdispersion implied by the Negative-Binomial distribution.

Estimation Results

The (best-fitting) Negative Binomial model is significant as a whole ($\chi^2(18) = 270.8$, $p = .000$) and explains the variance of the number of comments reasonably well (*Pseudo* $R^2 = 24.21\%$). Table 7 contains the corresponding parameter estimates for this model.

[INSERT TABLE 8 ABOUT HERE]

In terms of content, we find support for hypotheses 1-2 that topics with more practical utility and controversy result in more comments. However, the self-centeredness of the post (H3) and the ambiguity of the topic (H4) did not significantly affect the amount of comments. The results reflect a lack of ambiguity aversion. This finding may be explained by the fact that the countries that are most represented in the group's membership (US, UK, The Netherlands, India) score relatively low on Hofstede's (2001) uncertainty avoidance dimension (respectively 46, 35, 53, and 40 versus a world average of 64).

With respect to post characteristics, the length of the post negatively affects the amount of comments, in support of H5. However, sentence length did not have a significant effect (H6). Including a hyperlink reduces the number of comments significantly (H7), while readability has a significant positive effect on the amount of discussion following a post, in support of H8. Explicitly phrasing a post as a question (H9) and encouraging members to respond (H10) both increase the number of comments. The emotionality of a post has no significant effect (H11-12). Regarding the degree of jargon, we find a positive effect, but it is not significant.

Social/expert status (SES) is the only author characteristic that significantly increases the number of comments a post receives, in support of H14. The number of connections (H13) did not have any effect. Posting in a weekend significantly reduces the number of following comments (H15). Finally, there is no evidence for the effect of the author's gender or for a trend in the data. Next, we compare the relative strength of each characteristic.

[INSERT FIGURE 3 ABOUT HERE]

Figure 3 displays the estimated elasticities corresponding to variables with a significant parameter estimate. The elasticities are evaluated under the average values of the variables and presented in the order of their absolute magnitude. Post readability has the largest elasticity; when readability increases by 1% the expected number of comments increases by 2.62%. Content controversy and social/expert status of the author are responsible for the second and third highest elasticities, with respectively 1.35% and 1.29%. It is interesting to note that post as well as content and author characteristics represent the top three elasticities. The two characteristics that complement the top 5 are presence of a hyperlink and practical utility. The presence of a hyperlink respectively a 1% increase in practical utility results in a 1.25% decrease respectively .98% increase in expected number of comments. Posting in a weekend, in sixth place, decreases the expected number of comments by .90%. The remaining elasticities are rather small. None of them exceeds 0.5.

Model Extension: Competing for Attention?

In our analyses so far we have not accounted for the possibility that posts that are published around the same time may (have to) compete for the attention of the forum members. To investigate this we have expanded our best-fitting model with a variable that, analogous to the Adstock variable used in the advertising literature (Gijsenberg et al. 2011), captures the stock of competing posts. Appendix B contains a detailed explanation of the exact definition of this variable. A decay parameter κ determines the rate of decay of the so-called Poststock. As the results in Appendix B show, irrespective of the chosen level of decay, the corresponding parameter estimate for the Poststock variable is never significant (p-values are at least .49). In addition, the AIC and BIC fit statistics indicate that the extra model complexity is not warranted for.

Hence, in our empirical application there is not enough evidence for a “competing for attention” effect. Perhaps this is not surprising given that in our sample period the discussion forum on average only witnessed 1.4 new posts per day. However, in online settings with a higher volume of contributions it may be worthwhile to include the Poststock variable in the analyses.

Discussion

Summary of Findings and Implications

With the continued rise of social media, online discussion forums have become important channels for firms to interact with their customers. Our study investigates what features and characteristics affect the number of comments that a post receives on an online discussion forum. Our empirical setting involves a global manufacturer (Philips) connecting with health care professionals through a LinkedIn discussion group. We projected that (i) content -, (ii) post -, (iii) author -, and (iv) timing characteristics of a post jointly determine the number of comments it receives. The basis for testing our conceptual framework is formed by a collection of 316 threads; i.e. a post and following comments. Using count data models we established the effects of the different types of characteristics on the number of comments. In particular, the number of comments is higher for posts that (i) are more readable (elasticity η of 2.62%), (ii) are more controversial (η = 1.35%), (iii) are written by an author with higher perceived social/expert status (η = 1.29%), (iv) contain no hyperlink (η = -1.25%) , (v) have higher practical utility (η = .98%), and (vi) are not written in the weekend (η = -.90%).

We believe that our methodology is a substantial advancement over industry practice of merely studying descriptive statistics. In fact, our study was the first in-depth statistical analysis of behavior of members of the focal discussion group. It has ignited a broader research agenda by the hosting firm Philips and LinkedIn. The results of our study were used by the involved firms in an attempt to increase the amount of discussion on the group.

Our study addresses the implications of new media platforms for marketing communications, in particular how firms can best "seed" customer-to-customer interactions – a key research priority as identified by the Marketing Science Institute (2008). Our research contributes to the emerging stream of research on connection platforms (Malthouse and Hofacker 2010). Our results may enable firms hosting online discussion forums to start more promising discussions, and thus increase the appeal of the forum and consequently the sponsoring firm as thought-leader in the industry. However, as our sample only included posts started by members instead of posts of the sponsoring firm, it remains an open question if our results generalize to firm-generated content as well. In fact, Goh et al. (2013) show that demand elasticities are much lower for marketer-generated content than user-generated content. To overcome this potential problem, the sponsoring firm could also approach leading members (e.g., authors with a high SES or authors of posts with a lot of comments) to start discussions on certain topics. The responsiveness to such ‘fertilized’ posts (Trusov et al. 2009) is an important topic for future research.

Generalizability and Boundary Conditions of Our Findings

While our cost-benefit conceptual framework and methodology are generalizable, our findings for a B2B online discussion forum may only partially transfer to other contexts. Our choice for the given forum was the result of convenience sampling. Together, the sponsoring firm and LinkedIn gave us the opportunity to collect the data required for our study. It is difficult to determine how representative this forum is for other online discussion foruma. Only on LinkedIn, more than 1.5 million groups are listed. From the time of data collection to date, the focal discussion forum has been one of the largest on LinkedIn, especially in the health domain. When clicking on the “similar groups” option in LinkedIn, 46 groups show up[8]. Only four of those are larger in terms of membership. A striking difference is that the ratio of the number of posts to the number of members is far lower for the focal discussion forum (.10) than for the 46

[8] We have done this on September 2, 2015.

similar groups (mean = .30, median = .25). Hence, there seems to be less discussion in our forum than one would expect based on the membership level. Future research should attempt to generalize our study across multiple discussion forums that differ in terms of membership level, industry, and amount of discussion.

In addition, how generalizable is the finding that, for the set of characteristics we used and without considering unobserved heterogeneity, content, and not author characteristics have the highest impact on post comments? While it speaks against the dominance of 'key opinion leaders' popular since Katz and Lazarsfeld (1955), recent studies find similar importance of content characteristics (e.g. Berger and Milkman 2012, Stephen and Lehmann 2009a) going so far as stating that 'almost anyone can be impactful' (Stephen and Lehmann 2009a, page 5). The boundary condition for this result is likely a strong heterogeneity in popularity or in perceived expertise. As to the former, microblogging sites such as Twitter are dominated by a few celebrities with millions of followers. For a tweet to 'go viral', being noticed by such a celebrity is key (e.g. Goel, Watts and Goldstein 2012). As to the latter, an online community may be dominated by a few members who have a lot more (perceived) expertise than others, for instance in offering innovation in technical environments (e.g. Girotra et al. 2010). But even in such environment, Bayus (2013) finds that an individual's past success is negatively related to the likelihood of offering further implementable ideas.

A few variables may see their effect reversed in other settings. For one, the use of jargon is likely to put off people in a less specialized, social setting such as Facebook. Moreover, post length could increase comments if it indicates higher quality (because the poster has put more effort in the post[9]). Finally, topic ambiguity may decrease comments in environments with low

[9] We thank an anonymous reviewer for this insight.

tolerance for uncertainty (Hofstede 2001). Other drivers, such as posing a question in the post, appear to increase comments in both our B2B and in B2C settings (De Vries et al. 2012).

Limitations and Directions for Future Research

In this section, we describe some limitations and possible extensions of our study. The first limitation of our study is the sample size. The use of subjective data coded by professional judges restricted the number of threads we could use. However, we believe that this is compensated for by the depth of insights.

The amount of variance in the dependent variable that is explained by our model (R^2 of 24.2%) is in the same ballpark as that reported by De Vries et al. (2012) for respectively their models of liking (15%) and commenting (30%). Still, there is room for improvement. Following Stephen et al. (2010) we could extend our model with additional author characteristics such as connectivity (how well are they connected within the discussion group?) and activity (how frequently do they post?). Another interesting author characteristic for future research to consider is author tenure (length of membership). As reciprocity ("I comment to your post because you commented on mine") may be an important reason for members to comment (Gatignon and Robertson 1986), we could also account for past commenting behavior of the author. Another interesting content characteristic would be the novelty of the post topic, but this may prove to be hard to code. Finally, we could control for the membership level (number of forum members). Unfortunately, this information was not available to us, but controlling for it could be especially important when analyzing longer data sets.

Our base model makes two assumptions that future research should attempt to verify. The first is that posts are conditionally independent. Realistically, posts compete for forum members' limited time and attention, especially when they are posted close to one another. In our model extension we have relaxed this assumption by including a stock variable of competing posts as additional control variable. A more elaborate approach is to model the dependency through a more general count model with correlated error terms. The second assumption is that comments are only given to the original posts. However, in reality, comments may also be a reaction to other comments. The only way to account for this would be to model the arrival process of comments, resulting in a completely different model. Here the time-varying arrival rate of new comments would be a function of both the characteristics of the (opening) post and those of the comments made up until that point. There would be a lot of interesting dynamics to consider here. For instance, a very controversial comment may really get things going, while a huge consensus in comments ("convergence") may lead the thread to finish. We believe that this represents a very exciting and challenging avenue for research.

Our study emphasizes the quantity of discussion rather than the quality of discussion. Future research could look into the challenging task of operationalizing and measuring the quality of the discussion. This would probably not only depend on the characteristics of the initial post but also on those of the following comments. Especially promising would be a joint model of quality and quantity, including their interdependency.

The ultimate goal of the company running the discussion forum in our empirical application (Philips) is to be perceived as thought leader. The link between membership of the discussion group and activity on the platform on the one hand and perceptions of thought leadership on the other still needs to be formally proven. The focal firm is currently undertaking a study in joint cooperation with LinkedIn to empirically test this causal relation.

The quest to determine the ROI on online engagement continues for many in marketing. To what extent do more post comments reflect engagement? To what extent do more discussions, higher-quality discussions, active versus passive behavior of members lead to an increase in relevant metrics for the firm such as brand attitude and purchase intention? Within Philips one of the leading metrics is the Net Promoter Score (NPS; Reichfeld 2003). Currently, Philips and LinkedIn are jointly investigating how group membership and activity within the group drive NPS scores. Initial results show that membership has the ability to increase both perceptions of thought leadership as well as NPS scores. Further research will be undertaken to put more trust into these findings. In addition, they will study how successful the online group is in terms of generating insights, sales leads and partnerships for innovation.

As already highlighted by Steyer, Garcia-Bardidia, and Quester (2006), online discussion groups have the potential to be great sources for data collection, as the discussions can be recorded in real time and information is available regarding the source and the sequence of the messages. We hope our study inspires research into how this potential can be unlocked.

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TABLE 1
OVERVIEW OF SOCIAL MEDIA TYPES AND CHARACTERISTICS

Social media type	Level of self-disclosure	Informative vs. entertaining	Personal page	Post frequency per user	Media richness
Collaboration	low	Informative	no	low	low
Online gaming	low	Entertaining	no	medium	high
Multi-media uploading	low	mostly entertaining	yes[a]	low	high
Weblog	high	Both	yes	medium	low
Microblog	high	Both	yes	High	low
Social networking site	high	mostly entertaining	yes	Medium	high
Discussion group	low	mostly informative	no	Medium	low

Note. The dotted lines illustrate that our empirical application, an online discussion forum for healthcare professionals on LinkedIn can be seen as a hybrid between a discussion group and a social networking site.
[a] There are also multi-media uploading sites that do not have personal pages.

TABLE 2
SUMMARY OF THE HYPOTHESES

Variable	Benefits	Costs
Content (What)		
Practical Utility (*H_1*)	+	
Controversiality (*H_2*)	+	
Self-centeredness (*H_3*)		-
Topic ambiguity (*H_4*)		-
Post (How)		
Post length (*H_5*)		-
Sentence length (*H_6*)		-
Hyperlink (*H_7*)		-
Readability (*H_8*)	+	
Question in title (*H_9*)	+	
Encouragement (*H_{10}*)	+	
Positivity (*H_{11}*)	+	
Negativity (*H_{12}*)		-
Author (Who)		
Number of connections (*H_{13}*)	+	
Social/expert status (*H_{14}*)	+	
Timing (When)		
Weekend (*H_{15}*)		-

Note. The variables and corresponding hypotheses are classified according to whether they represent a benefit or a cost according to our application of Grice's (1975) theory of conversation.

TABLE 3
VARIABLE DESCRIPTION

Variable	**Definition**
$PRACT_i$	the perceived practical utility of post *i*
$CONTR_i$	the perceived controversiality of post *i*
$SELF_i$	the perceived self-centeredness of post *i*
$AMBIG_i$	the perceived topic ambiguity of post *i*
$POST\_LENGTH_i$	the length of post *i* (in number of words)
$SENT\_LENGTH_i$	the average sentence length of post *i* (in number of words)
$HYPER_i$	1 if post *i* contains a hyper link, 0 otherwise
$READ_i$	the perceived readability of post *i*
$QUESTION_i$	1 if post i includes a question, 0 otherwise
$ENCOUR_i$	1 if the authors of post *i* encourages readers to comment, 0
POS_i	the amount of positive information contained in post *i*
NEG_i	the amount of negative information contained in post *i*
$JARGON_i$	the perceived degree of jargon used in post *i*
$NUM\_CONNECT_i$	the number of connection of the author of post *i*
SES_i	the perceived social/expert status of the author of post *i*,
$WEEKEND_i$	1 if post *i* was posted in a weekend (Saturday or Sunday), 0
$FEMALE_i$	1 if the author of post *i* is female, 0 otherwise
$TREND_i$	monthly trend value for post *i*

TABLE 4
DESCRIPTIVE STATISTICS

Variable	**Average**	**Std.**	**Min.**	**Max.**
Number of comments	3.67	19.27	0.00	312
Content characteristics				
Practical utility	2.31	1.25	1.00	7.00
Controversiality	1.88	1.29	1.00	7.00
Self-centeredness	3.41	2.04	1.00	7.00
Topic ambiguity	4.87	1.27	1.00	7.00
Post characteristics				
Post length	134.50	127.95	8.00	629.00
Sentence length	14.73	6.91	2.00	73.00
Hyperlink	.62	.49	0.00	1.00
Readability	3.74	1.00	1.00	6.00
Question	.43	.50	0.00	1.00
Encouragement	.12	.33	0.00	1.00
Positivity	3.23	2.81	0.00	16.67
Negativity	.72	1.67	0.00	12.50
Degree of jargon	2.38	1.32	1.00	7.00
Author characteristics				
Popularity	341.69	419	0.00	2,424.00
Social/expert status	4.50	1.25	1.00	7.00
Timing characteristic				
Weekend	.16	.37	0.00	1.00
Control variable				
Author gender (female)	.29	.45	0.00	1.00

TABLE 5
CORRELATION MATRIX

	Correlations								
Variable	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
1. Number of comments	1.00								
2. Practical utility	.09	1.00							
3. Controversiality	.38***	.11*	1.00						
4. Self-centeredness	-.12**	-.26***	-.42***	1.00					
5. Topic ambiguity	-.20***	-.44***	-.48***	.34***	1.00				
6. Post length	-.08	-.10*	-.10*	.28***	.11*	1.00			
7. Sentence length	.05	.00	.02	-.02	-.05	.30***	1.00		
8. Hyperlink	-.12**	.02	-.03	.40***	.07	.17***	-.31***	1.00	
9. Readability	.19***	.38***	.35***	-.42***	-.53***	-.33***	-.05	-.13**	1.00
10. Question in title	.08	.16***	.35***	-.47***	-.36***	-.06	-.09	-.10*	.18***
11. Encouragement	.14**	.07	.09*	-.01	-.14**	.03	.06	.00	.14**
12. Positivity	-.01	.10*	-.05	-.01	.01	-.01	.04	-.09*	.02
13. Negativity	.04	.04	.33***	-.15***	-.22***	.03	-.02	-.02	.13**
14. Degree of jargon	-.01	.22***	.05	-.11*	-.12**	.08	-.01	-.05	-.08
15. Number of connections	-.04	.00	-.11**	.24***	.09	.06	-.16***	.15**	-.07
16. Social/expert status	.07	.19***	.21***	-.12**	-.15***	.04	.01	.20***	.14**
17. Weekend	-.06	-.02	-.08	.08	.09	.02	-.05	-.04	-.06
18. Gender	-.05	-.04	-.15***	.11*	.01	-.07	.09	-.03	.00
19. Month	-.09	-.17***	-.15***	.08	.09	.00	.02	.15***	.17***

	Correlations									
Variable	10	11	12	13	14	15	16	17	18	19
10. Question in the title	1.00									
11. Encouragement	.01	1.00								
12. Positivity	.03	.04	1.00							
13. Negativity	.12**	-.02	.18***	1.00						
14. Degree of jargon	.18***	.06	-.07	.04	1.00					
15. Number of connections	-.15***	-.07	-.03	-.08	-.03	1.00				
16. Social/expert status	.20***	.09	-.05	.09	.12***	-.07	1.00			
17. Weekend	-.07	-.01	.12**	-.02	.03	.06	-.15***	1.00		
18. Gender	-.13**	-.01	.13**	.00	-.21***	-.21***	-.10*	.06	1.00	
19. Month	-.01	-.10*	.03	-.06	-.19***	-.02	.02	-.07	-.02	1.00

$^{*}p < .10$.
$^{**}p < .05$.
$^{***}p < .01$.
Note. All p-values correspond to two-tailed tests of significance.

TABLE 6
COMPARISON BETWEEN POSTS WITH AND WITHOUT COMMENTS

	Average for posts			
Variable	**with comments**	**without comments**	**T-statistic**	**P-value**
Content characteristics				
Practical utility	2.97	1.88	7.47	.00
Controversiality	2.59	1.42	7.72	.00
Self-centeredness	2.35	4.11	-8.66	.00
Topic ambiguity	4.16	5.34	-8.75	.00
Post characteristics				
Post length	106.31	152.95	-3.46	.00
Sentence length	14.50	14.88	-.48	.64
Hyperlink	.53	.65	-2.04	.04
Readability	4.27	3.40	8.46	.00
Question	.63	.29	6.22	.00
Encouragement	.22	.06	3.74	.00
Positivity	3.01	3.38	-1.14	.26
Negativity	1.02	.53	2.32	.02
Degree of jargon	2.70	2.16	3.48	.00
Author characteristics				
Number of connections	269.86	388.70	-2.91	.00
Social/expert status	4.89	4.24	4.53	.00
Timing characteristic				
Weekend	.13	.18	-1.35	.18
Control variables				
Author gender (female)	.21	.34	-2.64	.01

Note. Two-tailed p-values.

TABLE 7
OVERVIEW OF MODEL FIT

	Fit statistic		
Model	**Log-likelihood**	**AIC**	**BIC**
Poisson	-795	1,628	1,699
Negative-Binomial	**-424**	**888**	**963**
Zero-inflated Poisson	-722	1,488	1,571
Zero-inflated Negative-Binomial	-424	892	974

Note. In bold the best-fitting model.

TABLE 8
PARAMETER ESTIMATES FOR NEGATIVE BINOMIAL MODEL

Parameter	Hypothesized sign	Coefficient	Standard error	Z-value	P-value
Intercept	N.A.	-.17	.30	-.56	.57
Content characteristics					
Practical utility	+	**.53**	.10	5.18	.00
Controversy	+	**.93**	.09	10.04	.00
Self-centeredness	–	.10	.16	.61	.54
Topic ambiguity	–	.20	.13	1.56	.12
Post characteristics					
Post length	–	**-.36**	.14	-2.56	.01
Sentence length	–	-.06	.12	-.46	.64
Hyperlink	–	**-.81**	.25	-3.23	.00
Readability	+	**.70**	.14	4.95	.00
Question	+	**.69**	.25	2.80	.01
Encouragement	+	**.69**	.26	2.67	.01
Positivity	+	.03	.11	.26	.79
Negativity	–	-.08	.08	-1.00	.32
Degree of jargon	N.A.	.09	.09	.92	.36
Author characteristics					
Number of connections	+	-.05	.16	-.30	.77
Social/expert status	+	**.36**	.10	3.56	.00
Timing characteristic					
Weekend	–	**-.64**	.32	-1.98	.05
Control variables					
Author gender (female)	N.A.	.10	.24	.41	.68
Monthly trend	N.A.	-.04	.04	-1.02	.31

Note. In bold the parameters that are significant at 95%.

FIGURE 1
SCREEN SHOT OF THE INNOVATIONS IN HEALTH GROUP

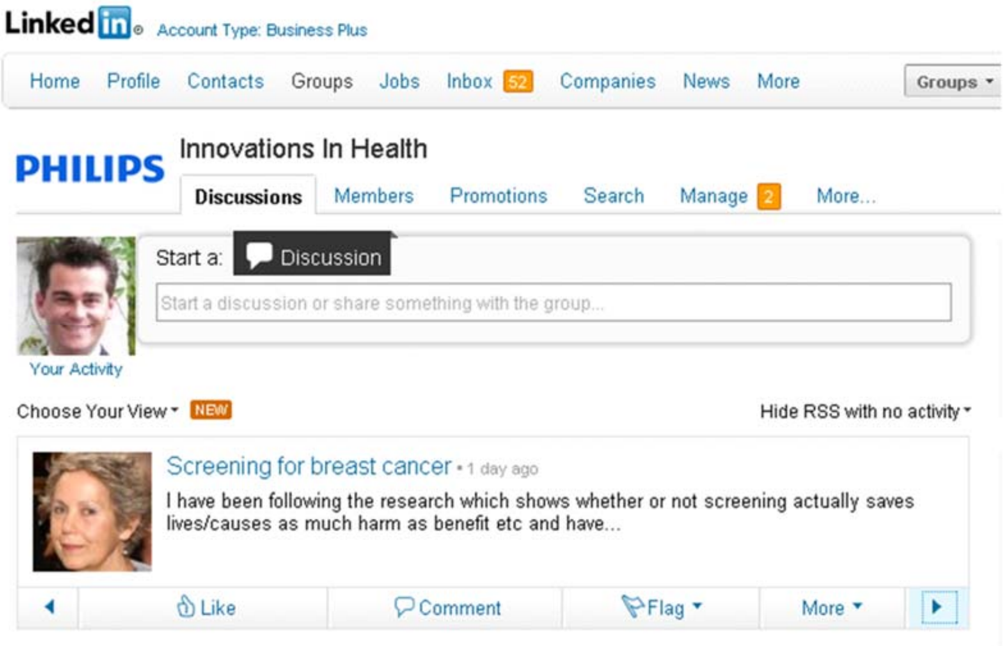


FIGURE 2
DISTRIBUTION OF NUMBER OF COMMENTS

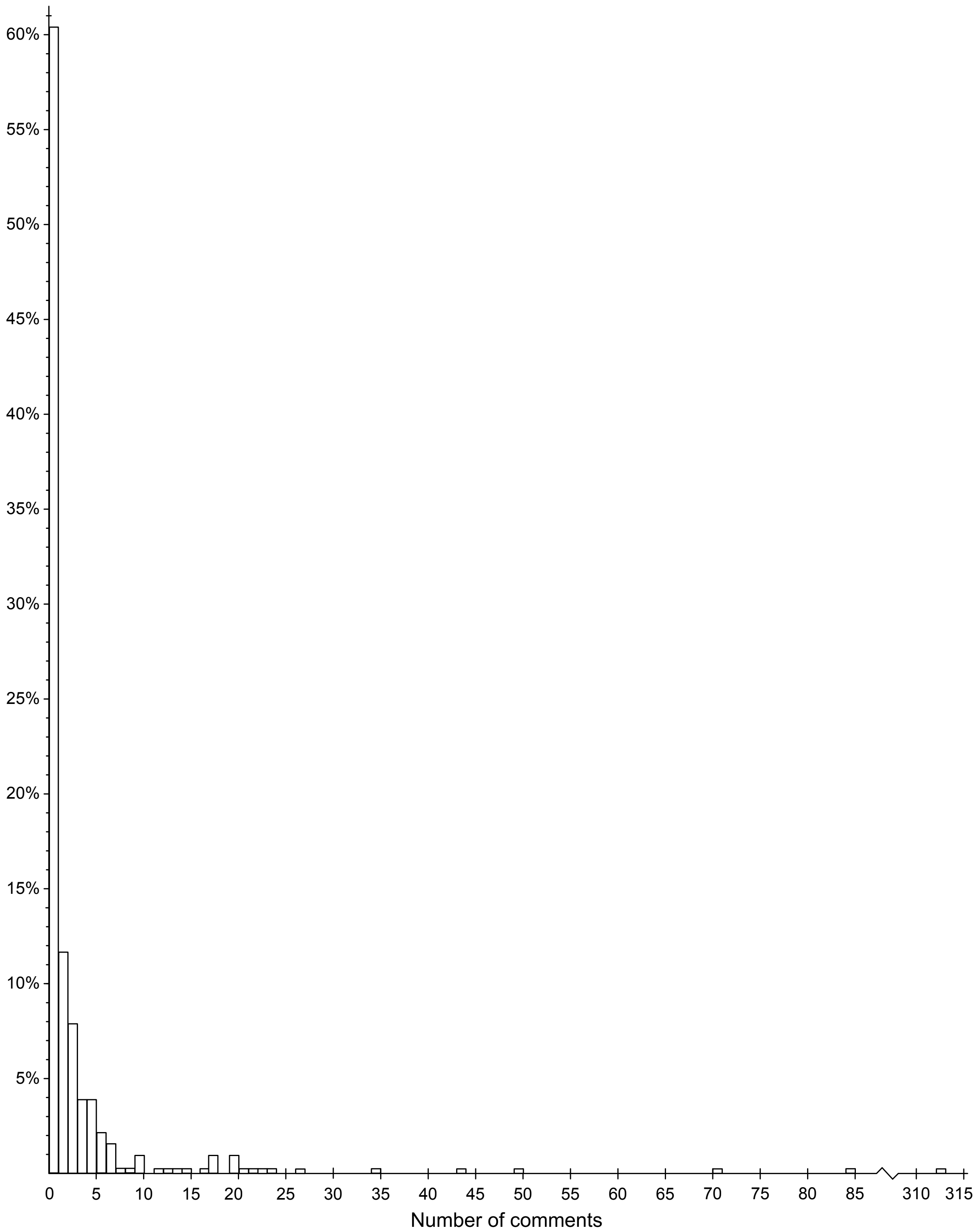
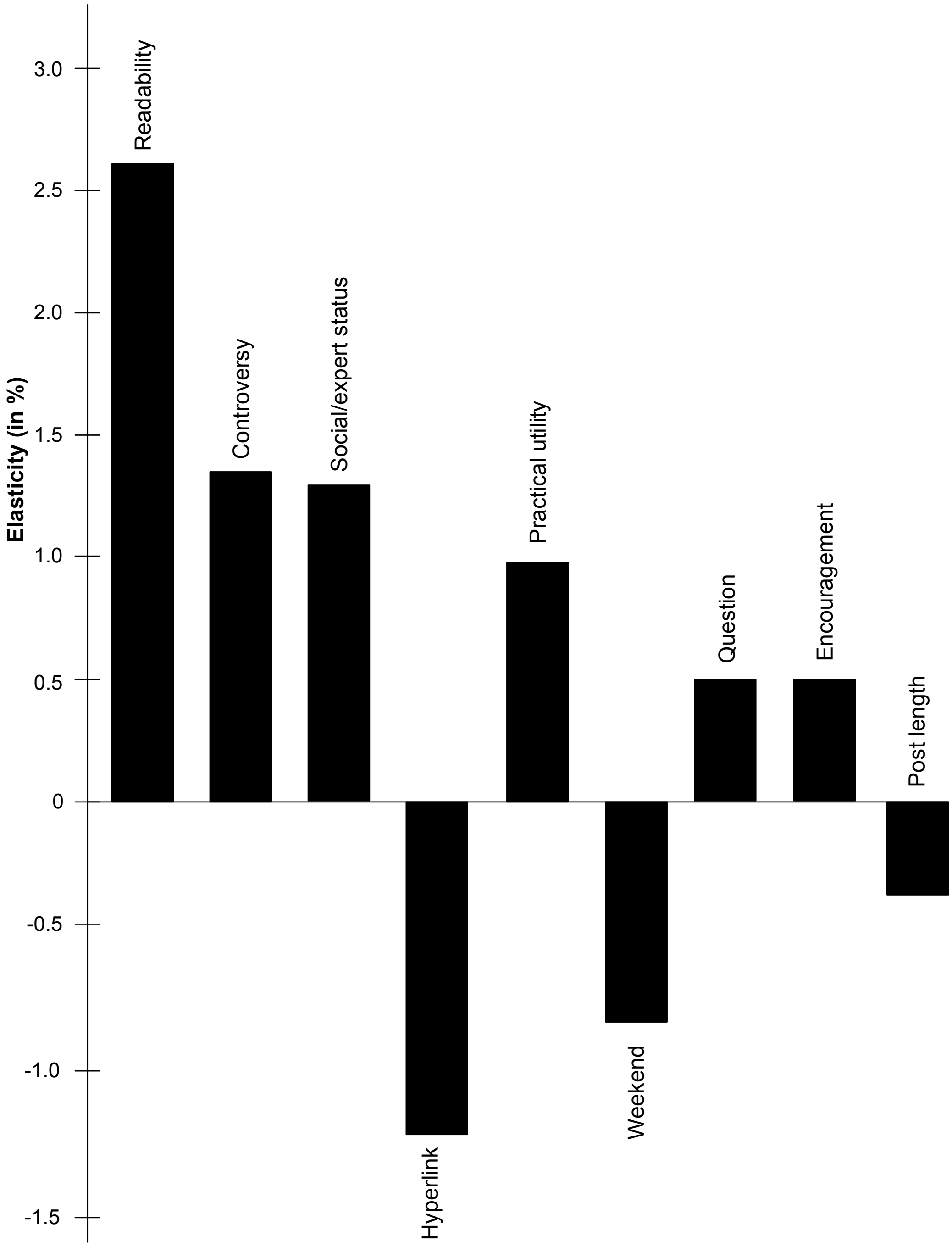


FIGURE 3
OVERVIEW OF ELASTICITIES



Note. Only elasticities pertaining to significant parameters are depicted. The elasticities are evaluated for the average value of the corresponding variable. The order of depiction is based on their absolute magnitude.

APPENDIX A: ADJUSTING ELASTICITIES FOR STANDARDIZATION

In this Appendix we show how to adjust the formula for the elasticity with respect to a metric variable (cf. Equation (3)) when estimating the model with the standardized versions of the metric variables. Suppose we include the metric variable j, x_{ij}, in its standardized form. That is we include z_{ij} instead, which is given by:

$$z_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j}, \tag{A1}$$

where μ_j and σ_j are respectively the average and standard deviation of the j^{th} variable across posts. Suppose that $\underline{\beta}_j$ now refers to the coefficient corresponding to the standardized variable z_{ij} instead of the unstandardized variable x_{ij}. We can now rewrite the elasticity in terms of the coefficient of the standardized variable as follows:

$$\begin{aligned}\eta_{x_{ij}}^{\lambda_i} &= \frac{\partial \lambda_i}{\partial x_{ij}} \cdot \frac{x_{ij}}{\lambda_i} = \left(\frac{\partial \lambda_i}{\partial z_{ij}} \cdot \frac{\partial z_{ij}}{\partial x_{ij}}\right) \cdot \left(\frac{z_{ij}}{\lambda_i} \cdot \frac{x_{ij}}{z_{ij}}\right) = \underbrace{\left(\frac{\partial \lambda_i}{\partial z_{ij}} \cdot \frac{z_{ij}}{\lambda_i}\right)}_{\substack{=\eta_{z_{ij}}^{\lambda_i} \text{ according} \\ \text{to Equation (3)}}} \cdot \left(\frac{\partial z_{ij}}{\partial x_{ij}} \cdot \frac{z_{ij}}{x_{ij}}\right) = \underline{\beta}_j z_{ij} \cdot \left(\frac{\partial z_{ij}}{\partial x_{ij}} \cdot \frac{x_{ij}}{z_{ij}}\right) = \\ &= \underline{\beta}_j x_{ij} \cdot \frac{\partial z_{ij}}{\partial x_{ij}} = \frac{\underline{\beta}_j x_{ij}}{\sigma_j}\end{aligned} \tag{A2}$$

APPENDIX B: ACCOUNTING FOR THE SIMULTANEOUS PRESENCE OF OTHER POSTS

In this Appendix we investigate the extent through which (the number of comments to) posts suffer from the presence of other posts that compete for the time and attention of the forum members. We refer to these simultaneously present other posts as competing posts. To investigate the effect of competing posts we have extended our best-fitting model (the Negative-Binomial) with an additional variable that captures the amount of competing posts for the focal posts.

Analogous to an Adstock variable commonly used to measure advertising goodwill (Gijsenberg et al. 2011) we have defined a so-called Poststock variable that captures the stock of competing posts. Our extended recursive definition accounts for the fact that (a) posts do not compete with themselves (i.e., should be excluded from their own poststock), but (b) may compete with posts in the near future (i.e., should be part of future poststocks):

$$POSSTOCK_i = (1-\kappa)\cdot NUM\_COMP\_POSTS_{i,t(i)} + \kappa \cdot POSSTOCK^*_{t(i)-1} \qquad \text{(B1)}$$

, where

$$POSSTOCK^*_t = (1-\kappa)\cdot NUM\_POSTS_t + \kappa \cdot POSSTOCK^*_{t-1} \qquad \text{(B2)}$$

, with

$POSTSTOCK_i$	= the stock of posts competing with post *i* when it is posted,
κ	= the decay factor,
$t(i)$	= the day on which post *i* was posted,
$NUM\_COMP\_POSTS_{i,t(i)}$	= the number of posts, other than post *i*, that are posted on day $t(i)$,
$POSSTOCK^*_t$	= the stock of posts on day *t*,
NUM_POSTS_t	= the number of posts that is posted on day *t*.

We note that smaller values for κ imply a faster decay of the poststock. A special case of formulation is κ=0, which implies no carry-over and renders the poststock for post *i* to the number of posts other than post *i* that are posted on the same day as post *i*.

We have initialized the stock of posts at the beginning of our sample, $POSTSTOCK^*_0$, as the average number of posts that are published on a given day (1.4). Next, we have re-estimated the best-fitting model (Negative-Binomial) with the addition of the Poststock variable. We have done so for a wide selection of decay factors (κ=0.0, 0.1, 0.2,…, 0.9). For every value of kappa

Table B1 shows the estimated Poststock parameter, the corresponding p-value, and resulting model fit in terms of log-likelihood, and fit statistics AIC and BIC.

TABLE B1
PERFORMANCE OF THE POSTSTOCK VARIABLE PER DECAY LEVEL κ

κ	**Coefficient**	**P-value**	**Log-likelihood**	**AIC**	**BIC**
0.0	-.07	.49	-424	891	974
0.1	-.07	.52	-424	891	974
0.2	-.06	.58	-423	891	974
0.3	-.05	.67	-424	891	974
0.4	-.03	.80	-424	891	974
0.5	-.01	.96	-424	891	974
0.6	.02	.83	-424	891	974
0.7	.05	.61	-424	891	974
0.8	.08	.43	-423	891	973
0.9	.05	.61	-423	891	974

The results show that for none of the values of κ the corresponding parameter estimate becomes significant. In addition, based on both the AIC and BIC the simpler model without the Poststock variable is preferred (AIC of base model is 888, BIC = 963, cf. Table 7).