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As social media and virtual communities increase in popularity, the spread of word of mouth becomes easier, challenging firms to measure and manage the success of marketing initiatives in online community environments. This research examines how consumers react to firms' active participation in consumer-to-consumer conversations in an online community setting. The authors develop a tailored community-matched measure of consumer reaction (consumer sentiment) and analyze more than 115,000 consumer posts from ten online forums with active firm participation. The results indicate that consumers show diminishing returns to active firm engagement, which, at very high levels, can undermine consumer sentiment. Further subgroup analyses by conversation type indicate that these relationships hold for conversations that address consumers' functional needs but do not hold for conversations that address social needs. Finally, the results show diminishing returns to firm engagement for consumers primarily interested in product-related support but show no relationship for consumers primarily interested in inspiration and entertainment. These findings provide insights for marketing performance measurement and resource allocation in online communities.

Keywords: active firm engagement, consumer sentiment, marketing performance measurement, sentiment analysis, social media

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Measuring and Managing Consumer Sentiment in an Online Community Environment

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The increasing popularity of social media has led firms to recognize the power of word of mouth in online settings, in which consumers use technologies to communicate with others about products and services (Godes and Mayzlin 2004). Within those settings, online communities play a prominent role. An online community comprises "an aggregation of individuals or business partners who interact based on a shared interest, where the interaction is at least partially supported or mediated by technology and guided by certain protocols and norms" (Porter and Donthu 2008, p. 115). In contrast to other online marketing instruments, such as viral marketing campaigns or advertising on social networking sites, online communities facilitate consumer-to-consumer online conversations and enable firms to interact with consumers directly and transparently (Dellarocas 2003, 2006).

A firm's role in online community management can be either passive or active (Dholakia et al. 2009). Passive

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engagement involves offering a platform for online conversations in which, notably, the firm does not engage in conversations among consumers. In contrast, active engagement entails direct interactions with community members, such as replies to consumer postings or the opening of new discussion threads by a corporate employee. Companies following an active engagement strategy often employ a hybrid approach that comprises both active and passive elements of interaction with their customers (Dholakia et al. 2009; Schau, Muñiz, and Arnould 2009).

Empirical results of consumer reactions to these types of engagement are rather mixed and limited in scope. Whereas Porter and Donthu (2008) find no significant relationship between firms' passive efforts to encourage interaction and positive beliefs about the firm, recent research has shown that active management of a community stimulates user-generated content (Miller and Tucker 2013). Offline purchase expenditures have, at best, weak associations with firm engagement (Goh, Heng, and Lin 2013), leading to the question of why firms engage in this type of behavior. Moreover, much research in this area has been largely theoretical rather than empirical or has been applied in a single firm setting instead of being aimed at detecting similar data patterns in a group of firms (Goh, Heng, and Lin 2013; Miller and Tucker 2013; Rishika et al. 2013).[1] Our study contributes by using an empirical approach of measuring the performance of active firm engagement in an online community setting over a variety of firms.

Such an approach requires a performance measure that directly reflects changes in consumer attitudes and is therefore able to isolate the influence of online firm engagement from other offline marketing initiatives (Chevalier and Mayzlin 2006). In our context, this measure should be tailored to a specific online forum context instead of being constructed from more generic external inputs such as lexicons. In light of these observations, we use a supervised approach for sentiment analysis. Although an unsupervised approach does not need any manually precoded data, it is usually less accurate (Vohra and Teraiya 2013; Zhou and Chaovalit 2008) because supervised techniques are customized to a specific sample and are especially powerful for extracting sample-specific semantic expressions that are often lost with reliance on standard dictionaries (Pang and Lee 2008). Depending on the specific research question and setting, researchers typically prefer one over the other (Antweiler and Frank 2004; Tirunillai and Tellis 2012, 2014).[2] Online communities, which are the subject of our investigation, require a tailored method because participants in these forums commonly communicate in company-, product-, or theme-specific jargon. We conceptualize consumer sentiment as a measure of the valence of consumers' posts in firm-sponsored online communities, and we employ it as the main dependent variable in analyzing consumer reactions to active firm engagement in ten online forums.[3]

Our first research question addresses consumers' overall reaction to active firm engangement.[4] Prior literature has argued that consumers benefit from active firm engagement in online forums either functionally or socially (Dholakia et al. 2009). Functional benefits mainly derive from the utility of receiving purchase- or consumption-related information that enables consumers to better understand, use, modify, or repair a product. Social benefits, in contrast, derive from the development of social ties with firm representatives and the establishment of interpersonal relationships. Here, utility mainly emerges from social exchange, the achievement of social status through interaction with company representatives, or the feeling of being part of an organization (Dellarocas 2003; McAlexander, Schouten, and Koenig 2002; Nambisan and Baron 2007; Porter and Donthu 2008). Our first research question pertains to this baseline relationship and leads to the examination of whether and how consumers respond to firms' active engagement in online forums:

RQ_1: How do consumers react to active firm engagement in an online community?

Beyond this basic relationship, a second aspect that requires attention is the type of online conversation. Several contributions based on case-study evidence and interviews have emphasized the importance of addressing social needs in an online context (McAlexander, Schouten, and Koenig 2002; Muñiz and O'Guinn 2001; Schau, Muñiz, and Arnould 2009). In contrast, empirical findings in consumption-related online settings with a focus on problem solving have emphasized the importance of functional interactions, such as solving problems or offering technical advice (Köhler et al. 2011; Van Dolen, Dabholkar, and De Ruyter 2007). Our second research question addresses whether consumer response to firm engagement differs depending on the type of conversation we observe:

RQ_2: Does consumer reaction to active firm engagement differ with the type of online conversation?

Finally, recent work in social media participation has highlighted the role of consumer characteristics and the differing reactions of various consumer segments to firms' social media initiatives (Chen and Xie 2008; Godes and Mayzlin 2009; Rishika et al. 2013). Our analysis targeting our third research question explores the effects of active firm engagement for two consumer segments. The first segment comprises consumers particularly interested in product-related support (in our empirical setting, "home improvement"). Consumers in this segment likely approach an online forum to talk about problems and expect information for problem solving and technical advice. Here, the potential value provided by active firm engagement might be comparably high owing to product-specific technical knowledge offered by firm experts. However, consumers in

[1]Not many studies have covered and found empirical patterns over multiple firms. Notable exceptions are Netzer et al. (2012) and Tirunillai and Tellis (2012, 2014), neither of which study (or intend to study) an online community setting.

[2]For example, prior research has exploited user-generated content with unsupervised techniques over different markets (Netzer et al. 2012; Tirunillai and Tellis 2014). Because specific jargon is less apparent in these settings, being able to analyze larger data sets with these techniques outweighs the potential loss in accuracy.

[3]Web Appendix A provides selected studies showing associations between machine-generated sentiment and corporate performance over a variety of settings.

[4]Subsequently, we refer to consumers who use the online community as either "community members" or simply "users" and refer to the group of firm moderators as either "firm moderators" or "firm representatives."

this segment are likely to contact company representatives with more severe problems and may raise more complaints.

The second segment comprises consumers looking for inspiration for new ways to use products, such as in art or creative work (in our empirical setting, "home decoration"). Here, consumers predominantly look for inspiration and entertainment—in which product-specific expert knowledge is less critical—and might be satisfied with talking to other forum users. In general, they would have lower expectations of firm representatives.

How these two segments react to active firm engagement is an open empirical question. An analysis can therefore contribute to recent literature proposing a "fit" between firm postings in an online forum originally designed for product-related support and the forum's targeted consumer segments (Miller and Tucker 2013), raising the following research question:

> RQ_3: Do consumer reactions to active firm engagement differ between consumer segments with different interests?

We examine these questions using 11 independent samples drawn from ten online forums (including a field experiment), and we generate online forum–tailored sentiment measures over a total of approximately 115,000 consumer posts. In addressing RQ_1, we find that consumers show diminishing returns to progressively more firm engagement, which at very high levels may even undermine consumer sentiment in some cases. In addressing the second and third research questions, we separate posts on the basis of the conversational topic as well as consumer interests. Results for RQ_2 reveal that the relationship between firm engagement and consumer sentiment is primarily apparent for topics on which firms provide consumers with product-related information (functional engagement), but not for topics that focus on social needs (social engagement). Finally, for RQ_3, the results show diminishing returns to firm engagement for consumers primarily interested in product-related support but provide no evidence of a relationship for consumers primarily interested in inspiration and entertainment. Although the underlying data structure does not allow us to make causal claims, these findings provide insights for marketing performance measurement and resource allocation in online communities providing active consumer support (Miller and Tucker 2013).

RESEARCH SETTING AND MODEL

Online Community Data Sets

Our two samples comprised data from two online settings. For sample 1, we used two data sets from the online forum of a firm-sponsored online community targeting do-it-yourselfers. For sample 2, we obtained nine data sets from an online platform consisting of travel-related forums. All data sets are independent, with each set referring to only a single firm. No formalized overlap exists of firm moderators engaging in several communities or of user posts showing up in several of our communities simultaneously. We treat all data sets as independent. In our main analyses, we pool the data on the industry level (i.e., do-it-yourself, airline, and hotel) and over all firms for different analyses.

All online forums consist of several threads, each covering a specific topic. Consumers can either respond to a post from another user or stimulate a new series of posts by opening a thread under a new, self-chosen topic. The thread's title indicates the overall topic of discussion and is followed by the first message within that topic. Subsequent posts consist of the posting's date and time and the text of the respective message. For all data sets, all moderator engagement is fully transparent to all users, as firm representatives' posts either carry special signs or make references within the post indicating that the person posting is part of the firm-sponsored moderator team (for an example, see Web Appendix B).

Samples 1 and 2 differ in the availability of data. Sample 1 consists of two data sets from a large do-it-yourself company. The baseline data set ("do-it-yourself baseline") includes threads and posts of the firm's online community forum for a period of 12 months. To strengthen the internal validity of our findings, we also ran a field experiment in close cooperation with the firm, operating the respective online community for a period of three weeks ("do-it-yourself field experiment"). The experimental period took place after we had extracted the baseline data set. No time or data overlap exists between the two data sets.

In the field experiment with the do-it-yourself firm, we randomized firm engagement on the thread level. We encouraged firm representatives to provide high engagement in threads that had opened at odd hours (e.g., 11:20 A.M.) and to supply low engagement in threads that had opened at even hours (e.g., 4:40 P.M.). We analyzed descriptive statistics after the three-week period and, as expected, found significant differences in consumer engagement for high-firm-engagement and low-firm-engagement threads ($p < .001$).

Sample 2 contains nine firm data sets drawn from travel-related online forums. We chose the airline and hotel industries because they allow both within- and between-industry comparison of firms and show a pattern of conversation types similar to that of our do-it-yourself firm. Each firm pursues an active, transparent engagement strategy. The key distinction of sample 1 is the absence of user data offered during the registration process, such as the consumer's primary interests.

Consumer Sentiment Analysis (Dependent Variable)

To generate our main dependent variable, consumer sentiment, we employed supervised sentiment analysis to determine the positivity of the statement in each online post (Pang and Lee 2008). Whereas unsupervised approaches use external input such as lexicons to classify text messages, supervised approaches use machine-learning techniques that require training data as input (Pang, Lee, and Vaithyanathan 2002).

To perform the sentiment classification, we carried out several steps. First, we preprocessed the data to remove all HTML tags, numbers, single alphabetic characters, and special symbols, and we lowercased the text to ensure equal treatment of all words. We also deleted all quotes referring to previous posts and replaced specific tokens, such as emoticons, with placeholders if the tokens were relevant for sentiment extraction (Dave, Lawrence, and Pennock 2003). Second, we generated separate training data sets for each of our 11 samples by randomly selecting posts from the samples and manually preclassifying these posts as positive and negative. Only unambiguous posts were included in the training data sets, and all training data sets consisted of the same number of positive and negative posts (Durant and Smith 2006; for illustrative examples, see Web Appendix

C). In a third step, we created separate lists for each sample with all words and their number of occurrences in the respective training data sets. Using different thresholds, we then removed very rare terms from the word lists. To be included in the various word lists of a sample, words had to appear more often than the respective threshold—for example, two times if the threshold was one (Dave, Lawrence, and Pennock 2003; Nicholls and Song 2010). In the last step, using different score values for the various word lists of a sample, we classified the remaining words as either positive or negative and removed any words that were not clearly positive or negative (Nicholls and Song 2010).

$$\text{Score}_{\text{absolute}}(\text{w}) = \frac{\text{n}_{\text{pos}}(\text{w}) - \text{n}_{\text{neg}}(\text{w})}{\text{n}_{\text{pos}}(\text{w}) + \text{n}_{\text{neg}}(\text{w})}. \quad (1)$$

The numerator measures the difference between the absolute frequency of a word (w) in positive posts and the absolute frequency of a word (w) in negative posts of a training data set. The denominator measures the absolute frequency of a word (w) within both negative and positive posts. The value of this fraction lies between (–1) and (+1). The closer this fraction is to (+1), the more often a word occurs in positive posts; the closer it is to (–1), the more often a word occurs in negative posts. Accordingly, the closer this fraction is to either (+1) or (–1), the better suited the word is to discriminate between positive and negative posts, respectively. Words with score values greater than the threshold value (+r) are considered positive, while words with score values smaller than (–r) are considered negative. Depending on the choice of r, the word-selection process results in different word lists, with higher values for r making the selection more restrictive and the resulting word lists shorter.

A drawback of this process is that it requires an equal or nearly equal number of words within both the positive and negative posts (Nicholls and Song 2010). Therefore, we use relative rather than absolute frequencies of words (Dave, Lawrence, and Pennock 2003). The adjusted Formula 2 is as follows:

$$\text{Score}_{\text{relative}}(\text{w}) = \frac{\frac{\text{n}_{\text{pos}}(\text{w})}{\text{n}_{\text{pos}}} - \frac{\text{n}_{\text{neg}}(\text{w})}{\text{n}_{\text{neg}}}}{\frac{\text{n}_{\text{pos}}(\text{w})}{\text{n}_{\text{pos}}} + \frac{\text{n}_{\text{neg}}(\text{w})}{\text{n}_{\text{neg}}}}. \quad (2)$$

Both inputs restricting the selected word list are naturally the result of the researcher's choice. To find the final word list that resulted in the highest classification accuracy, we varied the threshold from 0 to 10 and used ratios of .5, .33, .25, and .2. For each training data set, this process yielded 44 word lists of varying sizes, which were used for vector generation as input for the machine-learning algorithm.

In our analysis, we used a support vector machine (SVM) algorithm[5] because SVMs are well accepted for many classification tasks and yield more accurate results than most other classifier algorithms (Cui and Curry 2005; Deng, Tian, and Zhang 2012; Pang, Lee, and Vaithyanathan 2002; Vohra and Teraiya 2013; for a formal description, see Web Appendix D). We built the SVM classifier models using stratified tenfold cross-validation. First, each training data set was divided randomly into ten parts of equal size. Second, for each training data set, training was performed on the first nine samples. Third, the estimated model was used to classify the posts of the tenth sample (the holdout sample). We compared the results with the manual classification and calculated the error rate using the tenth set. This learning process was executed ten times (with every part of the training sample serving as a holdout sample once), and classification accuracy was calculated over these ten iterations (Witten, Frank, and Hall 2011).

This process was performed separately for each training data set and word-list configuration. For the best-performing word-list configurations, we further assessed their performance on separate validation data sets. For each data set, we manually coded additional subsamples not used for training and calculated classification accuracies on these validation samples. Using the results achieved on training and validation, we chose the best-performing classifier model for each data set. Web Appendix E reports resulting accuracies. We applied that model to the remaining sample of unclassified posts to estimate their sentiment.

Finally, all user posts of the sample (apart from the posts in the training set) were assigned the sentiment probability calculation on the basis of the best-performing model. We measured the degree to which a post was positive by the probability of a post being positive.[6] Accordingly, consumer sentiment is the probability of a post being positive on a continuous scale from 0 to 1. In measuring the valence of posts, we refer to this probability as the degree of positivity.

Empirical Identification Strategy

Our field setting is characterized by potential self-selection and endogeneity, which we attempt to mitigate through several approaches. First, differences in sentiment can occur as various user types self-select into clear-cut threads addressing specific topics. Moreover, threads can show different levels of sentiment depending on the topic or problems being discussed. We attempt to address both issues by including fixed effects for threads and users. Our main specification analyzes whether firm engagement is associated with consumer sentiment beyond thread- or user-specific influences as a within-thread and within-user response. Thus, we control for the mean sentiment per thread (i.e., topic-specific influences on sentiment) and for the mean sentiment per user (i.e., the consumer's specific influence on sentiment).

Second, the problem or pleasant event being discussed within a thread likely influences consumer sentiment on the one hand and firm engagement behavior on the other hand. We control for this influence by using several control variables. We include the sentiment value of the previous consumer post as a control variable; our reasoning is that a (non)problematic discussion likely affects the writer of the

[5]We used the Weka machine-learning software version 3.6.6, which implements the sequential minimal optimization algorithm for training a support vector classifier developed by Platt (1999) and advanced by Keerthi et al. (2001).

[6]We thank an anonymous reviewer for clarification. We relied on a continuous scale to exploit all available information. Therefore, we performed the SVM algorithm with the fitting of a logistic model to obtain probability estimates (Witten, Frank, and Hall 2011).

previous post (positively) negatively and therefore adjusts to some extent for the atmosphere around a consumer post. That is, if consumer 1 starts a series of negative posts dealing with a critical issue, the response of consumer 2 to moderator engagement is likely influenced by the sentiment of consumer 1. Moreover, we control for the promptness of the firm moderator's reaction after a consumer post and take this measure as a control for the severity of a problem for this particular consumer post. Note that this variable does not capture whether a consumer values a speedy moderator response, as this reaction time is unknown to the consumer when posting an issue. In addition, longer threads often deal with more problematic topics that cannot be handled quickly, and therefore, longer threads may show higher levels of firm engagement. By using a relative rather than an absolute engagement measure, we ensure that our results are not driven by thread size per se. A relative measure also adjusts for the position of firm intervention within a thread by using the number of previous user posts as a scaling variable.

Third, moderator engagement is likely to be at least partly endogenous and influenced either by previous postings in a thread or by the anticipation of quantity, content, and sentiment of future consumer posts. We therefore conducted a field experiment with our cooperating do-it-yourself firm (sample 1), in which online forum moderators were encouraged to post only in a randomized subsample of threads. We encouraged firm representatives to be highly engaged in threads that had opened at odd hours (e.g., 11:20 A.M.) and to be only slightly engaged in threads that had opened at even hours (e.g., 4:40 P.M.). In addition, after the experiment, we checked whether firm moderators had replaced quantity of responses with higher-quality responses. Using a manual coding of moderators' post quality in both treatments, we found no substantial differences ($p = .94$). In this way, reaction or anticipation effects of firm moderators can be excluded to some extent, in that differences between low and high engagement are randomized by design. Although each of our approaches can reduce the potential empirical biases to a degree, our results do not allow us to make causal statements. Rather, they represent a set of associations to shed some light on our three research questions.

Measurement of Independent Variables

Relative firm engagement. Because we wanted to assess the relationship of active firm engagement with consumer sentiment, we had to generate a variable that measures the firm's online interaction in consumer-to-consumer conversations. We define a firm intervention as a post written by a firm representative. Thus, absolute firm engagement on the post level is the number of posts firm representatives made in a thread before a given user post was written. To allow for a comparison between firms and threads and between different stages within a thread, our main variable relative firm engagement is the total number of posts firm representatives have made within a single thread, divided by all previous consumer posts in that thread. Because we can randomize absolute but not relative engagement (the scaling variable thread length is mainly driven by user posting activity), we present the field experiment results for absolute engagement measures and show their robustness for relative engagement measures in Web Appendix F.

Control variables. As our identification strategy indicates, we control for characteristics of the post itself as well as for the communication environment, the response time of the moderators, and the unobserved heterogeneity on the thread, user, and time level. On the post level, we control for the length of the posts (post length), which is measured by the number of words and other relevant characters, such as emoticons, within each post (Das and Chen 2007). The communication evironment is proxied by the sentiment of each previous post within the thread (sentiment previous post), losing the first user post in each thread for analysis (Moe and Trusov 2011). Finally, we capture moderator response time by the time lag between moderator and most recent user post (moderator response quickness). Our measure is the natural logarithm of the time lag between moderator and most recent user post multiplied by (–1). For user posts without any follow-up moderator engagement, we used the maximum response time of the respective thread to retain those observations. For threads without any moderator engagement, we used the maximum response time for the full data set.[7] We employed fixed effects for the respective thread (thread fixed effects), the respective user (user fixed effects), and the respective month to control for seasonality effects, such as summertime or the Christmas season (time fixed effects). In case the data spanned more than one year, we controlled for the respective calendar year. Notably, the scaling of our main independent variable, relative firm engagement, adjusts for the position of the post within a certain thread.

Thread categorization. To assess differences in firm engagement between conversations satisfying social versus functional needs, we classified all threads in all data sets into these two categories. Two people independently categorized the threads, settling all disagreements by discussion. The social thread category (subgroup social) contains conversations that help create and sustain social ties among community members as well as between community members and the respective firm without having a direct relationship to the purchase or consumption of the firm's products (McAlexander, Schouten, and Koenig 2002). The second category (subgroup functional) relates to the consumption of the firm's products or services. Typically, this category includes discussions about purchase- or consumption-related aspects of the firm and its offerings, such as conversations about forthcoming special promotions or the optimal use of the firm's products as well as the sharing of product- or firm-related experiences, including complaints. Here, firm representatives directly answer questions or respond to complaints (Mathwick 2002; Nambisan and Watt 2011).

Consumer segments. To assess differences by consumer interests, we relied on the fact that community users of the do-it-yourself firm classified themselves during initial registration. Two check boxes enabled users to designate themselves as having either a particular interest in do-it-yourself core activities such as renovating, repairing, and maintenance or a particular focus on decoration, art, or creative work. We label the first segment "home improvement" and the second segment "home decoration." We considered only

[7]We believe the assumptions behind this approach are plausible because resulting values are associated with an extremely slow response time, which is equivalent to the idea of no moderator response.

users that could be clearly assigned to one group or to neither of those groups (the latter represent only 5% of observations). These categories, which are available solely for the do-it-yourself data set, offer the opportunity to examine whether and how self-classified customer segments react differently to firm engagement.

Final Data Sets and Descriptive Statistics

For the final data set, we required values for all relevant control variables and eliminated all posts used for data training. The mean value of consumer sentiment for sample 1 is similar for both data sets, with .467 (do-it-yourself baseline data set) and .446 (do-it-yourself field experiment). Relative engagement is, on average, .078 posts per user and thread in the do-it-yourself baseline data set and .040 in the do-it-yourself field experiment data set. Approximately 17% of the threads of the do-it-yourself baseline data set belong to the social subgroup, and 83% of the threads belong to the functional subgroup (do-it-yourself field experiment: 18% and 82%, respectively). The mean value of consumer sentiment for sample 2 ranges from .211 to .525 for the airline and hotel data sets. Relative engagement ranges from .010 to .090 firm posts per previous user posts. Furthermore, much like our do-it-yourself data, airline and hotel data consist mainly of functional threads, with an average of 88% of threads being categorized as belonging to the functional subgroup and an average of 12% of threads being categorized as belonging to the social subgroup. We provide a comprehensive overview of descriptive statistics for the final sample as well as correlations in Web Appendices G–I.

EMPIRICAL ANALYSES AND RESULTS

Econometric Approach and Functional Form

As we have previously described, we measured the sentiment of each post. The resulting variable of interest, consumer sentiment, is bounded by 0 and 1, with higher values being interpreted as reflecting a higher degree of positivity of the respective post. To fully exploit the information content of our sentiment variable, we estimated our model using quasi-maximum likelihood (Papke and Wooldridge 1996). This approach was developed for fractional dependent variables such as market shares, pension plan participation rates, export sales ratios, and store choice probabilities, which, like consumer sentiment, are all bounded by 0 and 1 (Haans and Gijsbrechts 2010; Papke and Wooldridge 2008).

All three research questions address how consumers react to firm engagement in an active online community and allow for several potential functional forms of response. We therefore specify a linear model as a baseline model, as shown in Equation 3. As an alternative to this linear model, we specify two nonlinear models: a squared (level) model including a squared term for testing a U-shaped relationship (Equation 4) and a logarithmic model in which we take the natural logarithm of firm engagement to test for diminishing (but still positive) returns (Equation 5).[8] In summary, we ran the following econometric models on the post level i:

$$(3)\ E(\text{Consumer Sentiment}_i \mid x) = F(\alpha + \beta \times \text{Relative Firm Engagement}_i + \theta \times \text{Sentiment Previous Post}_i + \vartheta \times \text{Moderator Response Quickness}_i + \mu \times \text{Post Length}_i + \Sigma_k\rho_k \times \text{Thread}_k + \Sigma_l\sigma_l \times \text{User}_l + \Sigma_m\tau_m \times \text{Time}_m),$$

$$(4)\ E(\text{Consumer Sentiment}_i \mid x) = F(\alpha + \beta \times \text{Relative Firm Engagement}_i + \gamma \times \text{Relative Firm Engagement}_i^2 + \theta \times \text{Sentiment Previous Post}_i + \vartheta \times \text{Moderator Response Quickness}_i + \mu \times \text{Post Length}_i + \Sigma_k\rho_k \times \text{Thread}_k + \Sigma_l\sigma_l \times \text{User}_l + \Sigma_m\tau_m \times \text{Time}_m), \text{ and}$$

$$(5)\ E(\text{Consumer Sentiment}_i \mid x) = F(\alpha + \beta \times \text{LOG}(\text{Relative Firm Engagement}_i) + \theta \times \text{Sentiment Previous Post}_i + \vartheta \times \text{Moderator Response Quickness}_i + \mu \times \text{Post Length}_i + \Sigma_k\rho_k \times \text{Thread}_k + \Sigma_l\sigma_l \times \text{User}_l + \Sigma_m\tau_m \times \text{Time}_m),$$

where F(·) is specified as a logistic function and controls are post length, sentiment previous post, moderator response quickness, and fixed effects for user, thread, and time on the post level. LOG is the natural logarithm. We cluster standard errors on the thread level (Arellano 1987; Petersen 2009; Wooldridge 2010).

To investigate RQ_1, we applied these three models to four samples: the do-it-yourself baseline data set, the do-it-yourself field experiment, a pooled data set for all airline data, and a pooled data set for all hotel data. To investigate RQ_2, we pooled all data sets and split our sample into two subgroups according to the social–functional classification scheme described previously. Finally, for analyzing RQ_3, we relied on available data in the do-it-yourself baseline data set.[9] Web Appendices J and K show the disaggregated results for individual firms, which, throughout all samples and subgroups, are consistent with those presented in Tables 1, 2, and 3.

Empirical Results for RQ_1

In posing RQ_1, we wanted to examine how consumers react to active firm engagement in an online community. Figure 1 shows for all three firm types the plots of relative firm engagement and a consumer sentiment index adjusted for fixed effects and control variables. The trend is similar over all settings and shows diminishing returns with respect to increasing firm engagement. These results are consistent

[8]To retain observations with a relative engagement of zero and allow for a model comparison by log-likelihood and Akaike information criterion (AIC), we replaced zero observations with the lowest positive value in the data of .0000001 (Kennedy 2013, p. 104).

[9]We thank the associate editor for making the suggestion of using pooled data for the main analyses.

Table 1

FIRM ENGAGEMENT AND CONSUMER SENTIMENT

Data Set	*Do-It-Yourself Baseline Data Set (One Firm)*			*Do-It-Yourself Field Experiment (One Firm)*			*Airlines (Five Firms)*			*Hotels (Four Firms)*		
Dependent variable	*Consumer Sentiment*			*Consumer Sentiment*			*Consumer Sentiment*			*Consumer Sentiment*		
Independent variable	*Relative Firm Engagement*			*Absolute Firm Engagement*			*Relative Firm Engagement*			*Relative Firm Engagement*		
	(1)	*(2)*	*(3)*	*(1)*	*(2)*	*(3)*	*(1)*	*(2)*	*(3)*	*(1)*	*(2)*	*(3)*
Firm engagement	.474**	1.206**		–.006	.137*		1.856***	4.077***		1.000***	2.250***	
	(.001)	(.001)		(.798)	(.039)		(.000)	(.000)		(.000)	(.000)	
Firm engagement^2		–.803*			–.018*			–3.034***			–1.677***	
		(.018)			(.013)			(.000)			(.000)	
Log(firm engagement)			.013**			.082			.017***			.012***
			(.002)			(.290)			(.000)			(.000)
Sentiment previous post	–.012	–.013	–.012	.093	.090	.091	.110***	.106***	.117***	.037	.037	.039
	(.724)	(.706)	(.728)	(.193)	(.208)	(.204)	(.000)	(.000)	(.000)	(.122)	(.131)	(.107)
Moderator response quickness	–.016	–.014	–.015	.017	.017	.018	.006	.006	.006	.034	.035	.034
	(.181)	(.241)	(.198)	(.476)	(.477)	(.449)	(.615)	(.640)	(.630)	(.427)	(.415)	(.425)
Post length	–.327***	–.328***	–.327***	–.928***	–.931***	–.927***	–.484***	–.484***	–.487***	–.386***	–.387***	–.388***
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Thread fixed effect	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
User fixed effect	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Time fixed effect	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Log-likelihood	–14,227.789	–14,225.764	–14,227.536	–2,731.821	–2,730.304	–2,731.596	–24,084.967	–24,070.252	–24,098.837	–21,097.915	–21,090.813	–21,101.565
AIC	1.133	1.132	1.133	.897	.896	.896	1.056	1.056	1.057	1.151	1.150	1.151
Size (n)	26,298	26,298	26,298	6,551	6,551	6,551	46,713	46,713	46,713	38,204	38,204	38,204

*$p < .05$.
**$p < .01$.
***$p < .001$.

Notes: Two-tailed tests of significance. Dependent variable is consumer sentiment in all regressions. The field experiment with absolute firm engagement as main independent variable also includes a fixed effect for the respective position of the post in a thread. Results for the field experiment with relative firm engagement appear in Web Appendix F. A constant term is included in all estimations but is not shown. All standard errors are clustered at the thread level.

Table 2

FIRM ENGAGEMENT AND CONSUMER SENTIMENT BY THREAD TYPE

Data set: pooled data (all firms)
Dependent variable: consumer sentiment
Independent variable: relative firm engagement

Thread Type	*Functional*			*Social*		
	(1)	*(2)*	*(3)*	*(1)*	*(2)*	*(3)*
Firm engagement	1.082***	2.589***		.341	1.086	
	(.000)	(.000)		(.155)	(.064)	
Firm engagement^2		–1.865***			–.891	
		(.000)			(.117)	
Log(firm engagement)			.016***			.003
			(.000)			(.460)
Sentiment previous post	.043*	.041*	.045**	.127***	.127***	.128***
	(.012)	(.018)	(.008)	(.000)	(.000)	(.000)
Moderator response quickness	.008	.010	.006	–.003	–.003	–.003
	(.516)	(.410)	(.600)	(.824)	(.854)	(.824)
Post length	–.447***	–.447***	–.449***	–.362***	–.363***	–.362***
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Thread fixed effect	Included	Included	Included	Included	Included	Included
User fixed effect	Included	Included	Included	Included	Included	Included
Time fixed effect	Included	Included	Included	Included	Included	Included
Log-likelihood	–48,767.206	–48,743.335	–48,773.568	–14,386.728	–14,385.870	–14,387.202
AIC	1.127	1.126	1.124	1.067	1.067	1.067
Size (n)	90,121	90,121	90,121	27,567	27,567	27,567

*$p < .05$.
**$p < .01$.
***$p < .001$.
Notes: Two-tailed tests of significance. Dependent variable is consumer sentiment in all regressions. A constant term is included in all estimations but is not shown. Sample size slightly differs from Table 1 due to the deletion of some observations in the relative firm engagement sample for the do-it-yourself field experiment (Web Appendix H). All standard errors are clustered at the thread level.

Table 3

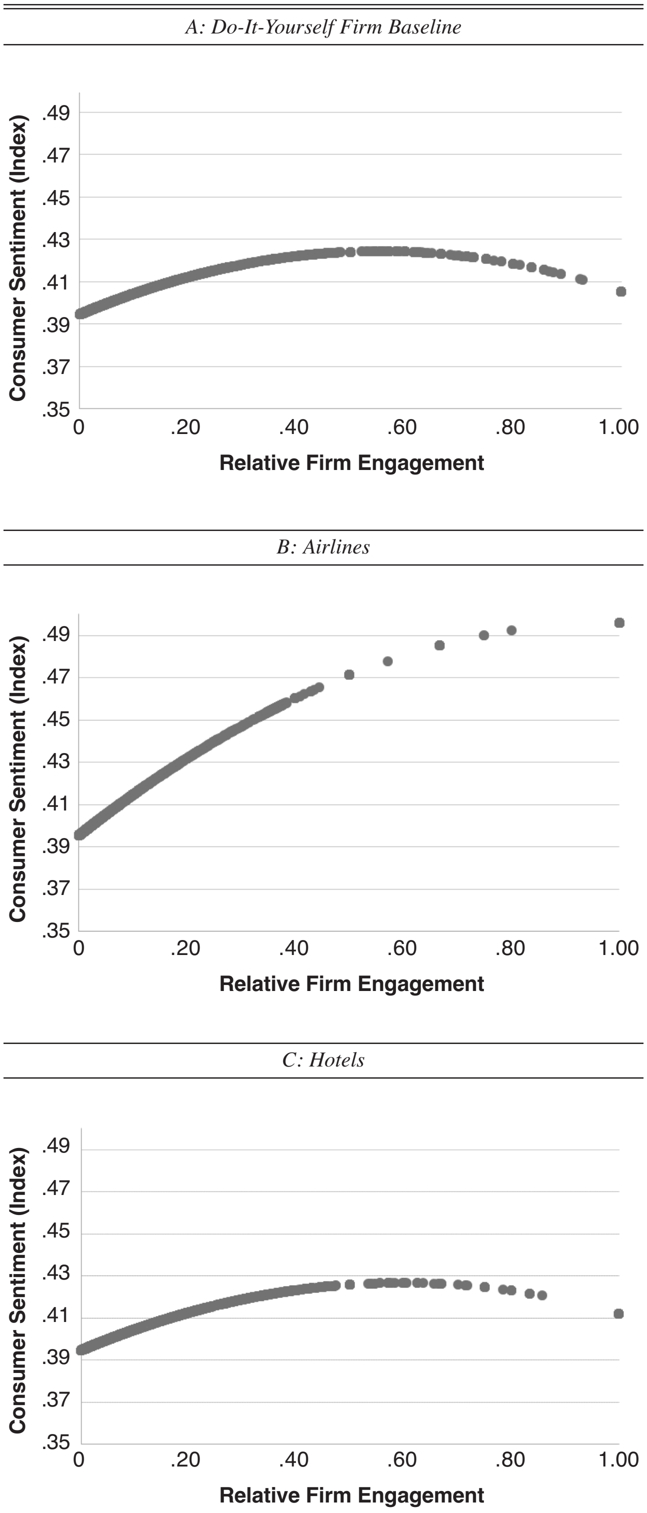
FIRM ENGAGEMENT AND CONSUMER SENTIMENT BY CONSUMER INTEREST

Data set: pooled data (all firms)
Dependent variable: consumer sentiment
Independent variable: relative firm engagement

User Segment Type	*Home Decoration*			*Home Improvement*		
	(1)	*(2)*	*(3)*	*(1)*	*(2)*	*(3)*
Firm engagement	.941	–.369		.418	1.577**	
	(.216)	(.837)		(.071)	(.003)	
Firm engagement^2		1.444			–1.292*	
		(.484)			(.016)	
Log(firm engagement)			.001			.018**
			(.962)			(.002)
Sentiment previous post	.147	.148	.150	–.050	–.053	–.051
	(.067)	(.066)	(.063)	(.257)	(.240)	(.255)
Moderator response quickness	–.041	–.039	–.041	–.034*	–.030	–.033*
	(.054)	(.072)	(.055)	(.038)	(.063)	(.046)
Post length	–.177***	–.177***	–.175***	–.407***	–.407***	–.407***
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Thread fixed effect	Included	Included	Included	Included	Included	Included
User fixed effect	Included	Included	Included	Included	Included	Included
Time fixed effect	Included	Included	Included	Included	Included	Included
Log-likelihood	–1,973.954	–1,973.717	–1,974.596	–6,075.326	–6,073.335	–6,072.727
AIC	1.177	1.179	1.180	1.131	1.129	1.133
Size (n)	3,673	3,673	3,673	11,629	11,629	11,629

*$p < .05$.
**$p < .01$.
***$p < .001$.
Notes: Two-tailed tests of significance. Dependent variable is consumer sentiment. A constant term is included in all estimations but is not shown. Net sample size refers only to consumers who self-classified into one or neither of the groups. All standard errors are clustered at the thread level.

Figure 1
FIRM ENGAGEMENT AND CONSUMER SENTIMENT



Notes: The vertical axis does not show the raw values of consumer sentiment but rather an indexed value adjusted by thread and user fixed effects and further control variables. Index ranges from .35 to .50 for comparison purposes. The horizontal axis shows relative firm engagement in raw values.

with the ones shown in Table 1. The returns for relative firm engagement on consumer sentiment are positive but diminish with respect to increasing firm engagement. Because we can randomize absolute but not relative engagement (the scaling variable thread length is mainly driven by user posting activity), here we present the field experiment results for absolute engagement measures, which show a very similar empirical pattern (the corresponding figure and results for the field experiment for relative firm engagement appear in Web Appendix F).

As Table 1 shows, model fit, indicated by lower log-likelihood and AIC values, is slightly better for nonlinear models of response than for linear models (Kieschnick and McCullough 2003). Moreover, an inverted U-shaped functional form slightly dominates a logarithmic one, as indicated by lower log-likelihood ratios and partly lower AIC values. Here, the pattern of results suggests that a decrease in consumer sentiment is (only) prevalent for exceptionally high levels of firm engagement. However, the differences between both the inverted U-shaped and the logarithmic equation specifications are minor and preclude strong conclusions about the specific character of the functional form between relative firm engagement and consumer sentiment.

Control variables often show an expected sign and are partly significant. In three of four cases, the sentiment of the previous post is positively related to consumer sentiment (although in two of those three cases, not significantly), which supports the assumption that this variable can proxy for the discussion environment around a post. Moderator response quickness is not substantially related to consumer sentiment. Post length is negatively related to our dependent variable, indicating that negative posts have significantly more words than positive ones.

Empirical Results for RQ_2

To further investigate whether the underlying topic influences the association between firm engagement and consumer sentiment, we split our sample into two subgroups according to the social–functional classification scheme described previously. We estimated all three models of the previous section for these two subgroups.

Table 2 shows the regression results for both samples split by subgroup. Remarkably, we do not find a significant association for the social subgroup but observe the relationship indicating diminishing returns for functional subgroups. Although this “nonfinding” does not equate with a conclusion that no relationship exists between firm engagement and consumer sentiment, it is nevertheless noteworthy given unconditional statements in the literature and public press that firms should actively and specifically address consumers’ social needs (e.g., Schau, Muñiz, and Arnould 2009). A caveat emerges with respect to the analyzed number of observations, which is smaller than in the functional thread group, though there should be sufficient statistical power to detect significant associations.

Regarding the functional subgroup category, the results resemble our findings from our analysis of RQ_1. In functional threads, the association between firm engagement and consumer sentiment is positive but shows diminishing returns with increasing firm engagement. Again, the range of AIC values as a criterion is very narrow and does not allow for strong conclusions regarding a dominant functional nonlinear form. Overall, the association between firm engagement and resulting consumer sentiment seems to be especially prevalent for functional conversations.

Empirical Results for RQ_3

RQ_3 refers to potential differences between consumer segments for the do-it-yourself firm. We split the data set into two groups as determined by consumers' self-classification in the registration process. Approximately 72% of the analyzed users were interested in core do-it-yourself activities ("home improvement"), and the remaining users were primarily interested in creative work ("home decoration"; 23%) or had no specific interests (5%). For the first subgroup, the results are consistent with evidence provided previously. Here, the pattern of results documented in Table 3 suggests diminishing returns with increasing firm engagement. For the second group, we find the coefficient for firm engagement to be not significant ($p > .05$) in each of the three models. Together, these results seem to imply that active firm engagement can provide value for consumers if the type and topic of conversation (e.g., functionally oriented product support) matches the core value contribution of an online community that was originally designed for product-related support, technical problem solving, and complaint management.

Additional Analyses and Robustness Checks

We applied several additional analyses and robustness checks, which we outline in the following subsections. Web Appendices L–O more extensively document the results.

Quality of firm engagement: field data. We manually coded all posts written by firm moderators to evaluate their quality level. We used these ratings to evaluate (1) whether higher engagement is negatively related to post quality and (2) whether our results hold when controlling for this proxy of engagement quality. Two independent raters manually coded all 6,922 moderator posts over all data sets. Differences in coding were settled by discussion. We did not find a consistent significant negative association between relative firm engagement and engagement quality. Furthermore, for the subset of observations with positive firm engagement, we reran all baseline regressions and found consistent results.

Similarly, a potential concern for the field experiment is that firm moderators might substitute or complement the quantity of engagement with the quality of their postings' content in different treatments. For example, threads in the low-engagement group might contain moderator posts of higher quality. We conducted a robustness check by comparing whether our two experimental conditions differ in quality (i.e., whether firm moderators in the low-engagement treatment had fewer but higher quality responses compared to moderators in the high-engagement treatment group). As outlined in the "Empirical Identification Strategy" subsection, we found no substantial differences between the two treatment groups ($p = .94$).

Endogenous thread length. When firm moderators respond to problems raised by consumers, thread length is potentially endogenous and depends on whether a problem is easy to fix (i.e., short thread length) or deserves more attention and involves other consumers' participation in the discussion (i.e., long thread length). Thus, longer threads potentially entail greater firm engagement because more critical problems need more interventions from firm moderators. To some extent, we control for this sort of endogeneity in our field experiment with the thread fixed effect and our proxies for problem severity. As an additional check, we also compared consumer sentiment levels between small and large threads by slicing the data into five quintiles. The results show no significant differences between the first (second) and the fifth (fourth) quintiles in terms of consumer sentiment values, providing some evidence that thread length itself is not an exclusive explanation for our findings.

Alternative engagement measure. To this point, we have used relative firm engagement measures as the main independent variable. As an alternative, we reran the main analyses with the absolute unscaled number of posts by a firm representative within a single thread. Over all data sets, we found the relationships to be confirmed for absolute firm engagement measures as well.

Sentiment calculation. To check the stability of our results with respect to the machine-learning algorithm, we ran our regressions using different algorithms and different parameters t and r, representing different word lists (e.g., with different elimination criteria for rare words and different levels of discrimination between words considered as positive and negative). We used the do-it-yourself baseline data set for these stability tests. For all analyses based on these alternative algorithms, our results confirm the results of our main analyses.

Sample of last posts per thread. In another robustness check, we considered a subsample of posts. In particular, we restricted our analyses to the last available group of posts in each thread[10] on the assumption that these posts better represent a "mature" sentiment level in each thread and that consumers are better able to evaluate the ongoing discussion. Although this approach probably enhances the power of the empirical setting, it lowers statistical power and reduces the number of covariates that can be included to ensure model convergence. We therefore restricted this robustness check to a subset of firms, posts, and controls to ensure convergence of our models. In particular, we chose only firm data sets with at least 100 threads and selected the last four, six, or seven posts in each of these threads (depending on the firm and data structure). Overall, we find the same pattern of results as in our main analyses.

DISCUSSION AND CONCLUSION

Academic Discussion

In this article, we analyze how consumers react to active firm engagement in an online community setting. We contribute to the literature by employing a supervised approach for sentiment analysis to generate our performance measure of consumer sentiment (Pang, Lee, and Vaithyanathan 2002;

[10]In online forums, each user can contribute to old threads. Therefore, the last posts we analyzed represent the last posts in these threads only at the time we extracted the data.

Tirunillai and Tellis 2012). Applying this consumer sentiment measure, we analyze the association between active firm engagement and consumer sentiment on average, depending on the type of conversation and the type of consumer interests.

Controlling for post-, user-, thread-, and time-specific influences, we find that consumers respond with diminishing returns to active firm engagement, which in some cases even undermines sentiment at very high levels of engagement. Further subgroup analyses by conversation type indicate that these relationships hold for conversations that address consumers' functional needs but do not hold for conversations that focus on social needs. Finally, results show diminishing returns to firm engagement for consumers who are primarily interested in product-related support and no relationship for consumers who are primarily interested in inspiration and entertainment.

Although we are cautious about generalizing our results to primarily socially oriented online platforms or offline marketing communication, these findings provide insights for marketing performance measurement and resource allocation in online communities. Moreover, they are consistent with recent contributions regarding companies' traditional relational communication with their customers. For example, studies examining offline types of customer–firm communication usually find diminishing returns to firms' communication efforts with regard to repurchases (Godfrey, Seiders, and Voss 2011), purchase frequency (Venkatesan and Kumar 2004), and purchase timing (Kumar, Venkatesan, and Reinartz 2008). Thus, our findings complement findings from the offline marketing relationship literature.

Moreover, we find that the underlying communication type seems to be especially relevant. Our findings with regard to consumers' functional needs, but not social needs, are to some extent contrary to recent marketing contributions based primarily on case-study evidence emphasizing the importance of addressing social needs in online communities (McAlexander, Schouten, and Koenig 2002; Schau, Muñiz, and Arnould 2009). However, two studies in the online environment support our results. Both studies involved the financial industry, which, like our settings, is characterized by mainly utilitarian products for which product-related advice and problem solving dominate. Here, consumers show more positive reactions to functional interactions (Köhler et al. 2011), and participants in an online chat prefer moderators who are task oriented rather than socially oriented (Van Dolen, Dabholkar, and De Ruyter 2007).

Finally, we also find differences between consumers with dissimilar interests who belong to different consumer segments. As with the underlying motive of the conversation, we find no substantial association for consumers who are primarily interested in inspiration and entertainment. A possible explanation for these results is that consumers seeking advice for home decoration mostly benefit from conversations with other consumers, whereas consumers looking for guidance for technical problem-solving benefit from conversations with firm representatives. Furthermore, self-selection is likely to explain those results because consumers interested in home decoration and creative work have a higher proportion of social conversations than functional conversations (43%) compared with consumers in do-it-yourself pursuits (36%). Thus, consumers interested in technical discussions likely self-select into more functional threads. These results are consistent with the view that active firm engagement can provide value for consumers if the type and topic of conversation matches the value contribution of the firm, which in our do-it-yourself firm setting is technical guidance and complaint handling (Miller and Tucker 2013).

Limitations and Avenues for Further Research

Our study is subject to several limitations. First, our data sets are dominated by functionally oriented conversations, and the firms in our study use these online forums mainly for addressing product- or service-related topics. Therefore, caution is warranted in generalizing our results to online settings in which the major communication motive is social interaction and consumers do not expect functional support from company moderators.

Second, fully addressing all potential endogeneity concerns is a difficult issue in a field setting such as ours. For example, greater firm engagement can be accompanied by severe problems that then influence the resulting consumer sentiment. Moreover, we cannot exclude the possibility that firm moderators anticipate consumer sentiment correctly and adjust the intensity or quality of their engagement, resulting in reverse causation and simultaneity. Moreover, self-selection problems are likely. These issues manifest in a choice by consumers to contribute to some discussions but not to others, which potentially drives their resulting response to firm intervention. We attempt to address those concerns through our field experiment and a rigorous set of controls. Still, endogeneity cannot be completely ruled out.

Third, we operationalize the degree of consumer sentiment by the probability that a post is positive. This operationalization is the consequence of performing the support vector machine algorithm with the fitting of a logistic model to get probability estimates. Although we acknowledge that a probability contains uncertainty whereas a degree does not, we believe that expectancy values of probabilities and degrees should not deviate systematically in large samples such as ours. Nevertheless, the literature will benefit from alternative sentiment algorithms that overcome these problems.

Fourth, this study focuses primarily on the intensity of firm engagement, a starting point that seems natural given the research approach of comparable studies in an offline setting (e.g., Kumar, Venkatesan, and Reinartz 2008). However, future studies could analyze the quality of firms' posts regarding the content and style of firm representatives' interaction (Van Dolen, Dabholkar, and De Ruyter 2007) or the role of trust in firm-engaged consumer-to-consumer conversations (Porter and Donthu 2008). Further research might evaluate the quality of firm posts from other perspectives such as those of key users or experts.

Managerial Issues

Our results raise several managerial issues, especially for firms running or participating in primarily functionally oriented online forums with an active engagement approach. Although the underlying data structure does not allow for making causal claims, these findings provide some insights for marketing performance measurement and resource allocation in online communities.

First, firms can rely on sentiment measures as a performance metric to assess the reactions to active firm engagement and to evaluate the success of marketing initiatives in online settings in a timely manner. This performance measure might be more closely related to online interventions than sales or stock returns, and feedback is potentially timelier. In particular, our results suggest that active firm engagement through firm representatives can be an effective marketing tool. Our subgroup analyses reveal that in specific settings such as ours, firms should be wary of allocating untargeted resources to all types of conversations. Study results suggest that if consumers view the online forum as primarily an environment for getting product-related advice and solutions for problem solving, firms should check whether they might be better off engaging in online conversations aimed mainly at satisfying consumers' functional needs (e.g., product-related forums, specialized blogs).

Second, a firm-owned online community differs from other social media in that firms acquire personal information about customers (e.g., in the registration process) and thus are able to segment customers. An efficient approach could be to target online engagement to specific customer types through market segmentation. As with approaches to offline marketing, resources could be allocated along the economic value of customers or their technical background instead of making an undifferentiated response to each forum community member. This allocation might result in differences in the timing of the response, the content of the response itself, and potentially the position and educational level of the firm moderator addressing the response.

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WEB APPENDIX

Measuring and Managing Consumer Sentiment in an Online Community Environment

Christian Homburg
Laura Ehm
Martin Artz

Online Appendix A

Selection of Empirical Studies on Consumer Sentiment (Valence) and Firm Performance

Authors (Year)	*Outlet*	*Data Source*	*Product Category*	*Performance Measure*
Chevalier and Mayzlin (2006)	*Journal of Marketing Research*	Amazon.com and BN.com	Books	Online sales ranks
Chintagunta, Gopinath, and Venkataraman (2010)	*Marketing Science*	Yahoo! Movies website	Movies	Opening-day revenue
Dellarocas, Zhang, and Awad (2007)	*Journal of Interactive Marketing*	Yahoo! Movies website	Movies	Box-office revenues
Duan, Gu, and Whinston (2008)	*Journal of Retailing*	Variety.com, movies.yahoo.com, boxofficemojo.com	Movies	Box-office revenues
Godes and Mayzlin (2004)	*Marketing Science*	Usenet newsgroups	TV shows	Household ratings
Gopinath, Thomas, and Krishnamurthi (2014)	*Marketing Science*	Howard Forums	Cellular Phones	Sales
Luo, Zhang, and Duan (2013)	*Information Systems Research*	Consumer ratings from CNET.com	No single category	Stock returns, idiosyncratic firm risk
Liu (2006)	*Journal of Marketing*	Yahoo! Movies website	Movies	Box-office revenues
McAlister, Sonnier, and Shively (2012)	*Marketing Letters*	Third party-collection of internet comments	Technical products	Stock returns
Onishi and Manchanda (2012)	*International Journal of Research in Marketing*	Dentsu Buzz Research Inc.	Movies, cell phone subscriptions	Sales volume
Sonnier, McAlister, and Rutz (2011)	*Marketing Science*	Third party-collection of internet comments	Technology firm	Revenues
Tirunillai and Tellis (2012)	*Marketing Science*	amazon.com, epinions.com, and Yahoo!Shopping	Electronics, consumer goods	Stock returns

Notes: Studies appear in alphabetical order by author and include only research contributions related to valence-related consumer sentiment measures. A more extensive list can be found in Floyd et al. (2014). Onishi and Manchanda (2012) further provide an overview including non-valence-related measures. Investor sentiment has been studied by Antweiler and Frank (2004) as well as by Das and Chen (2007).

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Online Appendix B

Illustrative Thread with Active Firm Engagement in the Do-it-yourself Baseline Dataset

Thread title: Circular table saw XYT-45 and dust extraction

User	*Date / Time of Posting*	*Text of Posting*
AndrewH	Jun 7, 20xx 7:19 p.m.	Hi there, I'm the new one and have a problem. Some time ago I bought the XYT-45 circular table saw and a dust extraction kit. The vacuum cleaner has a power of 1250 watts. Unfortunately, when sawing, more dust is generated than goes into the vacuum cleaner. The dust remains in the saw and part of it comes out on the front part of the table saw. The hose is properly connected to the saw. My answer from [*do-it-yourself firm*] about that problem was very disappointing. They just told me that it is very difficult to build a 100% dust collection attachment. I'm not talking about a little dust. It’s a lot of sawdust that I have to vacuum afterwards all the time. Any ideas how I can change that situation? Thanks in advance Andrew
DIYfan	Jun 7, 20xx 7:25 p.m.	Have you tested the suction hose to see that suction power is good? Is the bag or container empty? Have you looked at the saw to see if something might be in the way? Is there perhaps something like plugs or transport caps that need to be removed?
AndrewH	Jun 7, 20xx 7:29 p.m.	Yes the hose is free, it's all fixed, the vacuum cleaner works, it also happens with a new empty bag and there’s no cap or anything else
Timber07	Jun 7, 20xx 8:09 p.m.	I have a table saw from [*brand name*] and a vacuum cleaner from [*brand name*], both of them not exclusive brands, rather cheap versions. If I cut laminate, sawdust generation is actually quite low, so the vacuum cleaner is able to suck almost all of it up with the connection. Maybe the connection piece of the saw is a bit too big for the vacuum hose? I have that problem too, but it can be sealed with adhesive tape. Since I always seal it, the connection works properly as stated above
AndrewH	Jun 8, 20xx 4:26 p.m.	This is really great news and interesting. I'm gonna check all that you have written, but I am really angry that such an expensive part does not work properly. Best Andrew
DIYaddict77	Jun 10, 20xx 9:46 p.m.	Hi Andrew, your report is exactly my experience. I have already tried different vacuum cleaners, without effect! When I read that you should seal the connection with tape, then I ask myself: was it a bad buy? A no-name saw would have been the same. A short time ago, the locking screw for the slide stop broke, tape does not work here ... Also, I am disappointed with the precision of the saw. Regards

Timber07	Jun 11, 20xx 1:08 a.m.	For me, sealing with adhesive tape is only necessary at the hose of the vacuum cleaner. In the vacuum cleaner instructions it’s stated that the vacuum cleaner works with [*do-it-yourself firm*] circular table saws, but eventually a [*do-it-yourself firm*] vacuum cleaner would fit exactly: confused. In my case, the two different “brands” don’t fit together perfectly and if some 15-20cm of tape and 10 seconds are sufficient to seal the whole thing, then I would do that regardless of the consequences. ;)
SawyXYT	Jun 11, 20xx 1:17 p.m.	and that though the dust extraction attachment looks so useful :-(actually that calls for a revised version, because for me just the dust extraction would be a buy- or no-buy reason.
[*Do-it-yourself firm*]_ModeratorX	**Aug 3, 20xx 11:02 a.m.**	**Hi Andrew, the dust extraction will only suck out some of the dust. So far, there’s only a one-point connection to connect the saw with the dust extraction system, as there was no suitable adapter. The Y adapter (and a short hose) are coming. But at the moment I have no information about item number and delivery time. Please be patient just a little longer. Greetings [*do-it-yourself firm*]_ModeratorX**
AndrewH	Aug 5, 20xx 8:20 p.m.	Thank you [*do-it-yourself firm*]_ModeratorX. How do I know if there is something new? Best Andrew
DIYaddict77	Aug 5, 20xx 8:28 p.m.	Hopefully it will be possible to upgrade the “old” [*specific product*] (?) Regards
[*Do-it-yourself firm*]_ModeratorY	**Aug 6, 20xx 8:53 a.m.**	**[*do-it-yourself firm*]_ModeratorX will update you as soon as possible whether the new equipment is available, but you are invited to remind us from time to time if nothing comes up here ;=)**
Thomas	Jan 3, 20xx 3:59 p.m.	This week I have bought the machine at XXX, but the new accessories are still not available. Since Aug this seems to be a fairly long period of time ...
[*Do-it-yourself firm*]_ModeratorX	**Jan 3, 20xx 5:55 p.m.**	**Hi Andrew, I checked this. The Y adapter is apparently not yet available. Since I’ll be in the factory next week I'll ask there. Wednesday or Thursday, I will give you a heads-up on this. [*do-it-yourself firm*]_ModeratorX**
AndrewH	Jan 5, 20xx 6:16 p.m.	Hello [*do-it-yourself firm*]_ModeratorX, in advance a big THANK YOU, even though currently working with the machine is no fun. After each sawing there’s dirt on the floor and I think more dirt ends up on the floor than in the vacuum cleaner bag. In this price range I really had expected something else. But let’s wait and see what is still to come, in that sense, regards Andrew

Notes: Illustrative excerpt of a thread with active firm engagement. Fictional posts made by firm representatives are in bold.

Online Appendix C

Coding Examples from the Training Sample (Do-it-yourself)

Classification of Post	*Thread*	*User post*
Negative post	#1	"It's already mid of October and still you cannot buy the saw."
Negative post	#1	"Could it be that currently [*do-it-yourself firm*] has trouble introducing new products? It's weird – there is none of the anticipated autumn products on the market. Also the [*specific product*] is not in sight yet even if it is only mid-October. Do they have any bigger issues?"
Negative post	#2	"Hey guys. Just a few days ago I wanted to post a knowledge article. However your website messed up! The control and navigation is – if I may say so – absolutely stupidly set up. I have been working on a post for three hours until I decided to save it as a draft. All over a sudden I got ejected and logged off from the system even though I had ticked the 'stay logged on' box. The whole article was gone. Now just ask me whether I am mad about that…!"
Positive post	#3	Hello everyone, I registered just a few weeks ago but being rather shy I hold back writing so far. My name is [*user name*] and the big 50 is visible on the horizon… My interest in home improvement was revived last autumn when I helped one of my friends to build a wooden terrace with corner steps on a hillside. On this occasion my father in law taught me his 3-4-5 rule on how aligning the sub construction in the right angle to the garden house. During this time I came across your website. Since then, I regularly checked the page from time to time. It is very informative and I get a lot of new ideas and inspirations. Thanks a lot!
Positive post	#1	When the "accounting department" gets aware of my wish list they will probably hit the ceiling ;) Great device, the [*specific product*] is the most perfect completion to the [*specific product*]. It leaves almost no dreams open. Excellent product!
Positive post	#5	Great – Thanks!

Online Appendix D

Support Vector Machine Algorithm

Support vector machine (SVM) algorithms are widely used machine learning algorithms (Joachims 2002; Vapnik 1995). Based on the feature vectors of the training data (in our case the generated word vectors of the training posts) and the associated class label (in our case positive and negative), the SVM algorithm estimates a linear discriminant function that maximizes its own distance to the nearest feature vectors for each class: the so-called maximum margin hyperplane. The maximum margin hyperplane provides the greatest separation between these two classes and defines the maximum margin classifier that can be used to classify the rest of the data. The feature vectors nearest to the maximum margin hyperplane are the support vectors that uniquely define this function (Burges 1998; Deng, Tian, and Zhang 2012; Pang, Lee, and Vaithyanathan 2002; Witten, Frank, and Hall 2011). The use of kernel functions allows the SVM algorithm to find the maximum margin hyperplane in a transformed n-dimensional feature space and thus allows the SVM algorithm to solve nonlinear classification problems (for a detailed description, please refer to Burges 1998; Joachims 2002). Additionally, slack variables are used to allow for classification errors during classifier training (Cortes and Vapnik 1995).

More formally, let D = $\{(\mathbf{x}_1,y_1),(\mathbf{x}_2,y_2),\ldots,(\mathbf{x}_n,y_n)\}$ be the set of training data with $x_i=1,\ldots,n$, $\mathbf{x}_i \in R^n$ representing the feature vector of post i and $y_i \in \{-1,1\}$ the class label, with -1 indicating negative and +1 indicating positive polarity. For the nonlinear optimization problem, the SVM finds the optimal classification function of the form

(1) $$f(\boldsymbol{x}) = \sum_{i=1}^{N_s} \propto_i y_i K(\boldsymbol{s}_i, \boldsymbol{x}) + b$$

with $\mathbf{s}_i$ being the support vectors, N_s the number of support vectors, *K* the kernel function, b the bias (intercept) and α_i the Lagrange multiplicators by maximizing subject to constraints

(2) $$0 \leq \propto_i \leq C$$

(3) $$\sum_i \propto_i y_i = 0$$

where C is a parameter defining the slack variables that account for classification errors. The Lagrange multiplicators α_i reflect the chosen weights of the training vectors, thus defining the support vectors. Every specific choice of Lagrange multiplicators α_i constitutes a trained classificator that can be used on the remaining, unclassified data (Burges 1998). Subsequently, the fitting of a logistic model gives probability estimates for the classified posts (Witten, Frank, and Hall 2011).

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Online Appendix E

Classification Accuracies for Sentiment Estimation

Dataset	*Word List Configuration*		*Training Sample*	*Validation Sample*
	t*	r**	Classification Accuracy***	Classification Accuracy****
Do-it-yourself Baseline	1	0.5	91.1%	99.5%
Do-it-yourself Field Experiment	9	0.2	91.6%	84.0%
Airline 1	2	0.5	87.8%	86.0%
Airline 2	1	0.5	86.7%	76.7%
Airline 3	1	0.5	90.2%	85.6%
Airline 4	4	0.5	87.7%	82.5%
Airline 5	2	0.5	85.0%	90.0%
Hotel 1	2	0.5	95.8%	100%
Hotel 2	3	0.5	88.9%	90.0%
Hotel 3	0	0.5	85.2%	88.2%
Hotel 4	1	0.5	93.6%	86.0%

Notes:

*Words appearing less frequently than the threshold value t were removed from the word list.

** Words with score values ($Score_{relative}$) greater than the threshold value (+r) were kept and treated as positive, while words with score values smaller than (-r) were kept and treated as negative. All other words not fulfilling these criteria were removed from the word list.

***Stratified 10-fold cross-validation accuracy for the selected SVM classifier model. Classification accuracy indicates the percentage of posts over the ten hold-out samples that have been categorized correctly as being either positive or negative by the respective SVM classifier model.

****Classification accuracy achieved on validation samples not used for algorithm training.

Online Appendix F

Do-it-yourself Field Experiment Manipulation & Robustness Check

Panel A. Ex-post Check of Treatment Manipulation

Treatment	*Sample Size*		*Thread Size*			
			User Posts per Thread		*Firm Posts per Thread*	
	Posts	*Threads*	*Mean*	*SD*	*Mean*	*SD*
Low engagement	2,075	97	148.86	177.08	1.08	1.93
High engagement	4,476	114	648.56	622.90	2.12	2.44

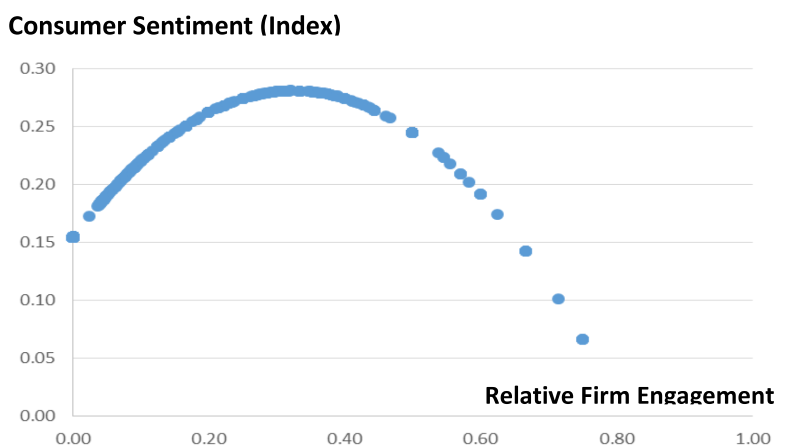
Notes: Sample size refers to the final sample of user posts used for analyses. The high engagement treatment refers to threads opened at odd hours (e.g., 11:20) while the low engagement refers to threads opened at even hours (e.g., 16:40).

Panel B. Robustness Check – Relative Engagement and Consumer Sentiment (Only Within Experimental Period Opened Threads)

Model	*Relative Engagement*			*Controls*	*FE*	*Size (n)*	*Log likelihood*	*AIC*
	Linear Term	*Squared Term*	*Log Term*					
Linear	-.070 (.899)			Included	Included	3,116	-1496.103	.989
Squared	2.671 (.064)	-5.570* (.047)		Included	Included	3,116	-1495.021	.981
Log			.000 (.940)	Included	Included	3,116	-1492.916	.984

Notes: The main independent variable is relative firm engagement; the dependent variable is consumer sentiment; a constant term is included in all regression estimations but not shown; controls include post length, sentiment of previous post and moderator response quickness; FE: fixed effect for thread, user, and time; top 0.5% of observations for relative firm engagement are truncated to restrict the influence of outliers; all standard errors are clustered on the thread level; p values in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed).

Panel C. Figure – Relative Engagement and Consumer Sentiment



Notes: The vertical axis shows not the raw values of consumer sentiment but an indexed value which is adjusted by thread and user fixed effects and further control variables. The horizontal axis shows relative firm engagement in raw values.

Online Appendix G

Descriptive Summary Statistics for all Datasets

Sample	*Dataset*	*Sample Size*		*Variables*									
				Consumer Sentiment		*Relative Firm Engagement (Absolute for Field Experiment)*		*Post Length*		*Sentiment Previous Post*		*Moderator Response Quickness*	
		Posts	*Threads*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
1	Do-it-yourself Baseline	26,298	880	.467	.382	.078	.159	3.167	.950	.466	.382	-17.118	3.167
	Do-it-yourself Field Exp.	6,551	211	.446	.403	1.141	1.813	3.088	.866	.443	.403	-16.598	3.658
2	Airline 1	11,493	148	.405	.391	.021	.068	3.733	1.016	.404	.391	-14.837	3.689
	Airline 2	13,971	249	.396	.425	.033	.071	3.598	1.066	.394	.425	-16.041	2.589
	Airline 3	14,689	74	.359	.397	.010	.041	3.661	1.035	.359	.397	-15.654	3.809
	Airline 4	2,734	73	.301	.346	.093	.147	3.563	1.106	.299	.346	-18.169	2.125
	Airline 5	3,826	43	.421	.349	.025	.064	3.761	1.011	.421	.349	-15.744	2.331
	Hotel 1	2,491	25	.211	.403	.043	.084	3.700	.991	.211	.403	-15.678	1.950
	Hotel 2	8,429	274	.490	.362	.027	.077	3.678	1.038	.488	.363	-17.599	2.248
	Hotel 3	9,622	290	.525	.493	.046	.107	3.816	1.095	.527	.493	-16.989	2.081
	Hotel 4	17,662	310	.460	.469	.090	.117	3.643	1.093	.459	.469	-21.195	.842

Notes: Consumer sentiment is the outcome of the supervised sentiment analysis. Relative engagement is the total number of posts firm representatives made within a single thread divided by all previous user posts in this thread. Post length is the natural log of the number of words and other relevant characters (e.g., emoticons) within each post. Sentiment previous post is lagged consumer sentiment on the thread level. Moderator response quickness is the natural log of the time distance between (last) user post and resulting moderator post multiplied by -1 (i.e., higher values represent faster response).

Online Appendix H

Final Sample Selection Datasets

		Sample#1			*Sample#2*								
		Do-it- yourself			*Airlines*					*Hotels*			
		Baseline	*Field Exp. – absolute firm engagement*	*Field Exp. – relative firm engagement*	*Airline 1*	*Airline 2*	*Airline 3*	*Airline 4*	*Airline 5*	*Hotel 1*	*Hotel 2*	*Hotel 3*	*Hotel 4*
Training Posts		1,200	800	800	500	600	630	130	160	120	370	420	800
Validation Posts		200	200	200	100	150	160	40	40	30	90	110	200
Gross sample	=	27,254	6,786	6,786	11,644	14,232	14,796	2,810	3,877	2,516	8,725	9,943	18,009
Relative engagement > 1	./.	81	0	78	0	0	0	1	1	0	0	3	18
	=	27,173	6,786	6,708	11,644	14,232	14,796	2,809	3,876	2,516	8,725	9,940	17,991
Missing prior sentiment	./.	875	234	234	143	241	73	72	43	25	275	291	298
	=	26,298	6,552	6,474	11,501	13,991	14,723	2,737	3,833	2,491	8,450	9,646	17,693
Empty posts	./.	0	1	1	6	20	34	3	7	0	13	15	31
	=	26,298	6,551	6,473	11,495	13,971	14,689	2,734	3,826	2,491	8,437	9,634	17,662
Missing user identification	./.	0	0	0	2	0	0	0	0	0	8	12	0
	=	26,298	6,551	6,473	11,493	13,971	14,689	2,734	3,826	2,491	8,429	9,622	17,662
Final sample		26,298	6,551	6,473	11,493	13,971	14,689	2,734	3,826	2,491	8,429	9,622	17,662
Share gross sample		96.5%	97.6%	95.4%	98.7%	98.2%	99.3%	97.3%	98.7%	99.0%	96.6%	96.8%	98.1%

Note: Small differences between the number of missing values for prior sentiment and the number of threads can occur owing to the former deletion of training sample posts. Training posts are not included but validation posts are included into the final analyses. In case of smaller sample sizes (airline 4 and 5, hotel 1) the number of trainings posts was selected as the result of a trade-off between keeping the sample for final analyses as large as possible and achieving acceptable classification accuracies (see Online Appendix F).

Online Appendix I

Panel A: Summary Statistics for the Distribution of Postings

	Dataset	*Sample Sizes*						*Thread Size*			
								User Posts per Thread		*Firm Posts per Thread*	
		Posts	*Threads*	*Threads Functional*	*Threads Social*	*Posts Functional*	*Posts Social*	*Mean*	*SD*	*Mean*	*SD*
Sample 1	Do-it-yourself Baseline	26,298	880	729	151	10,425	15,873	29.88	142.13	2.23	4.42
	Do-it-yourself Field Experiment	6,551	211	174	37	2,867	3,684	31.05	119.69	1.62	2.40
Sample 2	Airline 1	11,493	148	134	14	10,844	649	77.66	180.69	1.64	3.06
	Airline 2	13,971	249	224	25	12,711	1,260	56.11	90.09	1.88	1.90
	Airline 3	14,689	74	57	17	11,609	3,080	198.5	392.90	1.54	1.27
	Airline 4	2,734	73	58	15	2,193	541	37.45	68.36	4.00	18.03
	Airline 5	3,826	43	34	9	3,212	614	88.97	134.68	1.74	1.31
	Hotel 1	2,491	25	21	4	2,314	177	99.64	163.58	3.28	6.15
	Hotel 2	8,429	274	251	23	7717	712	30.76	66.85	1.06	0.83
	Hotel 3	9,622	290	274	16	9,354	268	33.17	64.75	1.59	2.17
	Hotel 4	17,662	310	295	15	16,935	727	56.97	111.63	6.02	11.68

Panel B: Correlations for the Do-it-yourself Datasets (Sample 1)

Do-it-yourself Baseline Dataset

	1.	2.	3.	4.	5.
1. Consumer sent.	1.00				
2. Relative firm eng.	.035	1.00			
3. Sent. prev. post	.067	.029	1.00		
4. Mod. resp. quickn.	.012	.000	.015	1.00	
5. Post length	-.167	.185	-.038	-.148	1.00

Note: Correlations larger than |0.015| are significant at least at the $p < 0.05$ level (two-tailed).

Do-it-yourself Field Experiment Dataset

	1.	2.	3.	4.	5.
1. Consumer sent.	1.00				
2. Absolute firm eng.	.007	1.00			
3. Sent. prev. post	.145	.010	1.00		
4. Mod. resp. quickn.	.085	.131	.093	1.00	
5. Post length	-.382	-.022	-.114	-.206	1.00

Note: Correlations larger than |0.08| are significant at least at the $p < 0.05$ level (two-tailed).

Panel C: Correlations for the Airline and Hotel Datasets (Sample 2)

Airline 1

	1.	2.	3.	4.	5.
1. Consumer sent.	1.00				
2. Relative firm eng.	.081	1.00			
3. Sent. prev. post	.068	.081	1.00		
4. Mod. resp. quickn.	-.020	-.087	-.018	1.00	
5. Post length	-.246	-.069	-.038	-.020	1.00

Note: Correlations larger than |0.02| are significant at least at the $p < 0.05$ level (two-tailed).

Airline 2

	1.	2.	3.	4.	5.
1. Consumer sent.	1.00				
2. Relative firm eng.	.077	1.00			
3. Sent. prev. post	.108	.074	1.00		
4. Mod. resp. quickn.	.030	-.145	.029	1.00	
5. Post length	-.278	-.052	-.079	-.004	1.00

Note: Correlations larger than |0.01| are significant at least at the $p < 0.05$ level (two-tailed).

Airline 3

	1.	2.	3.	4.	5.
1. Consumer sent.	1.00				
2. Relative firm eng.	.075	1.00			
3. Sent. prev. post	.154	.078	1.00		
4. Mod. resp. quickn.	-.165	.041	-.166	1.00	
5. Post length	-.362	-.044	-.081	.128	1.00

Note: All correlations are significant at least at the $p < 0.05$ level (two-tailed).

Airline 4

	1.	2.	3.	4.	5.
1. Consumer sent.	1.00				
2. Relative firm eng.	.101	1.00			
3. Sent. prev. post	.125	.117	1.00		
4. Mod. resp. quickn.	-.066	-.214	-.067	1.00	
5. Post length	-.301	.012	-.033	-.095	1.00

Note: Correlations larger than |0.06| are significant at least at the $p < 0.05$ level (two-tailed).

Airline 5

	1.	2.	3.	4.	5.
1. Consumer sent.	1.00				
2. Relative firm eng.	.039	1.00			
3. Sent. prev. post	.043	.029	1.00		
4. Mod. resp. quickn.	.008	.048	.012	1.00	
5. Post length	-.159	-.028	-.021	-.155	1.00

Note: Correlations larger than |0.03| are significant at least at the $p < 0.05$ level (two-tailed).

Hotel 1

	1.	2.	3.	4.	5.
1. Consumer sent.	1.00				
2. Relative firm eng.	.094	1.00			
3. Sent. prev. post	.065	.078	1.00		
4. Mod. resp. quickn.	-.108	-.200	-.108	1.00	
5. Post length	-.197	-.067	-.036	.115	1.00

Note: Correlations larger than |0.06| are significant at least at the $p < 0.05$ level (two-tailed).

Panel C: Correlations for the Airline and Hotel Datasets (Sample 2)

Hotel 2

	1.	2.	3.	4.	5.
1. Consumer sent.	1.00				
2. Relative firm eng.	.023	1.00			
3. Sent. prev. post	.124	-.011	1.00		
4. Mod. resp. quickn.	.045	-.066	.045	1.00	
5. Post length	-.324	-.006	-.094	-.059	1.00

Note: Correlations larger than |0.02| are significant at least at the $p < 0.05$ level (two-tailed).

Hotel 3

	1.	2.	3.	4.	5.
1. Consumer sent.	1.00				
2. Relative firm eng.	.060	1.00			
3. Sent. prev. post	.051	.071	1.00		
4. Mod. resp. quickn.	.023	-.055	.016	1.00	
5. Post length	.068	-.069	-.001	.002	1.00

Note: Correlations larger than |0.02| are significant at least at the $p < 0.05$ level (two-tailed).

Hotel 4

	1.	2.	3.	4.	5.
1. Consumer sent.	1.00				
2. Relative firm eng.	.018	1.00			
3. Sent. prev. post	.079	.011	1.00		
4. Mod. resp. quickn.	.001	-.099	.003	1.00	
5. Post length	-.311	-.017	-.069	-.031	1.00

Note: Correlations larger than |.015| are significant at least at the $p < 0.05$ level (two-tailed).

Online Appendix J

Firm Engagement and Consumer Sentiment: Analyses by Firm (Airlines and Hotels)

Panel A. Airline Datasets

Dataset	(A) Airline 1			(B) Airline 2			(C) Airline 3			(D) Airline 4			(E) Airline 5		
Dependent Variable	Consumer Sentiment			Consumer Sentiment			Consumer Sentiment			Consumer Sentiment			Consumer Sentiment		
Independent Variable	Relative Firm Engagement			Relative Firm Engagement			Relative Firm Engagement			Relative Firm Engagement			Relative Firm Engagement		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Firm Engagement	2.473***	4.850***		2.239***	4.882***		1.803**	4.570***		.509	2.902**		1.243	4.320***	
	(.000)	(.000)		(.000)	(.000)		(.002)	(.000)		(.389)	(.004)		(.097)	(.001)	
Firm Engagement²		-3.364***			-3.758***			-3.828**			-2.754**			-4.543**	
		(.001)			(.000)			(.004)			(.002)			(.002)	
Log(Firm Engagement)			.011			.022***			.021***			.015			.003
			(.075)			(.000)			(.001)			(.087)			(.680)
Sentiment previous post	.043	.037	.056	.040	.035	.052	.224***	.221***	.226***	.185	.187	.183	.013	.006	.018
	(.407)	(.475)	(.288)	(.386)	(.454)	(.251)	(.000)	(.000)	(.000)	(.097)	(.090)	(.102)	(.876)	(.944)	(.821)
Moderator response quickness	-.024	-.020	-.027	.021	.018	.017	-.078	-.077	-.073	-.012	-.008	-.013	-.073**	-.074*	-.074*
	(.594)	(.642)	(.536)	(.332)	(.409)	(.388)	(.238)	(.250)	(.294)	(.691)	(.775)	(.676)	(.002)	(.026)	(.020)
Post length	-.422***	-.421***	-.425***	-.445***	-.444***	-.451***	-.691***	-.690***	-.693***	-.634***	-.637***	-.635***	-.226***	-.225***	-.225***
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Thread Fixed Effect	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
User Fixed Effect	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Time Fixed Effect	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Log likelihood	-5728.554	-5725.132	-5736.916	-7031.111	-7023.336	-7037.850	-6517.056	-6514.548	-6516.712	-1116.650	-1115.325	-1116.209	-1848.066	-1846.112	-1848.915
AIC	1.022	1.021	1.024	1.043	1.042	1.044	.951	.950	.951	1.132	1.133	1.135	1.187	1.184	1.184
Size (n)	11,493	11,493	11,493	13,971	13,971	13,971	14,689	14,689	14,689	2,734	2,734	2,734	3,826	3,826	3,826

Notes: The main independent variable is relative firm engagement; the dependent variable is consumer sentiment; a constant term is included in all estimations but not shown; FE: fixed effect; all standard errors are clustered on the thread (user) level in case of more (less) than 100 threads; p values in parentheses; * $p < .05$, ** $p < .01$, *** $p < .001$ (two-tailed).

Panel B. Hotel Datasets

Dataset	(A) Hotel 1			(B) Hotel 2			(C) Hotel 3			(D) Hotel 4		
Dependent Variable	Consumer Sentiment			Consumer Sentiment			Consumer Sentiment			Consumer Sentiment		
Independent Variable	Relative Firm Engagement			Relative Firm Engagement			Relative Firm Engagement			Relative Firm Engagement		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Firm Engagement	2.060	8.524*		1.568**	3.801***		1.409**	3.035**		.687**	1.370**	
	(.157)	(.021)		(.003)	(.000)		(.002)	(.002)		(.004)	(.006)	
Firm Engagement²		-15.625			-3.667***			-2.066			-.898	
		(.121)			(.001)			(.066)			(.095)	
Log(Firm Engagement)			.031*			.014**			.017**			.009*
			(.038)			(.003)			(.001)			(.045)
Sentiment previous post	.038	.027	.039	.039	.035	.038	-.064	-.065	-.061	.057	.056	.058
	(.729)	(.807)	(.715)	(.496)	(.534)	(.510)	(.191)	(.186)	(.212)	(.059)	(.063)	(.054)
Moderator response quickness	.016	.014	.016	-.082	-.072	-.087	.040	.045	.038	.057	.057	.057
	(.778)	(.810)	(.775)	(.343)	(.407)	(.316)	(.362)	(.318)	(.387)	(.158)	(.161)	(.163)
Post length	-.449***	-.455***	-.457***	-.505***	-.505***	-.508***	.169***	.170***	.169***	-.686***	-.687***	-.687***
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Thread Fixed Effect	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
User Fixed Effect	-	-	-	Included	Included	Included	Included	Included	Included	Included	Included	Included
Time Fixed Effect	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Log likelihood	-1169.536	-1166.979	-1168.642	-4057.945	-4054.535	-4058.495	-5295.702	-5293.070	-5297.821	-10034.971	-10033.796	-10036.518
AIC	.953	.958	.949	1.026	1.025	1.027	1.161	1.160	1.161	1.171	1.171	1.171
Size (n)	2,491	2,491	2,491	8,429	8,429	8,429	9,622	9,622	9,622	17,662	17,662	17,662

Notes: The main independent variable is relative firm engagement; the dependent variable is consumer sentiment; a constant term is included in all estimations but not shown; FE: fixed effect; all standard errors are clustered on the thread (user) level in case of more (less) than 100 threads; *p* values in parentheses; * $p < .05$, ** $p < .01$, *** $p < .001$ (two-tailed).

Online Appendix K

Firm Engagement and Consumer Sentiment: Analyses by Firm and Thread Type

Panel A. Do-it-yourself Datasets

	Do-it-yourself Baseline Dataset						Do-it-yourself Field Experiment					
Dependent Variable	Consumer Sentiment			Consumer Sentiment			Consumer Sentiment			Consumer Sentiment		
Independent Variable	Relative Firm Engagement			Relative Firm Engagement			Absolute Firm Engagement			Absolute Firm Engagement		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Firm Engagement	.607*** (.000)	1.638*** (.000)		.073 (.779)	.251 (.710)		.015 (.727)	.281* (.020)		-.017 (.682)	.032 (.686)	
Firm Engagement²		-1.114** (.005)			-.204 (.760)			-.033* (.010)			-.006 (.552)	
Log(Firm Engagement)			.020*** (.000)			.000 (.901)			.220 (.165)			-.001 (.989)
Sentiment prev. post	-.151** (.002)	-.154** (.002)	-.151** (.003)	.084** (.004)	.084** (.004)	.084** (.004)	-.082 (.463)	-.088 (.425)	-.087 (.440)	.132 (.256)	.131 (.260)	.131 (.261)
Moderator response quickness	-.023 (.285)	-.017 (.425)	-.021 (.330)	-.006 (.637)	-.006 (.640)	-.006 (.637)	.006 (.847)	.002 (.931)	.007 (.818)	.045 (.455)	.045 (.429)	.045 (.454)
Post length	-.442*** (.000)	-.443*** (.000)	-.441*** (.000)	-.263*** (.000)	-.263*** (.000)	-.263*** (.000)	-1.114*** (.000)	-1.121*** (.000)	-1.115*** (.000)	-.746*** (.000)	-.747*** (.000)	-.744*** (.000)
Thread Fixed Effect	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
User Fixed Effect	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Time Fixed Effect	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Log likelihood	-5428.830	-5426.005	-5427.570	-8670.040	-8670.011	-8670.056	-1130.953	-1129.004	-1130.396	-1447.368	-1447.272	-1447.419
AIC	1.168	1.167	1.168	1.111	1.111	1.111	.907	.904	.907	.833	.833	.833
Size (n)	10,425	10,425	10,425	15,873	15,873	15,873	2,867	2,867	2,867	3,684	3,684	3,684

Notes: The main independent variable is relative firm engagement; the dependent variable is consumer sentiment; a constant term is included in all regression estimations but not shown; FE: fixed effect; all standard errors are clustered on the thread (user) level in case of more (less) than 100 threads; p values in parentheses; * $p < .05$, ** $p < .01$, *** $p < .001$ (two-tailed).

Panel B. Airline Datasets (Airlines 1 and 2)

Dataset	Airline 1						Airline 2					
Dependent Variable Independent Variable	Consumer Sentiment Relative Firm Engagement						Consumer Sentiment Relative Firm Engagement					
Thread Type	Functional			Social			Functional			Social		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Firm Engagement	2.290***	4.789***		7.217	10.964		2.358***	4.999***		-1.129	4.905	
	(.000)	(.000)		(.086)	(.073)		(.000)	(.000)		(.757)	(.372)	
Firm Engagement²		-3.531***			-8.284			-3.776***			-24.254	
		(.001)			(.328)			(.000)			(.148)	
Log(Firm Engagement)			.009			.028			.025***			-.003
			(.129)			(.340)			(.000)			(.890)
Sentiment previous post	.034	.028	.046	-.036	-.049	.020	.066	.060	.079	.005	-.012	.008
	(.545)	(.612)	(.406)	(.910)	(.878)	(.949)	(.179)	(.224)	(.099)	(.979)	(.953)	(.969)
Moderator response quickness	-.023	-.018	-.026	.414	.289	.636	.017	.014	.014	.138	.162	.138
	(.653)	(.722)	(.598)	(.785)	(.851)	(.668)	(.482)	(.580)	(.574)	(.260)	(.220)	(.261)
Post length	-.430***	-.429***	-.433***	-.399**	-.395**	-.369**	-.452***	-.451***	-.458***	-.443***	-.441***	-.444***
	(.000)	(.000)	(.000)	(.002)	(.002)	(.003)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Thread Fixed Effect	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
User Fixed Effect	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Time Fixed Effect	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Log likelihood	-5398.796	-5395.381	-5405.461	-253.501	-253.166	-254.891	-6380.840	-6373.532	-6387.395	-519.603	-518.370	-519.641
AIC	1.020	1.020	1.021	1.592	1.594	1.596	1.040	1.038	1.041	1.480	1.480	1.480
Size (n)	10,844	10,844	10,844	649	649	649	12,711	12,711	12,711	1,260	1,260	1,260

Notes: The main independent variable is relative firm engagement; the dependent variable is consumer sentiment; a constant term is included in all regression estimations but not shown; FE: fixed effect; all standard errors are clustered on the thread (user) level in case of more (less) than 100 threads; *p* values in parentheses; * $p < .05$, ** $p < .01$, *** $p < .001$ (two-tailed).

Panel B. Airline Datasets (Airlines 3 and 4)

Dataset	Airline 3						Airline 4					
Dependent Variable Independent Variable	Consumer Sentiment Relative Firm Engagement						Consumer Sentiment Relative Firm Engagement					
Thread Type	Functional			Social			Functional			Social		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Firm Engagement	1.575*	4.051**		2.052	6.764		.625	3.509*		.520	1.477	
	(.011)	(.007)		(.363)	(.126)		(.358)	(.019)		(.698)	(.348)	
Firm Engagement²		-3.367*			-6.559			-3.250*			-1.173	
		(.043)			(.121)			(.011)			(.632)	
Log(Firm Engagement)			.028***			-.003			.015			.027
			(.000)			(.844)			(.102)			(.462)
Sentiment previous post	.174***	.171**	.170**	.381***	.376***	.389***	.284*	.291*	.285*	-.212	-.210	-.213
	(.001)	(.002)	(.002)	(.000)	(.000)	(.000)	(.027)	(.023)	(.027)	(.459)	(.463)	(.452)
Moderator response quickness	-.035	-.032	-.016	-.175	-.186	-.174	.005	.004	.002	-.077	-.078	-.082
	(.607)	(.646)	(.817)	(.197)	(.149)	(.218)	(.920)	(.934)	(.959)	(.252)	(.256)	(.212)
Post length	-.715***	-.714***	-.716***	-.600***	-.601***	-.600***	-.766***	-.770***	-.766***	-.372***	-.375***	-.377***
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Thread Fixed Effect	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
User Fixed Effect	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Time Fixed Effect	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Log likelihood	-4959.634	-4958.224	-4956.104	-1316.856	-1315.786	-1317.517	-855.956	-854.727	-855.627	-212.852	-212.804	-212.693
AIC	.928	.927	.927	.982	1.316	.985	1.106	1.105	1.107	1.308	1.312	1.308
Size (n)	11,609	11,609	11,609	3,080	3,080	3,080	2,193	2,193	2,193	541	541	541

Notes: The main independent variable is relative firm engagement; the dependent variable is consumer sentiment; a constant term is included in all regression estimations but not shown; FE: fixed effect; all standard errors are clustered on the thread (user) level in case of more (less) than 100 threads; p values in parentheses; * $p < .05$, ** $p < .01$, *** $p < .001$ (two-tailed).

Panel B. Airline Datasets (Airline 5)

Dataset	Airline 5					
Dependent Variable	Consumer Sentiment					
Independent Variable	Relative Firm Engagement					
Thread Type	Functional			Social		
	(1)	(2)	(3)	(1)	(2)	(3)
Firm Engagement	.754	3.875**		-.309	.044	
	(.321)	(.006)		(.900)	(.991)	
Firm Engagement²		-4.577**			-.632	
		(.007)			(.798)	
Log(Firm Engagement)			.004			-.020
			(.676)			(.295)
Sentiment previous post	.037	.031	.041	-.151	-.152	-.162
	(.665)	(.721)	(.639)	(.494)	(.493)	(.459)
Moderator response quickness	-.152***	-.1.53***	-.151***	.094	.094	.087
	(.001)	(.000)	(.001)	(.158)	(.157)	(.164)
Post length	-.223***	-.224***	-.223***	-.286**	-.285**	-.297***
	(.000)	(.000)	(.000)	(.002)	(.002)	(.001)
Thread Fixed Effect	Included	Included	Included	Included	Included	Included
User Fixed Effect	Included	Included	Included	Included	Included	Included
Time Fixed Effect	Included	Included	Included	Included	Included	Included
Log likelihood	-1546.545	-1544.928	-1546.767	-256.796	-256.793	-256.626
AIC	1.264	1.263	1.259	1.335	1.331	1.344
Size (n)	3,212	3,212	3,212	614	614	614

Notes: The main independent variable is relative firm engagement; the dependent variable is consumer sentiment; a constant term is included in all regression estimations but not shown; FE: fixed effect; all standard errors are clustered on the thread (user) level in case of more (less) than 100 threads; *p* values in parentheses; * $p < .05$, ** $p < .01$, *** $p < .001$ (two-tailed).

Panel C. Hotel Datasets (Hotels 1 and 2)

Dataset	Hotel 1						Hotel 2					
Dependent Variable Independent Variable	Consumer Sentiment Relative Firm Engagement						Consumer Sentiment Relative Firm Engagement					
Thread Type	Functional			Social			Functional			Social		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Firm Engagement	1.808 (.243)	8.286* (.029)		7.000 (.249)	18.686 (.370)		1.806*** (.001)	4.091*** (.000)		1.034 (.551)	3.584 (.488)	
Firm Engagement²		-15.732* (.136)			-33.406 (.551)			-4.274*** (.000)			-2.634 (.599)	
Log(Firm Engagement)			.031* (.049)			.039 (.495)			.016** (.001)			.014 (.688)
Sentiment previous post	.022 (.845)	.012 (.915)	.020 (.858)	-.040 (.949)	-.073 (.902)	.023 (.971)	.028 (.644)	.026 (.671)	.028 (.646)	.235 (.458)	.238 (.452)	.222 (.482)
Moderator response quickness	.021 (.702)	.019 (.736)	.020 (.702)	-.618 (.328)	-.587 (.370)	-.621 (.306)	-.055 (.532)	-.043 (.619)	-.058 (.506)	-.807 (.487)	-.819 (.481)	-.777 (.498)
Post length	-.422*** (.000)	-.429*** (.000)	-.430*** (.000)	-.802*** (.001)	-.813*** (.001)	-.831*** (.001)	-.520*** (.000)	-.520*** (.000)	-.523*** (.000)	-.312* (.016)	-.310* (.016)	-.315* (.015)
Thread Fixed Effect	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
User Fixed Effect	-	-	-	-	-	-	Included	Included	Included	Included	Included	Included
Time Fixed Effect	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Log likelihood	-1098.382	-1096.095	-1097.368	-66.353	-66.161	-66.741	-3703.628	-3700.382	-3703.834	-290.648	-290.407	-290.645
AIC	.974	.970	.973	.908	.917	.912	1.023	1.022	1.023	1.684	1.686	1.684
Size (n)	2,314	2,314	2,314	177	177	177	7,717	7,717	7,717	712	712	712

Notes: The main independent variable is relative firm engagement; the dependent variable is consumer sentiment; a constant term is included in all regression estimations but not shown; FE: fixed effect; all standard errors are clustered on the thread (user) level in case of more (less) than 100 threads; *p* values in parentheses; * $p < .05$, ** $p < .01$, *** $p < .001$ (two-tailed).

Panel C. Hotel Datasets (Hotels 3 and 4)

Dataset	Hotel 3						Hotel 4					
Dependent Variable Independent Variable	Consumer Sentiment Relative Firm Engagement						Consumer Sentiment Relative Firm Engagement					
Thread Type	Functional			Social			Functional			Social		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Firm Engagement	1.424**	2.982**		.395	4.721		.620*	1.409**		.961	-2.673	
	(.002)	(.004)		(.814)	(.189)		(.011)	(.006)		(.739)	(.587)	
Firm Engagement²		-1.985			-5.336			-1.032			7.823	
		(.089)			(.165)			(.061)			(.391)	
Log(Firm Engagement)			.0180**			-.015			.009*			.025
			(.001)			(.701)			(.044)			(.511)
Sentiment previous post	-.061	-.062	-.059	-.152	-.147	-.146	.051	.050	.052	-.233	-.225	-.239
	(.223)	(.217)	(.239)	(.659)	(.671)	(.671)	(.107)	(.114)	(.102)	(.323)	(.339)	(.312)
Moderator response quickness	.038	.043	.037	.468	.439	.485	.059	.059	.059	.033	.518	-.299
	(.383)	(.337)	(.406)	(.481)	(.509)	(.469)	(.150)	(.153)	(.155)	(.982)	(.753)	(.746)
Post length	.170***	.170***	.170***	.104	.118	.099	-.690***	-.692***	-.691***	-.766***	-.761***	-.772***
	(.000)	(.000)	(.000)	(.450)	(.394)	(.476)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Thread Fixed Effect	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
User Fixed Effect	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Time Fixed Effect	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Log likelihood	-5154.786	-5152.497	-5156.357	-139.957	-138.976	-139.911	-9585.685	-9584.191	-9586.389	-312.920	-312.486	-312.758
AIC	1.160	1.160	1.161	1.283	1.283	1.282	1.166	1.166	1.166	1.581	1.583	1.581
Size (n)	9,354	9,354	9,354	268	268	268	16,935	16,935	16,935	727	727	727

Notes: The main independent variable is relative firm engagement; the dependent variable is consumer sentiment; a constant term is included in all regression estimations but not shown; FE: fixed effect; all standard errors are clustered on the thread (user) level in case of more (less) than 100 threads; *p* values in parentheses; * $p < .05$, ** $p < .01$, *** $p < .001$ (two-tailed).

Online Appendix L

Quality of Moderator Posts

All posts written by firm moderators are evaluated in terms of quality from two independent rates. A post is considered to be of high quality if it is relevant, which means that it should contribute to direct problem solving (e.g., by providing technical knowledge for a do-it-yourself product), indirect problem solving (e.g., providing information on where to find solutions to the problem), or add social value by responding to social talk of consumers in a meaningful way (e.g., by explaining the rules of a creativity contest for garden decoration). Each post is coded with "1" (high quality) or "0" (low quality).

Panel A. Test for Differences in Moderator Post Quality between Treatments in the Field Experiment

	Moderator Post Quality		
Treatment	*Mean*	*Standard Error*	*t-value (p-value)*
Low engagement	.845	.015	-.073
High engagement	.846	.007	(.941)

Panel B. Inclusion of Moderator Post Quality as Additional Control Variable (Subsample with Positive Prior Firm Engagement Only)

Model	*Do-it-yourself Baseline*	*Airline 1*	*Airline 2*	*Airline 3*	*Airline 4*	*Airline 5*	*Hotel 1*	*Hotel 2*	*Hotel 3*	*Hotel 4*
Linear	.35 (.023)	2.19^{***} (.000)	1.72^{***} (.000)	1.58^{*} (.013)	.09 (.880)	.94 (.199)	1.62 (.215)	.53 (.335)	1.11^{*} (.017)	$.69^{**}$ (.004)
Squared	1.14^{*} (.017)	4.96^{***} (.000)	4.07^{**} (.001)	1.14^{*} (.017)	2.54 (.113)	4.42^{*} (.043)	8.85^{*} (.045)	4.15^{***} (.000)	3.49 (.027)	1.49^{**} (.003)
	$-.75^{+}$ (.076)	-3.31^{**} (.003)	-2.90^{*} (.024)	$-.75^{+}$ (.076)	-2.54^{+} (.082)	-4.73^{+} (.053)	-11.11^{+} (.077)	-4.28^{**} (.001)	-2.57 (.120)	-1.04^{+} (.061)
Log	.04 (.171)	$.19^{***}$ (.005)	$.266^{***}$ (.000)	.04 (.171)	-.01 (.916)	$.20^{*}$ (.049)	-.16 (.293)	$.22^{***}$ (.000)	$.20^{*}$ (.014)	$.00^{*}$ (.033)
Controls	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Fixed Effects	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Observations	18,418	7,483	9,888	9,766	1,932	2,889	2,050	5,044	6,174	17,406

Notes: The dependent variable is consumer sentiment; the main independent variable is relative engagement; controls include moderator post quality, post length, sentiment of previous post, and moderator response quickness; a constant term is included in all regression estimations but not shown; all standard errors are clustered on the thread (user) level in case of more (less) than 100 threads; p-values are shown in parentheses; $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed).

Panel C. Moderator Post Quality and Firm Engagement
(Subsample with Prior Firm Engagement Only)

Dataset	*Model*	*Engagement*	*Moderator Response Quickness*	*Thread Size*	*Sample Size*	*Significant Association Engagement & Moderator Post Quality Proxy?*
Do-it-yourself Baseline	Relative Engagement	-.135 (.692)	.105 (.192)	-.000 (.987)	18,418	NO
	Absolute Engagement	.010 (.511)	.117 (.172)	-.000 (.921)	18,418	
Airline 1	Relative Engagement	-1.775 (.397)	.095 (.461)	-.003 (.224)	7,512	NO
	Absolute Engagement	-.085 (.216)	.093 (.469)	-.003 (.223)	7,512	
Airline 2	Relative Engagement	.401 (.904)	-.194 (.324)	$.007^{***}$ (.000)	9,924	NO
	Absolute Engagement	-.244 (.112)	$-.244^{+}$ (.078)	$.010^{**}$ (.001)	9,924	
Airline 3	Relative Engagement	8.603 (.625)	$.307^{*}$ (.024)	$.010^{***}$ (.000)	9,805	PARTLY
	Absolute Engagement	$-.777^{**}$ (.008)	$.4748^{+}$ (.064)	$.011^{***}$ (.000)	9,805	
Airline 4	Relative Engagement	-.356 (.689)	.097 (.586)	$.004^{**}$ (.001)	1,949	NO
	Absolute Engagement	-.006 (.553)	.090 (.635)	$.005^{**}$ (.002)	1,949	
Airline 5	Relative Engagement	6.961 (.535)	-.029 (.870)	$.012^{+}$ (.068)	2,903	NO
	Absolute Engagement	.165 (.726)	-.026 (.858)	$.010^{*}$ (.025)	2,903	
Hotel 1	Relative Engagement	-5.094^{***} (.000)	$-.238^{***}$ (.000)	.001 (.467)	2,051	PARTLY
	Absolute Engagement	-.247 (.124)	$-.520^{**}$ (.005)	.020 (.242)	2,051	
Hotel 2	Relative Engagement	-1.419 (.195)	.202 (.527)	$.003^{+}$ (.090)	5,075	NO
	Absolute Engagement	.142 (.245)	.218 (.476)	.003 (.136)	5,075	
Hotel 3	Relative Engagement	1.978 (.515)	.175 (.509)	-.000 (.705)	6,222	NO
	Absolute Engagement	.093 (.258)	.182 (.480)	-.001 (.517)	6,222	
Hotel 4	Relative Engagement	3.751 (.150)	--	.016 (.053)	16,288	PARTLY
	Absolute Engagement	$.290^{***}$ (.000)	--	.011 (.132)	16,288	

Notes: The dependent variable is post quality; a constant term is included in all regression estimations but not shown; -- indicates quasi-complete separation; *p*-values are shown in parentheses; all standard errors are clustered on the thread level; $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed).

ONLINE APPENDIX M

Estimation Results for Absolute Engagement Measures

Panel A. Sample 1 – Do-it-yourself Baseline Dataset

Dataset	*Model*	*Linear term*	*Squared term*	*Log term*	*Controls*	*Fixed Effects*	*AIC*
Do-it-yourself Baseline	Linear	.003 (.386)			Included	Included	1.134
	Squared	.028* (.017)	-.001* (.011)		Included	Included	1.134
	Log			.057^{+} (.061)	Included	Included	1.134

Notes: Firm engagement is measured by absolute firm engagement; a value of 1 is added for the log regression to retain zero observations; the dependent variable is consumer sentiment; post controls include post length, sentiment of previous post and moderator response quickness; a constant term is included in all regression estimations but not shown; *p*-values are shown in parentheses; top 2.5% observations of firm engagement are truncated to restrict the influence of outliers; $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed).

Panel B. Sample 2 – Airline and Hotel Datasets (1/2)

Dataset	*Model*	*Linear term*	*Squared term*	*Log term*	*Controls*	*Fixed Effects*	*AIC*
Airline 1	Linear	.064^{+} (.080)			Included	Included	.946
	Squared	.257** (.003)	-.068* (.017)		Included	Included	.946
	Log			.177* (.019)	Included	Included	.946
Airline 2	Linear	.042* (.029)			Included	Included	1.033
	Squared	.103** (.008)	-.006* (.045)		Included	Included	1.033
	Log			.304*** (.000)	Included	Included	1.033
Airline 3	Linear	.109* (.024)			Included	Included	.884
	Squared	.181^{+} (.066)	-.012 (.295)		Included	Included	.883
	Log			.308* (.023)	Included	Included	.883
Airline 4	Linear	-.000 (.705)			Included	Included	.901
	Squared	.008 (.195)	-.000^{+} (.059)		Included	Included	.901
	Log			.008 (.900)	Included	Included	.901
Airline 5	Linear	.069 (.148)			Included	Included	1.178
	Squared	.246* (.030)	-.040^{+} (.095)		Included	Included	1.179
	Log			.229*(.047)	Included	Included	1.178

Notes: Firm engagement is measured by absolute firm engagement; a value of 1 is added for the log regression to retain zero observations; the dependent variable is consumer sentiment; post controls include post length, sentiment of previous post and moderator response quickness; a constant term is included in all regression estimations but not shown; *p*-values are shown in parentheses; $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed).

Panel B. Sample 2 – Airline and Hotel Datasets (2/2)

Dataset	*Model*	*Linear term*	*Squared term*	*Log term*	*Controls*	*Fixed Effects*	*AIC*
Hotel 1	Linear	$-.024^{+}$ (.091)			Included	Included	.979
	Squared	.045 (.219)	$-.002^{*}$ (.029)		Included	Included	.979
	Log			.079 (.462)	Included	Included	.980
Hotel 2	Linear	$.122^{*}$ (.011)			Included	Included	1.014
	Squared	$.221^{**}$ (.003)	$-.026^{*}$ (.041)		Included	Included	1.013
	Log			$.295^{**}$ (.002)	Included	Included	1.014
Hotel 3	Linear	$.042^{*}$ (.042)			Included	Included	1.141
	Squared	$.117^{**}$ (.003)	$-.003^{**}$ (.009)		Included	Included	1.141
	Log			$.370^{***}$ (.000)	Included	Included	1.140
Hotel 4	Linear	$.009^{*}$ (.022)			Included	Included	1.094
	Squared	.009 (.200)	.000 (.946)		Included	Included	1.094
	Log			$.123^{*}$ (.012)	Included	Included	1.094

Notes: Firm engagement is measured by absolute firm engagement; a value of 1 is added for the log regression to retain zero observations; the dependent variable is consumer sentiment; post controls include post length, sentiment of previous post and moderator response quickness; a constant term is included in all regression estimations but not shown; *p*-values are shown in parentheses; $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed).

Online Appendix N

Results of Alternative Sentiment Calculation Procedures for the Do-it-yourself Baseline Dataset

Consumer Sentiment Calculation				*Relative Firm Engagement*					
Verbal Description of Word List Used	*Mathematical Description*			*Model*	*Linear term*	*Squared term*	*Log term*	*Controls & Fixed Effects*	*AIC*
	t	*r*	*Algorithm*						
Elimination of words appearing only twice or less times in training data; high level of discrimination between positive and negative words	2	0.5	SVM	Linear	.577*** (.000)			Included	1.107
				Squared	1.283*** (.000)	-.776* (.025)		Included	1.105
				Log			.015*** (.000)	Included	1.107
No elimination of rare words; low level of discrimination between positive and negative words	0	0.2	SVM	Linear	.374* (.048)			Included	1.215
				Squared	1.050* (.020)	-.744+ (.092)		Included	1.214
				Log			.010* (.034)	Included	1.215
No elimination of rare words; high level of discrimination between positive and negative words	0	0.5	SVM	Linear	.467** (.003)			Included	1.115
				Squared	1.473*** (.000)	-1.107** (.004)		Included	1.115
				Log			.014*** (.000)	Included	1.114
Elimination of words appearing ten times or less in training data; high level of discrimination between positive and negative	10	0.5	SVM	Linear	.659*** (.000)			Included	.964
				Squared	1.696*** (.000)	-1.122*** (.000)		Included	.963
				Log			.019*** (.000)	Included	.963
Elimination of words appearing only once in training data; high level of discrimination between positive and negative words	1	0.5	NB	Linear	.365* (.012)			Included	1.079
				Squared	1.14** (.001)	-.850** (.009)		Included	1.078
				Log			.009* (.015)	Included	1.079
Elimination of words appearing only twice or less times in training data; high level of discrimination between positive and negative words	2	0.5	NB	Linear	.396** (.003)			Included	1.058
				Squared	1.258*** (.000)	-.948** (.002)		Included	1.057
				Log			.011** (.006)	Included	1.058

Notes: The dependent variable consumer sentiment is built using different word list/algorithm combinations with t: threshold, r: ratio and SVM: support vector machine algorithm, NB: Naïve Bayes algorithm; main independent variable is relative firm engagement; a constant term is always included but not shown; all standard errors are clustered on the thread level; *p*-values are shown in parentheses; $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed).

ONLINE APPENDIX O

Estimation Results for Last Posts of Each Thread

Dataset	*Model*	*Relative Engagement* *Linear Term*	*Squared term*	*Log term*	*Controls and Fixed Effects*	*Number of last posts considered*	*Sample Size*
Do-it-yourself Baseline	Linear	.615 (.174)			Included	6	4,635
	Squared	2.175^{*} (.012)	-1.620^{+} (.053)		Included	6	4,635
	Log			$.023^{+}$ (.058)	Included	6	4,635
Airline 1	Linear	2.092 (.618)			Included	4	569
	Squared	30.333^{***} (.000)	-48.470^{*} (.031)		Included	4	569
	Log			$.265^{**}$ (.001)	Included	4	569
Airline 2	Linear	6.185^{*} (.028)			Included	6	1,412
	Squared	11.415^{**} (.002)	-9.247^{*} (.033)		Included	6	1,412
	Log			$.102^{**}$ (.002)	Included	6	1,412
Hotel 2	Linear	3.666^{**} (.002)			Included	6	1,388
	Squared	4.935^{**} (.003)	-2.216 (.419)		Included	6	1,388
	Log			$.0454^{**}$ (.009)	Included	6	1,388
Hotel 3	Linear	4.999^{*} (.010)			Included	4	1,090
	Squared	10.045^{***} (.000)	-5.742^{*} (.030)		Included	4	1,090
	Log			$.120^{***}$ (.000)	Included	4	1,090
Hotel 4	Linear	1.241 (.127)			Included	7	1,930
	Squared	5.004^{**} (.001)	-3.904^{**} (.014)		Included	7	1,930
	Log			$.040^{*}$ (.048)	Included	7	1,930

Notes: Choice of sample depends on sample size, resulting degrees of freedom, and obtaining a stable model convergence; the dependent variable is consumer sentiment; the main independent variable is relative firm engagement; controls include post length, sentiment of previous post, and moderator response quickness; a constant term is included in all regression estimations but not shown; all standard errors are clustered on the thread level; *p*-values are shown in parentheses; $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed).