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In this research, the authors jointly model the sentiment expressed in social media posts and the venue format to which it was posted as two interrelated processes in an effort to provide a measure of underlying brand sentiment. Using social media data from firms in two distinct industries, they allow the content of the post and the underlying sentiment toward the brand to affect both processes. The results show that the inferences marketing researchers obtain from monitoring social media are dependent on *where* they "listen" and that common approaches that either focus on a single social media venue or ignore differences across venues in aggregated data can lead to misleading brand sentiment metrics. The authors validate the approach by comparing their model-based measure of brand sentiment with performance measures obtained from external data sets (stock prices for both brands and an offline brand-tracking study for one brand). They find that their measure of sentiment serves as a leading indicator of the changes observed in these external data sources and outperforms other social media metrics currently used.

Keywords: social media, brand tracking, online word of mouth, social media analytics, social media research

Listening In on Social Media: A Joint Model of Sentiment and Venue Format Choice

In 2003, a controversy developed over the presence of trans fats in Oreo cookies. As part of its rapid response systems, Kraft Foods (the maker of Oreo) monitored the public sentiment expressed through blogs and decided to cut trans fats from its snack products (Terdiman 2006). In 2008, The Land of Nod, a division of Crate and Barrel that sells children's furniture, began monitoring comments posted on its ratings and review pages and using that information to inform its product and service improvement decisions (Stribling 2008). Overall, an increasing number of *Fortune* 500 companies, government agencies, and political campaigns have been turning to social media in an effort to gauge public opinion. As a result, an entire cottage industry of social media listening platforms and software has emerged (Hofer-Shall 2010).

However, the ability of social media to accurately inform decision makers depends on how the comments posted online are measured. Various studies have used data sourced from Twitter (e.g., Rui, Whinston, and Winkler 2009; Toubia and Stephen 2013), discussion forums and message boards (e.g., Godes and Mayzlin 2004; Kozinets 2002), and product review websites (e.g., Moe and Trusov 2011; Tirunillai and Tellis 2012), each at the exclusion of other types of social media venues. Even in studies that collect data from multiple websites, the research scope is still limited to a single venue format, such as ratings and review websites (Tirunillai and Tellis 2012). Although these studies have all advanced understanding of social media as a valuable data source for both insights and forecasts, such research has not considered that the venues from which data are collected may systematically differ, which in turn may lead to systematic differences in the comments posted to (and the metrics derived from) each venue.

In contrast, many marketers in practice employ listening platforms that collect comments posted across multiple social media venues. In some cases, they aggregate the data to construct simple averages. In other cases, they report venue-specific metrics (e.g., number of retweets, the num-

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ber of Facebook likes) without integrating the insights across venues. In other words, marketers are either ignoring differences across venues or finding it difficult to reconcile the differences they observe across venues. As a result, many end up using sentiment metrics that ultimately do not reflect underlying customer opinion.

Consider the case of a leading enterprise software firm. Figures 1 and 2 characterize the social media activity around the brand. In Figure 1, we plot the proportion of comments expressing positive, neutral, and negative sentiment across the three most common venue formats.[1] This figure conveys two key empirical observations. First, it shows that the sentiment expressed in social media venues can vary across different venue formats. In this context, blogs have the highest proportion of positive comments, while forums have the highest proportion of negative comments. As such, the sentiment toward a brand, when inferred from social media, depends on the sources from which the comments are drawn.

Second, venue format–specific measures of sentiment appear to exhibit stronger dynamics over time than an aggregate measure that simply averages sentiment across all posted comments regardless of venue format. In addition, these dynamics vary across venue formats. For example, for both blogs and microblogs, sentiment initially declines but then trends slightly upward. In contrast, the sentiment in discussion forums exhibits a more persistent decline, consistent with prior research that finds evidence of social dynamics (which discussion forums facilitate more so than blogs and microblogs) (e.g., Godes and Silva 2012; Moe and Schweidel 2012). These differences highlight the challenges in assessing brand sentiment from social media data that span multiple venue formats.

Figure 2 shows how the distribution of comments across venue formats can shift over time. For example, in month 11, we observe an increase in the number of comments posted to discussion forums and a decrease in the number of comments posted to blogs. If comments posted to blogs are generally more positive than those posted to forums (as Figure 1 suggests), any changes in sentiment metrics that aggregate data across social media venue formats will reflect not only changes in the underlying sentiment but also changes in venue format choice behavior, highlighting the need to model both expressed sentiment and venue format choice jointly.

This discussion highlights the shortcomings of social media metrics that do not account for differences across venues. Furthermore, that so little attention has been given to venue differences is particularly troubling given that the venue to which a consumer posts is a choice. Muniz and O'Guinn (2001) find that consumers often choose to participate in communities whose members share their interests and opinions. In addition, Chen and Kirmani (2012) show that goals influence where people choose to post a comment. These studies imply that what people post is related to where they post. Thus, if we measure brand sentiment using data from just one venue, our metric will reflect not just the

[1]Examination of the sentiment expressed for ten of the brand's most frequently mentioned products reveals a similar pattern to that shown in Figure 1.

Figure 1

DISTRIBUTION OF SENTIMENT FOR ENTERPRISE SOFTWARE BRAND

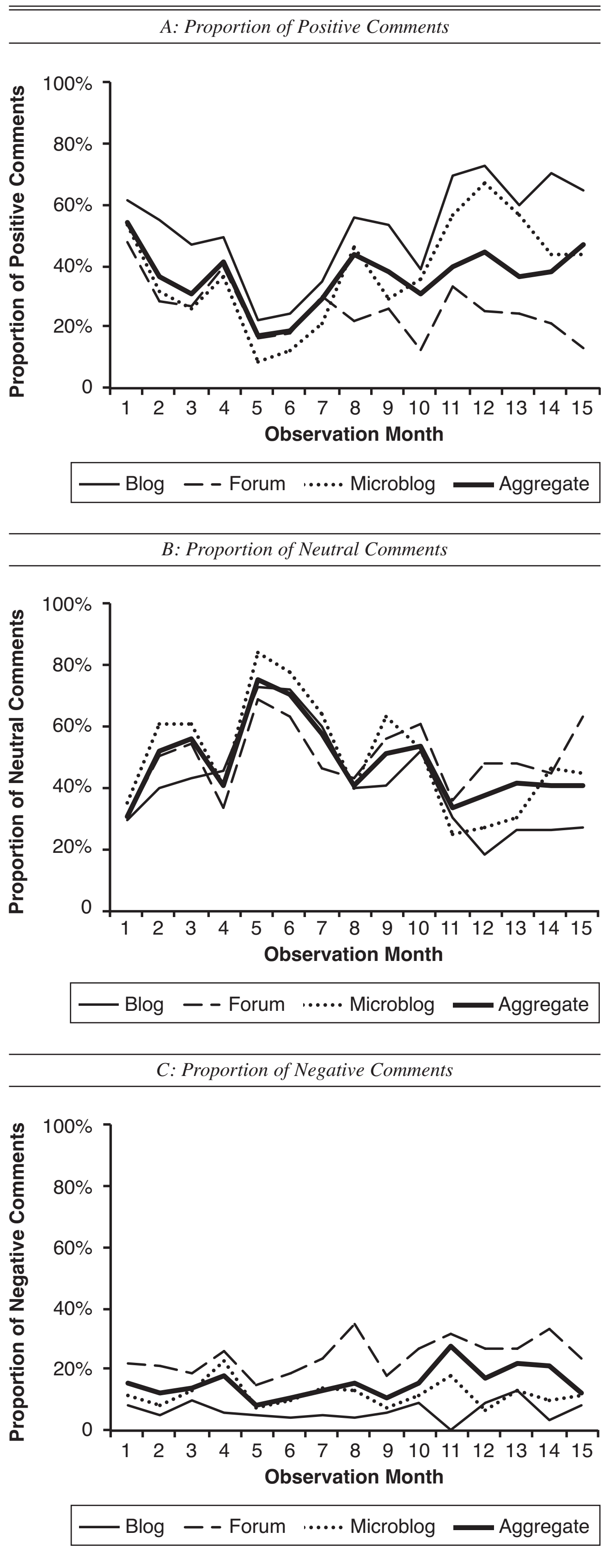
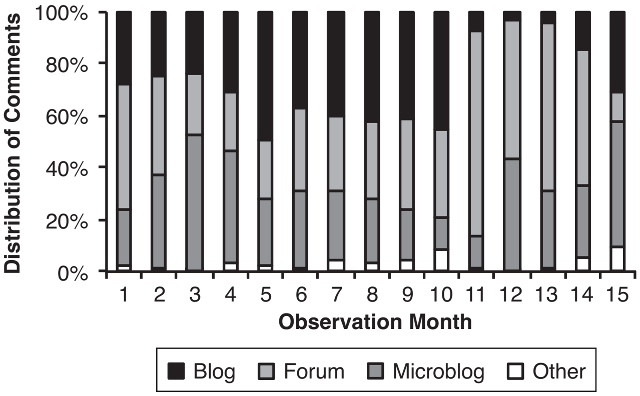


Figure 2
DISTRIBUTION OF COMMENTS ACROSS VENUES FOR ENTERPRISE SOFTWARE BRAND



consumers' opinions of the brand but also the venue from which we are tracking opinions.

We model the relationship between *what* people post and *where* they post in an effort to extract the underlying brand sentiment expressed across multiple social media venues. Specifically, we simultaneously model (1) the sentiment expressed in a posted comment and (2) the poster's venue format choice as a function of a latent construct we refer to as the "general brand impression" (GBI; Dillon et al. 2001). This construct links the two model components and represents, as we argue subsequently, the underlying brand sentiment.

We estimate our model using social media data related to leading brands in the enterprise software and telecommunications industries. For these two brands, the data consist of a sample of social media comments posted across a variety of online venues. Our results show significant variation in average sentiment across venue formats, highlighting the importance of separating the effects of venue format from any measure of brand sentiment.

To demonstrate the managerial implications of our model, we compare our GBI measure with alternative sentiment measures derived from the same social media data and show that brand sentiment metrics can vary dramatically depending on how the metric is constructed. We compare our measure of GBI with changes in the stock prices and find that GBI can serve as a leading indicator for shifts in stock prices. In addition, for one of the brands, we complement our analysis with data the firm collected from an offline brand-tracking survey and again find that our GBI measure can serve as a leading indicator for shifts in brand sentiment.

Before developing our model, we motivate our analysis by first discussing the differences across various social media venue formats and how these differences can affect posting behavior (which in turn affects social media data and metrics). We then describe our data and detail our proposed comment-level modeling approach. We compare our proposed model with several alternative modeling specifications to better understand how the sentiment and venue format choice processes are related. We focus on the enterprise software brand to empirically assess the performance of these different specifications. We then present the model results under the best-performing model specification for both the enterprise software brand and the telecommunications brand and highlight the importance of accounting for the variation across social media venue formats when measuring sentiment using social media data. As part of our empirical analysis, we compare our measure of GBI with other available offline metrics of the brand. We conclude by discussing the implications of our research for social media monitoring as a source of marketing intelligence.

SOCIAL MEDIA VENUE FORMATS

Research in social media marketing has grown rapidly in recent years. Several researchers have examined consumers' posting behaviors (Berger and Milkman 2012; Moe and Schweidel 2012; Schlosser 2005; Toubia and Stephen 2013), and others have examined the role of social networks (Goldenberg, Oestreicher-Singer, and Reichman 2012; Katona, Zubcsek, and Sarvary 2011; Mayzlin and Yoganarasimhan 2012; Watts and Dodd 2007) and social influence (Aral and Walker 2012; Trusov, Bodapati, and Bucklin 2010). Research has also investigated the link between social media and various performance measures, such as sales (Chevalier and Mayzlin 2006; Moe and Trusov 2011), television viewership (Godes and Mayzlin 2009), return on investment (Hoffman and Fodor 2010), and stock prices (Bollen, Mao, and Zeng 2011; Tirunillai and Tellis 2012). In this section, we discuss the role of venue formats on social media posting behavior and, in turn, social media metrics.

Consumers can post opinions in a variety of social media venues. The formats of these venues are replete with structural differences that can affect consumers' social media posting behaviors (e.g., for a review of various social media venue formats and their associated metrics, see Hoffman and Fodor 2010). For example, some venues, such as Twitter and many product ratings and review platforms, limit the length of posts, while blogs and discussion forums allow more depth of expression. Given the constraints on the length of posts, some venue formats (e.g., microblogs) encourage people to post extreme opinions so that they can convey their perspective in a limited number of characters, while other, lengthier venue formats (e.g., blogs) allow people to present richer and more nuanced opinions. At the same time, venue formats also differ in the degree to which they facilitate social interaction. Social networks such as Facebook are designed to maximize social exchanges. In contrast, ratings and review sites are designed for unidirectional communications from the poster to the reader. As a result, posters may be more subject to varying amounts of social dynamics, which can encourage more negative comments over time (Moe and Schweidel 2012).

We are not aware of any research that directly investigates the effects of these venue characteristics on posting behavior, though research has considered how users' motivations vary across venue formats. For example, Toubia and Stephen (2013) find that Twitter users are driven mostly by image-related motivations rather than intrinsic motivations, but they note that the findings may be specific to Twitter. Hsu and Lin (2008) find that bloggers are driven mostly by intrinsic motivations but also by image-related motivations (e.g., the desire to manage one's reputation). Yang et al. (2007) find that those who participate in online discussion forums are motivated by intrinsic motivations while image-related motivations have no effect. Together, these studies suggest that people's motivation to participate in social media activities varies across venue formats. Given both the structural differences and the variation in users' motivations, it stands to reason that we will observe systematic differences in posting behavior across venue formats.

From the perspective of a marketing researcher, this means that *what* we hear (in terms of the expressed sentiment and the focal topic of the comment) is related to *where* we listen. This is consistent with Smith, Fischer, and Yongjian (2012), who find that brand-related sentiment varies across YouTube, Twitter, and Facebook. Thus, if our goal is to construct a measure of brand sentiment from social media data, we must account for the venue from which the data are collected.

MODEL DEVELOPMENT

Our modeling objective is to separate the underlying brand sentiment from other factors that can affect the sentiment expressed in a social media comment (and subsequently skew our social media metrics). One of these factors is the venue format to which a comment is contributed. Because the decision of *what* to post is related to *where* it is posted, we jointly model both posted sentiment and venue format choice as two separate but related processes. This approach is consistent with multivariate statistical models that have appeared in the marketing literature (e.g., Du and Kamakura 2012; Kamakura et al. 2003; Park and Bradlow 2005; Schweidel, Park, and Jamal 2014). This is also in line with research that simultaneously models the impact of marketing actions on transactional behavior and the firm's marketing actions, recognizing that the two processes may be related (e.g., Manchanda, Rossi, and Chintagunta 2004; Schweidel and Knox 2013; Van Diepen, Donkers, and Franses 2009). Although we do not assume a causal relationship between the different model components, we view the posted sentiment and venue format choice as arising from a joint process.

In the sentiment model, our goal is to decompose observed variations in posted social media comments into three main components. The first component is a latent construct that we refer to as the GBI (Dillon et al. 2001). This construct affects the sentiment expressed in all mentions of the brand, regardless of the venue format (or website domain) in which the comment appears, and thus can be interpreted as the underlying brand sentiment that manifests in social media. The second component of the sentiment model allows for heterogeneity across venues. In addition to capturing time-invariant differences across venue formats and website domains, this component of the model allows for temporal shocks that are specific to particular venue formats.[2] Third, we account for variations in sentiment associated with the topic of the social media comment, which we specify as the focal product and brand attribute of the comment.

We specify the sentiment model as an ordered probit process in which the dependent variable is the expressed sentiment in a given comment, measured as negative, neutral, or positive. For comment j, let y_j denote the sentiment expressed such that $y_j = 1$ if the sentiment is negative, $y_j = 2$ if it is neutral, and $y_j = 3$ if it is positive. We assume that the latent sentiment driving the expressed sentiment for comment j (U_j), conditional on the venue to which comment j is contributed, is given by

$$U_j = GBI_{t(j)} + \beta_{v(j)} + \delta_{d(j)} + \phi_{v(j), t(j)} + \pi_{p(j)} + \alpha_{a(j)}, \tag{1}$$

where t(j), v(j), d(j), p(j), and a(j) are the time, venue format, domain, product, and attribute associated with comment j; $GBI_{t(j)} \sim N(0, \sigma^2_{GBI})$[3]; β reflects differences in the sentiment expressed in different venue formats; δ is a random effect to capture variation in sentiment across domains of the same venue format; and ϕ accounts for temporal shocks that are specific to venue format v. To account for differences in sentiment related to the content of comment j, we include π and α as random effects associated with the product and attribute discussed in comment j, respectively, and assume that these product and attribute effects are drawn from the distribution of $\pi_p \sim N(0, \sigma^2_\pi)$ and that $\alpha_a \sim N(0, \sigma^2_\alpha)$.

The likelihood with which a negative, neutral, or positive sentiment is expressed in comment j is then given by

$$\Pr\left(y_j = r\right) = \begin{cases} \Phi\left(-U_j\right), r = 1 \\ \Phi\left(\mu_{v(j)} - U_j\right) - \Phi\left(-U_j\right), r = 2 \\ 1 - \Phi\left(\mu_{v(j)} - U_j\right), r = 3 \end{cases}, \tag{2}$$

where μ_v are format-specific cut points, such that $\mu_v > 0$. Given the nature of our data, we employ an ordered probit process for the expressed sentiment; however, our modeling framework can be modified with ease to accommodate a continuous measure of sentiment, such as those provided by automated text analysis, as described in Appendix A.

The ordered probit model presented in Equations 1 and 2 captures the relationship between posted sentiment and GBI while accounting for the focal product and attribute mentioned in the comments, conditional on the venue format to which the comment is contributed. To account for the possible relationship between GBI and the venue format, we simultaneously model the venue format choice as being related to GBI. Furthermore, consistent with Moe and Schweidel (2012), we use random effects to control for heterogeneity arising from differences in the focal products and mentioned attributes across social media comments. This approach is also in line with Park and Bradlow (2005), who, in simultaneously modeling different aspects of auction bidding behavior, control for the characteristics of buyers, sellers, and products. Thus, we model the choice of venue format for comment j ($V_j = v$) as a multinomial logit model, as follows:

$$\Pr\left(V_j = v\right) = \frac{\exp\left(VenAtt_{j,v}\right)}{\sum_{v=1}^{Z} \exp\left(VenAtt_{j,v}\right)}, \tag{3}$$

[2]We incorporate temporal shocks that are specific to the venue format rather than the domain because many domains appear infrequently in our data. Our modeling approach can easily be generalized to include domain-specific temporal shocks.

[3]In our preliminary analysis, we considered a random walk structure for GBI, with $GBI_t = GBI_{t-1} + \tau_t$, where $\tau_t \sim N(0,\sigma^2_\tau)$. We found no substantive differences in our results.

where we define the latent attraction of a given venue format, v, for comment j ($VenAtt_{j,v}$) as

$$VenAtt_{j,v} = \gamma_v + \lambda_v VenLoc_j + \kappa_v GBI_{t(j)} \quad (4)$$

for venue formats v = 1, 2, ..., Z – 1 (we assume that $VenAtt_{j,Z}$ equals 0 for identification purposes).

The intercept γ_v captures baseline differences across formats. The term $VenLoc_j$ (which we define next) represents the location of comment j on a latent continuum (e.g., Li, Sun, and Wilcox 2005; Park and Bradlow 2005) and allows us to account for differences in the comments related to the focal attribute and product mentioned in the comment. To identify the model, we assume that $\lambda_1 = 1$. In other words, venue format 1 (in our case, blogs) represents our baseline venue format, and the coefficient λ_v reflects the similarity between the content that is attracted to venue format v and the content that is attracted to venue format 1. When $\lambda_v > 0$, the attraction to both venue formats 1 and v increases as $VenLoc_j$ increases. As such, the two venue formats may attract similar content. In contrast, when $\lambda_v < 0$, $VenAtt_{j,1}$ increases with $VenLoc_j$, while $VenAtt_{j,v}$ decreases with $VenLoc_j$, suggesting that the two venue formats attract different content.

To capture the variation in the content of comments, we specify $VenLoc_j$ as

$$VenLoc_j = \theta_{p(j)} + \omega_{a(j)}, \quad (5)$$

where $\theta_p \sim N(0, \sigma^2_\theta)$ and allows for variation in the attractiveness of venue format 1 for different products. Similarly, we specify $\omega_a \sim N(0, \sigma^2_\omega)$ to allow for the variation in attractiveness of venue format 1 for different attributes. By allowing comments that focus on different products and attributes to gravitate toward specific venue formats, our model accounts for the possibility that some social media comments are more (or less) likely to appear in certain venue formats.

The coefficient κ_v reflects the extent to which venue format v increases in attractiveness with an increase in GBI. If $\kappa_v = 0$ for all v, this would suggest that there is no relationship between expressed sentiment and venue format attractiveness. If $\kappa_v > 0$, this would indicate that venue format v becomes relatively more attractive as GBI increases. Thus, GBI serves as a latent factor that links the expressed sentiment and venue choice models. Other researchers have used similar approaches of employing a single latent factor to link multiple model components (e.g., Moe and Schweidel 2012; Park and Bradlow 2005).

Equations 1 and 2 present a model of posted sentiment conditional on the chosen venue format, and Equations 3–5 detail the model of venue format choice, both of which may be related to the inferred GBI. We estimate the model described in Equations 1–5 using WinBUGS with diffuse priors. We ran three independent chains for 10,000 iterations, with the first 5,000 iterations discarded as a burn-in. We assessed convergence both visually and using Gelman–Rubin statistics.

SOCIAL MEDIA DATA

Our social media data set was provided by Converseon, a leading online social media listening platform that monitors and records text-based user-generated content (e.g., blogs, product reviews, discussion streams, social network comments, microblog posts). Converseon monitors a large sample of website domains and identifies comments pertaining to clients' brands. These comments are recorded and the textual content is coded for a random sample of comments.

Converseon provided data related to a leading brand in the enterprise software industry. The data were collected between June 2009 and August 2010, yielding 7,565 comments from a 15-month window (for descriptive data statistics, see Table 1).

The textual content of the comments were manually coded by a team of analysts at Converseon.[4] Comments were coded for sentiment, such that each comment was identified as positive, negative, or neutral. The following snippet from one social media comment posted to a discussion forum illustrates the data Converseon provided:

> "Isn't this sector already dotted with high price systems offering 'XXX services' (like YYY, ZZZ)."

Here, XXX masks the category, and YYY and ZZZ mask two products available in the enterprise software industry, one from our focal company and one from a competitor. A human reader can easily discern that the topic of this comment is the cost of the services and that the sentiment is negative. For comparison purposes, the following is a comment coded as expressing a positive sentiment toward brand YYY on the topic of product quality:

> "One app that will keep me from switching right away is a good XXX app (ala YYY). I have to admin a bunch of computers and that app saves my bacon once a week."

For our analysis, we employ the coding provided by Converseon because of limitations in the automated text analysis we encountered (for a comparison of the manual

[4]To validate the sentiment coding provided, we assessed the sentiment expressed in each comment using Linguistic Inquiry and Word Count and found no substantive differences in our empirical results (for additional details, see Appendix A). To provide additional external validation for Converseon's sentiment coding, we randomly selected a sample of 200 comments from our data and independently coded them as positive, neutral, or negative. Although research generally recommends that such sentiment coding not be conducted by the authors of the research, we do so in this case as a "quick and dirty" check of the data, in addition to using Linguistic Inquiry and Word Count. Comparison of the coding from Converseon and each author yielded a resulting Krippendorf alpha of .86.Taken together, these assessments suggest that Converseon's sentiment coding did not introduce additional bias.

Table 1
DESCRIPTIVE DATA STATISTICS FOR ENTERPRISE SOFTWARE BRAND, JUNE 2009–AUGUST 2010

	Number
Comments	7,565
Positive comments	2,655
Neutral comments	3,804
Negative comments	1,106
Products mentioned	140
Attributes mentioned	59
Website domains in which brand is mentioned	886
Comments posted to blogs	2,274
Comments posted to forums	2,728
Comments posted to microblogs	2,333

coded data with data resulting from an automated analysis using Linguistic Inquiry and Word Count, see Appendix A). However, our modeling approach can be applied to any social media sentiment data, regardless of the sentiment coding method applied.

In addition to sentiment, our data contain the focal product and attribute of each comment. The enterprise software brand analyzed in this research offers a large product portfolio consisting of 140 different products. Attributes discussed in the comments also ranged widely, from customer service and support to product reliability. Comments for the enterprise software brand featured 59 different attributes. The consequence of the large number of unique attributes and products is that each product–attribute combination may be sparsely represented in the data. This is fairly typical of social media data. Thus, any effort to represent product- or attribute-specific sentiments using simple summary metrics would be based on small samples and thus would be unreliable. This characteristic of the data highlights the need for a statistical model that uses Bayesian inference.

The data collection process is based on a white list of popular social media domains maintained by Converseon. These domains can be categorized into different venue formats, with more than 90% of comments related to the enterprise software brand used in this analysis being drawn from blogs, forums, and microblogs. On a daily basis, Conversion collects all comments pertaining to the brand that appear on any of the domains included in the white list. From that universal data set, a sample was randomly selected to create the data set for this study. Because of the comprehensiveness of the white list and the randomness of the sample selection process, we believe that our data sample is representative of overall social media activity.[5] Overall, the enterprise software brand was mentioned in 886 different domains.

MODEL COMPARISONS: NESTED MODELS

In this and the next section, we present several model comparisons to demonstrate the value of our model specification. We estimate a series of nested models to assess the importance of including the various model components. In Model 1, we allow expressed sentiment to vary across formats (through β_v and $\phi_{v,t}$) and over time (through GBI_t and $\phi_{v,t}$) but assume that the expressed sentiment and venue format choice processes are independent processes ($\kappa_v = 0$) and unrelated to the product or attribute mentioned ($\pi_p = 0$, $\alpha_a = 0$, and $\lambda_v = 0$). This serves as our baseline model specification.

We proceed to relax these assumptions in the next two model specifications. In Model 2, we allow expressed sentiment and venue format choice to vary with the topic of a social media post (i.e., the mentioned product and attribute) by estimating π_p, α_a, and λ_v. However, Model 2 still assumes that the venue format choice is unrelated to the underlying sentiment toward the brand ($\kappa_v = 0$). We relax this assumption in Model 3 by estimating κ_v, which allows the attractiveness of venue format *v* to shift with changes in GBI_t.

In Table 2, we compare the fit of these nested models using the social media data from the enterprise software brand. We report the deviance information criterion (DIC), which is a likelihood-based measure that penalizes more complex models (Spiegelhalter et al. 2002). We also report the hit rate of the sentiment model and the hit rate of the venue format choice model.

When we compare Models 1 and 2, all three measures of model fit improve, suggesting that the expressed sentiment and venue format choice are related to the specific product and attribute mentioned in social media posts, an empirical finding that, to the best of our knowledge, has not previously been documented in the literature.

Next, comparing Models 2 and 3, we again observe a decrease in the DIC and an increase in the venue format hit rate. We would not expect the sentiment hit rate to improve as we move from Model 2 to Model 3 because the model for expressed sentiment has not changed. This model comparison suggests that shifts in the underlying sentiment toward the brand, which we infer from GBI, are indeed related to the venue format choice process. This further underscores the need to consider the sentiment and venue format choice processes simultaneously, as shifts in brand sentiment affect not only the expressed sentiment within a particular venue format but also the distribution of comments across venue formats.

MODEL COMPARISONS: ALTERNATIVE MODEL SPECIFICATIONS

Our proposed model assumes that the topic of the comment (i.e., the product and attribute discussed) and GBI drive both expressed sentiment and venue format choice jointly. In this section, we test this assumption and consider alternative model specifications in which expressed sentiment and venue format choice are conditionally independent processes—that is, sequential processes in which the decision of what sentiment to express precedes venue format choice or sequential processes in which venue format choice precedes the decision of what sentiment to express. We illustrate the conceptual differences between these modeling approaches in Figure 3.

Panel A of Figure 3 represents our proposed model. In Panel B, we assume that the topic of the comment and GBI affect both the venue format choice and sentiment processes but that these processes are conditionally independent. To test this alternative model specification, we eliminate any venue-specific terms (i.e., the venue format–specific intercepts, format-specific shocks, and domain-specific effect) from the model for U_j in Equation 1 and replace it with

$$U_j = \beta + GBI_{t(j)} + \pi_{p(j)} + \alpha_{a(j)}, \tag{6}$$

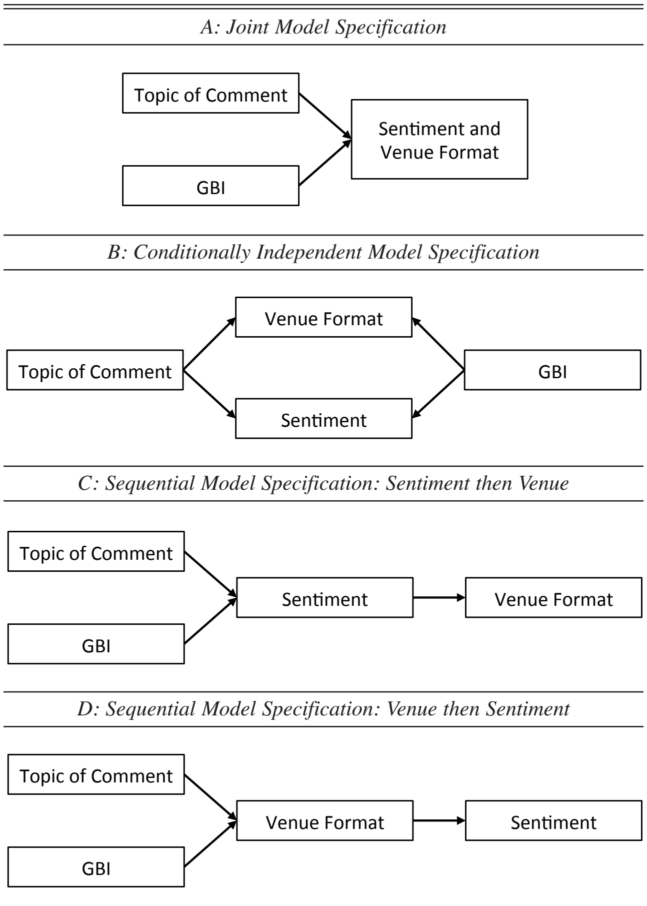
Table 2

MODEL COMPARISON FOR ENTERPRISE SOFTWARE DATA

	DIC	*Sentiment Hit Rate*	*Venue Format Hit Rate*
Model 1	32,587	.45	.32
Model 2	30,290	.47	.39
Model 3	29,529	.47	.42

[5]We are confident that Converseon's data sample is representative of online social media activity, though it is less clear how representative it is of overall customer opinion (i.e., both online and offline). In the software industry, many customers are active online. Thus, our context is one in which social media are likely to be consistent with overall opinion. However, this will vary across industries.

Figure 3
ALTERNATIVE MODELING FRAMEWORK



where β is the overall intercept. We also modify Equation 2 and replace the venue format–specific cut points μ_v with μ that is common across all venue formats. With this model specification, the sentiment hit rate is .44 and the venue hit rate is .42 (DIC = 30,246), suggesting that this model does not perform as well as our proposed joint model (for a summary of model comparison results, see Table 3). This analysis suggests that the two processes are related.

Next, we assess the performance of the sequential models illustrated in Figure 3, Panels C and D. In Panel C, we assume that the topic of the comment and GBI affect sentiment and, in turn, that sentiment affects the venue format choice process. In terms of model specification, we assume that U_j is given by Equation 6, the cut point μ is common across venue formats, and U_j affects the venue format choice. We do so by assuming that $VenAtt_{j,v}$ is given by

$$\text{VenAtt}_{j,v} = \gamma_v + \kappa_v U_j \tag{7}$$

for v = 1, 2, …, Z – 1. The hit rates for sentiment and venue format under this specification are .41 and .42, respectively (DIC = 30,915).

Alternatively, as Panel D of Figure 3 illustrates, we consider the specification in which GBI and the topic of the comment affect the venue choice, which in turn affects sentiment. In this model, the venue format choice process is given by Equations 3–5. For the sentiment submodel, we assume that U_j is affected by the likelihood with which comment j is posted to each venue format, which is given in Equation 3. That is,

$$U_j = \beta_0 + \sum_v \beta_v \Pr(V_j = v). \tag{8}$$

Under this specification, the hit rate is .42 for sentiment and .42 for venue (DIC = 30,448).[6]

Although these alternative specifications provide a comparable hit rate for the venue format choice process, the joint model specification (illustrated in Figure 3, Panel A) best fits our data according to DIC and the sentiment hit rate. To the best of our knowledge, an assessment of how venue format choice and sentiment are interrelated has not previously been conducted in the marketing literature. Our analysis suggests that venue format choice and sentiment are related to each other and are jointly driven by GBI and the topic of the comment.

Table 3
SUMMARY OF MODEL COMPARISON RESULTS

	DIC	*Sentiment Hit Rate*	*Venue Format Hit Rate*
Joint model specification (proposed model)	29,529	.47	.42
Conditionally independent model specification	30,246	.44	.42
Sequential model specification: sentiment then venue	30,915	.41	.42
Sequential model specification: venue then sentiment	30,448	.42	.42

MODEL RESULTS: ENTERPRISE SOFTWARE BRAND

In this section, we present the estimated parameters resulting from our proposed model for the enterprise software brand and discuss how the model results enable us to extract meaningful and managerially relevant inferences from social media data. We present the posterior means and standard deviations across iterations for parameters of interest pertaining to the blogs, microblogs, and forums (the three most prevalent venue formats in our data set) in Table 4.[7] Consistent with the exploratory analysis presented in Figure 1, the sentiment intercepts (β_v) reflect the low proportion of negative posts and differences in the sentiment expressed across venue formats. The large intercepts for the venue attractiveness model (γ_v) are consistent with the fact that blogs, forums, and microblogs account for the vast majority of social media comments in this data set.

The posterior means of the precisions (1/variance) for the random effects θ_p and ω_a, the sum of which yields the location on a one-dimensional continuum for comment j (VenLoc_j), are 7.90 and 14.47, respectively. This indicates that more variation in the continuum is attributable to the focal attribute than to the focal product. The coefficient λ_v allows

[6]We also consider a model variant in which the sentiment component includes the domain-specific random effect $\delta_{d(j)}$. Under this model specification, the hit rate is .44 for sentiment and .42 for venue (DIC = 30,252).

[7]Parameter estimates for all venue formats appear in Appendix B.

Table 4
ENTERPRISE SOFTWARE BRAND PARAMETER ESTIMATES

	Blog	*Forum*	*Microblog*
Sentiment intercept (β_v)	2.04 (.12)	.84 (.11)	1.28 (.18)
Sentiment cut point (log[μ_v])	.70 (.03)	.36 (.02)	.54 (.02)
Venue attractiveness intercept (γ_v)	5.05 (.30)	5.45 (.37)	5.25 (.31)
Content effect on venue attractiveness (λ_v)	1 (—)	–2.94 (.96)	1.01 (.13)
GBI effect on venue attractiveness (κ_v)	–1.46 (1.32)	5.19 (1.35)	3.14 (1.22)

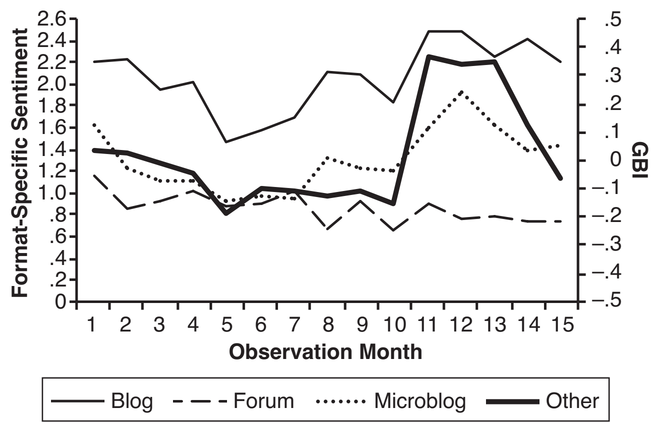
the focal product and attribute mentioned in a social media post to affect the propensity to post to different venue formats. For identification, we assumed $\lambda_v = 1$ for one of the venues—in this case, blogs—and thus social media comments with a positive value of $VenLoc_j$ are more likely to gravitate toward blogs. These comments should also gravitate toward microblogs, as reflected in the parameter $\lambda_v > 0$. In contrast, topics that are more likely to be posted to blogs and microblogs are less likely to be posted to forums, as indicated by the parameter $\lambda_v < 0$.

The implications of these findings are significant for companies engaged in social media monitoring. If a firm were to monitor microblogs (e.g., Twitter), the products and attributes it observes being discussed should be similar to those appearing in blogs. However, the products and attributes mentioned in microblogs are different from those likely to be posted to discussion forums. Thus, the firm might draw biased inferences from the overall prevalence with which products and attributes are mentioned in social media posts. Although we might expect the focal topic of the comment to affect expressed sentiment (e.g., Dillon et al. 2001), its relationship to the venue format choice process has not yet been examined in the social media literature.

We also find that venue format attractiveness varies with the latent GBI (κ_v). While positive shifts in GBI increase the attractiveness of forums and microblogs for social media posts, it decreases the attractiveness of blogs. In other words, increases in underlying brand sentiment are associated with increased activity in forums and microblogs but decreased activity in blogs. This effect is distinct from the time-invariant differences in expressed sentiment, given the venue format to which a comment is posted (β). That is, although period-to-period changes in underlying sentiment (or GBI) may affect the relative attractiveness of each venue format, some formats are generally more positive (or negative) than others.

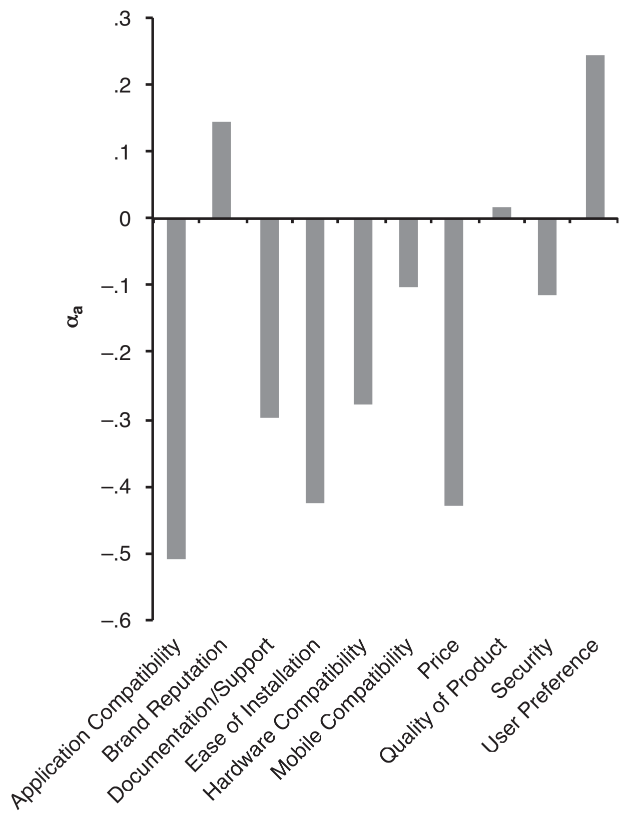
We present the posterior means of GBI and compare it with the format-specific sentiment (calculated as $GBI_t + \beta_v + \phi_{v,t}$) for blogs, forums, and microblogs in Figure 4. In the first few months of the observation period, we find a general decline among the three common venue formats and the GBI. The GBI reaches its lowest point in our observation period in month 5, the month after the enterprise software firm announced that it would not be participating in an industrywide event because of changes in the guidelines implemented by the organizers (which happened to be one of the firm's main competitors). Subsequent to this decline, however, we find some divergence among the sentiment expressed in the different venue formats. While the sentiment in blogs and microblogs increases, the sentiment in forums exhibits a slight decline. Note, however, that GBI remains relatively flat over these few months. As such, variation in the format-specific sentiments is driven by format-specific temporal shocks, $\phi_{v,t}$. While blogs and microblogs mirror an increase in GBI in month 11 (following a newly announced strategic partnership), no increase occurs in the forum-specific sentiment. Again, this suggests that different venue formats exhibit unique dynamics, illustrating the potential pitfalls from inferring sentiment and changes in sentiment from individual venue format data.

Figure 4
FORMAT-SPECIFIC SENTIMENT AND GBI FOR ENTERPRISE SOFTWARE BRAND



The product and attribute effects on expressed sentiment (π_p and α_a) also have significant managerial applications because these results can diagnose potential problems within the brand portfolio or with product design. As an illustration, we show the attribute random effects (α_a) for ten frequently mentioned focal attributes in our data set in Figure 5. Although these findings are not generalizable to other brands, we provide these results to demonstrate the ability of our modeling approach to attribute sentiment differences to various products and attributes. In this case, seven of the ten frequently mentioned attributes have a negative effect on expressed sentiment. The exceptions are brand reputation, product quality, and user preference. In other words, when posters focus on concrete attributes related to product performance, such as compatibility and security, the sentiments expressed in their comments are likely to be more negative. In contrast, social media comments focusing on holistic assessments of reputation, quality, and user preference tend to be more positive. For this brand, while product functionality may receive critical comments online, the overall brand may be benefiting from a positive halo effect from past successes. Such a result may

Figure 5
VARIATION IN SENTIMENT RELATED TO FOCAL ATTRIBUTE



be cause for concern for the long-term future of the brand if the criticisms of product performance persist and continue to be discussed.

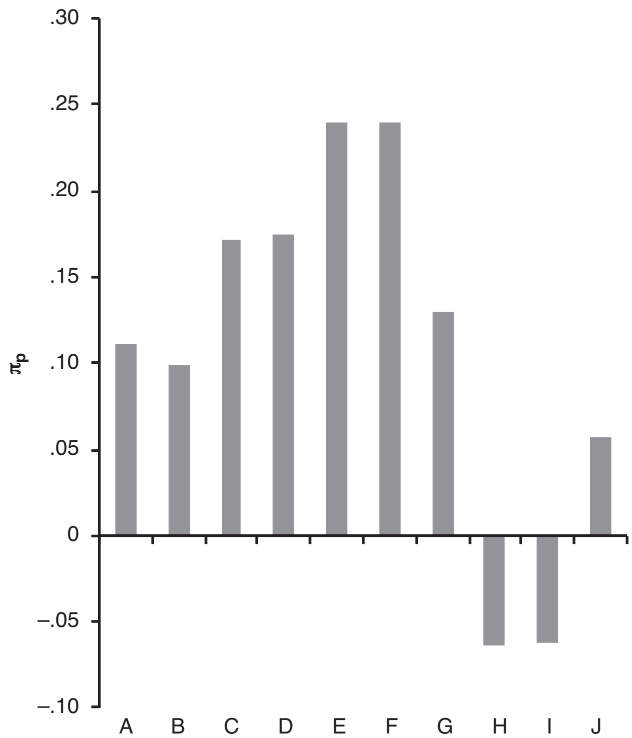
We can similarly examine the variation in sentiment across different products in the brand's portfolio. For the ten most frequently mentioned brands, Figure 6 provides the posterior estimates of π. In essence, these estimates reflect how each product is evaluated relative to the overall brand. For this brand, eight of the ten most frequently mentioned products positively contribute to the expressed sentiment. However, products H and I are viewed more negatively relative to the overall sentiment toward the brand. From a brand manager's perspective, these results could raise a red flag and may indicate that some intervention is necessary for these two products, again highlighting the diagnostic value of the model proposed herein.

GBI as a Measure of Brand Sentiment

To demonstrate that our GBI measure reflects brand sentiment, we compare it with data collected from a traditional offline brand-tracking survey conducted by the firm. This survey was administered by telephone to a sample of 1,055 registered customers in ten monthly waves from November 2009 to August 2010. This overlaps with the period during which our online data were collected. The survey measured customer satisfaction with the brand using seven questions (e.g., "What is your overall opinion about [brand]?" "How likely would you be to recommend [brand] to a peer or colleague?"). Given the high pairwise correlations among the survey items (ranging from .44 to .83), we averaged the responses across the seven items to represent our survey-based brand sentiment measure.[8] Figure 7 illustrates the relationship between the posterior mean of the GBI and the average survey response, showing that GBI leads the brand-tracking survey results.

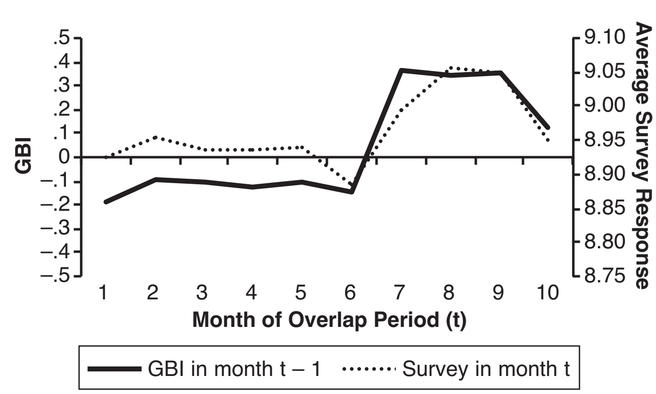
To more formally assess the relationship between the GBI in month t – 1 and the average survey response in

Figure 6
VARIATION IN SENTIMENT RELATED TO FOCAL PRODUCT



[8]A factor analysis also suggested a single factor onto which the seven items loaded.

Figure 7
GBI VERSUS BRAND-TRACKING SURVEY



month t, we calculate the correlation at each iteration of the Markov chain Monte Carlo (MCMC) sampler. The average correlation across all iterations is .88, with a standard deviation of .02, suggesting a strong relationship between the two measures and that the sentiment inferred from social media comments can serve as a leading indicator.

To determine how the GBI measure performs compared with simple empirical metrics currently used in practice, Table 5 provides the correlation coefficients between the offline survey results and various average sentiment metrics. Specifically, we consider the average sentiment computed by averaging sentiment scores across all comments, regardless of the venue to which they were posted, and the venue-specific averages for blogs, forums, or microblogs only. Not only does GBI outperform all these metrics in terms of reflecting the offline brand-tracking survey, but some of these commonly used metrics are also poorly correlated with the survey results. For example, the average sentiment across all comments has virtually no correlation with the offline survey (concurrent correlation = .01; lagged correlation = .17). If only one venue format is monitored (another common monitoring practice), correlation with the offline brand-tracking survey can be as poor as –.23 in the case of forums.

We also regressed the offline survey-based measures on the social media sentiment metric in the same month and the previous month to test how much variation both the concurrent and lagged measures together can explain. We report the resulting R^2 values in Table 5. Again, our model-based GBI measure outperforms both the average sentiment (computed across all comments regardless of venue) and the venue format–specific averages for blogs, forums, or microblogs in terms of reflecting the offline brand-tracking survey.

Table 5

CORRELATION WITH OFFLINE BRAND-TRACKING SURVEY

	Concurrent	*Lagged*	R^2
For All Products			
Average sentiment[a]	.01	.17	.03
Blogs only	.20	.53	.34
Forums only	–.23	.21	.06
Microblogs only	.39	.72	.55
For the Ten Most Popular Products Only			
Average sentiment[a]	–.17	–.35	.13
Blogs only	.16	.44	.20
Forums only	–.22	–.02	.06
Microblogs only	.57	.68	.52
GBI[b]	.38	.88	.80

[a]Average sentiment is computed by averaging the sentiment score across all posted comments regardless of the venue to which it was posted.

[b]The GBI measure is based on a Bayesian model, and thus the correlations and R^2 reported here are the median values across model iterations.

Finally, Table 5 also reports the correlations with the offline brand-tracking survey for the same sentiment metrics pertaining to only the ten most frequently mentioned products. Again, we find that GBI captures the variation in the brand-tracking survey better than the observed social media metrics.

Table 6 reports the detailed results of regressing the offline survey measures against both the concurrent measure of GBI and the lagged measure of GBI summarized across each model iteration. Across nearly all iterations, lagged GBI was significant at $\alpha = .01$, with an average coefficient of $\beta = .25$. In contrast, the concurrent GBI variable predicted survey responses (with $\alpha = .1$) in only 5% of the iterations. The average R^2 across iterations was .80, with 95% of the iterations having R^2 values in the interval (.71, .89), further demonstrating that GBI is related to changes in sentiment toward the brand.

This analysis underscores the limitations of attempting to draw inferences regarding brand sentiment directly from raw social media data. If we were to simply average the sentiment expressed across all comments regardless of venue format or within individual venue formats, we would find no relationship to the sentiment expressed through the offline brand-tracking survey. However, by using the GBI inferred from social media data, we demonstrate that social media comments can serve as a leading indicator of shifts in brand sentiment. Such a tool is of value to brand managers because it can provide an early warning of changes in consumers' brand perceptions. However, when deriving this measure, the venues to which comments are contributed and the topic of the comment must be taken into account. This requires a joint model of sentiment and venue format choice, as we propose herein.

GBI and Stock Price

Tirunillai and Tellis (2012) find that the sentiment expressed online can predict stock price movements. Thus, to further assess the relationship between GBI and brand performance, we collect stock market prices for the enterprise software brand at the close of each month and compare these prices with our GBI measure.

At each iteration of the MCMC sampler, we regress stock market price against Standard & Poor's (S&P) index at the close of the month (to capture market-level effects independent of the brand itself), GBI at the close of the month, and GBI at the close of the preceding month (Table 7). The average R^2 across iterations was .59, with 95% of iterations having R^2 values in the interval (.50, .68). The average value (across iterations) of the S&P index coefficient was

Table 6

SUMMARY OF BRAND-TRACKING SURVEY REGRESSIONS FOR ENTERPRISE SOFTWARE BRAND

	Mean Coefficient Estimate	*95% Confidence Interval*	*% of Iterations with p < .1*	*% of Iterations with p < .05*	*% of Iterations with p < .025*
Constant	8.96	[8.93, –8.97]	1.00	1.00	1.00
GBI(t)	–.06	[–.10, –.02]	.05	.01	.00
GBI(t – 1)	.25	[.17, .35]	1.00	1.00	1.00
R^2	.80	[.71, .89]			
Adjusted R^2	.75	[.62, .86]			

Table 7

SUMMARY OF STOCK PRICE REGRESSIONS FOR ENTERPRISE SOFTWARE BRAND

	Mean Coefficient Estimate	*95% Confidence Interval*	*% of Iterations with* p < *.1*	*% of Iterations with* p < *.05*	*% of Iterations with* p < *.025*
Constant	–68.09	[–79.99, –57.57]	.78	.16	.01
S&P	.10	[.093, .11]	1.00	1.00	1.00
GBI(t)	–16.43	[–25.54, –9.69]	.17	.01	.00
GBI(t – 1)	30.81	[20.64, 45.01]	1.00	.99	.78
R^2	.59	[.50, .68]			
Adjusted R^2	.46	[.35, .58]			

.10, with 95% of the iterations lying in the interval (.09, .11). In every iteration, the S&P coefficient was significant at α = .05. The average coefficient for GBI at the close of the same month was –16.4, with 95% of the regression coefficient lying in the interval (–25.54, –9.69), but only .01% of the iterations had concurrent GBI coefficients that were significant at α = .05. As a leading indicator, GBI at the close of the preceding month had an average coefficient of 30.81, with 95% of the coefficients being in the interval (20.64, 45.01). Regression coefficients from all iterations were significant at α = .10, and the coefficients from 99% of the iterations were significant at α = .05.

Thus, in addition to serving as a leading indicator for shifts in the brand-tracking survey, we find evidence that the GBI can serve as a leading indicator for changes in the stock price. Taken together, these findings indicate that the GBI construct captures shifts in brand sentiment.

MODEL RESULTS: TELECOMMUNICATIONS BRAND

In this section, we apply our model to a second social media data set collected for a telecommunications brand, again provided by Converseon. These data were collected over a 24-month period between January 2009 and December 2010, providing 4,173 comments (for descriptive data statistics, see Table 8).

The objective in this section is to provide an additional demonstration of our model. Thus, rather than discussing the results in detail as we did for the enterprise software brand, we highlight just a few results for the sake of parsimony.

Table 9 presents the posterior means and standard deviations across iterations of the MCMC sampler for parameters of interest. We also illustrate the format-specific sentiment and GBI in Figure 8. Again, we find that the venue formats differ in their baseline level of sentiment (β_v) and baseline level of attractiveness (γ_v). Moreover, the coefficients λ_v and κ_v that significantly differ from 0 suggest that the venue format to which social media comments are posted is related to the topic of the comment and the sentiment being expressed. These findings provide further support for the use of a joint model of venue format choice and expressed sentiment because the processes are not independent of each other.

Table 8

DESCRIPTIVE DATA STATISTICS FOR TELECOMMUNICATIONS BRAND, JANUARY 2009–DECEMBER 2010

	Number
Comments	4,173
Positive comments	1,604
Neutral comments	2,419
Negative comments	150
Products mentioned	24
Attributes mentioned	115
Website domains in which brand is mentioned	525
Comments posted to blogs	1,289
Comments posted to forums	665
Comments posted to microblogs	2,009

GBI and Stock Price

Although we do not have an offline brand-tracking survey from the telecommunications firm, we can assess the relationship between GBI and the firm's stock price. At each iteration of the MCMC sampler, we regressed the closing stock price for the month on the closing price of the S&P index in the same month, GBI in the same month, and GBI in the previous month (Table 10). The mean regression coefficient for the S&P index was .13, and the coefficient was significantly different from 0 for all iterations. The average coefficient for the concurrent GBI was 8.95 but was significant at α = .05 for only 28% of iterations. The coefficient for GBI in the previous month, however, was significantly different from zero for more than 99% of iterations and had a mean value of 19.49, with the regression coefficients for 95% of iterations in the interval (13.58, 26.66). The average R^2 of the regression model across iterations was .98, with 95% of iterations having R^2 values in the interval (.97, .98). Consistent with our findings for the enterprise software brand, this again suggests that GBI, a measure of brand sentiment inferred from social media comments after

Table 9

TELECOMMUNICATIONS BRAND PARAMETER ESTIMATE

	Blog	*Forum*	*Microblog*
Sentiment intercept (β_v)	2.56 (.16)	1.71 (.14)	1.80 (.32)
Sentiment cut point ($\log[\mu_v]$)	1.05 (.04)	.82 (.04)	.86 (.03)
Venue attractiveness intercept (γ_v)	6.36 (.53)	3.17 (.59)	6.81 (.56)
Content effect on venue attractiveness (λ_v)	1 (—)	5.66 (.90)	.05 (.23)
GBI effect on venue attractiveness (κ_v)	–.72 (1.15)	–2.91 (1.25)	3.90 (1.26)

Figure 8

FORMAT-SPECIFIC SENTIMENT AND GBI FOR TELECOMMUNICATIONS BRAND

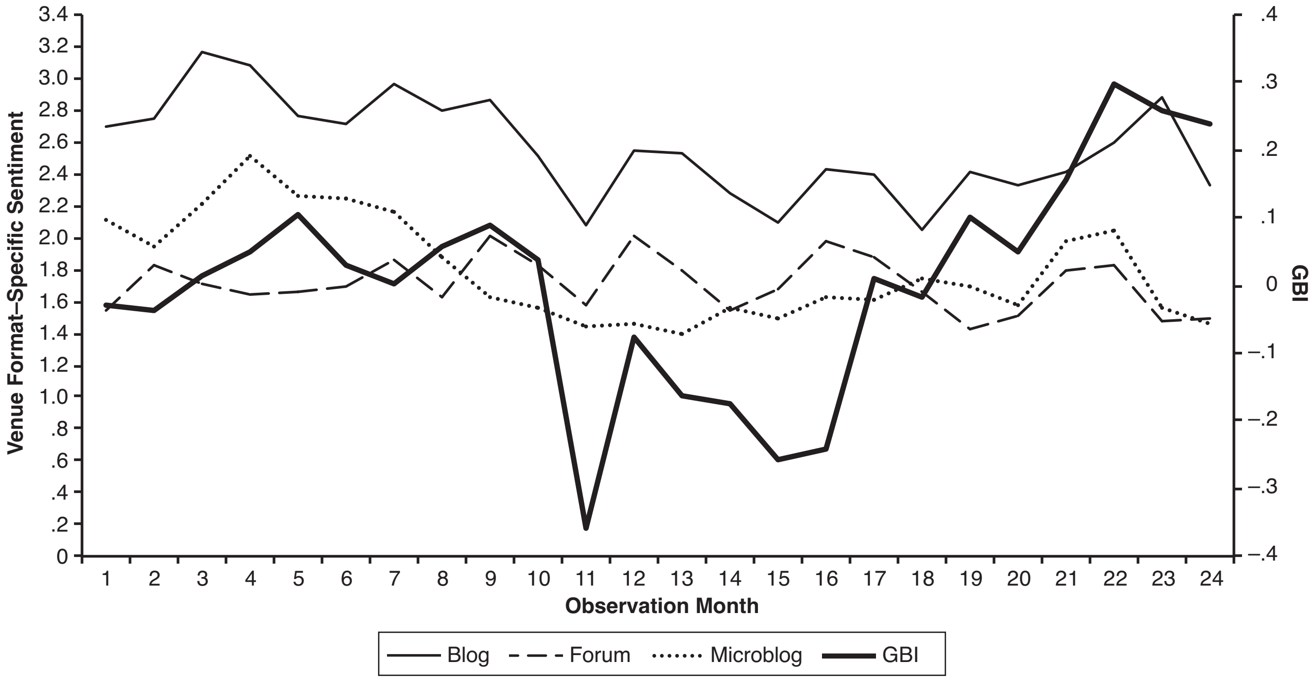


Table 10

SUMMARY OF STOCK PRICE REGRESSIONS FOR TELECOMMUNICATIONS BRAND

	Mean Coefficient Estimate	*95% Confidence Interval*	*% of Iterations with* $p < .1$	*% of Iterations with* $p < .05$	*% of Iterations with* $p < .025$
Constant	–47.55	[–51.78, –42.89]	1.00	1.00	1.00
S&P	.13	[.126, .134]	1.00	1.00	1.00
GBI(t)	8.95	[4.35, 16.20]	.56	.28	.11
GBI(t – 1)	19.49	[13.58, 26.66]	1.00	.99	.98
R^2	.98	[.97, .98]			
Adjusted R^2	.97	[.96, .98]			

accounting for other sources of variation in sentiment, can serve as a leading indicator for movements in the firm's stock price.

DISCUSSION

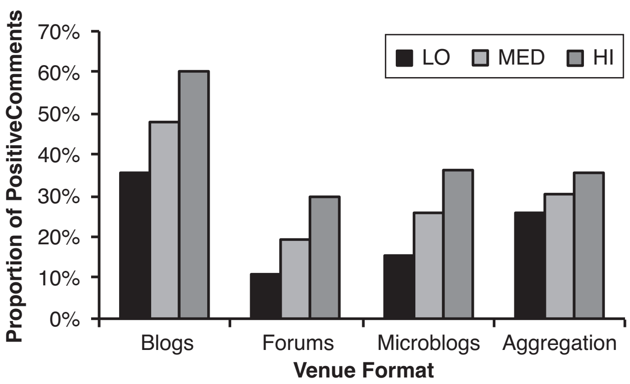
In this article, we simultaneously analyze the sentiment expressed in social media comments and the venue format to which the comments are posted and show that comments contributed to different social media venue formats vary in terms of the sentiment expressed and their focal topic (i.e., the product and attribute referenced). Moreover, we identify time-varying effects and separate time-varying dynamics that are specific to individual venue formats from those that are common across all venue formats. The latter, captured by our GBI construct, provides insights into how the underlying brand sentiment changes over time. We show that GBI is a leading indicator of changes in an offline brand-tracking study in one data set pertaining to an enterprise software brand and a leading indicator of stock market prices for both the enterprise software brand and a telecommunications brand. This finding provides strong evidence that our measure of GBI effectively captures movement in the underlying sentiment toward the brand.

Decomposing Brand Sentiment in Social Media

We show that the expressed sentiment we observe in social media is the outcome of two processes: one that drives the decision of *what* sentiment users post and one that drives the decision of *where* it is posted. We also show that when a brand experiences a shift in GBI, the shift affects both the sentiment expressed online and the venue format choice process. As a result, shifts in GBI are also associated with shifts in the distribution of comments across different venue formats.

As an illustration of how GBI affects the distribution of comments across venue formats, we conducted a simulation. For the enterprise software brand, we simulated the posting behavior associated with three levels of GBI (LO = –.25, MED = 0, and HI = .25). Figure 9 illustrates the proportion of positive comments contributed to each of the three most popular venue formats (blogs, forums, and microblogs). For comparative purposes, we also provide the

Figure 9
PROPORTION OF POSITIVE COMMENTS WITHIN VENUE FORMATS

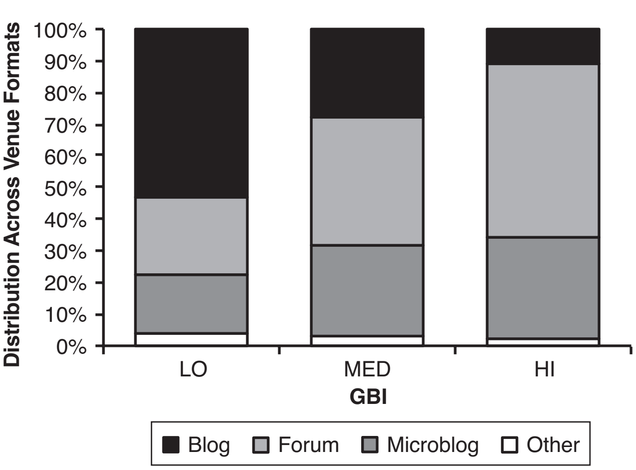


proportion of positive comments observed across all venues regardless of format (aggregation).

As we expected, the proportion of positive comments within each format increased with GBI, with the extent of the increase varying across venue formats. However, despite the relatively large increases in the proportion of positive comments observed within each venue format when GBI moves from LO to MED to HI, the increase in positive comments when aggregating across all formats was more modest. To shed light on this apparent inconsistency, Figure 10 illustrates how the distribution of comments across venue types shifts as GBI changes.

As Figure 10 shows, the share of comments contributed to blogs decreases as GBI increases, while the share of comments contributed to forums and microblogs increases. One potential explanation for this finding lies in the reasons that GBI declines. Should the underlying reasons for a decline in GBI motivate people to share the information with others (e.g., Berger and Milkman 2012), social media contributors may shift to platforms such as forums and microblogs that

Figure 10
DISTRIBUTION OF SOCIAL MEDIA CONTRIBUTIONS ACROSS VENUE FORMATS



facilitate more social interaction than blogs. In addition to differences in the venue formats to which social media comments are posted, we also find that the sentiment expressed in blogs tends to be more positive than that expressed in forums and microblogs, based on differences in the format-specific intercepts β_v. Thus, while the sentiment expressed in a given venue format increases with a rise in brand sentiment (operationalized as an increase in GBI), the increase in the aggregate sentiment (across all venue formats) is muted because relatively more comments are contributed to venue formats, in which a lower sentiment (based on β_v) tends to be expressed. As such, failing to account for the shift in the distribution of comments across venue formats and instead focusing on the sentiment expressed in the aggregated comments could lead managers to misestimate the degree to which sentiment has shifted. This may offer an explanation for why GBI, which is inferred from the data using a model that accounts for the venue format choice process, more closely aligns with the offline brand-tracking study than sentiment measured by aggregating all social media comments (as Table 5 shows). To the best of our knowledge, our research is the first to illustrate the impact of the venue format decision on expressed sentiment in social media.

Directions for Further Research

Our analysis also has implications for the growing industry of social media monitoring. While our results suggest that the information in social media comments is predictive of both offline brand-tracking surveys and financial performance, we also show that conclusions drawn from simpler metrics may be misleading. We encourage additional exploration of social media monitoring as a method of supplementing other customer insight tools but note the importance of drawing on social media comments collected from a wide array of venues.

Further research on the content of social media contributions and its relationship to where such contributions are posted is necessary. Our simultaneous analysis of what is posted and where it is posted is limited in its ability to draw conclusions about the causal mechanism at work. Although we account for differences in venue formats to which social media comments are contributed, we do not investigate the specific characteristics of various social media venues that may influence expressed sentiment. It might also be fruitful to examine how the sentiment observed in different venues may differentially drive sales or other key performance indicators. If sufficient data to estimate shifts in sentiment specific to an individual domain over time were available, examination of this sentiment could provide guidance to brands on which domains are most critical to monitor and actively engage social media contributors. Critical to this research direction would be further investigation of the consumer behavior driving the dynamics across venues and over time.

From a modeling perspective, our framework is sufficiently generalizable to easily accommodate covariates or individual-level effects into both the venue format choice and sentiment components should such data be available. Further research could also continue to build on our modeling framework by considering extensions to the proposed processes. For example, in addition to modeling sentiment and venue format choice, future work could model the specific domain to which an individual posts social media. Thus, the venue process could be considered a two-stage decision (e.g., Moe 2006) consisting of a format decision and a domain decision. It might also be worthwhile to consider choice models that are noncompensatory in nature (e.g., Gilbride and Allenby 2004).

In this article, we limited our analysis to data obtained from manually coding social media text data. However, with large volumes of text for analysis, such manual coding alone is impractical. In these cases, research has recommended a combination of manual coding and automated coding. For example, Hopkins and King (2010) propose a hybrid approach in which analysts manually code a small sample of the data in an effort to train an automated algorithm before applying it to the remainder of the data. Such machine learning approaches are often used in practice and have been found to be more accurate than fully automated approaches (Chaovalit and Zhou 2005). Although in our context we find that the analysis of manually coded sentiment produces results that are generally in line with the conclusions reached from an automated text analysis, we encourage further research in marketing that investigates the conditions under which each approach is most appropriate. However, our modeling approach is applicable to any sentiment data, regardless of the coding method used to obtain it. Finally, the current research demonstrates the potential for social media monitoring to supplement research programs, but further investigation using *both* social media and survey data from a range of categories is essential before market researchers can rely exclusively on social media for customer insights.

APPENDIX A: EMPLOYING AUTOMATED SENTIMENT ANALYSIS

Consider the following two comments presented previously, the first coded as negative and the second coded as positive:

> "Isn't this sector already dotted with high price systems offering 'XXX services' (like YYY, ZZZ)."

> "One app that will keep me from switching right away is a good XXX app (ala YYY). I have to admin a bunch of computers and that app saves my bacon once a week."

We analyze the two comments using Linguistic Inquiry and Word Count text analysis software (www.liwc.net), which scores text in terms of the proportion of words expressing positive and negative emotions (Kahn et al. 2007; Pennebaker and King 1999). The positive comment had a score of 2.94 on positive emotions and a score of 0 on negative emotions, consistent with the manual coding. However, the negative comment was scored as 0 on both positive and negative emotions. While a human reader can detect the negative sentiment around the high prices of existing products, the automated text analysis cannot. This example illustrates the potential shortcomings of automated text analysis and why many firms often employ a combination of manual coding and automated analysis (Chaovalit and Zhou 2005; Hopkins and King 2010).

Although we have some reservations in using automated content analysis, we use Linguistic Inquiry and Word Count to process the comments in our enterprise software data and compare Converseon's coding with the automated results. We find that the comments Converseon coded as positive scored higher on positive emotions than the comments Converseon coded as neutral or negative. Similarly, comments coded as negative scored higher on negative emotions than comments coded as neutral or positive. Table A1 provides the results of the analysis by comparing the average scores for comments coded as positive, neutral, or negative by Converseon analysts. Because all comments, on average, scored higher on positive than negative emotions, we report scores for positive and negative emotions for each category indexed to the overall average score for positive and negative emotions, respectively. The last column provides the difference between the positive score and the negative score for each comment, a metric that reflects the relative positivity of the text. Overall, Converseon's human coders are consistent with the Linguistic Inquiry and Word Count results.

To further demonstrate the flexibility of our modeling framework and the robustness of our findings, we modify the proposed model presented in Equations 1–5 to accommodate a continuous measure of sentiment. To do so, we replace the ordered probit model of sentiment shown in Equation 2 with the assumption that the net positivity score for comment j (denoted y_j) is distributed such that $y_j \sim N(U_j, \sigma^2)$.

The posterior means and standard deviations across iterations of the MCMC sampler appear in Table A2, and the posterior means of the sentiment inferences appear in Figure A1. Compared with our empirical analysis using Converseon's manually coded sentiment data, we find no substantive differences in the resulting inferences.

Table A1

TEXT ANALYSIS RESULTS FOR THE ENTERPRISE SOFTWARE BRAND

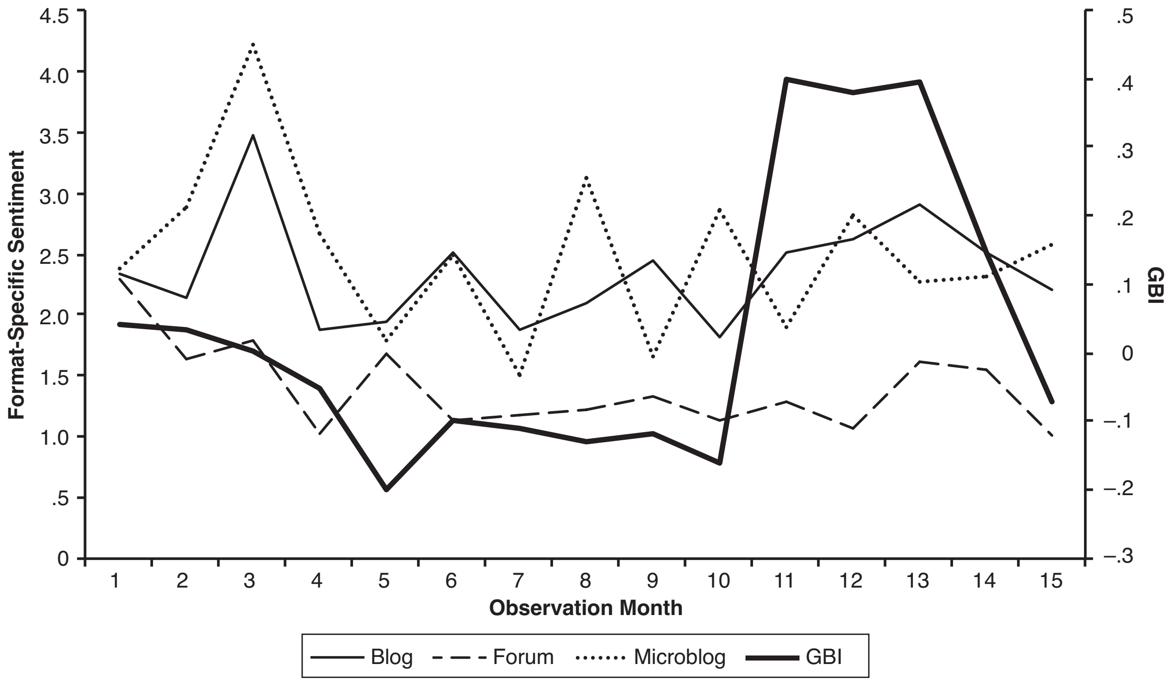
Sentiment Based on Human Analyst	*Indexed Average of Positive Emotion Score*	*Indexed Average of Negative Emotion Score*	*Average Positive and Negative Score*
Positive	1.38	.68	3.92
Neutral	.77	.68	1.94
Negative	.78	2.36	.67
Average	3.22	.78	2.44

Table A2

PARAMETER ESTIMATES USING TEXT-ANALYZED DATA FOR THE ENTERPRISE SOFTWARE BRAND

	Blog	*Forum*	*Microblog*
Sentiment Intercept (β_v)	2.31 (.29)	1.36 (.29)	2.46 (.51)
Venue attractiveness intercept (γ_v)	5.10 (.33)	5.49 (.42)	5.30 (.34)
Content effect on venue attractiveness (λ_v)	1 (—)	–2.53 (.97)	.99 (.12)
GBI effect on venue attractiveness (κ_v)	–1.47 (1.29)	4.75 (1.32)	2.88 (1.11)

Figure A1
FORMAT-SPECIFIC SENTIMENT AND GBI USING TEXT-ANALYZED DATA



Appendix B
ENTERPRISE SOFTWARE PARAMETER ESTIMATES

	Blog	*Forum*	*Mainstream Media*	*Microblog*	*Photo Sharing*	*Review Site*	*Social Network*	*Social News*	*Video Sharing*	*Wiki*
Sentiment intercept (β_v)	2.04 (.12)	.84 (.11)	2.38 (.52)	1.28 (.18)	–.07 (3.15)	.39 (.81)	2.07 (.35)	.75 (.43)	3.18 (1.72)	1.07 (.52)
Sentiment cut point ($\log[\mu_v]$)	.70 (.03)	.36 (.02)	1.10 (.18)	.54 (.02)	–.02 (3.18)	–.62 (1.04)	.31 (.12)	.02 (.35)	3.62 (1.76)	.23 (.40)
Venue attractiveness intercept (γ_v)	5.05 (.30)	5.45 (.37)	.32 (.45)	5.25 (3.1)	–4.53 (1.72)	–1.27 (.64)	2.30 (.31)	.53 (.37)	–1.00 (.59)	—
Content effect on venue attractiveness (λ_v)	1 (—)	–2.94 (.96)	2.60 (.62)	1.01 (.13)	–.43 (2.59)	–2.55 (1.67)	1.81 (.34)	–.12 (.81)	.78 (1.26)	—
GBI effect on venue attractiveness (κ_v)	–1.46 (1.32)	5.19 (1.35)	–2.52 (1.90)	3.15 (1.22)	.21 (3.02)	.88 (2.49)	1.22 (1.43)	2.00 (1.75)	–1.11 (2.47)	—

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