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More Than Words: The Influence of Affective Content and Linguistic Style Matches in Online Reviews on Conversion Rates

Customers increasingly rely on other consumers' reviews to make purchase decisions online. New insights into the customer review phenomenon can be derived from studying the semantic content and style properties of verbatim customer reviews to examine their influence on online retail sites' conversion rates. The authors employ text mining to extract changes in affective content and linguistic style properties of customer book reviews on Amazon.com. A dynamic panel data model reveals that the influence of positive affective content on conversion rates is asymmetrical, such that greater increases in positive affective content in customer reviews have a smaller effect on subsequent increases in conversion rate. No such tapering-off effect occurs for changes in negative affective content in reviews. Furthermore, positive changes in affective cues and increasing congruence with the product interest group's typical linguistic style directly and conjointly increase conversion rates. These findings suggest that managers should identify and promote the most influential reviews in a given product category, provide instructions to stimulate reviewers to write powerful reviews, and adapt the style of their own editorial reviews to the relevant product category.

Keywords: online customer reviews, affective content, linguistic style match, conversion rate, Internet marketing

Customer reviews have become one of the most frequently accessed online information sources, as consumers appear to be weary of traditional, marketer-dominated information channels (Godes and Mayzlin 2004). Online shoppers put 12 times more trust in peers' opinions than in marketer-initiated sources (eMarketer 2010), and according to a recent market study (ChannelAdvisor 2010), 92% of online customers read and use verbatim review comments in their purchase decisions. Online retailers thus recognize the effectiveness of customer reviews for converting customer visits into sales; Roku, the market leader in innovative applications for digital media, attributes a 20% lift in its online conversion rates to the appearance of approximately 17,000 (both positive and negative) customer reviews on its website (Bronto.com 2011). Yet the sheer volume and lack of structure of qualitative information in customer reviews continues to present a formidable challenge (Cao, Duan, and Gan 2011; Singh, Hillmer, and Ze 2011). Most online retailers believe their performance is hampered because they cannot efficiently decipher or reliably assess how online customers use the informational cues from their online conversations at a manageable, product category level (Bonnet and Nandan 2011). A recent market study by Econsultancy (2011) even shows that 81% of online retail sites have "limited" or "no understanding" of why customers leave without purchasing. Thus, there is a clear managerial need to develop insights into the influence of text-based customer reviews, to improve understanding of conversion behavior.

Current research on online reviews offers little guidance. Most studies focus nearly exclusively on "quantitative surrogates" of review contents (Mudambi and Schuff 2010,

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p. 195), and in this emerging stream, the empirical support for the predictive influence of numerical quality diagnostics, such as review volume or star ratings, on sales remains equivocal (Chen, Wu, and Jungsun 2004; Chevalier and Mayzlin 2006; Dellarocas, Xiaoquan, and Awad 2007; Duan, Gu, and Whinston 2008). Therefore, researchers are turning to the reviews' textual properties and assessing their impact on retail performance (Chevalier and Mayzlin 2006). In particular, affective cues provided in verbatim text (e.g., "I *love* the book," "*worst* book I ever read") might influence respondents' attitudes (Cohen et al. 2008), and the heuristic nature of online information processing seems likely to allow for the affective content contained in review texts to drive behavior (Das, Martinez-Jerez, and Tufano 2005; Jones, Ravid, and Rafaeli 2004). However, it is still unclear whether affective word cues serve as straightforward predictors of the collective impact of customer reviews on retail success, considering the limited evidence of nonlinear relationships between affective activation and product evaluations (Andrade 2005; Roehm and Roehm 2005). In particular, extreme (positive and negative) review content is prevalent and may threaten review diagnosticity (Streitfeld 2011). Beyond review content, recent theorizing in social psychology points to linguistic style, as manifested in an author's profile, as likely to shape the impact of information contained in reviews (Ireland and Pennebaker 2010). The inherent inseparability of content and style in reviews suggests that insights into linguistic style may extend beyond verbatim content to enhance understanding of their overall impact on customer decision making and thus retail performance.

In addition, reviews have long been related to sales (or its proxies), and yet there is growing consensus that online conversion rate offers a better metric for gauging online retail performance (Gurley 2000; Moe and Fader 2004). Small gains in conversion rates have powerful implications for firm performance, through increasing revenue and decreasing marketing costs as a percentage of sales. The impact of user-generated content on performance metrics also should be assessed dynamically rather than statically (Tirunillai and Tellis 2012) because conversion rate dynamics give a continuous indication of the potential business that retailers lose when customers leave the site without making a purchase. However, few efforts have explored the dynamics of customer conversion rates as a primary success metric (Moe and Fader 2004).

In light of these gaps and concerns, we aim to provide theoretical and managerial guidance on the influence of textual properties of consumer reviews on online retailers' conversion rates in three ways. First, we examine the collective impact of affective content from a dynamic perspective, by noting how changes in affective content influence changes in conversion rates over time. Little previous work on affect has featured longitudinal measures or analyses; to address this shortcoming, we study the impact of aggregate, weekly changes in the affective content of product reviews on shifts in product conversion rates. This novel approach to investigating affect in marketing is particularly important in the context of reviews because new reviews typically take prominent spots on the product display page, so changes in affective content likely provide strong drivers of changes in product conversion rate. We focus on their nonlinear impact, taking into account extreme positive and negative changes. Research into manipulations of affective states and their influence on responses to various stimuli (e.g., ads, products; Cohen et al. 2008) usually focuses on mean-level differences across experimental conditions. While experimental manipulations provide suggestive evidence of nonlinear relationships between affect and consumer thought and behavior (for demonstrations of nonlinear relationships between manipulated affect activation and product evaluations, see, e.g., Andrade 2005; Roehm and Roehm 2005), a rigorous test of this notion requires studying the effect of affect across a range of values, rather than at specific points on a spectrum primed by experimental procedures.

Second, we add to recent research by noting the impact of linguistic style of customer reviews on online conversion rates. Human communication theory (e.g., Giles 2009) posits that conversation style can elicit perceptions in conversational dyads. Furthermore, recent research has shown that synchronization in conversational style, or linguistic style match (LSM), irrespective of content, increases rapport, credibility, and shared perceptions among conversants (Ireland and Pennebaker 2010). Yet previous research on the impact of customer review texts has focused on content and has ignored linguistic style as a potential diagnostic cue. Beyond the importance of recommender similarity perceptions, as prior research has suggested (Menon and Blount 2003), we posit that the degree to which reviewers accommodate the linguistic style of the product interest group may determine the influence of the reviews on changes in customers' conversion behavior.

Third, content and linguistic style are inherently inseparable and may reinforce the impact of a review (Chaiken and Maheswaran 1994; Menon and Blount 2003), and their collective impact demands more empirical examination. Verbatim comments assume a pivotal role as the primary means to establish source perceptions and indicate reviewers' product experience. We supplement prior research on customer reviews by assessing how changes in the reviews' affective content and style jointly relate to subsequent conversion rate dynamics. In customer review settings, such a joint impact highlights the need to study content and style collectively when assessing the impact of customer reviews on retail success.

Conceptual Foundations

Feldman and Lynch (1988) posit that the relative weight of heuristic inferences, as decision inputs, depends on two context-dependent facets: their relative accessibility and their diagnosticity compared with alternative inputs. The sheer volume of online peer reviews often leads consumers to process information heuristically. We posit that at an aggregate level, this has a decisive influence on their online purchase decisions and website conversion rates (Jones, Ravid, and Rafaeli 2004). Existing research has accordingly focused on the diagnosticity of readily extractable, quantifiable customer review information cues, such as quality ratings (Chevalier and Mayzlin 2006), volume (Duan, Gu, and

Whinston 2008), and reviewer identity information (e.g., name, location; Forman, Ghose, and Wiesenfeld 2008), as well as on product-related aspects such as product popularity (Zhu and Zhang 2010) and price (Yong 2006). However, empirical investigations into the influence of numerical cues (e.g., star ratings) on sales often provide mixed or inconclusive results, which suggest some doubts about their diagnosticity and predictive ability (Yong 2006). Chevalier and Mayzlin (2006) find that additional favorable review ratings on Amazon.com increase book sales, whereas incremental negative ratings decrease them. Yet Chen, Wu, and Jungsun (2004) find no significant impact of positive ratings on sales, and Berger, Sorensen, and Rasumussen (2010) suggest that even negative ratings increase sales for products with lower awareness. In the movie industry, Dellarocas, Xiaoquan, and Awad (2007) indicate that numerical ratings are positively related to box office revenue, irrespective of the volume of reviews, whereas Duan, Gu, and Whinston (2008) and Yong (2006) find that review volume, not ratings, drives sales.

These mixed findings might stem from (1) methodological shortcomings, such as a cross-sectional context and inability to control for unobserved differences, including product quality (Zhu and Zhang 2010), or (2) the inability of numeric cues to do justice to the nuanced, fine-grained, and expressive nature of verbatim reviews (Cao, Duan, and Gan 2011; Pavlou and Dimoka 2006; Singh, Hillmer, and Ze 2011). Making use of recent advances in text analytics to systematically analyze large volumes of collections of customer review verbatim scripts and taking a dynamic perspective, which is more reflective of the rapid, continual changes in user-generated content (Tirunillai and Tellis 2012), may clarify the impacts of review content on conversion rates (Chevalier and Mayzlin 2006; Mudambi and Schuff 2010).

Emerging research on text-based communication suggests that both content and style elements of verbatim reviews are relevant decision inputs that help determine relative diagnosticity and accessibility (Huffaker, Swaab, and Diermeier 2011). This research distinguishes linguistic content and style: At a word level, "content words are generally nouns, regular verbs, and many adjectives and adverbs. They convey the content of a communication" (Tausczik and Pennebaker 2010, p. 29). Yet no content can be communicated without style words. As Tausczik and Pennebaker (2010, p. 29) state, "intertwined through these content words are style words, often referred to as function words. Style or function words are made up of pronouns, prepositions, articles, conjunctions, auxiliary verbs, and a few other esoteric categories." These categories identify not only what people convey (i.e., sentential meaning) but also how they write (sentential style), so both have diagnostic value that affects decisions (Bird, Franklin, and Howard 2002).

Affective content words (e.g., conveying emotions such as happiness, sadness, anger) reveal the intent of a text (Bird, Franklin, and Howard 2002; Das, Martinez-Jerez, and Tufano 2005). Affect in and of itself is not a linguistic property but refers to an "internal feeling state" (Cohen et al. 2008, p. 297) that is "consciously accessible as the simplest raw (nonreflective) feelings evident in moods and emotions" (Russell 2003, p. 148). The use of word cues may be the most effective way to make affect accessible (Ortony, Clore, and Foss 1987). In line with accumulating empirical support for treating feelings as information (Schwarz and Clore 1996), we find a clear underlying rationale for mining affectively laden content words in relation to online customer reviews. At the individual level, affective content words should be particularly likely to influence consumers whose motivation to engage in detailed cognitive processing is low and those with limited access to processing resources (e.g., because they are distracted or under time pressure), as well as when other bases of evaluation are ambiguous or unrevealing and when consumers lack expertise in the target domain (Cohen et al. 2008; Greifender, Bless, and Pham 2011; Lau-Gesk and Meyers-Levy 2009). The online purchase process reflects these conditions (Jones, Ravid, and Rafaeli 2004), in that text-based affective content words provide rapidly accessible and diagnostic signals about targets (Cohen et al. 2008). We argue that, at the aggregate level, affective content will influence conversion rates. Regarding accessibility, Zajonc's (1980) well-documented hypothesis on the primacy of affect in evaluative judgments indicates that affective cues are more accessible than factual or descriptive information. Pham et al. (2001) demonstrate that affective cues are registered more rapidly than cognitive assessments; the relative accessibility of affective cues also increases with their volume and evaluative clarity or intensity (Gorn, Pham, and Sin 2001). In addition to accessibility, affective cues provide decision inputs only if they are perceived as sufficiently diagnostic. Two facets of diagnosticity documented in prior literature seem relevant to (conversion) behavior: (1) perceived representativeness, which is related to the extent to which consumers believe that affective content reflects the target and whether the representation of the sender indicates qualifications to express his or her opinions, and (2) perceived validity, or whether affective cues appear consistent with other cues and across multiple sources (Gasper and Clore 1998). The anonymous nature of online review settings makes it difficult to establish sender qualifications, but extreme deviations in affective cues lower the value of feelings as information and elicit counterproductive effects by reducing diagnosticity (Andrade 2005). We investigate whether this phenomenon extends to the aggregate level.

In addition to affective content, the accessibility and diagnosticity of customer reviews and their impact on customer purchasing behavior is likely related to their linguistic style (i.e., the particular usage style of function words employed). Humans are highly attentive to the conveyance of messages (Giles and Smith 1979), and prior work in several scientific disciplines has demonstrated the importance of function words for determining conversational outcomes (Huffaker, Swaab, and Diermeier 2011). There are only approximately 500 function words in the English language, but this deceptively small category comprises roughly 55% of people's daily word usage and provides insight into conversants' personalities (Bird, Franklin, and Howard 2002). Consider three different descriptions of book experiences at Amazon.com:

•Reviewer A: "One of my favorite series."

•Reviewer B: "[…] The best in the world!! Loved it!"

•Reviewer C: "A very fine finish to a thrilling trilogy."

All three reviews say essentially the same thing, but the reviewers' ways of expressing themselves (i.e., pronoun usage, conjunctions, and other function word dimensions) provide additional information. Reviewer A is positive but in a relatively restrained manner; Reviewer B is more overtly positive and uninhibited; Reviewer C is rather formal and stiff. Thus, in addition to affective content, review texts communicate specific linguistic styles that reveal aspects of the authors' personality. The LSM, or degree of synchronization between two conversants in terms of their use of function words, also has behavioral implications (Ireland and Pennebaker 2010).

Traditional conceptualizations of common ground in conversations posit that shared perspective taking depends on conversational content (Clark and Brennan 1991). However, recent research drawing on communication accommodation theory (Giles and Smith 1979) has also suggested that common ground may be an automatic outcome of LSM, irrespective of content (Ireland and Pennebaker 2010). The use of similar function words—that is, high LSM between two conversation partners—represents a form of psychological synchrony (Ireland and Pennebaker 2010; Pickering and Garrod 2004). Thus, LSM elicits understanding and perceptions of a common social identity but decreases perceptions of social distance in verbal and written communications (Chung, Pennebaker, and Fiedler 2007). Ireland and Pennebaker (2010) find that for potential romantic couples on a first date, for example, the degree of match in their function words predicts their subsequent relationship initiation and stability. Furthermore, in online text-based negotiation settings, greater matches in function word usage increase interpersonal rapport and agreement among potential coalition partners (Huffaker, Swaab, and Diermeier 2011). However, convergence in communication styles is not exclusively a property of conversation dyads; research on online collectives that qualitatively monitors online text-based conversations reveals the phenomenon of so-called language games (Fayard and DeSanctis 2010, p. 154), in which members adhere to the collective's style of conversing to demonstrate their affiliation. Customer review forums similarly are collectives of customers who share a common interest (e.g., product interest groups). As Forman, Ghose, and Wiesenfeld (2008) demonstrate, many features of Amazon.com are designed to increase the salience of reviewers' membership in and identification with the community. Forman, Ghose, and Wiesenfeld highlight that reviewers typically post and read reviews for a particular product type, such as science fiction or political books. Thus, within Amazon.com, there exist subgroups sharing common interests, whose members are likely to have repeated encounters with one another. This necessitates studying the impact of customer reviews at the aggregate subgroup level of product interest group.

The three review comments we highlighted describe the same science fiction book *The Reckoning* on Amazon.com. Although readers process function words subconsciously, the relative match of each review with the pervasive communication style of the science fiction book interest group varies. In our example, Reviewer A reveals a much greater LSM with the product interest group than Reviewer C, which likely affects each review's diagnosticity.

Finally, the relevance of LSM in review settings is evident in research on the criticality of source characteristics in persuasion contexts (Pornpitakpan 2004). Experimental evidence highlights the perceptual and subjective nature of diagnosticity in heuristic consumer decision-making situations (Chaiken and Maheswaran 1994), which often invoke messenger bias (Menon and Blount 2003). Communicators perceived as highly similar also seem more representative, capable, and qualified to pass judgment than communicators who are perceived as less similar (Brown, Grzeskowiak, and Dev 2009). In an online customer review context, readers often have little but the review text to use to form their perceptions of the review's diagnosticity, so linguistic styles may serve as identity-descriptive information that, as a heuristic cue, shapes consumers' evaluations of the review and thus of the product. According to research on the diagnosticity of message source and content, an intricate interplay exists between affective content of a message and source cues (Pornpitakpan 2004). People who receive tailored messages from a similar source exhibit high levels of trust and tend to comply (Campbell et al. 1999). Czapiski and Lewicka (1979) also conclude that source credibility affects the weight an audience grants to positive and negative information in a message. We anticipate that LSM influences the perceived representativeness of the sender and influences the effectiveness of affective content conveyed in reviews. We next develop specific hypotheses about the dynamic influences of affective content and LSM on online retail site conversion behavior.

Hypotheses

Affective Content

Affect drives evaluation and decision making (Lench, Flores, and Bench 2011). Evidence from previous studies that use experimental manipulations to prime affective states suggests that exposure to affective cues influences evaluations and/or judgments of attitude objects, such as brands and products: Positive (negative) affective cues lead to more positive (negative) evaluations and judgments (e.g., Lau-Gesk and Meyers-Levy 2009). Simply reading a text with affective content may be sufficient to influence thoughts and behaviors (Lau-Gesk and Meyers-Levy 2009; Lench, Flores, and Bench 2011). Previous theory and research thus suggest that affective cues elicit automatic affective responses, which require few processing resources, emerge rapidly, and guide attitudes and actions (Baumeister et al. 2007; Cohen et al. 2008). The transfer of affect from such diagnostic cues and the corresponding automatic responses may be best understood according to a positive–negative continuum (Baumeister et al. 2007; Russell 2003); thus, research examining the content of online text has applied this approach to understand links between the mood of online messages and stock markets (Das, Martinez-

Jerez, and Tufano 2005) and changes in the affective content of blog posts before and after September 11, 2001 (Cohn, Mehl, and Pennebaker 2004). We use text analytics to capture positive and negative affective content and determine how changes in the affective tone of product reviews alter conversion rate dynamics at the collective level.

We examine both linear and quadratic effects in the relationship between changes in affective content and changes in conversion rate at aggregate levels. The linear relationship tests the notion from the affect transfer and priming literature that predominantly negative (positive) reviews over time increase the negative (positive) affect conveyed through reviews, leading to reduced (increased) product conversion rates. We test this relationship to corroborate previous research and to demonstrate the ability of text analytic techniques to detect theoretically meaningful, well-established relationships.

However, we also consider the quadratic relationship between affective content change and conversion rate change. When new reviews are exceedingly positive (negative), increases in positive (negative) affective content fall out of balance with the global (i.e., aggregate) affective impression conveyed by all other existing reviews. If such steep changes in affective content occur, consumers' suspicion may be aroused, leading them to correct for the influence of affect when making their product evaluations and choices (Petty, Fabrigar, and Wegener 2003). Scandals prompted when interested parties write glowing reviews of their own offerings (or harshly critique competitors'; Streitfeld 2011) have resulted in heightened public awareness of the existence of fake or planted reviews on e-commerce sites. Thus, new product reviews with an extreme imbalance of positive or negative affective content likely initiate consumer wariness and corrections to the influence of these affective cues (Petty, Fabrigar, and Wegener 2003). This line of reasoning suggests that small or modest changes toward more positive affective content should result in larger increases in conversion rate, while steep changes in positive affective tone should result in more moderate increases in conversion rate. Conversely, small or modest changes toward more negative affective content should result in larger decreases in conversion rate, while steep changes toward more negative affective content should result in more moderate decreases in conversion rate. Accordingly, we posit the following:

H_{1a}: There is a quadratic relationship between changes in aggregate positive affective content in a product's reviews and changes in conversion rate. At the extremes of positive affect change, each additional increase should have a smaller impact on conversion rate change.

H_{1b}: There is a quadratic relationship between changes in aggregate negative affective content in a product's reviews and changes in conversion rate. At the extremes of negative affect change, each additional increase should have a smaller impact on conversion rate change.

LSM

Social psychology and communication research shows that the manner or style in which a person communicates not only reveals personality but also elicits relational perceptions in the communication partner (Pennebaker 2011). According to communication accommodation theory (CAT; Giles and Smith 1979), greater degrees of synchronization in communication styles (e.g., voice, posture, gestures) in conversation dyads lead participants to perceive a common social identity, decrease their perceptions of social distance, and elicit more approval and trust (Pickering and Garrod 2004). Even in text-based (nonverbal) communication, dyadic LSM (i.e., similarities in the use of function words) transcend the actual content of the conversation to establish common ground perceptions (Ireland and Pennebaker 2010). Although LSMs and their implications have not been studied in group settings, members of online collectives, who share a common interest, tend to develop and adhere to a unique style of in-group communication (Fayard and DeSanctis 2010). In online customer reviews, the review "authors" are likely to read other reviews about their product of interest (e.g., science fiction books) and write reviews for an audience that shares this interest (Forman, Ghose, and Wiesenfeld 2008). Therefore, within the product interest groups, frequent readers and writers of reviews likely come to associate a certain linguistic style with that interest group and nonconsciously mimic it in their own writing. According to CAT, reviewers' adjustments to group-specific linguistic styles should elicit perceptions of shared identity and rapport among the reading collective (Giles 2009). Such perceived rapport provides readily accessible diagnostic information, which directly influences consumer judgments and behaviors if they process information heuristically, as is the case for online information searches (Chaiken and Maheswaran 1994; Jones, Ravid, and Rafaeli 2004). New reviews with a high LSM score help readers establish rapport with the reviewer, which stimulates them to rely on source cues to form attitudes, perhaps even to the exclusion of message content (Pornpitakpan 2004). Thus, an increase in reviews that match the linguistic style of the particular interest group should enhance conversion rates. In other words, if new reviews change the linguistic style such that there is a closer match with the interest group's linguistic style, we would expect a positive change in conversion rates. Therefore, we hypothesize the following:

H_2: A positive change in LSM between a product review and the interest group's linguistic style results in positive changes in conversion rates.

Joint Impact of Affective Content and LSM

The inherent inseparability of content and style in customer reviews almost dictates an investigation of their joint effect, and previous research confirms an interplay between perceived source attributes (e.g., physical attractiveness) and message elements (e.g., sidedness) with distinct explanatory power (beyond their individual effects) for recommendation persuasiveness (Pornpitakpan 2004). For example, when Feldman (1984) presented high school students with nutrition messages attributed to high-, medium-, or low-similarity sources, greater perceived similarity increased participants' likelihood to adopt the promoted nutrition behavior and attitudes. Noriega and Blair (2008) also show that the choice of language determines the effectiveness of advertis-

ing messages among bilingual consumers. Because we posit that LSM elicits similarity perceptions, the increasing match between the review and the product interest group's linguistic styles should make that review more appealing, as well as grant greater importance to changes in its content. Thus, a combination of positive changes in affective content and increasing degrees of LSM should exert a greater impact on conversion rate changes. Specifically, we predict positive effects on conversion rate changes when positive changes in affective content combine with positive changes in LSM in customer reviews:

H_3: There is an interaction between affective content and LSM, such that positive changes in a product review's positive affective content coupled with positive changes in LSM lead to greater positive changes in conversion rates.

Empirical Study

Setting

We gathered data using automated JavaScripts to access and parse HTML and XML pages describing books available for sale on Amazon.com, the leading electronic retailer. We chose this research context because of the unique traceability features of customer review information and their influence on conversion behavior on retail sites. All information is publicly accessible and updated frequently on the retailer's webpage. Therefore, in addition to the information conveyed through the customer reviews, we could collect and control for other product- and review-related information, such as price, review volume, review helpfulness, and advertising, all of which may affect consumers' purchase decisions. During the data collection, Amazon.com made customers' conversion behavior publicly available (Bray and Martin 2011), so we could also establish direct links between customer reviews and retail performance dynamics. Similar data about the conversion rates of websites could be obtained from software packages designed to track or retrace online visitor behavior. Finally, online customer reviews, conversion behavior, and product-related information represent high-frequency data that can be collected repeatedly—a prerequisite for obtaining a sufficient number of observations for dynamic panel data analysis.

Sample

Our initial sample included 641 unique books across all subgenres, released between April 15 and May 5, 2010, which received at least one customer review during the observation period. We selected only books launched in this time period to ensure that the sample books were in approximately the same stage in their product life cycle. To explore how changes in customer reviews influence the conversion behavior dynamics of visiting customers, we retrieved conversion rates and customer reviews, along with general product and price information, at weekly intervals for 17 consecutive weeks. To preserve any causality implications, we collected dynamic product and customer review information from Saturdays to Thursdays and conversion rate information (our outcome measure) on Fridays. However, we eliminated 36 books that were unavailable for purchase (out of stock) for some period of time during the data collection. The final sample consisted of 591 books and 18,682 customer reviews. In a second stage, two independent coders assigned the books to subgenres using Amazon.com's official genre classification (Krippendorf's alpha for the original coding was 95%; discrepancies between coders were resolved through discussion). The final sample included books across all subgenres (see Table 1), including 49% nonfiction books.

Measurement Development

We obtained conversion behavior data from the conversion rate information provided by Amazon.com, namely, the "What Do Customers Ultimately Buy After Viewing This Item" information, which listed the percentage of customers who bought the product featured on the retail page (Bray and Martin 2011).

To assess the affective content and LSM of the review texts, we then conducted a content analysis of the reviews' qualitative text comments. Content analysis is an increasingly popular method to study user-generated posts online (Singh, Hillmer, and Ze 2011). To transform text comments into quantitative data, content analysis uses automated, systematic procedures that ensure the objectivity, reproducibility, and reliability of the data analysis (Chung, Pennebaker, and Fiedler 2007). Preparing the data for automated text analysis entails archiving the review texts and converting them into text files, a process that produced several review text files for each product (minimum = 1, maximum = 503).

TABLE 1
Final Sample

Subgenre	Number of Books	Number of Reviews
Nonfiction		
Art	20	141
History	22	582
Education	19	725
Craft, hobbies, and travel	14	204
Cooking	30	561
Technology	11	323
Business	24	638
Biography	31	1163
Sports	17	362
Science	22	331
Religion	26	382
Political and current events	34	1180
Philosophy	11	99
Family	16	483
Humor	3	91
Fiction		
Fiction and literature	56	1931
Graphic novel	27	191
Horror	10	796
Mystery and crime	68	2199
Romance	15	549
Science fiction	96	4337
Thriller	25	1113
Western	8	574

Next, the customer review texts were automatically analyzed using the linguistic inquiry and word count (LIWC) program (Pennebaker et al. 2007). Originally developed to analyze emotional writing, LIWC dictionaries offer strong, reliable convergence between the dimensions they extract and content ratings performed by human coders (Pennebaker et al. 2007). Their validity also has been confirmed in more than 100 studies that applied this methodology to various texts, including online content such as blogs (Cohn, Mehl, and Pennebaker 2004) and instant messaging (Slatcher and Pennebaker 2006). The LIWC approach recently appeared in marketing to unearth sentiment in newspaper articles (Humphreys 2010). Using word counts for a given text, LIWC calculates the proportion of words that match predefined dictionaries.

We used two LIWC dictionaries related to affective content and function words. The automatic retrieval of the word count for affect-laden, positive (happiness) and negative (fear, anger, disgust, sadness) words in the review texts produced our measure of affective content. For example, "disappointing" would appear in the negative affect dictionary and be counted as 1 in the total amount of negative affective content words in the review. If the word "hate," which also belongs to the negative affect dictionary, appeared in the same review text, it would be counted, and the total score for negative affective content would be 2. At the end of the content analysis, LIWC calculates the total number of times the dictionary words appear in a review, divided by the total number of words in the review, to determine the percentage of the text that falls into a particular linguistic category. We aggregated all review scores for the same product to derive a mean level for each week, that is, an intensity percentage or summary score between –1 and 1, depending on relative intensity of negative or positive affective content across all reviews for that product in a given week. Because review titles are particularly prominent, we mined and conducted separate calculations for title and text intensities similar to Cao, Duan, and Gan (2011). The aggregation is as follows:

$$(1)\quad AC_{it} = \frac{\sum_{i=1}^{n} PA_{itT} - \sum_{i=1}^{n} NA_{itT}}{\sum_{i=1}^{n} N_{itT}} + \frac{\left(\frac{\sum_{i=1}^{n} PA_{itB} - \sum_{i=1}^{n} NA_{itB}}{\sum_{i=1}^{n} N_{itB}}\right)}{2},$$

where AC_{it} represents the overall intensity of affective content in reviews for product i in week t; $\Sigma_{i=1}^{n} PA_{itT}$ is the sum of positive affective content words (PA) in the title (T) across all reviews (j to n) posted on product (i) in week (t); $\Sigma_{i=1}^{n} NA_{itT}$ is the sum of negative affective content words in the title; and $\Sigma_{i=1}^{n} N_{itT}$ represents the sum of all words used in the title. The subscript (B) denotes the body of the review text, and the calculations for affective content of the review body are the same as those for titles but denoted by $\Sigma_{i=1}^{n} PA_{itB}$, $\Sigma_{i=1}^{n} NA_{itB}$, and $\Sigma_{i=1}^{n} N_{itB}$, respectively.

We next operationalized the degree of LSM between each review and the common linguistic style of the product interest group in three steps. First, book subgenres represent special product interest groups in the overall Amazon.com community, so we segmented reviews according to book genre (Forman, Ghose, and Wiesenfeld 2008). Research into collective settings has examined group similarities using direct consensus models, which take the group average as the preferred mode of aggregation (Bliese 2000). We constructed the common linguistic style for reviews of a particular subgenre by averaging their usage intensity separately for every function word in the English language. To empirically justify this aggregation procedure, we calculated the intraclass correlation (ICC 1) coefficients for nine function word categories separately (Table 2). The ICC 1 coefficient provides a ratio of between-group to total variance and thereby captures both within- and between-genre variation in the usage of function words. Our results empirically justify the data aggregation of individual linguistic styles in reviews to derive a common "genre" linguistic style; for all the function word variables, the ICC 1 values are significant (F-values, $p < .05$), ranging from .62 to .94. That is, each function word category possesses a sizable amount of between-genre variance, which is convincing evidence of reliable genre means for linguistic styles.

Second, having established a common usage intensity for each function word in a given book genre, we calculated separate LSM scores for each function word, using the following formula to derive the difference in usage intensity of a particular word (e.g., "his") between $review_i$ and the average usage intensity of that same word in the subgenre of $review_i$:

$$(2)\quad LSM_{\text{“his” review}i} = 1 - \left|\frac{\left(\frac{\sum \text{“his”}_i}{\sum N_i - \mu\text{“his”}_j}\right)}{\mu N_j}\right|,$$

where $LSM_{\text{“his”}i}$ is the similarity in the usage intensity of the word "his" between a review and the general subgenre

TABLE 2
Word Categories Used to Calculate LSM and Affective Content

Category	Examples
Affective Content	
Positive affective content	*Love, nice, sweet*
Negative affective content	*Ugly, dumb, hate*
LSM	
Personal pronouns	*I, his, their*
Impersonal pronouns	*it, that, anything*
Articles	*a, an, the*
Conjunctions	*and, but, because*
Prepositions	*in, under, about*
Auxiliary verbs	*shall, be, was*
High-frequency adverbs	*very, rather, just*
Negations	*no, not, never*
Quantifiers	*much, few, lots*

Notes: We conducted the text mining using the 2007 LIWC Program (Pennebaker et al. 2007).

style, Σ"his"$_i$ denotes the count of the word "his" in review i, ΣN_i refers to the total words in review i, μ"his"$_j$ is the average count of the word "his" in all reviews for the same subgenre j, and μN_j is the average words used in reviews in subgenre j.

Third, in line with Ireland and Pennebaker (2010), we derived the overall LSM score of a particular review by taking the average LSM score across all function words. For example, if a review used "despite" four times in a text of 100 words, it would yield an intensity of .04. If the average intensity across all reviews for the same subgenre was .02, the LSM score for "despite" in that review would be .98. After applying this approach for all function words, we averaged the LSM scores per review to yield a composite LSM score, bounded by 0 and 1; higher numbers represented greater stylistic similarity between a review and the subgenre style. Each review received a single LSM score. Similar to the affective content scores, all reviews for the same product in a particular week were aggregated at the mean level. Therefore, we obtained a measure of overall LSM for reviews published about a particular product in a given week. We conducted a pilot study (see the Appendix) to confirm the validity of the LSM measure, in terms of actually eliciting social identification by the target audience and strengthening the impact of the reviews on purchase intentions.

Control Measures

We constructed our control variables from observed Amazon.com data. In addition to the traditional star rating measure, which offers a five-point product quality rating per review, we controlled for the effects of increased review quantity posted in a particular week for each book. Review quantity is the count of reviews posted on the product site of product i during week t. Because price dynamics influence online purchase decision making (Xinxin and Hitt 2010), we also considered the impact of changes in discounts (percentage margin of the original price in week t). We include the helpfulness perceptions of reviewers, to control for potential differences in the "expertise" of reviewers. To derive these helpfulness perceptions, we divided the number of people who considered a review helpful by the total votes in response to the "Was this review helpful to you?" question featured on Amazon.com for each review. Using the same measure, Mudambi and Schuff (2010) show that the percentage of people who find a review helpful is related to the diagnosticity of the retail site. Noting important recent findings related to the impact of variance in purchase information on consumers' choices (Clemons, Gao, and Hitt 2006), we also include measures of variability in star rating and affective content; we decided to use the standard deviation, which reflects within-subject variability. Finally, we collected data about additional advertising of the books, but because there were virtually no such occurrences and the effect was highly insignificant, we did not include this variable in the final model.

Analyses and Results

To capture the influence of our explanatory variables on changes in product site conversion rates, we specified a dynamic panel data model. We assessed the impact of the preceding changes in the explanatory variables on subsequent changes in the product site's conversion rates, to reduce potential problems associated with autocorrelation and remove the impact of time-invariant unobservable factors. By studying the within-product changes rather than absolute levels, we could eliminate observed and unobserved differences between the books, which might influence conversion rates. Observed differences, such as the presence or absence of the "look inside" feature, may cause differences in conversion rates because customers can view and read pages before purchase and thereby better assess the quality of a book. However, this feature does not change over time, so we removed (by statistically controlling for) it with the general method of moments first-difference transformation. Unobservable product aspects that are constant over time, such as the inherent quality of books, may cause further unobserved differences in behavior. Past conversion behavior predicts future conversion behavior, and we want to test individual effects of our explanatory variables. Therefore, we included lagged and second-lagged differences of the dependent variables as controls, which enabled us to control for inertia and persistence in conversion rates. The initial condition was zero for all products; the launch date, as a first observation, produced a conversion rate of zero. Table 3 outlines the descriptive statistics and correlations; the level and change correlations between conversion rate and affective content in the review texts, linguistic similarity, and star ratings were all in the expected directions.

Overall Model

The overall model, transformed into first differences, is as follows:

$$\Delta CR_{it} = \alpha_1 \Delta CR_{i,t-1} + \alpha_2 \Delta CR_{i,t-2} + \beta_2 \Delta X_{it} + \beta_3 \Delta E_{it-1} + \Delta u_{it},$$

where

- $\Delta CR_{it} = CR_{it} - CR_{it-1}$ is the change in conversion behavior for book i from the previous week (t – 1) to the current week t;
- $\Delta CR_{i,t-1}$ and $CR_{i,t-2}$ represent changes in the lagged conversion behavior for book i from the previous two periods, (t – 1) and (t – 2), respectively;
- ΔX_{it} represents a matrix of changes in the explanatory variables in week t for product i, including all substantive hypotheses variables, affective content, LSM, the LSM × affective content interaction term, and the affect content squared term, as well as all exogenous variables, such as star rating, star rating variation, affective content variation, review quantity, the interaction between review quantity and LSM, and the interaction between review quantity and affective content;
- ΔE_{it-1} represents a matrix of changes in the endogenous explanatory variables, namely, PD_{it-1} or the price discount of book i and H_{it-1} or the helpfulness votes for all reviews of book i. We assume both are endogenous. We also assume that $E[\Delta u_{it} | \Omega_t] = 0$, where the expectation of change in the error term, given the information

TABLE 3
Descriptive Statistics and Correlation Matrix

Variables	N	M	SD	1	2	3	4	5	6	7	8	9	10
Levels of Variables													
1. Conversion rate	4763	.79	.12	1.00									
2. Conversion rate (t – 1)	4763	.79	.12	*.93*	1.00								
3. Affective content	4763	.22	.13	*.22*	*.17*	*1.00*							
4. LSM	4763	.04	.02	*.19*	*.15*	*.16*	*1.00*						
5. Star rating	4763	4.21	.64	*.18*	*.14*	*.46*	*.13*	*1.00*					
6. Review quantity	4763	20.82	32.5	*.01*	*.02*	*–.03*	*–.12*	*–.05*	*1.00*				
7. Helpfulness (t – 1)	4763	3.82	4.95	*.05*	*.07*	*.07*	*.05*	*–.21*	*.29*	*1.00*			
8. Price discount (t – 1)	4763	.34	.10	*.21*	*.19*	*.18*	*–.01*	*–.04*	.21	*.10*	*1.00*		
9. Quality rating variation	4763	.87	.52	.07	*.03*	*–.29*	–.14	*–.65*	.29	.22	*.08*	*1.00*	
10. Affective content variation	4763	.24	.13	.06	*.03*	*.14*	–.12	*–.12*	.21	.07	*.02*	*.31*	1.00
Changes in Variables													
1. Conversion rate	4763	.01	.03	1.00									
2. Conversion rate (t – 1)	4763	.01	.03	*.21*	1.00								
3. Affective content	4763	.01	.05	*.19*	*.13*	1.00							
4. LSM	4763	.01	.02	*.14*	*.07*	*.12*	1.00						
5. Star rating	4763	.01	.10	.01	.00	*.19*	*.03*	1.00					
6. Review quantity	4763	1.12	5.94	–.01	*–.03*	*–.03*	*–.08*	*.04*	1.00				
7. Helpfulness (t – 1)	4763	.06	6.83	*.05*	*.06*	.10	*.03*	*–.12*	*.30*	1.00			
8. Price discount (t – 1)	4763	.01	.10	.07	.02	.01	–.08	*–.06*	.12	.08	1.00		
9. Star rating variation	4763	.01	.66	.02	.01	.12	–.15	–.46	.27	.12	.19	1.00	
10. Affective content variation	4763	.01	.18	.04	.01	.15	–.14	–.15	.22	.07	.11	.30	1.00

Notes: Correlations in italics are significant at the 90% level.

set at time t, is 0, instrumented using the lagged value from the previous week (t – 1);

Δu_{it} is the change in the random error term (we excluded fixed effect errors from the model by first differencing); and

t denotes the week. Although CR_i was always collected on the last day of the current week (t = Friday), we collected predictor variables on the second-to-last day of the week (t = Thursday), to preserve causal implications.

Including the lagged dependent variable avoids a misspecified model because current values of the dependent variable are influenced by the prior values. Including the lagged dependent variables implies that the usual fixed effects estimator is biased (Nickell 1981).

We predict the price discount and helpfulness of reviewers to be endogenous regressors and thus not strictly exogenous. First, on the basis of past conversion behavior, Amazon.com likely adjusts its price discount, such that past levels of conversion behavior and price discounts, though potentially orthogonal to current disturbances, depend on prior levels. Second, the amount of past conversions should influence the amount of visibility of reviews. In this sense, past changes in conversion behavior may influence the amount of helpfulness votes that reviews on that site accumulate in a subsequent week. Collectively, the traditional fixed effects estimators therefore must be biased. In addition, idiosyncratic disturbances may have individual-specific patterns of heteroskedasticity and serial correlation. Finally, our estimators were designed for general use across customer review settings, so we do not assume that good instruments are available outside the immediate data set. The available instruments are internal and use the lags of the instrumented variables. Therefore, we used a general method of moments estimator (Arellano and Bond (1991). Specifically, we eliminated book-specific effects by first differencing and instrumenting the endogenous variables with their lags (for further information on this method, see Narasimhan, Rajiv, and Dutta 2006; Tuli and Bharadwaj 2009).

Hypothesis Testing

Table 4 outlines the results of the models. Because we used first differencing and the lagged values for conversion rate, the sample size for the models fell to 4763 observations (591 books). The pooled augmented Dickey-Fuller test verified that our series in conversion rates was stationary ($p < .01$); the conversion rate observations were independent of time (Levin, Lin, and Chu 2002). The Sargan/Hansen test to verify the joint validity of our moment instruments was insignificant, which indicates that the instruments in the estimation are valid (Tuli and Bharadwaj 2009). Furthermore, although it is to be expected that the full disturbance is autocorrelated, because it contains fixed effects that the estimators were designed to eliminate, we checked for second-order autocorrelation in the residuals using Arellano and Bond's (1991) test for first differences. There was insufficient evidence to reject the assumption of no autocorrelation in the differences, so our generalized method estimators likely yielded unbiased and constituent estimates (Arellano and Bond 1991). The exogenous variables indicated frequency (percentages of affect-laden positive and negative content words in the review text; match percentage in function words), so we mean-centered the variables and calculated the interaction term by multiplying mean-centered variable scores. We constructed the squared term similarly. In the hierarchical approach to test our hypotheses, we first estimated Model 1 with just the time-varying covariates, price discount, quantity of reviews, perceived review helpfulness, star rating, and variance in star rating, as recorded from Amazon.com. Next, we assessed the main effects (and

TABLE 4
Results

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Δ(Conversion rate)$_{i(t-1)}$	.917**	.712**	.725**	.727**	.763**
Δ(Conversion)$_{i(t-2)}$	–.056**	–.022*	–.021*	–.021*	–.005
$\Delta(LSM)_{it}$		.004**	.004**	.004**	.006**
Δ(Affective content)$_{it}$		.051**	.050**	.050**	
Δ(LSM × affective content)$_{it}$			.002**	.002**	
Δ(Affective content²)$_{it}$				–.004**	
Δ(Positive affect)$_{it}$					.055**
Δ(Negative affect)$_{it}$					.067**
Δ(Positive affect²)$_{it}$					–.007**
Δ(Negative affect²)$_{it}$					.005
Δ(Review quantity)$_{it}$	.003*	.002*	.002*	.002*	.005**
Δ(Helpfulness)$_{i(t-1)}$	.017*	.006*	.007*	.006*	.004
Δ(Price discount)$_{i(t-1)}$	.010**	.009*	.009**	.009**	.007**
Δ(Star rating)$_{it}$	.007	–.002	–.002	–.004	–.002
Δ(Star rating variation)$_{it}$	.005*	.005*	.005**	.004*	.003*
Δ(Affective content variation)$_{it}$			.003	.002	.002
Δ(LSM × review quantity)$_{it}$			.002**	.002**	.003**
Wald's chi-square	899.93 (7)**	2128.68 (9)**	2199.56 (12)**	2234.35 (13)**	2033.87 (14)**
N	4763	4763	4763	4763	4763

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

covariates) in Model 2, added interaction effects in Model 3, and included squared effects in Model 4. We compared the models by computing the chi-square difference test, which confirmed that the main, interaction, and squared effects added explanatory power to the original Model 1 ($p <$ .01). In Model 5, we additionally split up affective content into positive and negative affective content. We use the estimates reported from Model 4, including all hypothesized effects, to discuss our results.

Results

In general, we found a strong, positive, significant effect of increasing levels of positive affective content on subsequent conversion rate changes ($\beta_{\text{affective content}} = .050$, $p < .001$), whereas extreme intensity changes in affective content exhibited a quadratic (tapering-off) relationship on product conversion rates ($\beta_{\text{affective content}^2} = -.004$, $p < .001$), in support of the nonlinear relationship between affective content changes and conversion rate changes.

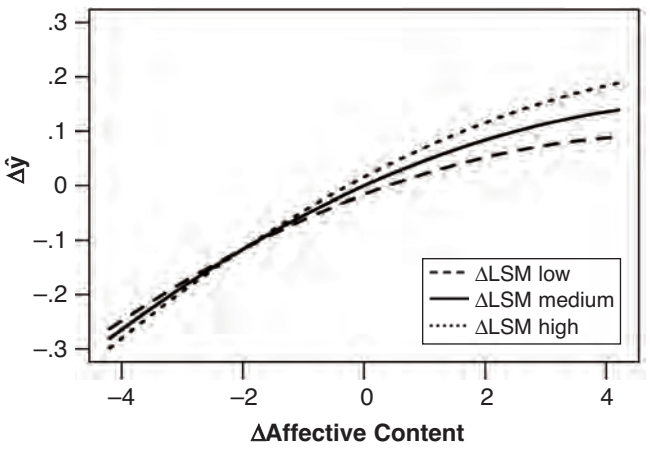
To test whether these positive and negative changes in affective content were attenuated at the extremes, as hypothesized ($H_{1a–b}$), we computed separate estimates for positive and negative changes (for a similar approach, see Mittal, Ross, and Baldasare 1998). We created two variables to reflect positive (negative) affective content changes by retaining all positive (negative) affective content changes and recoding all negative (positive) affective content changes and no affective content changes to equal 0. We squared the newly created variables to capture changes in squared positive and squared negative affective content changes (see Model 5). As we hypothesized, both changes toward positive affective content ($\beta_{\text{positive affect}} = .055$, $p <$ .001) and squared positive affective content ($\beta_{\text{positive affect}^2} =$ –.007, $p < .001$) had significant influences on conversion rate changes. The negative coefficient of the squared term for positive affective content indicates that the effect tapered off, so in line with H_{1a}, overtly positive changes in the affective content in customer reviews had a smaller positive impact on conversion rate, compared with moderate changes in positive affective tone. In the case of negative changes in conveyed affect, only changes in negative affective content ($\beta_{\text{negative affect}} = .067$, $p < .001$), not squared negative affective content, related significantly to subsequent changes in conversion rate. Thus, H_{1b} is not supported. The coefficient of a negative affect change emerged as positive; as affective changes became increasingly negative, the subsequent conversion rate of the product's retail site decreased more. The coefficients of positive and negative changes in affective content differed significantly ($p < .001$), and negative changes had stronger impacts on the conversion rate. Thus, our results indicated asymmetries in the relationship between changes in affective content conveyed in reviews and conversion rates: Negative changes in the affective content of customer reviews were more detrimental to a product site's conversion rate than were identical increases in the positive affective content.

The results in Table 4 support H_2, in that an increasing degree of LSM in reviews related to increases in conversion rates ($\beta_{\text{LSM}} = .004$, $p < .001$). Finally, the interaction between the increasing degrees of LSM and positive changes in the affective content of reviews significantly predicted increases in conversion rates ($\beta_{\text{LSM} \times \text{affective content}} = .002$, $p < .001$), in support of H_3. As Figure 1 illustrates, the predicted impact of changes to the affective content (Δaffective content) and LSM (ΔLSM) in the customer reviews on the subsequent conversion rate change ($\Delta\hat{y}$). Using the coefficients of Model 4, we plot the regression lines of change in conversion rate ($\Delta\hat{y}$) on ΔLSM, Δaffective content, Δaffective content^2, and the interaction term ΔLSM × affective content. The following regression line is thus plotted: $\Delta\hat{y} = .004\ \Delta(\text{LSM}) + .050\ \Delta(\text{affective content}) - .004\ \Delta(\text{affective content}^2) + .002\ \Delta(\text{LSM} \times \text{affective content})$.

For purposes of illustration, we rearranged the overall regression equation to show the regression of change in conversion rate on change in affective content at three levels of change in LSM. We chose values for LSM to be one standard deviation below the mean (low), at the mean (medium), and one standard deviation above the mean (high). The figure illustrates how a change in the reviews' content toward more positive affect leads to higher predicted changes in conversion rate and yet tapers off at extreme degrees of change. The impact is alleviated if this change toward more positive affective content is combined with an increase in LSM, and it is attenuated if the LSM of the reviews simultaneously decreases.

The results of the control variables largely aligned with prior marketing research; increases in the lagged price discount significantly and positively drove future conversion rates ($\beta_{\text{price discount}} = .009$, $p < .001$), so price remained a key determinant of purchase decisions. Changes in review quantity also had significant effects on changes in conversion rates ($\beta_{\text{review quantity}} = .002$, $p < .05$), in line with prior studies that have indicated that product sales can be explained by review volume (Godes and Mayzlin 2004). We found a significant, positive interaction effect of review quantity changes and increasing degrees of LSM on the subsequent conversion rate ($\beta_{\text{LSM} \times \text{review quantity}} = .002$, $p <$

FIGURE 1
The Combined Impact of Changes to Affective Content and LSM on Conversion Rate



.001); that is, the more reviews with greater LSMs are posted, the greater is the subsequent positive increase in conversion rate. Changes in helpfulness were weakly significant, positive predictors of subsequent conversion rate changes ($\beta_{helpfulness} = .006$, $p < .10$). We tested the effect of changes in star ratings on subsequent conversion rate changes, but in line with Yong (2006), we found no significant relationship. The descriptive information in Table 3 reveals that the average star rating for all products was mildly positive (4.15) and did not change much over time, in line with recent research that suggests star ratings converge to an average within a few weeks (Moe and Trusov 2011). In contrast, review texts are nuanced and still provide new and relevant information over time that may color overall product evaluations more than the overall star rating dynamics. However, we found a significant relationship between changes in the variability of star ratings ($\beta_{star\ rating\ variation} = .004$, $p < .05$) and conversion rate changes, similar to Clemons, Gao, and Hitt (2006). In contrast, variance in the weekly changes of affective content was not significantly related to subsequent conversion rate changes ($\beta_{affective\ content\ variation} = .002$, $p < .411$).

Theoretical Discussion

Extending Extant Research

This study contributes to contemporary research on customer reviews by outlining a method to dissect customer review texts to reveal their semantic content and style properties, as well as demonstrating the dynamic influence of text properties on conversion rates in online retail sites. We thus extend extant research in three important ways.

First, most research on affect as a driver of consumer behavior assumes and tests linear relationships, such as the positive association between positive affect and marketing performance indicators. Our results extend some initial experimental research (Andrade 2005; Roehm and Roehm 2005) by demonstrating a quadratic relationship between changes in affective content and changes in conversion behavior in a dynamic, online field study. By taking into account a broader range of affective content and intensity, we assess the impact of extreme positive and negative changes in reviews, which is both theoretically and managerially relevant. Various concerns persist about the validity of reviews (Mudambi and Schuff 2010), and we confirm that in the case of sharp increases in positive affective content, the conversion rate increases are smaller than if the positive affective content increase were more moderate. Yet we fail to find a similar attenuating effect for extremely negative changes. Thus, a negative change in the affective content of customer reviews is more detrimental to conversion rates than is an increase of the same size in the reviews' positive affective content. This finding, though unexpected, is consistent with previous research that indicates that negative affective cues can be more powerful than positive ones for driving judgment and behavior. This phenomenon may result from evolutionary processes, such that stronger evaluative and behavioral responses to negative stimuli (e.g., displays of negative emotions by others) provide a survival advantage by ensuring a rapid response to danger or threats (Baumeister et al. 2007; Cohen et al. 2008). Our research makes a theoretical contribution by demonstrating the nuanced relationship between affective content in online reviews and consumer behavior.

Second, CAT proposes that adaptations in communication style can elicit positive images among others (Pornpitakpan 2004), which suggests that LSM could be a good predictor of attitudes and behavior (Huffaker, Swaab, and Diermeier 2011; Ireland and Pennebaker 2010). However, the scope of extant research has been restricted to communication dyads or personal relationships; we extrapolate this research (Ireland and Pennebaker 2010) to derive the linguistic style commonalities across customer reviews embedded in a wide range of book genres. We thus show for the first time that in an anonymous customer review setting, the impact of linguistic style of reviews extends beyond their content, establishes source perceptions, and evokes a positive bias that subsequently shapes conversion rates.

Third, beyond the stand-alone influences of reviews' content or style, we underscore, in an online context, the importance of joint considerations of message and source characteristics (Pornpitakpan 2004). Reviews exert a greater influence on customer behavior when they convey affective content and match the typical linguistic style of the target audience. Online review settings remove the face-to-face contacts that traditionally have informed word-of-mouth recommendations, but our research reveals that the contents of reviews have significant effects when their linguistic style elicits source similarity perceptions. In line with experimental evidence about how the interaction between source and message elements shapes purchase intentions, we test and verify the joint influence of a review's content (particularly affective content) and its relative LSM on key outcomes.

Corroborating Extant Research

Customer review phenomena have stimulated exceptional research studies aimed at uncovering relationships between the information diagnostics provided in such settings and retail performance, and yet the field still lacks a good synthesis and reconciliation of evidently divergent findings (Zhu and Zhang 2010). In the process of empirically validating our hypothesized relationships, we include key decision-making diagnostics from previous research and offer some corroboration of extant research findings. First, in line with previous research (Dodds, Monroe, and Grewal 1991), we find that changes in price discounts induce changes in conversion rates. Although surprisingly little research on customer review settings considers price or price discounts, our results highlight that price dynamics remain a decisive purchase criterion, irrespective of any other information.

Second, in accordance with Duan, Gu, and Whinston (2008) and Yong (2006) but in contrast with Dellarocas, Xiaoquan, and Awad (2007), we note that the consideration of dynamic, rather than static, relationships reveals that *changes* in the volume of reviews posted on a particular product retail site significantly predict subsequent conver-

sion rates. If we include combined effects of increases in volume and LSM in reviews, we find that increases in review volume are even more effective for enhancing the subsequent conversion rate associated with the site if they match the linguistic style of the product interest group.

Third, in line with Mudambi and Schuff (2010), who argue that more helpful reviews increase the diagnosticity of an online retail page, we find that increases in helpfulness perceptions of featured customer reviews enhance subsequent conversion rates by enhancing site diagnosticity.

Fourth, we help reconcile equivocal prior findings regarding the influence of customer reviews' star ratings. By collecting longitudinal weekly data and converting our model into first differences, we statistically removed fixed product effects, such as inherent quality, which could account for previous mixed findings (Zhu and Zhang 2010). Similar to Chen, Wu, and Jungsun (2004), we find no significant impact of changes in star ratings on the retail site's conversion rate for that product. Importantly, overall star ratings still contain useful and meaningful information about product quality for customers. Yet the ratings tendency to quickly converge to a product-specific baseline level over time, which then becomes resistant to change (Moe and Trusov 2011), renders the incremental impact of new star ratings negligible. The addition of another new four-star rating thus has little additional effect on the conversion rate after the baseline score has been reached.

Fifth, in line with Clemons, Gao, and Hitt (2006), we find that greater variability (or dispersion) of star ratings increases the conversion rate. Clemons, Gao, and Hitt discuss the benefits of hyperdifferentiation in ratings, but this positive variation effect might stem from enhanced objectivity perceptions evoked among readers who have been presented with both the pros and cons of a product.

Limitations and Further Research

Our results are consistent with the proposition that customers read and rely on review text information in their purchase decision making (Chevalier and Mayzlin 2006). However, several limitations of our study provide worthwhile avenues for research. First, although we consider all function class categories, our empirical study featured only one content word category: affective content words. Affective content has a strong impact on behavior (Lau-Gesk and Meyers-Levy 2009), but additional research should involve uncovering other content word categories that offer readily accessible diagnostics for online customers.

Second, our modeling approach takes into account dynamic changes to a product's retail site, prominent purchase decision-making information (e.g., reviews, price), and fixed effects (e.g., product quality); however, in the online retail environment, the presence of substitute or complementary products also could affect the focal items' retail success. Online retailers, such as Amazon.com, increasingly prompt customers with complementary or alternative product choices to cross- and up-sell, so ongoing research should investigate how these products might affect the conversion success of a focal product.

Third, we chose books as our sample product category—a relatively low-involvement product class. Because online information tends to be processed heuristically (Jones, Ravid, and Rafaeli 2004), peripheral cues such as affective content and LSM should be relevant and influential, whereas in higher-involvement product categories (e.g., cars), the results may differ because customers often read and process texts more carefully, and rely less on simple heuristics, when making these purchase decisions. Researchers should test different types of products, especially those for which a more central route to persuasion is likely.

Fourth, affective connotations in customer reviews are not always literal. Ironic connotations use subtleties to communicate the opposite of the actual word meaning. In our study setting, the detection of irony is less crucial because heuristic processing often prevents consumers from perceiving irony, which instead requires extensive reading time and processing motivation (Jones, Ravid, and Rafaeli 2004). Nonetheless, further research might investigate linguistic properties that characterize ironic statements, especially in higher-involvement purchase situations. Such insights could help identify the sentiment orientation of user-generated content and enable companies to avoid erroneous opinion mining.

Fifth, following CAT (Giles 2009), greater LSMs reflect greater identification with a conversant (Ireland and Pennebaker 2010). Conversely, a greater mismatch in linguistic style may indicate that a conversant derives a sense of self by distancing him- or herself from the particular conversational partner or collective. Such disidentification and its implications present a worthwhile avenue for further research (Elsbach and Bhattacharya 2001).

Finally, our operationalization of LSM is based on research by Pennebaker and colleagues and quantifies the function word similarity between individual reviews and all other reviews in the product category. Although this approach offers a computationally simple tool for establishing linguistic synchrony by computing the differences between individual-level and group-level function word usage, further research could develop and validate alternate computational means of deriving LSM in group settings.

Managerial Implications

Online feedback mechanisms have amplified and accelerated marketers' reach, to the point that nearly any customer comment about products and services can function as an influential product recommendation or dissuasion. The sheer volumes of qualitative customer reviews posted daily have intensified efforts to gauge their impact accurately. We illustrate the use of text analytics to systematically analyze specific aspects of customer reviews, a method that can be applied while monitoring customer opinions and subsequent impacts in real time. Text analytics is an emergent and growing field; Forrester Research (see Owens et al. 2009) predicts its value to increase from $499 million in 2011 to $978 million in 2014. This tool enables marketers to analyze vast amounts of unstructured data and quantify information that is mostly qualitative. Thus, it is ideal for

retailers and product manufacturers that need to gather marketing intelligence from online customer reviews. Beyond collecting, categorizing, and monitoring customer sentiment, text analytics can help companies predict customer behavior and more effectively converse with customer target groups. Our results also suggest several ways online retailers can increase the effectiveness of their retail sites.

To improve conversion rates, online retailers should encourage customers to describe their product experiences in a way that reflects their emotions vividly and in a writing style that is consonant with a particular genre or product class. Because the alignment of style and affective content in customer review texts increases their impact on conversion rates, review writing guidelines could be invaluable. For example, retailers might prompt customers to express their emotions through questions such as "How did you feel about this book?" They also can provide examples of how other customers typically express their opinions about a product. Moreover, the preferred content and style alignment should be reflected in the other types of textual communication on retailer websites, such as editorial comments or product descriptions. This study's insights into people's emotional states and their interaction with the development of a shared language, retrievable through function word usage, suggest that text-based sentiment analysis of customer reviews should incorporate these words. That is, for retailers, mining customers' particular use of affective content and function words may open up a trove of insights into their personal backgrounds, emotional states, and preferences.

Another means to improve conversion rates might entail changing the order in which the customer reviews appear. Instead of showing the most recent reviews first, online retailers might order customer reviews according to their projected impact on conversion rates, such that reviews with strong affective content and an aligned linguistic style appear first. Reviews perceived as most helpful also tend to display the highest degree of LSM with the target audience, which increases their positive impact on conversion rates. However, we also note a caveat for ranking customer reviews: Online retailers should ensure that the most visible reviews represent diverse viewpoints. Our findings of a negative squared effect of extremely positive review changes and a positive effect for changes in the variation of star ratings indicate that customers discount overtly positive and/or similar reviews as biased or fake.

Our results also offer important insights for producers, publishers, and other retail managers who buy customer reviews from Amazon.com or other sites and post them on their website (e.g., as testimonials) or add them to product descriptions (Mudambi and Schuff 2010). These purchasers could improve their return on the significant investments in customer reviews by selecting those reviews that are most impactful in terms of conversion rates, as determined by the elicited affective content and linguistic style convergence.

Conversion rates average approximately 2%–3% across online retail sites, and yet deceptively small increases of even 1% in conversion rate at retailers such as Amazon.com can translate into millions of dollars in sales revenues (Econsultancy & RedEye 2011). The rapid growth of narrative, user-generated content and increased sharing of customer opinions and experiences across a wide variety of social media platforms makes the real-time analysis of customer sentiment an increasingly vital predictor of market trends and customer intent and behavior. This study emphasizes that developing insights into how customers express their views is crucial because the linguistic properties of reviews ultimately influence purchase decisions. Furthermore, our study offers a glimpse of how customers talk among themselves, which can help companies fine-tune their dialogue with customers to participate in natural, authentic conversations with them. By establishing a common ground based on what customers say and how they say it, companies can establish a firm foundation for longer-lasting relationships with customers.

Appendix
Pilot Study

Method

For the pilot study, we solicited the cooperation of 230 business students who were in at least their third year of study (119 women [51.7%], mean age = 21 years [SD = 2.32]), to ensure that they had substantial exposure to business jargon over the course of their studies. The self-reported mean number of business books read was 15 (SD = 5).

Procedure

Participants were invited by e-mail to an online experiment. After instructing them to picture themselves in a situation in which they needed to buy a new business book, they were randomly assigned to one of four experimental groups and sequentially shown two typical Amazon.com pages featuring a business book with two customer reviews respectively, taken from our review sample. We used a 2×2 between-subjects factorial design, in which we manipulated LSM and affective content by showing (1) two positive reviews that closely matched the linguistic style of the business book genre (high LSM), (2) two positive reviews that did not match the linguistic style well (low LSM), (3) two negative reviews with a high LSM, or (4) two negative reviews with low LSM. The dependent variables in our pilot study consisted of purchase intention and identification with the reviewer. We employed a five-point Likert-type scale to measure participants' purchase intentions using the following scale: "The likelihood of purchasing this book is: (very low to very high)" (adapted from Dodds, Monroe, and Grewal 1991). We used four multiple-item, seven-point Likert-type scales (coefficient $\alpha = .952$) to measure participants' perceived identification with the reviewers (Prendergast, Ko, and Yuen 2010).

Results and Discussion

The goal of the study was to determine the degree to which LSM (1) influenced participants' identification with the reviewers and (2) interacts with affective content to increase (or attenuate in the case of low LSM) the impact of the reviews on purchase intention. Analyses between conditions indicated that high levels of LSM resulted in greater identification (M = 5.52, SD = 1.45) than low levels of

LSM (M = 4.31, SD = 1.41), irrespective of the valence of the reviews' affective content (F = 40.55, $p < .001$). The main effect of affective content and the interaction effect were not significant. Considering the results for the second part of the pilot study, positive affective content increased purchase intentions (M = 3.39, SD = 1.20), in contrast to negative affective content (M = 1.53, SD = .74; F = 246.81, $p < .001$). The results also indicated that LSM significantly influences purchase intention (F = 7.16, $p < .05$): Reviews with a high LSM increased purchase intentions. Finally, we found a significant, positive interaction effect between affective content and the LSM of reviews (F = 27.39, $p < .001$), such that reviews that convey positive affective content had a significantly stronger positive influence on purchase likelihood if they matched the linguistic style of the business book target audience (high levels of LSM) (M = 3.97, SD = 1.04) than if they diverged from it (M = 3.00, SD = 1.19). Similarly, negative reviews were more detrimental to purchase likelihood if they used a matching linguistic style (high LSM) (M = 1.39, SD = .83) than if not (low LSM) (M = 1.70, SD = .62). This pilot study presents first evidence for our hypothesized effects in H_2 and H_3, in a controlled experimental setting.

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