COMPETITIVE AND ASYMMETRIC NATURE OF RELATIONSHIPS BETWEEN EXPERT BLOG SENTIMENT AND GENERAL CONSUMER BRAND PERCEPTION

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Abstract

Expert blogs have become an important source from which consumers obtain information about products and brands. Consumers heed information from such blogs because they are provided by fellow consumers who are regarded as experts and yet are not restrained to speak for a particular company. Thus, expert blogs are considered more credible, and it is likely that when expert bloggers choose to write favorably about a brand, consumer perception about the brand is enhanced. Furthermore, expert blogs may influence not only consumer perception of a focal brand, but also that of competing brand. By analyzing a novel, comprehensive dataset that combined expert blog sentiment of competing brands in the PC industry and consumer perception of the brands at a daily level, our study unveils three insights: 1) expert blog sentiment on a focal brand is positively related to consumer perception about the brand while negatively related to that of its competitors; 2) the focal brand’s blog sentiment has a reinforcing relationship with its future blog sentiments, while a cannibalistic relationship with that of its competitors; and 3) the extents of the positive and reinforcing relationships depend on the firms’ position (leading vs. non-leading). Implications for research and practice are discussed.

Keywords: Expert blog sentiment, general consumer brand perception, social media, vector autoregression.
1 INTRODUCTION

Social media, particularly blogs, can help companies increase the visibility of their brands among the consumers without spending millions of advertising dollars (Aggarwal et al. 2012b). A report by Nielsen Global Survey suggests that blogs are considered a more trusted source of information than traditional media such as advertisements (ACNielsen 2007). Among the various forms of social media, a Technorati’s 2013 Digital Influence Report indicates blogs contributed by consumers who are regarded as experts in their fields to be the most influential to consumers (Technorati Media 2013).

The influence of expert blogs, such as those found on the blogging platforms of Engadget and Techcrunch, may be attributed to a mix of their characteristics that make them different from traditional media as well as other social media. Of the various forms of social media, expert blogs are akin to online journals, written and published not by ordinary consumers but bloggers who are considered experts in their areas (Aggarwal et al. 2012a; Scoble and Israel 2006). As described in a Social Media Influence web article, “… bloggers are not musing wannabe writers, then, but individuals active and respected in their fields.” These blogs provide commentary and/or news on particular subject areas such as technologies, stock markets, and health-related issues. Yet different from traditional journals written by professional editors who are often hired by a company, expert blogs are written by independent consumers who are not obligated to speak for a particular firm. Also as expert blogs are written more candidly than traditional journals, information on these spaces may be considered more unaltered opinions (Aggarwal et al. 2012a; Thomas and Barbara 2004). Their relatively unbiased nature, coupled with the recognized expertise of the bloggers, make expert blogs a particularly credible and influential source of information to consumers (Thomas and Barbara 2004). Additionally, as expert opinions are widely quoted among news media, expert blogs can be virally disseminated via traditional word-of-mouth (WOM), which may in turn influence the general population. That is, despite some consumers are never directly exposed to expert blogs, these blogs could still have substantial influence on the general consumer brand perception. Thus, when expert bloggers write favorably about a brand in their specialized industry, their blogs should enhance general consumer perceptions about the brand.

However, whether blogs can indeed emanate their influence beyond the online context in shaping general consumer brand perception, and the nature and extent of such influences, are still not well understood. Furthermore, blogs may enhance not only consumer perception about the focal brand, but also undermine that of its competitors. In addition, it will be valuable to consider whether such an influence is subject to the relative position of a brand e.g., leading versus non-leading, in an industry – that is, whether leading brands or non-leading brands would enjoy a greater benefit from the influence of expert blogs. Prior literature indicated that leading firms tend to benefit more from traditional media compared to weaker firms (Erickson 2009; Naik et al. 2005), but again it is unclear whether this applies to expert blogs given their different characteristics from traditional media (e.g., consumers but not firms communicate the brand-related information). Therefore, our research questions are, “do expert blogs influence general consumer brand perception? If so, do such influences demonstrate competitive and asymmetric nature?”

Although the extant literature has shown that word-of-mouth (WOM) information on blogs in particular and social media in general can lead to favorable outcomes such as increased sales (e.g., Chevalier and Mayzlin 2006; Dellarocas et al. 2007; Dhar and Chang 2009; Goh et al. 2013; Stephen

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1 A brand is defined as “a name, term, sign symbol, or coordination of them which is intended to identify the goods and services of one seller or group of sellers and to differentiate them from those of competitors” (Kotler 1991, p. 442).


3 It is to be noted that a relatively small portion of blogs are required to write for a company that provides the bloggers with monetary compensations. However, by doing so they risk losing their audiences who desire unbiased information, and the Federal Trade Commission mandates that bloggers disclose information about any material connections they have with companies (see http://www.theguardian.com/commentisfree/2012/mar/09/bloggers-upfront-sponsored-content).
and Galak 2012), stock prices (e.g., Chen et al. 2011; Luo et al. 2013) and customer-firm interactions (Rishika et al. 2013), there has been very limited research on the relationships between expert blogs and general consumer brand perception. Establishing this link is important for at least two reasons: 1) brands are heralded as one of the most valuable and sustainable assets of a firm (Clifton 2009; Kotler and Pfoertsch 2006); favorable consumer brand perception may cultivate their affection and loyalty towards the brand in the long term (Fournier 1998); 2) consumer brand perception constitutes a pertinent explanatory factor for outcomes such as product sales (Grewal et al. 1998) and stock trading (Lane and Jacobson 1995). Indeed extant social media research has often assumed, explicitly or implicitly, that enhanced consumer brand perception could be an underlying mechanism linking social media to product sales and firm performances. For instance, Luo et al. (2013) call for extending their research that relates social media volume to stock prices by investigating the effects of social media content on consumer brand perception, based on the assumption that better brand perception should contribute to firm equity value.

Among the limited studies have attempted to investigate the brand-related implications of social media, Singh and Sonneburg (2012) propose guidelines on how firms should engage social media to achieve better brand performances, e.g., the need to understand the audiences and their role. However, the relationship between social media and general consumer brand perception is not assessed in this study. Corstjens and Umblijis (2012) develop a set of social media indicators that incorporate social media sentiments on a brand and its competitors, and use the indicators to predict sales. It is assumed in the study that social media sentiments can be extended offline to reflect general consumer brand perception, but the link was not empirically validated. Similarly, Schweidel et al. (2012) propose the use of social media content to infer brand sentiments. Their study finds fairly high correlations between social media sentiments and offline tracking surveys conducted on a technology brand. However, the dynamics in the relationship between social media sentiments and consumer brand perception is not explored. Also as their study focuses on a single brand, the potential competitive and asymmetric nature of social media cannot be assessed.

A few other studies have also attempted to directly examine the link between social media sentiments and consumer brand perception. Through laboratory experiments, Naylor et al. (2012) show that the disclosure of more information about participants on a firm’s brand community page (e.g., demographics), who shared brand-related information, could lead to improved brand perception by the experiment subjects relative to competitors. Laroche et al. (2013) use a survey method to show that social media brand community may cultivate customers’ brand loyalty through fostering brand trust among the customers. Our research complements these lab experiment- and survey-based studies by using field data, which allows the actual dynamics in the relationship between social media sentiments and consumer brand perception to be better examined.

Specifically, we assembled a novel, comprehensive dataset that combined 1) online expert blog sentiment of brands competing in the personal computer industry; and 2) perception of the brands collected from a representative sample of general/ordinary consumers at the daily level from BrandIndex provided by YouGov Group, which specializes in consumer panels and monitors global and local brands in the U.S., U.K., and Germany. Together the data contains 7,871 brand-day observations, which we analyzed using vector autoregressive model with exogenous covariates (VARX). VARX is a flexible time-series approach that can estimate the long-term, accumulative effects of a set of antecedents and assess how such effects unfold non-monotonically over time (Adomavicious et al. 2012; Luo 2009).

In the followings, we discuss the conceptual foundation and the research hypotheses of this study.

2 CONCEPTUAL FOUNDATION AND RESEARCH HYPOTHESES

In developing our hypotheses, we build primarily on the WOM theoretical framework (Lovett et al. 2013) and supplemented it with signaling theory (Aggarwal et al. 2012a; Spence 1973). Expert blogs can be seen as a form of WOM contributed by consumers who possess expertise on a subject matter (Aggarwal et al. 2012a, 2012b; Scoble and Israel 2006). We apply the framework to understand the conditions under which bloggers are likely to produce favorable WOM for a brand. In arguing for our
hypotheses, we then employ signaling theory (Spencer 1973) where appropriate to explain how such WOM produced by expert blogs could be particularly effective in influencing general consumer brand perception.

2.1 WOM Theoretical Framework

Noting that WOM and brands are closely related but their relationship has not been adequately examined, Lovett et al. (2013) summarize the previous literature and develop a WOM theoretical framework to explain what may stimulate consumers to spread WOM for brands. According to the framework, consumers produce WOM for brands as a result of three major drivers: social, functional, and emotional.

Social driver is related to the desire to send signals to others about one’s expertise, uniqueness, or social status (Lovett et al. 2013). To socialize, and to converse with others constitutes a basic human desire, which may be fulfilled through spreading WOM. Adding to this, when consumers use WOM to socialize with others, they also desire for self-enhancement, i.e., raising their image and reputation among other consumers (Dichter 1966; Wojnicki and Godes 2011). Functional driver is related to the need to obtain information and the desire to provide information. Such a driver is fundamental to WOM communication as WOM serve to reduce the information asymmetry between sellers and buyers (Ba and Pavlou 2002; Gu et al. 2012). By providing WOM, consumers share what they know and their experience, while at the same time exchange information with others that adds to their knowledge and expertise. Emotional driver is related to emotion sharing, whereby a consumer desire to share feelings about brands to balance emotional arousal (Lovett et al. 2013). The driver is in line with the notion of product involvement highlighted by Dichter (1966), which concerns how WOM may act as a tension-releasing mechanism that drives consumers to share what they know or feel about a brand and its products.

Through analyzing a comprehensive dataset that entailed both online and offline WOM, Lovett et al. (2013) find that whereas emotional driver emerges to be the most important driver for offline WOM, the primary drivers for online WOM are social and functional drivers. Therefore, we pay particular attention to the social and functional drivers to understand what motivate bloggers to produce favorable WOM about a brand. Previous literature suggests that WOM communications by highly motivated consumers such as bloggers are more influential, in that they are likely to be deemed more convincing by the audiences (Dichter 1966). Below while arguing for the hypotheses we employ signaling theory (Spence 1973) to supplement this point.

2.2 Hypotheses on the Relationships between Expert Blog Sentiments and General Consumer Brand Perception

We expect that the expert blog sentiments on a focal brand to be positively related to general consumer perception about the brand, and negatively related to general consumer perception about the brand’s competitors. The expected positive relationship between expert blog sentiment and consumer brand perception is in line with previous studies that indicate favorable social media influences (e.g., Chevalier and Mayzlin 2006; Luo et al. 2013; Rishika et al. 2013), and may be understood through the WOM theoretical framework (Lovett et al. 2013).

As stipulated by the WOM theoretical framework (Lovett et al. 2013), consumers voluntarily share their feedback and recommendations on social media to enhance their self-image and help reduce information asymmetry for other consumers, i.e., social and functional drivers respectively (Dichter 1966; Dellarocas and Narayan 2010; Lu et al. 2013). This applies well to the context of expert blogs, whereby bloggers are keen to uphold their status as a recognized expert among consumers, and the information they provide could help other consumers understand an issue, a product, or a brand better (Aggarwal et al. 2012; Ekdale et al. 2010; Huang et al. 2007). In addition, it has been noted that for the purpose of gaining recognition, positive WOM is more effective than negative, because experts are “expected to identify high-quality products better than novices” (Lovett et al. 2012; p.429).
Owing to their relatively unbiased nature, coupled with the recognized expertise of bloggers, the positive WOM provided by expert bloggers on a brand (i.e., expert blog sentiments) should act as a particularly efficacious signal of brand quality (Spence 1973). Specifically, blogger involvement in generating WOM about a brand implies that they deem it worthy to invest their effort in doing so for the brand given their capacity constraints (Aggarwal et al. 2012a; Nardi et al. 2004). Additionally, the expert bloggers bear reputation cost in providing timely information to general consumers, given that they are expected to identify high-quality products better than novices; any inaccurate information communicated may hurt their reputation. Thus, the WOM information provided by an expert blogger on a brand satisfies the criterion of cost for an efficacious signal. Per the signaling theory, this higher cost entailed in a signal, the more efficacious or influential it is (Spence 1973). Furthermore, the prevalence of expert blogs as an information source to consumers and increasingly news media (ACNielsen 2007; Technorati Media 2013) and the persistent nature of blogs mean that bloggers’ positive sentiments about the brand is likely to be widely distributed to other consumers, thus satisfying the criterion of signal observability, i.e., the signal can be easily observed (Spence 1973). Therefore, positive expert blog sentiments on a focal brand are expected to act as a leading indicator and have a positive predictive relationship with how general consumers perceive the brand.

Positive expert blog sentiments on a focal brand not only enhance consumer perception about the focal brand, but may also undermine consumer perception about the competing brands. When bloggers choose to write favorably about a focal brand over other brands in an industry, the choice sends a signal to the readers about the bloggers’ preference (Aggarwal et al. 2012a; Spence 1973). This signal may then induce a preference shift in the consumers. Prior literature has shown a high correlation between consumer brand preference and their brand perception of brands within a given consideration set, in that preferred brands are associated with favorable brand attitudes whereas non-preferred brands are associated with lower brand attitudes (Bass and Talarzyk 1972). Such effects may be particularly salient in product markets in which the product consumption is infrequent and entails considerable cost to consumers, such as PCs (Spangenberg et al. 1997; Wills et al. 1997).

Thus, it can be expected that, when consumers are influenced by bloggers to favor a brand by the positive blog sentiments it garnered, their perception of other brands that compete within the same market would be undermined. Similar predictive competitive effects have been documented for traditional media such as TV advertising and direct mailing (Erickson 2009; Diepen et al. 2009; Naik et al. 2005). This led us to the following hypotheses:

\[ H1a. \text{Positive expert blog sentiments on a focal brand have a positive predictive relationship with general consumer perception about the brand.} \]

\[ H1b. \text{Positive expert blog sentiments on a focal brand have a negative predictive relationship with general consumer perception about its competing brands.} \]

### 2.3 Hypotheses on the Dynamic Nature of Expert Blog Sentiments

Besides a direct predictive relationship with general consumer brand perception, we expect expert blogs to demonstrate dynamic properties on future expert blogs. Specifically, we propose that the expert blog sentiments on a focal brand have a reinforcing relationship with its own subsequent sentiments (e.g., positive current sentiments about a focal brand would lead to positive future sentiments about the brand), but a cannibalistic relationship with its competitors’ subsequent sentiments.

It has been argued that the persistent nature of WOM on social media platforms, including blogs, could stimulate further WOM communication among the consumers (Dellarocas et al. 2010). The availability of WOM information allows consumers to observe, engage with, and respond to what others are saying about a brand. When expert bloggers observe favorable sentiments on a brand that signal its quality (i.e., high quality brands receive more positive blog sentiments), they will be motivated by social or functional drivers to also discuss favorably about the brand as predicted by the WOM theoretical framework (Lovett et al. 2013). For instance, expert bloggers may be driven to respond to another blogger’s positive posting on a brand by posting their own blogs to show that they...
possess equal expertise to identify quality attributes of the brand concerned. They may also engage in the WOM communication for the purpose of further reducing uncertainty or information asymmetry about the brand.

Expert blogs on a brand may also cannibalize those of its competitors in the subsequent period. As blogger attention shifts to a focal brand due to positive signals from other bloggers (Spence 1973), it reduces their attention on competing brands given capacity constraint, which may lead to a negative feedback process undermining the extent of future blog sentiments on the competing brands. Taken together, subsequent sentiments garnered by competing brands are likely to suffer (Wu and Huberman 2008). Therefore, we hypothesize:

\[ H2a: \text{Expert blog sentiments on a focal brand have a reinforcing relationship with its own subsequent sentiments.} \]

\[ H2b: \text{Expert blog sentiments on a focal brand have a cannibalistic relationship with its competitors’ subsequent sentiments.} \]

2.4 Hypotheses on the Asymmetric Nature of the Relationships between Expert Blog Sentiments and General Consumer Brand Perception

Finally, we posit that the relationships between expert blogs and general consumer brand perception for a focal brand are asymmetric depending on the standing of the brand in the market. This is in line with previous literature on traditional marketing media, such as TV advertising, that notes the relative gains bestowed by such media on competing firms are contingent on their standing in the market (Erickson 2009; Naik et al. 2005). However, our position differs in that we posit weaker brands will benefit more from expert blog sentiments compared to leading brands, based on the distinct characteristics of social media in general and expert blogs in particular compared to traditional media. Specifically, bloggers instead of firms generate the brand-related information on social media; this characteristic should have a significant bearing on the influence of expert blogs on the general consumer population.

First, signaling theory suggests that the strength of the signal varies with the cost of the signal. In the context of blogging, bloggers incur higher costs in writing favorably about non-leading brands. Specifically, there may be a greater reputation cost for expert bloggers to endorse a non-leading brand compared to a leading brand, as they are more likely to be criticized and lose their following if such endorsements turn out to be incorrect. As previous research notes, going against the mainstream could incur a higher reputation cost (Schmidt 2010). In addition, expert bloggers tend to be familiar with the condition of the market in which they specialize, and so when they deliberately choose to endorse a brand lagging in the market they may expend more effort to justify their choice. Together, the resultant higher signaling costs entailed in the expert blogs on non-leading brands should make them to have a stronger influence on general consumer brand perception about the non-leading brands.

\[ H3a: \text{The positive relationship between expert blog sentiments and general consumer brand perception is stronger when the focal brand is a non-leading brand compared to when it is a leading brand.} \]

Second, per WOM framework (Lovett et al. 2013), bloggers are particularly motivated to spread WOM information about brands that allow differentiating from the majority (i.e., a social driver). Such a tendency is tied to an individual’s desire to express personality and uniqueness. As noted by Dichter (1966), “consumers are proud to use what they consider an ‘underdog’ product,” because “[t]hey feel gratified in defying the majority by publicly using an unpopular brand; but the real self-confirmation lies in converting others to their own ‘peculiar’ choice” (p.150). The link between individuals’ desire for uniqueness and their enthusiasm to contribute has been supported in the literature (Karau and Williams 2000; Ling et al. 2005). This implies that expert bloggers may be especially motivated to write favorably about non-leading brands when opportunity arises. In particular, when they see that there are expert bloggers who wrote for these brands, they are likely to join force with them to defy the mainstream as the cost of doing so is reduced, and they are able to
signify their expertise to also identify quality attributes of such underdog brands. This discussion suggests that expert blogs on non-leading brands are especially apt to spread to others and reinforce the current favorable sentiments, more so than for a leading brand. Therefore, we hypothesize:

\[ H3b. \text{The reinforcing relationship (from current expert blog sentiment to future sentiments) is stronger when the focal brand is a non-leading brand compared to when it is a leading brand.} \]

3 DATA DESCRIPTION

We assembled a novel, comprehensive dataset that captures both expert blog sentiments and general consumer brand perception. We selected the PC industry as our research context because of the value of brand equity in this intensively competitive industry. Also the importance of expert blogs is likely to be particularly salient in product markets where domain knowledge is sought after but consumers lack self-expertise, and they are highly involved in the product purchase thus desiring credible and timely information for purchase decision-making (Aqueveque 2006; Gu et al. 2012; Reinstein and Snyder 2005). The PC industry we focused represents one such market. Our dataset is at daily level, including the following brands: Acer, Apple Mac, Compaq, Dell, Gateway, HP, Lenovo, Sony Vaio, and Toshiba with 7,871 brand-day observations.

3.1 Measures for General Consumer Brand Perception

We capture individual consumer perception of the brands on a daily basis. The data were obtained from BrandIndex, collected by a global market research agency YouGov Group, which specializes in consumer panels and monitors global and local brands in the U.S., U.K., and Germany. For the U.S. market, YouGov monitors about 1,025 brands in 20 different industry sectors. It surveys about 5,000 consumers daily out of all relevant demographic groups from a panel size of 1,500,000 consumers. To ensure that the brand perception collected represents the general population, the respondents are weighted by age, race, gender, education, income, and geography (region) using census data. The large panel size is advantageous because it can be more representative of the brand user universe (Tirunillai and Tellis 2012). Also, the daily frequency of our consumer brand perception data is beneficial because it can timely reflect the changes in consumer perception of the brands, and allow us to observe and identify dynamic relationships.

YouGov collects the data in the following manner. First, for a given industry sector, the respondents select all brands for which they have a positive response to a given brand indicator (e.g., good brand quality). Then, they select all brands for which they have a negative response to a given brand indicator (e.g., poor brand quality). The rest of the brands are then rated as neutral. Hence, for each brand three responses are possible: positive, negative, and neutral. Brand competition effects are also controlled for because respondents rate the competing brands within one sector simultaneously. Further, to reduce common method bias from the same survey respondent, the brand perception indicators are measured independently across respondents. That is, any respondent is asked about her perception of only one brand indicator for a particular sector, not all six brand indicators for the same industry. The indicator-industry combination is randomized.

Brand perception is captured by the consumer responses to the questions of “For which brands do you have a 'generally positive' or 'generally negative' feeling?” We calculated the brand perception scores by taking the differences of the number of respondents who agree with the positive judgments and the number of respondents who agree with the negative judgments divided by the total number of respondents (\((\text{positive votes} - \text{negative votes}) / (\text{positive} + \text{negative} + \text{neutral votes})\)).

YouGov provided us with data for all the focal brands surveyed between January 1, 2008 and August 31, 2011. Apple Mac, Lenovo and Sony Vaio have shorter time-series. Therefore we obtained a sample of 9 brands with 410 to 957 time-series observations for each brand. The final total number of brand-day observations is 7,871, for which we matched the brand perception data with expert blog data to test the hypotheses. Descriptive statistics of the data are presented in Table 1.
<table>
<thead>
<tr>
<th>Variables</th>
<th>Expert Blog Sentiment</th>
<th>Expert Blog Volume</th>
<th>General Consumer Brand Perception</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACER</td>
<td>0.58</td>
<td>1.37</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>(0.24)</td>
<td>(1.65)</td>
<td>(0.08)</td>
</tr>
<tr>
<td>Apple MAC</td>
<td>0.83</td>
<td>59.38</td>
<td>0.24</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(13.27)</td>
<td>(0.10)</td>
</tr>
<tr>
<td>COMPAQ</td>
<td>0.48</td>
<td>0.11</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td>(0.10)</td>
<td>(0.36)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>DELL</td>
<td>0.62</td>
<td>2.91</td>
<td>0.38</td>
</tr>
<tr>
<td></td>
<td>(0.24)</td>
<td>(2.49)</td>
<td>(0.10)</td>
</tr>
<tr>
<td>GATEWAY</td>
<td>0.51</td>
<td>0.59</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td>(0.21)</td>
<td>(0.92)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>HP</td>
<td>0.55</td>
<td>3.00</td>
<td>0.48</td>
</tr>
<tr>
<td></td>
<td>(0.23)</td>
<td>(2.39)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>LENOVO</td>
<td>0.58</td>
<td>1.11</td>
<td>0.01</td>
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<tr>
<td></td>
<td>(0.24)</td>
<td>(1.47)</td>
<td>(0.04)</td>
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<td>SONY VAIO</td>
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<tr>
<td></td>
<td>(0.14)</td>
<td>(4.91)</td>
<td>(0.06)</td>
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<td>TOSHIBA</td>
<td>0.61</td>
<td>1.67</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td>(0.26)</td>
<td>(1.98)</td>
<td>(0.08)</td>
</tr>
</tbody>
</table>

Table 1. Descriptive statistics of variables

### 3.2 Measures for Expert Blog Sentiments and Volumes

There are a vast number of blogs in the blogosphere. They vary in topic, author, number of followers, etc. A search of “Dell” in Google blog search on August 22, 2011 returns 1,250,000 results not counting those trimmed by Google due to redundancy. The returned blog posts were from various sites like engadget.com, laoptopmag.com, and personal blog hosted by typepad.com.

Fortunately, expert bloggers are much fewer and most of the tech expert bloggers concentrate in specialized blog platforms tracked by blog search engine Technorati. For this study, we collected blog posts about the targeted brands from the top 4 tech blogs ranked by Technorati: Engadget, Techcrunch, Mashable, and Arstechnica during the same time period as with the brand perception data. In total, we obtained 131,759 blog posts that include 27,307 from Mashable, 35,867 from Techcrunch, 24,998 from Arstechnica, and 43,587 from Engadget for the text mining procedures. We first downloaded the web pages of all the blog posts at those sites during the research period. We further analyzed the sentiments of the blog posts and aggregated them by posting date for each brand. This analysis included the following steps:

1. Developing the training set: a group of three graduate student evaluators were hired to read and judge the sentiment of randomly selected 1,600 blogs from the downloaded ones under the majority rule. They were asked to first classify a blog training set into either "objective" or "subjective" category. 394 blog posts were identified as objective posts while the remaining posts were labeled as "subjective". For the subjective blog posts, the evaluators were further asked to identify their sentiments. 314 blog posts were identified as negative; 420 posts were identified as positive and 442 posts were identified as neutral. Inter-rater reliability test of each pair of evaluators shows a consistency rating (Cohen’s Kappa) of over 0.95, which is well above the recommended level of 0.75 (Neuendorf 2002). The training blog posts were excluded from the subsequent text mining procedures.

2. Text mining: the text mining procedure was performed by Rapidminer version 5. We employed a linear Support Vector Machine (SVM) classifier for both the subjectivity analysis and the sentiment analysis. The type of Kernel is dot (linear). The accuracy of the classifier for sentiment analysis and subjectivity analysis is 82.05% and 72.04% respectively. We also employed an out-of-sample validation set of 1,000 positive and 1,000 negative movie review posts available in Pang and Lee (2004). The accuracy of the SVM classifier employed in all of our procedures was 82.79%.

3. Brand classification: We employed Term Frequency-Inverse Document Frequency (TF-IDF) method to classify blog posts to our brand list. We first prepared a list of brand names. The list contains the following brands: Acer, Apple (iMac, Mac, MacBook, Time Capsule, AirPort), Compaq, Dell, Gateway, HP, Lenovo, Sony (Sony Vaio), and Toshiba. We include Apple product names such
as Mac, and MacBook because bloggers frequently refer to these product names without mentioning the Apple brand, while they always mention the brand name in discussing other products (e.g., Sony Vaio). A word vector was then created based on the words in the list above. It is worth noting that both the word vector and the blog posts were tokenized and transformed to lower case. The classifier then estimates the relevance of each post with every word in the word vector based on the frequency of occurrences of that word in the blog post. The classifier employed in this procedure was Linear Support Vector Machine with dot Kernel. Since the word vector is provided manually, no training dataset is required for this procedure. We then calculated the sentiment score of all blogs on the targeted brands on a daily basis to derive the measure of daily blog sentiments on a brand.

3.3 Measures for Control Variables

Following the widely used firm valuation models in the IS and accounting literature (Trueman et al. 2000, Brynjolfsson et al. 2002, Ferreira and Laux 2007, Luo et al. 2013), we control for a comprehensive set of exogenous covariates, including revenue (sales), firm size, financial leverage, liquidity, return on asset (ROA), industry competitive intensity, industry M&A (merger & acquisition), R&D expenditures, new product announcement, and advertising spending.

We control firm financial conditions with revenue (sales), firm size, financial leverage, liquidity, and return on asset (ROA). Revenue is the REVQT variable in the COMPUSTAT database. Firm size is measured by total assets of the firm (variable ATQ). Financial leverage is the ratio of long-term book debt (DLTTQ) to total assets. Liquidity is the current ratio of a firm (LCTQ/ACTQ). Return on assets measures firm profitability and is calculated as the ratio of a firm’s operating income (OIBDPQ) to its book value of total assets. To match those quarterly financial variables with our daily blog and conventional metrics, we adopted the VAR-bootstrapping scheme, which uses 5,000 simulated databases to generate the values of those variables for each observed day (Hamilton 1994; Luo 2009; Statman et al. 2006). In addition, we control for industry and economic conditions with competitive intensity and M&A announcements. Competitive intensity is gauged by the Hirschmann-Herfindahl index measure of industry concentration. It is the sum of squared market shares of firms in the industry derived from total sales

\[ \sum_{i=1}^{N} s_i^2 \], where \( s_i \) is the market share of firm \( i \) in each of the computer hardware and software industries (Hou and Robinson 2006). We collected M&A announcements from Lexis/Nexis news search.

We also control firm innovation and advertising efforts with R&D expenditures, new product announcement, and advertising spending. R&D expenditure is measured as research and development expenses (XRDQ) scaled by total assets from COMPUSTAT. New product announcements are collected from the Lexis/Nexis news search (Sood and Tellis 2009). The advertising data are collected from Ad$pending by Kantar Media, which provides top-level firm advertising expenditures in twelve major media, including radio, TV, newspapers, magazines, and Internet.

4 MODEL SPECIFICATION AND ESTIMATION

We use a VARX model to examine the relationships between expert blogs and general consumer brand perceptions, where endogenous variables are the brand perceptions and expert blogs. As we mentioned earlier, we also control for a set of exogenous variables to capture the size, investment, and industry effects. VARX model allows us to capture dynamic interactions and feedback effects (Adomavicius et al. 2012; Dekimpe and Hanssens 1999; Luo 2009). For our study, it has several advantages over alternative models. Specifically, it can track not only the direct relationships between expert blog sentiments and general consumer brand perception but also their dynamic and competitive nature. In addition, it accounts for biases due to endogeneity, auto correlations, and reversed causality. VARX models also capture complex feedback loops that include the reversed impact of brand perception on future blog sentiment metrics (feedback effects). Thus, VARX can model complex chained effects in a complete cycle, uncovering the full predictive value of expert blog metrics. We use VARMAX procedure in SAS for VARX model analyses (which can be done with EViews and R.
language as well). Our time-series analysis in the following steps is applied to each firm separately (Srinivasan et al. 2010).

### 4.1 Model Specifications

To test H1a, H2a, H3a and H3b, we built the following VARX model:

\[
Y_t = \alpha + \sum_{p=1}^{n} \Phi_p Y_{t-p} + \Gamma X_t + \epsilon_t, \text{ or }
\]

\[
\begin{bmatrix}
\text{Brand Perception}_{it} \\
\text{Blog Sentiment}_{it} \\
\text{Blog Volume}_{it}
\end{bmatrix}
= 
\begin{bmatrix}
\alpha_1 + \delta_{11} t \\
\alpha_2 + \delta_{12} t \\
\alpha_3 + \delta_{13} t
\end{bmatrix}
+ \sum_{p=1}^{P} \begin{bmatrix}
\phi_{11,1}^p & \ldots & \phi_{11,3}^p \\
\phi_{12,1}^p & \ldots & \phi_{12,3}^p \\
\phi_{13,1}^p & \ldots & \phi_{13,3}^p
\end{bmatrix}
\begin{bmatrix}
\text{Brand Perception}_{it-p} \\
\text{Blog Sentiment}_{it-p} \\
\text{Blog Volume}_{it-p}
\end{bmatrix}
+ \begin{bmatrix}
\tau_{11,1} & \ldots & \tau_{11,10} \\
\tau_{12,1} & \ldots & \tau_{12,10} \\
\tau_{13,1} & \ldots & \tau_{13,10}
\end{bmatrix}
\begin{bmatrix}
X_{11t} \\
X_{12t} \\
X_{13t}
\end{bmatrix}
+ \begin{bmatrix}
\epsilon_{11t} \\
\epsilon_{12t} \\
\epsilon_{13t}
\end{bmatrix}
\tag{1}
\]

where \(i (i = 1, 2 \ldots 9)\) represents the focal brand, \(t\) represents time, \(p\) is lag length, and \(P\) is maximum lags. \(\alpha_{ik} (k = 1, 2, 3)\) denotes constant. \(\delta_{ik}, \phi_{ik,l}^p, \tau_{ik,s} (k, l = 1, 2, 3, s = 1, 2 \ldots 10)\) are coefficients: \(\delta_{ik}\) reflects the seasonality effect, \(\phi_{12,1}^p\) is the coefficient of the blog sentiment of brand \(i\) \(p\)-day ago on the current brand perception, \(\phi_{12,2}^p\) reflects the feedback effect, and \(\phi_{12,3}^p\) reflects the reinforcing effect of the past blog sentiment on the current one. \(x_{ist} (s = 1, 2 \ldots 10)\) represents the exogenous variables: revenue (sales), firm size, financial leverage, liquidity, return on asset (ROA), industry competitive intensity, R&D expenditures, new product announcement, M&A acquisition, and advertising expenditures.

To test hypotheses H1b and H2b, we added the endogenous variables of the rival brand (denoted by \(j\)) in the VARX model and obtained an extended form of the VARX model for the focal and competing firms (Steenkamp et al. 2005), which is specified as:

\[
\begin{bmatrix}
\text{Brand Perception}_{it} \\
\text{Blog Sentiment}_{it} \\
\text{Blog Volume}_{it} \\
\text{Brand Perception}_{jt} \\
\text{Blog Sentiment}_{jt} \\
\text{Blog Volume}_{jt}
\end{bmatrix}
= 
\begin{bmatrix}
\alpha_1 + \delta_{11} t \\
\alpha_2 + \delta_{12} t \\
\alpha_3 + \delta_{13} t \\
\alpha_4 + \delta_{14} t \\
\alpha_5 + \delta_{15} t \\
\alpha_6 + \delta_{16} t
\end{bmatrix}
+ \sum_{p=1}^{P} \begin{bmatrix}
\phi_{11,1}^p & \ldots & \phi_{11,6}^p \\
\phi_{12,1}^p & \ldots & \phi_{12,6}^p \\
\phi_{13,1}^p & \ldots & \phi_{13,6}^p \\
\phi_{14,1}^p & \ldots & \phi_{14,6}^p \\
\phi_{15,1}^p & \ldots & \phi_{15,6}^p \\
\phi_{16,1}^p & \ldots & \phi_{16,6}^p
\end{bmatrix}
\begin{bmatrix}
\text{Brand Perception}_{it-p} \\
\text{Blog Sentiment}_{it-p} \\
\text{Blog Volume}_{it-p} \\
\text{Brand Perception}_{jt-p} \\
\text{Blog Sentiment}_{jt-p} \\
\text{Blog Volume}_{jt-p}
\end{bmatrix}
+ \begin{bmatrix}
\tau_{11,1} & \ldots & \tau_{11,10} \\
\tau_{12,1} & \ldots & \tau_{12,10} \\
\tau_{13,1} & \ldots & \tau_{13,10} \\
\tau_{14,1} & \ldots & \tau_{14,10} \\
\tau_{15,1} & \ldots & \tau_{15,10} \\
\tau_{16,1} & \ldots & \tau_{16,10}
\end{bmatrix}
\begin{bmatrix}
X_{11t} \\
X_{12t} \\
X_{13t} \\
X_{14t} \\
X_{15t} \\
X_{16t}
\end{bmatrix}
+ \begin{bmatrix}
\epsilon_{11t} \\
\epsilon_{12t} \\
\epsilon_{13t} \\
\epsilon_{14t} \\
\epsilon_{15t} \\
\epsilon_{16t}
\end{bmatrix}
\tag{2}
\]
4.2 Elasticities of the Expert Blog Sentiments

We used the estimated parameter matrices of the full VARX model $\Phi_i^p$ ($p = 1, 2 \ldots P$) to generate the Generalized Impulse Response Functions (GIRFs) with $\Psi_i(t)$ capturing the net effects of endogenous variable vector at time $t$ (Dekimpe and Hanssens 1999).

$$\Psi_i(t) = \sum_{p=1}^{\min p,t} \Phi_i^p \Psi_i(t - p), \quad t \geq 1.$$  

Standard errors are derived by simulating the fitted VARX model by Monte Carlo simulation with 1,000 runs to test the statistical significance of parameters ($p = 0.05$). Note that because the white-noise residuals can be contemporaneously correlated and thus generate misleading results, we apply an orthogonal transformation to correct this bias (Luo 2009).

For each GIRF, we derived the cumulative response elasticity that combines all effects across “dust-settling” periods. We next reported them in a matrix format and plotted the time-varying elasticities4 (Pauwels 2004, Srinivasan et al. 2010).

5 FINDINGS

5.1 Test for Stationarity in Time Series

The process of estimating VARX models begins with the unit-root tests to check whether variables are evolving or stationary. Stationarity implies that, although an unexpected change in endogenous variables in VARX can induce fluctuations over time, its effects dissipate ultimately. That is, endogenous variables revert back to the deterministic (mean + trend + seasonality) pattern without a permanent regime shift. The variance of stationary variables is finite and time-invariant. We conduct the augmented Dickey-Fuller (ADF) tests to check stationarity (Dekimpe and Hanssens 1999). The ADF tests for the data series range from -31.97 to -4.26, all of which are less than the critical value (2.89). Therefore we can reject the null hypothesis of a unit root with a 95% confidence level, suggesting that the variable series do not cointegrate in equilibrium (Hamilton 1994).

5.2 Test for Granger Causality

Following Tirunillai and Tellis (2012) and Luo et al. (2013), we conduct Granger Causality tests (Granger 1969). The results suggest that blog sentiment metrics have significant ($p$ from 0.02 to 0.04) temporal-based relationships with the consumer perception of the focal brand across all brands except Apple Mac ($p = 0.09$). With regard to competitive relationships, expert blog sentiments on a focal brand “Granger cause” consumer perception of rival brands for most of the competition pairs ($p < 0.05$). These results confirm the temporal predictive relationship between expert blog sentiments and general consumer brand perception, providing initial evidence for H1a and H1b.

5.3 Results on Impulse Responses of General Consumer Brand Perception to Expert Blog Sentiments

From the VARX models, impulse-response functions were derived that trace the over-time incremental effect of an unexpected change in expert blog sentiments. Table 2 reports the cumulative impulsive response elasticities. The magnitude of elasticity results reflects the change in general consumer brand perception in response to one unit of unexpected change in expert blog sentiments.

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4 Due to space limitations we are unable to depict the corresponding tables and figures in this paper; they are available upon request.
As Table 2 shows, expert blog sentiments have a significantly positive predictive relationship with general consumer brand perception (0.015 to 0.068), and negative relationships with the rival firms’ brand perceptions (-0.007 to -0.070). These results support the H1a and H1b for almost all brands and brand-pairs. Comparing the effect size in magnitude, our results quantify that the positive predictive relationship for the focal brand is from 2 to 11 times bigger than the negative predictive relationship for the competing brands.

5.4 Results on the Dynamics of Expert Blog Sentiments

Table 3 shows the results of the responses of expert blog sentiments in the next period to the expert blog sentiments in the previous period. The diagonal in Table 3 shows the carry-over effects of expert blog sentiments of own brand, and the off-diagonal estimates are impulse responses to the past expert blog sentiments of rival brands.

As Table 3 shows, there is a significant cross-over effect in the focal brand’s own expert blog sentiments (p <0.001) across all brands. This result strongly supports H2a. The competitive effects are largely negative and significant, suggesting a cannibalistic carry-over effect on competitor’s subsequent expert blog sentiments. This supports H2b.
results on the asymmetric relationships with brand heterogeneity

Table 3. Auto-regression of expert blog sentiments: Focal and competing brands

5.5 Results on the asymmetric relationships with brand heterogeneity

We categorize the brands into two groups: leading brands and non-leading brands, based on the market share of these brands during the research period. The leading brands include Acer, Dell, HP, and Lenovo, and the non-leading brands are Compaq, Gateway, Sony Vaio, and Toshiba (note that these categorizations are in a relative sense based on the market share of the brands). Apple Mac is on the border due to its fluctuating market share over the research period. As Table 3 shows, non-leading brands demonstrate stronger elasticities response to the change of blog sentiments than leading brands in terms of both magnitudes and significance (group mean 0.061 vs. 0.050, p <.05). This supports H3a. When examining the carry-over effect on the subsequent expert blog sentiments, we find that the expert blog sentiments of leading brands show stronger reinforcing effects than non-leading brands (group mean 0.241 vs. 0.156 p <.01), as shown in Table 3. This is contrary to H3b. However, this finding is not totally unreasonable because leading brands tend to have more IT and R&D resources, which may facilitate the virtuous cycle (strong past expert blog sentiments lead to strong future expert blog sentiments). In contrast, non-leading brands may face IT and R&D resource constraints and hence are not able to effectively leverage past expert blog sentiments to influence future expert blog sentiments (Razorfish 2009).

6 DISCUSSION AND CONCLUSION

With the growing influence of social media, firms are considering investing in social media as part of their business strategy. In this study, we focus on one particular form of social media, expert blogs, which have been indicated as among the most influential to consumers. Yet, such blogs have not received the extent of firm investment they deserve, as with other forms of social media. This discrepancy may arise from doubts in the industry regarding whether and how social media such as expert blogs create sustainable value for firms. Firms typically make investment decision in media communication for long-term goals such as to build up their brand among consumers in a market. However, few studies have examined how social media in general and expert blogs in particular can provide sustainable value for firms beyond short-term gains such as product sales, and even fewer have considered the their strategic implications on firm competition. In this study, we use an extended form of the VARX model to capture the complete dynamics between expert blog sentiments and general consumer brand perception among multiple competing firms within the personal computer industry. Our analysis provides new insights to both academic researchers and business practitioners.

From the research perspective, this study makes contributions on three fronts. First, this study is among the first to assess the competitive nature of social media influences through a focus on expert blogs. Prior studies on social media mainly focus on the standalone effect of social media on a focal firm, overlooking its potential effect on competitors. By incorporating all major firms in the computer industry in our model, we show that the expert blog sentiments of a focal brand not only enhance its own brand perception by consumers, but also undermine that of its competitors. This finding highlights the value of expert blogs in a firm’s competitive strategy. Furthermore, our analysis shows that the competitive influence is dynamic: expert blog sentiments have a reinforcing relationship on itself (i.e., carry-over) and a cannibalistic relationship with the subsequent sentiments of its competitors. Thus, social media-based expert blogs can enable brands to achieve competitive advantages in consumer mindsets.

Second, we quantify the relationship between expert blogs on general consumer brand perception. While numerous studies on social media have analyzed their influences on online product sales, little
is known regarding whether the accumulation of consumer opinions in online expert blogs influences firm reputation as captured by general consumer brand perceptions. The results from our unique dataset present clear evidence that expert blog sentiments have a significant real-time relationship with ordinary consumer perception of a brand.

Third, our study paves the way for assessing the asymmetric nature of the relationships between expert blog sentiments and general consumer brand perception by proposing a focus on comparing leading brands vs. non-leading brands. Contrary to findings in the offline context, we found that the positive relationship of expert blog sentiments with general consumer brand perception is stronger when the focal brand is a relative non-leading (versus leading) brand. This finding provides evidence that non-leading brands benefit from social media, and may shed light on why non-leading firms appear to be keener on engaging in social media\(^5\). At the same time, the advantage bestowed to non-leading brands has limits. While the direct relationship is stronger for non-leading brands, its reinforcing relationship with future expert blog sentiments is weaker than leading brands. This finding offers a more holistic and nuanced understanding about the competitive and dynamic nature of the influences of expert blogs.

From a managerial perspective, our findings inform firms on the strategic use and competitive implications of expert blogs. As such, our findings help firms gain a comprehensive understanding of how their brand is affected by expert blog sentiments of their own brand as well as those of their competing brands. Our detailed model of the dynamics between expert blog sentiments and general consumer brand perception and the moderating effect of brand standing help firms set more realistic expectations about their gains from engaging in social media relative to their competitors (Sun and Zhu 2013). Likewise, when their competitors launch social media initiatives via expert blogs, our model allows firms to better estimate how it may undermine general consumer perception about their brand and the sentiments of future expert blogs.

Nonetheless, the findings from this study need to be interpreted in light of its limitations. First, we do not have data on firms’ own engagement in social media via expert blogs. As firms increasingly engage in such media, consumer reactions to sentiments on these media could be influenced by firms’ participation. In our analysis, we cannot differentiate expert blog sentiments influenced by firms’ engagement from the sentiments of true, third-party independent assessments. It will be useful for future research to explicitly model firms’ engagement in social media such as expert blogs. Second, our current analysis is limited to sentiments of expert blogs. Expert blogs are but one form of social media. While expert blogs play an especially important role for the computer industry, it will be valuable for future research to include other forms of social media in the analysis. Finally, future research may also investigate other contexts (e.g., mobile phones) to extend the generalizability of our findings.

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