Social media-based expert blogs are a crucial and credible online information source for consumers, yet little is known about the role of expert blogs for general consumer brand perceptions that bestow long-term value for the firm. On the basis of a novel dataset with 7,871 brand-day observations of over 131,000 expert blogs on major brands in the PC industry, this study reveals how expert blogs may act as a quality signal leading general consumers’ perceptions of rival brands. Our analyses reveal three key insights: (1) Expert blog sentiments and volume on a focal brand have a positive relationship with consumer perceptions of the focal brand but a negative relationship with those of its competing brands. (2) The focal brand’s blogs have a reinforcing relationship with its subsequent blogs and a cannibalistic relationship with competitors’ subsequent blogs. (3) Brand position (leading versus non-leading in the market) plays a nontrivial role in these competitive, dynamic relationships. For example, a 1 percent unexpected increase in Acer’s expert blog sentiment would be associated with a 1.5 percent lift in its own brand quality as perceived by consumers, thus winning more consumer hearts and minds. Also, a 1 percent unexpected increase in Acer’s expert blog sentiment would be associated with a .7 percent (Toshiba) to 1.5 percent (Sony Vaio) drop in its rival brand quality, thus undermining consumer hearts and minds of competing brands in the same industry. Also, the effects are asymmetrical across leading versus non-leading brands as a 1 percent unexpected increase in expert blog sentiment is associated with a 1.6 percent drop in rival-brand quality perceptions among consumers for non-leading brands, vis-à-vis only a 0.88 percent drop for leading brands. For researchers and managers, these results unravel some neglected benefits of expert blogs.

**Keywords:** Expert blog, consumer brand perception, social media, vector auto-regression

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1Sulin Ba was the accepting senior editor for this paper. Gal Oestreicher-Singer served as the associate editor.

The appendices for this paper are located in the “Online Supplements” section of the *MIS Quarterly*’s website (http://www.misq.org).

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Introduction

Blogs are a crucial, credible, and among the most influential sources from which consumers obtain information about products and brands (ACNielsen 2007; Aggarwal et al. 2012b; Technorati Media 2013). In particular, highly reputed blogging platforms, such as Techcrunch, Engadget, Mashable, and ArsTechnica, are referenced by many sites and could have a profound impact on general consumers. These platforms provide reviews on technology products such as personal computers (PCs) by featured consumer experts who specialize in the technology industry.

While having a social media origin, expert blogs are unique in three aspects (see Table 1). First, they are contributed by consumer experts with subject matter experiences instead of general, nonexpert consumers. Second, their contents consist of professional product evaluations and industry insights, not general consumption experiences. And third, their contributors and contents are organized around a reputed platform rather than scattered across independent, individual blog websites, making them highly recognizable and identifiable. Different from conventional media such as newspapers and magazines, their contributors retain a certain degree of autonomy in what they write. Indeed, Degeler (2013, p. 62) concludes that whereas an information piece is heavily edited in conventional media, an expert blogger’s voice on a platform such as Engadget is usually preserved for originality and objectivity. Even when edits are conducted, “editors take care not to edit the author’s voice out of a piece. Moreover, the expert author is normally involved in the editing process” (SOURCE???). These characteristics may thus render expert blogs more unbiased and trustworthy. Table 1 depicts how expert blogs are distinct from other media.

Because expert opinions are widely referenced by other sites and also quoted in the news media, expert blogs can be virally disseminated via word-of-mouth (WOM) and, thus, may influence general consumer perceptions. That is, these blogs could still act as quality and impartial signals and thus have substantial influence on consumer brand perceptions by shaping news media and WOM, even when consumers are not directly exposed to expert blogs. Furthermore, in practice, consumers turn to expert blogs as a main source of product information and are likely to be influenced by expert blogs in their brand perceptions and preference attitude (Technorati 2013). Consequently, when expert bloggers write favorably about a brand in their specialized industry, such expert blogs as trustworthy and influential information should enhance general consumer perceptions about the focal brand and win consumer hearts away from competing brands.

The importance of expert blogs is likely to be salient in high-involvement product markets where consumers lack self-expertise and thus desire credible information (Gu et al. 2012). An example of high-involvement product markets is PCs due to their complexity to consumers (Spangenberg et al. 1997). They generate high consumer interest and curiosity, but their complexity requires consumers to expend effort to understand their features. Also lay consumers usually lack knowledge about the features of a PC (e.g., what various versions of a central processing unit mean). In this sense, the availability of expert knowledge and insights via expert blogs is likely to be instrumental. In addition, as with other information-intensive markets, the PC industry is highly dynamic and competitive (Bayus et al. 2003). This makes it likely that expert bloggers must decide which PC brand to write about at a particular point in time given resource constraints (e.g., to understand and/or evaluate new products and write reviews). Therefore, as expert blogs embody a higher level of expertise and have less biases for the competitive brands reviewed, they may not only enhance consumer perception about a focal brand, but also undermine that of competing brands in the same industry.

Against this background, we investigate how expert blogs may shape consumer perceptions and gain brand competitive advantages in the PC industry. Specially, we explore these research questions:

1. Can expert blog sentiments and volume on a focal brand increase consumer perception about the focal brand and, more importantly, decrease consumer perception about competing brands in the PC industry?

2. Would the focal brand’s blogs have a reinforcing relationship with its future blogs and a cannibalistic relationship with competitors’ future blogs dynamically?

3. Are such competitive and dynamic relationships stronger when the focal brand is a non-leading or leading player?

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2These blogging platforms scored high in Technorati’s authority score which considers how often content in a blog is referenced by other websites (http://en.wikipedia.org/wiki/Technorati).

3We acknowledge the senior editor and one anonymous reviewer for suggesting this terminology.

4For example, PC Magazine extensively cites TechCrunch in its report of a new seven-inch tablet from Amazon (http://www.pcmag.com/article2/0,2817,2392403,00.asp).


6We thank an anonymous reviewer for this insight.
Table 1. Conceptual Differences between Expert Blog and Other Media

<table>
<thead>
<tr>
<th></th>
<th>Expert Blog</th>
<th>General Social Media (Nonexpert Blog)</th>
<th>Conventional Media (e.g., Magazines)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contributors</td>
<td>Experts in the technology industry</td>
<td>Nonexperts in the technology industry</td>
<td>Experts in the technology industry</td>
</tr>
<tr>
<td>Contents</td>
<td>Professional product evaluations and industry insights</td>
<td>General product consumption experiences</td>
<td>Professional product evaluations and industry insights</td>
</tr>
<tr>
<td>Nature of organization</td>
<td>Organized around a reputed blogging platform</td>
<td>Little or no organization</td>
<td>Organized around a publisher brand name</td>
</tr>
<tr>
<td>Editorial management</td>
<td>Little (more candid) and decentralized</td>
<td>Generally none</td>
<td>Heavy and centralized</td>
</tr>
<tr>
<td>Extent of authority</td>
<td>High (referenced by many sites)</td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td>Source of trust</td>
<td>Expertise of technology industry, reputed blogging platform, and relative independence in writing</td>
<td>Unclear</td>
<td>Expertise of technology industry, reputed publisher company</td>
</tr>
<tr>
<td>Reputation costs</td>
<td>High</td>
<td>Low</td>
<td>High</td>
</tr>
</tbody>
</table>

To answer these questions, we compiled a novel, comprehensive dataset. This dataset combined online expert blogs on products offered by major brands competing in the PC industry and consumer perceptions of the brands collected from a representative sample of ordinary consumers at the daily level from a professional marketing research agency. The professional marketing research agency specializes in consumer panels and monitors global and local brands in the United States, United Kingdom, and Germany. Together, the data contains 7,871 brand-day observations matched with over 131,000 expert blogs on major brands in the PC industry, which allow us to use vector autoregressive models with exogenous covariates (VARX). These models are flexible time-series approaches that can estimate the long-term, accumulative effects and assess how such effects unfold non-monomonotonically over time (Adomavicious et al. 2012; Luo 2009).

The data analyses suggest that expert blog sentiments and volume about a brand indeed have a positive relationship with consumer perceptions about the brand. Moreover, they also suggest a negative relationship with consumer perceptions about competing brands. Also, a focal brand’s current expert blogs have a positive reinforcing relationship with its future expert blogs, and a cannibalistic relationship with the future blogs of competing brands dynamically. Third, compared with leading brands, non-leading brands may in general reap greater benefits from expert blogs in terms of enhanced consumer perceptions of product quality and, to some extent, from cannibalizing the subsequent blog sentiments of competitor brands leading in the market.

These findings contribute to the literature in terms of both theory and practice. Theoretically, to the best of our limited knowledge, this paper is among the first in the IS and marketing disciplines to conceptualize how expert blogs shape consumer brand perceptions in competitive and dynamic settings. In IS, despite the pertinence of expert blogs, prior research pays scant attention to them, let alone their relevance for brand competition dynamically (Aggarwal et al. 2012b; Tan and Kuo 2013). In marketing, although brands are heralded as the most valuable and sustainable assets of a firm (Keller 1993), existing studies on social media with product reviews reveal few insights into how the social media-based expert blogs are related to brand competition (Chevalier and Mayzlin 2006; see Appendix A). Contributing to both IS and marketing, we unravel the brand-relevant role of expert blogs and suggest that social media investments on expert blogs may garner long-term benefits to the firm, given the long-lasting value of brands (Keller 1993). We reveal that expert blogs engender dual benefits: a lift in consumer perceptions of the focal brand and a drop in those of rival brands. Thus, we proffer new insights regarding how social media-based expert blogs may act as a long-run effective business strategy.
Our work extends prior research by conceptualizing the competitive implications of expert blogs for rival brands in the social media age. This is nontrivial because competition is prevalent in theory (Bayus et al. 2003), yet there is a dearth of research on expert blogs’ inferences for competitive advantages over rival brands. Existing social media research either focuses on a single brand or treats multiple firms as isolated entities, but does not address both focal and competing brands simultaneously (Schweidel and Moe 2014). Related to this, we also conceptualize the heterogeneous implications across leading versus non-leading brands. We reveal that such asymmetry differs from traditional media such as TV where small brands are at a disadvantage in competitive markets (Diepen et al. 2009; Dubé and Manchanda 2005; Naik et al. 2005). In stark contrast, non-leading brands may reap greater benefits from online expert blogs in terms of (1) lifts in brand perceptions and (2) cannibalization of competing brands’ subsequent blog sentiments. These are interesting and new to the literature because they imply that smaller, weaker brands are no longer necessarily at a disadvantage in the digital social media age. Rather, non-leading brands can win marketplace rivalry and consumer mind by prudently leveraging social media-based expert blogs. Moreover, existing research assumes that consumer brand perceptions are a mechanism linking social media to brand sales and firm equity value (Luo et al. 2013; Rishika et al. 2013). We tackle this assumption empirically and corroborate the premised value of IT and social media with the relevance of expert blogs for a more immediate market outcome of consumer perceptions.

Practically, our findings are timely for an industry plagued with doubts and skepticism about social media. For instance, a report by IBM (2011, p. 3) states, “social media is no longer the adorable baby everyone wants to hold, but the angst-filled adolescent—still immature yet no longer cute—who inspires mixed feelings.” Echoing this, a McKinsey report (2012) suggests “many companies find that it’s difficult to justify devoting significant resources.” Indeed, some Fortune 500 firms are putting a brake on investing in social media.7 Of the marketing budget spent online, only 10% is allocated to social media,8 6% of which is spent on blogs (Schweidel and Moe 2014; Technorati 2013). We add to the confidence of investing in social media-based expert blogs to the extent that expert blogs may boost consumer-based sustainable value for the focal brand and win advantages over rival brands. Expert blogs might help companies increase the visibility of their brands without spending millions of advertising dollars. Thus, we broaden the importance of social media with a focus on expert blogs that have received low attention among managers but have high pertinence to consumer brand perceptions.

**Theory and Hypotheses**

In developing hypotheses relating expert blogs to general consumer brand perceptions, we build on the WOM theoretical framework and signaling theory with regard to WOM communication. Expert blogs can be seen as a form of WOM contributed by consumers who possess expertise. We apply the WOM theoretical framework (Lovett et al. 2013) to understand the extent to which expert bloggers are motivated to write for a brand over its competitors. Signaling theory (Aggarwal et al. 2012a; Spencer 1973) is then used to explain the efficacy of expert blogs in influencing general consumer brand perceptions. These two theoretical perspectives in combination provide a more holistic picture of the competitive and asymmetric relationships between expert blogs and brand perceptions by catering to both the producer (expert bloggers) and the receiver (consumers).

**WOM Theoretical Framework**

WOM is defined as “person-to-person communication between a receiver and a communicator whom the receiver perceives as non-commercial, regarding a brand, a product, a service or a provider” (Arndt 1967). 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. According to the framework, consumers produce WOM for brands as a result of three major drivers: social, functional, and emotional.

The social driver is related to the desire to send signals to others about one’s expertise, uniqueness, and social status (Lovett et al. 2013). Socialization with others constitutes a basic human desire, which may be fulfilled by spreading WOM. As consumers use WOM to enhance their perceived expertise, they are likely to engage in WOM communication for those brands that allow them to differentiate themselves from others and elevate their image and reputation among others (Berger and Heath 2007). A social driver is thus likely to be salient in explaining expert bloggers’ motivation to contribute WOM for a brand over others in an industry.
The *functional driver* is related to the need to obtain and provide information. Such a driver is fundamental as WOM serves to reduce information asymmetry (Ba and Pavlou 2002). By providing WOM, consumers share what they know and their experience, while at the same time they exchange information with others that adds to their own knowledge and expertise. Consumers may be particularly motivated to share WOM information for those brands where there is high information asymmetry between buyers and sellers in high-involvement product markets (Peres et al. 2010). As with a social driver, a functional driver is likely to be salient in explaining expert bloggers’ motivation to share WOM for a brand, given their expertise is sought after for addressing information asymmetry.

The *emotional driver* is related to emotion sharing, whereby a consumer desires to share feelings about brands to balance emotional arousal (Lovett et al. 2013). This driver concerns how WOM may act as a tension-releasing mechanism that drives consumers to share what they know or feel (Dichter 1966). Consumers are motivated to express their emotions on brands that they feel excited about (Roberts 2004). Indeed, consuming or thinking about a brand can evoke emotions that consumers want to share with others (Peters and Kahsima 2007). Whereas the emotional driver is the key motivator for offline WOM, it is less likely so in the online context (Ekdale et al. 2010). This is because the online context lacks the personal, intimate elements that are conducive for sharing emotions compared with the offline face-to-face setting.

Instead, social and functional drivers are the primary motivators for online WOM (Lovett et al. 2013). The online context is suited for social signaling given its broadcasting nature that allows WOM to reach a wider audience (Hennig-Thurau et al. 2004), in contrast to offline WOM that works within limited social contact boundaries (Lu et al. 2013). Additionally, compared with the transient nature of offline WOM that “disappears into thin air” (Bhatnagar and Ghose 2004), online WOM is digitally recorded, which allows for a longer influence span (Dellarocas et al. 2010). Together, these may persistently aid in status building and reducing information asymmetry, thereby better fulfilling the social and functional drivers of WOM communication. Given the high relevance of social and functional drivers in the online WOM context, we focus on these two drivers to explicate what motivates expert bloggers to produce favorable WOM on a brand in relation to others in a market. The above discussion highlights the drivers that may motivate expert bloggers, and below we leverage the signaling theory to analyze the influence of expert blogs on general consumer perceptions.

### Signaling Theory

The signaling theory posits that in situations of information asymmetry (where information is not evenly distributed among all parties), observable attributes can serve as a signal of quality. In his foundational work, Spence (1973) shows how job applicants use a higher education degree as a signal to distinguish themselves from competitors in the labor market and enhance their selection by prospective employers who lack information about job candidate quality. Signaling theory has been widely employed in marketing, as firms often use marketing media as signals to promote their brands and products. For instance, advertising may signal a firm’s commitment to its product quality (Nelson 1974), which consumers may use as cues in their purchase decision making (Kirmani 1990). Research has noted the effects of signaling on movie revenues (Basuroy et al. 2006), consumers’ product ratings (Caves and Greene 1996), and prepurchase attitudes (Dean 1999). Also, in IS, Aggarwal et al. (2012a) use signaling theory to show that WOM from bloggers may serve as quality signals that influence investors’ decisions to finance a new venture. In line with this literature, we employ signaling theory to understand how WOM produced by expert bloggers out of different motivations may influence general consumer brand perceptions.

Specifically, for a signal to be effective, it needs to possess two key features: a high cost associated with generating the signal and high observability (Connelly et al. 2011). *Signal costs* in the traditional media context involve the financial resource and effort that a firm invests in communicating the signal to the consumers. For instance, airing a TV advertisement repeatedly, during prime time slots or with celebrity spokespeople, indicates a high signal cost. Signals can be generated not only by firms but also by external sources (Aggarwal et al. 2012a; Fombrun and Shanley 1990). In the context of online social media such as expert blogs where consumer experts produce signals in the forms of WOM, salient signal costs may include (1) the effort costs bloggers spend on writing and communicating the WOM given their capacity constraints, and (2) their reputation costs when deciding to write for a brand (i.e., their reputation may hurt if they misinterpret or misreport certain information; Bourjade and Jullien 2010). Signals with high signaling costs enhance receivers’ perceptions of the signaler over alternatives (Spence 1973). To develop our hypotheses, we integrate the WOM theoretical framework with signaling theory.

### Hypotheses on the Competitive Nature of the Relationships between Expert Blogs and General Consumer Perceptions

We surmise expert blogs of a focal brand have a positive relationship with consumer perceptions, but a negative relation-
ship with consumer perceptions of its rival brands. Our logic is grounded in both the WOM framework (Lovett et al. 2013) and signaling theory applied to WOM communication (Aggarwal et al. 2012a; Spence 1973). Specifically, the WOM framework holds that expert bloggers involve in sharing their views on social media to enhance their self-image and help reduce information asymmetry (i.e., social and functional drivers, respectively). Expert blogger involvement in generating WOM about a focal brand implies the worth of their effort costs (Nardi et al. 2004). Also, expert bloggers bear reputation costs,9 given they are expected to identify “high-quality products better than novices” (Lovett et al. 2012, p. 429); inaccurate WOM may hurt their reputation. Thus, the WOM provided by expert bloggers on a focal brand satisfies the cost criterion for an efficacious signal, which likely shapes consumer perceptions of the focal brand. Furthermore, expert blogs may provide a persistent and impartial information source widely quoted among news media and virally disseminated to consumers, thus satisfying the observability criterion for an influential signal to mold consumer perceptions. In other words, consumers may both directly consult social-media expert blogs and indirectly rely on them via other websites and online WOM as a specialized and credible source of brand information (Ekdale et al. 2010; Technorati 2013). Given their unbiased and trustworthy nature, expert blogs of a focal brand are a leading quality signal, thus likely leading consumer perceptions and preference for the brand.

Also, expert blogs on a focal brand may undermine consumer perceptions about its competing brands. When bloggers choose to write favorably about a focal brand over other brands in an industry, the choice signals to readers the bloggers’ preference. This signal may induce a preference shift in consumers (Aggarwal et al. 2012a; Spence 1973). Prior literature has shown a high correlation between consumer brand preferences and their brand perceptions within a given consideration set, such that preferred brands are associated with favorable brand attitudes whereas non-preferred brands are associated with lower attitudes (Bass and Talarzyk 1972). Such competitive effects may be particularly salient in product markets in which the product consumption is infrequent and entails considerable search costs, such as our industry setting of PCs (Gu et al. 2012).

In sum, this discussion suggests that when expert bloggers write favorably about a focal brand in their specialized industry, their blogs, as an influential and trustworthy WOM signal, should win consumer favor over rival brands (i.e., enhance general consumer perceptions of the focal brand and undermine those of competing brands). That is,

H1. Ceteris paribus, expert blogs of a focal brand have (a) a positive relationship with consumer perceptions about the focal brand and (b) a negative relationship with consumer perceptions about its competing brands.

Hypotheses on the Dynamic Nature of the Relationship between Expert Blogs and Consumer Perceptions

We also expect expert blogs to demonstrate dynamic properties on future expert blogs. Specifically, expert blogs on a focal brand have a reinforcing relationship with its own subsequent blogs, but a cannibalistic relationship with its competitors’ subsequent expert blogs. This is because the persistent nature of WOM on social media including expert blogs could stimulate subsequent communication (Dellarocas et al. 2010). The availability of WOM information allows peer experts to observe, engage with, and respond to what other expert bloggers are saying about a focal brand. When expert bloggers observe favorable blogs on a brand that signal its quality (i.e., high quality brands receive more blog sentiments), expert bloggers may respond to positive postings on the focal brand by posting their own blogs to show that they possess equal or more precise expertise to identify quality attributes of the brand concerned. To signal their specialized knowledge and safeguard their reputation (Lovett et al. 2013), they may also more diligently engage in WOM to further reduce uncertainty or information asymmetry about the focal brand (social and functional drivers), thus likely inducing a reinforcing relationship with subsequent expert blogs for the focal brand. In addition, expert blogs on a focal brand may also cannibalize those of its rival brands in the subsequent period. This is because as blogger attention shifts to a focal brand due to positive signals from other bloggers (Aggarwal et al. 2012a; Spence 1973), it reduces their attention on competing brands given their attention capacity constraints, which likely leads to a negative feedback process undermining the extent of future expert blogs on competing brands (Ekdale et al. 2010; Wu and Huberman 2008). Due to this possible cannibalization, subsequent expert blogs garnered by competing brands are likely to suffer.

H2. Ceteris paribus, expert blogs on a focal brand have (a) a reinforcing relationship with subsequent expert blogs of the focal brand and (b) a cannibalistic relationship with subsequent expert blogs of competing brands.

9We thank the associate editor for this insight.
Hypotheses on Brand Asymmetries in the Competitive and Dynamic Relationships

The salience of these competitive and dynamic relationships may depend on the standing of the brand in the market. Specifically, signaling theory suggests that the strength of the signal varies with the costs of the signal (Spence 1973). In our context, expert bloggers more likely incur higher reputation costs in writing favorably about a focal non-leading brand. That is, there are greater reputation costs for expert bloggers to endorse a non-leading focal brand compared with a leading one, as they are more likely to be criticized and lose their followers if such endorsements are incorrect (Schmidt 2010). Also, expert bloggers are familiar with conditions of the market in which they specialize, so when they advocate a focal brand that is lagging in the market they may expend more effort to justify their choice. The higher signaling cost involved in expert blogs on a non-leading focal brand should make them be perceived, directly or indirectly, as more specialized, trustworthy, and influential WOM signals to consumers (Aggarwal et al. 2012a), thus likely winning consumer minds and hearts for a non-leading focal brand, more so than for a leading focal brand.

H3a. When the focal brand is a non-leading rather than leading brand, the positive relationship between expert blogs and consumer brand perception is stronger.

Also, expert bloggers seek opportunities to spread and share WOM information about brands with others to reduce information uncertainty (i.e., a functional driver) and to signal their expertise (i.e., a social driver). As noted by Dichter (1966), “people are proud to use what they consider an underdog product, because they feel gratified in defying the majority by publicly using an unpopular brand” (p. 150). This implies that expert bloggers are especially motivated to write about non-leading focal brands when opportunities arise (Karau and Williams 2010; Ling et al. 2005). That is, when peer expert bloggers write for these brands, they are likely to seize this opportunity to signify their more precise and better-deliberated expertise and thus subsequently further identify quality attributes of such underdog brands. This discussion suggests that expert blogs are especially apt to reinforce subsequent ones for a non-leading focal brand, more so than for a leading focal brand.

H3b. The reinforcing relationship (from current expert blogs to future ones) is stronger when the focal brand is a non-leading brand compared with a leading brand.

As noted previously, because endorsing a non-leading focal brand is likely to incur higher reputation costs to expert bloggers, the signal should be more efficacious in inducing the preference shift and thus penalizing the competing leading brands among general consumers (Aggarwal et al. 2012a; Bass and Talarzyk 1972). As a result, within a consideration set, consumer preference should shift more strongly from rivals to the non-leading focal brand, per the signaling theory (Spence 1973). In other words, expert blogs may be more likely to undermine consumer perception of rival brands when the focal brand is non-leading and rival brands are leading, compared with the reverse case.

H4a: The cannibalistic relationship between a focal brand’s expert blogs and competing brand perceptions is stronger when the focal brand is non-leading and competitor brands are leading, compared with the reverse case.

Similar logic may apply for a stronger cannibalization process that undermines the future blog of rival brands when the focal brand is a non-leading one. This is because the stronger positive signals sent from earlier expert bloggers on a non-leading focal brand should be particularly efficacious in attracting other expert bloggers’ attention to the underdog focal brand and hence away from rival brands. This may present an especially salient opportunity for expert bloggers to show their more precise expertise and shift more subsequent attention away from rival brands to the non-leading focal brand (Dichter 1966; Schmidt 2010). Consequently, expert blogs are more likely to undercut the subsequent expert blogs of competing brands when the focal brand is non-leading and rival brands are leading, compared with the opposite case.

H4b: The cannibalistic relationship between a focal brand’s current expert blogs and the subsequent expert blogs of the competing brands is stronger when the focal brand is non-leading and competitor brands are leading, compared with the reverse case.

Data

We assembled a novel, comprehensive dataset that captures both expert blogs and general consumer brand perceptions. We selected the PC industry as our research context because of the value of brand equity in this intensely competitive industry. Our dataset is at the daily level, including the top nine brands: Acer, Apple Mac, Compaq, Dell, Gateway, HP, Lenovo, Sony Vaio, and Toshiba with 7,871 brand-day observations.
Measures for General Consumer Brand Perceptions

We capture individual consumer perceptions of the brands on a daily basis. The data were obtained from a professional marketing research agency, which specializes in consumer panels and monitors global and local brands in the United States, United Kingdom, and Germany. For the U.S. market, the professional marketing research agency 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 perceptions collected represent 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 reflect the changes in consumer perceptions of the brands in a timely manner, and allow us to observe and identify dynamic relationships.

The professional marketing research agency 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.

This study focuses on the indicator of brand affect, or the consumers’ responses to the question “For which brands do you have a generally positive or generally negative feeling?” because it is the most direct measure of a brand’s perception. We calculated the brand rating 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 ((positive votes-negative votes)/(positive + negative + neutral votes)). Thus the brand perception value represents the net percentage of positive ratings (Luo et al. 2013).

The professional marketing research agency provided us 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 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 the 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, latopmag.com, and a 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 the blog search engine Technorati. For this study, we collected blog posts about the targeted brands from the top four tech blogs ranked by Technorati: Engadget, Techcrunch, Mashable, and Artstechica. In total, we obtained 131,759 blog posts that include 27,307 from Mashable, 35,867 from Techcrunch, 24,998 from Artstechica, 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. Several steps are involved.

(1) Developing the training set: A group of three graduate student evaluators were hired to read and judge the sentiment of a randomly selected sample of 1,176 blogs from the downloaded ones under the majority rule. The evaluators were asked to identify the sentiment of each post. Of the blog posts, 314 were identified as negative, 420 were identified as positive, and 420 were identified as neutral. The inter-rater reliability between each pair of evaluators shows a consistent rating (Cohen’s Kappa) of over 0.95, which is well above the recommended level of 0.75 (Neuendorf 2002). The training expert 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 Support Vec-
Table 2. Descriptive Statistics of Variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>General Consumer Brand Perception</th>
<th>Expert Blog Sentiment</th>
<th>Expert Blog Volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACER</td>
<td>0.02 (0.08)</td>
<td>0.68 (0.13)</td>
<td>2.19 (15.25)</td>
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<td>Apple MAC</td>
<td>0.24 (0.10)</td>
<td>0.59 (0.53)</td>
<td>145.56 (204.14)</td>
</tr>
<tr>
<td>COMPAQ</td>
<td>0.09 (0.09)</td>
<td>0.48 (0.07)</td>
<td>0.13 (2.14)</td>
</tr>
<tr>
<td>DELL</td>
<td>0.38 (0.10)</td>
<td>0.65 (0.33)</td>
<td>10.39 (30.51)</td>
</tr>
<tr>
<td>GATEWAY</td>
<td>0.07 (0.09)</td>
<td>0.65 (0.22)</td>
<td>3.84 (16.87)</td>
</tr>
<tr>
<td>HP</td>
<td>0.48 (0.09)</td>
<td>0.57 (0.37)</td>
<td>6.88 (18.36)</td>
</tr>
<tr>
<td>LENOVO</td>
<td>0.01 (0.04)</td>
<td>0.69 (0.25)</td>
<td>5.34 (21.87)</td>
</tr>
<tr>
<td>SONY VAIO</td>
<td>0.21 (0.06)</td>
<td>0.66 (0.24)</td>
<td>3.47 (13.04)</td>
</tr>
<tr>
<td>TOSHIBA</td>
<td>0.28 (0.08)</td>
<td>0.66 (0.23)</td>
<td>7.12 (25.72)</td>
</tr>
</tbody>
</table>

Note: The standard deviations are in the parentheses.

The dot kernel is defined by $k(x, y) = x^T y$ (i.e., it is inner product of $x$ and $y$). The kernel cache was set at 200 and convergence epsilon was set at 0.001 with 100,000 maximum iterations.

We also assess the robustness of the cross-validation method with 5 and 10 equal-sized folds. The results are consistent.

It is worth noting that the cross-validation method is an efficient way of evaluating the accuracy of the classifier as it uses all of the training records for both training and validation without increasing the chance of over-fitting.
(3) Brand classification: We employed the term frequency-inverse document frequency (TF-IDF) method to classify blog posts in our brand list. TF-IDF provides a statistical measure that can be used to evaluate the importance of a word in a document in a collection of documents or corpus. The importance increases proportionally to the number of times a word appears in the document but is offset by the frequency of the word in the corpus. To mitigate the aggregation bias and control the impact of product lines in each brand, we first needed to determine if the blog post is about the following three product categories: desktop, laptop, and server. For each product category, we prepared a keyword list. Then we employed TF-IDF to determine to which product category a blog post belongs. Then, we created a list of the following brands: Acer, Apple (iMac, Mac, MacBook, Time Capsule, AirPort), Compaq, Dell, Gateway, HP, Lenovo, Sony (Sony Vaio), and Toshiba. We included 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). Then we again used the TF-IDF algorithm to determine the relevance of each expert blog to each brand. In both product category and brand classifications, we used the term frequency algorithm in Rapidminer Version 5 to perform this task, with this formula: 

\[
wv[i] = \frac{\text{frequencies}[i]}{\text{totalTermNumber}}\]

where \(wv[i]\) is the \(i^{th}\) brand name in the vector, \(\text{frequencies}[i]\) is the number of occurrences of the \(i^{th}\) brand name in the review, and total term number is the total number of words in the expert blog. After that, the software normalizes the calculated frequencies by the square root of the sum of all frequencies in this document. Based on this algorithm, the software creates probabilities of an expert blog being relevant to a brand name. It is worth noting that if the probability of an expert blog for a brand was higher than 50%, we classified that expert blog as being relevant to that brand. In cases where the blog post is determined to be relevant to more than one brand, we looked at the title and the tags of the blog post to determine the dominant brand in the blog post. For instance, if a blog post is found to be relevant to both Acer and Toshiba, we looked at the title and the tags of the blog post to see which one is mentioned there. The logic is that the author of the post may mention the dominant brand in the title or the tags. With this approach, we determined the dominant brand for all of the blog posts with more than one brand with the exception of 34 blog posts. In these 34 blog posts, more than one brand was mentioned in the title of the blog post. Therefore, we removed these blog posts from the data set and continued with the rest.15

(4) We then calculated the sentiment score of all expert blogs for each product category of the targeted brands on a daily basis to derive the measure of daily expert blogs on a brand under a product category. Finally, to generate the daily aggregate expert blog measures for a brand, we weigh the expert blog sentiments of each product line of a given brand by the relative popularity of the product line. The motivation was that most expert blogs are about specific products or product lines. The impact of these blogs on consumers’ overall perception of a brand is correlated with the popularity of the product or product line mentioned. For example, the reputation of a brand that is known for its servers is likely to be less influenced by an expert blog on the quality of its laptops than an expert blog on the quality of its servers. To account for this popularity effect, we obtained data from Google Trend using phrases that combine each brand name with each of its product lines. The relative popularity of each product line of a brand is then used as the weight in aggregating the expert blog sentiment on product lines to an overall expert blog sentiment for the brand.

We plot the expert blog data and general consumer perception for each brand in Appendix B (Figure B1). To aid visual inspection of the correlation between expert blogs and brand perception, we use the brand HP as an example and show a magnified view of its brand perception and expert blog sentiments in a shorter period of two months (Figure B2). Those graphs show correlation between the time series of expert blog sentiments and brand perceptions. This correlation relationship between expert blogs and brand perceptions is more evident in the sliding-window time average graphs.

**Measures for Control Variables**

Following the widely used firm valuation models in the IS and accounting literatures (Brynjolfsson et al. 2002; Ferreira and Laux 2007; Luo et al. 2013; Trueman et al. 2000), we

15To determine the accuracy of product category and brand classifications, we hired two graduate students who manually determined the product category and the dominant brand(s) for 94 blog posts by reading the title, the body, and the tags of each blog post. The raters had 100% agreement on both product category and the dominant brand. Then we applied our algorithm to these 94 blog posts. The algorithm had 100% accuracy in determining the product category and correctly determined the dominant brand for 96.81% of the blog posts.
controls for a comprehensive set of exogenous covariates, including revenue (sales), firm size, financial leverage, liquidity, return on assets (ROA), industry competitive intensity, industry M&A (merger and acquisition), R&D expenditures, new product announcements, and advertising spending.

We control firm financial conditions with revenue (sales), firm size, financial leverage, liquidity, and return on assets (ROA). Revenue is the REVTQ variable in the COMPSTAT database. Firm size is measured by total assets of the firm (the ATQ variable). 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 from the Lexis/Nexis news search engine.

We also control for firm innovation and advertising efforts with R&D expenditures, new product announcements, and advertising spending. R&D expenditures are measured as research and development expenses (XRDQ) scaled by total assets. To match those quarterly financial variables with our firm’s operating income (OIBDPQ) to its book value of total assets from the Lexis/Nexis news search engine needed. New product announcements are collected from the Lexis/Nexis news search engine needed.

In addition, we control for firm innovation 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 \( \sum s_i^2 \), 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 the Lexis/Nexis news search engine.

We also control for firm innovation and advertising efforts with R&D expenditures, new product announcements, and advertising spending. R&D expenditures are measured as research and development expenses (XRDQ) scaled by total assets from COMPSTAT. New product announcements are collected from the Lexis/Nexis news search engine needed (Sood and Tellis 2009). The advertising data are collected from AdSpender by Kantar Media, which provides top-level firm advertising expenditures in twelve major media, including radio, TV, newspapers, magazines, and Internet. Table B1 in Appendix B reports a summary of the advertising expenditures.

### Model Specifications

We develop a VARX model in which endogenous variables are the brand perceptions and expert blogs. Our model controls for a set of exogenous variables to capture the size, investment, and industry effects. A 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 blogs and consumer brand perceptions but also their dynamic and competitive nature. In addition, it provides a better control for biases due to endogeneity, auto correlations, and reversed causality. VARX models also capture complex feedback loops that include the reverse impact of brand perception on future expert blog metrics (feedback effects). Thus, VARX can model complex changes in each of the computer hardware and software industries (Hou and Robinson 2006). We collected M&A announcements from the Lexis/Nexis news search engine.

Model Specifications

To test hypotheses on the relationships between expert blogs and consumer brand perceptions of the focal brand, we built the following VARX model:

\[
Y_i = \alpha + \sum_{p=1}^{n} \phi_{p} Y_{t-p} + \Gamma X_i + \varepsilon_i, \quad \text{or}
\]

\[
\begin{bmatrix}
\text{Brand Perception}_i \\
\text{Blog Sentiment}_{it} \\
\text{Blog Volume}_{it}
\end{bmatrix} = 
\begin{bmatrix}
\alpha_1 + \delta_{1t} \\
\alpha_2 + \delta_{2t} \\
\alpha_3 + \delta_{3t}
\end{bmatrix}
+ 
\begin{bmatrix}
\phi_{11} & \phi_{12} & \phi_{13} \\
\phi_{21} & \phi_{22} & \phi_{23} \\
\phi_{31} & \phi_{32} & \phi_{33}
\end{bmatrix}
\begin{bmatrix}
Y_{t-1} \\
Y_{t-2} \\
Y_{t-3}
\end{bmatrix}
+ 
\begin{bmatrix}
\Gamma_{it} \\
\epsilon_{it} \\
\epsilon_{it}
\end{bmatrix}
\]

where \( i = 1, 2, \ldots, 9 \) represents the focal brand, \( t \) represents time, \( p \) is lag length, and \( P \) is maximum lags. \( \alpha_k (k = 1, 2, 3) \) denotes the constant. \( \delta_{it}, \phi_{ij}, \tau_{ij} (k, l = 1, 2, 3, s = 1, 2, \ldots 10) \) are coefficients: \( \delta_{it} \) reflects the seasonality effect, \( \phi_{ij} \) is the

\[16\] However, the relationships modeled here are still correlation-based Granger causality. The brand and blog causality can only be tested by experiments as in Aral and Walker (2011) and Burtch et al. (2015).
coefficient of the expert blog sentiment of brand $i$ $p$-day ago on the current brand perception, $\phi_{i,t,p}^p$ is the coefficient of the expert blog volume of brand $i$ $p$-day ago on the current brand perception, $\phi_{i,t,1}^p$ and $\phi_{i,t,1}^p$ reflect the feedback effect, and $\phi_{i,t,3}^p$ and $\phi_{i,t,3}^p$ denote the reinforcing effect of the past blog sentiment on the current one. $\epsilon_i$ ($k = 1, 2, 3$) represents the white-noise residual. $x_{i,t}$ ($s = 1, 2, \ldots, 10$) represents the exogenous variables: revenue (sales), firm size, financial leverage, liquidity, return on assets (ROA), industry competitive intensity, R&D expenditures, new product announcements, M&A acquisitions, and advertising expenditures.

To test hypotheses on the competitive nature of relationships, 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 brands (Steenkamp et al. 2005), which is specified as

$$
\begin{bmatrix}
\text{Brand Perception,} \\
\text{Blog Sentiment,} \\
\text{Blog Volume,} \\
\text{Blog Sentiment,} \\
\text{Blog Volume,}
\end{bmatrix}
= \begin{bmatrix}
\alpha_{i,t} + \delta_f & \phi_{i,t,1}^p & \phi_{i,t,2}^p & \phi_{i,t,3}^p & \phi_{i,t,4}^p \\
\alpha_{j,t} + \delta_f & \phi_{j,t,1}^p & \phi_{j,t,2}^p & \phi_{j,t,3}^p & \phi_{j,t,4}^p \\
\alpha_{i,t} + \delta_f & \phi_{i,t,1}^p & \phi_{i,t,2}^p & \phi_{i,t,3}^p & \phi_{i,t,4}^p \\
\alpha_{j,t} + \delta_f & \phi_{j,t,1}^p & \phi_{j,t,2}^p & \phi_{j,t,3}^p & \phi_{j,t,4}^p \\
\alpha_{i,t} + \delta_f & \phi_{i,t,1}^p & \phi_{i,t,2}^p & \phi_{i,t,3}^p & \phi_{i,t,4}^p
\end{bmatrix}
\begin{bmatrix}
x_{i,t} \\
x_{j,t} \\
x_{i,t-1} \\
x_{j,t-1} \\
x_{i,t-2} \\
x_{j,t-2} \\
x_{i,t-3} \\
x_{j,t-3} \\
x_{i,t-4} \\
x_{j,t-4}
\end{bmatrix} + \begin{bmatrix}
\epsilon_{i,t} \\
\epsilon_{j,t} \\
\epsilon_{i,t-1} \\
\epsilon_{j,t-1} \\
\epsilon_{i,t-2} \\
\epsilon_{j,t-2} \\
\epsilon_{i,t-3} \\
\epsilon_{j,t-3} \\
\epsilon_{i,t-4} \\
\epsilon_{j,t-4}
\end{bmatrix}
$$

(2)

**Response Elasticities of the Expert Blogs**

We used the estimated parameter matrices of the full VARX model $\Phi^p (p = 1, 2, \ldots, P)$ to generate the generalized impulse response functions (GIRFs) with $\Psi_i (t)$ capturing the net effects of the unanticipated shock in expert blogs at time $t$ on future brand perception responses (Dekimpe and Hanssens 1999; Luo et al. 2013).

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 for 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 (Tables 4–6) and plotted the time-varying elasticities (Figures 1 and 2) (Pauwels 2004; Srinivasan et al. 2010). Following Dekimpe and Hanssens (1999), Tirunillai and Tellis (2012), and Luo et al. (2013), we use 70% of the sample to fit the VARX models (in-sample) and the remaining 30% of the sample for analyses of the predictions and hypotheses testing (out-of-sample).

Following prior VARX modeling literature (Adomavicius et al. 2012; Luo et al. 2013), Schwartz’s Bayesian Information Criterion (BIC) and final prediction error (FPE) are used to determine the lag order. We also checked various assumptions of VARX residuals including White heteroskedasticity tests, omission-of-variables bias, multivariate normality, and Portmanteau autocorrelation, and the results did not suggest violations of these assumptions at the 95% confidence level.

**Findings**

**VARX Stationarity and Granger Causality Results**

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). As reported in Table 3, the ADF tests for the data series range from -32.67 to -4.60, 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).

Following Tirunillai and Tellis (2012) and Luo et al. (2013), we conduct Granger Causality tests (Granger 1969). Granger causality test model is specified below:

$$Y_t = \sum_{j=1}^{n} \alpha_j Y_{t-j} + \sum_{j=1}^{m} \beta_j X_{t-j} + \gamma_t,$$

$$X_{t-1} = \sum_{j=1}^{m} \phi_j Y_{t-j} + \sum_{i=1}^{n} \omega_j X_{t-i-1} + \tau_i,$$

where $Y$ can be brand ratings. $X$ is expert blogs. In the above equations, if all the coefficients are significant, then $Y$ and $X$ mutually lead to (Granger cause) each other. If only the coefficients of $\beta_j$ are significant, then $X$ grangerly causes
Table 3. Augmented Dickey-Fuller Unit Root Tests

<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>-30.29</td>
<td>-12.72</td>
<td>-7.02</td>
</tr>
<tr>
<td>Apple MAC</td>
<td>-29.45</td>
<td>-12.76</td>
<td>-20.78</td>
</tr>
<tr>
<td>COMPAQ</td>
<td>-30.15</td>
<td>-30.23</td>
<td>-30.82</td>
</tr>
<tr>
<td>DELL</td>
<td>-31.88</td>
<td>-18.30</td>
<td>-18.94</td>
</tr>
<tr>
<td>GATEWAY</td>
<td>-31.55</td>
<td>-32.67</td>
<td>-20.08</td>
</tr>
<tr>
<td>HP</td>
<td>-27.68</td>
<td>-28.48</td>
<td>-30.17</td>
</tr>
<tr>
<td>LENOVO</td>
<td>-30.05</td>
<td>-27.40</td>
<td>-4.60</td>
</tr>
<tr>
<td>SONY VAIO</td>
<td>-32.66</td>
<td>-26.61</td>
<td>-4.89</td>
</tr>
<tr>
<td>TOSHIBA</td>
<td>-23.12</td>
<td>-18.33</td>
<td>-29.96</td>
</tr>
</tbody>
</table>

Y. And if only the coefficients of $\phi_j$ are significant, then $Y$ grangerly causes $X$. Wald $F$ test determines the significance of the equations. This test statistics is specified as below:

$$F = \frac{(SSR1 - SSR2) / q}{SSR2 / (n - s)}$$

where SSR1 is defined as the sum of squared residuals in the restricted equation (in which $\beta_j$ and $\phi_j$ are restricted to be zero) and SSR2 is the sum of squared residuals in the unrestricted equation. In addition, $q =$ the number of restrictions, $n =$ the number of observations, $s =$ the number of independent variables in the unrestricted equation. In Table 4, we report the $p$-value directly associated with the $F$ statistics, following the prior VAR literature in marketing (Dekimpe and Hanssens 1999) and IS (Adomavicius et al. 2012; Luo et al. 2013) which also report the $p$-value only in Granger causality tests. The results in Table 4 show that expert blog sentiment and volume metrics have significant ($p$ from 0.003 to 0.044) temporal-based relationships with the consumer perception of the focal brand across almost all brands. For example, for Acer, expert blog Granger causes its own brand quality perception of consumers ($p = .044$ with sentiment and .032 with volume). Also, Acer’s expert blog Granger causes its rival brand Dell’s quality perception ($p = .017$ with sentiment and .03 with volume). Some few exceptions are Compaq ($p = 0.069$) and Apple Mac ($p = 0.068$) that have weakly significant Granger Causal relationships. With regard to competitive relationships, expert blogs on a focal brand “Granger cause” consumer perceptions of rival brands for most of the competition pairs as well ($p < 0.05$). These results provide some initial evidence for the temporal relationship between expert blogs and consumer perceptions.

Results on the Competitive Nature of the Relationships between Expert Blogs and Consumer Perceptions

Table 5 reports the cumulative impulsive response elasticities. The magnitude of elasticity results reflects the change in consumer brand perceptions in response to one unit of unexpected change in expert blog sentiments and volume. The diagonal in Table 5 shows the own-brand effects of expert blog sentiments on consumer perceptions, and the off-diagonal estimates are rival-brand effects. Results in brackets are for expert blog volume. These results are used to test H1 and H3.

Table 5 suggests that expert blog sentiments have a significantly positive relationship with own-brand perceptions (0.009 to 0.031) and negative relationships with rival-brand perceptions (-0.007 to -0.033). For example, Acer’s expert blog sentiments are positively related to own-brand perceptions with cumulative impulsive response elasticities of .015, but negative related to rival brand perceptions with cumulative impulsive response elasticities of -.010 for Dell, -.014 for HP, -.011 for Lenovo, -.013 for Compaq, -.009 for Gateway, -.015 for Sony Vaio, -.007 for Toshiba, and -.021 for Apple Mac. The same pattern follows for the other brands, regarding the positive cumulative impulsive response elasticities of own-brand perceptions but negative cumulative impulsive response elasticities of rival-brand perceptions, with only several insignificant cases (Compaq’s expert blog sentiment is insignificantly related to Sony Vaio’s, and Gateway’s expert blog sentiment is insignificantly related to Lenovo’s).

Beside statistical significance, the economic magnitude is also substantial. Given the cumulative impulsive response elasti-
Table 4. Summary of the Results of Granger Causality Tests

<table>
<thead>
<tr>
<th>Expert Blog Sentiment (Volume)</th>
<th>ACER</th>
<th>COMPAQ</th>
<th>DELL</th>
<th>GATEWAY</th>
<th>HP</th>
<th>SONY VAIO</th>
<th>TOSHIBA</th>
<th>LENOVO</th>
<th>Apple MAC</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACER</td>
<td>0.044**</td>
<td>(0.032**)</td>
<td>0.076*</td>
<td>0.017**</td>
<td>0.097*</td>
<td>0.097*</td>
<td>0.019**</td>
<td>0.002**</td>
<td>0.052*</td>
</tr>
<tr>
<td>COMPAQ</td>
<td>0.077*</td>
<td>(0.070*)</td>
<td>0.014**</td>
<td>0.023**</td>
<td>0.037**</td>
<td>0.035**</td>
<td>0.099*</td>
<td>0.039**</td>
<td>0.048**</td>
</tr>
<tr>
<td>DELL</td>
<td>0.080*</td>
<td>(0.004***)</td>
<td>0.031**</td>
<td>0.033**</td>
<td>0.042**</td>
<td>0.037**</td>
<td>0.013**</td>
<td>0.047**</td>
<td>0.040**</td>
</tr>
<tr>
<td>GATEWAY</td>
<td>0.028**</td>
<td>(0.036**)</td>
<td>0.011**</td>
<td>0.049**</td>
<td>0.010**</td>
<td>0.035**</td>
<td>0.041**</td>
<td>0.048**</td>
<td>0.062*</td>
</tr>
<tr>
<td>HP</td>
<td>0.070*</td>
<td>(0.090*)</td>
<td>0.097*</td>
<td>0.059*</td>
<td>0.043**</td>
<td>0.019**</td>
<td>0.007***</td>
<td>0.024**</td>
<td>0.079*</td>
</tr>
<tr>
<td>SONY VAIO</td>
<td>0.017**</td>
<td>(0.006***)</td>
<td>0.040**</td>
<td>0.037**</td>
<td>0.012**</td>
<td>0.040**</td>
<td>0.003**</td>
<td>0.036**</td>
<td>0.077*</td>
</tr>
<tr>
<td>TOSHIBA</td>
<td>0.022**</td>
<td>(0.038**)</td>
<td>0.025**</td>
<td>0.040**</td>
<td>0.037**</td>
<td>0.035**</td>
<td>0.010</td>
<td>0.044**</td>
<td>0.043**</td>
</tr>
<tr>
<td>LENOVO</td>
<td>0.077*</td>
<td>(0.080*)</td>
<td>0.096*</td>
<td>0.029*</td>
<td>0.098*</td>
<td>0.047**</td>
<td>0.024**</td>
<td>0.015**</td>
<td>0.037**</td>
</tr>
<tr>
<td>Apple MAC</td>
<td>0.004***</td>
<td>(0.073*)</td>
<td>0.048**</td>
<td>0.090*</td>
<td>0.026**</td>
<td>0.076*</td>
<td>0.005**</td>
<td>0.042**</td>
<td>0.034**</td>
</tr>
</tbody>
</table>

Note: The estimates in a cell are the p-values of the joint Wald statistics of expert blog sentiment (expert blog volume) of the row brand Granger causing the brand perception of the column brand. For example, for Acer, expert blog Granger causes its own brand quality perception of consumers (p = .044 with sentiment and .032 with volume). Also, Acer’s expert blog Granger causes its rival brand Dell’s quality perception (p = .017 with sentiment and .03 with volume).

*p < .10, **p < .05, ***p < .01.

Table 5. Responses of General Consumer Brand Perception to Expert Blog Sentiments: Focal and Competing Brands (Responses of General Consumer Brand Perception to Expert Blog Volume in the parentheses.)

<table>
<thead>
<tr>
<th>Unanticipated shock in Expert Blog Sentiment (Volume)</th>
<th>Response of general consumer brand perception</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACER</td>
<td>0.015** (0.010*)</td>
</tr>
<tr>
<td>DELL</td>
<td>-0.010** (-0.013*)</td>
</tr>
<tr>
<td>HP</td>
<td>-0.011* (-0.012*)</td>
</tr>
<tr>
<td>LENOVO</td>
<td>-0.014* (-0.012*)</td>
</tr>
<tr>
<td>COMPAQ</td>
<td>-0.010* (-0.010*)</td>
</tr>
<tr>
<td>GATEWAY</td>
<td>-0.014* (-0.027*)</td>
</tr>
<tr>
<td>SONY VAIO</td>
<td>-0.021** (-0.011*)</td>
</tr>
<tr>
<td>TOSHIBA</td>
<td>-0.012** (-0.011*)</td>
</tr>
<tr>
<td>Apple MAC</td>
<td>-0.018** (-0.015*)</td>
</tr>
</tbody>
</table>

Note: The diagonal estimates are impulse responses of brand perception to blog sentiments (volume) of own brand, and the off-diagonal estimates are impulse responses of brand perception to the blog sentiments (volume) of rival brands. For example, Acer expert blog sentiments are positively related to own-brand perceptions with cumulative impulsive response elasticities of .015, but negative related to rival brand perceptions with cumulative impulsive response elasticities of -.010 for Dell, -.014 for HP, -.011 for Lenovo, -.013 for Compaq, -.009 for Gateway, -.015 for Sony Vaio, -.007 for Toshiba, and -.021 for Apple Mac.

*p < .10, **p < .05, ***p < .01.
cities of .015, it means that a 1% unexpected increase in Acer’s expert blog sentiment would be associated with a 1.5% lift in its own brand quality as perceived by consumers, thus winning more consumer hearts and minds. In addition, a 1% unexpected increase in Acer’s expert blog sentiment would be associated with a .7% (Toshiba) to 1.5% (Sony Vaio) drop in its rival brand quality, thus undermining consumer hearts and minds of competing brands in the same industry.

In addition, Table 5 results in brackets show that expert blog volume metrics also have a significant positive relationship with own-brand perceptions (0.007 to 0.033), and negative relationships with rival-brand perceptions (-0.004 to -0.032). These results hold across almost all brands and brand pairs. The results with expert blog volume are consistent with sentiments and robustly confirm the positive cumulative impulsive response elasticities of own-brand perceptions but negative cumulative impulsive response of elasticities rival-brand perceptions.

Figure 1 presents results of the VARX models, impulse-response functions that trace the over-time incremental effect of an unexpected change in expert blog sentiments. As shown in Figure 1, with one standard deviation-based confidence interval (Luo et al. 2013; Tirunillai and Tellis 2012), the focal brand’s expert blog sentiments and volume have a positive relationship with its own-brand perceptions (the two charts on the left). In stark contrast, the focal brand’s expert blog sentiments and volume have a negative relationship with the rival-brand perception (the two charts on the right). Specifically, the top chart on the left pictorially shows that one unexpected shock in Apple’s expert blog sentiments can lead to increases in own-brand perceptions over the course of the following two weeks, in a nonlinear pattern. Such positive responses are steadily increasing during the first four days, then settling with some ups and downs before stabilizing at the equilibrium level. Similarly, the bottom chart on the left pictorially shows that one unexpected shock in Apple’s expert blog volume can also lead to perception drops in rival-brand Lenovo over the course of the following two weeks, in a nonlinear pattern. Most of such drops happen after the first week and peak on day 13. Thus, these results suggest that expert blog sentiment also has a quicker rival-brand relationship than expert blog volume.

Overall, the above results support H1a and H1b for a vast majority of brand pairs. Thus, these results corroborate that when expert bloggers write favorably about a focal brand in their specialized industry, their blogs, as an influential and trustworthy WOM signal, should win consumer favor over rival brands (i.e., enhance general consumer perceptions of the focal brand and undermine those of competing brands). That is, expert blogs of a focal brand indeed may act as a leading indicator and have a positive (negative) relationship with consumer perceptions of the focal brand (competing brands).

Results on the Dynamic Nature of the Relationships between Expert Blogs and Consumer Perceptions

Table 6 and Figure 2 show the results of the dynamic responses of expert blog sentiments in the future period to the expert blog sentiments in the current period. The diagonal in Table 6 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. These results are used to test H2 and H4. As Table 6 shows, Dell’s expert blog sentiments are positively related to own-brand future expert blog sentiment with cumulative impulsive response elasticities of .128, and negatively related to rival-brand expert blog sentiment with cumulative impulsive response elasticities of -.019 for Acer, -.013 for HP, -.015 for Lenovo, -.015 for Compaq, -.014 for Gateway, -.012 for Sony Vaio, -.011 for Toshiba, and -.051 for Apple Mac, as expected. The same pattern follows for the other brands, regarding the positive cumulative impulsive response elasticities of own-brand carryover but negative cumulative impulsive response elasticities of rival-brand cannibalistic cross-over effect. The economic magnitude is also meaningful. A 1% unexpected increase in Dell’s expert blog sentiment would be associated with a 12.8% lift in its own brand’s future blog sentiment (own brand positive carryover), as well as a 1.1% drop for Toshiba and a 5.1% drop for Apple Mac in terms of its rival brands’ future blog sentiment.

Similarly, for the other brands, the results of expert blog sentiments are consistent, suggesting there is a significant carry-over effect in the focal brand’s own expert blog sentiment (p < 0.001) across all brands. This result strongly
Note: The top left chart pictorially shows that one unexpected shock in Apple’s expert blog sentiments can lead to increases in own-brand perceptions over the course of the following two weeks, in a nonlinear pattern. Such positive responses are steadily increasing during the first four days, then settling with some ups and downs before stabilizing in the equilibrium level. Similarly, the bottom left chart pictorially shows that one unexpected shock in Apple’s expert blog volume can also lead to increases in own-brand perceptions over the course of the following two weeks, in a nonlinear pattern. However, such positive responses are not salient in the first five days, but then quickly build up and stabilize in the next week. Thus, these results suggest that expert blog sentiment has a faster own-brand responses than expert blog volume. Moreover, the top right chart shows that that one unexpected shock in Apple’s expert blog sentiments can lead to decreases in rival-brand Lenovo’s perceptions over the course of the following two weeks. Such negative responses take about two days to become salient and peak around day six and then settle until the equilibrium level. Similarly, the bottom left chart pictorially shows that one unexpected shock in Apple’s expert blog volume can also lead to drops in rival-brand Lenovo perceptions over the course of the following two weeks, in a nonlinear pattern. Most of such drops happen after the first week and peak on day 13. Thus, these results suggest that expert blog sentiment also has a quicker rival-brand relationship than expert blog volume.
Table 6. Feedback Response for Expert Blog Sentiments: Focal and Competing Brands (Expert Blog Volume in the parentheses.)

<table>
<thead>
<tr>
<th>Unanticipated shock in Expert Blog Sentiment (Volume)</th>
<th>Response of expert blogs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ACER</td>
</tr>
<tr>
<td>ACER</td>
<td>0.098*** (1.281***</td>
</tr>
<tr>
<td>DELL</td>
<td>-0.019*** (-0.362***</td>
</tr>
<tr>
<td>HP</td>
<td>-0.012*** (-0.135*)</td>
</tr>
<tr>
<td>LENOVO</td>
<td>-0.006* (-0.380***</td>
</tr>
<tr>
<td>COMPAQ</td>
<td>-0.013* (-0.206**)</td>
</tr>
<tr>
<td>GATEWAY</td>
<td>-0.019*** (-0.147**)</td>
</tr>
<tr>
<td>SONY VAIO</td>
<td>-0.013* (-0.386**)</td>
</tr>
<tr>
<td>TOSHIBA</td>
<td>-0.019* (-0.403***</td>
</tr>
<tr>
<td>Apple MAC</td>
<td>-0.022* (-0.960**)</td>
</tr>
</tbody>
</table>

Note: The diagonal shows the carry-over effects of blog sentiments (volume) of own brand, and the off-diagonal estimates are impulse responses to the past blog sentiments (volume) of rival brands. For example, Dell’ expert blog sentiments are positively related to own-brand future expert blog sentiment with cumulative impulsive response elasticities of .128, but negative related to rival brand expert blog sentiment with cumulative impulsive response elasticities of -.019 for Acer, -.013 for HP, -.015 for Lenovo, -.015 for Compaq, -.014 for Gateway, -.012 for Sony Vaio, -.011 for Toshiba, and -.051 for Apple Mac.

*p<.10, ** p<.05, *** p<.01.
Figure 2. Accumulated Feedback Response of Expert Blog Sentiments/Volume to the Unanticipated Shock in Past Sentiments/Volume (The dotted lined are the confidence bound of ± $\sigma$.)

Note: Figures here suggest that the focal brand HP’s expert blog sentiments and volume have a positive carry-over effects on its own brand (the left two charts), but negative cannibalistic effects on the rival brand of Sony (the right two charts) over the next two weeks. However, the nonlinear pattern is interesting, as the own brand carry-over is much less volatile and more stabilized over the course of subsequent two weeks. In contrast, the cannibalistic cross-over effects on rival brand are much more volatile with substantial drops in the first two days then another deep drop in day 10 for the expert blog volume. As such, these results seem to indicate that own-brand reinforcing carry-over effects are more stable but rival-brand cannibalistic effects are relatively more volatile and capricious in the industry.

supports H2a. The competitive effects are largely negative and significant (most cases $p < 0.001$), suggesting a cannibalistic cross-over effect on a competitor’s subsequent expert blog sentiment. This supports H2b.

Moreover, Table 6 results in brackets that consistently show there is a significant carry-over effect in the expert blog volume of a focal brand on its future expert blog volume ($p < 0.001$) across all brands. This strongly supports H2a for the blog volume metric as well. Also, the competitive effects are largely negative and significant, suggesting a cannibalistic cross-over effect on competitors’ subsequent expert blog volume. Again, this supports H2b for the volume metric, in addition to the sentiment metric of expert blogs.

As illustrated in Figure 2, impulse-response function results suggest that the focal brand HP’s expert blog sentiments and volume have a positive carry-over effect on its own brand (the two charts on the left), but negative cannibalistic effects on the rival brand of Sony (the two charts on the right) over the next two weeks. However, the nonlinear pattern is interesting, as the own brand carry-over is much less volatile and more stabilized over the course of subsequent two weeks. In contrast, the cannibalistic cross-over effects on rival brand are much more volatile with substantial drops in the first two days and another deep drop in day 10 for the expert blog volume. As such, these results seem to indicate that own-brand reinforcing carry-over effects are more stable but rival-brand cannibalistic effects are relatively more volatile and capricious in the industry. More response functions of other brands are presented in Appendix C.
Results on the Asymmetric Relationships with Brand Heterogeneity

We categorize the brands into two groups, leading 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. Apple Mac is on the border due to its fluctuating market share over the research period.17

As Table 5 shows, non-leading brands demonstrate stronger elasticity responses to the change in blog sentiments than leading brands in terms of both magnitude and significance (group mean 0.023 versus 0.013, p < 0.01). The asymmetric economic magnitude is also substantial and interesting. That is, a 1% unexpected increase in expert blog sentiment is associated with a 2.3% lift in own-brand quality perceptions among consumers for non-leading brands, vis-à-vis an only 1.3% lift for leading brands. The group means are significantly different from each other (T-test statistics = 3.41, p = .007; Man-Whitney Test z-ratio = 2.19, p=.007) as summarized in Table 7. As such, these results support H3a.

However, the results do not support H3b. As shown in Table 6, when examining the carry-over effect on subsequent expert blog sentiments, we find that the expert blog sentiments of leading brands show stronger reinforcing carryover effects than non-leading brands (group mean 0.111 versus 0.083 for sentiments p < 0.01). Nevertheless, this finding is not entirely unreasonable and consistent with some prior studies because leading brands tend to have more IT and R&D resources, which may facilitate the virtuous cycle (strong past blog sentiments lead to strong future 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).

Table 5 results in brackets also show that non-leading brands demonstrate stronger elasticity responses to the change in blog sentiments than leading brands in terms of both magnitude and significance (group mean 0.024 versus 0.009, p < 0.01). The group means are significantly different from each other (T-test statistics = 4.29 p = .003; Man-Whitney Test z-ratio = 2.3, p = .006) as summarized in Table 7. Again, this supports H3a. Also, when examining the carry-over effect on subsequent blog volume, the blog volumes of leading brands have insignificant asymmetrical effects than non-leading brands (p = 0.12). Hence our results are largely consistent for the relations between the sentiment and volume metrics of expert blogs.

To test H4a, we summarize the impulse responses of consumer perceptions of each leading brand to the expert blogs of various non-leading brands based on the results in Table 5, and compare them with reverse cases. We find that the cannibalistic relationship between a focal brand’s expert blog sentiments and competing brand perceptions is stronger when the focal brand is non-leading while competitor brands are leading, compared to the reverse case (group mean of means 0.016 versus 0.0088, p < 0.05). The asymmetric economic magnitude is also substantial. That is, a 1% unexpected increase in expert blog sentiment is associated with a 1.6% drop in rival-brand quality perceptions among consumers for non-leading brands, vis-à-vis an only 0.88% drop for leading brands. The group means are significantly different from each other (T-test statistics = 2, p = .027; Man-Whitney Test z-ratio = 1.68, p = .046) as summarized in Table 7. Thus, H4a is supported.

Similarly, we test H4b with the elasticity results in Table 6. We find that the cannibalistic relationship between a focal brand’s current expert blog sentiments and the subsequent expert blog sentiments is stronger when the focal brand is non-leading while the competitor brands are leading, compared to when they are reversed (group mean 0.021 versus 0.016, p < 0.05). That is, a 1% unexpected increase in expert blog sentiment is associated with a 2.1% drop in rival-brand future sentiments for non-leading brands, vis-à-vis an only 1.6% drop for leading brands. The group means are significantly different from each other (T-test statistics = 1.8, p = .041; Man-Whitney Test z-ratio = 1.94, p = .026) as summarized in Table 7. Thus, H4b is supported as well.

We also test H4a and H4b with expert blog volume based on results in brackets in Table 5 and Table 6, respectively. The cannibalistic relationship between a focal brand’s expert blog volume and competing brand perceptions is shown to be significantly asymmetric: it is stronger when the focal brand is non-leading while competitor brands are leading, compared to the reverse (group mean 0.015 versus 0.010, p < 0.05; and T-test statistics = 2.41, p = .0011; Man-Whitney Test z-ratio = 2.3, p = .001). Thus, H4a is supported with blog volume. The cannibalistic relationship between a focal brand’s current...
Table 7. Hypotheses Testing Results

<table>
<thead>
<tr>
<th></th>
<th>Expert Blog Sentiments</th>
<th>Expert Blog Volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1a</td>
<td>Supported</td>
<td>Supported</td>
</tr>
<tr>
<td>H1b</td>
<td>Largely Supported</td>
<td>Largely Supported</td>
</tr>
<tr>
<td>H2a</td>
<td>Supported</td>
<td>Supported</td>
</tr>
<tr>
<td>H2b</td>
<td>Largely Supported</td>
<td>Supported</td>
</tr>
<tr>
<td>H3a</td>
<td>Supported</td>
<td>Supported</td>
</tr>
<tr>
<td>H3b</td>
<td>Not supported</td>
<td>Not supported</td>
</tr>
<tr>
<td>H4a</td>
<td>Supported</td>
<td>Supported</td>
</tr>
<tr>
<td>H4b</td>
<td>Supported</td>
<td>Supported</td>
</tr>
</tbody>
</table>

expert blog volume and the subsequent expert blog volume of competing brands (Table 6) is stronger when the focal brand is non-leading while the competitor brands are leading, compared to the reverse (group mean 0.340 versus 0.171, \( p < 0.01 \) and T-test statistics = 3.23, \( p = 0.002 \); Man-Whitney Test z-ratio = 3.6, \( p = 0.002 \)). Accordingly, H4b is also supported when expert blog volume is of concern.

Although not hypothesized, we also assess whether there are differences in the strength of the cannibalistic relationships (with respect to brand perception and future blog sentiments) when the focal-competitor brands are both leading/non-leading. That is, is there a difference in the extent to which the expert blogs of one brand cannibalizing the others when both the focal and competitor brands are leading, compared to when both are non-leading? We found no significant difference in this regard when both sentiments and volume are concerned, suggesting that the asymmetric cannibalizing effects of expert blogs are only salient when leading and non-leading brands are considered as direct competitors (i.e., non-leading impacting leading, and vice versa).

More Robustness Checks

We test additional VARX models to check the robustness of the results, and summarize the results in Table 8. We first check the result robustness with separate models for expert blog metrics. That is, we run VARX models separately: one with sentiments of expert blogs and another with volume only. The impulse response results are reported in Table D1 in Appendix D, and hypotheses testing results are included in Table 8. All of the hypotheses testing results are consistent with our main model.

In addition to the analyses of brand competition via brand pairs presented above, we also test the VARX model for each focal brand under the industry effect (i.e., via the focal brand versus all other brands, rather than the brand pairs). The impulse response results presented in Table D2 in Appendix D suggest that, again, almost all hypotheses are significantly supported for expert blogs with one exception for H4b, as summarized in Table 8.

Moreover, we conducted additional VAR analyses with positive and negative blog numbers. This is because aggregated normalized measures of how positive the sentiment for a focal brand is across all blogs do not gauge well the volumetric information. Thus, rather than examining sentiment and volume of expert blogs separately, we look at both simultaneously and thus generate positive and negative blog numbers. As summarized in Table 8, these additional VAR tests show that the results are robust and consistently support our key hypotheses.

Conclusion and Implications

With the growing influence of social media platforms, 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
Table 8. Hypotheses Testing Results of Alternative VARX Models

<table>
<thead>
<tr>
<th>Separate VARX Models with either Blog Expert Blog Sentiments or Expert Blog Volume</th>
<th>Focal Brand vs. All other Brands in the Industry (i.e., Industry Spillover Effects) of VARX Models</th>
<th>VARX Model with Positive and Negative Blog Volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1a</td>
<td>Supported</td>
<td>Supported</td>
</tr>
<tr>
<td>H1b</td>
<td>Supported</td>
<td>Supported</td>
</tr>
<tr>
<td>H2a</td>
<td>Supported</td>
<td>Supported</td>
</tr>
<tr>
<td>H2b</td>
<td>Supported</td>
<td>Supported</td>
</tr>
<tr>
<td>H3a</td>
<td>Supported</td>
<td>Supported</td>
</tr>
<tr>
<td>M-W test Z-ratio = 2.51, p = 0.006</td>
<td>M-W test Z-ratio = 2.51, p = 0.006</td>
<td>M-W test Z-ratio = 2.51, p = 0.006</td>
</tr>
<tr>
<td>H3b</td>
<td>Not supported, t = -4.28, p = 0.003</td>
<td>Not Supported</td>
</tr>
<tr>
<td>M-W test Z-ratio = -2.51, p = 0.006</td>
<td>M-W test Z-ratio = -2.51, p = 0.006</td>
<td>M-W test Z-ratio = -2.51, p = 0.006</td>
</tr>
<tr>
<td>H4a</td>
<td>Supported</td>
<td>Supported</td>
</tr>
<tr>
<td>M-W test Z-ratio = 2.51, p = 0.006</td>
<td>M-W test Z-ratio = 2.51, p = 0.006</td>
<td>M-W test Z-ratio = 2.51, p = 0.006</td>
</tr>
<tr>
<td>H4b</td>
<td>Supported</td>
<td>Supported</td>
</tr>
<tr>
<td>M-W test Z-ratio = 1.46, p = 0.072</td>
<td>M-W test Z-ratio = 1.46, p = 0.072</td>
<td>M-W test Z-ratio = 1.46, p = 0.072</td>
</tr>
</tbody>
</table>

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 expert blogs. Prior studies of 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 brands 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 as among the most influential for consumers. Yet, such blogs have not received the extent of firm investment they deserve, as have 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 decisions 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’ brand equity beyond short-term gains such as product sales, and even fewer have considered their strategic implications for firm competition. In this study, we use an extended form of the VARX model to capture the complete dynamics between expert blogs and consumer brand perceptions among major competing brands within the personal computer industry. This paper uses expert blogs data to model consumer brand perception (as reflected in survey data). This is the first study to look at brand perception modeling using expert blogs. The paper also could provide a more holistic understanding of this domain as it evaluates effects among competing brands as well as asymmetric effects among different brands. Our analysis provides new insights to both academic researchers and business practitioners.
undermine that of its competitors. Furthermore, our analysis shows that this competitive influence is dynamic: expert blog sentiments have a reinforcing relationship on themselves dynamically (i.e., carry-over) and a cannibalistic relationship with the subsequent sentiments of its competitors (i.e., cross-over). Thus, social media-based expert blogs can enable brands to achieve competitive advantages, insights that are crucial yet neglected in the literature regarding the potential value of expert blogs for brand positioning and winning consumer hearts and minds over rival brands in the industry.

Second, we quantify the relationship between expert blogs and consumer brand perceptions. While numerous studies on social media have analyzed their influence in online product sales, little is known regarding whether the accumulation of online expert blogs influences firm reputation as captured by general consumer brand perceptions. Brand equity is one of the most important assets that bestow lasting financial and attitudinal value to the firm; more positive WOM leads to repeated purchases and beneficial network effects beyond short-term gains such as product sales. The results from our unique dataset present clear evidence that expert blog sentiments have a significant relationship with consumer perceptions of a brand. We are the first to find that a 1% unexpected increase in Acer’s expert blog sentiment would be associated with a 1.5% lift in its own brand quality as perceived by consumers, thus winning more consumer hearts and minds. In addition, a 1% unexpected increase in Acer’s expert blog sentiment would be associated with a .7% (Toshiba) to 1.5% (Sony Vaio) drop in its rival brand quality, thus undermining consumer hearts and minds of competing brands in the same industry. Also, the effects are asymmetrical across leading versus non-leading brands because a 1% unexpected increase in expert blog sentiment is associated with a 1.6% drop in rival-brand quality perceptions among consumers for non-leading brands, vis-à-vis an only 0.88% drop for leading brands.

Third, our study paves the way for assessing the asymmetric nature of the relationships between expert blogs and consumer brand perceptions by comparing leading brands versus non-leading brands. Contrary to findings in the offline context, we found that the positive relationship of expert blog sentiments with general consumer brand perceptions is stronger when the focal brand is a non-leading versus leading brand. This result provides evidence that non-leading brands may benefit more from social media, and sheds light on why smaller firms appear to be keener on engaging in social media. Yet, there is a catch; 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. Managers may gain a more comprehensive understanding of how their own brand is affected by expert blog sentiments as well as rival-brand responses. Our detailed model of the dynamics between expert blogs and consumer brand perceptions and the moderating effect of brand standing help firms set more realistic expectations about their gains from engaging in social media relative to their rivals. Likewise, when their competitors launch social media initiatives via expert blogs, our model allows firms to better estimate how they may undermine consumer perceptions 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. As firms increasingly engage in such media, consumer reactions to sentiments on these media could be influenced by firm participation (which might be more subjective than expert blogs). In our analysis, we cannot differentiate expert blog sentiments influenced by firm engagement from the sentiments of true, third-party independent assessments. It will be useful for future research to explicitly model firm engagement in social media. Second, our current analysis is limited to 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 (e.g., Schweidel and Moe 2014). Third, this study focuses on the PC industry, which has a number of unique characteristics. In particular, this competitive, dynamic industry is characterized by frequent new product introductions and the difficulty for any single firm to establish a long-term competitive advantage (Bayus et al. 2003). These characteristics of the industry, coupled with its knowledge-intensive nature, make the role of expert blogs in affording consumers the needed timely domain knowledge for assessing product brands and for making purchase decisions particularly salient. Other industries that share largely similar characteristics to the PC industry may benefit from this study, such as mobile phones, computer hardware gadgets, and cosmetic and skincare products, among others. However, some other industries, such as telecommunications and airlines, are relatively stable in their product offerings despite also being highly competitive. Additionally, knowledge required for making brand assessment and purchase decision-making in these industries varies from low (e.g., favoring an airline company in air ticket purchases) to medium (e.g., switching to a new telecommunications service provider when a new major technology is introduced, such as 4G). The role and impor-
tance of expert bloggers in these industries need to be further investigated. Future research may extend our investigation to other industries where the competitive and asymmetric nature of social media could also be pertinent, such as telecommunications, airlines, and mobile phone industries. Finally, while we found a brand’s market standing moderates the relationships between expert blogs and consumer brand perceptions, market standing is unlikely to be the only pertinent brand heterogeneity aspect that matters. As noted, we analyzed other aspects of brand heterogeneity, including age, size, and target market. We did not find any significant moderating effects. Future research may leverage Netzer et al.’s (2012) proposed methodology to employ UGC on social media to derive a comprehensive understanding of the market structure, and analyze whether further insights can be obtained about the asymmetric nature of the influences of expert blogs and, generally, social media across brands.

In conclusion, this study is a small but important step toward deepening our understanding of the relationships between expert blogs and consumer perceptions for not only the focal brand but also the competing brands, as well as their dynamic and asymmetric nature. We hope to provide the impetus for future research on expert blogs in the new social media era.

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References


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# Expert Blogs and Consumer Perceptions of Competing Brands

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## Appendix A

**Summary of Literature on Brand-Related Implications of Social Media and Comparison with this Study**

<table>
<thead>
<tr>
<th>Authors (Year)</th>
<th>Objective</th>
<th>Relevance</th>
<th>Methodology and Data</th>
<th>Single-Firm/Multiple-Firm Focus</th>
<th>Consideration of Expert Blogs</th>
<th>Consideration of Competitive Property</th>
<th>Consideration of Dynamic</th>
<th>Consideration of Asymmetric</th>
<th>Implications</th>
</tr>
</thead>
</table>
| Corstjens and Umblijs (2013) | Develop a set of social media indicators that incorporate social media participant sentiments on a brand and its competitors, and use the indicators to predict sales | Consider social media participants' mentions of brand names as parts of the proposed social media rating parameters | Multivariate time series regression (data from a manufacturer for flat screen TVs and an Internet broadband service provider) | Multiple firms | X | √ (only to a limited extent by considering the mentioning of competing brand names in analyzing social media content) | X | X | - Developed a manageable set of social media rating parameters  
- Social media, whether they are positive, neutral, or negative, have a significant effect on sales  
- The effect of social media on sales depends on product category and industry competition |
<table>
<thead>
<tr>
<th>Authors (Year)</th>
<th>Objective</th>
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<th>Methodology and Data</th>
<th>Single-Firm/ Multiple-Firm Focus</th>
<th>Consideration of Expert Blogs</th>
<th>Consideration of Competitive Property</th>
<th>Consideration of Dynamic</th>
<th>Consideration of Asymmetric</th>
<th>Implications</th>
</tr>
</thead>
</table>
| Goh et al. (2013) | Investigate the impact of social media contents in brand community that are generated by consumers and marketers on consumers' repeated apparel purchase expenditures | Getting customers to repeatedly deal with a firm is an important precursor of brand building | Qualitative and quantitative analysis based on propensity score matching technique with difference-in-differences approach (data comprising social media contents and customers' purchase records from fan pages) | Single firm | X | X | X | X | *Engagement in social media leads to a positive increase in purchase expenditures*
*Social media contents affect consumer purchase behavior through embedded information and persuasion*
*Contents contributed by consumers exhibit a stronger impact than contents contributed by marketers on consumer purchase behavior*

| Laroche et al. (2013) | Examine how the setting up of a social media brand community may bring forth enhanced customers' brand loyalty | Focus on brand loyalty as the outcome | Survey (441 respondents who are members of social media brand communities) | No specific focus on a particular firm | X | X | X | X | *The setting up of a brand community enhances relationships with customers, which in turn promote brand trust and eventually improve brand loyalty*

| Luo et al. (2013) | Examine the effect of social media (blogs and consumer ratings) on firm equity value, and its relative impact compared to conventional online behavioral metrics | A firm's equity value is highly associated with its brand equity | Vector auto-regressive models (a combination of data from Alexa.com, Google Insights for Search, CNet) | Multiple firms | ✓ (not explicitly mentioned, but they considered blogs from sources such as Techcrunch and Engadget where expert blogs are prevalent) | X | X | X | *Social media metrics are leading predictors of firm equity value, more so than conventional online behavioral metrics (e.g., search engines)*
*Social media has a faster predictive value, i.e., shorter “wear-in” time, than conventional online media*

| Naylor et al. (2012) | Investigate whether revealing information of a brand's online supporters would affect its other consumers' perception about the brand | Examine how consumers evaluate a brand | Laboratory experiments (scenario-based, non-field data) | Multiple firms | ✓ | ✓ | X | X | *Demographic information of brand supporters on a social media website will influence a target consumer's brand evaluations and purchase intentions, even when the presence of these supporters is only passively experienced and virtual*
*Framework for brand managers when deciding whether to reveal the identities of their online...*
<table>
<thead>
<tr>
<th>Authors (Year)</th>
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<th>Relevance</th>
<th>Methodology and Data</th>
<th>Single-Firm/ Multiple-Firm Focus</th>
<th>Consideration of Expert Blogs</th>
<th>Consideration of Competitive Property</th>
<th>Consideration of Dynamic</th>
<th>Consideration of Asymmetric</th>
<th>Implications</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rishika et al. (2013)</td>
<td>Examine the effect of customer’s participation in a firm’s social media community on the intensity of relationship between the firm and its customers</td>
<td>Interaction between firms and its customers may cultivate/ enhance brand image</td>
<td>Propensity score matching technique in combination with difference-in-differences analysis</td>
<td>Single firm</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>• There are positive links between customers’ participation in a firm’s social media community and the intensity of customer-firm interactions</td>
</tr>
<tr>
<td>Schweidel and Moe (2014)</td>
<td>Propose metrics to measure brand sentiments based on social media content</td>
<td>Assessment of brand sentiments Analysis of comments posted by consumers (data from various social media platforms)</td>
<td>Multiple firms (in separate industries: an enterprise software firm and a telecommunication firm)</td>
<td>(Although the study considers blogs, it is not stated whether they are expert blogs)</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>• Comments contributed to different social media types vary in the sentiment expressed and their focal topic (i.e., the product and attribute referenced)</td>
</tr>
<tr>
<td>Singh and Sonneburg (2012)</td>
<td>Suggest how firms should engage social media for better brand performances</td>
<td>Ways of improving consumer brand perception are proposed</td>
<td>Qualitative analysis based on an improvisation theater model (data from various social media campaigns)</td>
<td>Multiple firms</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>• Show that social media brand owners do not tell brand stories alone but co-create brand performances in collaboration with the consumers</td>
</tr>
<tr>
<td>This study</td>
<td>Examine the competitive relationships between expert blog and general consumer brand perception, taking into considerations the dynamic and asymmetric nature of the relationships between leading vs. non-leading brands</td>
<td>Focus on general consumer brand perception</td>
<td>Vector auto-regressive model (data combining online expert blogs, and offline general consumer perception of the brands at a daily level)</td>
<td>Multiple firms</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>• Expert blogs on a brand not only have a positive relationship with consumer perception about the brand, but also a negative relationship with that of its competitors</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>• Demonstrate the dynamics in the influences of expert blogs</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>• Highlight the asymmetric nature of the competitive and dynamic influences of expert blogs between leading and a non-leading brands</td>
</tr>
</tbody>
</table>
Appendix B

Data Illustrations

Figure B1. Blog Sentiments Versus General Consumer Brand Perceptions
Figure B1. Blog Sentiments Versus General Consumer Brand Perceptions (Continued)

Figure B2. A “Zoomed In” View of General Consumer Brand Perception and Expert Blog Sentiments of HP (Aug-Oct 2008)
Table B1. Summary Statistics of Monthly Advertising Spending for Each Brand

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>adAcer</td>
<td>904.41</td>
<td>853.56</td>
<td>0</td>
<td>3910.20</td>
</tr>
<tr>
<td>adApple</td>
<td>7164.56</td>
<td>8370.80</td>
<td>0</td>
<td>23663.50</td>
</tr>
<tr>
<td>adCompaq</td>
<td>344.31</td>
<td>618.82</td>
<td>0</td>
<td>2527.10</td>
</tr>
<tr>
<td>adDell</td>
<td>21644.54</td>
<td>12177.05</td>
<td>5175.30</td>
<td>65393.60</td>
</tr>
<tr>
<td>adGateway</td>
<td>64.08</td>
<td>233.62</td>
<td>0</td>
<td>1427.30</td>
</tr>
<tr>
<td>adHp</td>
<td>16105.97</td>
<td>7679.38</td>
<td>3828.50</td>
<td>39194.80</td>
</tr>
<tr>
<td>adLenovo</td>
<td>1888.35</td>
<td>3368.74</td>
<td>1.80</td>
<td>19445.10</td>
</tr>
<tr>
<td>adSony</td>
<td>1367.16</td>
<td>2134.83</td>
<td>0.10</td>
<td>8222.60</td>
</tr>
<tr>
<td>adToshiba</td>
<td>2245.43</td>
<td>1946.97</td>
<td>54.30</td>
<td>9780.40</td>
</tr>
</tbody>
</table>

Note: Based on ad$ponder by Kantar Media, in thousands.

Appendix C
More Impulse Response Functions

Figure C1. Accumulated Response of General Consumer Brand Perception to the Unanticipated Shock in Expert Blog Sentiment (The dotted lines are the confidence bound of ±$\sigma$)
Figure C1. Accumulated Response of General Consumer Brand Perception to the Unanticipated Shock in Expert Blog Sentiment (The dotted lines are the confidence bound of ±σ) (Continued)
Figure C1. Accumulated Response of General Consumer Brand Perception to the Unanticipated Shock in Expert Blog Sentiment (The dotted lines are the confidence bound of ±σ) (Continued)
Appendix D

Robustness Tests

Models 1a: VARX Model with Expert Blog Sentiments Only

\[
\begin{bmatrix}
\text{Brand Perception}_{it} \\
\text{Blog Sentiment}_{it}
\end{bmatrix} = \begin{bmatrix}
\alpha_1 + \delta_i t \\
\alpha_2 + \delta_i t \\
\alpha_3 + \delta_i t
\end{bmatrix} + \sum_{p=1}^{P} \begin{bmatrix}
\phi_{1,1}^{s} \ldots \phi_{1,9}^{s} \\
\phi_{2,1}^{s} \ldots \phi_{2,9}^{s} \\
\phi_{3,1}^{s} \ldots \phi_{3,9}^{s}
\end{bmatrix} \begin{bmatrix}
\text{Brand Perception}_{j-p} \\
\text{Blog Sentiment}_{j-p}
\end{bmatrix} + \begin{bmatrix}
\tau_{1,1} \ldots \tau_{1,10} \\
\tau_{2,1} \ldots \tau_{2,10} \\
\tau_{3,1} \ldots \tau_{3,10}
\end{bmatrix} + \begin{bmatrix}
\epsilon_{11} \\
\epsilon_{12} \\
\epsilon_{13}
\end{bmatrix}
\]

where \( i (i = 1, 2 \ldots 9) \) represents the focal brand, \( t \) represents time, \( p \) is lag length, and \( P \) is maximum lags. \( \alpha_k (k = 1, 2, 3) \) denotes the constant. \( \delta_i, \phi_{1,1}^{s} \tau_{i,s} (k, l = 1, 2, 3, s = 1, 2 \ldots 10) \) are coefficients: \( \delta_i \) reflects the seasonality effect, \( \phi_{1,2}^{s} \) is the coefficient of the expert blog sentiment of brand \( i \) \( p \) days ago on the current brand perception, \( \phi_{1,3}^{s} \) is the coefficient of the expert blog sentiment of brand \( j \) \( p \) days ago on the current focal brand \( i \)'s perception, \( \phi_{2,2}^{s} \) and \( \phi_{3,2}^{s} \) reflect the feedback effect, and \( \phi_{2,3}^{s} \) and \( \phi_{3,3}^{s} \) denote the reinforcing effect of the past blog sentiment on the current one. \( \epsilon_i (k = 1, 2, 3) \) represents the white-noise residual. \( x_{is} (s = 1, 2 \ldots 10) \) represents the exogenous variables.

Models 1b: VARX Model with Expert Blog Volume Only

\[
\begin{bmatrix}
\text{Brand Perception}_{it} \\
\text{Blog Volume}_{it}
\end{bmatrix} = \begin{bmatrix}
\alpha_1 + \delta_i t \\
\alpha_2 + \delta_i t \\
\alpha_3 + \delta_i t
\end{bmatrix} + \sum_{p=1}^{P} \begin{bmatrix}
\phi_{1,1}^{s} \ldots \phi_{1,9}^{s} \\
\phi_{2,1}^{s} \ldots \phi_{2,9}^{s} \\
\phi_{3,1}^{s} \ldots \phi_{3,9}^{s}
\end{bmatrix} \begin{bmatrix}
\text{Brand Perception}_{j-p} \\
\text{Blog Volume}_{j-p}
\end{bmatrix} + \begin{bmatrix}
\tau_{1,1} \ldots \tau_{1,10} \\
\tau_{2,1} \ldots \tau_{2,10} \\
\tau_{3,1} \ldots \tau_{3,10}
\end{bmatrix} + \begin{bmatrix}
\epsilon_{11} \\
\epsilon_{12} \\
\epsilon_{13}
\end{bmatrix}
\]

\( \text{MIS Quarterly Vol. 41 No. 2–Appendices/June 2017} \)
Model 2: VARX Model of Focal Brand Versus All Other Brands in the Industry

\[
\begin{bmatrix}
\text{Brand Perception}_i \\
\text{Blog Sentiment}_i \\
\text{Blog Volume}_i \\
\text{Blog Sentiment}_{i,t} \\
\text{Blog Volume}_{i,t}
\end{bmatrix} = \begin{bmatrix}
\alpha_1 + \delta_1 \tau \\
\alpha_2 + \delta_2 \tau \\
\alpha_3 + \delta_3 \tau \\
\alpha_4 + \delta_4 \tau \\
\alpha_5 + \delta_5 \tau
\end{bmatrix} + \sum_{p=1}^{P} \begin{bmatrix}
\phi_{i,1}^p \\
\phi_{i,2}^p \\
\phi_{i,3}^p \\
\phi_{i,4}^p \\
\phi_{i,5}^p
\end{bmatrix} \begin{bmatrix}
\text{Brand Perception}_{i,t-p} \\
\text{Blog Volume}_{i,t-p} \\
\text{Blog Sentiment}_{i,t-p} \\
\text{Blog Volume}_{i,t-p}
\end{bmatrix} + \begin{bmatrix}
\tau_{1,1} \\
\tau_{2,1} \\
\tau_{3,1} \\
\tau_{4,1} \\
\tau_{5,1}
\end{bmatrix} + \begin{bmatrix}
\varepsilon_{i,1} \\
\varepsilon_{i,2} \\
\varepsilon_{i,3} \\
\varepsilon_{i,4} \\
\varepsilon_{i,5}
\end{bmatrix}
\]

where \( \text{Blog Sentiment}_{i,t} \), \( \text{Blog Volume}_{i,t} \) are the average blog sentiment (blog volume) of all other brands than \( i \) at time \( t \).

Model 3. VARX Model with Positive and Negative Blog Volumes

\[
\begin{bmatrix}
\text{Brand Perception}_i \\
\text{Blog Pos Volume}_i \\
\text{Blog Neg Volume}_i \\
\text{Blog Pos Volume}_{i,t} \\
\text{Blog Neg Volume}_{i,t}
\end{bmatrix} = \begin{bmatrix}
\alpha_1 + \delta_1 \tau \\
\alpha_2 + \delta_2 \tau \\
\alpha_3 + \delta_3 \tau \\
\alpha_4 + \delta_4 \tau \\
\alpha_5 + \delta_5 \tau
\end{bmatrix} + \sum_{p=1}^{P} \begin{bmatrix}
\phi_{i,1}^p \\
\phi_{i,2}^p \\
\phi_{i,3}^p \\
\phi_{i,4}^p \\
\phi_{i,5}^p
\end{bmatrix} \begin{bmatrix}
\text{Brand Perception}_{i,t-p} \\
\text{Blog Pos Volume}_{i,t-p} \\
\text{Blog Neg Volume}_{i,t-p} \\
\text{Blog Pos Volume}_{i,t-p} \\
\text{Blog Neg Volume}_{i,t-p}
\end{bmatrix} + \begin{bmatrix}
\tau_{1,1} \\
\tau_{2,1} \\
\tau_{3,1} \\
\tau_{4,1} \\
\tau_{5,1}
\end{bmatrix} + \begin{bmatrix}
\varepsilon_{i,1} \\
\varepsilon_{i,2} \\
\varepsilon_{i,3} \\
\varepsilon_{i,4} \\
\varepsilon_{i,5}
\end{bmatrix}
\]
Table D1. Additional VARX Model Results with Expert Blog Sentiments and Volume Modeled Separately

### Panel A: Responses of General Consumer Brand Perception to Expert Blog Sentiments

<table>
<thead>
<tr>
<th>Expert Blog Sentiment</th>
<th>ACER</th>
<th>COMPAQ</th>
<th>DELL</th>
<th>GATEWAY</th>
<th>HP</th>
<th>SONY VAIO</th>
<th>TOSHIBA</th>
<th>LENOVO</th>
<th>Apple MAC</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACER</td>
<td>0.044**</td>
<td>-0.063***</td>
<td>-0.032</td>
<td>-0.049**</td>
<td>-0.026*</td>
<td>-0.083**</td>
<td>-0.046*</td>
<td>-0.032</td>
<td>-0.032</td>
</tr>
<tr>
<td>COMPAQ</td>
<td>-0.015**</td>
<td>0.057***</td>
<td>-0.008</td>
<td>-0.026**</td>
<td>-0.017*</td>
<td>-0.021*</td>
<td>-0.023*</td>
<td>-0.014**</td>
<td>-0.015**</td>
</tr>
<tr>
<td>DELL</td>
<td>-0.018**</td>
<td>-0.033**</td>
<td>0.051**</td>
<td>-0.057**</td>
<td>-0.066**</td>
<td>-0.026***</td>
<td>-0.053***</td>
<td>-0.011**</td>
<td>-0.035***</td>
</tr>
<tr>
<td>GATEWAY</td>
<td>-0.012**</td>
<td>-0.033***</td>
<td>-0.008***</td>
<td>0.062**</td>
<td>-0.010*</td>
<td>-0.022*</td>
<td>-0.032**</td>
<td>-0.005***</td>
<td>-0.014*</td>
</tr>
<tr>
<td>HP</td>
<td>-0.021*</td>
<td>-0.034**</td>
<td>-0.017**</td>
<td>-0.070**</td>
<td>0.054**</td>
<td>-0.069**</td>
<td>-0.049*</td>
<td>-0.016*</td>
<td>-0.018**</td>
</tr>
<tr>
<td>SONY VAIO</td>
<td>-0.011**</td>
<td>-0.032*</td>
<td>-0.015*</td>
<td>-0.061***</td>
<td>-0.022**</td>
<td>0.057**</td>
<td>-0.107***</td>
<td>-0.009*</td>
<td>-0.012*</td>
</tr>
<tr>
<td>TOSHIBA</td>
<td>-0.011***</td>
<td>-0.021*</td>
<td>-0.016***</td>
<td>-0.041*</td>
<td>-0.010***</td>
<td>-0.044***</td>
<td>0.068***</td>
<td>-0.021*</td>
<td>-0.018*</td>
</tr>
<tr>
<td>LENOVO</td>
<td>-0.015**</td>
<td>-0.022**</td>
<td>-0.019*</td>
<td>-0.045**</td>
<td>-0.007*</td>
<td>-0.055*</td>
<td>-0.044***</td>
<td>0.052**</td>
<td>-0.019*</td>
</tr>
<tr>
<td>Apple MAC</td>
<td>-0.008***</td>
<td>-0.046*</td>
<td>-0.017*</td>
<td>-0.033***</td>
<td>-0.008**</td>
<td>-0.027**</td>
<td>-0.021*</td>
<td>-0.012**</td>
<td>0.015*</td>
</tr>
</tbody>
</table>

Note: The diagonal estimates are impulse responses of brand perception to blog sentiments of own brand, and the off-diagonal estimates are impulse responses of brand perception to the blog sentiments of rival brands. *p < .10, **p < .05, ***p < .01.

### Panel B: Auto-Regression of Expert Blog Sentiments

<table>
<thead>
<tr>
<th>Expert Blog Sentiment</th>
<th>ACER</th>
<th>COMPAQ</th>
<th>DELL</th>
<th>GATEWAY</th>
<th>HP</th>
<th>SONY VAIO</th>
<th>TOSHIBA</th>
<th>LENOVO</th>
<th>Apple MAC</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACER</td>
<td>0.266***</td>
<td>0.019*</td>
<td>-0.068</td>
<td>-0.031**</td>
<td>-0.015*</td>
<td>-0.022*</td>
<td>-0.014*</td>
<td>-0.082***</td>
<td>-0.025***</td>
</tr>
<tr>
<td>COMPAQ</td>
<td>-0.038*</td>
<td>0.110***</td>
<td>-0.065</td>
<td>-0.023***</td>
<td>-0.011*</td>
<td>-0.031***</td>
<td>-0.018*</td>
<td>-0.030*</td>
<td>-0.003*</td>
</tr>
<tr>
<td>DELL</td>
<td>-0.033***</td>
<td>-0.004</td>
<td>0.231***</td>
<td>-0.035**</td>
<td>-0.059*</td>
<td>-0.017*</td>
<td>-0.058***</td>
<td>-0.014***</td>
<td>-0.052***</td>
</tr>
<tr>
<td>GATEWAY</td>
<td>-0.051***</td>
<td>-0.023***</td>
<td>-0.039*</td>
<td>0.156***</td>
<td>-0.026**</td>
<td>-0.015**</td>
<td>-0.017*</td>
<td>-0.014*</td>
<td>-0.012*</td>
</tr>
<tr>
<td>HP</td>
<td>-0.048***</td>
<td>-0.002*</td>
<td>-0.044***</td>
<td>-0.025*</td>
<td>0.249***</td>
<td>-0.025***</td>
<td>-0.014***</td>
<td>-0.033*</td>
<td>-0.024***</td>
</tr>
<tr>
<td>SONY VAIO</td>
<td>-0.029***</td>
<td>-0.042***</td>
<td>-0.062***</td>
<td>-0.027**</td>
<td>-0.018*</td>
<td>0.170***</td>
<td>-0.033*</td>
<td>-0.048*</td>
<td>-0.016***</td>
</tr>
<tr>
<td>TOSHIBA</td>
<td>-0.043***</td>
<td>-0.010**</td>
<td>-0.059**</td>
<td>-0.023**</td>
<td>-0.046**</td>
<td>-0.008**</td>
<td>0.188***</td>
<td>-0.052***</td>
<td>-0.015*</td>
</tr>
<tr>
<td>LENOVO</td>
<td>-0.034***</td>
<td>-0.014*</td>
<td>-0.065***</td>
<td>-0.034***</td>
<td>-0.048***</td>
<td>-0.057***</td>
<td>-0.066***</td>
<td>0.217***</td>
<td>-0.022*</td>
</tr>
<tr>
<td>Apple MAC</td>
<td>-0.071*</td>
<td>-0.019</td>
<td>-0.068***</td>
<td>-0.099***</td>
<td>-0.070*</td>
<td>-0.022*</td>
<td>-0.055*</td>
<td>-0.039</td>
<td>0.082***</td>
</tr>
</tbody>
</table>

### Panel C: Responses of General Consumer Brand Perception to Expert Blog Volume

<table>
<thead>
<tr>
<th>Expert Blog Volume</th>
<th>ACER</th>
<th>COMPAQ</th>
<th>DELL</th>
<th>GATEWAY</th>
<th>HP</th>
<th>SONY VAIO</th>
<th>TOSHIBA</th>
<th>LENOVO</th>
<th>Apple MAC</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACER</td>
<td>0.023***</td>
<td>-0.018**</td>
<td>-0.007*</td>
<td>-0.024***</td>
<td>-0.012*</td>
<td>-0.018***</td>
<td>-0.007*</td>
<td>-0.004*</td>
<td>-0.016*</td>
</tr>
<tr>
<td>COMPAQ</td>
<td>-0.005*</td>
<td>0.028**</td>
<td>-0.025***</td>
<td>-0.025**</td>
<td>-0.099**</td>
<td>-0.003*</td>
<td>-0.010**</td>
<td>-0.003*</td>
<td>-0.015</td>
</tr>
<tr>
<td>DELL</td>
<td>-0.012*</td>
<td>-0.018*</td>
<td>0.019**</td>
<td>-0.018*</td>
<td>-0.016*</td>
<td>-0.021*</td>
<td>-0.015***</td>
<td>-0.031*</td>
<td>-0.031*</td>
</tr>
<tr>
<td>GATEWAY</td>
<td>-0.017***</td>
<td>-0.008</td>
<td>0.015**</td>
<td>0.024***</td>
<td>-0.010**</td>
<td>0.009**</td>
<td>-0.012*</td>
<td>-0.009*</td>
<td>-0.016</td>
</tr>
<tr>
<td>HP</td>
<td>-0.014*</td>
<td>-0.012</td>
<td>-0.017***</td>
<td>-0.019*</td>
<td>0.021**</td>
<td>-0.013**</td>
<td>-0.023***</td>
<td>-0.011**</td>
<td>-0.019*</td>
</tr>
<tr>
<td>SONY VAIO</td>
<td>-0.012*</td>
<td>-0.008***</td>
<td>0.016**</td>
<td>-0.016***</td>
<td>-0.005</td>
<td>0.023***</td>
<td>-0.018*</td>
<td>-0.012*</td>
<td>-0.009*</td>
</tr>
<tr>
<td>TOSHIBA</td>
<td>-0.011*</td>
<td>-0.009**</td>
<td>-0.008*</td>
<td>-0.007</td>
<td>-0.009</td>
<td>0.014**</td>
<td>0.027**</td>
<td>-0.007**</td>
<td>-0.021**</td>
</tr>
<tr>
<td>LENOVO</td>
<td>-0.004***</td>
<td>-0.015***</td>
<td>-0.008*</td>
<td>-0.018**</td>
<td>-0.012*</td>
<td>0.012*</td>
<td>-0.014**</td>
<td>0.018**</td>
<td>-0.017</td>
</tr>
<tr>
<td>Apple MAC</td>
<td>0.026***</td>
<td>-0.014*</td>
<td>-0.016**</td>
<td>-0.012**</td>
<td>0.024***</td>
<td>-0.011***</td>
<td>-0.021***</td>
<td>-0.008**</td>
<td>0.043*</td>
</tr>
</tbody>
</table>

Note: The diagonal estimates are impulse responses of general consumer brand perception to the expert blog volume of own brand, and the off-diagonal estimates are impulse responses of brand perception to the blog volume of rival brands. *p < .10, **p < .05, ***p < .01.
Table D1. Additional VARX Model Results with Expert Blog Sentiments and Volume Modeled Separately (Continued)

Panel D: Auto-Regression of Expert Blog Volumes

<table>
<thead>
<tr>
<th>Expert Blog Volume</th>
<th>ACER</th>
<th>COMPAQ</th>
<th>DELL</th>
<th>GATEWAY</th>
<th>HP</th>
<th>SONY VAIO</th>
<th>TOSHIBA</th>
<th>LENOVO</th>
<th>Apple MAC</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACER</td>
<td>1.417***</td>
<td>-0.118*</td>
<td>0.729**</td>
<td>0.353***</td>
<td>-0.360**</td>
<td>-1.212</td>
<td>-0.739**</td>
<td>0.589*</td>
<td>3.687</td>
</tr>
<tr>
<td>COMPAQ</td>
<td>-0.066</td>
<td>0.347***</td>
<td>-0.436***</td>
<td>-0.259*</td>
<td>0.262</td>
<td>-0.458</td>
<td>-0.558**</td>
<td>-0.225</td>
<td>-1.700*</td>
</tr>
<tr>
<td>DELL</td>
<td>0.877**</td>
<td>-0.092**</td>
<td>3.525***</td>
<td>-0.369***</td>
<td>1.197***</td>
<td>2.854***</td>
<td>1.065**</td>
<td>-0.646**</td>
<td>-6.993**</td>
</tr>
<tr>
<td>GATEWAY</td>
<td>-0.250*</td>
<td>-0.873**</td>
<td>-0.297*</td>
<td>0.613***</td>
<td>-0.129*</td>
<td>0.946***</td>
<td>-0.462***</td>
<td>-0.240*</td>
<td>-1.209*</td>
</tr>
<tr>
<td>HP</td>
<td>0.556**</td>
<td>0.057**</td>
<td>1.219**</td>
<td>-0.108*</td>
<td>3.658***</td>
<td>-2.212**</td>
<td>0.435**</td>
<td>-0.383**</td>
<td>3.896*</td>
</tr>
<tr>
<td>SONY VAIO</td>
<td>-0.311*</td>
<td>-0.065*</td>
<td>-0.392**</td>
<td>-0.044*</td>
<td>-0.537*</td>
<td>2.735***</td>
<td>0.703***</td>
<td>-0.283</td>
<td>1.401</td>
</tr>
<tr>
<td>TOSHIBA</td>
<td>0.409**</td>
<td>-0.029</td>
<td>-0.247**</td>
<td>-0.138**</td>
<td>-0.113</td>
<td>1.429**</td>
<td>1.634***</td>
<td>-0.177***</td>
<td>3.960*</td>
</tr>
<tr>
<td>LENOVO</td>
<td>0.494</td>
<td>0.141***</td>
<td>-0.360*</td>
<td>0.173*</td>
<td>-1.136*</td>
<td>1.463***</td>
<td>-0.281*</td>
<td>1.243***</td>
<td>-1.719</td>
</tr>
<tr>
<td>Apple MAC</td>
<td>-1.318***</td>
<td>-0.204*</td>
<td>1.830*</td>
<td>-0.474***</td>
<td>-0.221</td>
<td>-2.615***</td>
<td>-1.197**</td>
<td>-0.167**</td>
<td>8.105***</td>
</tr>
</tbody>
</table>

Note: The diagonal shows the carry-over effects of blog volume of own brand, and the off-diagonal estimates are impulse responses to the past blog volume of rival brands. *p < .10, **p < .05, ***p < .01.
### Table D2. Additional VARX Model Robustness Test of the Industry Spillover Effects

#### Panel A: Impulse Response of Brand Perception to Unanticipated Shock in Blog Sentiments (Volume) of its Own Brand and the Industry Spillover Effects

<table>
<thead>
<tr>
<th>Expert Blog Sentiment (Volume)</th>
<th>Brand Perception of Own Brand</th>
<th>Industry Spillover Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACER</td>
<td>0.007*** (<strong>0.010</strong>*)</td>
<td>-0.006** (<strong>-0.007</strong>*)</td>
</tr>
<tr>
<td>DELL</td>
<td>0.009*** (<strong>0.008</strong>*)</td>
<td>-0.008</td>
</tr>
<tr>
<td>HP</td>
<td>0.012** (<strong>0.013</strong>*)</td>
<td>-0.006* (<strong>-0.016</strong>*)</td>
</tr>
<tr>
<td>LENOVO</td>
<td>0.007*** (<strong>0.006</strong>*)</td>
<td>-0.005** (<strong>-0.007</strong>*)</td>
</tr>
<tr>
<td>COMPAQ</td>
<td>0.024*** (<strong>0.017</strong>*)</td>
<td>-0.015*** (<strong>-0.010</strong>*)</td>
</tr>
<tr>
<td>GATEWAY</td>
<td>0.017** (<strong>0.010</strong>*)</td>
<td>-0.010* (<strong>-0.018</strong>*)</td>
</tr>
<tr>
<td>SONY VAIO</td>
<td>0.012** (<strong>0.014</strong>*)</td>
<td>-0.012* (<strong>-0.009</strong>*</td>
</tr>
<tr>
<td>TOSHIBA</td>
<td>0.015** (<strong>0.016</strong>*)</td>
<td>-0.010* (<strong>-0.009</strong>*)</td>
</tr>
<tr>
<td>Apple MAC</td>
<td>0.019** (<strong>0.018</strong>*)</td>
<td>-0.020** (<strong>-0.009</strong>*)</td>
</tr>
</tbody>
</table>

**Panel B: Impulse Response of the Blog Sentiments (Volume) to itself and the Industry Spillover Effects**

<table>
<thead>
<tr>
<th>Expert Blog Sentiment (Volume)</th>
<th>Expert Blog Sentiment (Volume) of Own Brand</th>
<th>Industry Spillover Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACER</td>
<td>0.068*** (<strong>2.160</strong>*)</td>
<td>-0.012** (<strong>-0.178</strong>*)</td>
</tr>
<tr>
<td>DELL</td>
<td>0.103*** (<strong>3.112</strong>*)</td>
<td>-0.010* (<strong>-0.318</strong>*)</td>
</tr>
<tr>
<td>HP</td>
<td>0.107*** (<strong>2.928</strong>*)</td>
<td>-0.008* (<strong>-0.189</strong>*)</td>
</tr>
<tr>
<td>LENOVO</td>
<td>0.072*** (<strong>1.108</strong>*)</td>
<td>-0.007* (<strong>-0.674</strong>*)</td>
</tr>
<tr>
<td>COMPAQ</td>
<td>0.104*** (<strong>0.326</strong>*)</td>
<td>-0.025** (<strong>-0.059</strong>*)</td>
</tr>
<tr>
<td>GATEWAY</td>
<td>0.199*** (<strong>0.682</strong>*)</td>
<td>-0.022** (<strong>-0.168</strong>*)</td>
</tr>
<tr>
<td>SONY VAIO</td>
<td>0.126*** (<strong>3.424</strong>*)</td>
<td>-0.021** (<strong>-0.225</strong>*)</td>
</tr>
<tr>
<td>TOSHIBA</td>
<td>0.105*** (<strong>2.260</strong>*)</td>
<td>-0.013** (<strong>-0.225</strong>*)</td>
</tr>
<tr>
<td>Apple MAC</td>
<td>0.021*** (<strong>13.281</strong>*)</td>
<td>-0.017*** (<strong>-4.741</strong>*)</td>
</tr>
</tbody>
</table>