

# HOW DO CONSUMER BUZZ AND TRAFFIC IN SOCIAL MEDIA MARKETING PREDICT THE VALUE OF THE FIRM?

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## ABSTRACT

*Consumer buzz* in the form of user-generated reviews, recommendations and blogs signals consumer attitude and advocacy can influence firm value. *Web traffic* also affects brand awareness and customer acquisition, and is a predictor of the performance of a firm's stock in the market. The information systems (IS) and accounting literature have treated buzz and traffic separately in studying their relationships with firm performance. We consider the interactions between buzz and traffic, as well as competitive effects that have been overlooked heretofore. To study the relationship between user-initiated web activities and firm performance, we collected a unique data set with metrics for consumer buzz, web traffic and firm value. We employed a *vector autoregression with exogenous variables (VARX) model* that captures the evolution and interdependence between the time-series of dependent variables. This model enables us to examine a series of questions that have been raised but not fully explored to date, such as dynamic effects, interaction effects and market competition effects. Our results support the dynamic relationships of buzz and traffic with firm value, and the related mediation effects of buzz and traffic. They also reveal significant market competition effects, including effects of both a firm's own and its rivals' buzz and traffic. The findings also provide insights for e-commerce managers regarding website design, customer relation management, and how to best respond to competitors' strategic moves.

**Keywords:** Consumer buzz, firm value, online reviews, social media, stock market performance, vector autoregression, web traffic

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Web 2.0 technologies enhance users' web experiences from traffic representing their visits, and from buzz, representing their engagement in information sharing. They are not only readers of the content prepared by the site owners, but also active content-generators to share their personal experiences, provide feedback, and express their sentiments [7]. Jeff Bezos, Amazon.com's CEO, described the power of the online consumer buzz: "If you make customers unhappy in the physical world, they might each tell 6 friends. If you make customers unhappy on the Internet, they can each tell 6,000 friends." *Consumer buzz* refers to user-generated word-of-mouth messages, such as product reviews that are voluntarily posted on a website by consumers about their consumption experiences [10, 28, 70]. *Website traffic* captures consumer attention to the web site, and is recognized as important in many industries. From the business perspective, buzz signals consumer attitudes, such as awareness, affection and faith, toward a brand or company [8, 43]. Thus buzz may drive consumers' future interactions with the company, for example, consumer search and evaluation behaviors, as partly reflected by web *traffic*, and also software adoption [20].

Information systems (IS) and e-commerce researchers have begun to establish the connection between each of these activities and firm performance separately. As a proxy for the number of potential customers, web traffic affects consumer purchase conversions, and therefore may influence firm cash flows [4, 5, 33]. Also, in a forward-looking view, web traffic can create "future growth potential through network effects and customer relationships" [62, p. 20] and affect performance [17, 30, 73]. In parallel research, buzz has been shown as an effective tool to generate cash flows, launch new products, and enhance firm economic value [42].

Besides the connections between buzz or traffic and firm performance, the relationships of buzz and traffic with firm performance are complicated, involving direct and mediated relationships, and time-series relationships of itself and competitor spillover relationships. For example, Li and Hitt [43] showed that the impact of buzz on firm performance varies over time, which suggest examining the time variations of online ratings. Dewan et al. [18] suggested that a portal website manager could optimally control web traffic over time by allocating content and ads to maximize firm value. Yet there is little research that takes an integrative and dynamic approach to address all those questions.

We use a *vector autoregression with exogenous variables (VARX) model* to consider all the intricate relationships among the metrics for buzz, traffic and stock performance. These complicated relationships include the carryover effect of the lagged buzz or traffic on the current stock performance, the cross-effects of buzz in channeling the value of traffic, the reverse effects of stock performance on buzz or traffic, and the competitive effects of rival firms' buzz or traffic on the focal firm's stock performance. For this study, VARX has several advantages over alternative models: it can account for a series of biases, such as endogeneity, autocorrelation, omitted variables and reverse causality. Besides showing the dynamic relationships between the user metrics for buzz and traffic, and firm stock market performance, we especially focus on the competitive effects and the cross-effects.

A study combining buzz, traffic and firm performance metrics has the potential for impacting practice and theory. Today, managers scramble to harness the power of social networking technologies and advances in web applications. While the leading metrics used to measure social success have focused on higher site traffic and referral ratings [3], managers cannot justify investments in social media by using these soft metrics alone. Rather, their decisions hinge upon hard financial results. Managers also want to learn about the relative effects of buzz and traffic on firm performance in order to balance resources for their digital marketing strategies.

We next present background on our research setting, theory and methods, including this study's main hypotheses. Then we test our hypotheses using the VARX estimation model on a panel data from the computer hardware and software industries.

## **RESEARCH BACKGROUND AND FRAMEWORK**

### **Literature**

The prior literature on consumer buzz has mainly focused on its impact on product sales. (See Table 1.) Chevalier and Mayzlin [8] found that consumer review ratings increase firm sales, and Hu et al. [36] showed that they reduce consumer uncertainty, although some consumers prefer to experience some uncertainty with their purchases [48]. Liu [44] showed that movie reviews affect box office revenues. Sene-

cal and Nantel [66] reported that individuals who consult product review recommendations are twice as likely to buy recommended products compared to those who do not. Morgan and Rego [53] suggested that word-of-mouth has a positive association with market share.

#### INSERT TABLE 1 ABOUT HERE

Further, some studies examined the relationships of buzz and firm financial value. Tellis and Johnson [71] suggested that review ratings on product quality influence investor valuation of firm products and, thus, firm stock prices. Echoing this, Luo [45] found that negative word-of-mouth has a harmful effect on cash flows and stock prices, and Luo et al. [46] showed that social media metrics have a stronger relationship with firm value than digital user behavior metrics.

Some contrary findings have been reported too though. Various authors found no relationship between the valence of buzz and product sales [19, 44]. Chintagunta et al. [9] showed that, except for buzz rating, buzz volume and variance have no impact on box office earnings. These mixed results may be due to other consumer metrics, such as traffic, that are correlated with buzz and firm value. To that end, we will examine the relationships in a model that endogenizes buzz, traffic and firm financial performance.

At the early stage of e-commerce, a stream of studies [16, 17, 38, 40, 65] suggested that traffic explains firm value. However, after the dotcom bubble shakeout in March 2000, financial analysts have been cautious with using web traffic to assess firm value [30].

Marketing researchers have been working to restore the credibility of these traffic measures in terms of how they capture the effects on the online sales of the firm. Consumers often visit a firm's website for information related to products or services, and such visits enable consumer learning [37], and enhance the odds of conversion to consumer purchases that lead to higher firm sales [5, 50]. Attracting more site visitors is likely to be associated with greater firm value [4]. This is because the more popular site is, the higher the brand-name recognition to acquire new users, the higher switching costs for registered users, and the lower the average cost per customer will be. There has been little research to re-examine the relationship of traffic and firm value after the dotcom crash, however. A related paper by studied relationships among word-of-mouth, traditional marketing, and new sign-ups [74].

Our research adopts a similar methodology but is unique. First, we focus on the impact of social media and consumer online activities on firm performance in the stock market. Second, we go beyond comparing the effect of social media on firm performance with that of traditional marketing: we also uncover the mediation effects of buzz (traffic) in the relationship of traffic (buzz) with firm performance. Third, we examine the competing effects of other firms' buzz or traffic on the focal firm's financial performance.

### **Framework**

As shown by the conceptual model in Figure 1, our framework integrates the time-varying relationships among endogenous variables of online buzz, site traffic, and firm performance. The endogenous treatment of consumer metrics of site traffic and buzz online implies that they are explained by both past variables of themselves (autoregressive carry-over effects) and past variables of each other (cross-effects from buzz to traffic, or vice versa). We also consider the ramifications of market competition by tracking the relationship between a firm's own and rival buzz (or traffic) and firm performance. Thus, our theoretical framework and the empirical VARX model can account for complex *chained effects* in a cycle, uncovering the full performance relationship of buzz and traffic. The chain is as follows: current site traffic → future buzz → future performance, or current buzz → future traffic → future performance.

INSERT FIGURE 1 ABOUT HERE

We focus on examine the following relationships shown in our conceptual model.

**The Relationship between Online Buzz (Traffic) and Firm Value.** Consumers often visit a firm's website for information search and evaluation, and site traffic reflects consumers' brand interest. Site visits are closely related with customer acquisition through attracting higher user attention and loyalty (more time spent and more pages viewed). By affecting brand awareness and association as well as customer acquisition, the extent of viewership may predict firm performance. In addition, consumer buzz often occurs when consumers share their opinions about a firm's products and services in the market. Online buzz is closely connected to consumer attitudes and advocacy that can boost firm value. Thus, buzz can raise customer attachment, generate higher margins, and expand the customer base, all of which are precursors of customer value and firm performance [16, 29, 62, 72]. Hence, we propose:

- **Hypothesis 1 (The Firm's Consumer Buzz, Web Traffic and Firm Stock Performance Hypothesis).**
  - **Hypothesis 1a:** *Consumer buzz has a positive relationship with firm stock performance.*
  - **Hypothesis 1b:** *Web traffic has a positive relationship with firm stock performance.*

**The Relationship between Rival Buzz (Traffic) and Firm Value.** As content becomes more abundant and available, consumer attention is the limiting factor in the consumption of information. Firms are fighting for attention to their promotional messages, web sites, products and services. An increase in one firm's buzz may overshadow its competitors' word-of-mouth, build consumer attention, and influence their product selection. Likewise, more visits to a firm's website should bring it more attention, while other other firms experience relatively less. With these observations in mind, we assert:

- **Hypothesis 2 (Competitors' Buzz and Traffic Indirect Relationships with Firm Stock Performance).**
  - **Hypothesis 2a:** *The competitors' consumer buzz has an indirect relationship with the focal firm's stock performance.*
  - **Hypothesis 2b:** *The competitors' web traffic has an indirect relationship with the focal firm's stock performance.*

**Indirect Relationship between Performance and Traffic (or Buzz) via Buzz (Traffic).** Our framework suggests that there is a mediating role for traffic (or buzz) in the relationship between buzz (or traffic) and firm performance. The more visitors to the site, the higher the brand awareness and the more potential customers engage in advocating the brands and products. Consumer advocacy may also convince other users to search and evaluate the recommended products. This implies a system of chained effects, which reveal the additional, indirect relationship between traffic (and buzz) and performance via the underlying mechanism of buzz (traffic). In other words, increasing site traffic (buzz) may also boost brand performance via the strength of buzz (traffic). Our framework suggests that the effects of online consumer buzz and web traffic have direct and indirect relationships with firm performance. We posit:

- **Hypothesis 3 (Mediating Effects on Firm Stock Performance).**
  - **Hypothesis 3a:** *The relationship between consumer buzz and firm stock performance is mediated by traffic.*

- **Hypothesis 3b:** *The relationship between web traffic and firm stock performance is mediated by buzz.*

We will develop and analyze VARX models to track the relationships by endogenizing the interactions among the three groups of metrics: traffic, buzz, and performance metrics.

## **DATA**

We focused on computer hardware and software industries. First, firms in this industry frequently introduce new products, resulting in a lot of word-of-mouth data over the research period. Second, customers of computer or software products are more likely to actively engage in online buzz and web visits. We selected nine top firms in the hardware industry (HP, Dell, Acer, Toshiba, Apple, and Sony) and software industry (Microsoft, Adobe, and Corel). These firms were selected because they were publicly-traded, so that their stock price data were readily available. Also their products needed to have enough reviews available. For the computer hardware industry, Dell, HP, Acer, Apple, and Toshiba are the top five PC brands, accounting for about an 80% share of the U.S. market. We supplemented this list with Sony from among the other top PC manufacturers (including Sony, NEC, Gateway, Fujitsu-Siemens). Thus, these firms are representative of the computer hardware industry. Software vendors such as Microsoft, Adobe, and Corel were selected because they dominate the software market. We excluded other vendors such as Sun and Oracle because they are business client-oriented, and their products are not actively reviewed by consumers on CNET.com.

For each of these firms, we collected daily data from multiple databases, such as CNET, Alexa, CRSP and Yahoo Finance from August 1, 2007 to July 31, 2009. We acquired a total of 4,518 usable observations, representing the nine firms over 505 trading days. Only Acer had 478 days. Descriptive statistics are summarized in Table 2.

INSERT TABLE 2 ABOUT HERE

### **Data and Measures for Buzz**

We collected data on consumer buzz from the popular electronic product review website, CNET.com. With 97 million users per month, CNET is a comprehensive data source for consumer reviews on over

300,000 consumer electronics products. CNET lists consumer reviews on the products of most major firms in high-tech markets. CNET appears first in the search results for the keyword “computer reviews” at Google.com. Online reviews from CNET represent consumer sentiment about the targeted companies.

CNET provides two dimensions of consumer buzz: level and volume. The *level*, or *buzz rating*, is measured as the average rating score of consumer reviews of all products of each firm on a daily basis. A higher buzz rating represents greater customer acceptance and advocacy for the firm. *Buzz volume* is measured as the number of consumer reviews for each firm every day. A higher buzz volume indicates greater consumer popularity and resonance with products of the firm.

### **Data and Measure for Traffic**

We designed a software agent in PERL to search CNET.com for all of the products of the nine firms. It parses HTML code on each product review page to collect review dates and ratings, and saves them into a file. The resultant data include 17,486 consumer reviews for 1,939 unique products of the targeted firms.

We also collected traffic data from the widely-adopted web crawler, Alexa.com, for academic and practical research [41, 56, 57]. This data crawling technique with an automated software agent for publicly-available websites has been applied in marketing and IS [11, 26, 27, 57, 76]. We downloaded traffic data for the selected companies on the domain level through the Alexa Web Information Service (AWIS).

We obtained two traffic metrics from Alexa: pageview and reach. We use them to measure web traffic in our model, consistent with the literature [72]. *Pageview* is measured as the number of pages browsed by website visitors. It reflects the total volume of traffic and suggests site popularity [16, 38]. To avoid inflating the pageview measure, Alexa counts multiple views of the same page made by the same user on the same day only once. *Reach* is gauged by the rate of visitors per one million Internet users tracked by Alexa. A website with a greater reach has a larger share of potential consumers. Compared with another commonly-used metric of unique visitors that also measures audience size, reach is typically calculated as a percentage, and thus is more comparable across firms. On average, the pageviews of the firms in our data set range from about 13.3 to 1,593.1 per million users per day, daily reach ranges from 225.5 to 48,681.3 per million users.



## Data and Measure for Firm Value

Prior studies [67, 69] suggest that there are two common measures of firm value: stock returns and risk.<sup>1</sup> *Stock returns* or *abnormal returns* are the returns beyond what is expected on average in the stock market based on the extended Fama-French model [22, 23]. *Risk* or *idiosyncratic risk* refers to the volatility of cash flows, and reflects the risk associated with firm-specific strategies [49, 75].

To measure the expected returns and volatility of the firms' stock prices in the market, we follow the extended Fama-French model:

$$R_{it} - R_{ft} = \beta_{0i} + \beta_{1i}(R_{mt} - R_{ft}) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}MOM_t + e_{it} \quad (1)$$

where  $R_{it}$  is the observed returns for firm  $i$  on day  $t$ ,  $R_{ft}$  is the risk-free rate,  $R_{mt}$  is the market returns,  $SMB_t$  is a size-based risk premium factor,  $HML_t$  is a value-based risk premium factor,  $MOM_t$  represents Carhart's momentum effects [6], and  $e_{it}$  represent the model's residuals. Stock price data were obtained from the Center for Research in Security Prices (CRSP) database and Yahoo Finance. The Fama-French factors ( $R_{mt}$ ,  $R_{ft}$ ,  $HML_t$ ,  $SMB_t$ , and  $MOM_t$ ) data are from Professor Ken French's data library at the Tuck School of Business at Dartmouth College.

We ran the model in Equation 1 for a rolling window of 250 trading days prior to the target day. *Abnormal returns* ( $AR_{it}$ ) were calculated as a difference between observed returns and expected returns:

$$AR_{it} = (R_{it} - R_{ft}) - (\hat{\beta}_{0i} + \hat{\beta}_{1i}(R_{mt} - R_{ft}) + \hat{\beta}_{2i}SMB_t + \hat{\beta}_{3i}HML_t + \hat{\beta}_{4i}MOM_t). \quad (2)$$

*Risk* is the standard deviation of the model residuals. As shown in Table 2, the mean value of firm daily returns ranges from -0.03% to 0.05%, while the mean value of daily stock risk ranges from 1.47 to 3.58.

## Data for Exogenous Control Variables

Following widely-used firm valuation models in finance, accounting, and marketing [25, 49, 72], we use the following variables as exogenous controls: *Quality*, *Revenue*, *FirmSize*, *ROA*, *ITAssets*, *R&D*, *Leverage*, *Liquidity*, *Competitiveness* and *Crisis*. *Quality* is the expert review score reported by the editors of CNET.com. *Revenue* is measured by the revenue variable from the CRSP Stock Databases. *FirmSize* is

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<sup>1</sup> Compared with historical accounting firm performance measures such as sales and profits, firm economic value measures are forward-looking and gauge long-term impacts of customer metrics [36, 67].

measured by total assets of the firm. *ROA* (Return on Assets) measures firm profitability and is calculated as the ratio of a firm's operating income to its book value of total assets. *ITAssets* (IT-related intangible assets) measure the IT investment of those technological firms that can potentially create value in the future, collected from the 10-Q forms of firms' financial reports. *R&D* (R&D expenditure) is measured as research and development expenses scaled by total assets. *Leverage* is the ratio of long-term book debt to total assets. *Liquidity* is the current ratio of a firm (Current Assets/total Assets). *Competitiveness*, or the competition intensity of the industry, is gauged by the Herfindahl industry concentration index  $= \sum_{i=1}^N s_i^2$ ,

where  $s_i$  is the market share of firm  $i$  in an industry with  $N$  firms [34]. In addition, our research period overlaps with the financial crisis and recession that began in December 2007 and ended in June 2009, according to the U.S. National Bureau of Economic Research. We constructed a dummy variable *Crisis* to control for the possible influence of economy fluctuations and financial crisis. We coded *Crisis* = 1 for the time period from December 2007 to June 2009, and *Crisis* = 0 otherwise. To match the quarterly financial variables with our daily endogenous variables, we adopted the VAR-bootstrapping scheme, which uses 5,000 simulated databases to generate the values of those variables for each observed day [32, 45].

## VARX MODEL SPECIFICATION

Leveraging the impulse responses functions and the error term variance decomposition, we use the VARX models [12] to analyze the effects of the focal firm's time-varying interactions among buzz, traffic and firm performance, and also the effects of the competitors' buzz and traffic. This approach has several advantages over alternative models, because it can account for biases, such as endogeneity, auto correlations, omitted variables, and reversed causality. It has been adopted by IS researchers also [1, 39, 46].

Our empirical time-series analysis proceeds in the following steps that are applied to each firm separately [68]. First, we will estimate the dynamic interactions among traffic, buzz, and firm stock performance using the VARX models. The *short-term impact* is the elasticity result in the immediate period (the next day), while the *long-term impact* is the elasticity result in a relatively longer period (20 days) when

the effect stabilizes. Second, we quantify the influence of a firm's own buzz and its competitors' buzz versus traffic metrics on firm value with *generalized forecast error variance decomposition* (GFEVD). Third, we track long-term firm value responses to a one-unit shock from buzz or traffic through *generalized impulse response functions* (GIRF). Finally, we derive the indirect relationship with firm value, and the extent to which traffic explains buzz and vice versa. Table 3 summarizes the steps.

INSERT TABLE 3 ABOUT HERE

**Step 1: Vector-autoregressive Model Specification.** We estimate a VARX model for each firm. The endogenous variables include: the firm stock performance metrics (return and idiosyncratic risk); the consumer buzz metrics (rating and volume); the traffic metrics (pageview and reach); and the competitive variables (rival buzz and rival traffic metrics). We also control for exogenous variables such as product quality, sales, firm size, R&D expenditures, IT-related intangible assets, return on assets, financial leverage, firm liquidity, competitive intensity, and whether there is an economy crisis. The VARX model is

$$\begin{bmatrix} \text{Return}_{it} \\ \text{Risk}_{it} \\ \text{Buzz\_Rating}_{it} \\ \text{Buzz\_Vol}_{it} \\ \text{Pageview}_{it} \\ \text{Reach}_{it} \\ \text{Buzz\_Rating}_{-it} \\ \text{Buzz\_Vol}_{-it} \\ \text{Pageview}_{-it} \\ \text{Reach}_{-it} \end{bmatrix} = \begin{bmatrix} \alpha_1^i + \delta_1^i t \\ \alpha_2^i + \delta_2^i t \\ \alpha_3^i + \delta_3^i t \\ \alpha_4^i + \delta_4^i t \\ \alpha_5^i + \delta_5^i t \\ \alpha_6^i + \delta_6^i t \\ \alpha_7^i + \delta_7^i t \\ \alpha_8^i + \delta_8^i t \\ \alpha_9^i + \delta_9^i t \\ \alpha_{10}^i + \delta_{10}^i t \end{bmatrix} + \sum_{j=1}^J \begin{bmatrix} \phi_{1,1}^{ij} & \dots & \phi_{1,10}^{ij} \\ \phi_{2,1}^{ij} & \dots & \phi_{2,10}^{ij} \\ \phi_{3,1}^{ij} & \dots & \phi_{3,10}^{ij} \\ \phi_{4,1}^{ij} & \dots & \phi_{4,10}^{ij} \\ \phi_{5,1}^{ij} & \dots & \phi_{5,10}^{ij} \\ \phi_{6,1}^{ij} & \dots & \phi_{6,10}^{ij} \\ \phi_{7,1}^{ij} & \dots & \phi_{7,10}^{ij} \\ \phi_{8,1}^{ij} & \dots & \phi_{8,10}^{ij} \\ \phi_{9,1}^{ij} & \dots & \phi_{9,10}^{ij} \\ \phi_{10,1}^{ij} & \dots & \phi_{10,10}^{ij} \end{bmatrix} \begin{bmatrix} \text{Return}_{i,t-j} \\ \text{Risk}_{i,t-j} \\ \text{Buzz\_Rating}_{i,t-j} \\ \text{Buzz\_Vol}_{i,t-j} \\ \text{Pageview}_{i,t-j} \\ \text{Reach}_{i,t-j} \\ \text{Buzz\_Rating}_{-i,t-j} \\ \text{Buzz\_Vol}_{-i,t-j} \\ \text{Pageview}_{-i,t-j} \\ \text{Reach}_{-i,t-j} \end{bmatrix} + \begin{bmatrix} \tau_{1,1}^i & \dots & \tau_{1,10}^i \\ \tau_{2,1}^i & \dots & \tau_{2,10}^i \\ \tau_{3,1}^i & \dots & \tau_{3,10}^i \\ \tau_{4,1}^i & \dots & \tau_{4,10}^i \\ \tau_{5,1}^i & \dots & \tau_{5,10}^i \\ \tau_{6,1}^i & \dots & \tau_{6,10}^i \\ \tau_{7,1}^i & \dots & \tau_{7,10}^i \\ \tau_{8,1}^i & \dots & \tau_{8,10}^i \\ \tau_{9,1}^i & \dots & \tau_{9,10}^i \\ \tau_{10,1}^i & \dots & \tau_{10,10}^i \end{bmatrix} \begin{bmatrix} \text{Quality}_{it} \\ \text{Revenue}_{it} \\ \text{FirmSize}_{it} \\ \text{ROA}_{it} \\ \text{ITAssets}_{it} \\ \text{R \& D}_{it} \\ \text{Leverage}_{it} \\ \text{Liquidity}_{it} \\ \text{Competitiveness}_{it} \\ \text{Crisis}_{it} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t}^i \\ \varepsilon_{2t}^i \\ \varepsilon_{3t}^i \\ \varepsilon_{4t}^i \\ \varepsilon_{5t}^i \\ \varepsilon_{6t}^i \\ \varepsilon_{7t}^i \\ \varepsilon_{8t}^i \\ \varepsilon_{9t}^i \\ \varepsilon_{10t}^i \end{bmatrix} \quad (3)$$

Here, *Return* is firm return, *Risk* is idiosyncratic risk, *Buzz\_Vol* = buzz volume, *i* = the focal firm, *-i* = the competing firms, *t* = time,  $\alpha_k^i$  ( $k = 1, 2, \dots, 10$ ) are constants,  $\delta_k^i$ ,  $\phi_{k,l}^{ij}$ ,  $\tau_{k,l}^i$  ( $k, l = 1, 2, \dots, 10, j = 1, 2, \dots, J$ ) are the coefficients, *j* = lag length, and  $\varepsilon_{kt}^i$  ( $k = 1, 2, \dots, 10$ ) are white-noise residuals. We use natural logarithms of all the traffic metrics (*Pageview<sub>it</sub>*, *Reach<sub>it</sub>*, *Pageview<sub>-it</sub>*, *Reach<sub>-it</sub>*) to remove the scaling effects.

The optimal lag length of the VARX model is 2 according to Schwartz's Bayesian information criterion (SBC). We also tested various issues with the VARX residuals, including multivariate normality and White heteroskedasticity tests. We found no violations of these assumptions at the 95% confidence level.

To show the mediating effect of traffic (buzz) in the relationship between buzz (traffic) and stock performance, we estimate two benchmark VARX models. One was obtained by deleting the four traffic metric equations from the full model, and the other one by deleting the four buzz equations from the full model.

**Step 2: Generalized Forecast Error Variance Decomposition (GFEVD).** Based on VARX parameters, we derive GFEVD estimates to examine the following questions: to what extent do buzz metrics explain the variance of firm value beyond the effect of traffic? And to what degree do traffic metrics affect firm value incremental to buzz? Like  $R^2$ , GFEVD can gauge the relative power over time of shocks initiated by each endogenous variable in explaining firm value, without assuming a causal ordering [55]. GFEVD estimates are derived from:

$$\theta_{ij}(n) = \frac{\sum_{t=0}^n (\psi_{ij}(t))^2}{\sum_{t=0}^n \sum_{j=0}^m (\psi_{ij}(t))^2}, \quad i, j = 1, \dots, m. \quad (3)$$

The parameter  $\psi_{ij}(t)$  is the value of a *generalized impulse response function* (GIRF) following a one-unit shock to variable  $i$  on variable  $j$  at time  $t$  [61]. GFEVD attributes 100% of the forecast error variance in each firm value metric to past values of all endogenous variables. The relative importance of endogenous variables is established based on GFEVD values at 20 days, which reduces sensitivity to short-term fluctuations. To establish the statistical significance of GFEVD estimates ( $p = 0.05$ ), we obtained standard errors using Monte Carlo simulations with 1,000 runs.

We apply GFEVD to the three models: the full VARX model in Equation 3, and the two benchmark models. A comparison of the GFEVD results across these models allows us to assess whether buzz (traffic) metrics yield additional explanatory power in a model that already accounts for endogeneity, dynamic interactions, competition effects, and complex feedback loops.

**Step 3: Generalized Impulse Response Functions (GIRF).** We also inspect the GIRFs based on the estimated parameters of the full VARX model. The impulse response function estimates the net result of a shock to buzz or traffic on firm value relative to their baselines (their expected points in the absence of

the shock). Specifically, we measure cumulative firm value responses to a one-unit shock with the simultaneous-shocking approach [13]. The residual variance-covariance matrix of Equation 3 is used to derive a vector of expected instantaneous shock values.

We derive the following summary statistics from each GIRF: (1) the *immediate relationship with firm value metrics*, which is readily observable and applicable to managers; (2) the *total cumulative relationship*, which combines all effects across dust-settling periods and helps managers scrutinize whether buzz and traffic contribute to firm value in the long run; and (3) the *immediate and cumulative elasticities of buzz to traffic and vice versa*.

## RESULTS

We conducted augmented Dickey-Fuller (ADF) tests to check whether variables are evolving or stationary [13]. As reported in Table 2, the ADF test results range from -2.97 to -30.05, all of which are significant ( $p < 0.05$ ). Thus, the null hypothesis of a unit root can be rejected with a 95% confidence level, suggesting that the series are stationary and do not cointegrate in equilibrium [23]. This led us to estimate VARX models with different levels of the endogenous variables. To report the findings, we averaged results across all firms in each industry [68]. Next we will answer our research questions with the empirical results obtained from our models.

### How Do Buzz and Traffic Predict Firm Value?

For each firm value metric, we summarized the GFEVD results for the full model in Equation 3 and the restricted benchmark models. The results are reported in four different categories: (1) own vs. (2) rival buzz effects and (3) own vs. (4) rival traffic effects. We show the results in Tables 4a and 4b.

#### INSERT TABLES 4A AND 4B

Table 4a suggests that both buzz and traffic add meaningful explanatory power for the firm value metrics, after accounting for the control variables. Buzz accounts for 10.75% (= own 5.94% + rival 4.81%) of the total variation of stock returns, and traffic accounts for 8.54% (= own 4.59% + rival 3.95%) of the

total variation of stock returns. Also, buzz (traffic) metrics account for an 11.49% (9.04%) of the variation in stock idiosyncratic risk.

Table 5 shows the short-term and long-term elasticities of the endogenous variables. Figure 2 visually depicts these dynamic impulse response functions for the firm HP. As shown in Table 5, buzz rating has a significant positive predictive relationship with firm returns for both the short term and long term (2.28 and 28.21 basis points,  $p < 0.05$ ), and weakly significantly reduces long-term risk (-0.236%,  $p < 0.1$ ). So an unexpected increase in buzz rating will predict a surge in daily stock returns by 0.00023 in the short term and by 0.00282 in the long term. Similarly, the buzz volume and traffic metrics have significant relationships with the firm value metrics. For example, pageview has a cumulative elasticity -0.0012 to stock risk. This means a 10% increase in the pageview of a firm's web traffic will cause a future 1.21% reduction in the firm's idiosyncratic risk. Even though these elasticities are in small units, the impulses are large in value terms. For example, all else being equal, increasing buzz alone by 10% will translate into an increase of US\$750 million on average in the firm's market capitalization.

INSERT TABLE 5 AND FIGURE 2 ABOUT HERE

All of the evidence above supports the Firm's Consumer Buzz, Web Traffic and Stock Performance Hypotheses (H1a and H1b), which state that both buzz and traffic are predictors of the firm's stock performance. Buzz explains more variance of the firm value metrics than traffic does, as shown in Table 4a.

### **Competitive Effects**

Competitive or rival effects play an important role in explaining variation of firm value. Compared with the own effects on the firm, its rivals' buzz and traffic account for a similar percentage of the variation in firm value. Table 4a shows that rivals' buzz and traffic account for 4.81% and 3.95% of the total variation of stock returns, and for 4.96% and 3.79% of the total variation in stock risk. The results in Table 4a also suggest that rival buzz explains more variation in the firm value metrics than rival traffic does. Similar results hold for both the hardware and software industries. (See Table 4b.)

As shown in Table 5, rivals' buzz rating has a significant negative predictive relationship with the focal firm's short-term returns (-1.29 basis points,  $p < 0.05$ ), and weakly significant relationships with the

focal firm's long-term returns (-16.61 basis points,  $p < 0.10$ ) and long-term risk (0.10%,  $p < 0.10$ ). Rivals' buzz volume has a significant negative predictive relationship with the focal firm's returns in the short term and long term (-1.90 and -20.69 basis points,  $p < 0.05$ ), and significantly increase the focal firm's short-term risk (0.012%,  $p < 0.05$ ). Rivals' pageview significantly predicts focal firm's short-term returns (-3.25 basis points,  $p < 0.01$ ), short- and long- term risks (0.036% and 0.072%,  $p < 0.05$ ), and weakly significantly predicts focal firm's long-term returns (-7.17 basis points,  $p < 0.10$ ). Rivals' traffic reach predicts the focal firm's short-term returns (-0.94 basis points,  $p < 0.01$ ), and weakly significantly predicts the focal firm's short-term and long-term risks (0.037% and 0.126%,  $p < 0.05$ ). The magnitudes of the elasticities for the rival variables are smaller than those of the firm's own elasticities in absolute terms.

Thus, our results support the Competitors' Buzz and Traffic Indirect Impacts on Firm Stock Performance Hypotheses (H2a and H2b). A firm's stock performance is not only associated with its own buzz and traffic, but also is connected with the competitors' buzz and traffic.

### **Interactions Involving Traffic or Buzz**

The results in Table 4a suggest that both buzz and traffic add additional explanatory power to the firm value metrics compared with the benchmark models. In the buzz-only model, buzz (including own and rivals') explains 8.92% (= own 4.99% + rival 3.93%) of the variation in stock returns. After adding traffic, buzz accounts for 10.75% (= own 5.94% + rivals' 4.81%) of the total variation in stock returns. Similarly, traffic explains 6.53% (= own 3.73% + rivals' 2.83%) of the total variation in stock returns in the traffic-only model. After adding buzz, traffic accounts for 8.54% (= own 4.59% + rivals' 3.95%) of the total variation. This same result also holds for stock risk: buzz (traffic) metrics account for a significant percentage of the variation ranging from 8.81% to 11.49% (6.98% to 9.04%) in stock idiosyncratic risk. The results in Table 4b confirm that our full VARX model outperforms the benchmark counterparts across both the hardware and software industries.

Moreover, our full model outperforms the restricted benchmark models in explaining firm value metrics with an adjusted  $R^2$  of 0.49, larger than 0.41 in the buzz-only model and 0.28 in the traffic-only model. Therefore, the findings not only reveal evidence that both buzz and traffic explain a significant propor-

tion of variance in firm returns, but also confirm the mediating effect of traffic (buzz) in the predictive relationship between buzz (or traffic) and firm value [24]. Thus, the Mediating Effects on Firm Stock Performance Hypotheses (H3a and H3b) are also supported.

The elasticity results for the interactions between buzz and traffic in Table 6, Panel A show that traffic has a significant predictive relationship with buzz. Pageview is positively related to the buzz rating in the short term ( $0.013, p < 0.1$ ) and long term ( $0.073, p < 0.05$ ). It is also positively related to buzz volume in the short term ( $0.193, p < 0.001$ ) and long term ( $0.602, p < 0.1$ ). Table 6, Panel B shows that reach has a weakly significant long-term relationship with buzz rating, and a significant relationship with buzz volume in both the short and long terms ( $0.602$  and  $0.226, p < 0.05$ ). Similarly, the buzz metrics also have a positive association with the traffic metrics, which support the presence of interactions between buzz and traffic. Therefore buzz and traffic have indirect relationships with firm performance via each other.

#### INSERT TABLE 6 ABOUT HERE

Buzz is a traffic-builder, according to the elasticity results shown in Table 6, Panel B. A positive shock in a firm's own buzz rating and volume (and also a negative shock in rival buzz) will help attract more customer interest in the firm and its products and boost search activities and site traffic. These findings show the extent of the interactions between the buzz and traffic metrics. They encourage managers to consider the interactive effects when making marketing decisions.

## CONCLUSION

This research was motivated by the observation that financial impacts of consumer website metrics are increasingly important for research. We investigated the relationship between buzz and traffic, and their predictive power for firm value. Our findings indicate that buzz and traffic explain a substantial portion of the total variance of firm value. This confirms the relevance of consumer word-of-mouth and website visits in contributing to firm value.

The competing firms' buzz and traffic are also associated with firm value. Furthermore, we quantified the indirect impact of traffic channeled by buzz, as well as the indirect impact of buzz via traffic on firm



value. Our results show that buzz and traffic are mutually dependent in the way they affect firm value. They have greater explanatory power together in the full than in the benchmark models with either metric.

### **Theoretical Implications**

This study considers the interactions between consumer buzz and web traffic in their relationships with firm value. We derived the interaction effects between buzz and traffic and used them to estimate their total relationships with firm performance. The competing effects incorporated in our model were significant. We also used a time-series model to examine the relationships over time. Our results suggest to researchers that these effects should be considered when investigating relationships involving social media, web traffic, and firm performance.

After the Internet shakeout, academic researchers and industry practitioners have shied away from using web traffic to predict a firm's stock performance. We re-examined this relationship in a model that includes consumer buzz. We found that web traffic not only has a direct relationship with firm performance but also builds the foundation for buzz to have an impact on firm performance. Our results are applicable to online advertising. Firms invest in online advertising to improve web traffic and improve conversion. Our results suggest that adding the indirect relationship between web traffic and its associated payoffs, mediated by buzz, is helpful for understanding the impacts of online marketing effort.

### **Managerial Implications**

Should managers seek to improve consumer buzz or web traffic to increase firm value? Given the significant direct and indirect value impacts, both metrics should be monitored. Yet, if managers face resource constraints and investment choices, then the answer to this question will depend on a number of different factors, based on our results.

Although some have doubted the usefulness of buzz and site visits [2], our results also provide actionable recommendations to managers. For example, we show that buzz and traffic metrics have predictive value for financial performance. Managers can monitor them to achieve their firm's financial goals. For example, managers should allocate more resources to social media initiatives to boost their firm's buzz scores. Yet, firms should look for deeper engagement beyond driving traffic. The results suggest that buzz

determines a higher percentage of variation in firm value than traffic. Thus, to stand out from the crowd, a firm should improve its buzz to coax consumers to come together to promote the firm's brand.

These results suggest that, even though firms have more control over their own metrics, they cannot ignore the value impacts of competitors' metrics. With reduced search costs and intensified competition due to information technologies, consumers can easily receive word-of-mouth buzz about any firms and switch to competitor websites. Thus, it is crucial to consider rival firms' metrics along with the firm's own metrics to gauge their impact on firm value. Managers should scrutinize and respond to their own and their competitors' consumer metrics. Our results quantify the impacts of competitors' consumer metrics on firm economic value. Rival effects play such an important role that competitors' buzz and traffic metrics may account for comparable percentages of the variations in firm value to the firm's own metrics.

Strategies to manage buzz and traffic for higher firm value are not easy to implement. Not all firms reap benefits of social media for customer relationship and brand reputation management. Many firms that invested in social media have uninstalled the software and have not achieved effective payback [3].

### **Limitations and Future Research**

There are some limitations in the current study that call for future research. First, the VARX model can only show relationships among endogenous variables but cannot assure causality. Future studies involving surveys or experiments should be considered. Second, we chose an industry with rapid new product innovation, in which consumers share online word-of-mouth and make web visits. The results may not apply to all industries though, so it will be worthwhile to test the results with products in other categories.

Third, we propose the application of our results to online marketing to evaluate online advertising costs. This will allow the assessment of direct and indirect buzz-mediated benefits of web traffic generated by online advertising, and a comparison of the total benefits to the costs of online advertising. Finally, there is a need for research to investigate consumer social graphs and new search technologies, such as vertical search, visual integration, and map or picture-based mobile search. Future research can also examine whether higher marketing accountability can be achieved by exploiting synergistic social media innovations (i.e., Twitter search combining buzz and search or Google's social search option).

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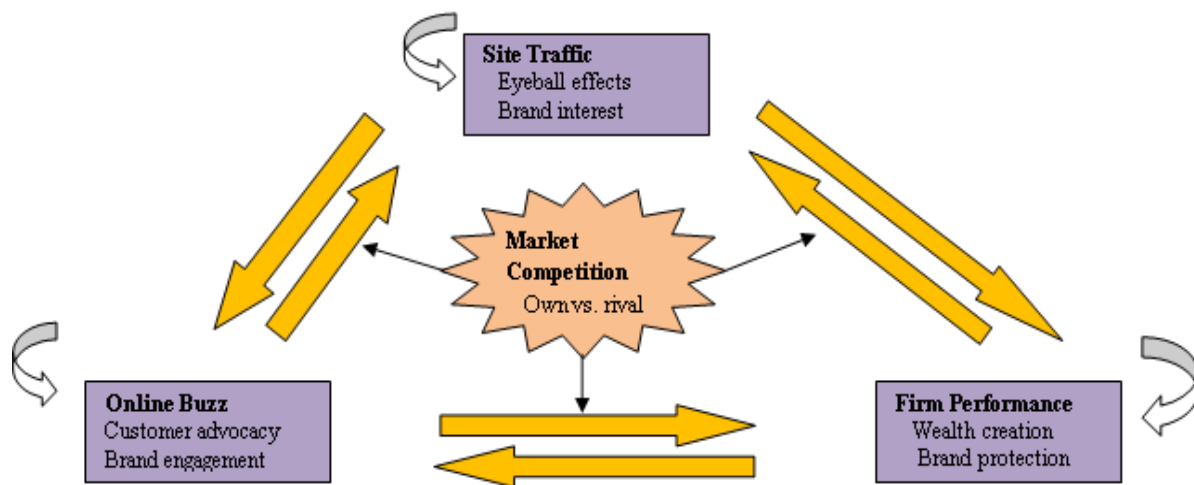
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**Figure 1. Conceptual Framework**



**Note.** As we have noted, the prior research suggests that web traffic leads to positive abnormal returns on the firm's stock price and buzz-driven ratings lead to positive abnormal returns and negative idiosyncratic risk.

Figure 2. Impulse Response Functions over Time (Days)



Note: blue curve: response to own, red curve: response to rival

**Table 1. A Summary of Buzz and Traffic Literature**

<b>Buzz Studies</b>	<b>Key Findings</b>	<b>Traffic Studies</b>	<b>Key Findings</b>
Resnick and Zeckhauser [64]	Buzz rating → (+) Sales (✓)	Trueman et al. [72]	Traffic (Pageview, reach) → Stock prices (✓)
Senecal and Nantel [66]	Buzz rating → (+) Sales (✓)	Jorion and Talmor [38]	Traffic (Pageview, duration, reach) → Stock prices (✓)
Liu [44]	Buzz rating → Sales (x) Buzz volume → (+) Sales (✓)	Demers and Lev [16]	Traffic (reach) → Returns (✓)
Chevalier and Mayzlin [8]	Buzz rating → (+) Sales (✓)	Trueman et al. [73]	Traffic (Pageview, duration, reach) → Returns (✓)
Morgan and Rego [53]	Buzz volume → (+) Market share (✓)	Keating et al. [40]	Traffic (Pageview, reach) → Returns (✓)
Dellarocas et al. [15]	Buzz rating → (+) Sales (✓)	Rajgopal et al. [63]	Traffic (Reach) → Returns (✓)
Tellis and Johnson [71]	Buzz rating → (+) Returns (✓)	Johnson et al. [37]	Traffic (Reach) → (-) Consumer search duration (✓)
Duan et al. [19]	Buzz volume → (+) Sales (✓) Buzz rating → Sales (x) Sales → (+) Buzz volume (✓)	Bucklin and Sismeiro [5]	Traffic (Pageview, duration) → Consumer search (✓)
Luo [45]	Buzz rating → (+) Returns (✓) Buzz rating → (-) Volatilities (✓)	Montgomery et al. [51]	Traffic (Browsing paths) → Consumer purchase conversion (✓)
Chintagunta et al. [9]	Buzz rating → (+) New product launch/adoption (✓) Buzz volume/variation → New product launch/adoption (x)	Moe and Fader [50]	Traffic (Repeat visits) → Consumer purchase conversion (✓)
Moon et al. [52]	Buzz rating → (+) Sales (✓) Sales → (+) Buzz volume (✓)	Park and Fader [58]	Traffic (Visit pattern) → Consumer purchase conversion (✓)
Zhu and Zhang [77]	Buzz rating → (+) Sales (✓) Buzz volume → (+) Sales (✓) Buzz variation → (-) Sales (x)	Ho et al. [34]	Traffic (Pageview) → Consumer buzz (✓)
Luo et al. [46]	Buzz rating → (+) Returns (✓) Buzz volume → (+) Returns (✓)	Luo et al. [46]	Traffic (Pageview, reach) → Returns (✓)

Note: + positively associated; - negative association; ✓ supported; x not supported.



**Table 2. Descriptive Statistics**

<b>Variable Name</b>	<b>Return</b>	<b>Risk</b>	<b>Buzz Rating</b>	<b>Buzz Volume</b>	<b>Pageview</b>	<b>Reach</b>
<b>Acer</b>	-0.02 (2.77) [-22.84]	2.53 (0.27) [-19.56]	2.97 (0.97) [-22.34]	0.69 (1.08) [-2.97]	28.6 (13.51) [-4.59]	1737.51 (919.73) [-5.19]
<b>Adobe</b>	-0.02 (2.04) [-23.23]	1.72 (0.39) [-22.38]	2.90 (0.78) [-22.22]	0.37 (0.65) [-18.72]	416.3 (57.1) [-18.24]	13619.1 (936.8) [-23.46]
<b>Apple</b>	0.05 (2.39) [-22.65]	2.22 (0.26) [-21.58]	3.64 (0.79) [-10.46]	5.60 (4.81) [-10.93]	605.9 (113.1) [-9.18]	11505.0 (1572.4) [-8.94]
<b>Corel</b>	-0.03 (5.46) [-24.01]	3.58 (1.62) [-18.32]	2.95 (0.89) [-22.23]	0.37 (0.64) [-20.14]	16.6 (3.8) [-16.64]	407.2 (61.4) [-22.84]
<b>Dell</b>	-0.01 (2.51) [-22.65]	2.04 (0.62) [-22.45]	2.78 (1.22) [-22.49]	1.53 (1.51) [-5.89]	356.0 (59.0) [-20.82]	5280.8 (565.2) [-26.35]
<b>HP</b>	0.01 (1.78) [-21.96]	1.48 (0.44) [-22.42]	2.75 (1.00) [-21.49]	3.89 (2.35) [-18.51]	270.7 (24.0) [-3.32]	4368.6 (287.2) [-4.06]
<b>Microsoft</b>	-0.01 (1.81) [-9.85]	1.47 (0.40) [-22.32]	3.13 (0.94) [-23.16]	4.76 (3.66) [-7.15]	1593.1 (141.4) [-21.17]	48681.3 (6080.5) [-20.50]
<b>Sony</b>	-0.01 (2.26) [-21.29]	1.93 (0.45) [-21.80]	3.54 (0.68) [-19.29]	6.65 (3.30) [-5.96]	31.7 (6.0) [-19.45]	656.5 (86.8) [-30.05]
<b>Toshiba</b>	0.002 (3.43) [-28.17]	2.81 (0.76) [-22.63]	3.03 (1.02) [-21.95]	0.73 (0.97) [-10.51]	13.3 (2.8) [-3.28]	225.5 (38.8) [-5.59]

**Note:** (1) Entries are means across all brands of the firm, with standard deviation marked with parentheses and augmented Dickey Fuller (ADF) test statistics denoted by brackets. (2) The ADF test statistics are based on the first-difference of Risk, and natural log of Pageview and Reach. (3) The ADF test statistic critical value: -2.89 (5% level confidence interval).

**Table 3. Overview of Analysis Steps**

Method	Econometrics Studies	Marketing Studies	Research Questions
1. Unit root tests			
Augmented Dickey-Fuller (ADF)	Enders [21]	Dekimpe and Hanssens [12, 14]	Is each variable (mean/trend) stationary or evolving (unit root)?
Structural break test	Perron [60]		Is there a structural break in the time series of each variable?
2. Vector autoregressive model with exogenous variables (VARX)	Lutkepohl [47]	Nijs et al. [55]	How do key variables interact, accounting for exogenous factors?
3. Variance decomposition Forecast error variance decomposition	Enders [21]	Pauwels [59]	Do consumer buzz and user online traffic metrics matter in explaining firm performance over time...?
Generalized forecast error variance decomposition (GFEVD)	Pesaran and Shin [61]		... without imposing a causal ordering on the variables?
4. Impulse response functions			
Generalized Impulse Response Functions (GIRF)	Enders [21]	Nijs et al. [54]	What are the net performance responses of the consumer buzz and user online traffic impulses?
5. Indirect effects	--	--	To what extent do buzz (traffic) metrics affect firm value indirectly via the channel of traffic (buzz) over time?

**Table 4a. Variance of Firm Performance Variables Explained by Buzz and Traffic from GFEVD**

Response to	Return			Risk		
	Buzz only	Traffic only	Full Model	Buzz only	Traffic only	Full Model
Own...						
<i>Buzz Rating</i>	2.53%		2.99%	2.35%		3.23%
<i>Buzz Volume</i>	2.46%		2.95%	2.52%		3.30%
<b>Total Own Buzz</b>	<b>4.99%</b>		<b>5.94%</b>	<b>4.87%</b>		<b>6.53%</b>
Rivals ...						
<i>Buzz Rating</i>	2.12%		2.37%	1.69%		2.36%
<i>Buzz Volume</i>	1.81%		2.44%	2.25%		2.60%
<b>Total Rivals' Buzz</b>	<b>3.93%</b>		<b>4.81%</b>	<b>3.94%</b>		<b>4.96%</b>
Own...						
<i>Pageview</i>		2.20%	2.43%	2.01%		2.87%
<i>Reach</i>		1.53%	2.16%	1.97%		2.48%
<b>Total Own Traffic</b>		<b>3.73%</b>	<b>4.59%</b>	<b>3.98%</b>		<b>5.25%</b>
Rivals ...						
<i>Pageview</i>		1.51%	2.08%	1.45%		1.67%
<i>Reach</i>		1.29%	1.87%	1.55%		2.12%
<b>Total Rivals' Traffic</b>		<b>2.80%</b>	<b>3.95%</b>	<b>3.00%</b>		<b>3.79%</b>
Test	own Buzz > rival Buzz > own Traffic > rival Traffic			own Buzz > own Traffic > rival Buzz > rival Traffic		
Kruskal-Wallis' statistic	40.82***			54.09***		
F statistic	14.76***			62.88***		

\*\*\*  $p < 0.01$

**Table 4b. Variance of Firm Performance Variables Explained by Buzz and Traffic from GFEVD**

Response to	Computer Hardware Industry						Computer Software Industry					
	Return			Risk			Return			Risk		
	<i>Buzz only</i>	<i>Traffic only</i>	Full Model	<i>Buzz only</i>	<i>Traffic only</i>	Full Model	<i>Buzz only</i>	<i>Traffic only</i>	Full Model	<i>Buzz only</i>	<i>Traffic only</i>	Full Model
Own...												
<i>Buzz Rating</i>	2.87%		3.51%	2.62%		3.90%	1.85%		1.96%	1.82%		1.90%
<i>Buzz Volume</i>	2.57%		3.18%	2.96%		3.88%	2.24%		2.49%	1.64%		2.13%
<b>Total Own Buzz</b>	<b>5.44%</b>		<b>6.69%</b>	<b>5.58%</b>		<b>7.78%</b>	<b>3.09%</b>		<b>4.45%</b>	<b>3.46%</b>		<b>4.03%</b>
Rivals ...												
<i>Buzz Rating</i>	2.81%		3.12%	2.05%		2.99%	0.72%		0.87%	0.97%		1.11%
<i>Buzz Volume</i>	2.01%		2.77%	2.85%		2.35%	1.43%		1.77%	1.07%		1.11%
<b>Total Rivals' Buzz</b>	<b>4.82%</b>		<b>5.89%</b>	<b>4.90%</b>		<b>6.34%</b>	<b>2.15%</b>		<b>2.64%</b>	<b>2.04%</b>		<b>2.22%</b>
Own...												
<i>Pageview</i>		2.51%	2.74%		2.18%	3.17%		1.58%	2.16%		1.66%	2.26%
<i>Reach</i>		1.94%	2.46%		2.14%	2.89%		0.70%	1.54%		1.64%	1.65%
<b>Total Own Traffic</b>		<b>4.45%</b>	<b>5.20%</b>		<b>4.32%</b>	<b>6.06%</b>		<b>2.28%</b>	<b>3.70%</b>		<b>3.30%</b>	<b>3.91%</b>
Rivals ...												
<i>Pageview</i>		2.15%	2.56%		2.10%	2.31%		0.23%	0.77%		0.16%	0.39%
<i>Reach</i>		1.64%	2.10%		1.85%	2.37%		0.58%	1.40%		0.97%	1.61%
<b>Total Rivals' Traffic</b>		<b>3.79%</b>	<b>4.66%</b>		<b>3.95%</b>	<b>4.68%</b>		<b>0.81%</b>	<b>2.17%</b>		<b>1.13%</b>	<b>2.00%</b>

**Table 5. Firm Economic Value Elasticity Relative to Buzz and Traffic**

	<b>Response to</b>	<b>Return</b>	<b>Risk</b>
<b>Immediate</b>			
Own	<i>Buzz Rating</i>	2.28**	-0.019
	<i>Buzz Volume</i>	2.79*	-0.026**
	<b>Total Own Buzz</b>		
	<i>Pageview</i>	5.01**	-0.057***
	<i>Reach</i>	7.73***	-0.076***
<b>Total Own Traffic</b>			
Rivals'	<i>Buzz Rating</i>	-1.29**	0.016
	<i>Buzz Volume</i>	-1.90***	0.012**
	<b>Total Rival Buzz</b>		
	<i>Pageview</i>	-3.25***	0.036**
	<i>Reach</i>	-0.94***	0.037*
<b>Total Rivals' Traffic</b>			
<b>Cumulative</b>			
Own	<i>Buzz Rating</i>	28.21***	-0.236*
	<i>Buzz Volume</i>	23.98***	-0.200***
	<b>Total Own Buzz</b>		
	<i>Pageview</i>	8.69	-0.121**
	<i>Reach</i>	12.82*	-0.200*
<b>Total Own Traffic</b>			
Rivals'	<i>Buzz Rating</i>	-16.61*	0.100*
	<i>Buzz Volume</i>	-20.69**	0.032
	<b>Total Rivals' Buzz</b>		
	<i>Pageview</i>	-7.17*	0.072**
	<i>Reach</i>	-5.04	0.126*
<b>Total Rivals' Traffic</b>			

**Note:** The coefficients of returns are in basis points (1 basis point = one hundredth of a percentage). The coefficients of risk are percentage values. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

**Table 6. Dynamic Interactions between Consumer Buzz and User Online Traffic Metrics**

<b>Panel A: Elasticities of Buzz to Traffic</b>					
<b>Impact on consumer buzz metric of a shock to ...</b>		<b>Buzz Rating</b>		<b>Buzz Volume</b>	
		<b>Immediate</b>	<b>Cumulative</b>	<b>Immediate</b>	<b>Cumulative</b>
Own	<i>Pageview</i>	0.013*	0.073**	0.193***	0.602*
	<i>Reach</i>	-0.016	-0.027*	0.102**	0.226***
Rivals'	<i>Rivals' Pageview</i>	0.007*	0.055**	-0.015***	-0.021**
	<i>Rivals' Reach</i>	-0.006*	-0.011	-0.057**	-0.292*

<b>Panel B: Elasticities of Traffic to Buzz</b>					
<b>Impact on user traffic metric of a shock to ...</b>		<b>Pageview</b>		<b>Reach</b>	
		<b>Immediate</b>	<b>Cumulative</b>	<b>Immediate</b>	<b>Cumulative</b>
Own	<i>Buzz Rating</i>	0.002***	0.034***	0.004*	0.029***
	<i>Buzz Volume</i>	0.007***	0.041***	0.004***	0.077***
Rivals'	<i>Rivals' Buzz Rating</i>	-0.001*	-0.013**	-0.002	-0.024**
	<i>Rivals' Buzz Volume</i>	-0.004***	-0.041**	-0.003***	-0.031***

**Note:** \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

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